frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 23 May 2025
DOI 10.3389/fenvs.2025.1578559

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RECEIVED 17 February 2025
ACCEPTED 08 May 2025
PUBLISHED 23 May 2025

CITATION
Sun W, Li Q and Uddin I (2025) Financial inclusion, environmental technology, and sustainable environment in China: evidence from an N-shaped EKC.
Front. Environ. Sci. 13:1578559.
doi: 10.3389/fenvs.2025.1578559

Financial inclusion, environmental technology, and sustainable environment in China: evidence from an N-shaped EKC

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Financial inclusion (FI) and technological innovation (TI) are pivotal in advancing SDG 13 (Climate Action) by enabling access to sustainable solutions and promoting low-carbon technologies. FI allows marginalized communities and businesses to invest in renewable energy (RE) and energy-efficient technologies, while TI drives the development of clean energy solutions and CO_2 emissions (CO_2E) reducing innovations. Together, they empower societies to take significant action against climate change, fostering a global transition to a low-carbon economy and helping achieve the targets of SDG 13. Previous studies have focused exclusively on the impact of either FI or TI on CO_2E in China under the N-shaped Environmental Kuznets Curve (EKC). To address this gap, the current study examines the combined effects of FI and TI on CO_2E within the EKC framework for the Chinese economy. This study utilizes the Autoregressive Distributed lag (ARDL), fully Modified ordinary least square (FMOLS), and Dynamic ordinary least square (DOLS) methods by using the time series quarterly data from 2006Q1 to 2022Q4. The ARDL long-run and short-run results confirm that there is an inverted N-shaped EKC between GDP and CO_2E. While FI, TI, and RE have negative effects on CO_2E. This study has several policy recommendations for policymakers to promote environmental sustainability in China.

KEYWORDS

financial inclusion, technological innovation, Co_2e, N-shaped EKC, China

1 Introduction

One of the most significant environmental challenges influencing the long-term, sustainable economic growth of almost every country in the world is climate change (CC). The most controversial issues nowadays are environmental degradation, CC, and global warming. The aforementioned factors are the primary causes of the average global temperature increase and the incidence of severe weather. CC, CO_2 emissions (CO_2E), and global warming are the leading causes of distortions in consumption and production activities (Uddin et al., 2023). The rise in CO_2E poses a critical threat to the environment and the planet. These emissions primarily result from human activities, including burning fossil fuels for energy, industrial processes, and deforestation. The escalating CO_2E levels intensify the greenhouse effect, trapping heat in the atmosphere and driving a steady increase in global temperatures (Le and Pham, 2024). Moreover, CO_2E is regarded as one of the fundamental markers of pollution. According to the literature, CO_2E comes from two primary sources. The primary source of CO_2E is natural processes, including respiration, decomposition, and ocean discharge. Industrial pollution further exacerbated the unsafe amounts of CO_2E that have been absorbed by the atmosphere due to human activity. Human activities, including burning fuels like coal, oil, natural gas, cement, and deforestation, are the second source of CO_2E (Azam et al., 2022). China, as the world's largest emitter of carbon dioxide (CO_2), accounted for over 31% of global CO_2 emissions in 2022, highlighting its substantial influence on the global carbon footprint (Statista, 2022). This stems from its status as the world's most populous country and its rapid economic development, which relies heavily on energy-intensive industries and fossil fuel consumption. Power generation, manufacturing, and transportation sectors contribute significantly to these emissions, with coal being a primary energy source. China's role in climate change mitigation is critical due to its sheer share of emissions. The country has made efforts to transition towards renewable energy, becoming a global leader in solar, wind, and electric vehicle technologies. Despite these advances, its reliance on coal for energy production continues to pose challenges.

As the global community advances toward sustainable development and poverty eradication, financial inclusion (FI) has become a crucial priority. Ensuring access to formal financial services is increasingly recognized as a vital means of empowering individuals and communities—especially in developing countries, where many people still lack connection to the formal financial system (Razzaq et al., 2024). According to Verma and Giri (2024) reported that FI indicators highly influence income inequality disparity in Asian economies. FI is also one of the most important tools for reducing CO_2E by providing access to green financing and promoting renewable energy adoption. It enables individuals and businesses to transition to sustainable practices, reducing dependence on fossil fuels. This promotes environmentally friendly economic growth and mitigates CC. According to Le and Pham (2024), there have been conflicting findings on the relationship between environmental sustainability and FI. Numerous writers agree that FI lowering the CO_2E helps mitigate CC and promote environmental sustainability. Finance plays a part in allocating resources as efficiently as possible. With more logical and effective distribution, the growth of finance can help resources go to green industries. Households are, therefore, more likely to access and invest in green energy when financial resources are readily available. FI benefits companies by lowering the cost of updating eco-friendly machinery and industrial methods, which encourages the adoption of green initiatives. According to Qin et al. (2021), Zheng and Li (2022), Shahbaz et al. (2022), and Hussain et al. (2024) found that FI raises environmental sustainability and reduces CO_2E. Conversely, increasing financial inclusion may result in higher CO_2E by improving access to money for both individuals and societies, accelerating environmental deterioration, and lowering environmental quality; financial inclusion can increase the total capacity for industrial output. Increasing production levels frequently results in increased energy consumption and, therefore, higher CO_2 emissions; they argue that although financial inclusion may encourage and enhance production and industrial activities, it can also raise carbon emissions (Le and Pham, 2024). According to Le et al. (2020), Zaidi et al. (2021), Mehmood (2022), Tsimisaraka et al. (2023), and Cheikh and Rault (2024) found that FI raises environmental pollution.

Technological innovation (TI) is one of the most effective tools for reducing CO_2E, as it enhances energy efficiency, promotes renewable energy adoption, and introduces cleaner production techniques. It drives the transition from traditional carbon-intensive methods to sustainable alternatives, enabling industries to minimize their environmental footprint. More government officials and academics are realizing the importance of technical innovation in lowering CO_2E as their intensity increases (Saqib et al., 2023). Recent research highlights the crucial role of technological innovation in reducing CO_2E emissions, mainly through patents, which are seen as key indicators of sustainable advancements Chen and Lee (2020), Cheng et al. (2021), Wang et al. (2019), Yu and Du (2019), Bilal et al. (2021) and Abid et al. (2022). China is currently the largest market in the world for environmental technology products and services, with a market size exceeding \$260 billion in 2022. More than 86% of Guangdong's total operating income from environmental technologies was generated by the subsectors of the environmental technologies industry that produced the vast majority of goods and services, including solid waste disposal, recycling, and water and wastewater treatment solutions. Despite the province's vast geographic area, most of Guangdong's environmental businesses are centered in Guangzhou, Foshan, Shenzhen, Dongguan, and Zhongshan (China Environmental Technologies, 2024).

Recent discussions highlight a growing interest in understanding the influence of FI and TI on CO_2E, given their critical role in sustainable development. Despite this increasing attention, existing studies present mixed and often inconclusive findings regarding their relationship. Moreover, most research has primarily focused on their individual effects rather than their combined impact, particularly in the context of China. Additionally, previous studies have largely overlooked the potential existence of an N-shaped EKC in the FI, TI and CO_2E nexus. The N-shaped EKC framework suggests that CO_2E may initially rise with economic growth, then decline as advancements in TI and FI improve environmental outcomes, but could eventually rise again due to structural changes or increased resource consumption. Given this gap in the literature, a comprehensive examination of these relationships is necessary to provide a clearer understanding of their dynamics in China. Therefore, this study aims to investigate the impact of FI and TI on CO_2E within the N-shaped EKC framework, focusing specifically on the Chinese context. Our research seeks to address the following key questions.

How does FI affect CO_2E?
How does TI affect CO_2E?
Does an N-shaped EKC exist or not?

The Chinese government's launch of the "Plan for Promoting the Development of Inclusive Finance" in 2015 has significantly expanded digital financial inclusion in China (Lai et al., 2020). According to this plan, financial inclusion aims to ensure that financial institutions provide access to financial products and services to all population segments within their jurisdictions based on principles of equal opportunity, commercial sustainability, and cost-effectiveness. Additionally, the surge in global demand following the pandemic has accelerated the adoption of digital channels, with governments, businesses, and the public showing heightened interest in fintech solutions. Inclusive finance services particularly aim to support disadvantaged groups, such as farmers, the elderly, and low-income populations (Liu et al., 2024; Becha et al., 2025). This study makes several significant contributions to the existing literature. First, it examines the impact of FI and TI on CO_2E in China, an area that has been largely overlooked in previous research. While prior studies have explored various determinants of CO_2E, the role of FI and TI in shaping environmental outcomes in the Chinese context remains underexplored. By addressing this gap, our study provides new insights into how these factors influence CO_2E. Second, this research tests the existence of an N-shaped EKC for China while incorporating FI and TI into the analysis. However, the potential for an N-shaped EKC, where CO_2E may rise again after a decline, has not been thoroughly examined, particularly in the presence of FI and TI. By integrating these variables into the EKC framework, this study offers a more comprehensive understanding of the dynamics shaping CO_2E in China. Third, this study extends the analysis by investigating the combined effects of FI, TI, and renewable energy on CO_2E under the N-shaped EKC framework. Previous research has often treated these factors in isolation, failing to account for their interactive effects on environmental outcomes. By examining their joint influence, this study provides a more holistic perspective on the mechanisms through which FI, TI, and renewable energy impact CO_2E. The analysis spans from 2006Q1 to 2022Q4, ensuring a robust and up-to-date assessment of these relationships. Finally, the study's findings offer valuable insights for policymakers seeking to balance economic growth with environmental sustainability. By identifying the roles of FI, TI, and renewable energy in shaping CO_2E, this research provides a solid foundation for designing targeted policies that promote sustainable development in China.

The rest of the study is structured as follows: Section 2 reviews the relevant literature, while Section 3 outlines the model, methodology, and data. Section 4 presents the findings and discussion, and Section 5 concludes with policy recommendations.

2 Literature review

2.1 Financial inclusion and CO_2E nexus

Le et al. (2020) analyzed the impact of FI on CO_2E in Asia using data from 31 countries between 2004 and 2014. Principal Component Analysis (PCA) was used to create FI indicators. The results revealed that income, energy use, urbanization, industrialization, and FI increased CO_2E. In contrast, greater trade openness was found to reduce emissions. The study demonstrated that the results remained robust to alternative FI proxies and model specifications. Notably, the study found no synergies between FI and CO_2 reduction policies. As a result, FI should be integrated into climate adaptation strategies at all levels to mitigate its environmental impact. Zaidi et al. (2021) examined the dynamic relationships between FI, energy use, CO_2E, infrastructure, corruption, and economic growth in 23 OECD countries from 2004 to 2017. The study constructed FI and infrastructure indexes using Principal Component Analysis (PCA). The CS-ARDL method was applied to analyze long-term relationships while accounting for cross-sectional dependence. The results showed a positive relationship between FI, energy use, and CO_2E, indicating that FI exacerbates environmental degradation. Infrastructure development and economic growth also contributed to increased emissions. The study emphasized aligning FI strategies with environmental policies to achieve sustainable development goals.

Policymakers were urged to balance FI objectives with energy consumption patterns and environmental regulations. Qin et al. (2021) investigated how FI, globalization, and renewable power generation influenced CO_2E in seven developing economies from 2004 to 2016. A panel quantile regression approach was used to account for the non-normality of data. The findings showed that FI significantly reduced emissions at the 25th and 50th quantiles but had no significant effect at the 75th and 95th quantiles. Globalization and renewable power generation consistently reduced CO_2E across all quantiles. The Kao and Johansen cointegration tests also validated long-term relationships among the variables. The study confirmed the seven economies' Environmental Kuznets Curve (EKC) hypothesis. Based on these findings, the authors recommended improving FI, encouraging globalization, and increasing renewable energy use to promote sustainable economic growth.

Mehmood (2022) examined the relationship between FI, renewable energy, globalization, and CO_2E in South Asia from 1990 to 2017. Using the cross-sectional ARDL technique, the study accounted for cross-sectional dependence in panel data for reliable findings. The Westerlund test confirmed a long-term relationship among the variables. The results showed that FI contributed to rising CO_2E, indicating the need to incorporate cleaner environmental measures into FI policies. In contrast, renewable energy use was found to reduce emissions, highlighting its role in environmental sustainability. The study also revealed that globalization and economic growth further increased emissions. Based on the findings, Mehmood advised South Asian countries to update foreign trade policies to reduce environmental degradation. Wang et al. (2022) explored the effect of digital FI on CO_2E in 284 Chinese cities at the prefecture level. Using a spatial econometric model, the study assessed digital FI's local and spillover effects. The findings revealed that digital FI increased CO_2E in local cities while reducing emissions in neighboring cities due to spatial spillover effects. Additionally, the study examined the three facets of digital FI (breadth, depth, and usage) and their impacts on CO_2E. Mediation analysis showed that industrial structure and economic growth were pathways through which digital FI influenced emissions. The study highlighted regional differences, noting that eastern, western, and northeastern cities benefited more. The findings underscored the importance of region-specific policies to balance FI and environmental sustainability. Liu et al. (2022) investigated the role of FI and education in limiting CO_2E in China using the ARDL approach. The study evaluated the impact of five proxies for FI on environmental quality and found that four positively influenced CO_2 reduction. Education was also identified as a critical factor in lowering emissions by increasing public awareness and promoting eco-friendly practices. However, research and development activities were found to increase carbon emissions, while GDP and population growth further exacerbated environmental degradation. The authors emphasized the importance of innovation through knowledge in developing energy-efficient technologies. They recommended allocating financial resources to eco-innovations and strengthening environmental education campaigns to combat global warming. The study concluded that education and FI are essential for achieving environmental sustainability.

Zheng and Li (2022) explored the effect of digital FI on CO_2E in 30 Chinese provinces from 2013 to 2020. Using instrumental variable regression and GMM, they found that digital FI reduces emissions, mainly through usage depth and digitization level. Heterogeneity analysis revealed more substantial impacts in central regions and low-emission areas. Mechanism tests indicated that digital finance lowers emissions by reducing *per capita* energy consumption and increasing GDP, supporting its role in achieving carbon neutrality. Shahbaz et al. (2022) studied the role of FI in reducing pollutant and carbon emissions across 30 Chinese provinces from 2011 to 2017. Empirical results showed that FI supports joint reductions in pollutants and CO_2E, mainly through energy consumption and renewable energy development. The effects were region-specific, with stronger impacts in less polluted areas. FI indirectly lowered emissions by improving energy structure and consumption patterns, highlighting its potential in provincial and national development plans. Hussain et al. (2023) explored the FI-carbon emissions relationship in 102 countries from 2004 to 2020 using the STIRPAT framework and PCA. The study found an N-shaped EKC relationship, where FI initially increases emissions, then decreases, followed by a rise again. The nonlinear relationship was robust in low-income countries but weak in developed ones. The study recommended well-directed financial policies to improve inclusion while addressing income, governance, and laws disparities. Tsimisaraka et al. (2023) examined the short- and long-term impacts of FI, ICT, renewable energy, globalization, and economic growth on CO_2E in the OBOR region. Using the CS-ARDL method with data from 2004 to 2019, the results demonstrated a strong positive correlation between FI, ICT, and CO_2E. Renewable energy reduced emissions in both timeframes, while globalization had a long-term negative impact. Economic growth positively affected emissions, highlighting the need for green foreign investment and ICT infrastructure development.

Khan et al. (2023) investigated the impact of digital FI on carbon emissions across 76 emerging markets and developing economies. Using the Global Findex database, they constructed an overall digital FI index and sub-indices. A dynamic two-step system GMM approach was employed, and results showed that digital FI positively impacts carbon emissions. The findings remained robust when using sub-indices and traditional FI as control variables.

Prempeh et al. (2023) specifically examined the impact of banking sector development on environmental degradation in 11 Economic Community of West African States (ECOWAS) by using the Augmented Mean Group (AMG) estimators from 1990 to 2019. They found that banking sector development generally reduces environmental degradation, its associated technological effects tend to worsen environmental quality. Hussain et al. (2024) investigated the FI-carbon emissions nexus in 26 Asian nations, distinguishing between developed and emerging economies. Using PCA for FI indices, the results showed a positive long-term and negative short-term effect of FI on emissions. Cheikh and Rault (2024) analyzed threshold effects of FI on CO_2E in 70 nations using panel threshold models. Their findings showed that FI's impact varies with economic growth. FI increases emissions in low-income regimes, while it improves environmental quality at higher economic stages.

Arshad and Parveen (2024) empirically examined the impact of FI on CO_2E in 29 developing countries over the period 2004 to 2018 by using the CS ARDL methods. Their findings suggest that financial inclusion is positively associated with CO_2E. In a broader cross-country context, Le and Pham (2024) investigate the dual roles of FI and digitalization on CO_2E in 38 countries from 2006 to 2020. Using the system GMM approach and fixed-effect panel threshold models. Their results reveal that the environmental impact of financial inclusion decreases as countries reach higher levels of financial access and digitalization.

Prempeh et al. (2024) investigates the roles of economic growth, financial development, globalization, renewable energy, and industrialization in mitigating environmental degradation in 10 ECOWAS countries from 1990 to 2019 using the panel quantile regression. The study validates the N-shaped EKC hypothesis. The Key findings reveal that financial development and renewable energy adoption contribute to lower environmental degradation, whereas globalization and industrialization exacerbate it. Expanding the regional focus to Sub-Saharan Africa (SSA), Prempeh et al. (2024) explore how financial development influences renewable energy consumption within the renewable energy-environmental Kuznets curve (REKC) framework. Analyzing a panel of 38 SSA countries from 2002 to 2019 using PCSE and FGLS models, they validate the REKC hypothesis. Surprisingly, financial development, economic growth, governance, trade openness, and urbanization were all found to negatively impact renewable energy consumption.

2.2 Technological innovation and CO_2E nexus

Santra (2017) analyzed the effect of TI on energy and CO_2 emission productivity in the BRICS countries. The study found that technological progress positively impacts emission productivity, with significant improvements in energy efficiency observed in countries with higher levels of innovation. The research suggested that TI is a key driver of sustainable development in emerging economies. Lin and Zhu (2019) focused on the determinants of renewable energy TI in China under CO_2E constraints. They found that CO_2 emission reduction targets significantly influenced the pace of renewable energy technological development. Setting strict environmental regulations could drive TI in the renewable energy sector. Yu and Du (2019) examined the impact of TI on CO_2E and the projection of emissions trends in China's "New Normal" economy. Using panel data from Chinese provinces (1997–2015), they developed an extended STIRPAT model to assess how TI affects CO_2E. The sample was divided into two groups: high-speed and low-speed growth groups. The study also included scenario simulations to forecast CO_2E from 2016 to 2030. The findings showed that TI contributed more to increasing CO_2E in the low-speed growth group, while it had a significant reduction effect in the high-speed growth group. Projections suggested that China could reduce CO_2E substantially if appropriate policies promoting TI are implemented.

Chen and Lee (2020) investigated the relationship between TI and CO_2E in a cross-country context. They employed panel data for a group of countries and used dynamic panel methods to assess how TI impacts CO_2E. The results indicated that TI negatively correlates with CO_2E in high-income countries, but this effect is less pronounced in low-income countries. They concluded that enhancing TI is an essential policy tool for reducing emissions, particularly in developed nations. Wang et al. (2019) investigated the multiple impacts of technological progress on CO_2E in China using a panel quantile regression approach. The results indicated that technological progress has a varied effect across different quantiles of CO_2E. The authors found that TI has a significant negative impact in regions with high emissions, suggesting that innovation could be a powerful tool for emission reduction in industrial areas. Wen et al. (2020) examined the spillover effects of TI on CO_2E. The study found that TI directly reduces emissions and has positive spillover effects on neighboring regions and countries. This suggests that collaborative technological efforts could amplify global emission reductions. Cheng et al. (2021) analyzed how TI mitigates CO_2E in OECD countries. Using panel quantile regression, the authors found that TI significantly negatively affects CO_2E, especially in high-emission countries. Their findings underscore the importance of fostering innovation to meet environmental targets in developed nations.

Bilal et al. (2021) explored the relationship between green technology innovation, globalization, and CO_2E. Using a panel data approach, they found that globalization amplifies the impact of green TI on emissions, particularly in developed countries. Their study emphasized the need for global cooperation to leverage TI to reduce CO_2E. Zhao et al. (2021) examined the effect of financial risk on global CO_2E, emphasizing the role of TI. Using a panel data approach, they found that financial risk negatively impacts TI, reducing its potential to mitigate CO_2E. The study highlighted the need for stable financial systems to foster technological progress and achieve emission reduction targets. Acheampong et al. (2022) investigated the impact of transport infrastructure and TI on economic growth and CO_2E. Their findings indicated that while TI promotes economic growth, it also increases emissions in the short term. However, long-term effects showed that TI could help reduce emissions, especially with sustainable transport policies. Abid et al. (2022) explored the impact of TI, foreign direct investment (FDI), and financial development on CO_2E in the G8 countries. The study used a panel data approach and found that TI significantly reduces CO_2E, particularly when combined with financial development.

The authors suggested that policies promoting technological advancement and FDI could further reduce emissions in these countries. Udeagha and Ngepah (2022) examined the asymmetric effect of TI on CO_2E in South Africa using a Quantile Autoregressive Distributed Lag (QARDL) approach. The study found that TI has a more substantial impact on reducing emissions in the long run compared to the short run. The results suggested that innovation policies need to be strengthened for South Africa to achieve its climate goals. Obobisa et al. (2022) investigated the role of green TI and institutional quality in reducing CO_2E across African countries. Their results indicated that green innovation and better institutional quality are crucial for reducing emissions. The study highlighted the need for African nations to improve their institutions and invest in green technologies to achieve sustainable development.

2.3 Theoretical review

Theoretically, FI can have both positive and negative effects on CO_2E (Le et al., 2020). On the positive side, FI enhances access to financial resources, enabling businesses and individuals to invest in green technologies. By improving accessibility, affordability, and adoption of sustainable practices, an inclusive financial system can contribute to reducing environmental degradation. This is particularly crucial for marginalized communities, where limited capital often restricts investment in clean energy solutions. For instance, FI can help farmers secure credit for solar energy microgrids, a cost-effective alternative that emits significantly less CO_2E than coal-based energy sources. Conversely, better access to financial services supports and encourages industrial and manufacturing activity, which might raise CO_2E and contribute to global warming. Additionally, increased financial inclusion makes it possible for consumers to purchase energy-intensive consumer items like air conditioners, refrigerators, and cars, all of which pose a significant environmental risk due to their increased emissions of greenhouse gases (GHG). In addition to promoting economic activity, inclusive financial systems boost demand for polluting energy sources, raising greenhouse gas emissions (Lee et al., 2020). The Environmental Kuznets Curve (EKC) theory, developed by Grossman and Krueger (1991), examines the relationship between economic growth (GDP) and environmental sustainability, mainly focusing on CO_2 emissions. According to the EKC hypothesis, as economies grow, environmental degradation (ED) initially increases, but after reaching a certain economic threshold, the relationship between GDP and environmental degradation changes. Du et al. (2023) support the view that the impact of economic development on the environment follows a non-linear pattern, with environmental damage rising during the early stages of industrialization and later decreasing as income and technology improve. The EKC contrasts pre-industrial and post-industrial development, aiming to explain how CO_2 emissions evolve as economies progress. Jahanger et al. (2023) argue that, as economic development progresses, the intensity of emissions decreases due to the shift towards cleaner, more energy-efficient technologies and improved industrial practices. Figure 1, in theory, illustrates the N-shaped pattern, showing that environmental degradation and *per capita* income initially rise together. However, after a certain income level, they diverge as emissions intensity falls. The N-shape pattern, as described by Awan and Azam (2022), shows that environmental degradation may initially worsen as income increases. However, the relationship reverses over time as economies mature and adopt greener technologies. This suggests that while early stages of economic growth may harm the environment, long-term development and technological progress lead to environmental improvements. The EKC theory thus provides a framework for understanding how economic development and environmental sustainability can be balanced over time, with the potential for future reductions in emissions as economies continue to develop.

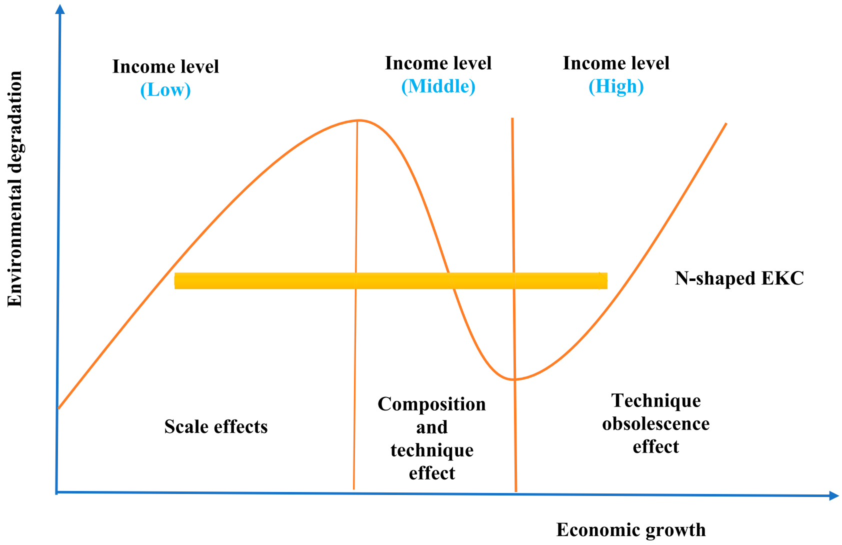

FIGURE 1
N-Shaped EKC. Source: Authors own compilation based on literature.

Although previous studies have examined various determinants of CO_2E, the specific roles of FI and TI in influencing CO_2E in China remain underexplored. Particularly, there is limited research investigating the potential existence of an N-shaped EKC while accounting for FI and TI. Moreover, most earlier research has analyzed FI, TI, and renewable energy separately rather than exploring their combined interactive effects on environmental outcomes. Thus, there is a lack of comprehensive studies that integrate FI, TI, and renewable energy into a unified framework to assess their joint impact on CO_2E in China over a recent and extensive period (2006Q1–2022Q4).

3 Methodology and data

3.1 Model specification

This study examines the impact of financial inclusion and technological innovation on CO_2E sustainable environment; under the EKC framework. The following model has been emerged from the literature:

$$CO2E_t = \vartheta_0+\vartheta_1 GDP_t+\vartheta_2 GDP_t^{\ 2} + \vartheta_3 GDP_t^{\ 3}+\vartheta_4 FI_t + \vartheta_5 TI_t+\vartheta_6 RE_t + u_t \tag{1}$$

where in Equation 1, CO_2E, *GDP*, GDP^2, GDP^3, *FI*, *TI* and *RE* represent the Carbon emission, Gross domestic product, GDP square, GDP cube, financial inclusion, technological innovation and renewable energy respectively. Where residual, countries and time periods are represented by Where u_{it}, the subscript (i = 1. . .. . .n), and the subscript (t = 1. . .. . .t). CO_2E, is a dependent variable while *GDP*, GDP^2, GDP^3, *FI*, *TI* and *RE* are independent variable. ϑ_0 is intercept, while $\vartheta_1 to\, \vartheta_6$ are the slope coefficient of the respective explanatory variables. There are seven types of interpretation about the EKC shapes concerning coefficients. If the coefficient of $\vartheta_1 > 0$, $\vartheta_2 = \vartheta_3 = 0$ called Monotonically increasing, if $\vartheta_1 < 0$, $\vartheta_2 = \vartheta_3 = 0$ called Monotonically decreasing, if $\vartheta_1 > 0, \vartheta_2 < 0, \vartheta_3 = 0$ called inverted U-shaped, if $\vartheta_1 < 0, \vartheta_2 > 0, \vartheta_3 = 0$ called U-shaped, if $\vartheta_1 > 0, \vartheta_2 < 0, \vartheta_3 > 0$ called N-shaped, if $\vartheta_1 < 0, \vartheta_2 > 0, \vartheta_3 < 0$ called Inverted-N shaped and if $\vartheta_1 = \vartheta_2 = \vartheta_3 = 0$ called at level EKC (Awan and Azam, 2022; Du et al., 2023).

3.2 Estimation strategy

The first step of any time series analysis, is testing the unit root. This study employs the Augmented Dickey-Fuller (ADF) test, developed by Dickey and Fuller (1979), and the Phillips-Perron (PP) test, introduced by Phillips and Perron (1988), to examine stationarity, with the ADF test based on Equation 2:

$$\Delta H_t = \phi + \beta t + \delta H_{t\text{-}1} + \sum_{i=1}^{p} \beta_i \Delta H_{t-i} + e_t \tag{2}$$

where ΔH_t represents the first difference of the series, ϕ is a drift term, βt is a deterministic time trend, δH_{t-1} represents the lagged level of the series, $\sum_{i=1}^{p} \beta_i \Delta H_{t-i}$ accounts for the lagged differences of the dependent variable, e_t is the white noise error term, and p is the number of lagged difference terms, while the null hypothesis (H_0) that $\delta = 0$ implies the presence of a unit root (nonstationarity), and the alternative hypothesis (H_1) that $\delta < 0$ suggests stationarity (Gujarati and Porter, 2009). In contrast, the PP test uses non-parametric methods to adjust the t-statistic of the δ coefficient for serial correlation and heteroscedasticity without requiring the inclusion of lagged difference terms, as is necessary in the ADF test (Zhang et al., 2025).

After performing the unit root test, the study applies the Johansen and Juselius (1990) Cointegration test to examine long-run relationships among time series variables. Cointegration

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suggests that despite being individually non-stationary, variables share a common trend and move together over time. Identifying Cointegration is crucial to prevent spurious regression results. Methods such as the JJ Cointegration test and the ARDL bounds test help ensure the model captures meaningful long-term relationships, improving prediction accuracy and enhancing policy implications. The JJ test is particularly effective in detecting long-run equilibrium relationships in multivariate time series (Zhang et al., 2025).

Following the Cointegration analysis, the study employs the Autoregressive Distributed Lag (ARDL) model developed by Pesaran et al. (2001) to assess both long-run and short-run dynamics. This model is estimated to investigate the relationships among the variables, as presented in Equation 3 below.

$$\begin{aligned}\Delta CO2E_t =& \beta_0 + \phi_1 CO2E_{t-1} + \phi_2 GDP_{t-1} + \phi_3 GDP^2_{t-1} + \phi_4 GDP^3_{t-1} \\ &+ \phi_5 FI_{t-1} + \phi_6 TI_{t-1} + \phi_7 FI_{t-1} + \phi_8 TI_{t-1} + \sum_i^n \vartheta_1 \Delta CO2E_{t-1} \\ &+ \sum_i^n \vartheta_2 \Delta GDP_{t-1} + \sum_i^n \vartheta_3 \Delta GDP^2{}_{t-1} + \sum_i^n \vartheta_4 \Delta GDP^3{}_{t-1} \\ &+ \sum_i^n \vartheta_5 \Delta FI_{t-1} + \sum_i^n \vartheta_6 \Delta TI_{t-1} + \sum_i^n \vartheta_7 \Delta RE_{t-1} + e_t\end{aligned} \tag{3}$$

Equation 3 is estimated using the ordinary least squares (OLS) method, and the joint significance of the lagged variables' coefficients is assessed through the Wald F-test to determine the presence of a long-run relationship. The null hypothesis of no cointegration $(Ho\colon \phi_1\ to\ \phi_8 = 0)$ is tested against the alternative hypothesis of cointegration $(Ha\colon \phi_1\ to\ \phi_8 \neq 0)$. According to Pesaran et al. (2001), the null hypothesis is rejected if the computed F-test value exceeds the upper bound critical value, confirming a long-run relationship. Conversely, if the F-test value falls below the lower bound, no cointegration is established. If the F-test value lies between the lower and upper bounds, the result remains inconclusive. Following this, the short-run dynamics are examined using the error correction model (ECM), specified as follows in Equation 4:

$$\begin{aligned}\Delta CO2E_t =& \vartheta_0 + \sum_{i=0}^n \vartheta_1 \Delta CO2E_{t-1} + \sum_{i=0}^n \vartheta_2 \Delta GDP_{t-1} + \sum_{i=0}^n \vartheta_3 \Delta GDP^2{}_{t-1} \\ &+ \sum_{i=0}^n \vartheta_4 \Delta GDP^3{}_{t-1} + \sum_{i=0}^n \vartheta_5 \Delta FI_{t-1} + \sum_{i=0}^n \vartheta_6 \Delta TI_{t-1} \\ &+ \sum_{i=0}^n \vartheta_7 \Delta RE_{t-1} + \omega_1 \mathrm{ECM}_{t-1} + e_t\end{aligned} \tag{4}$$

A negative and statistically significant coefficient of ECM_{t-1} (ω_1) indicates that any short-term deviation between the dependent and explanatory variables will gradually adjust back to the long-run equilibrium (Ali et al., 2016). This suggests the presence of a stable correction mechanism that restores equilibrium over time.

For the Robustness, FMOLS (Fully modified OLS) and the DOLS (dynamic OLS) developed by Phillips and Hansen (1990) and Stock and Watson (1993) created the FMOLS (Fully modified OLS) and the DOLS (dynamic OLS). Because they account for endogeneity and serial autocorrelation, they result in the creation of asymptotically efficient coefficients. They are only used for all variables in the I(1) situation. The latter reduces their adaptability and appeal. When variables are cointegrated but nonstationary, OLS is biassed, whereas FMOLS is not. For a number of reasons, DOLS outperforms the FMOLS technique (Kao and Chiang, 2001). Compared to FMOLS, DOLS minimizes bias more effectively and is computationally easier. Compared to the statistics derived from the OLS or the FMOLS, the t-statistic derived by DOLS more closely resembles the standard normal density. Pre-estimation and non-parametric correction are not necessary for DOLS estimators because they are completely parametric. The main advantage of DOLS, is that it takes into account the heterogeneous order of integration of variables in the cointegration framework (Menegaki, 2019).

3.3 Data

This study examines the impact of financial inclusion (FI) and technological innovation (TI) on CO_2E under the EKC framework in China from 2006Q1 to 2022Q4 based on data availability. The data has been obtain from World Development Indicators (WDI), and Global financial development websites, Table 1 shows the variable measurement. The financial development index developed from four indicators such as Life insurance premium (LIP) Nonlife insurance premium (NLIP), Depositors with commercial banks (DCB) and Automated teller machines (ATMs) by using the principle component analysis (PCA). Table 2 shows the PCA output for FI index. The PCA output reveals that the first component (Comp1) explains 79.7% of the variance, indicating it captures the overall financial inclusion trends, with high positive loadings for ATMs, DCM, NLIP, and LIP. The second component (Comp2) explains 14.7% of the variance and is strongly associated with LIP, reflecting financial literacy or product availability, while having negative relationships with DCM and NLIP. The third component (Comp3) accounts for 4.6% of the variance and highlights a trade-off between financial service types, especially mobile payments and traditional banking. The fourth component (Comp4) explains 1% of the variance and focuses on infrastructure-related dimensions, with negative associations with ATMs and positive with NLIP. Based on these findings, we developed the financial inclusion index primarily using the first component (Comp1), as it explains the largest proportion of the variance and incorporates key indicators of financial access and inclusion.

4 Results and discussions

4.1 Results

Table 3, shows the mean values for the variables show that CO_2E average is 9.224, GDP is 8.884, GDP^2 is 79.044, GDP^3 is 704.230, FI is 0.000, TI is 13.529, and RE is 13.476. The standard deviations indicate low variability in CO_2E (0.180), moderate variability in GDP (0.337) and TI (0.710), and high variability in GDP^3 (78.971) and RE (1.583). The Jarque-Bera test shows that CO_2, FI, and TI

TABLE 1 Variable measurement.

Symbol(s)	Variable(s)	Measurement(s)	Source(s)
CO_2E	CO_2 emissions	Total (Mt CO_2E)	WDI
GDP	Gross domestic product	Per capita (constant 2015 US$)	
FI	Financial inclusion	Life insurance premium (LIP) volume to GDP (%)	Global financial development
		Nonlife insurance premium (NLIP) volume to GDP (%)	
		Depositors with commercial banks (DCB) (per 1,000 adults)	WDI
		Automated teller machines (ATMs) (per 100,000 adults)	
TI		Sum of resident and Nonresident patient application	
RE	Renewable energy	% of total final energy consumption	

TABLE 2 Financial inclusion index.

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	3.19	2.602	0.797	0.797
Comp2	0.588	0.404	0.147	0.944
Comp3	0.184	0.145	0.046	0.99
Comp4	0.039	—	0.010	1
Principal components (eigenvectors)				
Variable	Comp1	Comp2	Comp3	Comp4
ATMs	0.543	−0.238	0.129	−0.795
DCM	0.522	−0.123	−0.802	0.263
LIP	0.402	0.906	0.131	0.024
NLIP	0.521	−0.327	0.568	0.546

TABLE 3 Descriptive statistics.

	CO_2E	GDP	GDP^2	GDP^3	FI	TI	RE
Mean	9.224	8.884	79.044	704.230	0.000	13.529	13.476
Median	9.286	8.927	79.692	711.409	−0.049	13.741	13.400
Maximum	9.451	9.355	87.522	818.798	1.198	14.277	16.400
Minimum	8.846	8.243	67.946	560.079	−1.471	12.257	11.300
Std. Dev	0.180	0.337	5.956	78.971	0.985	0.710	1.583
Skewness	−0.742	−0.341	−0.294	−0.247	−0.125	−0.523	0.283
Kurtosis	2.383	1.956	1.917	1.884	1.399	1.729	1.887
Jarque-Bera	7.321**	4.411	4.301	4.221	7.440**	7.684**	4.413
Probability	0.026	0.110	0.116	0.121	0.024	0.021	0.110
Observations	68	68	68	68	68	68	68

Note: *, ** and *** represent 1%, 5% and 10% significance level.

significantly deviate from normality, while GDP, GDP^2, GDP^3, and RE exhibit near-normal distributions, with probabilities indicating a slight deviation from normality for most variables.

Table 4, shows the three different unit root rest results. The ADF test shows that CO_2E, GDP, TI and RE are non-stationary at level and becomes stationary after first difference, while FI is stationary at

TABLE 4 Unit root test.

	ADF		PP	
	I(0)	I(1)	I(0)	I(1)
CO_2E	−1.797	−3.024**	−2.903***	−9.339*
GDP	−1.576	−3.824*	−3.513**	−12.168*
FI	−4.989*	−3.608*	−0.880	−9.182*
TI	−1.050	−3.497*	−2.026	−9.371*
RE	−0.497	−4.177*	−1.165	−8.002*
ZA				
	I(0)		I(1)	
	t-Statistic	Break	t-Statistic	Break
CO_2	−3.69	2010Q1	−4.989**	2012Q1
GDP	−2.381	2010Q1	−5.377*	2011Q3
FI	−3.295	2019Q1	−4.932**	2015Q2
TI	−1.681	2019Q1	−5.092**	2011Q4
RE	−4.753**	2010Q1	−4.862***	2015Q2

Note: *, ** and *** represent 1%, 5% and 10% significance level. ZA, unit root critical value at 1%, 5% and 10% are −5.34, −4.93 and −4.58 respectively.

TABLE 5 Cointegration test.

Johansen cointegration					
Hypothesized	Trace			Max-Eigen	
No. of CE(s)	Eigenvalue	Statistic	Prob	Statistic	Prob
None	0.672*	151.349	0.000	72.365*	0.000
At most 1	0.437*	78.984	0.002	37.339**	0.011
At most 2	0.249***	41.645	0.067	18.604	0.333
At most 3	0.178	23.042	0.108	12.759	0.348
At most 4	0.146	10.283	0.115	10.283	0.115
ARDL bound test					
Test Statistic	Value	Critical Value			
F-statistic	8.560*	Significance	I (0)	I (1)	
K	6	10% 5% 1%	2.46 2.947 4.093	3.46 4.088 5.532	

Note: *, ** and *** represent 1%, 5% and 10% significance level.

level. The PP test also confirms that CO_2E and GDP are stationary at level, while FI, TI and RE are stationary after fist difference. The ZA test shows that At level (I(0), the variables that are stationary are CO_2E, GDP, FI and RE, with structural breaks occurring in 2010Q1 for CO_2, 2010Q1 for GDP, 2019Q1 for FI, and 2010Q1 for RE. At first difference (I(1)), the variables that become stationary are CO_2, GDP, FI, TI, and RE, with structural breaks occurring in 2012Q1 for CO_2, 2011Q3 for GDP, 2015Q2 for FI, 2011Q4 for TI, and 2015Q2 for RE.

Table 5 presents the results of the Johansen Cointegration and ARDL bounds tests. The Trace statistics from the Johansen Cointegration test confirm the presence of 2 cointegrated equations, while the Max-Eigen statistics indicate 1 cointegrated equations. Additionally, the ARDL bounds test shows that the

TABLE 6 ARDL estimates.

Variable	Coefficient	Std. Error	t-Statistic	Prob
Long run				
GDP	−216.656*	77.862	−2.783	0.008
GDP^2	24.321*	8.935	2.722	0.009
GDP^3	−0.904*	0.341	−2.652	0.011
FI	−0.108*	0.029	−3.701	0.001
TI	−0.171**	0.082	−2.081	0.042
RE	−0.047*	0.016	−2.981	0.004
C	651.253*	226.426	2.876	0.006
Short run				
GDP	−98.956*	28.499	−3.472	0.001
GDP^2	11.046*	3.260	3.389	0.001
GDP^3	−0.407*	0.124	−3.283	0.002
FI	−0.068*	0.012	−5.591	0.000
TI	−0.051***	0.028	−1.845	0.071
RE	−0.037*	0.006	−6.587	0.000
ECM(-1)	−0.266*	0.072	−3.677	0.001
ARDL Diagnostic analysis				

Test	F stats	Prob	
Normality test-Jarque–Bera	1.873	0.653	
Autocorrelation test-LM	1.820	0.174	
Heteroscedasticity test-ARCH	1.372	0.435	
Stability test-Ramsey RESET	0.574	0.452	

Note: *, ** and *** represent 1%, 5% and 10% significance level. Dependent variable: CO_2E.

F-statistic (8.560) exceeds the critical value of 5.53, confirming the presence of Cointegration among the variables.

In Table 6, shows the ARDL long run estimates, the coefficient of GDP, GDP^2 and GDP^3 -216.656, 24.321 and −0.904 respectively. The coefficient of GDP is −216.656, which indicates that in the initial stages of economic growth, an increase in GDP is associated with a decrease in CO_2E. The coefficient for GDP^2 is 24.321, which is positive. This suggests that after a certain level of GDP, the decrease in CO_2 emissions slows down, and emissions may begin to increase again as the economy grows further. The coefficient of GDP^3 is −0.904, which is negative. This indicates that at very high levels of GDP, the relationship between GDP and CO_2 emissions turns negative again, suggesting emissions start to decline as GDP continues to grow. With a -GDP, +GDP^2, and -GDP^3 relationship, the pattern represents an inverted-N shaped EKC in China.

The coefficient for FI is −0.108, with a p-value of 0.001, which is statistically significant at the 1% level. This suggests that an increase in financial inclusion is associated with a decrease in the dependent variable, as the negative coefficient implies an inverse relationship. The coefficient for TI is −0.171, and it is statistically significant at the 5% level (p-value = 0.042). This indicates a negative relationship between the Technology Index and the dependent variable, meaning that as technology increases, the CO_2E decreases. The coefficient for RE is −0.047, with a p-value of 0.004, which is statistically significant at the 1% level. This indicates a negative relationship between renewable energy and the CO_2E. As renewable energy usage increases, the CO_2E decreases.

The short run ARDL estimates also confirms that an inverted N shaped exist in china. The financial inclusion, technological innovation and renewable energy have negative effect on CO_2E. The coefficient of the error correction term (ECM) is −0.266, significant at the 1% level (p = 0.001). The negative and significant value indicates that approximately 26.6% of the deviation from the long-run equilibrium is corrected each period. This suggests a relatively moderate speed of adjustment toward the long-run relationship.

The ARDL diagnostic tests confirm that the model is well-specified and reliable. The Jarque-Bera test (p = 0.653) indicates normally distributed residuals, while the LM test (p = 0.174) shows no autocorrelation. The ARCH test (p = 0.435) confirms homoscedasticity, and the Ramsey RESET test (p = 0.452) verifies the correct functional form. The CUSUM and

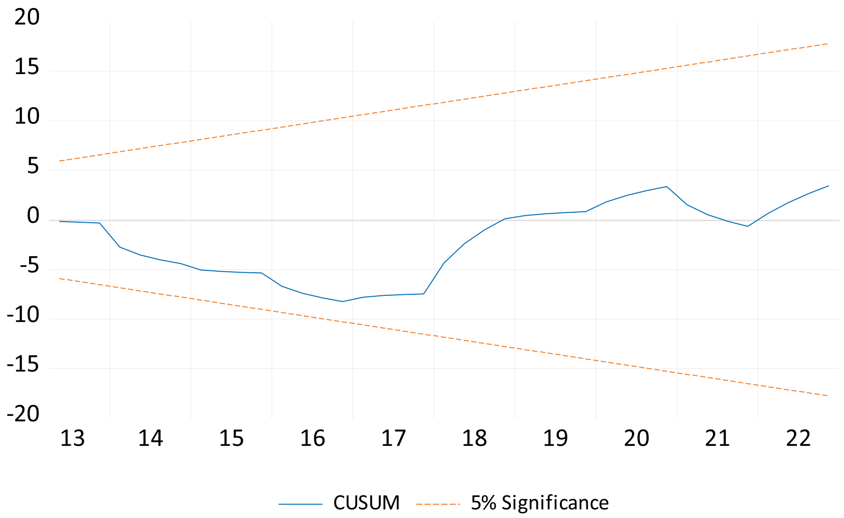

FIGURE 2
The cumulative sum of the recursive residual plot.

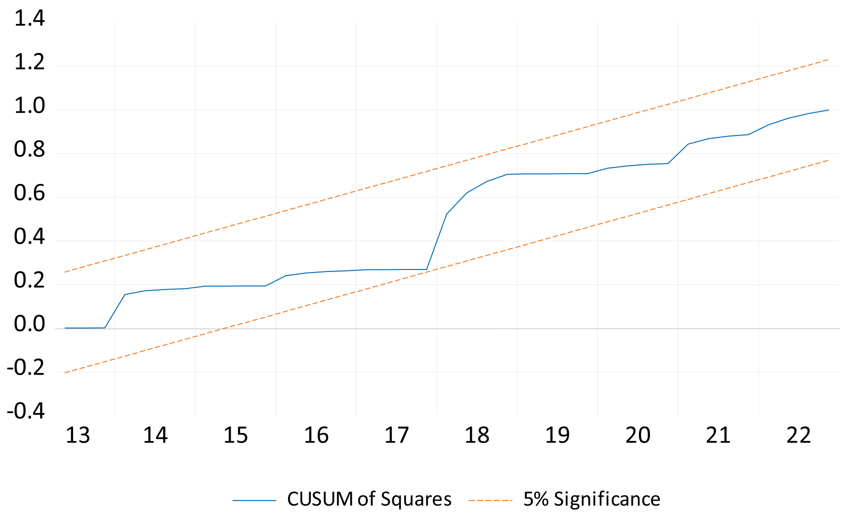

FIGURE 3
The cumulative sum of the square of the recursive residual plot.

CUSUMSQ tests indicate that the ARDL model is stable over time see (Figures 2, 3). This confirms that the parameters remain consistent and the model is reliable for explaining the relationship between the variables. Combined with the other diagnostic results, the ARDL model is robust, well-specified, and suitable for interpretation.

Table 7 shows the Robustness analysis, The FMOLS and DOLS estimators confirm the robustness of the ARDL model findings, as both methods yield similar results in terms of the sign. Both FMOLS and DOLS estimators confirm the robustness of the ARDL results. All variables exhibit the same signs (negative for GDP, financial inclusion, technology, and renewable energy) and are statistically significant, indicating consistent findings across different estimation techniques. This consistency supports the reliability and robustness of the model in explaining the relationship between economic factors and CO_2E.

4.2 Discussions

In both the long run and short run, the coefficients of GDP, GDP^2, and GDP^3 have negative, positive, and negative effects on CO_2E. This implies that in the Initial stage decline in CO_2E as GDP increases, then a rise in CO_2E during industrialization and growth, and a Final decline in CO_2E at high GDP levels as economies adopt cleaner technologies and policies. This pattern is consistent with

TABLE 7 Robustness analysis.

Variable	Coefficient	Std. Error	t-Statistic	Prob
FMOLS				
GDP	−202.573	40.506	−5.001	0.000
GDP^2	22.791	4.648	4.903	0.000
GDP^3	−0.849	0.177	−4.787	0.000
FI	−0.124	0.016	−8.005	0.000
TI	−0.119	0.040	−2.957	0.004
RE	−0.040	0.008	−4.831	0.000
C	607.576	117.779	5.159	0.000
DOLS				
GDP	−226.062	56.252	−4.019	0.000
GDP^2	25.487	6.460	3.945	0.000
GDP^3	−0.952	0.247	−3.859	0.000
FI	−0.126	0.020	−6.398	0.000
TI	−0.138	0.055	−2.489	0.017
RE	−0.039	0.011	−3.641	0.001
C	675.841	163.418	4.136	0.000

Note: *, ** and *** represent 1%, 5% and 10% significance level. Dependent variable: CO_2E.

the idea that higher income levels enable investments in cleaner energy sources, stricter environmental regulations, and better technology to reduce CO_2E. In the early stages of economic development, CO_2 emissions in China declined as GDP rose. This may be attributed to structural transformation from heavy industry to services, improvements in energy efficiency, and initial environmental regulations during the early 2000s. The relationship turned positive as China moved into middle-income status, indicating that emissions increased with further economic growth. This period aligns with the rapid urbanization, infrastructure expansion, and high energy consumption that followed the global financial crisis (2008–2015). At higher income levels, emissions appear to decline again, likely due to the scaling up of renewable energy, carbon trading pilots, green finance, and China's growing commitment to environmental governance (e.g., the 2020 carbon neutrality pledge for 2060). The finding is consistent with the line of Abbasi et al. (2023), Huang et al. (2023), and Wang et al. (2023). Abbasi et al. (2023) found an inverted N-shape EKC shows that nuclear and RE alleviate pollution while non-renewable energy enhances it. Huang et al. (2023) reported that Ecological land area has an inverted "N" connection with GDP. Wang et al. (2023) indicated that income inequality has altered the relationship between economic growth and CO_2E, shifting it from an inverted U-shape to an N-shape. This suggests that income inequality redefines the EKC and adds complexity to decoupling economic growth from CO_2E.

Financial inclusion has a negative effect on CO_2E. FI can reduce CO_2E by enabling access to green financing, which supports investments in clean technologies and renewable energy. It also empowers individuals and businesses to adopt energy-efficient practices and sustainable consumption. Moreover, improved financial services can promote environmental awareness and green initiatives. In the Chinese context, financial inclusion is not just about reducing poverty but also a strategic decarbonization tool. By equipping households and firms with the financial means and incentives to act sustainably, financial inclusion helps accelerate China's shift toward a low-emission, inclusive green economy. The finding is consistent with the line of Qin et al. (2021), which found that FI significantly reduced CO_2E at the 25th and 50th quantiles. Zheng and Li (2022) reported that Digital financial inclusion reduces emissions, particularly through usage depth and digitization level. Shahbaz et al. (2022) found that FI supports reductions in CO_2E by improving energy structure and consumption patterns. Hussain et al. (2024) found that FI negatively affects emissions in emerging economies. The finding contradict with the finding of Arshad and Parveen (2024) found that FI significantly increases emissions due to higher industrial activity and energy demand from urbanization. Cheikh and Rault (2024) reported that financial inclusion increases emissions in low-income regimes.

Technological innovation has a negative effect on CO_2E. TI reduces CO_2E by improving energy efficiency and promoting cleaner energy sources. It enables the development of low-carbon technologies, such as renewable energy, electric vehicles, and energy-efficient machinery. Innovations in production processes can minimize waste and reduce resource consumption. Moreover, technological advancements drive the transition to a more sustainable and less carbon-intensive economy. The finding is consistent with the line of Chen and

Lee (2020) reported that TI has a negative relationship with CO_2E in high-income countries, but the effect is less in low-income countries. Cheng et al. (2021) found that TI significantly negatively affects CO_2E, especially in high-emission countries. Yu and Du (2019) indicated that TI significantly reduced CO_2E in the high-speed growth group in China. Abid et al. (2022) found that TI significantly reduces CO_2E, particularly when combined with financial development. The finding contradicts the finding of Acheampong et al. (2022) that TI promotes economic growth, but it leads to increased emissions in the short term, suggesting a positive effect in the short run.

Renewable energy has a negative effect on CO_2E; RE reduces CO_2E by replacing fossil fuels with clean energy sources like solar, wind, and hydropower. Unlike coal or natural gas, these energy sources produce little to no carbon emissions during generation. As renewable energy use increases, reliance on carbon-intensive energy sources decreases. This transition helps mitigate climate change by significantly reducing greenhouse gas emissions. The finding is consistent with the line of Jie and Rabnawaz (2024) and Akbar et al. (2024).

5 Conclusion and policy recommendations

This study examined the impact of financial inclusion and technological innovation on CO_2E in China under the N-shaped EKC framework from 2006Q1 to 2022Q4. This study utilized the unit root test, Cointegration test, ARDL, FMOLS, and DOLS estimators. The unit root test finding showed that all variables are in a mixed order of data stationarity. The Cointegration test confirmed that there is a long-run nexus between the variables. The long-run and short-run ARDL results confirmed an inverted N-shaped EKC between GDP and CO_2E. While financial inclusion, technological innovation, and RE have negative effects on CO_2E.

This study has several policy recommendations for policymakers to promote environmental sustainability in China. First, Chines Governments should increase access to financial services, particularly for underserved populations, to facilitate investments in green technologies, RE, and energy-efficient practices. Second, Governments should specifically introduce and expand green financial products, such as green bonds, low-interest loans, and microcredit, to fund sustainable projects. These should be accessible to businesses and individuals, particularly in underserved areas. Increased access to green financing can empower businesses and households to invest in energy-efficient technologies, renewable energy systems, and eco-friendly infrastructure, significantly reducing CO_2E. Third, Policymakers should support research and development in clean technologies, provide incentives for adopting low-carbon solutions, and encourage industries to innovate in energy efficiency. Fourth, Governments should implement policies that incentivize the transition to renewable energy, such as subsidies, tax incentives, and investment in infrastructure for solar, wind, and other sustainable energy sources. Fifth, reducing income inequality can help reshape the Environmental Kuznets Curve, ensuring that economic growth does not come at the cost of environmental degradation. Policies should focus on equitable wealth distribution and social safety nets to support inclusive, sustainable development. Fifth, Enforce stricter environmental regulations and standards to guide industries toward cleaner production methods, reduce carbon emissions, and promote sustainability. Six, China should expand digital finance infrastructure (internet coverage, fintech services) in less-developed provinces like Gansu, Qinghai, and Xinjiang, enabling local residents to access green savings products, carbon credit markets, and clean energy investment schemes. Seven, The Chinese government should partner with rural credit cooperatives, agricultural banks, and digital finance platforms like Alipay and WeBank to provide low-interest green microloans to farmers and small enterprises for renewable energy adoption (e.g., solar irrigation systems, biogas digesters).

This study has certain limitations that provide directions for future research. First, while our analysis focuses exclusively on the Chinese economy, future studies could broaden the scope to include developed, emerging, and developing nations to offer a more comparative perspective on the FI, TI and CO_2E nexus. Expanding the geographical coverage would help assess whether the observed relationships hold across different economic contexts. Second, although we incorporated key explanatory variables, several macroeconomic, demographic, social, and health-related factors influencing CO_2E were not included due to data constraints. Future research could integrate these factors to provide a more comprehensive understanding of the determinants of CO_2E. Third, this study did not employ asymmetric analysis, quantile regression, or structural break tests, which could offer deeper insights into heterogeneous effects and regime shifts in the FI, TI and CO_2E relationship. Future research could apply these advanced econometric techniques to extend and refine the analysis. Fourth, our FI index was constructed using four indicators, as data limitations prevented the inclusion of additional FI-related variables. Future studies could enhance the index by incorporating a broader set of indicators to improve the measurement of FI and its impact on CO_2E. Finally, our dataset spans from 2006Q1 to 2022Q4, constrained by data availability. Extending the time period in future studies could help capture long-term trends and structural changes in the relationship between FI, TI, and CO_2E. Addressing these limitations will strengthen future research and contribute to a more nuanced understanding of the dynamics shaping environmental outcomes.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

WS: Conceptualization, Investigation, Writing – original draft, Writing – review and editing. QL: Data curation, Formal Analysis, Funding acquisition, Methodology, Project administration, Supervision, Writing – original draft, Writing – review and editing. IU: Formal Analysis, Methodology, Resources, Validation, Visualization, Writing – review and editing.

Funding

The author(s) declare that no financial support was received for the research and/or publication of this article.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that Generative AI was used in the creation of this manuscript. The authors have used ChatGPT and Grammarly to assist in English translation, grammar checking, and editing.

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