

Article

Digital Inclusive Finance, Digital Technology Innovation, and Carbon Emission Intensity

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Abstract: Decreasing carbon emission intensity (CEI) has emerged as a crucial strategy for nations to attain low-carbon economic growth. Nevertheless, a definitive conclusion about the correlation between financial development and CEI has not been reached. This research examines the influence of digital inclusive finance (DIF), a novel financial sector, on CEI, and the role of digital technology innovation (DTI) in this impact. Firstly, this study analyzes the influence of DIF on CEI from the perspectives of technology effect and scale effect and proposes the hypothesis that the impact of DIF on CEI is U-shaped. Then, using a double fixed-effect model and a sample of 30 provinces in China from 2011 to 2021, this study verifies the accuracy of the hypothesis. Subsequently, this study examines the mechanism by which DIF impacts CEI, and the results indicate that DIF can exert a U-shaped influence on CEI via enhancing DTI. Then, this study further investigates the impact of DIF on CEI from three angles: geographical location, human capital level, and green finance. It also explores the geographical spillover effect and spatial heterogeneity by employing the Durbin model. Lastly, drawing from the aforementioned analysis, this report proposes some recommendations.

Keywords: digital inclusive finance (DIF); digital technology (DTI); carbon emission intensity (CEI); spatial spillovers



Citation: He, Q.; Jiang, H. Digital Inclusive Finance, Digital Technology Innovation, and Carbon Emission Intensity. *Sustainability* **2024**, *16*, 6407. <https://doi.org/10.3390/su16156407>

Academic Editor: Bruce Morley

Received: 8 June 2024

Revised: 16 July 2024

Accepted: 24 July 2024

Published: 26 July 2024



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1. Introduction

Global warming causes climate instability, threatening the world's food, water, ecology, energy, infrastructure, and people, along with their property. The threat to human health will be further exacerbated if action to combat climate change continues to be delayed [1]. Finding effective solutions to global warming has become a top priority for many countries and organizations. CO₂ is the main cause of climate change [2]. Since the industrial revolution, economic growth has been closely linked to CO₂ emissions. Economic expansion requires large amounts of energy, including electricity and oil. The generation of energy and the consumption of fossil fuels such as oil and natural gas emit large amounts of CO₂. In 2023, global CO₂ emissions are projected to reach a historic 37.4 billion tons, an increase of 1.1% from the previous year [3]. China, as the world's largest emerging economy, has surpassed all other countries in energy consumption and CO₂ emissions since its reform and opening up. Uncontrolled economic growth has caused air pollution, contributing to this problem [4]. As shown in Figure 1, in 2021, China already accounts for three-quarters of the world's CO₂ emissions. In fact, as a world power, the Chinese government pledged in 2020 to achieve carbon neutrality by 2060 and peak CO₂ emissions by 2030 [5]. Nevertheless, economic expansion is inevitable. CEI, which measures economic development and CO₂ emissions, is crucial for addressing climate issues and achieving sustainable development.

CEI is heavily dependent on financial development [6]. The provision of capital by the financial sector is crucial to the functioning of the real economy. Its development will significantly impact firms, industries, communities, and even countries throughout the low-carbon transition process [7,8]. By 2030, underdeveloped countries will need USD 127 billion annually for climate change adaptation and USD 295 billion by 2050 [9]. The

effectiveness of the financial system determines the mobilization, investment, allocation, and utilization of funds [10]. Businesses can combat pollution through enhanced financial development. Financial development encompasses financing businesses that develop pollution prevention and environmental-protection technologies. This allows firms to achieve green technology breakthroughs and develop DTI that minimize CO₂ emissions [11,12]. However, it is important to note that financial development can also result in increased CEI through the stimulation of economic growth.

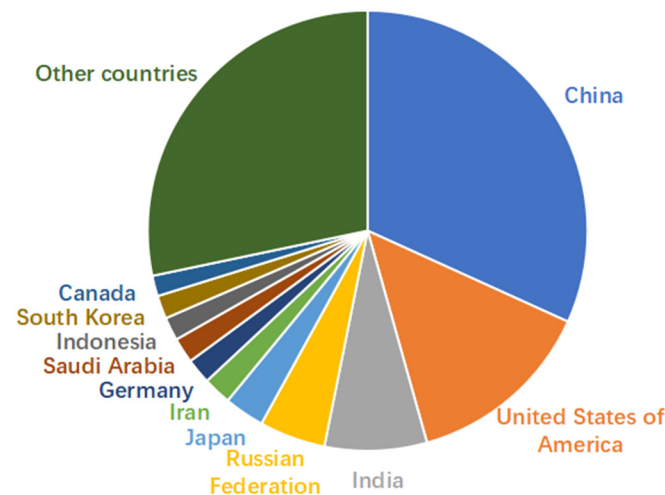


Figure 1. Global carbon emissions in 2021.

Currently, the research on the impact of finance on CEI is broadly categorized into two types: the belief that finance has the potential to reduce CEI and the view that finance can enhance CEI. First, from the perspective that finance can reduce CEI, Yang, et al. [13] argue that financial development has the potential to decrease energy consumption per unit of GDP and mitigate CO₂ emissions. This can be achieved through the rational and efficient allocation of projects rich in technological innovation, as well as by providing increased financial resources for investment in such projects. Acheampong, et al. [14] explored the impact of financial development on CEI. Their findings indicate that the overall development of financial markets significantly reduces the CEI of developed and emerging financial economies by 1%. Furthermore, they note that the effect of financial development on CEI is not always linear but can also be nonlinear. Lee, et al. [15] utilized the DID model to demonstrate that integrating financial market instruments into environmental governance can effectively reduce CEI through decreased energy intensity and capital renewal. Xiong, et al. [16] conducted a study using panel data from 30 provinces in China spanning the period from 2000 to 2017. They employed the fixed-effects model and the mediation-effects model to investigate the correlation between financial development and per capita CO₂ emissions. Their study's findings suggest that financial development plays a crucial role in reducing CEI through technological innovation and industrial structure.

Second, from the view that finance increases CEI, Guo and Tu [17] argue that financial instruments contribute to the escalation of CEI due to the “gas pedal” effect of finance, which stimulates economic growth, resulting in increased energy use and subsequent CO₂ emissions. Sharma, et al. [18] employed CS-ARDL methodology to analyze data from four South Asian nations spanning the years 1990 to 2016. Their research demonstrates that the growth of the stock market in these countries can worsen CEI, with a statistical significance of 5%. Fang, et al. [19], using the ARDL-ECM model, demonstrated that a larger financial size tends to have a higher CEI in the short term, and when the financial size expands by 1%, CEI will increase by 0.5845%. Shahbaz, et al. [20] analyzed the factors that contribute to CO₂ emissions in the UK. Based on the results, it seems that the UK's financial progress is significantly correlated with CO₂ emissions. Specifically, it is projected

that an increase of 0.0428% in CO₂ emissions is anticipated for every 1% improvement in financial development.

The decarbonization effect of DIF has been a research hotspot since October 2023, when the State Council's Implementing Opinions on Promoting the High-quality Development of Inclusive Finance proposed accelerating the development of DIF as a revolutionary financial tool to promote environmentally sustainable practices and the development of green technologies.

DIF is a revolutionary financial service model that utilizes cutting-edge technologies such as big data, artificial intelligence, blockchain, and electronic payments. Its main goal is to provide cost-effective, efficient, and economical financial services while enhancing product quality. Compared to traditional finance, this model is more inclusive and convenient. It lowers the barriers to entry for financial services, increases diversity and accessibility, and facilitates the dissemination of financial information [21]. These advantages offer innovative ways to achieve carbon-emission-reduction targets. Initially, DIF can eliminate time and space constraints on factor mobility, reduce financing costs, and increase output. Furthermore, DIF can reduce information asymmetry, improve green supply and demand, and optimize resource allocation, thereby reducing CO₂ emissions [22]. Furthermore, the emergence of DIF can result in increased investment in innovation and reduced risk associated with innovation, fostering environmentally oriented technical advancements and ensuring advancements in green technology, hence decreasing CEI. Lastly, DIF can improve the accuracy and efficiency of identifying environmentally friendly business identification, directing the flow of capital toward clean and renewable energy companies, causing investors to increase their expected expectations of these companies, which in turn leads to an increase in the share price of these companies. In turn, the expected market share of carbon-intensive industries will consequently decrease, resulting in a lower capacity, which in turn will reduce the demand for fossil fuels and carbon credits, ultimately resulting in a decrease in CEI [23].

Therefore, the majority of scholars believe that DIF can effectively reduce CEI, and they have proposed various explanations for the mechanisms through which DIF influences CEI. Song, et al. [24] employed a double logit method to explore the correlation between DIF and CEI. Their findings showed that DIF significantly reduces CEI, with a 1% rise in DIF resulting in a 0.488% decrease in CEI. Furthermore, DIF can mitigate CEI through the advancement of science and technology. Sun, et al. [25] used a panel quantile regression model to demonstrate that DIF can effectively and consistently decrease CEI at a significance level of 1%. Their study also found that technical innovation and energy structure play a crucial role in moderating this relationship. Lu, et al. [26] employed various analytical techniques, including the fixed-effects model, instrumental variables method, and mediation-effects model, to investigate how DIF affects CEI. Their research indicates that DIF significantly lowers CEI by changing patterns of energy usage and reducing energy intensity. Furthermore, the effect of DIF is observed to vary across different regions and time periods.

DIF and CO₂ emissions exhibit a regional spreading effect [27]. The spatial-spillover mechanism of DIF on CEI has been subject to varying interpretations among experts. According to Zhao, et al. [28], the Durbin model reveals a significant spatial-spillover effect of DIF on urban CEI. Moreover, the impact of DIF on urban CEI is more prominent in cities with comparable economic attributes, as opposed to geographically contiguous cities. Lee and Wang [29] employed a geographic Durbin model with fixed effects to examine the spatial-spillover effect of DIF on CEI. Their findings indicate that this effect is observed exclusively within a range of 350–400 km. Guo and Tu [17] discovered that a city's DIF has a positive effect on the CEI of nearby cities.

Nevertheless, the above research possesses certain limitations. Firstly, all these studies have only considered the positive decarbonization effect of DIF, ignoring the fact that DIF may also lead to an increase in CO₂ emissions by promoting economic growth and industrial expansion, just like traditionally [17,24,28]. In other words, these studies have

only examined the linear impact of DIF on carbon emissions, disregarding any nonlinear effects. Second, while the above studies give multiple answers as to the mechanism through which DIF affects CEI [22,24,29,30], there is a distinct lack of research on DTI, which is closely related to DIF. DTI integrates the digital and real economies. The fusion creates new technology, products, industries, business models, and structures. DTI requires significant funding. Financial institutions struggle to evaluate SMEs' creditworthiness and growth potential due to their lack of transparency. Consequently, many companies struggle to attract external funding, impeding their digital technology development. DIF's digital features enhance corporate data visibility and financial institutions' lending trust, helping enterprises address financing issues and drive digital technology advancements. Traditional companies utilize digital technology to upgrade their industrial structures and reduce fossil fuel use, thereby lowering CEI. Advances in DTI can reduce CEI. Digital technology has eliminated the spatial constraints of traditional technological exchanges and demand feedback, facilitated the rapid dissemination of technology and resource allocation, improved energy efficiency, and reduced CO₂ emissions. Second, automation and digital tools can reduce labor and time inputs, increase productivity, and boost high-value-added product output, which boosts export trade through the scale effect and GDP growth. CEI decreases with GDP growth and carbon reduction [31]. Finally, none of the previous studies have considered the heterogeneity of spatial spillovers in the impact of DIF on CEI due to different factors.

Therefore, this study will leverage previous research to investigate the direct and indirect effects of DIF on CEI. This study will also explore how recent advancements in digital technology affect the relationship between DIF and CEI. Given that China is the world's largest developing nation, with the eighth-highest DIF development level globally [32] and a significant carbon emission problem, its strategy of developing DIF to address carbon emissions can offer valuable guidance to other developing nations and emerging economies that are just getting started with DIF and also dealing with carbon emission issues, making it a highly relevant case study. China is thus used as a sample in this study's research.

The main contributions of this study are as follows: (1) This study employs nonlinear techniques to investigate the impact of DIF on CEI. It demonstrates that the effect of DIF on CEI follows a U-shaped curve, thus addressing the limitation of previous studies that only considered the linear relationship between DIF and CEI [17,24,28]. (2) From the perspective of DTI, this study examines how DIF mediates the interaction between CEI, thereby revealing the nonlinear relationship between DIF and CEI. This perspective furthermore addresses the neglect of DTI in previous research and broadens our understanding of the various mechanisms through which DIF affects CEI [22,24,29,30]. (3) A geographic Durbin model is constructed by combining geographic and economic elements, demonstrating that DIF can effectively increase the CEI in neighboring provinces. This study offers novel perspectives and methodologies for achieving the goal of reducing CO₂ emissions. Furthermore, this study delves deeper into spatial heterogeneity and discovers that the spatial-spillover effect of DIF is insignificant in eastern provinces and significantly positive in the middle and western parts of the country. This bridges the gap in research on the spatial-spillover effect of DIF.

The rest of this paper is structured as follows: in the second part, we provide a synopsis of previous studies and lay out our hypotheses. The third part outlines the methodology, variables, and data used in our research. The fourth part presents our initial findings, including tests for robustness and endogeneity, analysis of heterogeneity, mechanisms, and spatial effects. Finally, in the fifth part, we present our conclusions and offer recommendations.

2. Research Hypotheses

The environmental pollution caused by DIF can be attributed to two factors: the "scale effect" and the "technology effect". While technology tends to have a detrimental influence,

the scale effect is generally helpful. The coexistence of these two impacts introduces uncertainty regarding the influence of DIF development on environmental pollution, as well as its impact on CEI [33–35].

From a scale impact perspective, DIF reduces financing constraints, encouraging businesses to make significant investments in energy-intensive and high-pollution projects in order to maximize profits. This, in turn, leads to increased production and energy consumption, ultimately resulting in higher CO₂ emissions [36]. Furthermore, DIF reduces the minimum requirement for accessing financial services and alters the lending approach. Individuals may benefit from affordable loans that are easily accessible, complementing their current income and encouraging increased spending [37]. This boosts economic growth while also increasing carbon emissions [38].

From a technical perspective, the utilization of digital technology in the context of DIF addresses the issue of information asymmetry between borrowers and lenders, thus enhancing the alignment between the availability of financial resources and the credit demand for environmentally sustainable firms. This approach has the potential to reduce the associated costs of green financing for enterprises; improve the efficacy of green technology innovation within enterprises; facilitate the adoption of environmentally friendly practices in enterprises with significant inputs, pollution, and emissions; and ultimately tackle the issue of air pollution caused by enterprise production [26]. By leveraging ICT, DIF can provide financial services to consumer segments that are typically inaccessible to traditional financial institutions, such as residents and companies in underdeveloped or remote areas. The introduction of DIF enables improved financial services to be provided to economically disadvantaged regions and low-income individuals in the central and western districts. Farmers, in particular, can benefit from digital inclusive funding, which allows them to utilize renewable energy and clean technologies, thereby reducing CO₂ emissions during the production process [39,40].

Based on the aforementioned analysis, the subsequent research hypotheses can be formulated:

H1: *There is a nonlinear effect of DIF on CEI.*

DIF has the potential to spur innovation in digital technologies. From a capital supply perspective, DIF lowers the financing barrier for businesses, broadens the range of financing options, and mitigates the “long-tail effect” in the financing process of innovative businesses, thereby increasing the availability of R&D funds and enhancing the innovation capacity of enterprises in the digital technology sector [41]. DIF effectively reduces the financial burden of financial institutions in obtaining enterprise information through the use of big data, cloud computing, and other digital technologies. This reduction in financing costs enables small- and medium-sized enterprises (SMEs) to secure additional funding for innovative activities [42]. From a competitive perspective, the inclusion of DIF provides regular and cost-effective financial assistance to an increasing number of SMEs. This helps to enhance overall resources in the digital technology sector and stimulates greater competition within the industry. As a result, the competitive impact of digital inclusion encourages enterprises to engage in technological innovation in order to gain distinct competitive advantages [43].

Digital technological advancements have the potential to decrease CEI. The implementation of DTI has the potential to enhance resource allocation, facilitate the transition of production factors from inefficient to efficient sectors, contribute to the overall improvement of total factor productivity within society, mitigate resource wastage, and foster the low-carbon transformation of urban areas [44]. Furthermore, the connectivity, sharing, and openness of DTI are critical in allowing firms to effectively disintermediate [45]. This disintermediation reduces transaction costs while enhancing company potential and income. As a result, the financial stability of the firm improves, and more resources can be utilized for green technology research and development [46]. The spillover effects of DTI across industries and borders not only result in increased non-fossil energy production but also

function as an efficient technique for storing this energy [47]. As a result, non-fossil energy use increases [48].

Based on the aforementioned analysis, the subsequent research hypotheses can be formulated:

H2: *DTI significantly mediated the nonlinear effect of DIF on CEI.*

Unlike traditional finance, digital finance collects, manages, and analyzes data using digital technology and network platforms [49]. This technique eliminates barriers to data access and information exchange among financial market participants. It also surmounts the time, place, and geographical constraints imposed by traditional finance. It establishes direct linkages between borrowers and lenders, enabling the efficient movement of capital and the effective utilization of information, technology, and other resources [27]. The easy transfer of technology and factor resources across nearby provinces may result in the “siphoning effect”, “imitation effect”, and “radiation effect” on carbon emissions.

According to the siphoning effect, when DIF in a specific area is successful, there will be a stronger demand for key variables such as labor, capital, and information in that location. This is because the benefits derived from these characteristics are greater, leading to their migration from less developed DIF locations [17].

In terms of imitation, when a province emerges as a leading region by actively promoting DIF development and successfully enhancing its development level while reducing carbon emission intensity, neighboring and interconnected provinces will economically emulate its development model, policy system, and innovative experiences and adjust their own policies or economic activities accordingly. Furthermore, this indicates that the carbon emission intensity of neighboring provinces tends to influence each other through spatial effects resulting from policy learning and policy transfer.

DIF’s radiation effect has the following characteristics: universality, low cost, wide reach, and speed. These traits help to overcome time and space constraints, minimizing the impact of the geographic distance on DIF’s spillover effect and spatial friction. Consequently, this affects the CEI of neighboring provinces. As the quantity of DIF development increases, it becomes more difficult for polluting firms in the province to obtain financing, leading them to potentially shift to nearby provinces, thereby increasing the CEI in such areas [33].

Based on the aforementioned analysis, the subsequent research hypotheses can be formulated:

H3a: *There is a positive spatial-spillover effect of DIF on CEI.*

H3b: *There is a negative spatial-spillover effect of DIF on CEI.*

The transmission mechanism of DIF is shown in Figure 2. In conclusion, DIF’s technological and scale effects can either increase or decrease CEI with the mediating role of DTI, and DIF’s geographical spillover effect on CEI can have either a good or negative outcome.

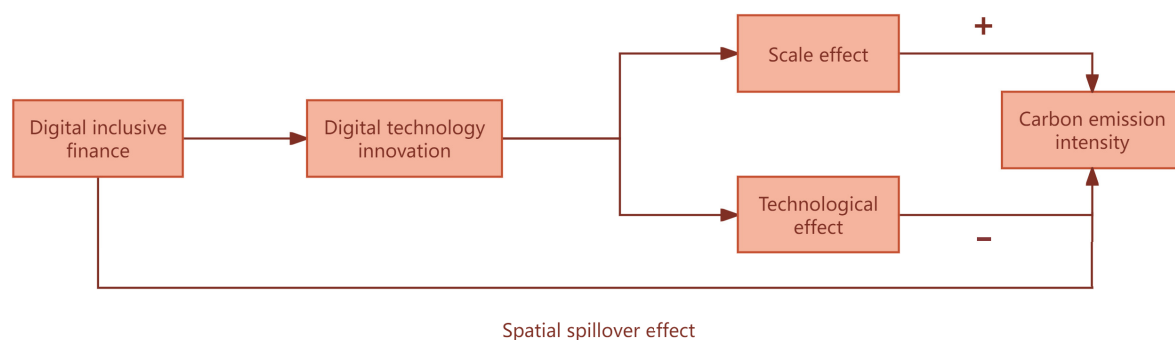


Figure 2. Mechanisms by which DIF affects CEI.

3. Variables, Model, and Data

3.1. Variables

3.1.1. Explained Variable

Carbon emission intensity (CEI) serves as the independent variable, calculated by dividing the annual total CO₂ emissions of each province by its regional gross domestic product. The primary source of CO₂ emissions stems from the utilization of fossil fuels to power energy needs, enabling quantification through the measurement of fossil energy consumption [26]. Moreover, the cement manufacturing process also contributes significantly to carbon dioxide emissions [36]. Consequently, this study aims to quantify not only the CO₂ emissions arising from fossil energy combustion but also those associated with the cement manufacturing process.

Referring to the study by Sun, Chen and Wang [22], the precise equation for computing CO₂ emissions resulting from the combustion of fossil fuels is as follows:

$$EC = \sum_{i=1}^7 EC_i = \sum_{i=1}^7 E_i \times CF_i \times CC_i \times COF_i \times \frac{44}{12} \quad (1)$$

where EC denotes the total estimated CO₂ emissions from various types of energy consumption; i denotes the types of energy consumption, including coal, coke, gasoline, kerosene, diesel, fuel oil, and natural gas; and E_i is the total amount of energy consumed in each province. i is the total amount of energy consumption for each type of energy; CF_i is the calorific value; CC_i is the carbon content; COF_i is the oxidation factor; $44/12$ is the factor that converts carbon to CO₂.

The equation utilized to compute carbon dioxide (CO₂) emissions resulting from the process of cement manufacture is as follows:

$$CC = Q \times 0.527 \quad (2)$$

where CC denotes the emission of CO₂ during the cement production process, Q denotes the total amount of cement production, and 0.527 is the CO₂ emission factor for cement production.

CEI represents a ratio for each province. The ratio of the CEI is compared to the GDP of the province. The sum of all CEIs is also analyzed. Based on the outcomes of the aforementioned formula's computations, the spatial distribution of CEI in 2021 is plotted using ArcGIS 10.8, as shown in Figure 3.

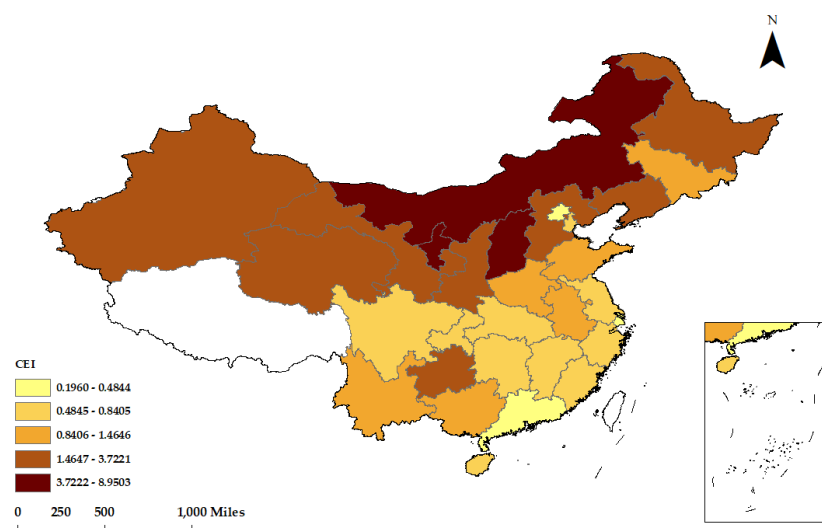


Figure 3. Spatial distribution of CEI in China in 2021 (data are from <https://edgar.jrc.ec.europa.eu> (accessed on 3 February 2024)).

3.1.2. Explanatory Variable

Digital inclusive finance (DIF) serves as the explanatory variable. The current methods of measuring DIF can be broadly categorized into three types: the first type of indicator measures the level of regional digital finance development by searching for keyword frequencies and matching regions on the web using web-crawler methods. The second category uses dummy variables to assess the policy effect of digital financial development by taking the digital financial development policy at the national level as an explanatory variable. The third category constructs digital finance indexes from one or more perspectives, using different calculation methods to measure the development level of digital finance. The third type of measurement is generally accepted by academics, with the digital inclusion index being the most widely used [50]. Referring to Sun, Li, Zhong and Liang [25], we utilized the DIF Index compiled by the Digital Inclusive Finance Research Center of Peking University to gauge the extent of DIF in each province. This is achieved by scaling the index down to a percentage (dividing it by 100). This set of indices encompasses the DIF Index, along with measures of DIF coverage, the scope of DIF utilization, and the digitization level of inclusive finance. Together, these indices offer a scientifically measurable assessment of the development level of DIF in each region.

3.1.3. Control Variables

The intensity of environmental regulation (ERI), measured by the ratio of completed investments in industrial pollution control to industrial value added, serves as an indicator of the rigor of environmental regulations. Companies tend to increase their green investments and develop or adopt cleaner production processes to meet these regulations, which, in turn, reduces CEIs [51]. The foreign direct investment (FDI) level is determined by dividing the amount of foreign direct investment by the GDP of a province. FDI serves as a gauge of a city's openness, and higher levels of openness can lead to the "pollution haven" effect and "carbon leakage", ultimately causing an increase in the CEI [28]. The population size (POP) is calculated based on the number of residents in each province. The relationship between population size and CO₂ emissions can be viewed from two perspectives. Firstly, population growth increases energy consumption, resource utilization, and environmental pressures, leading to higher CO₂ emissions. Secondly, population growth can foster technological advancements and enhance the utilization of public infrastructure, thereby partially mitigating CO₂ emissions [26]. Marketization (MARKET) is measured by indicators such as government–market relationship, non-state economic development, product market development, factor market development, intermediary organization development, and legal system development. This is quantified by the average growth rate [52]. By fostering trade and technological innovation among businesses, marketization can lower CEIs. The energy structure (STRUC) is measured by dividing the provincial electricity consumption by national electricity consumption. Electricity is a significant source of energy consumption and CO₂ emissions, and the scale of electricity consumption plays a crucial role in the CEI [53]. Green technology innovation (GTEC) is measured by the logarithm of the number of green patents granted. GTEC can minimize carbon emissions by optimizing industrial factor allocation and reducing environmental costs while also improving economic efficiency by lowering unit production costs. Ultimately, reducing carbon emissions and enhancing economic efficiency will lead to a lower CEI [54].

3.1.4. Mediating Variable

Digital technology innovation (DTI), assessed by the number of patents in each province related to the digital economy, serves as a mediator. Utilizing the Statistical Classification of the Digital Economy and its Core Industries 2021 in conjunction with the primary classification number of the patent, this research identifies patents that correspond to relevant digital technology areas [55].

All variables are defined as shown in Table 1.

Table 1. Definition of variables.

Variable Type	Variable Name	Definition
Explained variable	CEI	GDP per unit of CO ₂ emissions
Explanatory variable	DIF	Digital Inclusive Finance Index
Control variables	FDI	GDP per unit of foreign direct investment
	ERI	Ratio of completed investments in industrial pollution control to industrial value added
	POP	Number of residents
	MARKET	Marketization index
	STRUC	Ratio of provincial electricity consumption to national electricity consumption.
	GTEC	Number of green patents granted
Mediating variable	DTI	Number of digital economy patents

3.2. Model

3.2.1. Fixed-Effects Model

The two-way fixed-effects model offers substantial benefits in the study of panel data. Firstly, it can simulate both causal and inverse relationships, enabling a more comprehensive examination of the impacts between variables. Furthermore, it can incorporate fixed effects in both individual and time dimensions, thereby effectively addressing endogeneity and enhancing the model's explanatory capacity. Ultimately, it can address the issues of heteroskedasticity and serial correlation, hence enhancing the precision of estimation. Thus, this article uses the dual fixed-effects model to investigate the impact of DIF on CEI. The specific formula is displayed below:

$$CEI_{it} = \beta_0 + \beta_1 DIF_{it} + \beta_2 DIF_{it}^2 + \sum_{m=1}^6 a_m Control_{mit} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

CEI_{it} represents the carbon emission intensity of province i in year t . DIF_{it} represents the DIF development index of province i in year t . $Control_{it}$ is a set of control variables that may affect the CEI, including the foreign direct investment level, environmental regulation intensity, population size, and marketization. μ_i represents region fixed effects, λ_t represents time fixed effects, and ε_{it} is a random error term.

3.2.2. Intermediary Effects Model

Models were constructed to explore the pathways through which digital financial inclusion affects CEI:

$$CEI_{it} = \beta_0 + \beta_1 DIF_{it} + \beta_2 DIF_{it}^2 + \sum_{m=1}^6 a_m Control_{mit} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

$$DTI_{it} = \beta_0 + \beta_1 DIF_{it} + \sum_{m=1}^6 a_m Control_{mit} + \mu_i + \lambda_t + \varepsilon_{it} \quad (5)$$

$$CEI_{it} = \beta_0 + \beta_1 DIF_{it} + \beta_2 DIF_{it}^2 + \beta_3 DTI_{it} + \sum_{m=1}^6 a_m Control_{mit} + \mu_i + \lambda_t + \varepsilon_{it} \quad (6)$$

Of which DTI_{it} is the province i in the t level of digital technology innovation in the year.

3.2.3. Spatial Durbin Model

Given the potential existence of geographical effects between DIF and CEI within each province, this study used the Durbin model to examine the spatial-spillover impact of DIF on CEI as follows:

$$CEI_{it} = \alpha + \rho \sum_{j=1}^n W_{ij} CEI_{it} + \beta X_{it} + \sum_{j=1}^n W_{ij} \gamma X_{it} + \mu_i + \varepsilon_i \quad (7)$$

where ρ is the spatial autoregressive coefficient, reflecting the influence of neighboring provinces' CEI on the province's CEI; W_{ij} is the spatial weight matrix, including the geographic distance weight matrix, economic distance weight matrix, and economic–geographic nested matrix [22]; β is the regression coefficient of DIF on CEI, which reflects indicates the influence of DIF on CEI; X_{it} is the province i in the t year for each explanatory variable, including DIF and other control variables; and γ is the spatial effect of DIF, which is used to measure the impact of DIF in neighboring provinces on CEI in the province.

The construction of the spatial weight matrix is outlined below. The geographic distance weight matrix is derived by taking the inverse of the square of the geographic distance between two provinces. The economic distance weight matrix is calculated by taking the inverse of the absolute value of the difference in GDP per capita between two provinces. The nested economic–geographic distance matrix is produced by combining the economic distance and geographic distance weight matrices.

3.3. Data

The purpose of this study is to explore the impact of DIF on CEI in China. To accomplish this, a panel dataset was created, encompassing 30 provinces (excluding Tibet), spanning the period from 2011 to 2021. The primary sources of raw data for the relevant indicators are the China Statistical Yearbook and the statistical yearbooks of each province from 2012 to 2022. Table 2 shows the descriptive statistics of each variable.

Table 2. Descriptive statistics.

VarName	Obs	Mean	SD	Min	Median	Max
CEI	330	2.003	1.603	0.196	1.539	10.556
CO ₂	330	11.307	8.677	3.398	8.329	53.380
DIF	330	2.315	1.033	0.183	2.385	4.590
FDI	330	0.020	0.018	0.000	0.018	0.121
ERI	330	0.003	0.004	0.000	0.002	0.031
POP	330	8.207	0.741	6.342	8.278	9.448
MARKET	330	8.039	1.914	3.359	8.171	12.390
STRUC	330	0.033	0.023	0.004	0.026	0.095
GTEC	330	7.688	1.349	3.219	7.749	10.740
DTI	330	7.832	1.429	3.892	7.883	10.998

To further illustrate the relationship between the variables, this study utilizes the aforementioned data to plot the time trends of DIF, DTI, and CEI in the East, Mid, and West regions. As depicted in Figure 4, from 2011 to 2021, DIF and DTI in the East, Mid, and West regions exhibited an upward trend, whereas CEI showed a downward trend. Western provinces had the highest CEI values, while eastern provinces had the lowest. Additionally, eastern provinces demonstrated the fastest DTI development, while western provinces had the slowest. All three regions displayed comparable DIF development rates, but the eastern provinces possessed higher DIF levels than the western and mid provinces. This discrepancy could potentially be attributed to the varying economic levels, energy demands, and geographical locations of the regions.

First, the level of economic development in eastern provinces is higher than that in the mid and western provinces. On the one hand, provinces with a higher level of economic development in the east have stronger market demand, a stronger demand for DIF products and services from financial institutions and consumers, an adequate financial supply, and

more robust financial innovation, all contributing to the development of DIF. Conversely, provinces in the mid and west, with lower levels of economic development, have a lower level of DIF development due to limited market demand, insufficient financial supply, and inadequate financial innovation. Furthermore, eastern provinces with higher economic growth have superior infrastructure, more advanced digital technology, and a larger pool of financial talents, all of which effectively support the development of DTI. Second, from the perspective of energy demand, in recent years, as high-energy-consuming industries have shifted westward, the energy demand in mid and western provinces has increased significantly, resulting in high carbon dioxide emissions and low emission efficiency. This has shifted the carbon emission center to the northwest [56], making the CEI of mid and western provinces considerably higher than that of eastern provinces, which rely primarily on tertiary industries.

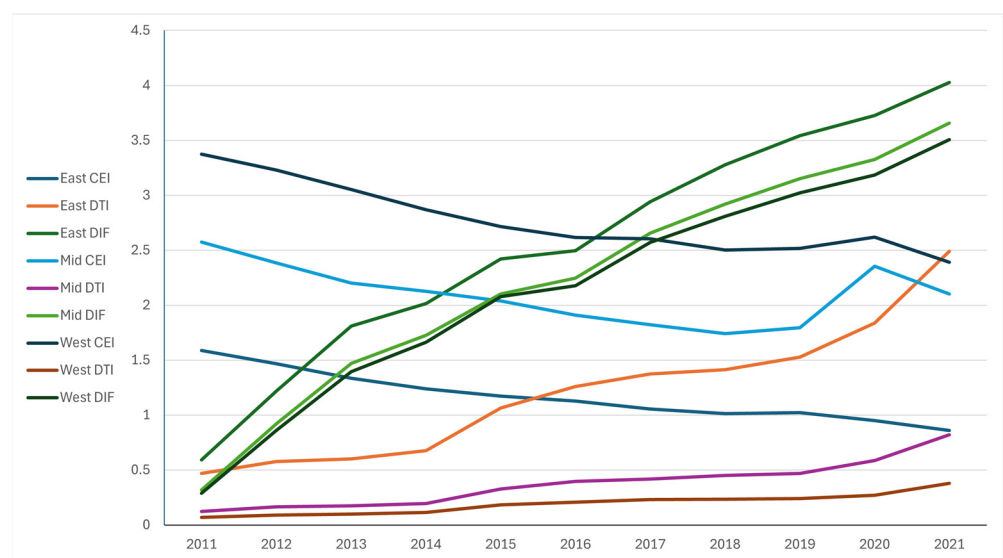


Figure 4. Time trends in CEI, DIF, and DTI by province.

4. Empirical Analysis

4.1. Unit Root Test

Before performing the regression analysis, we utilized the IPS, LLC, and PP panel unit root tests to ascertain the stationarity of each variable, thereby preventing spurious regression [57]. As indicated in Table 3, all variables reject the null hypothesis at a 1% significance level, suggesting that all variables are stationary.

Table 3. Unit root test.

Variables	IPS		LLC		Fisher	
	Statistic	p-Value	Statistic	p-Value	Statistic	p-Value
CEI	−5.6280	0.0000	−4.9256	0.0000	140.9520	0.0000
DIF	−5.6705	0.0000	−9.8112	0.0000	128.6724	0.0000
FDI	−6.3199	0.0000	−8.7053	0.0000	219.1840	0.0000
ERI	−8.3931	0.0000	−16.6072	0.0000	159.6358	0.0000
POP	−3.3184	0.0005	−9.4172	0.0000	159.8895	0.0000
MARKET	−6.2098	0.0000	−10.6275	0.0000	164.4431	0.0000
STRUC	−5.2603	0.0000	−11.8953	0.0000	140.3976	0.0000
GTEC	−6.5490	0.0000	−7.6787	0.0000	151.6336	0.0000
DTI	−7.3422	0.0000	−6.6312	0.0000	201.1682	0.0000

4.2. Baseline Regression

To eliminate data covariance, this study first utilized a multicollinearity test. As shown in Table 4, the VIF was 3.81, and all variables' VIF values were below 10, ruling out the possibility of multicollinearity. Secondly, this study decided which model to employ for analysis by utilizing the Hausman test and F test. The results indicate that both the Hausman test and F test rejected the null hypothesis, thereby recommending the adoption of the fixed-effect model.

Table 4. Multicollinearity test.

Variables	VIF	1/VIF
GTEC	8.323	0.120
MARKET	5.128	0.195
POP	4.023	0.249
STRUC	3.615	0.277
DIF	2.318	0.431
FDI	1.653	0.605
ERI	1.595	0.627
Mean VIF	3.808	.

Due to the multifaceted nature of the impact of DIF on CEI, its effects may vary depending on the level of DIF's development. In other words, there exists a nonlinear relationship between DIF and CEI. To examine this potential nonlinear relationship, this study incorporated the squared term of DIF. Subsequently, a stepwise regression analysis was conducted, as presented in Table 5. The results indicate that DIF has a suppressive effect on CEI at a significance level of 1%. Conversely, the squared term of DIF enhances CEI at a significance level of 1%. These findings suggest a significant U-shaped relationship between DIF and CEI, thereby confirming the validity of H1.

Table 5. Baseline regression.

Variables	(1)	(2)
	CEI	CEI
DIF	−3.737 *** (−6.59)	−3.526 *** (−9.81)
DIF ²	0.254 *** (6.40)	0.322 *** (8.38)
FDI		−0.177 (−0.23)
ERI		−32.013 ** (−3.13)
POP		−4.018 *** (−7.41)
MARKET		−0.150 *** (−5.10)
STRUC		35.253 *** (6.42)
GTEC		0.210 ** (3.07)
Constant	3.980 *** (17.71)	35.322 *** (8.11)
Observations	330	330
R-squared	0.329	0.419
Number of id	30	30
Area	YES	YES
Year	YES	YES

t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$.

According to Arcand, et al. [58], an overabundance of financial development may potentially have a direct adverse effect on the process of economic green transition and the mitigation of CO₂ emissions. The overdevelopment of DIF can significantly increase household credit, boost consumers' purchasing power, and encourage the purchase of energy-intensive goods, thereby leading to higher carbon emissions [59]. However, excessive expansion of the virtual economy, particularly in finance, can slow down the overall transition to virtualization. Idle capital in the financial sector hinders investment and financing growth, as well as the expansion of the green real economy. Instead, it stimulates overall demand for energy and consumption, which hinders the transition to a low-carbon economy. Thus, moderate development of DIF can effectively decrease CEI, but excessive development of DIF has a negative impact on CEI.

Furthermore, the coefficients of control variables in Table 5 demonstrate that FDI has a negative and minor effect on CEI, which is consistent with the findings of Zhao, Chen and Zhang [28], possibly due to the small sample size. ERI coefficients are notably negative, which differs from the findings of Sun, Li, Zhong and Liang [25], possibly due to the fact that they do not account for industrial value added when measuring ERI. POP has a considerable negative effect on CEI, which is consistent with the study by Jiang, Zhao and Qin [57]. The decrease in CO₂ caused by technical breakthroughs linked with population growth outweighs the increase in CO₂ caused by energy consumption connected with population growth. Similarly, MARKET had a strong negative effect on CEI, supporting the findings of Wang, Zhao, Zhang and Su [52]. The higher the level of marketization, the more it may promote the life of the carbon-trading market and the energy-trading market, guiding businesses to become more environmentally friendly and lowering the CEI. STRUC has a strong positive effect on CEI, which is consistent with the findings of Ye, et al. [60]. The more power consumed, the more energy and carbon emissions are required, resulting in an increase in CEI. GTEC has a significant positive effect on CEI, which is different from the study of Lee and Wang [29]. This may be due to the "rebound effect" of GTEC in this study because of the different control variables.

4.3. Robustness Tests and Endogenous Treatment

The results of the baseline regression analysis indicate that DIF significantly inhibits CEI. To ascertain the model's reliability, this study employs subsequent methodologies to evaluate its robustness.

4.3.1. Replacing the Explained Variable

To avoid the proxy variable selection bias impacting the regression findings, referring to Sun, Chen and Wang [22], this study employs the proxy variable approach for the robustness test. Once per capita CO₂ emissions were substituted for CEI as the principal explanatory variable, the regression was performed again, and the findings are presented in Table 6. Column (1) displays the outcomes: after replacing the explanatory variables, the non-linear effect of DIF remains significant.

Table 6. Robustness tests and endogeneity treatment.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	CO ₂	CEI	F.CEI	F2.CEI	CEI	CEI
DIF	−0.542 *** (−4.30)	−3.782 *** (−10.61)	−3.463 *** (−6.00)	−2.838 ** (−2.71)	−7.767 *** (−6.32)	−3.342 *** (−4.83)
DIF2	0.033 ** (2.47)	0.367 *** (8.79)	0.287 *** (5.61)	0.223 *** (3.45)	0.625 *** (5.78)	0.286 *** (4.61)
FDI	0.034 (0.16)	−3.021 *** (−3.21)	−0.555 (−0.43)	−0.651 (−0.34)	2.549 ** (2.76)	0.076 (0.03)
ERI	−3.338 (−0.97)	−32.664 ** (−2.76)	−10.049 (−0.84)	−9.554 (−0.54)	−25.638 ** (−2.64)	−34.234 *** (−3.32)
POP	−0.254 *	−4.466 ***	−4.084 ***	−4.969 ***	−0.000 ***	−3.361 ***

Table 6. Cont.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	CO ₂	CEI	F.CEI	F2.CEI	CEI	CEI
MARKET	(−1.91) −0.020 **	(−6.36) −0.150 ***	(−11.81) −0.131 ***	(−7.64) −0.064	(−9.04) −0.129 **	(−3.37) −0.152 ***
STRUC	(−2.32) 9.933 ***	(−4.25) 36.696 ***	(−3.72) 28.276 ***	(−1.70) 24.293 ***	(−2.82) 25.159 ***	(−2.80) 33.909 ***
GTEC	(5.47) 0.113 ***	(5.99) 0.249 **	(4.58) 0.144	(4.33) 0.023	(6.64) 0.222 ***	(3.61)
Constant	(6.29) 3.567 ***	(3.09) 39.193 ***	(1.30) 36.184 ***	(0.16) 43.487 ***	(3.30) 6.152 ***	(3.91) 31.354 ***
Observations	300	286	300	270	330	330
Number of id	30	26	0.319	0.216	0.947	0.415
R-squared	0.326	0.416	30	30	30	30
Area	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
Under-identification test					16.286 ***	
Weak identification test					16.664 (16.38)	

t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3.2. Excluding Special Samples

Since the policy system of municipalities directly under the central government differs from that of general provinces, to ensure the general applicability of the research findings and mitigate the influence of specific samples, this study excludes samples from Beijing, Shanghai, Chongqing, and Tianjin from the regression analysis [24]. The results in Table 6, column (2) show that the coefficients on DIF and DIF² remain significant.

4.3.3. Lag Treatment

This study employs first- and second-order lags for all explanatory variables to address the endogeneity issue stemming from bidirectional causation and to explore the potential temporal lag of DIF on CEI. Specifically, F.cei represents CEI advanced by one period, while F2.cei represents CEI advanced by two periods. The regression results for these lags are presented in columns (3) and (4) of Table 6. Notably, even at a 1% significance level, DIF and DIF² remain statistically significant in reducing CEI, thereby demonstrating the robustness of our findings.

4.3.4. Endogenous Treatment

To address the potential endogeneity issue in the regression model, this study employs the 2SLS model for regression. Based on previous studies [57], the primary and secondary terms of the product of the 1984 postal business volume and the pre-existing national Internet penetration rate were selected as instrumental variables IV1 and IV2 in this study. The IV value of the Kleiber-gen-Paap rk Wald F statistic for IV was greater than 10, indicating that the “weak instrumental variable” hypothesis was invalid.

The plausibility of IV1 and IV2 was confirmed. First, IV1 and IV2 are highly historical. The volume of postal business in 1984 is different from the main study period (2011–2019) of this study. Therefore, the perturbation term in the 2011–2021 model had no effect on the economic and social indicators in 1984. IV1 and IV2 meet the criterion that instrumental variables are uncorrelated with the perturbation term. In addition, IV1 and IV2 may alter DIF. The adoption of Internet technology began with the popularization of telephony and postal services, so the development of DIF is influenced by the prevalence of telephony and postal services. Provinces with a high volume of postal and telecommunication services have a better basis for the development of DIF.

As shown in Table 6, column (5), after considering the impact of instrumental variables, DIF still exerts a significant nonlinear effect on CEI, which aligns with the findings of the previous study.

4.3.5. Multicollinearity Treatment

According to the VIF test result, the highest VIF of GTEC is 8.323, which is greater than 5. To reduce the estimation bias due to the multicollinearity problem, GTEC is removed, and Equation (1) is re-estimated. The regression results are shown in Column 6, and the results are still robust after removing GTEC.

4.4. Heterogeneity Analysis

4.4.1. Heterogeneity of Geographic Location

The 30 provinces were classified into east, central, and west based on their geographic locations to examine potential variations in the manifestation of the link between DIF and CEI across different regions. According to Table 7, DIF has a significant nonlinear relationship with CEI in the eastern and western provinces, whereas the role of DIF is insignificant in the central provinces. This may be attributed to differences in resource endowment and economic development.

Table 7. Heterogeneity of geographic location.

Variables	(1) EAST	(2) MID	(3) WEST
	CEI	CEI	CEI
DIF	−1.434 *** (−3.83)	−2.203 (−0.63)	−6.477 *** (−5.60)
DIF ²	0.128 *** (4.60)	−0.292 (−0.66)	0.740 *** (4.59)
FDI	−3.909 ** (−2.90)	−30.627 (−1.78)	9.943 * (1.92)
ERI	5.662 (0.87)	−177.406 (−1.64)	−37.433 *** (−4.94)
POP	0.537 (1.04)	5.870 (1.09)	−4.797 *** (−5.39)
MARKET	−0.023 (−1.34)	−0.248 (−1.74)	−0.178 *** (−3.56)
STRUC	13.018 *** (4.03)	35.776 (1.79)	81.825 *** (7.03)
GTEC	−0.179 *** (−5.12)	0.731 * (2.17)	0.573 *** (3.40)
Constant	−0.959 (−0.22)	−49.903 (−1.08)	38.760 *** (5.68)
Observations	121	88	121
R-squared	0.895	0.369	0.798
Number of id	11	8	11
Area	YES	YES	YES
Year	YES	YES	YES

t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Firstly, the eastern provinces enjoy a superior level of economic advancement. Based on the theory of financial exclusion [61], financial institutions prioritize their development efforts in provinces with robust economic performance and significant resource concentration. As a result, the eastern provinces can effectively concentrate financial resources due to their economic advantages, leading to a higher degree of DIF development compared to the central provinces and a more effective reduction in carbon emissions. Furthermore, despite the economic underdevelopment of the western provinces, their unique geographical position endows them with abundant clean energy resources. By implementing DIF, this

endowment can be efficiently utilized, leading to a reduction in the consumption of fossil energy and thereby lowering CEI.

4.4.2. Heterogeneity of Green Finance Levels

Wang, et al. [62] found that green finance (GF) is critical in accelerating the transition to a low-carbon economy. Their study's findings illustrate the substantial impact of DIF in enabling the shift toward a low-carbon economy. In the context of CO₂ emission reduction, it is pertinent to explore the interplay between DIF and green finance (GF). Does this interplay differ based on the degree of GF advancement? In this study, the sample is divided into three groups, high, medium, and low, according to the development level of GF in each province. The level of GF development is measured by an evaluation system comprising green credit, green insurance, green investment, green bonds, green support, green funds, and green equity.

The regression findings for these groups are displayed in Table 8. In the group with a high level of GF, the impact of DIF is not significant. However, in the group with a medium-to-low level of GF development, DIF exhibits a significant U-shaped association with CEI at a 1% significance level. The correlation between DIF and CEI is more pronounced in regions with a lower degree of GF development. These findings indicate that DIF can help address some of the limitations of GF in the transition to a low-carbon economy.

Table 8. Heterogeneity of green finance levels.

Variables	(1) GF-HIGH	(2) GF-LOW	(3) GF-LOW
	CEI	CEI	CEI
DIF	1.377 (0.73)	−4.367 *** (−3.40)	−2.190 *** (−5.71)
DIF2	−0.068 (−0.34)	0.369 ** (2.94)	0.439 *** (7.43)
FDI	−26.358 (−1.25)	1.537 (0.57)	4.986 ** (2.76)
ERI	−94.028 (−1.75)	−32.923 *** (−4.93)	−6.608 (−0.62)
POP	−53.261 (−1.48)	−20.082 * (−2.04)	−41.093 *** (−4.63)
MARKET	−3.681 * (−2.37)	−1.346 ** (−2.26)	−0.047 (−0.21)
STRUC	2.691 *** (6.23)	1.080 ** (2.43)	1.699 *** (6.27)
GTEC	0.971 (1.98)	0.490 * (1.94)	0.054 (0.33)
Constant	120.922 (1.56)	52.461 ** (2.45)	95.482 *** (5.47)
Observations	96	117	117
R-squared	0.189	0.697	0.819
area	YES	YES	YES
year	YES	YES	YES

t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.4.3. Heterogeneity of Human Capital Levels

Human capital significantly impacts the effectiveness of DIF. Firstly, human capital drives the progress of digital technology. As DIF develops, the application of digital technology becomes increasingly prevalent and intricate, necessitating a pool of talents with relevant expertise and skills. Provinces with high human capital tend to boast a larger talent pool, effectively fostering the advancement of DIF. Secondly, the enhancement in the scale and quality of higher education contributes to reducing CEI [63]. Provinces with high human capital achieve this reduction by augmenting workers' income, heightening

environmental awareness, modifying consumption patterns, and diminishing the demand for high-carbon products.

The data in Table 9 reveal that, in provinces with high human capital, DIF exhibits a robust nonlinear effect with a 1% significance level, as seen in column (1). Conversely, in provinces with low human capital, the nonlinear effect of DIF is statistically insignificant, as indicated in column (2).

Table 9. Heterogeneity of Internet penetration.

Variables	(1)	(2)
	CEI	CEI
DIF	−3.053 *** (−5.98)	−2.449 (−1.44)
DIF2	0.245 *** (5.50)	0.489 (1.62)
FDI	0.291 (0.35)	−6.599 (−0.25)
ERI	−48.631 *** (−3.77)	15.768 (0.81)
POP	−3.783 *** (−6.91)	−4.044 (−0.55)
MARKET	−0.134 *** (−4.73)	0.122 * (1.81)
STRUC	15.916 *** (3.73)	79.367 ** (2.55)
GTEC	0.247 ** (3.10)	0.344 (1.00)
Constant	30.797 *** (7.54)	32.076 (0.51)
Observations	275	55
R-squared	0.947	0.991
Area	YES	YES
Year	YES	YES

t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5. Further Analysis

5.1. Impact Mechanism

Based on the results of the baseline regression analysis, it can be inferred that there is a U-shaped relationship between DIF and CEI, but it is necessary to investigate the mechanism behind this relationship in depth. Therefore, the mediating role of DTI was tested with reference to the traditional stepwise regression method [64]. Column (1) of Table 10 directly considers the relationship between DIF and DTI, and the results show that DIF can significantly enhance DTI; after taking DTI as an explanatory variable in column (2), DIF still has a significant U-shaped effect on CEI at the 1% level of significance, and H2 holds.

Table 10. Impact mechanism.

Variables	(1)	(2)
	DTI	CEI
DIF	0.641 ** (2.20)	−1.302 *** (−12.38)
DIF ²	0.003 (0.09)	0.169 *** (17.14)
FDI	1.344 (1.39)	3.178 *** (9.17)

Table 10. Cont.

Variables	(1)	(2)
	DTI	CEI
ERI	11.176 ** (2.58)	−17.298 *** (−11.05)
POP	−0.326 (−0.72)	−0.989 *** (−6.10)
MARKET	0.061 *** (2.71)	−0.038 *** (−4.69)
STRUC	5.421 (1.38)	5.612 *** (4.00)
GTEC	0.257 *** (4.35)	0.109 *** (4.98)
DTI		−0.053 ** (−2.49)
Constant	6.975 ** (1.99)	8.889 *** (7.59)
R-squared	0.917	0.999
Number of id	30	30
Area	YES	YES
Year	YES	YES

t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$.

5.2. Spatial-Spillover Effects Test

5.2.1. Spatial Autocorrelation Analysis

Before performing the spatial econometric analysis, we employed the worldwide Moran index to evaluate the geographical correlation of the variables. Initially, we measured Moran's index for DIF and CEI, and the annual global Moran's index is presented in Table 11. Notably, the Moran index consistently maintains a positive value throughout the observation period (2011–2021), indicating a spatial distribution of the two variables exhibiting either high–high (H-H) or low–low (L-L) clustering. Furthermore, it is worth mentioning that the Z-value associated with each year exceeds 1.96, indicating a significant spatial autocorrelation between DIF and CEI across all provinces during the period of 2011–2021. Specifically, this suggests the presence of a spatial-clustering phenomenon and a positive spatial correlation between DIF and CEI. Clustering occurs, and a positive spatial association is apparent.

Table 11. Spatial autocorrelation analysis.

Year	DIF		CEI	
	I	z	I	z
2011	0.347 ***	4.008	0.228 ***	2.934
2012	0.401 ***	4.619	0.244 ***	3.067
2013	0.378 ***	4.404	0.243 ***	3.059
2014	0.380 ***	4.432	0.240 ***	3.034
2015	0.326 ***	3.856	0.237 ***	3.007
2016	0.365 ***	4.283	0.244 ***	3.032
2017	0.374 ***	4.386	0.227 ***	2.902
2018	0.396 ***	4.580	0.221 ***	2.876
2019	0.407 ***	4.684	0.224 ***	2.922
2020	0.414 ***	4.764	0.185 ***	2.647
2021	0.429 ***	4.910	0.182 ***	2.570

t-statistics in parentheses, *** $p < 0.01$.

To further capture the local spatial correlation, we utilized the local Moran's I method to analyze the spatial autocorrelation of the variables DIF and CEI at a local level. Figure 5 depicts Moran's I scatter plots for DIF and CEI in each province for 2017 and 2021, revealing

a strong positive spatial association locally, as most provinces cluster in the first and third quadrants.

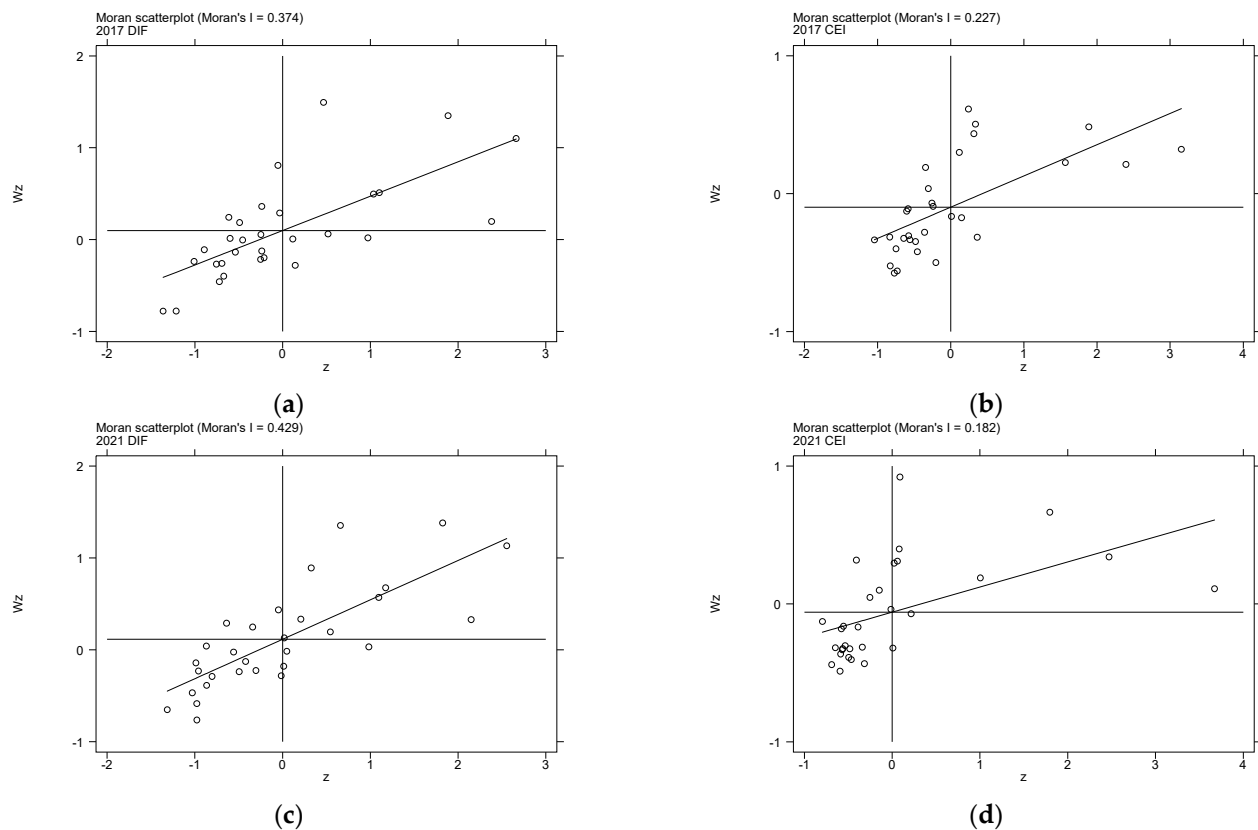


Figure 5. Local spatial autocorrelation analysis. (a) Description of Moran's I of DIF in 2017; (b) Description of Moran's I of CEI in 2017; (c) Description of Moran's I of DIF in 2021; (d) Description of Moran's I of CEI in 2021.

5.2.2. Spatial Model Suitability Tests

Before conducting model estimation, it is crucial to assess the Lagrange Multiplier (LM) alongside the Robust LM to ascertain the nature of spatial correlation, whether it manifests in the error term or the lag term. This evaluation aids in determining whether the Structural Equation Modeling (SEM) or the Spatial Linear Modeling (SLM) approach is more appropriate. Additionally, it is essential to determine whether the Structural Difference Method (SDM) can be simplified by utilizing Wald tests and likelihood ratio tests (LRTs) for both the SEM and SLM models. Table 12 demonstrates that all data in the LM test, excluding LM-spatial lag, are statistically significant. Hence, both the SLM model and SEM model are viable options. Furthermore, when comparing the results of the Wald test and LRT, it is evident that the initial hypothesis, suggesting that SDM reduces to SLM or SEM, cannot be rejected. Consequently, the SDM model is chosen for regression analysis.

Table 12. Spatial model suitability tests.

Method	Statistical Value	Pro	Method	Statistical Value	Pro
LM-spatial lag	1.180	0.277	Wald-spatial lag	50.22	0.000
Robust LM-spatial lag	14.625	0.000	LR-spatial lag	13.05	0.071
LM-spatial error	24.902	0.000	Wald-spatial error	48.31	0.000
Robust LM-spatial error	38.347	0.000	LR-spatial error	13.71	0.057

5.2.3. Space Spillovers and Decomposition

Based on the results of the baseline regression, it is evident that there is a notable U-shaped correlation between DIF and CEI. Therefore, the primary aim of this study was to investigate whether DIF exerts a U-shaped influence on CEI in neighboring provinces. The results, presented in Table 13, indicate that there is no substantial nonlinear effect of DIF on CEI in adjacent provinces.

Table 13. Nonlinear spatial-spillover effects.

	(1)	(2)	(3)	(4)	(5)
	Main	Wx	Direct Effect	Indirect Effect	Total Effect
DIF	−2.965 (−1.16)	13.486 * (1.87)	−3.347 (−1.23)	13.134 * (1.95)	9.787 (1.45)
DIF ²	0.291 (0.76)	−1.026 (−0.86)	0.311 (0.73)	−1.019 (−0.96)	−0.708 (−0.70)
FDI	−9.724 (−0.48)	244.433 *** (3.29)	−18.462 (−0.92)	222.395 *** (2.96)	203.934 ** (2.36)
ERI	60.433 *** (2.62)	−67.170 (−1.23)	65.740 *** (2.90)	−71.602 (−1.49)	−5.862 (−0.11)
POP	−1.625 *** (−5.15)	−2.312* (−1.94)	−1.559 *** (−4.70)	−1.805 (−1.59)	−3.364 *** (−3.21)
MARKET	0.055 (0.48)	−0.344 (−0.93)	0.068 (0.64)	−0.329 (−0.94)	−0.260 (−0.68)
STRUC	87.689 *** (6.08)	263.683 *** (4.17)	80.159 *** (5.50)	227.425 *** (3.36)	307.584 *** (4.42)
GTEC	−0.167 (−0.52)	−0.417 (−0.41)	−0.150 (−0.48)	−0.420 (−0.43)	−0.570 (−0.55)
Spatial rho	−0.178 (−1.03)				
Variance	0.556 *** (7.89)				
sigma2_e					
r ²	0.005				
N	330.000				

t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

This study further examines the linear relationship between DIF and CEI in neighboring provinces. As shown in column (2) of Table 14, when a province implements DIF, the CEI of its neighboring provinces tends to rise. However, the regression coefficients of the spatial econometric model do not directly capture the spatial-spillover effect of DIF on CEI. To address this, the spatial effect is decomposed into three components: the direct effect, the indirect effect, and the total effect. This decomposition is achieved using the spatial regression partial differentiation method. An analysis of columns (3), (4), and (5) reveals a positive spatial-spillover effect of DIF on CEI, thus providing empirical support for Hypothesis H3a. There is indeed a spatial relationship between economic and trade activities and atmospheric pollution. Furthermore, the flow of capital between provinces and the spatial dispersion of air pollutants contribute to the impact of financial development on CO₂ emissions. This influence transcends provincial boundaries, having the potential to affect other provinces as well.

Table 14. Linear spatial-spillover effects.

	(1)	(2)	(3)	(4)	(5)
	Main	Wx	Direct Effect	Indirect Effect	Total Effect
DIF	−1.389 (−0.99)	7.951 *** (2.62)	−1.613 (−1.08)	7.219 ** (2.57)	5.606 * (1.89)

Table 14. Cont.

	(1)	(2)	(3)	(4)	(5)
	Main	Wx	Direct Effect	Indirect Effect	Total Effect
FDI	−6.821 (−0.35)	247.639 *** (3.59)	−16.729 (−0.87)	226.426 *** (3.53)	209.697 *** (2.86)
ERI	62.743 *** (2.73)	−73.440 (−1.35)	68.327 *** (3.02)	−73.320 (−1.49)	−4.994 (−0.10)
POP	−1.537 *** (−5.07)	−2.807 ** (−2.56)	−1.450 *** (−4.66)	−2.296 ** (−2.21)	−3.746 *** (−3.75)
MARKET	0.022 (0.20)	−0.301 (−0.85)	0.031 (0.31)	−0.264 (−0.82)	−0.233 (−0.66)
STRUC	82.298 *** (6.09)	272.089 *** (4.38)	73.530 *** (5.99)	229.254 *** (3.58)	302.785 *** (4.59)
GTEC	−0.228 (−0.73)	−0.016 (−0.02)	−0.224 (−0.74)	0.048 (0.06)	−0.176 (−0.21)
Spatial rho	−0.175 (−1.01)				
Variance	0.561 *** (7.88)				
sigma2_e					
N	330.000				

t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2.4. Spatial Heterogeneity Test

Table 14 displays the spatial-spillover impact of national DIF on CEI. However, spatial-spillover effects may vary depending on a region's geographical position and resource availability. Therefore, we delve deeper into the diversity of the spatial spillover impact of DIF on CEI. To analyze the variation in the spatial-spillover effect across different geographic areas, we categorized the sample into three groups based on location: eastern, central, and western provinces. The results, depicted in Table 15, indicate that the spatial-spillover effect is insignificant in the eastern provinces, while it is significantly positive in the central and western provinces.

Table 15. Spatial heterogeneity test.

Region	Direct Effect	Indirect Effect	Total Effect	R ²
East	−0.302 * (−1.66)	0.019 (0.06)	−0.283 (−0.77)	0.893
Mid	−3.064 *** (−2.59)	10.069 *** (5.17)	7.005 *** (3.21)	0.028
West	−1.613 (−1.08)	7.219 ** (2.57)	5.606 * (1.89)	0.051

t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3. Discussion

Based on the above studies, we draw the following conclusions: (1) DIF interacts with CEI in a U-shaped manner, i.e., DIF initially inhibits CEI and then promotes it. This result contrasts with the general consensus among most scholars that DIF can only inhibit CEI [28,30,65,66], possibly due to the fact that the aforementioned scholars did not account for the CEI promotion resulting from the scale effect of DIF and overlooked the nonlinear relationship between DIF and CEI. (2) DTI has a nonlinear mediating effect on the impact of DIF on CEI, and DIF can affect CEI nonlinearly by promoting DTI. Although previous studies have examined the mediating effect of technological innovation, most of them focused on green technological innovation [7,50,67], overlooking the mediating effect of digital technological innovation, which is fundamental to the development of DIF. Additionally, most previous studies primarily examined the linear impact of mediating variables on CEI, disregarding their nonlinear relationship. (3) Heterogeneity analysis

reveals that the nonlinear effect of DIF is significant in eastern and western provinces, whereas DIF's role is not significant in central provinces. Additionally, the nonlinear effect of DIF is insignificant in provinces with a high level of green finance development but plays a significant role in provinces with a medium–low level of green finance development. Furthermore, the nonlinear effect of DIF is pronounced in regions with a high level of human capital. In comparison to previous studies, this study explores the heterogeneity of DIF from two novel perspectives: the degree of green financial development and human capital. (4) DIF in this province will positively influence CEI in neighboring provinces. Moreover, this study also analyzes geographic heterogeneity, indicating that DIF in central and western provinces has a greater promotional effect on CEI in adjacent provinces, whereas the spatial-spillover effect in eastern provinces is not apparent. Overall, this study substantially addresses the shortcomings of previous research and offers a fresh perspective on DIF.

However, this study also has some shortcomings. First, it lacks the derivation of the formula for the impact of DIF on CEI. Therefore, in future research, a general equilibrium model could be constructed, and partial derivatives employed to further explain the impact of DIF on CEI, thus rendering the conclusions of this study more reliable. Secondly, while this study investigates the carbon-reduction effect of DIF from the perspective of CEI, Lee, et al. [68] considered both carbon emission intensity and carbon sequestration, thus providing a more comprehensive exploration of the effect of DIF. Finally, this study does not identify the causal relationship between DIF and CEI with sufficient precision. Consequently, future studies need to further conduct a series of robustness tests, for instance, by lagging both the independent and control variables by one period or utilizing the instrumental-variable method.

6. Conclusions and Policy Implications

Based on the above findings, this study proposes a series of recommendations aimed at enhancing the contribution of DIF to achieving low-carbon goals and advocates for the promotion of digital technology innovation. This study suggests that digital technologies play a crucial role in facilitating interactions between DIF and CEIs. Specifically, DIFs have the ability to influence CEIs by fostering innovation in digital technologies. Therefore, it is imperative that governments fund R&D and innovation strategies for digital technologies. This includes financial and technical assistance for digital and high-tech businesses, as well as increasing the utilization of digital technologies in the financial sector. Advances in digital technology cannot be achieved without the development of digital infrastructure, and it is crucial to accelerate the development of digital infrastructure while encouraging digital technology innovation. To expedite data computation, information transmission, and lay a solid hardware foundation for high-quality digital technological innovation and application, data platforms, computation centers, and industrial bases must be constructed using state-of-the-art technology and robust security measures.

It is also important to develop DIF moderately and encourage the coordinated development of DIF and GF. In the development process, DIF will produce a technical effect and a scale effect. The technical effect can effectively reduce CEI, but the scale effect will increase it. In the early stages of DIF development, the technical effect outweighs the scale effect, suppressing CEI; however, in the later stages, enterprises may invest heavily in high-energy-consumption and high-pollution projects to pursue high profits and expand production, leading to the scale effect outweighing the technical effect and increasing CEI. Therefore, we should monitor the development process of DIF closely. The development of GF can effectively channel capital toward environmentally friendly enterprises and green technology, helping to mitigate the negative impact of the scale effect in the later stages of DIF development. Consequently, during the DIF-development process, it is essential to consider the coordinated development of DIF and GF. Specifically, financial institutions should develop financial instruments that balance both DIF and GF considerations. In terms of the service purpose, service path, and service technology of financial products, it is necessary

to take into account the unique characteristics of DIF and GF and develop products and services that cater to both. Additionally, it is crucial to strengthen the information-sharing mechanism, dismantle information silos, achieve interconnectivity between DIF and GF data, enhance the accuracy and efficiency of financial services, eliminate duplicate loans, and improve capital utilization efficiency.

Next, it is crucial to encourage the coordinated development of DIFs across all provinces: the siphoning effect and radiation effect of DIFs will have the DIFs in a province pull up the CEI of neighboring provinces, while the imitation effect will enable the DIFs in a province to assist neighboring provinces in reducing CEI, thereby also lowering the CEI within the province. Therefore, in the process of DIF development, it is crucial to foster coordinated development across all provinces to prevent a scenario where a few provinces' DIFs achieve better development, which could hinder the progress of neighboring provinces' DIFs. This coordinated approach will mitigate the potential for significant resource transfers from provinces with weaker DIF development to those with stronger DIFs, as well as the relocation of polluting enterprises from provinces with higher DIF levels to those with lower levels. Such relocations could ultimately lead to an increase, rather than a decrease, in the CEI of provinces with lower DIF levels, thereby hindering the achievement of carbon-neutrality goals. Therefore, communication and cooperation should be fostered throughout the DIF-development process. Specifically, eastern provinces with a high DIF development level should be encouraged to collaborate with central and western provinces with a lower DIF development level. Leveraging their advantages in technology, talent, market, policy, and industry, the eastern provinces can achieve breakthroughs in digital technology application and innovation, creating valuable experiences that can be replicated and extended in central and western provinces. Meanwhile, the central and western provinces should take the initiative in addressing challenges and strengthening technical exchanges and cooperation among government, universities, research institutes, and enterprises. Through these exchanges and collaborations, the provinces can jointly develop DIF while maximizing the goal of reducing carbon emissions.

In conclusion, DIF refers to the merging of digital technology and finance, creating a novel financial industry. As the integration of digital technology and finance continues to deepen, DIF is expected to experience rapid global growth. This growth will bring a series of economic effects and environmental effects that are worthy of attention.

Author Contributions: Conceptualization, H.J.; methodology, Q.H.; formal analysis, Q.H. and H.J.; funding acquisition, Q.H.; data curation, Q.H.; writing—original draft preparation, Q.H.; writing—review and editing, Q.H.; supervision, H.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Most of the data in this paper came from the China Statistical Yearbook (<https://www.stats.gov.cn/sj/ndsj>, accessed on 2 February 2024). The 2023 global climate data were from the World Meteorological Organization (<https://library.wmo.int/idurl/4/68835>, accessed on 3 February 2024). The data regarding DIF came from the Digital Inclusive Finance Research Center (<https://idf.pku.edu.cn/yjcg/zsbj/513800.htm>, accessed on 3 February 2024).

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Romanello, M.; Napoli, C.D.; Green, C.; Kennard, H.; Lampard, P.; Scamman, D.; Walawender, M.; Ali, Z.; Ameli, N.; Ayeb-Karlsson, S.; et al. *The 2023 Report of the Lancet Countdown on Health and Climate Change: The Imperative for a Health-Centred Response in a World Facing Irreversible Harms*; 0140-6736; Elsevier: Amsterdam, The Netherlands, 2023; pp. 2346–2394.

2. Allen, M.R.; Frame, D.J.; Huntingford, C.; Jones, C.D.; Lowe, J.A.; Meinshausen, M.; Meinshausen, N. Warming caused by cumulative carbon emissions towards the trillionth tonne. *Nature* **2009**, *458*, 1163–1166. [[CrossRef](#)] [[PubMed](#)]
3. *CO₂ Emissions in 2023*; IEA: Paris, France, 2024.
4. Li, S.; Wang, S. Examining the effects of socioeconomic development on China's carbon productivity: A panel data analysis. *Sci. Total Environ.* **2019**, *659*, 681–690. [[CrossRef](#)] [[PubMed](#)]
5. Xie, Q.; Ma, D.; Raza, M.Y.; Tang, S.; Bai, D. Toward carbon peaking and neutralization: The heterogeneous stochastic convergence of CO₂ emissions and the role of digital inclusive finance. *Energy Econ.* **2023**, *125*, 106841. [[CrossRef](#)]
6. Zhang, X.; Sun, H.; Wang, T. Impact of Financial Inclusion on the Efficiency of Carbon Emissions: Evidence from 30 Provinces in China. *Energies* **2022**, *15*, 7316. [[CrossRef](#)]
7. Cai, X.; Song, X. The nexus between digital finance and carbon emissions: Evidence from China. *Front. Psychol.* **2022**, *13*, 997692. [[CrossRef](#)] [[PubMed](#)]
8. Tsuji, C. The historical transition of return transmission, volatility spillovers, and dynamic conditional correlations: A fresh perspective and new evidence from the US, UK, and Japanese stock markets. *Quant. Financ. Econ.* **2024**, *8*, 410–436. [[CrossRef](#)]
9. IPCC. *Climate Change 2023: Synthesis Report*; IPCC: Geneva, Switzerland, 2023; pp. 35–115.
10. Bhatnagar, S.; Sharma, D. Evolution of green finance and its enablers: A bibliometric analysis. *Renew. Sustain. Energy Rev.* **2022**, *162*, 112405. [[CrossRef](#)]
11. Yu, Y. The Impact of Financial System on Carbon Intensity: From the Perspective of Digitalization. *Sustainability* **2023**, *15*, 1314. [[CrossRef](#)]
12. Xue, L.; Zhang, X. Can Digital Financial Inclusion Promote Green Innovation in Heavily Polluting Companies? *Int. J. Environ. Res. Public Health* **2022**, *19*, 7323. [[CrossRef](#)]
13. Yang, G.; Ding, Z.; Wu, M.; Gao, M.; Yue, Z.; Wang, H. Can digital finance reduce carbon emission intensity? A perspective based on factor allocation distortions: Evidence from Chinese cities. *Environ. Sci. Pollut. Res.* **2023**, *30*, 38832–38852. [[CrossRef](#)]
14. Acheampong, A.O.; Amponsah, M.; Boateng, E. Does financial development mitigate carbon emissions? Evidence from heterogeneous financial economies. *Energy Econ.* **2020**, *88*, 104768. [[CrossRef](#)]
15. Lee, C.-C.; Chang, Y.-F.; Wang, E.-Z. Crossing the rivers by feeling the stones: The effect of China's green credit policy on manufacturing firms' carbon emission intensity. *Energy Econ.* **2022**, *116*, 106413. [[CrossRef](#)]
16. Xiong, F.; Zhang, R.; Mo, H. The mediating effect of financial development on CO₂ emissions: An empirical study based on provincial panel data in China. *Sci. Total Environ.* **2023**, *896*, 165220. [[CrossRef](#)] [[PubMed](#)]
17. Guo, X.; Tu, Y. How digital finance affects carbon intensity—The moderating role of financial supervision. *Financ. Res. Lett.* **2023**, *55*, 103862. [[CrossRef](#)]
18. Sharma, R.; Shahbaz, M.; Sinha, A.; Vo, X.V. Examining the temporal impact of stock market development on carbon intensity: Evidence from South Asian countries. *J. Environ. Manag.* **2021**, *297*, 113248. [[CrossRef](#)]
19. Fang, Z.; Gao, X.; Sun, C. Do financial development, urbanization and trade affect environmental quality? Evidence from China. *J. Clean. Prod.* **2020**, *259*, 120892. [[CrossRef](#)]
20. Shahbaz, M.; Nasir, M.A.; Hille, E.; Mahalik, M.K. UK's net-zero carbon emissions target: Investigating the potential role of economic growth, financial development, and R&D expenditures based on historical data (1870–2017). *Technol. Forecast. Soc. Chang.* **2020**, *161*, 120255. [[CrossRef](#)]
21. Wu, M.; Guo, J.; Tian, H.; Hong, Y. Can Digital Finance Promote Peak Carbon Dioxide Emissions? Evidence from China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 14276. [[CrossRef](#)]
22. Sun, H.; Chen, T.; Wang, C.N. Spatial impact of digital finance on carbon productivity. *Geosci. Front.* **2023**, *15*, 101674. [[CrossRef](#)]
23. Cheng, J.; Jiang, Y. How can carbon markets drive the development of renewable energy sector? Empirical evidence from China. *Data Sci. Financ. Econ.* **2024**, *4*, 249–269. [[CrossRef](#)]
24. Song, X.; Yao, Y.; Wu, X. Digital finance, technological innovation, and carbon dioxide emissions. *Econ. Anal. Policy* **2023**, *80*, 482–494. [[CrossRef](#)]
25. Sun, B.; Li, J.; Zhong, S.; Liang, T. Impact of digital finance on energy-based carbon intensity: Evidence from mediating effects perspective. *J. Environ. Manag.* **2023**, *327*, 116832. [[CrossRef](#)] [[PubMed](#)]
26. Lu, F.; Li, Z.; Zhang, S. Does digital finance development affect carbon emission intensity: Evidence from China. *Int. Rev. Econ. Financ.* **2023**, *88*, 1272–1286. [[CrossRef](#)]
27. Tang, Y.; Zhang, X.; Lu, S.; Taghizadeh-Hesary, F. Digital finance and air pollution in China: Evolution characteristics, impact mechanism and regional differences. *Resour. Policy* **2023**, *86*, 104073. [[CrossRef](#)]
28. Zhao, H.; Chen, S.; Zhang, W. Does digital inclusive finance affect urban carbon emission intensity: Evidence from 285 cities in China. *Cities* **2023**, *142*, 104552. [[CrossRef](#)]
29. Lee, C.-C.; Wang, F. How does digital inclusive finance affect carbon intensity? *Econ. Anal. Policy* **2022**, *75*, 174–190. [[CrossRef](#)]
30. Wang, W.; Gao, P.; Wang, J. Nexus among digital inclusive finance and carbon neutrality: Evidence from company-level panel data analysis. *Resour. Policy* **2023**, *80*, 103201. [[CrossRef](#)]
31. Li, Z.; Lai, Q.; He, J. Does digital technology enhance the global value chain position? *Borsa Istanbul. Rev.* **2024**, *24*, 856–868. [[CrossRef](#)]
32. *Global Digital Economy Development Index Report*; CASS: Beijing, China, 2023.

33. Bai, L.; Guo, T.; Xu, W.; Liu, Y.; Kuang, M.; Jiang, L. Effects of digital economy on carbon emission intensity in Chinese cities: A life-cycle theory and the application of non-linear spatial panel smooth transition threshold model. *Energy Policy* **2023**, *183*, 113792. [\[CrossRef\]](#)
34. Yin, Y. Digital finance development and manufacturing emission reduction: An empirical evidence from China. *Front. Public Health* **2022**, *10*, 973644. [\[CrossRef\]](#)
35. Hong, H.; Sun, L.; Zhao, L. Exploring the Impact of Digital Inclusive Finance on Agricultural Carbon Emissions: Evidence from the Mediation Effect of Capital Deepening. *Sustainability* **2024**, *16*, 3071. [\[CrossRef\]](#)
36. Sousa, V.; Bogas, J.A. Comparison of energy consumption and carbon emissions from clinker and recycled cement production. *J. Clean. Prod.* **2021**, *306*, 127277. [\[CrossRef\]](#)
37. Yu, M.; Tsai, F.-S.; Jin, H.; Zhang, H. Digital finance and renewable energy consumption: Evidence from China. *Financ. Innov.* **2022**, *8*, 58. [\[CrossRef\]](#)
38. Hou, S.; Zhang, Y.; Song, L. Digital finance and regional economic resilience: Evidence from 283 cities in China. *Heliyon* **2023**, *9*, e21086. [\[CrossRef\]](#) [\[PubMed\]](#)
39. Wang, H.; Guo, J. Impacts of digital inclusive finance on CO₂ emissions from a spatial perspective: Evidence from 272 cities in China. *J. Clean. Prod.* **2022**, *355*, 131618. [\[CrossRef\]](#)
40. Zhong, R.; He, Q.; Qi, Y. Digital Economy, Agricultural Technological Progress, and Agricultural Carbon Intensity: Evidence from China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 6488. [\[CrossRef\]](#) [\[PubMed\]](#)
41. Li, J.; Ye, S.; Zhang, Y. How digital finance promotes technological innovation: Evidence from China. *Financ. Res. Lett.* **2023**, *58*, 104298. [\[CrossRef\]](#)
42. Li, W.; Pang, W. Digital inclusive finance, financial mismatch and the innovation capacity of small and medium-sized enterprises: Evidence from Chinese listed companies. *Heliyon* **2023**, *9*, e13792. [\[CrossRef\]](#)
43. Xiong, M.; Li, W.; Xian, B.T.S.; Yang, A. Digital inclusive finance and enterprise innovation—Empirical evidence from Chinese listed companies. *J. Innov. Knowl.* **2023**, *8*, 100321. [\[CrossRef\]](#)
44. Liu, Y.; Zhang, X.; Shen, Y. Technology-driven carbon reduction: Analyzing the impact of digital technology on China's carbon emission and its mechanism. *Technol. Forecast. Soc. Change* **2024**, *200*, 123124. [\[CrossRef\]](#)
45. Peng, Y.; Tao, C. Can digital transformation promote enterprise performance?—From the perspective of public policy and innovation. *J. Innov. Knowl.* **2022**, *7*, 100198. [\[CrossRef\]](#)
46. Yang, M.; Pu, Z.; Zhu, B.; Tavera, C. The threshold spatial effect of digital technology on carbon emissions. *J. Clean. Prod.* **2024**, *442*, 140945. [\[CrossRef\]](#)
47. Zhou, J.; Liu, W. Carbon Reduction Effects of Digital Technology Transformation: Evidence from the Listed Manufacturing Firms in China. *Technol. Forecast. Soc. Change* **2024**, *198*, 122999. [\[CrossRef\]](#)
48. Wang, L.; Chen, Y.; Ramsey, T.S.; Hewings, G.J.D. Will researching digital technology really empower green development? *Technol. Soc.* **2021**, *66*, 101638. [\[CrossRef\]](#)
49. Liao, Y.; Zhou, X. Can Digital Finance Contribute to Agricultural Carbon Reduction? Evidence from China. *Sustainability* **2023**, *15*, 15824. [\[CrossRef\]](#)
50. Chu, H.; Yu, H.; Chong, Y.; Li, L. Does the development of digital finance curb carbon emissions? Evidence from county data in China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 49237–49254. [\[CrossRef\]](#) [\[PubMed\]](#)
51. Javeed, S.A.; Latief, R.; Cai, X.; Ong, T.S. Digital finance and corporate green investment: A perspective from institutional investors and environmental regulations. *J. Clean. Prod.* **2024**, *446*, 141367. [\[CrossRef\]](#)
52. Wang, Y.; Zhao, Z.; Zhang, S.; Su, Y. Research on the impact of digital inclusive finance on regional carbon emissions: Based on the sustainable green innovation of small and medium-sized enterprises. *J. Clean. Prod.* **2023**, *428*, 139513. [\[CrossRef\]](#)
53. Zhou, Z.; Zeng, C.; Li, K.; Yang, Y.; Zhao, K.; Wang, Z. Decomposition of the decoupling between electricity CO₂ emissions and economic growth: A production and consumption perspective. *Energy* **2024**, *293*, 130644. [\[CrossRef\]](#)
54. Liao, T.; Yan, J.; Zhang, Q. The impact of green technology innovation on carbon emission efficiency: The intermediary role of intellectual capital. *Int. Rev. Econ. Financ.* **2024**, *92*, 520–532. [\[CrossRef\]](#)
55. Lu, J.; Li, H. Can digital technology innovation promote total factor energy efficiency? Firm-level evidence from China. *Energy* **2024**, *293*, 130682. [\[CrossRef\]](#)
56. Li, X.; Wang, J.; Zhang, M.; Ouyang, J.; Shi, W. Regional differences in carbon emission of China's industries and its decomposition effects. *J. Clean. Prod.* **2020**, *270*, 122528. [\[CrossRef\]](#)
57. Jiang, Y.; Zhao, R.; Qin, G. How does digital finance reduce carbon emissions intensity? Evidence from chain mediation effect of production technology innovation and green technology innovation. *Heliyon* **2024**, *10*, e30155. [\[CrossRef\]](#) [\[PubMed\]](#)
58. Arcand, J.L.; Berkes, E.; Panizza, U. Too much finance? *J. Econ. Growth* **2015**, *20*, 105–148. [\[CrossRef\]](#)
59. Zhao, H.; Yang, Y.; Li, N.; Liu, D.; Li, H. How does digital finance affect carbon emissions? Evidence from an emerging market. *Sustainability* **2021**, *13*, 12303. [\[CrossRef\]](#)
60. Ye, J.; Xu, W.; Hu, L. Digital inclusive finance, consumption structure upgrading and carbon emissions. *Front. Environ. Sci.* **2023**, *11*, 1282784. [\[CrossRef\]](#)
61. Kempson, H.; Whyley, C. Understanding and combating financial exclusion. *Insur. Trends* **1999**, *21*, 18–22.
62. Wang, J.; Tian, J.; Kang, Y.; Guo, K. Can green finance development abate carbon emissions: Evidence from China. *Int. Rev. Econ. Financ.* **2023**, *88*, 73–91. [\[CrossRef\]](#)

63. Wang, D.; Wang, Z.; Cai, W.; Wu, Q. Digital inclusive finance, higher education expansion and regional carbon emissions: Evidence from China. *Int. Rev. Econ. Financ.* **2024**, *89*, 1091–1101. [[CrossRef](#)]
64. Zhou, B.; Wang, Y.-L.; Bin, H. The nonlinear effects of digital finance on carbon performance: Evidence from China. *J. Innov. Knowl.* **2024**, *9*, 100484. [[CrossRef](#)]
65. Su, Z.; Cao, R. Impact of Digital Inclusive Finance on Urban Carbon Emission Intensity: From the Perspective of Green and Low-Carbon Travel and Clean Energy. *Sustainability* **2023**, *15*, 12623. [[CrossRef](#)]
66. Yang, A.; Yang, M.; Zhang, F.Y.; Kassim, A.A.M.; Wang, P.X. Has Digital Financial Inclusion Curbed Carbon Emissions Intensity? Considering Technological Innovation and Green Consumption in China. *J. Knowl. Econ.* **2024**, *30*, 1–30. [[CrossRef](#)]
67. Lei, T.; Luo, X.; Jiang, J.; Zou, K. Emission reduction effect of digital finance: Evidence from China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 62032–62050. [[CrossRef](#)] [[PubMed](#)]
68. Lee, C.C.; Wang, F.H.; Lou, R.C. Digital financial inclusion and carbon neutrality: Evidence from non-linear analysis. *Resour. Policy* **2022**, *79*, 15. [[CrossRef](#)]

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