Heliyon 10 (2024) e30155

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

How does digital finance reduce carbon emissions intensity? Evidence from chain mediation effect of production technology innovation and green technology innovation

Yan Jiang [a], Ruizeng Zhao [b,c], Guozhen Qin [d,*]

[a] College of Business, Shanghai University of Finance and Economics, Shanghai, 200433, China
[b] School of Economics and Management, Southwest University of Science and Technology, Mianyang, Sichuan, 621000, China
[c] School of Management, University of Science and Technology of China, Hefei, Anhui, 230026, China
[d] Sichuan Jiuzhou Investment Holding Group Co., Ltd, Mianyang, 621000, China

ARTICLE INFO

Keywords:
Digital finance
Low carbon development
Production technology innovation
Green technology innovation
Chain mediation effect

ABSTRACT

The digitalization of finance drives economic development and plays a crucial role in energy conservation and carbon emission reduction. Utilizing carbon emissions data from 2011 to 2020, we find that digital finance development can mitigate carbon emissions intensity (CEI) by approximately 0.14 %. Then, we employ a diverse set of robustness and endogeneity tests to assess the reliability of the empirical findings. Moreover, the study delves into how digital finance impacts CEI through production technology innovation (PTI) and green technology innovation (GTI). The results indicate a positive effect of PTI on CEI. GTI exerts a negative influence on CEI. In addition, there is a chain mediation effect between PTI and GTI in the baseline path. Finally, the impact of digital finance on CEI exhibits apparent regional heterogeneity.

1. Introduction

With the increasing global attention to environmental problems, achieving a harmonious and balanced development between the economy and the environment has emerged as a prominent and widely discussed topic [1,2]. China, the world's outstanding contributor to carbon emissions, is under immense pressure to reduce its emissions [3]. Based on achieving peaking carbon dioxide emissions by 2030 and carbon neutrality by 2060 [4,5], China clarifies the role of finance in securing action to achieve carbon peaks.

However, academics have no consensus on the relationship between financial development and the environment. There are two main points of disagreement. Some scholars impose that financial development can support environmentally friendly enterprises and projects, promote industrial restructuring, and enhance investment in energy-efficient technologies [6–8]. Therefore, they believe financial development can improve the environment and reduce CO_2 emissions. Contrarily, some researchers argue that financial development may also increase CO_2 emissions and degrade environmental quality, since financial development raises residents' income, increasing their purchases of energy-intensive products. Simultaneously, financial development can give rise to a rebound effect of technological progress, leading to an increase in energy consumption [9–12]. As an evolved mode of traditional finance, it is worth studying whether digital finance similarly impacts low-carbon development.

The prevailing body of literature indicates that digital finance possesses low-carbon and green attributes, thereby holding the

* Corresponding author.
E-mail addresses: yanjiang@163.sufe.edu.cn (Y. Jiang), zhaorz@mail.ustc.edu.cn (R. Zhao), 18381667908@163.com (G. Qin).

https://doi.org/10.1016/j.heliyon.2024.e30155
Received 2 December 2023; Received in revised form 13 April 2024; Accepted 21 April 2024
Available online 23 April 2024

potential to drive sustainable economic development. Additionally, digital finance has enhanced service delivery and expanded the service scope of traditional finance [13]. For example, Zhang and Liu [14] investigate the influence of digital finance on carbon emission efficiency in 283 cities. Their study reveals that digital finance can decrease offline transactions and direct capital flows to low-carbon industries. As a result, digital finance can exert a positive low-carbon impact, improving carbon emission efficiency. Besides, Wang et al. [15] also argue that financial development plays a vital role in carbon emissions in terms of exploring the relationship between the economy and the environment. Wang et al. [1] uncover that ICT on carbon emission presents a "U" shape under the influence of financial development, and the "U"-shaped turning point occurs when the level of financial development is low.

It is essential to acknowledge that the literature on the potential mechanisms through which digital finance influences carbon emissions is still in its infancy. Among these potential mechanisms, technological innovation has garnered significant attention. Wu et al. [16] believe technological innovation and upgrading industrial structure are essential chain mediation mechanisms. Hao et al. [17] and Lin and Ma [18] argue that digital finance positively affects emission reduction by promoting investment in green technology innovation (GTI). However, Wu et al. [16] find that technological innovation significantly inhibits carbon emission efficiency. Therefore, it is paramount to comprehensively analyze the disparities in emission reduction effects between production technology innovation (PTI) and GTI while acknowledging the intrinsic interconnections between these two aspects within a unified framework.

This paper mainly endeavors to explore the following three questions. First, does digital finance effectively contribute to actions aimed at reducing carbon emissions? Second, are there notable attribute differences in technological innovation for low-carbon development? Third, do PTI and GTI serve as chain intermediaries in the pathway through which digital finance influences carbon emission intensity (CEI)?

To answer these issues, we first analyze the direct effects of digital finance on CEI via a panel fixed effects model. Second, this paper constructs a chain mediation model to investigate the effects of different technological innovations on carbon emission reduction. Finally, we further investigate the characteristics of regional heterogeneity regarding the impact of digital finance on CEI.

This paper makes several potential contributions. First, this paper makes several potential contributions. First, Existing literature has extensively explored the relationship between the economy and the environment from a macroscopic perspective, such as Wang et al. [19] and Wang et al. [20] have shed light on the influence of trade openness and geopolitical changes on the environment. They identify financial development as a crucial moderating variable in the nexus between economic efficiency and environmental conservation. Digital finance represents an innovative paradigm within traditional financial systems, yet research on its emission reduction mechanisms needs further refinement. In contrast to the research conducted by Li et al. [21], this paper constructs the direct pathway through which digital finance influences carbon emissions intensity (CEI). Additionally, it investigates the potential indirect impact mechanisms of digital finance on CEI from the perspective of technological innovation. By delineating both direct and indirect pathways, this paper comprehensively explains the multifaceted relationship between digital finance and environmental sustainability.

Second, this paper fills a research gap by examining the distinctions in the attributes of both PTI and GTI in the context of the influence of digital finance on CEI. To our knowledge, this aspect has been underexplored by previous scholars in the field. Therefore, in this paper, we examine the disparities in emission reduction effects between PTI and GTI within a unified framework, which enriches the existing relevant studies. Third, existing studies tend to study the mediating effect of a single variable in a fragmented manner, and the chain relationship between multiple mediating variables is ignored. Therefore, based on the learning by doing (LBD) theory proposed by Arrow [22], we construct a more complex model to explore the chain mediation effect between PTI and GTI.

Finally, this paper makes targeted recommendations from digital finance and technological innovation perspectives. This study's research findings carry significant policy implications for governments striving to achieve carbon neutrality objectives and enhance regional coordinated development. The implementation of these recommendations can facilitate progress towards carbon neutrality targets while fostering regional harmonization and sustainable development.

The remainder of the paper is organized as follows. **Section 2** theoretically analyzes the potential impact mechanisms and presents the corresponding research hypotheses. The research methodology and data are presented in **Section 3**. **Section 4** enumerates the empirical results and provides an in-depth analysis of the valuable findings. Finally, **Section 5** summarizes the relevant findings and makes recommendations.

2. Theoretical mechanism and hypotheses

2.1. Digital finance and carbon emissions

Digital finance utilizes cutting-edge technologies such as artificial intelligence and blockchain to provide services, leading to a qualitative improvement in the efficiency of financial services [13]. Digital finance has two direct impacts on carbon emissions. On the one hand, financial institutions can directly provide credit products to borrowers through online platforms, avoiding the offline consumption of resources and energy and reducing associated CO_2 emissions [23]. Consequently, digital finance enhances resource allocation efficiency and effectively fulfills the requirements of green development [24].

On the other hand, digital finance's technological benefits can help alleviate the information asymmetry between lenders and borrowers [25]. By leveraging digital technology, financial institutions can accurately and efficiently identify environmentally friendly enterprises, enabling loans to low-consumption and low-emission businesses, thus contributing to alleviating environmental pressure. Therefore, we sorted out a hypothesis from the mechanism mentioned above analysis.

Hypothesis 1. Digital finance can curb carbon emissions, and it is negatively related to CEI.

2.2. The intermediary effect of technological innovation

Endogenous growth theory posits that technological progress is necessary for sustainable economic development. Brock and Taylor [26] propose the Green Solow model based on the Solow model [27], which takes into account the adverse impact of environmental pollution (i.e., carbon emissions) on economic production and incorporates technological progress into carbon emission reduction activities. According to Ref. [26], the growth rate of CO_2 emissions in the balanced growth path, i.e., $g_E = g_B + n - g_A$. g_E means the total growth rate of CO_2 emissions, which depends on the population growth rate n, the production technology growth rate g_B, and the rate of carbon emission reduction technology growth g_A.

However, the Green Solow model is inconsistent with reality. This model assumes that technological progress is exogenous. If the rate of technological progress is zero, socio-economic development will stagnate. The learning by doing (LBD) theory imposes that capital accumulation can promote technological progress [28], which provides theoretical support for exploring how digital finance can affect CEI.

Therefore, digital finance indirectly affects CEI through three potential mechanisms. First, digital financial capital can improve production and energy usage efficiency through technological innovation but increase CEI. As Wang and Wei [29] mentioned, the technology rebound effect leads to increased carbon emissions and environmental pressures as digital finance facilitates technological innovation in production. Similarly, According to Refs. [16,30], digital finance has the potential to stimulate technological innovation. However, they also acknowledge that technological innovation leads to a substantial increase in CO_2 emissions while simultaneously reducing carbon emission efficiency. They argue that technological innovation improves production efficiency and reduces production costs. Hence, technological innovation indirectly expands energy consumption, ultimately producing a rise in CO_2 emissions.

Second, it is essential to note that GTI and PTI possess distinct attributes. GTI, in particular, emphasizes advancements in environmentally friendly innovation domains [31]. With the government guiding financial capital into green innovation, digital finance can directly support green innovation R&D to reduce carbon emissions. Feng et al. [32] and Li et al. [33] point out that digital finance can alleviate financial constraints for companies, thereby increasing financing support for technological innovation, particularly in green technologies. The development and use of green technologies can generate direct environmental benefits.

Third, The LBD theory provides the basis for explaining the intrinsic link between digital financial capital and innovation. Production technology accumulates a large amount of valuable experience and innovation base in the process of continuous innovation. These skill reserves gained from PTI can provide practical innovation support for the subsequent GTI. Theoretically, there exists an inherent connection between technological innovations that drive production activities and those focused on promoting green governance.

Therefore, we propose three research hypotheses related to the aforementioned analysis.

Hypothesis 2. Digital finance can indirectly impact CEI through PTI. Meanwhile, PTI increases CEI.

Hypothesis 3. Digital finance can indirectly influence CEI through GTI. Meanwhile, GTI diminishes CEI.

Hypothesis 4. Digital finance can indirectly mitigate CEI through the chain relationship facilitated by PTI and GTI.

This study presents a diagram illustrating the influential mechanism of digital finance and CEI, as depicted in Fig. 1.

3. Methodology and indicator selection

3.1. Model

The Impact, Population, Affluence, and Technology (IPAT) model posits that environmental changes primarily result from the combined influence of three driving factors: population, economic activity, and technology. This model underscores the

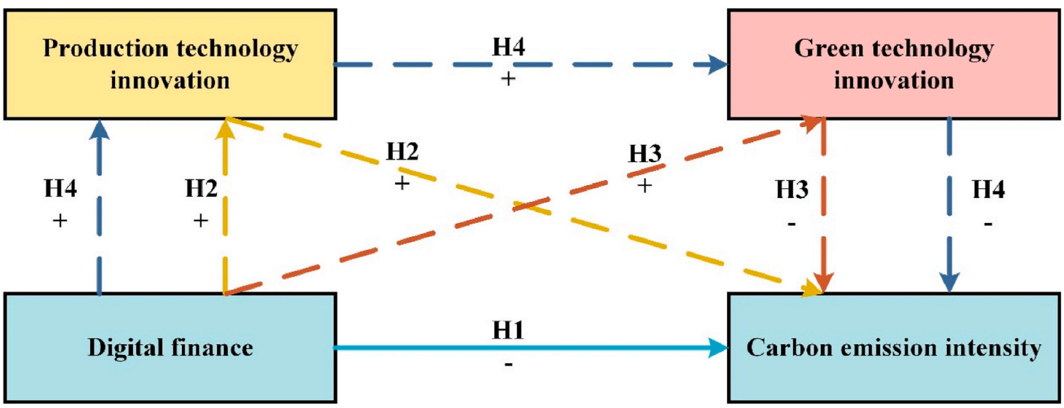

Fig. 1. Potential mechanism.

interconnectedness of these factors, highlighting that individual components cannot exert independent effects on environmental impacts. While the IPAT model serves as a valuable framework for studying environmental changes by isolating individual factors while keeping others constant, it possesses inherent limitations. The Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model, introduced by York et al. [34], represents an enhancement of the IPAT model by incorporating error elasticities and stochastic errors. Yu et al. [35] elucidate that the STIRPAT model offers greater structural composition flexibility than the traditional IPAT model. This flexibility allows for a nuanced decomposition of various influencing factors, enabling tailored environmental impact studies to suit diverse scenarios.

The model is expressed as follows: $I = aP^bA^cT^de$, where I denotes environmental pressure, P represents the total amount of population, A signifies affluence level, and T denotes technological level. a, b, c, and d represent the intercept term and the elasticity coefficients of the corresponding variables, respectively. e denotes error term.

This paper employs a logarithmic transformation to address the issues of trend and heteroscedasticity in the time series data, as Xu et al. [36] suggested. In line with our research objectives, the benchmark regression model can be reformulated as equation (1):

$$\ln CEI_{it} = \alpha + \beta \ln DIF_{it} + \sum_{m=1}^{s} \gamma_m \ln X_{m,it} + \mu_i + v_t + \varepsilon_{it} \tag{1}$$

where, i and t represent the province and year, respectively. CEI_{it} and DIF_{it} are this paper's core explained and explanatory variables, namely CEI and digital finance. $X_{m,it}$ includes a vector of control variables, such as financial development level, the total number of populations, energy structure, and government intervention. The notation $ln(\cdot)$ signifies taking the logarithmic form of the variable. In equation (1), our primary focus lies on the coefficient β, as it represents the specific object of our attention, which is the relationship between digital finance and CEI. We expect β to be significantly negative, suggesting that provinces with higher levels of digital finance may generate lower CEI. This would be lined with **H1**.

In addition, to differentiate the distinct effects of PTI and GTI on CEI and investigate whether they serve as potential mechanisms through which digital finance influences CEI, we establish several models as follows:

$$\ln PTI_{it} = \alpha_1 + \beta_1 \ln DIF_{it} + \sum_{m=1}^{s} \gamma_m \ln X_{m,it} + \mu_i + v_t + \varepsilon_{it} \tag{2}$$

$$\ln GTI_{it} = \alpha_2 + \beta_2 \ln DIF_{it} + \sum_{m=1}^{s} \gamma_m \ln X_{m,it} + \mu_i + v_t + \varepsilon_{it} \tag{3}$$

$$\ln GTI_{it} = \alpha_3 + \beta_3 \ln DIF_{it} + \delta_1 \ln PTI_{it} + \sum_{m=1}^{s} \gamma_m \ln X_{m,it} + \mu_i + v_t + \varepsilon_{it} \tag{4}$$

$$\ln CEI_{it} = \alpha_4 + \beta_4 \ln DIF_{it} + \delta_2 \ln PTI_{it} + \varphi_1 \ln GTI_{it} + \sum_{m=1}^{s} \gamma_m \ln X_{m,it} + \mu_i + v_t + \varepsilon_{it} \tag{5}$$

Combining equations (1)–(3) and (5), we could identify the multiple mediating effects of PTI and GTI. If β_1, β_2, δ_2, and φ_1 are statistically significant, PTI and GTI are potential mechanisms by which digital finance affects CEI. If both β_1 and δ_2 are significantly positive, then **H2** holds. If β_2 is significantly positive and φ_1 is significantly negative, the results are consistent with **H3**. $\beta_1\delta_2$ and $\beta_2\varphi_1$ are mediating effects of production technology innovation and green technology innovation, respectively. β_4 indexes direct effects. Therefore, the total effect of digital financial interference CEI can be quantified by $\beta = \beta_4 + \beta_1\delta_2 + \beta_2\varphi_1$.

Moreover, by jointing equations (1), (2), (4) and (5), we may analyze the chain mediation effect of PTI and GTI in the path of digital finance impacts CEI. $\beta_1\delta_2$ and $\beta_3\varphi_1$ are mediating effects of PTI on GTI, $\beta_1\delta_1\varphi_1$ means the chain mediation effect. The total indirect effects to be $\beta_1\delta_2 + \beta_3\varphi_1 + \beta_1\delta_1\varphi_1$, and the total effects of digital finance can be described as: $\beta = \beta_4 + \beta_1\delta_2 + \beta_3\varphi_1 + \beta_1\delta_1\varphi_1$. If all these coefficients are statistically significant, corresponding underlying mechanisms and chain mediation effects are valid. It is clear that **H4** holds as long as β_1 and δ_1 are significantly positive and φ_1 is negative.

3.2. Variables and data description

We leverage annual balanced panel data covering 30 provinces in China for 2011–2020. The variables are constructed as follows.

3.2.1. Dependent variable

The dependent variable, CEI, is measured as CO_2 emissions per unit of gross domestic product (GDP), as described in previous studies [37,38]. The CO_2 data is collected from Carbon Emission Accounts and Datasets (CEADs),[1] which provide a comprehensive measurement of carbon emissions data with high spatial accuracy and quality. GDP data derived from the China Statistics Yearbook.[2] The higher the CEI, the greater the CO_2 emissions per unit of GDP output and the worse the environmental quality.

[1] Carbon Emission Accounts and Datasets is available at https://www.ceads.net.cn/.

[2] GDP data is officially released by the National Bureau of Statistics, retrieved from http://www.stats.gov.cn/sj/ndsj/.

3.2.2. Independent variable

Following previous research by Guo et al. [39], we utilize digital inclusive finance as a proxy variable for digital finance, denoted as *DIF*. This indicator captures the level of development of digital finance based on three dimensions: breadth of coverage (*DIFbre*), depth of usage (*DIFdee*), and degree of digitization (*DIFdig*). We obtained the index information from the Peking University Institute of Digital Finance, which is widely used in existing studies [18,40–42].

3.2.3. Mediating variables

According to Ref. [16], technological innovation and industrial structure upgrading are essential chain mediation mechanisms. Some literature argues that digital finance positively affects emission reduction by promoting investment in green technology innovation (GTI) [17,18]. However, production technology innovation (PTI) significantly inhibits carbon emission efficiency [16]. Hence, it is imperative to concurrently examine the disparities in emission reduction effects between production technology innovation and green technology innovation, as well as their inherent connections, within a unified framework.

We propose two potential mechanisms by which digital finance could affect CEI. One of the mediating variables is the PTI. Following Furman et al. [43], the construction of PTI is obtained from the evolution of the Cobb-Douglas production function $A = \varepsilon R^{\alpha} S^{\beta}$, where A is the number of patents, R represents an investment in R&D, S is the number of researchers, and ε indicates technical level. Given constant returns to scale and conditional on $\alpha = \beta$, we can rewrite the production function as: $PTI = \varepsilon^2 = A^2/RS$. The model's numerator represents technical outputs, and the denominator denotes technical inputs. A higher value demonstrates a higher level of technological innovation. Relevant data can be obtained from the China Statistical Yearbook on Science and Technology.

According to Ref. [44], The other variable, GTI, is measured using the total number of green patent applications, this data is collected from the China National Intellectual Property Administration. Specifically, green patent applications are summed up at the provincial level according to the green patent list and international classification codes provided by the World Intellectual Property Organization.

3.2.4. Control variables

To comprehensively examine the determinants of CEI, drawing insights from the studies of Shahbaz et al. [8], Li et al. [33], and Xu et al. [36], we introduce a range of control variables that may be related to CEI into our estimation, including, financial development level (*FIN*), which is quantified by the balance of deposits and loans of financial institutions per unit of GDP; the population (*POP*); energy structure (*COA*), which is defined as the coal consumption; and government intervention (*GOV*), as a ratio of financial investment to GDP. All control variables information is retrieved from the Statistical Yearbook by Province. The descriptive statistics of the variables of interest are shown in Table 1.

In Table 1, the standard deviation of CEI is 2.08. The minimum and maximum values range from 0.20 to 12.16 Tons/10000 RMB, highlighting the significant variation in CEI levels across different provinces. This variation serves as the research basis and necessitates the testing of heterogeneity analysis regarding the influence of digital finance on CEI on a provincial scale.

4. Empirical analysis

4.1. Unit root test, co-integration test, and Hausman test

To address concerns regarding pseudo-regression issues, we conducted a unit root test to examine the stationarity of the variables. Additionally, we utilized the Hausman test to determine the suitable regression model for our analysis. These measures were taken to ensure the reliability and validity of our regression results. First, this research follows [45] to perform LLC, IPS, and PP panel unit root tests, and the results are presented in Table 2. The test results indicate that the data is stationary after the first differencing.

Then, we introduce the Kao test to verify the long-term co-integration relationship between variables. The outcomes are shown in Table 3. The co-integration test results show that all t-statistics are significant at a 5 % level, demonstrating a long-run co-integration relationship between the variables. Besides, we report the Hausman test estimator in Table 3. The p-value for χ^2 is less than 0.001, so the fixed effects model is the preferred choice.

4.2. Baseline regression and robustness test

4.2.1. Benchmark regression

In Table 4, M1 and M2 represent the results without and with control variables, respectively. The coefficients of digital finance are negative and significant at the level of 1 %, signifying that digital finance has a mitigating effect on carbon emissions, which is consistent with the **H1** and aligns with the finding of Lee et al. [46]. Moreover, our outcome reveals a significant negative influence of financial development on CEI, with a coefficient of −0.559. This result may be that the development of the financial sector can regulate the financing and loan structure of high-energy-consuming enterprises, thereby influencing their energy consumption and structure. This finding aligns with the conclusion of Acheampong et al. [47].

4.2.2. Robustness test

To ensure the reliability of the estimation results, we perform a series of robustness checks in this section, shown in Table 5. First, M3 shows outcomes for incorporating year-fixed effect. Second, we use alternative measurement (i.e., the ratio of CO_2 emissions to the

Table 1
Summary statistics.

Type	Variables	Unite	Obs	Mean	Std. Dev.	Min	Max
Dependent variable	CEI	Tons/10000 RMB	300	2.11	2.08	0.20	12.16
Independent variable	DIF	–	300	217.25	96.97	18.33	431.93
	DIFbre	–	300	198.01	96.33	1.96	397.00
	DIFdee	–	300	212.04	98.11	6.76	488.68
	DIFdig	–	300	290.24	117.64	7.58	462.23
Mediator variable	PTI	–	300	149.06	118.22	6.28	746.89
	GTI	piece	300	7568.89	10651.88	29.00	67258.00
Control variable	FIN	–	300	3.35	1.09	1.68	7.55
	POP	10000 people	300	4599.78	2837.85	568.00	12624.00
	COA	10000 tons	300	14587.13	11060.21	134.98	51331.61
	GOV	–	300	0.26	0.11	0.12	0.76

Table 2
Unit root tests.

Variables		LLC		IPS		Fisher-PP	
		trend and constant	constant	trend and constant	constant	trend and constant	constant
Levels	lnCEI	−9.9518***	0.0116	−3.5414***	3.2297	1.5437*	−1.3439
	lnDIF	−10.5349***	−26.8081***	−9.1291***	−21.2589***	116.2128***	121.3666***
	lnDIFbre	−86.8017***	−46.8479***	−78.3008***	−45.6670***	155.5588***	164.0372***
	lnDIFdee	−16.5215***	−33.0462***	−8.2469***	−16.0413***	76.3788***	90.2113***
	lnDIFdig	−30.5175***	−21.7400***	−12.5510***	−16.5597***	79.5307***	86.7705***
	lnPTI	−5.3671***	−4.9970***	−2.8571***	−0.2090	1.8015**	4.2765***
	lnGTI	−8.0462***	−6.4953***	−1.7481**	−0.4471	2.6673***	2.7964***
	lnFIN	−1.9252**	−1.6138*	1.3944	1.9979	−3.8161	−2.4566
	lnPOP	−11.8797***	−3.8880***	−1.2826*	−1.5130*	0.7035	39.0680***
	lnCOA	−6.5975***	−1.7815**	−1.7544**	0.8638	1.2360	2.1354**
	lnGOV	−8.3814***	−1.4296*	−1.3502*	0.5586	−0.1646	−1.9791
First difference	lnCEI	−47.3379***	−12.6609***	−19.4108***	−8.4850***	22.5027***	17.9002***
	lnDIF	−43.5341***	−15.0808***	−18.9157***	−16.8836***	93.6830***	115.2566***
	lnDIFbre	−21.1187***	−110.0000***	−42.3787***	−100.0000***	160.0000***	158.4162***
	lnDIFdee	−13.1117***	−16.9236***	−25.3201***	−12.2335***	56.5545***	84.0754***
	lnDIFdig	−48.3322***	−30.5020***	−59.3758***	−19.3861***	68.2668***	85.8872***
	lnPTI	−49.9526***	−8.4201***	−21.1031***	−8.6967***	21.7746***	18.7313***
	lnGTI	−45.6455***	−8.6244***	−13.0603***	−5.5342***	12.8451***	15.9004***
	lnFIN	−22.6435***	−5.3433***	−6.9366***	−3.3304***	1.8888**	2.6403***
	lnPOP	−20.6505***	−13.9357***	−4.7886***	−4.7287***	11.3819***	1.7931**
	lnCOA	−8.6287***	−10.0333***	−11.5523***	−7.1184***	10.7865***	14.3242***
	lnGOV	−64.5855***	−14.3667***	−31.6245***	−8.8208***	13.0674***	16.2428***

Note: ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 3
Co-integration test and Hausman test.

Kao test	t-statistics	p-value
Modified Dickey-Fuller	−2.9431	0.0016
Dickey-Fuller	−4.8516	0.0000
Augmented Dickey-Fuller	−2.2516	0.0122
Unadjusted modified Dickey-Fuller	−3.5951	0.0002
Unadjusted Dickey-Fuller	−5.1381	0.0000
Hausman test	chi2	p-value
	47.07	0.0000
Model type	Fixed effect model	

value added in the secondary sector, labeled as *lnCEI**) to take the place of the dependent variable in Model (1). The estimated outcome is shown in M4. Third, M5–M7 presents the regressing Model (1) results using the logarithm of three dimensions of digital finance indicators (*lnDIFbre*, *lnDIFdee*, *lnDIFdig*). Finally, we use a lagged one-period of digital finance (*L.lnDIF*) and green finance index (*lnGRF*) logarithm as an alternative. Regression results are described in M8 and M9.

As indicated in M2 to M9, all the digital finance coefficients are negative and statistically significant at the 1 % confidence interval, suggesting that digital finance diminishes CEI.

Table 4
Baseline results of digital finance on CEI.

Variables	M1	M2
	lnCEI	lnCEI
lnDIF	−0.2552*** (0.0150)	−0.1439*** (0.0215)
lnFIN		−0.5589*** (0.1336)
lnPOP		−2.6027*** (0.3114)
lnCOA		0.3977*** (0.0335)
lnGOV		0.4885*** (0.1196)
Constant	1.7542*** (0.0787)	20.1962*** (2.5714)
Time Effect	No	No
Individual Effect	Yes	Yes
N	300	300
Within R2	0.5198	0.7329

Note: ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively. Standard error in parentheses.

4.2.3. Endogeneity analysis

Endogenous problems may disrupt the reduction effect of digital finance on CEI. For instance, there is a possibility of overlooking unobservable variables that influence CEI and digital finance. Moreover, there are interactions among variables in the model. We address potential endogeneity issues using the Two-Stage Least Squares (2SLS) method with instrumental variables and lagged the one-period digital financial index as instrumental variables.

According to related literature, we construct two instrumental variables [12,48]. One is an artificially constructed instrumental variable (*lnINV*), comprising the product of the previous year's Internet users in the country and the number of fixed telephones per 100 people in each province in 1984. The other one is the lag term of digital finance. Historical telecommunications infrastructure can impact the phased adoption of internet technology by financial institutions, and the lagged digital finance development does not influence the current level of carbon emissions. Therefore, the instrumental variables selected in this paper are theoretically reasonable.

Employing the instrument variables, we perform a 2SLS regression to explore the influence of digital finance on CEI. We fitted and regressed the relationship between instrumental variables and digital finance in the first stage. In the second stage, we analyzed the fitting value of digital finance and CEI. The estimated outcomes are summarized in Table 6.

According to Table 6, the F-statistics for the weak instrumental variable test are all higher than 16.38 (i.e., the 10 % maximal IV size), indicating that the instrumental variables are valid. As presented in columns (3) and (5), the coefficients of *lnDIF* are still negative

Table 5
Robustness checks: alternative measures.

Variables	M3	M4	M5	M6	M7	M8	M9
	lnCEI	lnCEI*	lnCEI	lnCEI	lnCEI	lnCEI	lnCEI
lnDIF	−0.2551*** (0.0747)	−0.2460*** (0.0728)					
lnDIFbre			−0.1085*** (0.0165)				
lnDIFdee				−0.1159*** (0.0220)			
lnDIFdig					−0.0854*** (0.0174)		
L.lnDIF						−0.2337*** (0.0717)	
lnGRF							−0.7423*** (0.1703)
Constant	14.0331*** (2.9303)	10.6220*** (2.8576)	21.2143*** (2.5187)	22.4105*** (2.5872)	23.0013*** (2.5829)	15.0160*** (3.2008)	8.7799*** (3.0001)
Control Variables	YES	YES	YES	YES	YES	YES	YES
Time Effect	YES	YES	NO	NO	NO	YES	YES
Individual Effect	YES	YES	YES	YES	YES	YES	YES
N	300	300	300	300	300	270	300
Within R2	0.7704	0.6726	0.7314	0.7173	0.7138	0.7418	0.7765

Note: ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively. Standard error in parentheses.

and significant at the 1 % level, suggesting that the conclusion that digital finance effectively mitigates CEI remains valid.

4.3. Mediation effect analysis

In this section, we further identify the mediation effects of heterogeneous PTI and GTI on CEI and their potential roles in the influence of digital finance on CEI. We employ a stepwise regression approach to run equations (2)–(5), and the estimated results for the mediating and chain mediation effects are displayed in Table 7.

The coefficients in columns M13 and M14 demonstrate that digital finance significantly promotes PTI and GTI at the 1 % significance level because the inclusiveness of digital finance enables more small and medium-sized enterprises and underserved populations to access sufficient credit funding to support innovative project research and development [49], this finding aligns with the results of Lin and Ma [18] and Jiang et al. [50].

The results in column M15 indicate that increased PTI levels further promote GTI. The human resources engaged in PTI accumulate advanced experience while developing green technologies, laying the foundation for GTI [51,52]. The coefficient of PTI on CEI, displayed in column M16, exhibits a significant positive relationship at the 1 % significance level. Additionally, GTI demonstrates a significant negative correlation with CEI. This outcome suggests that PTI increases carbon dioxide emissions because the purpose of PTI is to enhance production efficiency, reduce production costs, and pursue high returns [53], whereas GTI reduces CEI.

Overall, the regression shows that digital finance impacts CEI through PTI and GTI. These results are lined with **H2** and **H3**. In addition, the results of columns M12, M13, M15, and M16 demonstrate a chain mediation effect between PTI and GTI. This implies that digital finance can indirectly mitigate CEI by sequentially promoting PTI and encouraging GTI along a chain pathway, which is lined with **H4**.

According to the regression coefficients in Table 7, we find the following conclusions. First, as shown in M16, the negative effect of GTI on CEI is significantly greater than the positive effect of PTI on CEI. Undeniably, the inherent green attributes of GTI are still a key driver in achieving sustainable and environmentally friendly economic development [54]. Second, we calculate the impact effect indicators of each mechanism. The results show that the direct effect of digital finance on CEI is −0.2782, and the indirect effects of PTI and GTI are 0.2123 and −0.0575, respectively. This result suggests that the mitigation effects of digital finance on CEI through GTI do not yet compensate for the positive effect of PTI, which is consistent with the related research [16]. Third, the chain mediation effect of PTI and GTI is −0.1317, and the total effect is −0.2551. This result indicates that digital finance can further promote the abatement efficacy of GTI by promoting PTI. Overall, the total emission reduction effect of digital finance and GTI is still more prominent than the carbon increase effect of PTI. Therefore, strengthening the development of digital finance and GTI and promoting the green transformation of PTI can help reduce carbon emissions.

4.4. Heterogeneity analysis

In this section, we further investigate regional heterogeneity in digital finance's inhibitory effect on CEI. These results can be viewed in Table 8. Columns M17–M19 represent the estimated outcomes for the Eastern, Central, and Western regions.

As presented in Table 8, digital finance reduces CEI in the Western region. This could be due to the reasonable industrial layout and solid economic foundation in the Eastern and Central areas, where there is currently a good decoupling between economic development and environmental governance [55]. Therefore, a significant reduction in emissions resulting from digital finance cannot be observed in the Eastern and Central regions. However, low-carbon development in the Western region still needs financial support. Therefore, the role of digital finance in decreasing emissions in the Western area is significant. Besides, PTI significantly drives CEI across all regions, while GTI has a mitigating influence on CEI in the Eastern and Western areas. Population size and energy structure also exert a clear regional heterogeneous impact on CEI.

Table 6
Two-stage least square (2SLS) regression.

Variables	M10		M11	
	lnDIF	lnCEI	lnDIF	lnCEI
lnDIF		−0.2687*** (0.0414)		−0.2752*** (0.0418)
lnINV	1.6939*** (0.1593)			
L.lnDIF			0.4840*** (0.0139)	
Control Variables	YES	YES	YES	YES
Time Effect	NO	NO	NO	NO
Individual Effect	YES	YES	YES	YES
N	300	300	270	270
Centered R2	0.8088	0.6990	0.9633	0.7258
Under-identification test		80.741***		201.075***
Weak identification test		113.054[16.38]		1213.945[16.38]

Note: ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively. Standard error in parentheses.

Table 7
Chain mediation effect analysis for innovation.

Variables	M12	M13	M14	M15	M16
	lnCEI	lnPTI	lnGTI	lnGTI	lnCEI
lnDIF	−0.2551***	1.4482***	0.5828***	0.1772*	−0.2782***
	(0.0747)	(0.2690)	(0.1150)	(0.0918)	(0.0720)
lnPTI				0.2801***	0.1466***
				(0.0202)	(0.0208)
lnGTI					−0.3247***
					(0.0488)
Constant	14.0331***	18.4628*	−7.2242	−12.3953***	8.9806***
	(2.9303)	(10.5577)	(4.5116)	(3.4344)	(2.7427)
Control Variables	YES	YES	YES	YES	YES
Time Effect	YES	YES	YES	YES	YES
Individual Effect	YES	YES	YES	YES	YES
N	300	300	300	300	300
Within R2	0.7704	0.6349	0.9238	0.9565	0.8124

Note: ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively. Standard error in parentheses.

5. Conclusion and implications

We first use data from 30 provinces in China from 2011 to 2020 and conduct a fixed-effects model to identify the relationship between digital finance and carbon emission reduction. Besides, we examine the chain mediation effect of PTI and GTI and the difference in their effects on CEI by constructing a chain mediation model.

The conclusions are as follows: 1) digital finance can significantly reduce CEI and is an enabler of green development. And the sub-dimension indicators of digital finance can also significantly inhibit CEI. 2) in the baseline path of digital finance affecting CEI, PTI and GTI have a chain intermediary effect. Among them, there is a significant positive relationship between PTI and CEI, while GTI has a significant negative effect on CEI. 3) significant regional heterogeneity exists in the effects of variables on CEI. Digital finance only significantly and negatively affects CEI in the Western region, GTI can significantly suppress CEI in the Eastern and Western regions, and PTI significantly contributes to carbon emission in all regions.

Based on the conclusions, we posit several policy implications. In light of our findings, First, digital finance significantly inhibits CEI. Therefore, it is essential to strengthen the digital development of finance, increase the construction of digital platforms and infrastructures, and expand the scope of digital finance usage. It is worth noting that green building materials need to be paid attention to in constructing digital infrastructure facilities to avoid endangering environmental quality. Equally important is the promotion of integrating and developing digital finance with traditional and green finance to transform financial services towards both green and digital aspects.

Additionally, digital finance can promote technological innovation in production, but technological innovation in production can increase CEI. In addition, digital finance can stimulate green technology innovation and thus reduce CEI. This observation highlights a distinct attribute difference between the effects of PTI and GTI on carbon emission reduction. This conclusion aligns with the perspective put forth by Wang et al. [56] and Feng et al. [57] regarding the promotion of green innovation. Consequently, investment in the development of green technology is necessary to facilitate the attainment of carbon peak targets, irrespective of financial or fiscal support. This paper argues that production-based and green technological innovation should form a dynamic complementarity to achieve more significant economic gains while safeguarding environmental quality from deterioration through specialized tools.

Furthermore, substantial regional heterogeneity exists in the impact of each variable on CEI. Thus, it is crucial to foster multi-regional linkage and synergistic development to accomplish the objective of low-carbon development. The Eastern region, with its good economic development foundation and advantages in green technology innovation, should share its management development experience and green technology achievements with regions with higher CEI. The development of digital finance in the Western region benefits carbon emission reduction. Therefore, government departments can further promote and expand the inclusiveness of digital finance in the Western region.

This paper can be further expanded. For example, the spatial and temporal characteristics of CEI are worth exploring. Moreover, the abatement effect of digital finance can be further studied using micro-data. Besides, we consider that analyzing the coordinated emission reduction effects of digital finance and green finance should be equally valuable for application.

Ethics permission and consent to participate

We verified the fact that this paper is original and not currently pending publication in another journal. This research is exempt from informed consent requirements and ethical clearance.

Consent for publication

Not applicable.

Table 8
Heterogeneity analysis results of different regions.

Variables	M17	M18	M19
	Eastern	Central	Western
	lnCEI	lnCEI	lnCEI
lnDIF	0.3060	−0.2567	−0.2185**
	(0.1842)	(0.1991)	(0.0863)
lnPTI	0.0941**	0.1236***	0.0423*
	(0.0396)	(0.0296)	(0.0247)
lnGTI	−0.3117***	0.0593	−0.1438**
	(0.1154)	(0.0750)	(0.0561)
lnFIN	−0.0547	−0.3667	−0.2626
	(0.2702)	(0.3036)	(0.1914)
lnPOP	−2.1140***	−3.3772***	−1.7649***
	(0.8035)	(0.5316)	(0.5905)
lnCOA	0.2711***	0.6892***	0.7235***
	(0.0382)	(0.0923)	(0.0646)
lnGOV	0.0837	−0.1228	0.4215**
	(0.1757)	(0.2440)	(0.1718)
Constant	16.4679**	22.8181***	10.6417**
	(6.5943)	(4.4294)	(4.3772)
Time Effect	YES	YES	YES
Individual Effect	YES	YES	YES
N	120	80	100
Within R2	0.8150	0.9521	0.9422

Note: ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively. Standard error in parentheses.

Funding

Shanghai University of Finance and Economics Postgraduate Innovation Fund Grant Program under Grant [number CXJJ-2023-414] and Research Center of Sichuan County Economy Development under Grant [number xy2023021].

Data availability statement

All data are fully available without restriction. The dataset are taken from several public repository, Carbon Emission Accounts and Datasets(https://www.ceads.net.cn/), the China Statistics Yearbook (http://www.stats.gov.cn/sj/ndsj/) and the China Statistical Yearbook on Science and Technology (https://cnki.nbsti.net/CSYDMirror/Trade/yearbook/single/N2022010277?z=Z018/).

CRediT authorship contribution statement

Yan Jiang: Writing – original draft, Validation, Project administration, Investigation, Funding acquisition, Formal analysis. **Ruizeng Zhao:** Visualization, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Guozhen Qin:** Writing – original draft, Methodology, Formal analysis, Data curation.

Declaration of competing 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] Q. Wang, S. Hu, R. Li, Could information and communication technology (ICT) reduce carbon emissions? The role of trade openness and financial development, Telecommun. Pol. 48 (2024) 102699, https://doi.org/10.1016/j.telpol.2023.102699.
[2] A. Zhang, R. Deng, Y. Wu, Does the green credit policy reduce the carbon emission intensity of heavily polluting industries? -Evidence from China's industrial sectors, J. Environ. Manag. 311 (2022) 114815, https://doi.org/10.1016/j.jenvman.2022.114815.
[3] J. Wang, K. Dong, X. Dong, F. Taghizadeh-Hesary, Assessing the digital economy and its carbon-mitigation effects: the case of China, Energy Econ. 113 (2022) 106198, https://doi.org/10.1016/j.eneco.2022.106198.
[4] Y. Pan, F. Dong, Design of energy use rights trading policy from the perspective of energy vulnerability, Energy Pol. 160 (2022) 112668, https://doi.org/10.1016/j.enpol.2021.112668.
[5] L. Xu, M. Fan, L. Yang, S. Shao, Heterogeneous green innovations and carbon emission performance: evidence at China's city level, Energy Econ. 99 (2021) 105269, https://doi.org/10.1016/j.eneco.2021.105269.
[6] E. Dogan, F. Seker, The influence of real output, renewable and non-renewable energy, trade and financial development on carbon emissions in the top renewable energy countries, Renew. Sustain. Energy Rev. 60 (2016) 1074–1085, https://doi.org/10.1016/j.rser.2016.02.006.
[7] N. Renzhi, Y.J. Baek, Can financial inclusion be an effective mitigation measure? evidence from panel data analysis of the environmental Kuznets curve, Finance Res. Lett. 37 (2020) 101725, https://doi.org/10.1016/j.frl.2020.101725.

[8] M. Shahbaz, S.J.H. Shahzad, N. Ahmad, S. Alam, Financial development and environmental quality: the way forward, Energy Pol. 98 (2016) 353–364, https://doi.org/10.1016/j.enpol.2016.09.002.
[9] T.-H. Le, H.-C. Le, F. Taghizadeh-Hesary, Does financial inclusion impact CO2 emissions? Evidence from Asia, Finance Res. Lett. 34 (2020) 101451, https://doi.org/10.1016/j.frl.2020.101451.
[10] A. Tamazian, B. Bhaskara Rao, Do economic, financial and institutional developments matter for environmental degradation? Evidence from transitional economies, Energy Econ. 32 (2010) 137–145, https://doi.org/10.1016/j.eneco.2009.04.004.
[11] D. Xu, M. Sheraz, A. Hassan, A. Sinha, S. Ullah, Financial development, renewable energy and CO2 emission in G7 countries: new evidence from non-linear and asymmetric analysis, Energy Econ. 109 (2022) 105994, https://doi.org/10.1016/j.eneco.2022.105994.
[12] B. Zhao, W. Yang, Does financial development influence CO2 emissions? A Chinese province-level study, Energy 200 (2020) 117523, https://doi.org/10.1016/j.energy.2020.117523.
[13] P. Liu, D. Dong, Z. Wang, The impact of air pollution on R&D input and output in China, Sci. Total Environ. 752 (2021) 141313, https://doi.org/10.1016/j.scitotenv.2020.141313.
[14] M. Zhang, Y. Liu, Influence of digital finance and green technology innovation on China's carbon emission efficiency: empirical analysis based on spatial metrology, Sci. Total Environ. 838 (2022) 156463, https://doi.org/10.1016/j.scitotenv.2022.156463.
[15] Q. Wang, Y. Ge, R. Li, Does improving economic efficiency reduce ecological footprint? The role of financial development, renewable energy, and industrialization, Energy Environ. (2023) 0958305X231183914, https://doi.org/10.1177/0958305X231183914.
[16] J. Wu, R. Zhao, J. Sun, What role does digital finance play in low-carbon development? Evidence from five major urban agglomerations in China, J. Environ. Manag. 341 (2023) 118060, https://doi.org/10.1016/j.jenvman.2023.118060.
[17] Y. Hao, C. Wang, G. Yan, M. Irfan, C.-P. Chang, Identifying the nexus among environmental performance, digital finance, and green innovation: new evidence from prefecture-level cities in China, J. Environ. Manag. 335 (2023) 117554, https://doi.org/10.1016/j.jenvman.2023.117554.
[18] B. Lin, R. Ma, How does digital finance influence green technology innovation in China? Evidence from the financing constraints perspective, J. Environ. Manag. 320 (2022) 115833, https://doi.org/10.1016/j.jenvman.2022.115833.
[19] Q. Wang, L. Wang, R. Li, Trade openness helps move towards carbon neutrality—insight from 114 countries, Sustain. Dev. 32 (2024) 1081–1095, https://doi.org/10.1002/sd.2720.
[20] Q. Wang, F. Ren, R. Li, Exploring the impact of geopolitics on the environmental Kuznets curve research, Sustainable Development n/a (n.d.). https://doi.org/10.1002/sd.2743.
[21] R. Li, Q. Wang, L. Li, S. Hu, Do natural resource rent and corruption governance reshape the environmental Kuznets curve for ecological footprint? Evidence from 158 countries, Resour. Pol. 85 (2023) 103890, https://doi.org/10.1016/j.resourpol.2023.103890.
[22] K.J. Arrow, The economic implications of learning by doing, Rev. Econ. Stud. 29 (1962) 155–173, https://doi.org/10.2307/2295952.
[23] R. Zhang, K. Wu, Y. Cao, H. Sun, Digital inclusive finance and consumption-based embodied carbon emissions: a dual perspective of consumption and industry upgrading, J. Environ. Manag. 325 (2023) 116632, https://doi.org/10.1016/j.jenvman.2022.116632.
[24] C.-C. Lee, M. Tang, C.-C. Lee, Reaping digital dividends: digital inclusive finance and high-quality development of enterprises in China, Telecommun. Pol. 47 (2023) 102484, https://doi.org/10.1016/j.telpol.2022.102484.
[25] M. Demertzis, S. Merler, G.B. Wolff, Capital markets union and the fintech opportunity, Journal of Financial Regulation 4 (2018) 157–165, https://doi.org/10.1093/jfr/fjx012.
[26] W.A. Brock, M.S. Taylor, The green Solow model, J. Econ. Growth 15 (2010) 127–153, https://doi.org/10.1007/s10887-010-9051-0.
[27] R.M. Solow, A contribution to the theory of economic growth, Q. J. Econ. 70 (1956) 65–94, https://doi.org/10.2307/1884513.
[28] K.S. Nell, The complementary nature between technological progress and capital accumulation in India's long-run growth transitions, Metroeconomica 66 (2015) 565–605, https://doi.org/10.1111/meca.12082.
[29] H. Wang, W. Wei, Coordinating technological progress and environmental regulation in CO2 mitigation: the optimal levels for OECD countries & emerging economies, Energy Econ. 87 (2020) 104510, https://doi.org/10.1016/j.eneco.2019.104510.
[30] X. Wang, X. Wang, X. Ren, F. Wen, Can digital financial inclusion affect CO2 emissions of China at the prefecture level? Evidence from a spatial econometric approach, Energy Econ. 109 (2022) 105966, https://doi.org/10.1016/j.eneco.2022.105966.
[31] K. Du, Y. Cheng, X. Yao, Environmental regulation, green technology innovation, and industrial structure upgrading: the road to the green transformation of Chinese cities, Energy Econ. 98 (2021) 105247, https://doi.org/10.1016/j.eneco.2021.105247.
[32] S. Feng, Y. Chong, G. Li, S. Zhang, Digital finance and innovation inequality: evidence from green technological innovation in China, Environ. Sci. Pollut. Res. 29 (2022) 87884–87900, https://doi.org/10.1007/s11356-022-21826-2.
[33] X. Li, X. Shao, T. Chang, L.L. Albu, Does digital finance promote the green innovation of China's listed companies? Energy Econ. 114 (2022) 106254 https://doi.org/10.1016/j.eneco.2022.106254.
[34] R. York, E.A. Rosa, T. Dietz, STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts, Ecol. Econ. 46 (2003) 351–365, https://doi.org/10.1016/S0921-8009(03)00188-5.
[35] S. Yu, Q. Zhang, J.L. Hao, W. Ma, Y. Sun, X. Wang, Y. Song, Development of an extended STIRPAT model to assess the driving factors of household carbon dioxide emissions in China, J. Environ. Manag. 325 (2023) 116502, https://doi.org/10.1016/j.jenvman.2022.116502.
[36] F. Xu, Q. Huang, H. Yue, C. He, C. Wang, H. Zhang, Reexamining the relationship between urbanization and pollutant emissions in China based on the STIRPAT model, J. Environ. Manag. 273 (2020) 111134, https://doi.org/10.1016/j.jenvman.2020.111134.
[37] Z. Dong, C. Xia, K. Fang, W. Zhang, Effect of the carbon emissions trading policy on the co-benefits of carbon emissions reduction and air pollution control, Energy Pol. 165 (2022) 112998, https://doi.org/10.1016/j.enpol.2022.112998.
[38] Z. Zhang, G. Hu, X. Mu, L. Kong, From low carbon to carbon neutrality: a bibliometric analysis of the status, evolution and development trend, J. Environ. Manag. 322 (2022) 116087, https://doi.org/10.1016/j.jenvman.2022.116087.
[39] D. Guo, A. Wang, A.T. Zhang, Pollution exposure and willingness to pay for clean air in urban China, J. Environ. Manag. 261 (2020) 110174, https://doi.org/10.1016/j.jenvman.2020.110174.
[40] G. Li, R. Zhang, S. Feng, Y. Wang, Digital finance and sustainable development: evidence from environmental inequality in China, Bus. Strat. Environ. 31 (2022) 3574–3594, https://doi.org/10.1002/bse.3105.
[41] Y. Wu, S. Huang, The effects of digital finance and financial constraint on financial performance: firm-level evidence from China's new energy enterprises, Energy Econ. 112 (2022) 106158, https://doi.org/10.1016/j.eneco.2022.106158.
[42] M. Yu, F.-S. Tsai, H. Jin, H. Zhang, Digital finance and renewable energy consumption: evidence from China, Financial Innovation 8 (2022) 58, https://doi.org/10.1186/s40854-022-00362-5.
[43] J.L. Furman, M.E. Porter, S. Stern, The determinants of national innovative capacity, Res. Pol. 31 (2002) 899–933, https://doi.org/10.1016/S0048-7333(01)00152-4.
[44] F. Shen, B. Liu, F. Luo, C. Wu, H. Chen, W. Wei, The effect of economic growth target constraints on green technology innovation, J. Environ. Manag. 292 (2021) 112765, https://doi.org/10.1016/j.jenvman.2021.112765.
[45] K.S. Im, M.H. Pesaran, Y. Shin, Reflections on "Testing for unit roots in heterogeneous panels,", J. Econom. 234 (2023) 111–114, https://doi.org/10.1016/j.jeconom.2023.01.022.
[46] C.-C. Lee, F. Wang, R. Lou, Digital financial inclusion and carbon neutrality: evidence from non-linear analysis, Resour. Pol. 79 (2022) 102974, https://doi.org/10.1016/j.resourpol.2022.102974.
[47] A.O. Acheampong, M. Amponsah, E. Boateng, Does financial development mitigate carbon emissions? Evidence from heterogeneous financial economies, Energy Econ. 88 (2020) 104768, https://doi.org/10.1016/j.eneco.2020.104768.
[48] N. Nunn, N. Qian, US food aid and civil conflict, Am. Econ. Rev. 104 (2014) 1630–1666, https://doi.org/10.1257/aer.104.6.1630.

[49] G. Li, H. Wu, J. Jiang, Q. Zong, Digital finance and the low-carbon energy transition (LCET) from the perspective of capital-biased technical progress, Energy Econ. 120 (2023) 106623, https://doi.org/10.1016/j.eneco.2023.106623.
[50] D. Jiang, W. Li, Y. Shen, S. Yu, Does air pollution affect earnings management? Evidence from China, Pac. Basin Finance J. 72 (2022) 101737, https://doi.org/10.1016/j.pacfin.2022.101737.
[51] Y. Li, W. Mbanyele, J. Sun, Managerial R&D hands-on experience, state ownership, and corporate innovation, China Econ. Rev. 72 (2022) 101766, https://doi.org/10.1016/j.chieco.2022.101766.
[52] K. Luo, Y. Liu, P.-F. Chen, M. Zeng, Assessing the impact of digital economy on green development efficiency in the Yangtze River Economic Belt, Energy Econ. 112 (2022) 106127, https://doi.org/10.1016/j.eneco.2022.106127.
[53] J.-F. Mercure, F. Knobloch, H. Pollitt, L. Paroussos, S.S. Scrieciu, R. Lewney, Modelling innovation and the macroeconomics of low-carbon transitions: theory, perspectives and practical use, Clim. Pol. 19 (2019) 1019–1037, https://doi.org/10.1080/14693062.2019.1617665.
[54] S. Shan, S.Y. Genç, H.W. Kamran, G. Dinca, Role of green technology innovation and renewable energy in carbon neutrality: a sustainable investigation from Turkey, J. Environ. Manag. 294 (2021) 113004, https://doi.org/10.1016/j.jenvman.2021.113004.
[55] X. Zhou, Welfare analysis of tacit coordination in the U.S. Airline industry, Front. Econ. China 12 (2017) 66–93, https://doi.org/10.3868/s060-006-017-0004-0.
[56] Q. Wang, T. Sun, R. Li, Does artificial intelligence promote green innovation? An assessment based on direct, indirect, spillover, and heterogeneity effects, Energy Environ. (2023) 0958305X231220520, https://doi.org/10.1177/0958305X231220520.
[57] S. Feng, R. Zhang, G. Li, Environmental decentralization, digital finance and green technology innovation, Struct. Change Econ. Dynam. 61 (2022) 70–83, https://doi.org/10.1016/j.strueco.2022.02.008.