European Journal of Sustainable Development (2025), **14**, 4, 869-890 ISSN: 2239-5938
Doi: 10.14207/ejsd.2025.v14n4p869

China's Sustainable Development Policies and FDI: Short-term Dynamics, Long-term Impact, and Forecast

By Xilin Zhang[1], Zhirui Zhang[1],Yaqian Liu[2]*,Yujiao Mao[3],Jiaxian Chen[4]*

Abstract:
In the context of the 2024 global economic recession, can China's sustainable development policies attract foreign direct investment to achieve industrial upgrading and drive economic growth?This paper examines the short-term dynamics, long-term impact, and forecast of the relationships between industrial policy, green clean energy, carbon pricing, and FDI.
The research uses the Autoregressive Distributed Lag (ARDL) model and the Vector Error Correction Model (VECM) to comprehensively study the short-run and long-run connection among the LFDI and the secondary industry growth, green energy generation and carbon pricing. China officially established its carbon market in 2013, with sustainable access to official data available since then.Although the duration of our research data is relatively short, we have already applied the corresponding models to analyze and compensate for the data insufficiencies.By using this methodological approach, the paper demonstrates how these variables affect LFDI across various time horizons and assesses their contribution to the sustainable development of the economy. Additionally, machine learning techniques are utilized to adopt a rolling forecast approach to predict LFDI levels.

Keywords: industrial upgrading, green clean energy, low carbon, ARDL model, VECM model, machine learning

1.Introduction

In recent years, China has shifted its approach to economic development, moving away from the traditional focus on GDP growth toward a path of green and sustainable development. With substantial government subsidies and investments in the energy sector, China's new energy generation has reached a mature scale and market. Since the introduction of the supply-side reform in 2015, the previous model of economic development, which relied on environmental degradation, has gradually shifted toward a new path driven by technology and innovation. This shift has significantly impacted China's industrial structure, with highly polluting low-end manufacturing industries being slowly upgraded to low-pollution, higher-output sectors. Since China first proposed the carbon market in 2011, the country has developed a complete carbon trading mechanism,

[1]Shandong Huayu University of Technology, Address: Dezhou, Shandong Province, China
[1]Shanghai Normal University, Address: Shanghai, China.
[2]Zhejiang University of Technology,Address:Hang Zhou, Zhejiang Province, China;*Author to whom correspondence should be addressed.
[3]School of Management, Universiti Teknologi Malaysia,Address:Jalan Iman, 81310 Skudai, Johor Darul Ta'zim, Malaysia.
[4]South China Agricultural University,Address: Guangzhou,Guangdong Province, China; *Author to whom correspondence should be addressed.

which has worked well at the policy level to complement the later supply-side reforms. However, in practice, while the carbon market has incentivized large enterprises to innovate and reduce carbon emissions, it appears to have had limited impact on promoting industrial upgrading and driving economic growth. China's economic development is still largely reliant on the government's long-term industrial policies and resource allocation, which have created a comprehensive industrial base. In 2024, China introduced the concept of "new quality productivity," aiming to drive economic development through industrial upgrading. However, China's prospects for independently achieving industrial upgrading remain limited. Despite years of central government advocacy and policies aimed at encouraging industrial transformation, local governments continue to rely heavily on land transfer revenues as a major source of fiscal income—a phenomenon rooted in the restructuring of central-local fiscal relations following the 1994 tax-sharing reform. The 1994 tax reform was implemented to address the fiscal imbalance between central and local governments, weak central fiscal control, and a fragmented tax system. After the reform, the central government gained a larger share of major tax revenues and greater control over tax collection, thereby enhancing its capacity for macroeconomic regulation. However, this shift significantly reduced the fiscal revenues available to local governments, while their responsibilities for public services and infrastructure either remained unchanged or even expanded. Faced with shrinking tax revenues and mounting expenditure pressures, local governments had to seek new sources of fiscal income. Land transfer fees became one of the few financial resources still under local control. Under this institutional arrangement, land finance gradually took shape: local governments promoted land development, urban expansion, and real estate construction to generate land transfer revenues and meet fiscal needs. This transmission mechanism fostered a strong dependence on land finance, creating a path dependency that not only entrenched local government behavior but also weakened their intrinsic motivation to pursue industrial upgrading and economic transformation, as these strategies could not address immediate fiscal pressures. It is noteworthy that the acceleration of urbanization has further reinforced this reliance on land finance. Against the backdrop of the central government's promotion of new-type urbanization and the ongoing influx of population into cities, the demand for urban construction land has continued to rise, increasing the share of land transfer revenues in local fiscal budgets. By accelerating urbanization, local governments can quickly realize land assets and secure ample fiscal resources. In this process, land finance and urbanization reinforce each other, deepening local governments' dependence on land-based revenues and further diminishing their incentive and capacity to promote industrial upgrading. Against this background, foreign direct investment (FDI) plays a crucial role in China's industrial upgrading by introducing advanced technologies and management expertise, partially alleviating the structural constraints arising from local governments' entrenched reliance on land finance.

The contribution of this research is based on the fact that it offers an inclusive investigation of the short-term and long-term effects of the low-carbon green energy industry on FDI attraction in China hence this topic is especially relevant in the present world economy and environmental management policies. With the deepening of the impact of global climate change on the economy and society, the construction of low-carbon green technologies has become a global focus. China’s policies and actions in the area of low-carbon green energy not only have significant impacts on the country’s domestic economic restructuring but also on the international system of environmental governance and sustainable development.

Through the comprehensive examination of the effects of the growth of the low-carbon green energy industry on the attractiveness of foreign investment, this study offers solid evidence and detailed analysis to enable policymakers and business leaders to assess the efficiency of these policies in reality and also can provide useful information for other countries. Especially for those countries that hope to attract foreign direct investment through government sustainable development policies to drive economic growth.

Finally, this study underscores the need to encourage the use of low-carbon technologies around the world and attain carbon reduction goals. It offers the international community a practical approach to the enhancement of environmental stewardship and economic growth through technology and partnership which not only improves the comprehension of the green economy’s possibilities but also provides realistic strategies for attaining sustainable development goals worldwide.

The main purpose of this paper is to conduct an in-depth analysis of the short-term dynamics, long-term impacts, and forecasts of the relationship between government sustainable development policies and the foreign direct investment (FDI), providing strategic recommendations for countries like China to enhance their competitiveness in the global economy through sustainable technologies. Specifically, the paper will explore how green energy policies, carbon market policies, and the comprehensive industrial base formed through years of sustained government investment attract FDI, and further examine the role of these investments in driving China's industrial upgrading and economic transformation.

The specific research questions include:

1. How do key economic indicators such as green energy generation, secondary industry growth, and carbon pricing affect the flow of foreign direct investment in the short term?

2. How do these factors shape China's attractiveness to foreign investment in the long term?

3. What are the forecasts for China's attractiveness to foreign investment by 2030?

4. What lessons can be drawn from China's experience on a global scale, particularly for other developing countries in balancing economic sustainability and environmental protection in policy-making?

By delving into the above questions, this paper aims to provide a comprehensive analytical framework to evaluate and optimize China's strategic choices in the global green economic transition and the potential impact of these strategies on the global investment landscape. The research findings not only offer decision-making support for China's policymakers but also provide practical guidance and strategic insights for global sustainable development.

2.Related Work

Research Directions in the Low-Carbon Green Economy

Hussain et al. (2023) point out that green economic policies can significantly reduce carbon emissions and achieve sustainable development goals, thus providing a theoretical foundation for analyzing how China's sustainable development policies attract foreign direct investment (FDI). Meanwhile, Gielen et al. (2019) emphasize the critical role of fluctuations in renewable energy usage in economic transformation. However, existing international research remains divided on the effectiveness and transferability of green economic policies in attracting foreign investment. Studies such as Gonzalo H et al. (2025) and Sunghoon Chung (2014) suggest that stringent environmental policies can help promote FDI inflows into countries. In contrast, Mehmet Akif Destek and Ilyas Okumus (2023) point out that in newly industrialized countries with relatively weak institutional environments, similar policies may actually inhibit foreign investment.

Against the backdrop of the global economic recession in 2024, this paper systematically evaluates, based on the existing literature, how China leverages its policy-driven low-carbon economic advantages to attract foreign investment that supports industrial upgrading and economic growth. By conducting a structured comparison with policy approaches in other countries, this study aims to clarify the effective conditions for green policies to attract FDI and to identify the unique characteristics of the Chinese model—namely, how the world's largest developing country innovates in environmental policy to maintain a steady inflow of FDI. This systematic comparison helps position the Chinese experience within the broader international research context and assesses the transferability and limitations of China's model for other economies.

Determinants of Attracting Foreign Direct Investment

Ben Jebli et al. (2019) show that factors such as geographic location, technological advancement, and economic growth collectively influence FDI inflows, while Namahoro et al. (2021) highlight that energy costs and environmental burdens adversely affect the supply of renewable energy. Based on these findings, our study incorporates energy and environmental factors into the analytical framework, aiming to reveal how these determinants affect FDI inflows and promote industrial upgrading during periods of global economic downturn.

The Impact of Carbon Pricing on Attracting Foreign Direct Investment

Yu, X., Kuruppuarachchi, D., & Kumarasinghe, S. (2024) argue that effective carbon pricing policies can reduce emissions while attracting foreign investment, and Yüksel et al. (2020) find that higher carbon prices stimulate investment in low-carbon technologies. With China having established its carbon market in 2013 and maintaining a robust longitudinal dataset, our research uses this data to explore both the immediate and lagged effects of carbon pricing on FDI, providing empirical insights for policy-making in an era of global economic uncertainty.

The Impact of Green Energy Generation on Attracting Foreign Direct Investment

Wall, R et al. (2019) notes that energy factors—especially renewable energy—play a crucial role in attracting foreign investment, while Ali et al. (2022) further demonstrate the positive impact of green energy on sustainable development. By analyzing recent data on green energy generation in China, this study aims to quantify the positive and negative effects of green energy development on FDI and to assess its role in driving industrial upgrading during periods of economic recession.

The Effect of Secondary Industry Expansion on Foreign Direct Investment

Research by Emako et al. (2022) and Çemberci et al. (2022) reveals that growth in the secondary industry, particularly in manufacturing, has a positive impact on attracting FDI. Considering the current state of China's industrial policies and industrial upgrading, our study employs the Secondary Industry Growth Index as a measure of industrial advancement. We analyze both the short-term and long-term impacts of industrial growth on FDI, with a particular focus on how industrial transformation under economic recession pressure influences the attractiveness of foreign investment.

3. Research Methods and Data

3.1 Data

To deeply investigate the short-term dynamic relationship and long-term impact of the low-carbon green energy industry on attracting foreign investment in China, this study covers the following key variables: secondary industry growth index, green energy generation, carbon pricing, and the level of foreign direct investment (FDI). These variables respectively represent the key economic factors of the government's green energy policies, carbon market policies, and industrial policies.These variables are selected based on their crucial roles in the green economy and foreign investment flows. The specific data sources include:

1.Level of Foreign Direct Investment: The foreign direct investment data for the quarterly periods from 2013 to 2021 is sourced from the "China Statistical Yearbook" and the National Bureau of Statistics of China.These data provide detailed information on foreign investment inflows across various industries and regions in China, forming a critical basis for analyzing FDI trends. Given the close relationship between FDI and GDP growth, merely considering FDI might overlook the impact of GDP growth, potentially leading to omitted variable bias. Therefore, we introduce a new concept: the level of FDI, which is the ratio of foreign direct investment to GDP, to more comprehensively reflect the direct impact of FDI on China's GDP.

2.Secondary Industry Growth Index: This index reflects the overall development level and growth rate of China's secondary industry, including manufacturing and construction. The data for this indicator is sourced from the National Bureau of Statistics of China, covering quarterly data from 2013 to 2021, reflecting the development trends of industrial upgrading and technological innovation.

3.Green Energy Generation: This includes the total generation of wind, solar, and hydropower energy. The data was collected from the National Energy Administration and the annual reports of relevant green energy companies for the quarterly periods from 2013 to 2021. These data help evaluate China's efforts and effectiveness in promoting renewable energy.

4.Carbon Pricing: Considering the impact of carbon pricing on business operating costs and investment decisions, this study collected the average trading price in the carbon trading market as a representation of carbon pricing. The data is sourced from China's carbon emissions trading market for the quarterly periods from 2013 to 2021, including the average carbon emission price for each trading period.

Table 1 shows the abbreviations and meanings of each variable, as well as their measurement units and data sources. Additionally, Table 2 provides descriptive data of the time series data for the Chinese economy. The results indicate that all variables except CP are normally distributed, as suggested by the Jarque-Bera test results. Pairwise correlation analysis shows positive correlations between the variables LFDI, SIGI, GEEG, and CP. The skewness and kurtosis characteristics of these variables are as follows:

1. The somewhat positive LFDI skewness of 0.0303 suggests a distribution that is slightly skewed to the right, with more data points on the right side. A flatter circulation is shown by the LFDI's kurtosis of 1.7780, which is less than the kurtosis of 3 for the normal distribution. This implies that compared to a normal distribution, LFDI has fewer extreme values.

2. With more data points on the left side, the circulation is somewhat left-skewed as indicated by the SIGI's skewness of -0.4084 which is slightly negative where SIGI's kurtosis is 3.4358 which is somewhat higher than the kurtosis of 3 for the normal distribution and suggests a slightly leptokurtic distribution. As a result, SIGI has more extreme variable values than a normal distribution, which is represented by heavier tails.

3. The GEEG skewness is 0.1073 which is quite near to 0 suggesting a distribution that is almost symmetrical. A flatter distribution is shown by the GEEG's kurtosis of 2.0666, which is less than the kurtosis of 3 for the normal distribution which indicates that GEEG is less extreme than a normal distribution.

4. Given the pronounced right-skewness and leptokurtic features of the CP variable (with an original skewness of 2.2322 and kurtosis of 7.8847), this study applied a logarithmic transformation to normalize the distribution. After the transformation, the skewness of CP decreased to 0.58 and the kurtosis to 1.11, indicating a significant improvement in both the symmetry and tail behavior of the data. This adjustment renders the CP variable much closer to a normal distribution, thereby providing a more reliable statistical foundation for subsequent empirical analyses.

One statistical technique used to check for normalcy is the Jarque-Bera test. The Jarque-Bera test has a p-value of 0.3573 for LFDI, where it is greater than 0.05; 0.5547 for SIGI, which is greater than 0.05; and 0.5322 for GEEG, which is greater than 0.05. The LFDI, SIGI, and GEEG variable distributions are close to normal, according to these findings. Nonetheless, the Jarque-Bera test for CP yields a p-value of 0.000, where it is less than 0.05, signifying a substantial deviation of CP's distribution from the normal distribution. To sum up, all the variables (LFDI, SIGI, GEEG) have kurtosis values that are similar to those of a normal distribution, with the exception of CP, which exhibits modest left or right skewness.

Table1. Variables.

Variables	Implication	Units	Sources
LFDI	Level of foreign direct investment	% of FDI	The China Statistical Yearbook , 2021
SIGI	Secondary industry growth index	% of last year (last year is 100%)	The China Statistical Yearbook , 2021

GEEG	Green energy electricity generation	One hundred million kilowatt hours	The China Statistical Yearbook , 2021
CP	Carbon pricing	Yuan / ton	China's carbon emissions trading market, 2021

Table2. Descriptive statistics.

	LFDI	SIGI	GEEG	CP
Average	0.0202	105.8955	15158.06	30.917
Maximum	0.0253	108.7	19951	74.24
Minimum	0.0153	102.5	10614.9	19.7
Median	0.0211	105.925	14951	29.135
Skewness	0.0303	-0.4084	0.1073	2.2322
Kurtosis	1.7780	3.4358	2.0666	7.8847
Jarque-Bera	2.0582	1.1788	1.2614	60.2139
P-value	0.3573	0.5547	0.5322	0.0000
Observations	33	33	33	33

3.2 Research Methods

This study investigates the relationships between the secondary industry growth index, green energy generation, carbon pricing, and the level of foreign direct investment (FDI). When examining the short-term dynamic relationship and long-term impact of the low-carbon green energy industry on attracting foreign investment in China, employing both the Autoregressive Distributed Lag (ARDL) model and the Vector Error Correction Model (VECM) offers multiple advantages. Firstly, the ARDL and VECM models can offer short-run and long-run insights which enables the research to capture the dynamics of the variables in question where the ARDL model can accommodate I(0) and I(1) mixed data while the VECM model is particularly suited for cointegration analysis, thus making the combination of the two models flexible to data characteristics. Secondly, the short-term dynamic analysis that is offered by the ARDL model can be in use to supplement the long-term equilibrium analysis of the VECM model thus making the research findings more robust and credible where the advantage of using both models is that the results can be checked and compared which increases the confidence in the conclusions.

1. The ARDL model can accommodate I(0) and I(1) variables, and does not necessarily impose all the variables to be of the similar order of integration which is very useful when analyzing several economic variables.

2. Long-term and short-term dynamic relations: The ARDL model can capture long-run cointegrating relationships and offer a rich short-run dynamic adjustment path and can also show the dynamic relationships between variables at different time horizons by estimating the autoregressive and distributed lag parts.

3. Superior performance with small samples: In comparison with other cointegration testing methods, the ARDL model is relatively robust to small sample conditions which is a major advantage in empirical research where small samples are often encountered and also the ARDL model can solve the endogenic problem, where it makes the estimation outcomes much reliable.

In conclusion, through the use of the ARDL and VECM models, the short-term and long-term impacts of the low-carbon green energy industry on FDI attraction in China can be analyzed comprehensively which can provide significant references for policy-making and practical application.

Handling Non-stationary Data: The VECM model is particularly suitable for non-stationary time series data and identifies the long-run equilibrium relationships among the variables through cointegration which is important for economic time series data as these are often non-stationary.

Cointegration and Error Correction: The VECM model can successfully identify the variables that are cointegrated and explain the dynamics of short-term deviations from the long-term equilibrium through an error correction mechanism which gives a detailed mechanism analysis for understanding how variables go back to equilibrium in the long run and how they are related.

Forecasting and Policy Analysis: The VECM model has an advantage in forecasting and policy analysis since it can capture both the long-run relationship and short-run changes among the variables. By using the model, one can perform scenario and impulse response analyses to assess the long-run and short-run impacts of various policy measures on FDI inflows. However, it should be noted that this approach does not account for the psychological and behavioral responses of foreign investors. Future research could integrate perspectives from behavioral economics to improve our understanding of how foreign firms respond to changing carbon costs and green incentives, particularly under conditions of economic uncertainty.

In this particular model specification, the ARDL and VECM models are in use to capture the long-run and short-run effects of the secondary industry growth index, green energy generation and carbon pricing on FDI attraction in China. It is essential to examine for the existence of cointegration relationships, indicating a long-term equilibrium connection among China's ability to attract foreign investment and other variables. To establish the relationship between LFDI (Level of Foreign Direct Investment), SIGI (Secondary Industry Growth Index), GEEG (Green Energy Generation), and CP (Carbon Pricing), we propose the following equation (1):

$$LFDI=f(SIGI、GEEG、CP)$$

Equation (2) defines the model as follows:

$$LFDIt=\alpha0+\beta1SIGIt+\beta2GEEGt+\beta3CPt+\varepsilon t$$

Equation (3) below expresses several variables from equation (2) in their natural logarithmic form.

$LnLFDIt=\alpha0+\beta1LnSIGIt+\beta2LnGEEGt+\beta3LnCPt+\varepsilon t$

Where: $\alpha0$ denotes the constant term; $\beta1$ to $\beta3$ are the coefficients; εt represents the error term. LnLFDI, LnSIGI, LnGEEG, and LnCP refer to the natural logarithms of LFDI, SIGI, GEEG, and CP, respectively.

Equation (4) presents the formulation of the ARDL model:

$$D(LnLFDI_t) = \beta_0 + \sum_{i=1}^{p} \gamma_i D(LnLFDI_{t-i}) + \beta_1 LnLFDI_{t-1} + \sum_{i=1}^{q} \delta_i D(LnSIGI_{t-i}) + \beta_2 LnSIGI_{t-1} + \sum_{i=1}^{q} \epsilon_i D(LnGEEG_{t-i}) + \beta_3 LnGEEG_{t-1} + \sum_{i=1}^{q} \theta_i D(LNCP_{t-i}) + \beta_4 LNCP_{t-1} + \epsilon_t$$

Where

D stands for the first-difference operator. The error correction dynamics are signified by γ, δ, ϵ, and θ. The ARDL model's long-term relationships involving its variables are shown by β1 through β4.It is p and q that design the ideal lags.

Prior to beginning ARDL estimate, it is required to use The ADF test (Augmented Dickey-Fuller) and the DF-GLS test (Generalized Least Squares Dickey-Fuller) unit root tests to confirm the order of integration of all variables (check stationarity). Second, it's critical to use the Wald test to confirm whether or not the model's variables exhibit long-run cointegration. Less than 10% should be the F-statistic value. The following are the alternative hypothesis (H1) and the null hypothesis (H0):

H0. $\beta1 = \beta2 = \beta3 = \beta4 = \beta5 = \beta6 = \beta7 = \beta8 = \beta9 = 0$ (there are no long-term relations among variables)

H1. $\beta1 \neq \beta2 \neq \beta3 \neq \beta4 \neq \beta5 \neq \beta6 \neq \beta7 \neq \beta8 \neq \beta9 \neq 0$ (there are long-term relations among variables)

Thirdly, the long-term cointegration among the model's variables is found using the Bounds test. The last step involves capturing the way of short-term causation linkages among variables using the vector error correction model (VECM), developed to overcome certain constraints of the VAR framework. On the other hand, the cointegration term that gauges how quickly endogenic variables congregate to their long-run equilibrium is mentioned as the Error Correction Term (ECT). In addition to being significant, the ECT coefficient should be negative. It permits dynamic short-term modifications around the equilibrium.

The VAR can be expressed in equation (5) as follows:

$$D(LnLFDI_t) = Z_0 + \sum_{i=1}^{p} \gamma_i D(LnLFDI_{t-i}) + \sum_{i=1}^{q} \delta_i D(LnSIGI_{t-i}) + \sum_{i=1}^{q} \epsilon_i D(LnGEEG_{t-i}) + \sum_{i=1}^{q} \theta_i D(LNCP_{t-i}) + \epsilon_t$$

Across the error correction period (ECT), the VECM identifies the short-term changes and the long-term relationships among the variables. The ECT fundamentally captures the extent to which variables diverge from their long-run equilibrium state. On the other hand, the VECM shows how the econometric model's variables gradually acclimate to their long-run equilibrium.

Equation (6), which expresses the VECM model, is as follows:

$$D(LnLFDI_t) = \Pi_0 + \sum_{i=1}^{p} \gamma_i D(LnLFDI_{t-i}) + \sum_{i=1}^{q} \delta_i D(LnSIGI_{t-i}) + \sum_{i=1}^{q} \epsilon_i D(LnGEEG_{t-i}) + \sum_{i=1}^{q} \theta_i D(LNCP_{t-i}) + \phi ECT_{t-1} + \epsilon_t$$

In practice, the white noise error term is denoted by ε, and the factors are μ, γ, δ, σ, and φ. Error correcting terminology is ECT.

4.Estimation and Discussion

Thus, the following procedures or tests are used in our empirical work: ARDL estimation, Wald, Bounds, Autocorrelation, and ADF and DF-GLS testing.

4.1 Tests of unit root

To determine the order in which variables integrate (stationarity), the ADF tests are employed. Table 3's results demonstrate that while certain variables are not stationary at the level (I0), all of the variables are inactive in the first difference (I1), indicating that all of the variables are integrated in the first difference.

Table3. Stationarity tests.

Tests	ADF test		DF – GLS test	
	Order of integration		Order of integration	
Variables	(I0)	(I1)	(I0)	(I1)
LFDI	-1.71***	-5.19*	-12.87*	-5.19*
SIGI	-1.53	-5.57*	-1.74***	-5.49*
GEEG	0.46	-3.04*	1.84***	-2.18**
CP	-3.06	-2.29**	-1.39	-1.97**

*, ** and *** denote the significance at the 1%, 5%, and 10% criteria, respectively.

4.2 Test of wald

Do the Wald test to ensure that the variables have long-term cointegration. The F-statistic result (3.813) is substantial at 1%, 5%, and 10%, this points to long-run cointegration between LFDI and the explanatory variables, with results detailed in Table 4.

Table4. Wald test.

Test Statistic	Value	df	Probability
F-statistic	4.542	(1,28)	
Chi-square	4.542	1	0.042

*, ** and *** denote the significance at the 1%, 5%, and 10% criteria, respectively.

4.3Bounds test

To assess the existence of long-term associations among the variables, the Bounds test is employed. Its F-statistic (13.0976) is significant at the 1%, 5%, and 10% thresholds, suggesting the existence of long-term connections among the variables. The results are shown in Table 5.

Table 5. Bounds test.

F-statistic	Optimal lag length	F-statistic
FLFDI(SIGI,GEEG,CP)	(2,1,1)	13.0976
Significance level	Critical Value bounds I(0)	I(1)
10%	2.72	3.77
5%	3.23	4.35
1%	4.29	5.61

*, **, and *** denote the implication at the 1%, 5%, and 10% criteria, respectively.

4.4 Autocorrelation Test

The model was examined for serial correlation using the Breusch-Godfrey LM test, with the outcomes detailed accordingly shown in Table 6:

Table 6. Breusch-Godfrey serial correlation LM test results.

Breusch-Godfrey Serial Correlation LM Test			
Null Hypothesis: No Serial Correlation Up to 4 Lags			
F-statistic	0.525	Prob. F (4,14)	0.719

The test examines whether serial correlation is absent in the model; the resulting chi-square p-value of 0.456 is above the 0.05 significance level, as per the findings of the serial correlation test. This implies that the null hypothesis can be acknowledged, and it could be said that there is no serial connection among the model's residuals.

4.5Long run ARDL estimation

According to Table 7, the ARDL model shows that all three independent variables positively impact the level of foreign direct investment. The outcomes show that an increase of one unit in SIGI has a significant impact on LFDI by 0.9832%. Economically, during the early stages of China's reform and opening up, foreign trade was a crucial driver of economic growth. In the early 21st century, China had abundant demographic dividends and attracted global capital to set up factories with its low labor costs. China then earned foreign exchange by exporting processed industrial products. The foreign trade-driven economic boost started to decline gradually from 2023. However, due to the long-term foreign trade-oriented economy, China maintained a position in the international trade system as a low-end manufacturer, becoming the world's factory with a complete industrial chain and a comprehensive supply chain. As China's degree of reform and opening up continues to expand, it has also continuously increased policy incentives to encourage foreign investment to set up factories in China. Consequently, as China's industrial level and policies improve, its attractiveness to foreign investment continues to rise. This creates a virtuous upward spiral, where both factors reinforce each other. The government continues to expand the level of reform and opening up, hoping to attract foreign investment by further improving China's industrial level and hosting mid-to-high-end manufacturing industries from Europe, thus further promoting China's industrial upgrading. We further observe that GEEG also has a significant positive impact on LFDI. For each unit increase in GEEG, the significant impact on LFDI is 0.2591%. As China's policies for green and sustainable development are continuously implemented, the government has provided tax incentives, subsidies, and other measures to directly promote large-scale investment in wind, hydro, and other green energy sectors. With continuous investment in green energy infrastructure and technology research and development, China has established an almost complete green energy system. This comprehensive energy system cant meet only domestic energy requirements but also offer stable and sustainable energy supplies to foreign investors. This positions China as a leader in the green energy sector, showcasing its market potential to global investors, who are thus willing to make long-term investments in China. Additionally, China's Belt and Road Initiative has further encouraged cooperation in the green energy sector with countries along the route, expanding investment opportunities and market size. From Table 7, we also find that CP has a significant positive impact on LFDI. For each unit increase in CP, the significant impact on LFDI is 0.1633%. Since the Chinese government began piloting the carbon market in 2011, the market has become more mature and the system more robust. Observing the carbon market prices, it is evident that carbon prices are rising. This increase reflects China's emphasis on environmental protection and sustainable development. High carbon prices incentivize domestic companies to accelerate green transformation and technological upgrades, eliminating overcapacity and highly polluting low-end manufacturing, thus enhancing competitiveness. This positive policy signal attracts foreign investors who value environmental protection and sustainable development. By investing, foreign companies can participate in and support local companies' green transformation, gaining opportunities in environmental technology and innovation. However, the degree to which rising carbon prices attract foreign investment is lower than that of green energy projects. Green energy projects, such as wind and solar power, offer direct economic returns and market potential, providing long-term stable returns for investors. In contrast, carbon pricing can only indirectly affect production costs, leading to indirect economic returns for low-pollution mid-to-high-end manufacturing. Additionally, the carbon market's maturity and stability require more time, and changes in market mechanisms and policy adjustments can bring some uncertainties, making foreign companies more cautious in their investment decisions. Foreign companies prefer to invest in mature and stable markets, where policies and markets in the green energy sector are relatively more stable and transparent.

Table 7. Results of long run ARDL estimations.

Independent variables	Coefficients	Std. Error	t-Statistic	Probabilities
SIGI	0.9832	0.061	8.725	0.000*
GEEG	0.2591	0.023	9.841	0.027**
CP	0.1633	0.014	2.021	0.039**
Stability tests		CUSUM test		Stable
		CUSUM SQ test		Stable

*, ** and *** denote the significance at the 1%, 5%, and 10% criteria, respectively.

4.6 Final Model Interpretation

The null hypothesis states that the model's variables are unable to predict or affect the availability of renewable energy in the near future. The variable explains the short-term influence on renewable energy supply if the p-value is less than 0.05, rejecting the null hypothesis. It is acknowledged that the explanatory variable cannot, in the short term, explain or affect the supply of renewable energy, but, if the p-value is more than 0.05.Table 8 indicates that the variable D(LNLFDI(-1)) has a probability larger than 0.05, indicating that the null hypothesis is not rejected for this variable. The lagged one-period level of foreign direct investment (LFDI) does not have a significant impact on the current period LFDI, showing that short-term changes in LFDI do not have an important self-sustaining impact. However, in the long term, LFDI does exhibit self-sustainability. When using a longer historical period to predict the future, we can observe that it has a self-sustaining effect. The Probability of the variable D(LNSIGI) is better than 0.05, so the null hypothesis is not rejected for this variable, indicating that the current period secondary industry growth index (SIGI) does not have a significant effect on LFDI. However, observing D(LNSIGI(-1)) and D(LNSIGI(-2)), we find that the Probability for both the lagged one-period and two-period SIGI is less than 0.05, so the null hypothesis is rejected for these variables. This indicates that the lagged one-period and two-period SIGI have a significant effect on LFDI, suggesting that the growth of the subordinate industry has a delayed effect on attracting foreign direct investment, possibly because investors need time to observe and respond to economic growth trends. Furthermore, we observe that the lagged one-period and two-period growth of the subordinate industry has a substantial positive impact on LFDI, indicating that foreign investment responds to industrial growth with a lag. Foreign investors usually need time to observe and assess the sustainability of industrial growth before making investment decisions.The Probability of the variables D(LNGEEG) and D(LNGEEG(-1)) is less than 0.05, so the null hypothesis is rejected for these variables, showing that both the current period and the lagged one-period green energy generation (GEEG) have a significant impact on LFDI. However, upon closer examination, we find that the coefficient for the current period GEEG is -1.808288, while the coefficient for the lagged one-period GEEG is 1.958652. This indicates that current period GEEG has a substantial negative effect on LFDI, whereas the lagged one-period GEEG has a substantial positive effect on LFDI. This may reflect the high initial costs and market adjustments associated with green energy investments, but as the market stabilizes and policy support increases, the long-term investment potential in the green energy sector is recognized by foreign investors, resulting in a positive effect on attracting FDI.The Probability of the variables D(LNCP) and D(LNCP(-1)) is less than 0.05, so the null hypothesis is rejected for these variables, showing that both the current period and the lagged one-period carbon pricing (CP) have a significant impact on LFDI. Further examination reveals that the coefficient for the current period CP is -0.180849, while the coefficient for the lagged one-period CP is 0.180495. This indicates that upsurging carbon prices have a adverse impact on FDI in the current period, suggesting that increased operational costs may suppress FDI. However, the positive impact in the lagged period shows that foreign companies continue to invest, expecting long-term returns after adapting to the new cost structure. The gradual maturity of the carbon pricing mechanism also boosts foreign investors' confidence.The Probability of the error correction term is

0.0000*, far below 0.05, indicating rejection of the null hypothesis, and the error correction term is highly significant. Further observation reveals that the coefficient of the error correction term is -1.126310, showing that the error correction term has a substantial negative impact on LFDI. This shows that the system has a strong equilibrium adjustment mechanism in the long term. Short-term deviations will be quickly adjusted back to the long-term equilibrium state. The Adjusted R-squared is 0.8278, showing that the explanatory variables in the model demonstrates 82.78% of the variation in the level of foreign direct investment.

Table 8. Outputs of final model.

Variable	Coefficient	Std. Error	Probability
D(LNLFDI(-1))	0.054857	0.103287	0.6018
D(LNSIGI)	-0.620503	0.395576	0.1342
D(LNSIGI(-1))	1.048787	0.314714	0.0011*
D(LNSIGI(-2))	0.510605	0.135789	0.0017*
D(LNGEEG)	-1.808288	0.738483	0.0248**
D(LNGEEG(-1))	1.958652	0.643267	0.003*
D(LNCP)	-0.180849	0.052544	0.0007*
D(LNCP(-1))	0.180495	0.052544	0.0009*
CointEq (−1) *	-1.126310	0.208297	0.0000*
R-squared	0.8852		
Adjusted R-squared	0.8278		

*, ** and *** denote the implication at the 1%, 5%, and 10% criteria, respectively.

5.Model Prediction

In the prediction section, we employ machine learning methods to perform rolling forecasts on the dependent variable. Since the dependent variable already contains information from all independent variables, including linear and non-linear parts, rolling forecasts of the dependent variable will yield the outcome of following this path and whether it will, in turn, promote low-carbon green economic development.

5.1 Model Theory

5.1.1 RNN Model

The Recurrent Neural Network (RNN) is typically employed for chronological data analysis instead of a standard Neural Network (NN) due to its unique memory function, which reflects the sequential nature of data, including time series and text . The RNN processes input sequences and captures inter-sequence relationships through its network architecture, often outputting sequences as well. It utilizes a hidden state vector to detect long-term correlations among samples, as illustrated in Formula (1).

$$h(t) = \sigma(W_{hx}x(t) + W_{hh}h(t-1) + b_h) \tag{1}$$

Each node can learn an offset thanks to the bias vector, and the hidden layer and feature have a recurrent weight matrix that connects to itself over adjacent time steps. With a layer every time step and shared weights throughout, Figure 1 illustrates the network's deep design, which makes it possible to use the Backpropagation Through Time (BPTT) algorithm for training over a large number of time steps.

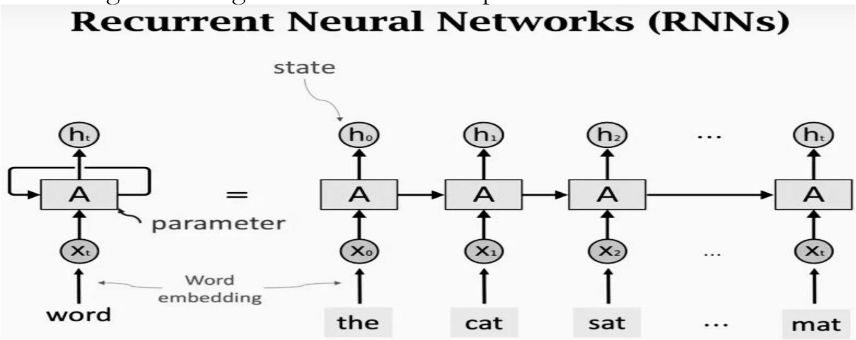


Fig. 1. The structure of the RNN

5.1.2 LSTM Model

An internal gating mechanism is added to the Recurrent Neural Network (RNN) in the Long Short-Term Memory (LSTM) model to address the issue of long-term dependency where the LSTM is a well-liked time series forecasting model because of this process, which also improves the long-term memory capacity of RNNs and solves the gradient vanishing problem . Fig. 2 depicts the fundamental layout of the LSTM unit with the forgetting gate, input gate, cell state, and output gate represented, respectively and are the bias vector and weight coefficient matrix that relate to them and are the activation functions for hyperbolic and sigmoid tangents, respectively. First, a new input is created by combining the higher output and the external input. Passes through the forgetting gate, which keeps only pertinent data. The screening procedure is indicated in Formula (2)

$$f_t = \sigma (W_f \cdot [h_{t-1}, x_t] + b_f) \quad (2)$$

Concurrently, x_t' enters the input gate where it defines the in formation kept in the unit nature to get the output i_t. The updating procedure is shown in Formula (3)

$$i_t = \sigma (W_i \cdot [h_{t-1}, x_t] + b_i) \quad (3)$$

x_t' is stimulated by the tanh function to get output $\tilde{c}_t$, and the stimulation procedure is indicated in Formula (4)

$$\tilde{c}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (4)$$

Through the combined action of the first three outputs, the state of the memory cell c_{t-1} in the preceding stage is restructured to state c_t, and the restructuring procedure is indicated in Formula (5)

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t \quad (5)$$

x_t' enters the output gate where it shows the nature of the output unit. Calculated by Formula (6), the output o_t is obtained

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{6}$$

The final output of the LSTM unit, indicated as or, is the otcome of the output statistics following activation through the tanh function and the new state. The method is displayed in Formula (7).

$$y_t = h_t = o_t \cdot \tanh(c_t) \tag{7}$$

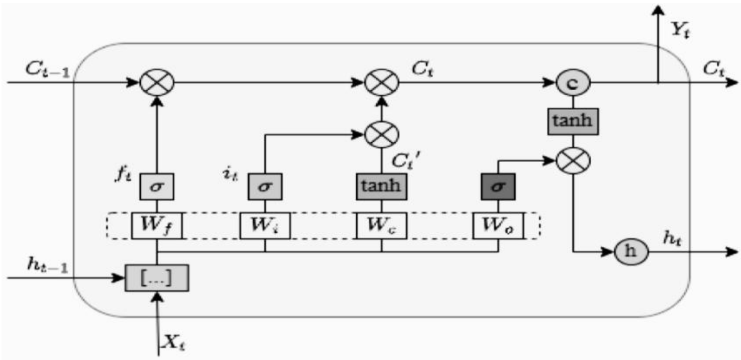


Fig. 2. The basic structure of the LSTM unit.

5.1.3 GRU Model

To address the gradient vanishing and gradient explosion issues inherent in RNNs, Kyunghyun (2014) proposed the GRU model, which contains fewer gates compared to LSTM.[31] The major structure of the GRU unit is indicated in Fig. 3. The GRU model uses reset and update gates to process data. It replaces the cell state in LSTM with Formula (8). In the Formula (8), $1 - z_t$ means how many it will least from the previous layer, z_t means the remaining portion in this layer. So the cell state can be explained by allocating different proportion to the previous layer and the current layer, which is the most different part between LSTM and GRU.

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{8}$$

Where, h_t is the concealed state of current step, z_t is the output of update gate , $\odot$ denotes element-wise multiplication, $\tilde{h}_t$ is the candidate concealed state of current step. The apprise gate U_t and reset gate r_t function likewise to the forgetting and input gateways of the LSTM, as shown in Formula (9) and Formula (10):

$$U_t = \sigma(W_U \cdot [h_{t-1}, x_t] + b_U) \tag{9}$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r) \tag{10}$$

The candidate hidden state $\tilde{h}_t$ is obtained after r_t is calculated:

$$\tilde{h}_t = \tanh\left(W \cdot [r_t \odot h_{t-1}, x_t]\right) \tag{11}$$

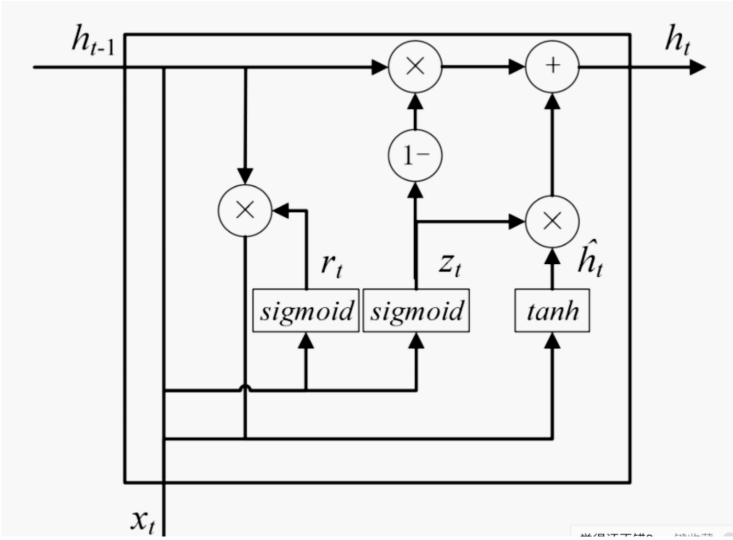


Fig. 3. *The basic structure of the GRU unit*

5.1.4 ARIMA Model

Known by many as the Box-Jenkins approach, the ARIMA model is applied to construct a time series model using univariate time series observations.[32] Moving average (MA), integrated (I), and autoregressive (AR) are the three terms that make up the model. Whereas the MA term indicates the autocorrelation pattern of residuals (errors), the AR term expresses autocorrelation among past and current observations. Integration is necessary because the majority of univariate time series data show an increasing and decreasing tendency, where it is non-stationary. The differentiation level of observations is used to represent the integrated (I) portion, which converts a non-stationary series into a stationary one.[33] Generally, an ARIMA model, expressed by Formula (12), uses three hyperparameters (p, d, q) that can be confirmed in the ADF test and PADF test, where p denotes the AR model, d represents the differencing level, and q indicates the MA model. We finally use (8, 1, 0) by the ADF test and PADF test. If the series is stationary, the amalgamation of AR and MA models (ARMA) is useful:

$$X_t = c + \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \cdots + \alpha_p X_{t-p} + \varepsilon_t + \beta_1 \varepsilon_{t-1} + \cdots + \beta_q \varepsilon_{t-q} \tag{12}$$

Where, $\alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \cdots + \alpha_p X_{t-p}$ denotes the AR term, $\beta_1 \varepsilon_{t-1} + \cdots + \beta_q \varepsilon_{t-q}$ denotes the MA term, ε_t is the error term.

5.1.5 Random Forest Model

The foundation of Random Forests is decision trees. A decision tree is a tree-like model that recursively divides input features into leaf nodes, each corresponding to a category or value. When constructing decision trees, criteria such as information gain and the Gini index are usually used for feature selection and node partitioning. One of the core ideas of Random Forests is random feature selection. When constructing each decision tree, a subset of features is randomly selected for partitioning, which helps increase the diversity of the model. Random Forest adopts the idea of Bagging (Bootstrap Aggregation). By constructing multiple models, each trained on different subsets, and integrating their prediction results, the generalization ability of the models is improved.

5.1.6 SVR Model

Compared with OLS regression, the Support Vector Regression (SVR) model uses the kernel function to maximize the utilization of high-dimensional data. The SVR model creates a hyperplane in high-dimensional space with the broadest margin to match data, and the data concepts that are closest to the hyperplane are turned into support vectors. These support vectors aid in the model's construction by influencing the hyperplane's orientation and position. Finding a model that can precisely match the training set samples is the aim of regression. In order to identify the model, the widely used method entails creating a loss function between sample labels and model predictions and reducing the loss function.

5.2 Evaluation criteria

The forecasting impact of the underlying models is assessed using the following seven criteria: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (\hat{y}_i - y_i)^2 \qquad (12)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (\hat{y}_i - y_i)^2} \qquad (13)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i| \qquad (14)$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} \frac{|\hat{y}_i - y_i|}{y_i} \qquad (15)$$

5.3 Forecasting and models comparison

As the evaluation criteria this paper talked in the last section, we use MSE, RMSE, MAE, MAPE to evaluate the performance of different data showed in the Table 9. Among all of the models, ARIMA model shows the best performance because ARIMA can sufficiently figure out the sequential feature of data. And the hybrid model ARIMA+LSTM also perform better compare with other models. Then the models forecast green economy from 2021Q2 to 2031Q1 showed in the Fig. 4. The paper deletes the RNN model because of the abnormal forecasting performance. Fig. 5 shows the forecasting performances for the simulated data without RNN model

Table 9. Forecasting evaluation criteria of each model for simulated data.

Criteria	MSE	RMSE	MAE	MAPE
ARIMA+LSTM	2.07E-06	0.001437325	0.001185381	7.819983378
ARIMA	2.15422E-08	0.000146773	9.29432E-05	0.559176489
RNN	0.019844887	0.140871882	0.137677945	838.3404212

LSTM	0.0007 05652	0.0265 64118	0.0259 92611	158.33 47054
GRU	0.0136 22818	0.1167 1683	0.1165 38628	714.66 96276
RF	1.1275 7E-06	0.0010 61873	0.0008 7225	5.5219 09692
SVR	6.6275 8E-06	0.0025 74409	0.0024 11285	15.061 21059

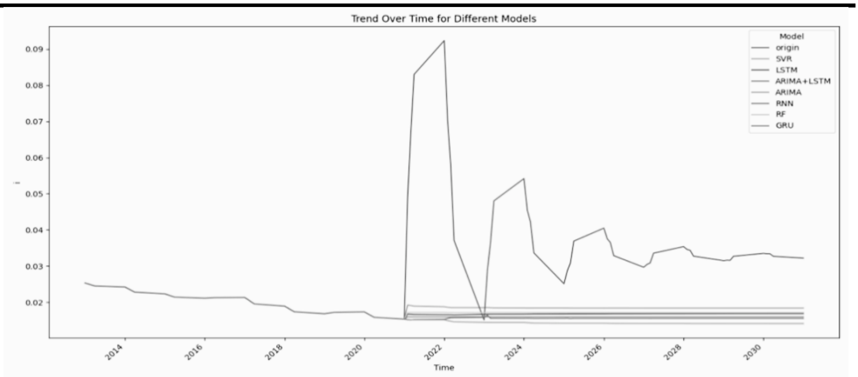
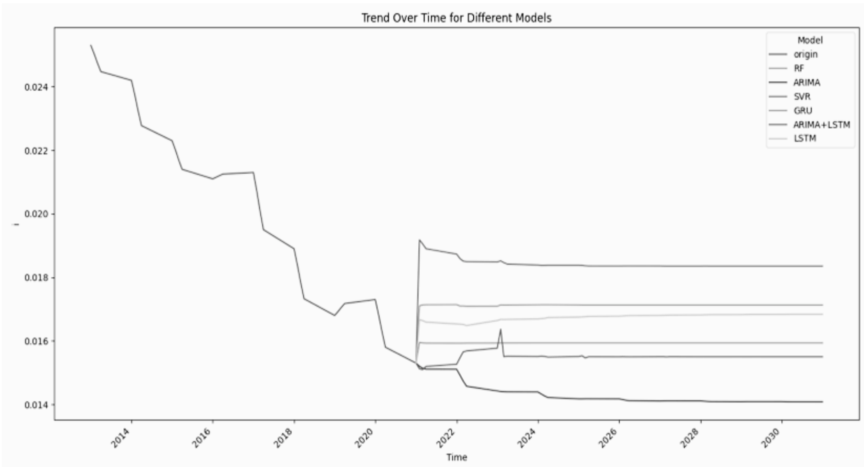


Fig. 4. Forecasting performance for the simulated data.
Fig. 5. Forecasting performance for the simulated data without RNN.

6.Conclusion

This study systematically investigates the short-term dynamic effects and long-term impacts of various renewable energy factors on attracting foreign direct investment (FDI). Based on the empirical results of the ARDL and VECM models, the growth of the



secondary industry, green energy generation, and carbon pricing are all found to exert significant positive effects on FDI inflows. Further predictions using machine learning models indicate that China’s FDI levels are expected to maintain a steady upward trajectory through 2030, underscoring the effectiveness of a renewable energy-driven path to secondary industry development in attracting foreign investment.

Nevertheless, it is essential to recognize that global investment flows are subject to considerable uncertainty due to a multitude of external factors. Geopolitical risks, evolving patterns of international trade, and intensified competition in green technologies may all exert substantial influence on both the scale and direction of FDI. Against this backdrop, while this study affirms the positive effects of China' s low-carbon industrial model, policy-making should proactively account for potential fluctuations in the external environment by building a more resilient and adaptive policy framework. Only by continuously enhancing risk management and policy preparedness can China' s low-carbon industries maintain their advantage in attracting FDI amid future global uncertainties and competition.

Using China, a developing country, as an example, it is evident that if a nation needs to attract foreign investment, upgrade its industry, or promote economic development, following a green and sustainable development path is viable. After losing its demographic dividend, China can further expand its reform and opening up based on renewable energy to attract foreign investment into the country. This demonstrates the urgent global need for low-pollution and inexpensive renewable energy and shows that the vigorous development of renewable energy can drive sustainable economic growth in a country or region. This also further indicates the future direction of global energy development. This study encountered data limitations. The available research data for this paper is from 2013-2021. Due to the insufficient time series data, we used Eviews 10.0 software to alter the yearly data into quarterly data to expand the sample size.

Based on this study, we find that in the long term, the secondary industry progress index has a important positive effect on the level of foreign direct investment. In the short term, the lagged one-period and two-period secondary industry growth index also has a important positive impact on the level of foreign direct investment. This shows that the secondary industry growth index has a substantial positive impact on foreign direct investment, suggesting that China should encourage the growth of the minor industry. China should continue to carry out supply-side reforms, gradually eliminate high-pollution, high-energy-consumption, and low-capacity low-end manufacturing, and promote technological revolution and R&D to achieve industrial upgrading, thereby further attracting foreign investment. Observing the green energy generation, we find that in the long term, green energy generation has an important positive impact on the foreign direct investment. In the short term, the current period's green energy economic growth (GEEG) has a substantial negative impact on LFDI, while the lagged one-period green energy economic development has a substantial positive impact on LFDI. This shows that China should encourage the growth of renewable energy. Although the developing effects of renewable energy may not be immediately visible, in the long term, promoting renewable energy development will further attract foreign investment. Therefore, the government should further promote green and sustainable development policies and increase investment in green energy. This includes increasing investment in wind, solar, and hydro energy projects, promoting energy structure transformation, and strengthening technology R&D and innovation. Supporting the growth and application of green energy technology will improve the efficiency and economic benefits of green energy. Observing carbon pricing, we find that in the long term, carbon pricing has an important positive impact on the level of investment from foreign directly. In the short term, increasing carbon prices have a negative impact on LFDI in the current period, but the lagged one-period carbon prices have a positive effect on LFDI. This indicates that China should further improve the operation and development of the carbon market. By ensuring that the carbon market reasonably prices carbon, carbon prices can reflect the cost of emissions without placing an excessive burden on business operations. Additionally, policies should provide support, technical assistance, and financial aid to enterprises significantly affected by carbon prices, helping them achieve green transformation and adapt to the new cost structure.

Additional Information

The authors declare no conflict of interest.

Data availability statement

All data utilized in this study are clearly indicated within the main text and are sourced from materials cited in the reference list. Detailed data sources can be found in the cited references. No proprietary or unpublished data were used.

Reference:

Hussain, M., Lu, T., Chengang, Y., & Wang, Y. (2023). Role of economic policies, renewable energy consumption, and natural resources to limit carbon emissions in top five polluted economies. Resources Policy, 83, 103605.

Gielen, D., Boshell, F., Saygin, D., Bazilian, M. D., Wagner, N., & Gorini, R. (2019). The role of renewable energy in the global energy transformation. Energy strategy reviews, 24, 38-50.

Ben Jebli, M., Ben Youssef, S., & Apergis, N. (2019). The dynamic linkage between renewable energy, tourism, CO2 emissions, economic growth, foreign direct investment, and trade. Latin American Economic Review, 28(1), 1-19.

Namahoro, J. P., Wu, Q., Zhou, N., & Xue, S. (2021). Impact of energy intensity, renewable energy, and economic growth on CO2 emissions: Evidence from Africa across regions and income levels. Renewable and Sustainable Energy Reviews, 147, 111233.

Yu, X., Kuruppuarachchi, D., & Kumarasinghe, S. (2024). Financial development, FDI, and CO2 emissions: does carbon pricing matter?. Applied economics, 56(25), 2959-2974.

Yüksel, S., Dinçer, H., Karakuş, H., & Ubay, G. G. (2020). The negative effects of carbon emission on FDI: A comparative analysis between E7 and G7 countries. In Handbook of research on sustainable supply chain management for the global economy (pp. 20-35). IGI Global.

Wall, R., Grafakos, S., Gianoli, A., & Stavropoulos, S. (2019). Which policy instruments attract foreign direct investments in renewable energy?. Climate policy, 19(1), 59-72.

Ali, N., Phoungthong, K., Techato, K., Ali, W., Abbas, S., Dhanraj, J. A., & Khan, A. (2022). FDI, green innovation and environmental quality nexus: new insights from BRICS economies. Sustainability, 14(4), 2181.

Emako, E., Nuru, S., & Menza, M. (2022). The effect of foreign direct investment on economic growth in developing countries. Transnational Corporations Review, 14(4), 382-401.

Çemberci, M., Civelek, M. E., & Cömert, P. N. The Role of Foreign Direct Investment In The Relationship Between Global Innovation Index and Gross Domestic Product.

Insah, B. (2013). Foreign direct investment inflows and economic growth in Ghana. International Journal of Economic Practices and Theories, 3(2), 115-121.

Chandran, V. G. R., & Krishnan, G. (2008). Foreign direct investment and manufacturing growth: The Malaysian experience. International Business Research, 1(3), 83-90.

Amin, S. B., Amin, Y. N., Khandaker, M. K., Khan, F., & Rahman, F. M. (2022). Unfolding FDI, renewable energy consumption, and income inequality nexus: Heterogeneous panel analysis. Energies, 15(14), 5160.

National Bureau of Statistics of China. (2022). China Statistical Yearbook 2013–2021. Beijing, China: China Statistics Press.

National Energy Administration. (2022). China Energy Statistical Yearbook 2013–2021. Beijing, China: NEA Press.

China Emissions Trading Registry. (2022). China Carbon Market Data 2013–2021. Retrieved April 29, 2025, from https://www.cets.org.cn/.

R. J. Williams and D. Zipser, "A Learning Algorithm for Continually Running Fully Recurrent Neural Networks," in Neural Computation, vol. 1, no. 2, pp. 270-280, June 1989.

Hochreiter S, Schmidhuber J. Long short-term memory[J]. Neural computation, 1997, 9(8): 1735-1780.

Yuping Song, Chunchun Cai, Dexiang Ma, Chen Li, Modelling and forecasting high-frequency data with jumps based on a hybrid nonparametric regression and LSTM model, Expert Systems with Applications, Volume 237, Part A, 2024, 121527, ISSN 0957-4174.

Cho K, Van Merriënboer B, Gulcehre C, et al. Learning phrase representations using RNN encoder-decoder for statistical machine translation[J]. arxiv preprint arxiv:1406.1078, 2014.

G.E. Box, G.M. Jenkins, 1976, Time series analysis: forecasting and control. vol 2nd Edition. John Wiley & Sons, Holden-Day, San Francisco, USA.

S. Ray, S.S. Das, P. Mishra, A.M.G. Al-Khatib, Time series SARIMA modelling and forecasting of monthly rainfall and temperature in the South Asian countries, Earth Syst. Environ. 5 (2021) 531–546.

Soto, G. H., Balsalobre-Lorente, D., & Martinez-Cobas, X. (2025). Environmental legislative shaping or green competitive advantages? The role of FDI among environmental regulations. Energy Economics, 145, 108445.

Chung, S. (2014). Environmental regulation and foreign direct investment: Evidence from South Korea. Journal of Development Economics, 108, 222-236.

Destek, M. A., & Okumus, I. (2019). Does pollution haven hypothesis hold in newly industrialized countries? Evidence from ecological footprint. Environmental Science and Pollution Research, 26, 23689-23695.

Zhang, X., Li, G., Wu, R., Zeng, H., & Ma, S. (2025). Impact of Carbon Emissions, Green Energy, Artificial Intelligence and High-Tech Policy Uncertainty on China’s Financial Market. Finance Research Letters, 107599.