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Original Research

Does Renewable Energy Development Reduce Regional CO_2 Emissions? A Case Study in China

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Abstract

This study uses an autoregressive distributed lag model to empirically examine the effect of renewable energy development on CO_2 emissions in Gansu Province, a renewable-energy-rich region in China. Our findings reveal a statistically significant positive relationship between renewable energy generation and CO_2 emissions. This implies that renewable energy development does not necessarily lead to a reduction in regional CO_2 emissions. We further analyze the underlying causes of this phenomenon and make corresponding policy recommendations. Additional results demonstrate positive and statistically significant associations between CO_2 emissions and total electricity generation, nonrenewable energy generation, economic growth, and export trade. By contrast, foreign direct investment exhibits a statistically significant negative correlation.

Keywords: autoregressive distributed lag model, renewable energy, CO_2 emissions, economic growth, nonrenewable energy

Introduction

Climate change poses an existential risk to the world [1]. Large-scale renewable energy development is widely recognized as an effective way to reduce carbon emissions and enhance environmental quality. Existing studies broadly confirm that renewable energy reduces CO_2 emissions at national and provincial scales [2, 3]. However, research on localized effects remains limited, especially in regions with abundant renewable energy resources, such as solar, wind, hydropower, and biomass. In China, renewable energy resources are concentrated in the northeast, north, and northwest, while energy demand is primarily located in the eastern coastal areas. This spatial mismatch, combined with regional differences in industrial structure, geography, and climate, complicates the direct connection between renewable energy generation and local emission reduction. Consequently, a question arises: Can the development and use of clean energy sources, such as photovoltaic and wind energy, in renewable-resource-rich regions help reduce CO_2 emissions in those areas?

To clarify the mechanism by which renewable energy development affects regional CO_2 emissions, this study focuses on Gansu Province, a region in China where renewable energy has been developed and utilized on a large scale. Using the autoregressive distributed lag (ARDL) method, we analyze the relationship between renewable energy generation and CO_2 emissions in the area. Surprisingly, the results indicate that as

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renewable energy development and use increase, CO_2 emissions do not decrease but exhibit a simultaneous upward trend.

Literature Review

Literature on CO_2 Emissions Reduced by Renewable Energy

Numerous studies have examined the effect of renewable energy on CO_2 emissions from a consumption perspective, consistently finding that greater renewable energy use reduces CO_2 emissions. For example, Destek and Sinha [2] and Chiu and Zhang [4] observed reduced emissions in OECD countries, attributable to renewable energy consumption. Dilanchiev et al. [5] confirmed that renewable energy reduces CO_2 emissions in the South Caucasus region. Al-Zubairi et al. [6] reported a negative correlation between renewable energy and CO_2 emissions in Arab countries. Sun et al. [7] found significant reductions in emissions in MENA countries associated with the use of renewable energy. Purwono et al. [8] concluded that adopting renewable energy mitigates CO_2 emissions across 77 countries. Rahman et al. [9] identified substantial reductions in emissions across 22 developed countries through the use of renewable energy. Similarly, conclusions were reached by Mahmood [10], Su et al. [11], Wang et al. [12], and Huang et al. [13], among many others.

The aforementioned research was mainly conducted using panel data. Some case-based studies have also confirmed that increasing renewable energy consumption can significantly reduce CO_2 emissions. For example, Naimoglu and Akal [14] and Somoye [15] found that renewable energy reduced CO_2 emissions in Turkey. Studies of Azerbaijan [16], Vietnam [17], Kenya [18], and Saudi Arabia [19-21] reached similar conclusions.

In China, Ahmad et al. [22] found that renewable power generation, particularly hydropower, significantly mitigated long-term CO_2 emissions. Chen et al. [23] confirmed that renewable energy negatively affects CO_2 emissions. Liu et al. [24] found that renewable energy consumption significantly reduced China's ecological footprint. These findings were largely based on national-level research, with limited regional investigations.

Literature on Renewable Energy Failing to Reduce CO_2 Emissions

The studies mentioned above found that higher renewable energy consumption helps reduce CO_2 emissions. Some other findings, however, suggest that renewable energy consumption does not necessarily lead to decreased CO_2 emissions. Using panel data, Altın [25] analyzed the effect of renewable energy consumption on carbon emissions in G7 countries and found a positive relationship between the two. Banday and Aneja [26] identified a significant causal relationship between renewable energy and CO_2 emissions in France, Italy, Japan, and the UK, but no such relationship in Canada, Germany, and the US. Studying 97 countries, Chen et al. [1] found that per capita growth in renewable energy consumption had a significantly negative effect on per capita CO_2 emissions once a threshold of renewable energy use had been exceeded. Liu et al. [27], meanwhile, found that renewable energy development increased CO_2 emissions in five East Asian countries. In case-specific studies, Rahman and Vu [28] found that renewable energy consumption had no statistically significant effect on CO_2 emissions in Canada, whereas it did in Australia.

Research Gaps

Most studies have analyzed renewable energy's effects on carbon emissions from a consumption perspective. Fewer studies, however, have investigated renewable energy's effect on emissions from the production side. Additionally, studies have not given sufficient attention to how renewable energy production in clean-energy-rich regions affects local CO_2 emissions. Furthermore, the separation between the production and consumption locations of renewable electricity has not been thoroughly examined for its effects on regional emissions.

To determine whether renewable energy development reduces regional emissions in renewable-resource-rich areas, this study uses an ARDL model to examine the effect of renewable electricity generation on CO_2 emissions from a production perspective in Gansu Province, located in northwestern China. We select Gansu mainly because, by the end of 2020, it had an installed solar power capacity of 9.82 million kilowatts, with total power generation capacity reaching 56.2 million kilowatts. Renewable energy sources, mainly wind and solar power, accounted for 41.9% of the installed capacity, making them the province's largest power source. Clean energy, including hydropower, accounted for 59% of total installed capacity. Additionally, a significant amount of electricity is transmitted to eastern China. Thus, studying Gansu Province can offer a new perspective for analyzing the effects of new-energy development and use on regional carbon emissions.

Material and Method

This study's research process is divided into four stages, as detailed in Fig. 1.

Data Preparation

Dong et al. [29] used ARDL to analyze the relationship between per capita CO_2 emissions, gross national product, and fossil, nuclear, and renewable energy consumption. He et al. [30] found a long-term

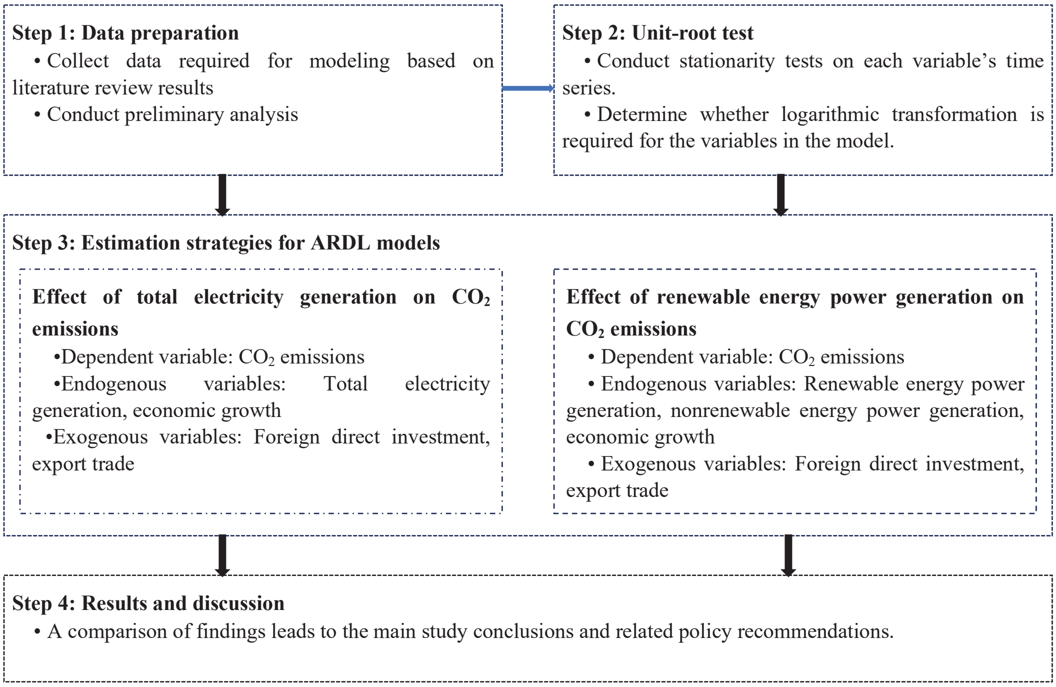

Fig. 1. Technical roadmap of this study's methods.

equilibrium between renewable energy consumption, economic growth, oil rents, natural resources, and greenhouse gas emissions. While those studies identified long-term cointegration relationships within their models, they did not account for the effects of foreign trade and foreign direct investment (FDI) on CO_2 emissions.

Some studies, however, have also confirmed long-term equilibrium relationships among foreign trade, FDI, CO_2 emissions, and economic growth. Chen et al. [23], for instance, identified a long-term equilibrium relationship involving per capita CO_2 emissions, gross national product, renewable energy, nonrenewable energy, and foreign trade. Similarly, Ahmad et al. [22] found long-term cointegration relationships among FDI, renewable energy generation, hydroelectricity, non-hydroelectricity generation, and per capita CO_2 emissions.

Based on prior research and data availability, CO_2 emissions, regional GDP, total power generation, thermal power generation, renewable power generation, export trade, and foreign direct investment (FDI) were selected to construct an autoregressive distributed lag (ARDL) model. Notably, although digital economic development has been shown to significantly reduce carbon emissions in some studies, its impact was excluded from this analysis owing to data unavailability and the region's relatively underdeveloped economic conditions. The dataset spans the period 1997-2020. CO_2 emission data were obtained from the China Carbon Accounting Database (CEADs) （https://www.ceads.net.cn/data/province）, which provides provincial-level emission inventories compiled based on the IPCC sectoral approach. These inventories primarily cover direct carbon emissions reported under Scope 1. They do not include indirect carbon emissions from Scope 2 or

Table 1. Explanation of variables and descriptive statistics.

Variable	Explanation	Unit	Mean	Maximum	Minimum	Std. dev. Deviation
CO_2	Carbon dioxide emissions	10^6 ton	110.114	175.870	50.313	45.884
GDP	Regional gross domestic product	10^8 yuan	3978.083	8979.700	793.600	2798.129
Telec	Total electricity generation	10^8 kWh	818.345	1762.350	246.420	486.480
Therm	Thermal power generation	10^8 kWh	487.446	875.950	144.920	248.633
Re	Renewable energy generation	10^8 kWh	330.898	886.400	82.510	249.957
Expo	Export trade turnover	10^8 yuan	127.194	361.058	20.754	97.499
FDI	Foreign direct investment	US $$10^4$	7312.833	13521.000	2044.000	3544.601

Scope 3 sources. Data on GDP, total power generation, thermal power generation, renewable power generation, export trade, and FDI were obtained from the National Bureau of Statistics (https://www.stats.gov.cn/sj). Table 1 provides variable definitions and descriptive statistics.

Fig. 2a) presents point-line graphs of carbon emissions, GDP, Telec, Therm, and RE, showing that these variables exhibit similar change trends. By contrast, Fig. 2b) shows that fluctuations in carbon emissions differ distinctly from those of Expo or FDI. We can preliminarily infer that there may be cointegration relationships between carbon emissions and GDP, Telec, Therm, and RE. The likelihood of cointegration among carbon emissions, Expo, and FDI is relatively low.

Unit-Root Test

Although ARDL models do not require all variables to share the same cointegration order, many ARDL applications assume that each variable must remain within a single integer order [23]. Therefore, conducting a unit-root test is essential for evaluating the stability of the time series associated with the variables. The most commonly used unit-root test methods – augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) – are effective for this purpose. The null hypothesis of the ADF and PP tests is that the time series has a unit root. Consequently, if the null hypothesis is rejected, we can conclude that the time series is stationary. By contrast, the KPSS test operates under the null of stationarity; rejecting it indicates the presence of a unit root. To facilitate a robust comparison of results, we perform unit-root tests on both the original and log-transformed time series of the variables using these established methods.

ARDL Estimation

ARDL combines autoregressive and distributed lag models and can examine both short- and long-term relationships between variables, thereby comprehensively capturing dynamic interactions; it has been widely applied in the field of energy economics [31-34]. Compared with other cointegration tests, ARDL performs better with small samples, giving it an advantage when dealing with limited data. We therefore use an ARDL model to analyze the effects of renewable and nonrenewable energy sources on CO_2 emissions.

Although ARDL can facilitate the examination of cointegration relationships among variables, model parameter specification – such as the treatment of deterministic trends and the identification of fixed regressors – remains critical in empirical applications. Previous studies typically included FDI, export trade, and other variables in the cointegration test, whereas we treat FDI and Expo as exogenous. This implies that the cointegration test equation should not include the FDI and export trade variables. The main reason is that FDI and export trade are driven primarily by foreign investment or commodity demand, so treating them as exogenous variables is more reasonable. Fig. 3 also provides graphical evidence that this estimation strategy is reasonable. We examine the long-term equilibrium between total power generation, renewable power generation, nonrenewable power generation, and CO_2 emissions by establishing ARDL models as follows:

$$CO_{2t} = a_0 + a_1 t + \sum_{i=1}^{p} a_{2i} CO_{t-i} + \sum_{i=0}^{q_1} a_{3i} GDP_{t-i} + \sum_{i=0}^{q_2} a_{4i} Telec_{t-i} + a_5 Expo + a_6 FDI + \varepsilon_{1t} \quad (1)$$

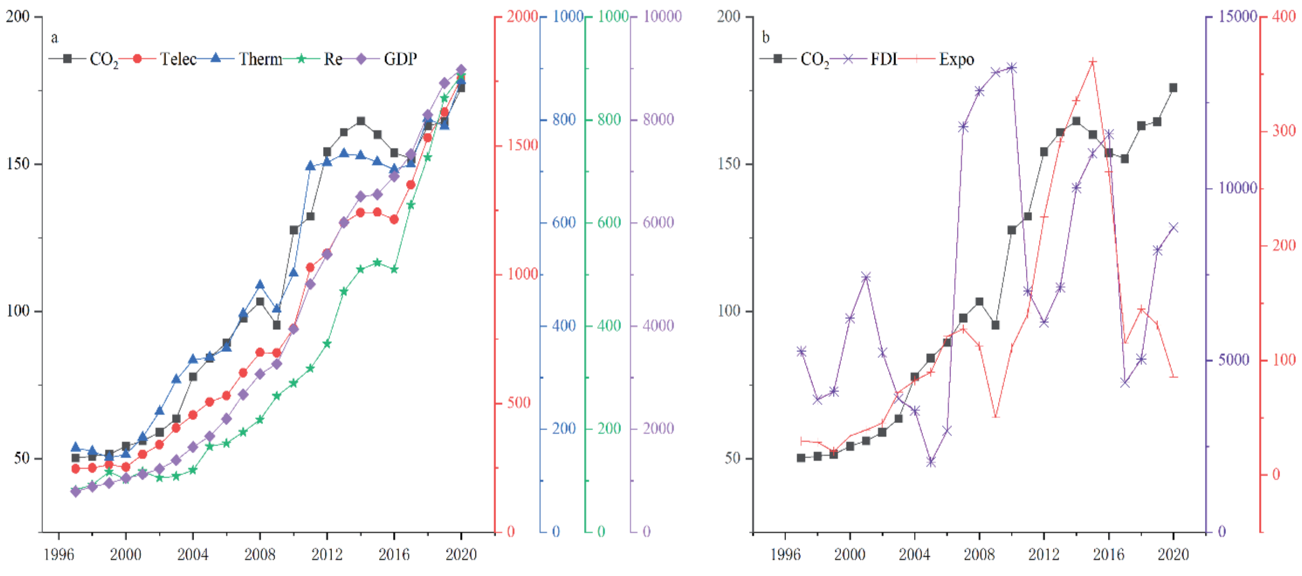

Fig. 2. Line chart of carbon emissions and explanatory variables. a) endogenous variables; b) exogenous variables.

$$CO_{2t} = b_0 + b_1 t + \sum_{i=1}^{p} b_{2i} CO_{t-i} + \sum_{i=0}^{q_1} b_{3i} GDP_{t-i} + \sum_{i=0}^{q_2} b_{4i} Therm_{t-i} + \sum_{i=0}^{q_3} b_{5i} Re_{t-i} + b_6 Expo + b_7 FDI + \varepsilon_{2t} \tag{2}$$

where p and q_i represent the order of the lag, and a_I, $a_{i,j}$, b_i, and $b_{i,j}$ denote the parameters that need to be estimated. Using Eq. (1), a relational equation can be formulated, as presented in Eq. (3), to verify the existence of long-term equilibrium among CO_2 emissions, regional GDP, and total electricity generation. Similarly, based on Eq. (2), Eq. (4) can be formulated, which tests for a long-term equilibrium relationship between CO_2 emissions, regional GDP, renewable energy generation, and nonrenewable energy generation:

$$\Delta CO_{2t} = a_0 + a_1 t + \sum_{i=1}^{p} a_{2i} \Delta CO_{2,t-i} + \sum_{i=0}^{q_1} a_{3i} \Delta GDP_{t-i} + \sum_{i=0}^{q_2} a_{4i} \Delta Telec_{t-i} + \lambda_1 GDP_{t-1} + \lambda_2 Telec_{t-1} + a_5 Expo + a_6 FDI + \varepsilon_{1t} \tag{3}$$

$$\Delta CO_{2t} = b_0 + b_1 t + \sum_{i=1}^{p} b_{2i} \Delta CO_{2,t-i} + \sum_{i=0}^{q_1} b_{3i} \Delta GDP_{t-i} + \sum_{i=0}^{q_2} b_{4i} \Delta Therm_{t-i} + \sum_{i=0}^{q_3} b_{5i} \Delta RE_{t-i} + \delta_1 GDP_{t-1} + \delta_2 Therm_{t-1} + \delta_3 Re_{t-1} + b_6 Expo + b_7 FDI + \varepsilon_{1t} \tag{4}$$

where Δ represents the first-order lag difference operator, and λ_i and δ_i are the parameters to be estimated.

The bounds testing approach uses an F-statistic to test for long-term cointegration in ARDL models. Pesaran et al. [35] provided two critical value bounds: one for I(0) and another for I(1). The test follows a three-part decision rule: a cointegration relationship is confirmed if the F-statistic exceeds the upper bound. There is no cointegration if the F-statistic is less than the lower bound, and it is inconclusive for intermediate values. This method eliminates the need for preliminary unit-root testing, making it robust to mixed-order integration scenarios.

In addition, based on Eqs. (3) and (4), the short-term dynamic equation for characterizing CO_2 emissions, regional GDP, and total electricity generation can be obtained, as shown in Eq. (5). Similarly, Eq. (6) is the short-term dynamic relationship for CO_2 emissions, regional GDP, renewable energy generation, and nonrenewable energy generation:

$$\Delta CO_{2t} = a_0 + a_1 t + \sum_{i=1}^{p} a_{2i} \Delta CO_{2,t-i} + \sum_{i=0}^{q_1} a_{3i} \Delta GDP_{t-i} + \sum_{i=0}^{q_2} a_{4i} \Delta Telec_{t-i} + a_5 Expo + a_6 FDI + \lambda_1 ECT_{t-1} + \varepsilon_{1t} \tag{5}$$

$$\Delta CO_{2t} = b_0 + b_1 t + \sum_{i=1}^{p} b_{2i} \Delta CO_{2,t-i} + \sum_{i=0}^{q_1} b_{3i} \Delta GDP_{t-i} + \sum_{i=0}^{q_2} b_{4i} \Delta Therm_{t-i} + \sum_{i=0}^{q_3} b_{5i} \Delta RE_{t-i} + b_6 Expo + b_7 FDI + \lambda_2 ECT_{t-1} + \varepsilon_{2t} \tag{6}$$

where ECT_{t-1} represents the error-correction term that illustrates the short-term dynamic adjustment relationship.

The lag order of the model is determined using the Akaike Information Criterion (AIC). Given the sample size, the maximum lag order for both explanatory and response variables is set to 2, with the optimal model automatically selected by the program.

Robustness Test

To verify the model's robustness, multiple methods are employed, including residual normality tests, Cumulative Sum Control Chart (CUSUM) tests, and lag order adjustments. Furthermore, the estimation results are compared with those from a vector error correction model (VECM).

Results

Unit-Root Test Results

Panel A of Table 2 presents the results of the stationary tests using ADF, PP, and KPSS for both the original and log-transformed series. For the original series, despite varying outcomes from the ADF, PP, and KPSS tests, there is general support for the hypothesis that a unit root exists in the time series of CO_2 emissions, GDP, Telec, and Re, suggesting instability in these series. Conversely, ADF and KPSS indicate that the export trade and FDI series are stationary. Analyzing the log-transformed time series, the ADF, PP, and KPSS tests indicate the presence of a unit root, except for the Expo series.

Panel B of Table 2 shows the results of the unit-root test after a first-order difference for both the original and log-transformed series. The ADF, PP, and KPSS results show that the original and log-transformed CO_2, Telec, Therm, Re, Expo, and FDI series are stationary after a first-order difference, and the GDP series is not stationary even after a first-order difference. However, when using the breakpoint unit-root test, we find that the logarithm of GDP is also stationary after a first-order difference. Therefore, log-transformed time series are more suitable for ARDL modeling.

ARDL Model Estimation Results

Effect of Total Electricity Generation on CO_2 Emissions

We estimate four ARDL models to determine whether our proposed Eq. (1) is reliable and accurate. Based on R^2 and AIC criteria, it is feasible to determine which variables to include in the model and to choose the best model. The optimal lag order is also determined based on the AIC for each model. In addition, we use a heteroskedasticity- and autocorrelation-consistent covariance matrix to ensure robustness in the presence of heteroskedasticity or serial correlation. Table 3 presents the diagnostic statistics of the four ARDL models.

Model T1 includes only CO_2, GDP, and total electricity generation. Its R^2 and adjusted R^2 are 0.9889 and 0.9852, respectively, indicating a perfect model fit. This suggests that nearly 98% of the changes in CO_2 can be explained by fluctuations in GDP and total electricity generation. When sequentially adding the export trade variable (Model T2) and the time-trend term (Model T3) to the model, R^2 and the adjusted R^2 continue to increase. The respective coefficient estimates are both statistically significant, implying that it is appropriate to include the export trade and time trend terms in the model. Including FDI in the model again (Model T4) increases R^2 and adjusted R^2 slightly, but the coefficients remain statistically insignificant. AIC can be used to select the optimal model. Since Model T4 has the lowest AIC statistic, it is considered the optimal model.

We can derive a long-term conditional error-correction equation for each model and use bounds testing to investigate the long-term cointegration relationship among CO_2 emissions, GDP, and total electricity generation. Table 4 shows the bounds test outcomes and the long-term cointegration relationship.

Initially, when the model excludes export trade, FDI, and the time trend, the F-bounds statistic is not significant at the 5% level, indicating the absence of a long-term cointegration relationship among CO_2 emissions, GDP, and total electricity generation. However, upon sequentially incorporating export trade, time trend, and FDI into the model, the F-bounds statistic for all models becomes statistically significant at the 1% level. This suggests that neglecting key explanatory variables can lead to substantial bias in coefficient estimates. Furthermore, the F-bounds statistic exhibits a progressive increase trend as export trade, time term, and FDI enter the model. This provides increasingly strong evidence of a long-term cointegration relationship among GDP, CO_2, and total electricity generation.

Table 5 presents the results of the short-term error-correction model. As export trade, time trend, and FDI

Table 2. Stationarity test results.

Panel A	Original form			Logarithmic form Logarithmic			
	ADF	PP	KPSS		ADF	PP	KPSS
CO_2	−2.0727	−2.2425	0.0879	LnCO_2	−1.2922	−1.4523	0.13364*
GDP	−2.4704	−2.1680	0.1728**	LnGDP	0.1617	−0.4499	0.1346*
Telec	−1.7857	−1.8149	0.1811**	LnTelec	−1.6664	−1.8269	0.1304*
Therm	−2.6005	−2.6956	0.0874	LnTherm	−1.2304	−1.2304	0.1542**
Re	0.5062	0.6163	0.1903**	LnRe	−5.7438***	−2.3622	0.1209*
Expo	−3.3107*	−1.333	0.0951	LnExpo	−1.0265	−1.0265	0.1382*
FDI	−3.1811*	−2.3630	0.0879	LnFDI	−3.4239**	−2.6506	0.0786
Panel B	First-order differencing for the original series			First-order differencing on logarithmic series			
	ADF	PP	KPSS		ADF	PP	KPSS
CO_2	−4.8464***	−4.8500***	0.0923	LnCO_2	−5.1049***	−5.1090***	0.1040
GDP	−2.6499	−2.5394	0.1238*	LnGDP	−2.5218	−2.4384	0.1630**
Telec	−3.9099**	−3.8430**	0.0581	LnTelec	−4.1749**	−4.2076**	0.0996
Therm	−4.2519**	−4.2996**	0.0946	LnTherm	−4.5278***	−5.0151***	0.0829
Re	−3.6699*	−5.3405**	0.1556**	LnRe	−2.0828	−5.3686***	0.0626
Expo	−3.2408*	−3.2057*	0.0960	LnExpo	−4.5707***	−4.5708***	0.0888
FDI	−3.8926**	−3.8913**	0.0616	LnFDI	−3.9560**	−4.0904**	0.0908

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively; Ln stands for logarithmic transformation.

Table 3. Goodness-of-fit statistics for each model (total electricity generation).

	Model T1	Model T2	Model T3	Model T4
Selected model	ARDL (2,1,0)	ARDL (1,2,2)	ARDL (1,0,2)	ARDL (1,0,2)
AIC	−2.8451	−3.2191	−3.6307	−3.6738
R^2	0.9887	0.9941	0.9957	0.9962
Adjusted R^2	0.9852	0.9904	0.9936	0.9939

Table 4. Long-term cointegration and bounds test results for each ARDL model (total electricity generation).

	Model T1	Model T2	Model T3	Model T4
LnGDP	-	-	0.3577** (0.1357)	0.4346** (0.1569)
LnGDP (−1)	−0.2921 (0.9519)	0.3348** (0.1306)	-	-
LnTelec (−1)	1.0622 (1.1858)	0.2041 (0.1595)	0.5949*** (0.1885)	0.5286** (0.2192)
C	−0.1325 (0.4126)	0.1868** (0.0639)	−1.8345*** (0.4095)	−1.8380*** (0.3896)
F-bounds	2.2509	6.8497***	19.3701***	20.8973***

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively; Ln stands for logarithmic transformation.

Table 5. Results of the short-term error-correction equation for each model (total electricity generation).

	Model T1	Model T2	Model T3	Model T4
$DLnCO_2$	−0.3827** (0.1413)	-	-	-
DLnGDP	0.9307*** (0.1178)	0.7283*** (0.2163)	-	-
DLnGDP (−1)	-	0.6665** (0.3046)	-	-
DLnTelec	-	−0.1022 (0.1449)	0.3749*** (0.0942)	0.2947*** (0.0918)
DLnTelec (−1)	-	−0.3085* (0.1688)	−0.3045** (0.1074)	−0.3192*** (0.1042)
Ln(Expo)	-	0.1088*** (0.0199)	0.0715*** (0.0083)	0.0688*** (0.0132)
TIME	-	-	−0.0576*** (0.0058)	−0.0615*** (0.0059)
Ln(FDI)	-	-	-	−0.0251*** (0.0057)
Coint (−1)	−0.3003*** (0.0919)	−1.3549*** (0.2333)	−1.5022*** (0.1549)	−1.5258*** (0.1504)
AIC	−3.1178	−3.4918	−3.9035	−3.9465
R^2	0.6759	0.8302	0.8768	0.8923
Adjusted R^2	0.6418	0.7772	0.8478	0.8586

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively; Ln stands for logarithmic transformation.

are entered sequentially into the model, the AIC statistic consistently decreases, while the R2 and adjusted R2 increase successively, reaffirming that Model 4 is optimal for exploring the nexus among CO2, GDP, and total electricity generation. In stark contrast to the results of the long-term conditional error equation, the FDI coefficient in the short-term error-correction equation is statistically significant. Thus, including these variables in the model is more appropriate, as their exclusion could lead to omitted-variable bias. Based on the results of Model T4, the main conclusions are as follows:

1) A long-term cointegration relationship exists between CO_2 emissions, GDP, and total electricity generation. Electricity generation is the main factor influencing CO_2 emissions; specifically, a 1% rise in electricity production results in a 0.529% increase in CO_2 emissions, demonstrating that power-system expansion is the main driver of rising emissions in the region. GDP also contributes to this increase, with a 1% rise corresponding to a 0.435% increase in CO_2 emissions.

2) The coefficient of the time-trend term is −0.065, indicating that CO_2 emissions are decreasing at an annual rate of 0.065%. The yearly decrease in CO_2 emissions indicates improved environmental quality in the area.

3) Export trade has a positive and statistically significant effect on CO_2 emissions. A 1% rise in export trade volume results in a 0.069% increase in CO_2 emissions.

4) FDI has a negative and statistically significant effect on CO_2 emissions. A 1% increase in FDI leads to a 0.025% reduction in CO_2 emissions, supporting the pollution halo hypothesis.

5) The coefficient of Coint (−1) is −1.5258. This suggests that the system is moving back toward long-term equilibrium at a rate of 1.53% per year.

In the short term, total power generation increases by 1% in the current period, accompanied by a 0.2947% rise in CO_2 emissions. With a one-period lag, total power generation again increases by 1%, but CO_2 emissions decrease by 0.3192% in the short term. This suggests that the effect of total power generation on CO_2 emissions exhibits short-term volatility, characterized by an initial increase followed by a subsequent decrease.

Effect of Renewable Electricity Generation on CO_2 Emissions

Total electricity generation comprises both renewable and nonrenewable electricity generation. While Model T4 shows that carbon emissions rise with increased total electricity generation, the effect of renewable energy development on regional carbon emissions remains unclear. To address this, we break total power generation into renewable and nonrenewable components and use

Table 6. Goodness-of-fit statistics for each model (renewable electricity generation).

	Model R1	Model R2	Model R3	Model R4
Selected model	ARDL (2, 1, 0, 0)	ARDL (1, 2, 2, 0)	ARDL (1, 0, 2, 0)	ARDL (1, 2, 2, 1)
AIC	−2.8125	−3.4543	−3.6795	−3.7855
R^2	0.9893	0.9957	0.9963	0.9977
Adjusted R^2	0.9851	0.9925	0.9940	0.9946

Table 7. Long-term cointegration and bounds test results for each ARDL model (renewable electricity generation).

	Model R1	Model R2	Model R3	Model R4
LnGDP (−1)	−0.2491 (0.1354)	0.3411*** (0.0978)	0.3394** (0.1354)	0.4266*** (0.0910)
LnTherm	0.7093 (0.1203)	-	-	-
LnTherm (−1)	-	0.1652 (0.1020)	0.2972** (0.1203)	0.2609** (0.0891)
LnRe	0.3160 (0.0558)	0.0329 (0.0762)	0.1862*** (0.0558)	-
LnRe (−1)	-	-	-	0.1074** (0.0464)
C	0.4715 (0.3067)	0.3000 (0.1420)	−0.8718** (0.3067)	−0.7552*** (0.2257)
F-bounds	1.9698	8.2396***	17.1882***	12.7016***

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively; Ln stands for logarithmic transformation.

the same modeling approach to analyze the effect of renewable energy on carbon emissions. Table 6 provides diagnostic statistics for each ARDL model.

Based on R^2, adjusted R^2, and AIC, we can be confident that Model R4 is the best. Table 7 presents the results of the long-term cointegration relationships and bounds test for each model. The F-bounds statistic is statistically significant at the 1% level in Model R4, suggesting that long-term cointegration exists between CO_2 emissions and GDP, renewable energy generation, and thermal generation.

Table 8 shows the results of the short-term error-correction model for renewable energy generation. We observe that short-term fluctuations in economic growth and thermal power generation significantly affect short-term carbon emissions. Conversely, short-term changes in renewable energy generation do not have a statistically significant effect on carbon emissions. Decomposing total electricity generation into renewable and thermal power components reveals that the coefficient for export trade increases from 0.068 to 0.0979, the time trend term's coefficient shifts from −0.0615 to −0.0428, the FDI coefficient rises from −0.0251 to −0.0338, and the cointegration coefficient changes from −1.5258 to −1.7680. Based on the results of Model R4, the main conclusions are as follows:

1) A long-term cointegration relationship exists between CO_2 emissions, GDP, nonrenewable energy generation, and renewable energy generation. A 1% increase in GDP corresponds to a 0.427% rise in CO_2 emissions, indicating that regional GDP growth significantly contributes to CO_2 emissions. This finding is consistent with [23] and [29], which examined China at the national level.

2) Nonrenewable energy generation results in increased CO_2 emissions. A 1% rise in nonrenewable energy production leads to a 0.261% increase in CO_2 emissions. Numerous studies [22, 23, 29, 36, 37] have confirmed that nonrenewable energy sources are the main drivers of increases in CO_2 emissions.

3) This study's most crucial finding indicates that renewable energy generation has a positive and statistically significant effect on CO_2 emissions, with a significance level of 1%. A 1% increase in renewable energy generation leads to a 0.107% increase in CO_2 emissions. This effect is smaller than that of nonrenewable energy generation, and it contradicts the conclusions of most existing studies [38-40]. Khezri et al. [41] indicated that in economically complex countries, as renewable electricity generation increases, CO_2 emissions also rise. Other studies have identified a threshold effect in renewable energy's influence on CO_2 emissions [1, 42] – its significance only becomes

Table 8. Short-term error-correction equation results for each model (renewable electricity generation).

	Model R1	Model R2	Model R3	Model R4
$DLnCO_2$ (−1)	−0.3873** (0.1371)	-	-	-
DLnGDP	0.8070*** (0.1113)	0.3341 (0.2223)	-	0.2173 (0.1969)
DLnGDP (−1)	-	0.7932** (0.2672)	-	0.6724** (0.2310)
DLnTherm	-	0.0924 (0.0827)	0.2508*** (0.0590)	0.2708*** (0.0779)
DLnTherm (−1)	-	−0.3405*** (0.0996)	−0.1815** (0.0610)	−0.3946*** (0.0867)
DLnRe	-	-	-	0.0585 (0.0667)
LnExpo	-	0.1227*** (0.0174)	0.0923*** (0.0086)	0.0979*** (0.0158)
TIME	-	-	−0.0401*** (0.0038)	−0.0428*** (0.0048)
LnFDI	-	-	-	−0.0338*** (0.0059)
Coint (−1)	−0.3644*** (0.1032)	−1.5540*** (0.2097)	−1.4862*** (0.1402)	−1.7680*** (0.1846)
AIC	−3.1761	−3.8179	−4.0432	−4.1491
R^2	0.6942	0.8775	0.8929	0.9330
Adjusted R^2	0.6621	0.8392	0.8677	0.8918

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively; Ln stands for logarithmic transformation.

apparent when renewable energy consumption exceeds the threshold.

4) Export trade has a positive and statistically significant effect on CO_2 emissions, with a 1% rise in export trade leading to a 0.098% increase in CO_2 emissions. Earlier studies yielded mixed results regarding the link between export trade and carbon emissions.

5) FDI has a negative and statistically significant effect on CO_2 emissions. A 1% rise in FDI is linked to a 0.034% reduction in CO_2 emissions, supporting the pollution halo hypothesis to some extent.

6) The coefficient of Coint (−1) is −1.7680, suggesting that the system returns to long-term equilibrium at a rate of 176.80% per year.

In the short term, economic growth exhibits a lagged effect on carbon emissions, with an insignificant immediate effect but a significant effect after one period. Nonrenewable energy generation significantly increases current carbon emissions, though its effect declines significantly after one period. By contrast, renewable energy does not have a statistically significant short-term effect on carbon emissions.

Robustness Test Results

Fig. 3 shows the fitting results for models T4 and R4. It is evident that the T4 model, based on total power generation, and the R4 model, which decomposes total power generation into thermal and renewable energy components, both achieve an excellent fit. However, the residual fluctuation range of Model R4 is smaller. The normality test of residuals does not reject the hypothesis that the residual sequence is normally distributed; the CUSUM and CUSUM of squares tests indicate that the estimated coefficients of the models are stable over the sample period.

To verify the robustness of the results, by altering the lag orders of T4 and R4, Table 9 presents the statistical results of the long-term cointegration relationship. We can see that, regardless of the lag order of the dependent variable or the explanatory variables, the conclusion that nonrenewable and renewable electricity generation are positively correlated with carbon emissions holds.

To further analyze the potential influence relationships among various economic variables, we again employ the vector error-correction model specified in Eq. (4). Table 10 and Fig. 4 present the Granger causality test results.

We can see that there is a unidirectional causal relationship from GDP and renewable electricity generation to carbon emissions, rather than a bidirectional causal relationship between nonrenewable electricity generation and carbon emissions. Additionally, there are unidirectional causal relationships from renewable electricity generation to GDP and from nonrenewable electricity generation to GDP. There exists a bidirectional causal relationship between nonrenewable energy and carbon emissions.

These causal relationships reveal that an increase in renewable electricity generation requires a synchronous increase in nonrenewable electricity generation. This is primarily because the intermittent and volatile characteristics of renewable energy affect the safe and stable operation of the power grid. To ensure grid operational stability, it is necessary to increase installed thermal power capacity in a synchronous manner, and this growth will inevitably lead to a synchronous increase in regional carbon emissions. Although the statistical results show a unidirectional causal relationship between renewable electricity generation and GDP, the p-value of the statistic from GDP to renewable electricity generation is 0.1084, which is very close to the 10% significance level. Therefore, we can consider that GDP development also promotes renewable energy development.

Discussion

This study finds a significant positive relationship between renewable energy generation and regional carbon emissions. The main reasons for this phenomenon are as follows:

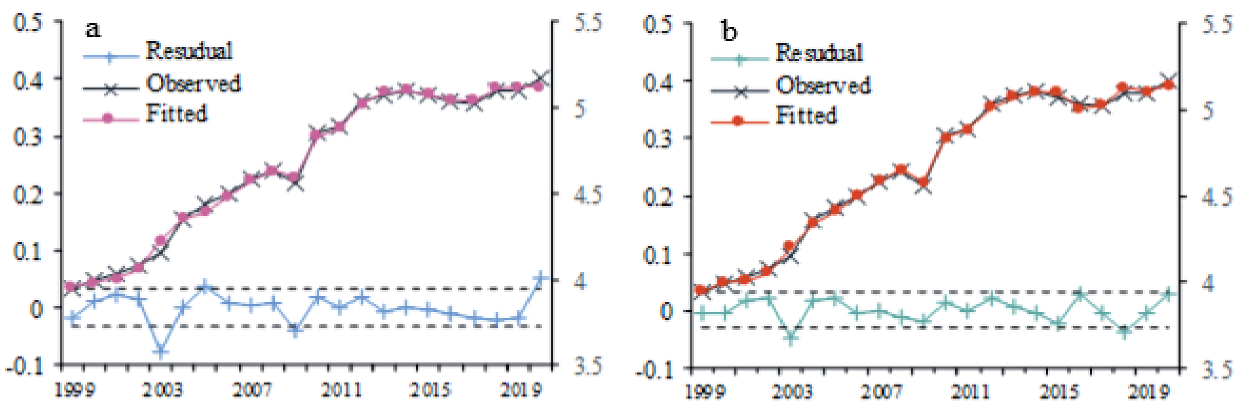

Fig. 3. The fitting results of the model: a) T4 and b) R4.

Table 9. Robustness test results based on the T4 and R4 models.

	Model T4-1 ARDL (1,0,1)	Model T4-2 ARDL (2,0,2)	Model T4-3 ARDL(1,2,1)	Model R4-1 ARDL (1,0,1,0)	Model R4-2 ARDL (1,1,1,1)	Model R4-3 ARDL (1,3,3,3)
$Ln(CO_2(-1))$	-	-	-	-	0.3732* (0.1856)	−0.3325 (0.4459)
LnGDP	0.5513*** (0.1231)	0.4942*** (0.0838)	-	0.4576*** (0.1350)	-	-
LnGDP (−1)	-	-	0.4817*** (0.1017)	-	-	-
LnTelec (−1)	0.2870* (0.1538)	-	-	-	-	-
LnTelec (−2)	-	0.2905*** (0.09432)	0.3217** (0.1178)	-	-	-
LnTherm (−1)	-	-	-	0.1732* (0.0848)	0.2221* (0.1200)	0.8957** (0.4080)
LnRe	-	-	-	0.1705* (0.0851)	-	-
LnRe (−1)	-	-	-	-	0.2337* (0.1257)	0.8453* (0.4223)
C	−1.3781*** (0.4399)	−1.4350*** (0.3468)	−1.0916** (0.4216)	−0.9376 (0.3755)	−0.9199* (0.5107)	−1.7872 (0.8529)
F-bounds	17.4906***	20.9636***	12.8234***	14.1289***	8.6974***	11.2675***

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively; Ln stands for logarithmic transformation.

Table 10. Granger causality test results.

	$DLn(CO_2)$	DLn(GDP)	DLn(THerm)	DLn(Re)
$DLn(CO_2)$	-	0.9338	0.0903*	0.9546
DLn(GDP)	0.0492**	-	0.1401	0.1084
DLn(THerm)	0.0013***	0.2418	-	0.2244
DLn(Re)	0.0001***	0.0400***	0.0416**	-

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively; Ln stands for logarithmic transformation.

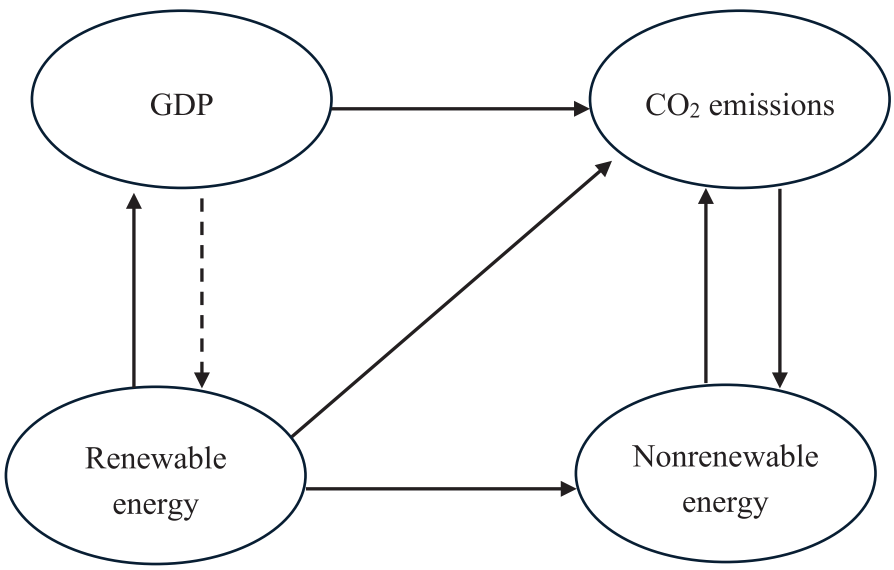

Fig. 4. Schematic diagram of the Granger causality test.

China's renewable energy resources are predominantly concentrated in economically underdeveloped regions, such as deserts, the Gobi, and wastelands. To fully harness these resources, the Chinese government has deployed large-scale ultra-high voltage (UHV) transmission infrastructure to deliver renewable electricity from the northwest to load centers in the east. However, the inherent intermittency and variability of renewable generation pose significant threats to grid security and stability. To ensure system resilience, it is essential to concurrently augment thermal power capacity. These plants provide stable, flexible output for critical functions like peak shaving, frequency regulation, and backup support.

Another key factor exacerbating carbon emissions is insufficient local capacity for renewable energy consumption. Constraints within regional distribution networks and coordination mechanisms often force curtailment of locally generated renewable energy, preventing its utilization even within the same region. This combination of "source-load spatial mismatch" and the operational challenges posed by high renewable penetration further entrenches the indispensable role of thermal power as a grid stabilizer. Consequently, an unintended feedback loop emerges: the expansion of renewable capacity indirectly drives the passive growth of thermal power, leading to an increase rather than a decrease in regional carbon emissions. This phenomenon highlights a structural contradiction in the energy transition – the physical integration of clean electricity has not yet translated into a low-carbon operational paradigm.

Granger causality tests indicate that renewable energy development significantly promotes local economic growth, while economic growth itself increases carbon emissions. However, no statistically significant causal relationship exists between the expansion of nonrenewable energy (primarily thermal power) and economic growth. This suggests that increases in thermal capacity are not driven by economic demand but are a passive response to grid stability constraints. Electricity generated by thermal power plants is often dispatched alongside wind and solar power and transmitted via UHV corridors for interregional delivery. Its core function is to ensure system inertia and frequency stability. Crucially, a bidirectional causal relationship exists between carbon emissions and nonrenewable energy, while GDP exhibits only marginal significance in driving renewable energy growth. This indicates that current regional economic growth and carbon emission pathways remain heavily reliant on systemic support from conventional energy.

Regarding external factors, export trade shows a positive correlation with carbon emissions, but its impact is limited due to its relatively low share of GDP. Foreign Direct Investment (FDI), while statistically significant in suppressing emissions, operates at a scale insufficient to dominate regional trends in emissions reduction. In the long term, domestically, efforts should focus on promoting industrial upgrading and increasing the share of high-tech products in exports. Internationally, continued attraction of high-quality FDI in advanced manufacturing, clean energy, and environmental technologies is crucial to building a "technology-driven" low-carbon development pathway.

Conclusions

This study uses an ARDL model to analyze the effect of renewable energy development on CO_2 emissions from a supply-side perspective in Gansu Province. Unlike previous research, we exclude export trade and FDI from the cointegration test when constructing the ARDL model. Instead, we focus exclusively on the long-term cointegration relationships among CO_2 emissions, economic growth, and electricity generation (including both renewable and thermal sources). Although the cointegration equation excludes export trade and FDI, they are treated as fixed regressors in the model to mitigate potential omitted-variable bias.

The results confirm long-term cointegration among CO_2 emissions, economic growth, and renewable and nonrenewable energy generation. Furthermore, renewable energy development does not necessarily reduce regional carbon emissions. The main reason is that, under current technological conditions, the development and use of renewable energy increases reliance on peak-load regulation by thermal power plants, whose operation entails high coal consumption, thereby increasing regional carbon emissions. We should note, however, that although renewable energy development has not reduced regional CO_2 emissions, regions receiving renewable energy can still derive significant benefits from this interregional transmission.

Based on these findings, we make the following policy recommendations:

1) Expand the development and use of renewable energy in the region to boost economic growth. Although the development of new energy in Gansu has not effectively reduced regional carbon emissions, it plays a significant role in promoting local economic growth. Moreover, electricity transmitted via ultra-high voltage (UHV) transmission lines effectively supports economic development in eastern China while reducing fossil fuel consumption. Therefore, from a national perspective, intensifying new energy development in this region remains both necessary and urgent.

2) Scale up energy storage infrastructure to reduce reliance on thermal power for peak-load regulation. Expanding energy storage not only minimizes renewable energy waste but also reduces dependence on thermal power peaking, while ensuring grid safety and reliability. As installed thermal power capacity growth slows, the associated increase in carbon emissions will decrease.

3) Develop a new power system to enhance the grid's capacity for distributed new-energy integration.

This modern system will enable a higher share of new energy to connect to the grid in a distributed way, maintaining safe and stable operations without increasing thermal power generation. Integrating more new energy will inevitably lower regional carbon emissions.

Although we use only Gansu Province as a case study to examine the relationship between renewable energy and carbon emissions, the methods and conclusions can still provide valuable references for China's new energy-rich regions, such as Xinjiang and Inner Mongolia. Note that the conclusions of this paper are based solely on direct carbon emissions data and exclude indirect emissions, such as those from purchased energy sources, primarily due to the current scarcity of data for statistics on indirect carbon emissions.

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Conflicts of Interest

The authors declare no conflicts of interest.

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