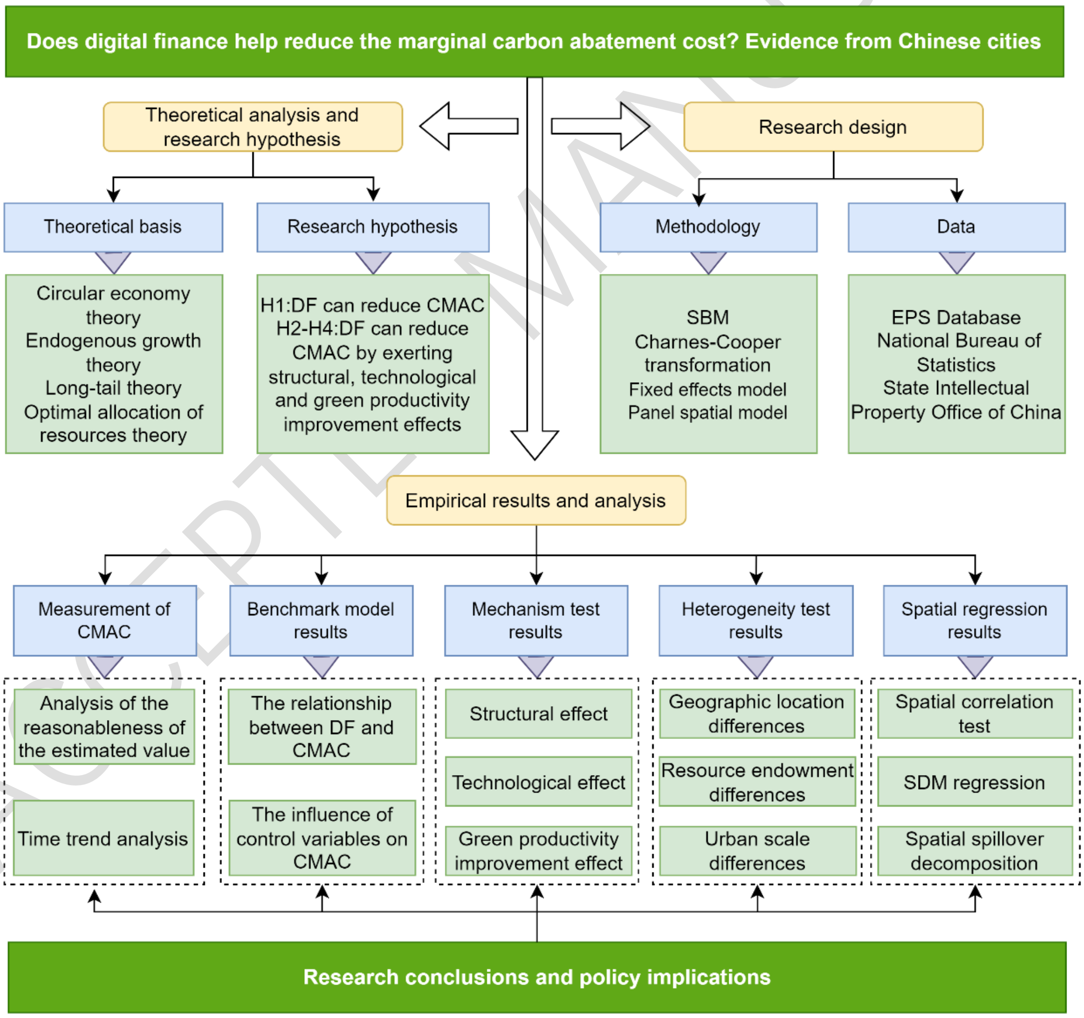
Does digital finance help reduce the marginal carbon abatement cost? Evidence from Chinese cities

Min Liu [a], Jiangfeng Hu [b*]

[a] College of Economics and Management Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China
[b] Chongqing Academy of Social Sciences, Chongqing 400020, China.
[*] Corresponding author: jiangfenghu2018@163.com
E-mail: liuminlmn@163.com

Graphical abstract



Abstract

The carbon abatement effects of digital finance (DF) have been widely studied, but existing studies have neglected its impact on the marginal carbon abatement cost (CMAC). The paper uses the SBM model to measure the CMAC of 264 cities in China for 2011-2021 and then constructs a two-way fixed effects model and a panel spatial model to explore the nexus between DF and CMAC. The findings are as follows. Firstly, the magnitude of change in CMAC shows an N-shaped trend of increasing, decreasing, and rising over the sample period. Secondly, DF can decrease CMAC, which is mainly achieved through three paths: optimizing industrial structure, promoting green technological innovation, and improving green production efficiency. Thirdly, the suppression of CMAC by DF is better when the cities belong to eastern, northeastern, central, non-resource-based, and large cities. Fourthly, DF has negative spatial spillover effects on CMAC, which helps decrease CMAC in local and neighboring cities. These findings can help tap the green value of DF and formulate targeted regional carbon emission reduction policies.

Keywords: digital finance; marginal carbon abatement cost; shadow price; spatial Durbin model

1. Introduction

Realizing carbon emission reduction at minimal economic costs is a key concern of national governments. To shoulder its responsibility as a major country, the Chinese government attaches great importance to carbon emission reduction. It has taken achieving carbon peaking and carbon neutrality as its national strategic goals ("dual carbon goals") and has undertaken many measures to push for greenhouse gas emissions reduction. For instance, it has established carbon emissions trading markets, increased the proportion of renewable energy use, vigorously developed carbon capture and storage technologies, and implemented green financial and carbon tax policies. However, for developing countries, large-scale carbon reduction must inevitably come at the expense of a certain level of economic output, the so-called marginal carbon abatement cost (CMAC). Based on data from the National Bureau of Statistics, China emitted approximately 11.477 billion tons of carbon dioxide (CO_2) in 2022, accounting for approximately 28.87% of the total global CO_2, and it is the world's largest carbon emitter. Carbon emission reduction efforts are under enormous pressure in China. Consequently, how to reduce CMAC and balance between energy saving, emission reduction, and economic growth has been an urgent proposition for Chinese economic development.

Finance plays a vital role in pushing the process of economic greening and decarbonization (Razzaq and Yang, 2023). With the booming development of information technologies (IT), traditional finance and IT continue to converge, enabling digital finance (DF) to be the key driver for enhancing the quality of economic development. DF is a new financial form that applies digital technologies to provide financial services. Compared with traditional finance, DF can overcome time and space restrictions and benefit green economic development with its advantages of low-threshold financing, financial service inclusiveness, service scope accessibility, and mobile payment convenience (Guo et al., 2023; Liu et al., 2023). From the perspective of inclusiveness and technicality, DF can reduce production, transaction, and operational costs involved in economic activities (Sun et al., 2023) by reducing information asymmetry in financial markets and mismatches in capital factor allocation processes (Razzaq and Yang, 2023). From the perspective of green attributes, DF can help mobilize the whole society to engage in energy saving and carbon reduction, such as advocating green production by corporates and assisting consumers to form green consumption concepts. Then, it will help improve green economic benefits (Li et al., 2023; Zhao et al., 2023). However, while DF brings many favorable effects, it also expands the corporate scale and consumption scale, which may have adverse effects on carbon reduction, energy saving, and environmental governance (Cheng et al., 2024). This makes the relationship between DF and low-carbon development effectiveness unclear. The question of how DF affects CMAC remains unanswered in academic studies. Especially in the constraint of the “dual carbon goals”, CMAC is a critical factor in determining the sustainability of large-scale carbon reductions. Exploring the impact of DF on CMAC is highly significant in determining whether China can achieve carbon peaking and neutrality at lower economic costs.

Existing studies related to GF and CMAC are mainly based on the following three points. Firstly, the measurement of CMAC. CMAC is the economic cost of reducing 1 unit of CO_2 (Cui et al., 2022; Wang et al., 2022a). It is difficult to obtain directly in actual production. Shadow price measures the expected output sacrificed or inputs added by decreasing 1 unit of pollutant (Lee, 2005), it can reflect trade-offs between expected and unexpected outputs (Färe et al., 1993). Hence, shadow price is commonly used to measure CMAC. Specifically, CMAC is obtained by constructing the distance function and applying dyadic theory, and its estimation is mainly by parametric and non-parametric methods. The parametric method describes the distance function by presetting specified functional forms, then uses parametric linear programming or stochastic frontier model estimation to obtain the CMAC. The non-parametric method applies the Data Envelopment Analysis (DEA) method for constructing the production frontier on the output distance function. Then, it estimates the CMAC according to the duality theory. DEA was first raised by Charnes et al. (1978), but it failed to consider non-zero slack of inputs or outputs. Tone (2001) introduced the Slack Based Measure (SBM) method to fill this gap. Subsequently, Färe and Grosskopf (2010) further proposed a more universal non-radial and non-oriented directional distance function for measuring efficiency. Notably, the parametric method may not be compatible with the actual situation because it needs to preset the functional form. Thus, the paper will use the non-parametric method to measure CMAC.

Secondly, the impact of DF on carbon emissions. From the aspect of promoting carbon emission reduction, DF can trace the carbon footprint with the help of intelligent optimization systems, green financial tools, etc., thus accelerating the commercialization of low-carbon technologies and promoting consumption changes (Li et al., 2023; Razzaq and Yang, 2023). This helps to optimize supply chain management, improve transport and logistics routes, reduce high-carbon activities, enhance environmental governance capacity (Guo et al., 2023), promote industrial structure upgrading (Zhong et al., 2023), etc., and ultimately help to reduce carbon emissions (Cai et al., 2024a; Zhao et al., 2023). From the aspect of increasing the potential risk of carbon emissions, DF can increase the energy consumption of digital infrastructure, stimulate high carbon demand, and expand the scale of production expansion (Guo and Tu, 2023), thus pushing the overconsumption of high-energy-consuming products (Cheng et al., 2024). Ultimately, this leads to an increase in pollution emissions. In summary, the impact of DF on carbon emissions is characterized by an obvious two-way dynamic game, and its net effect depends on the trade-offs among the choice of technological routes, the design of policy frameworks, the speed of industrial structural transformation, the scale effect, and so on. Therefore, the paper focuses on the impact of DF on CMAC.

Thirdly, the methodology was used to explore the nexus between DF and low-carbon development. Existing literature mainly tested the correlation between DE and carbon emission reduction using econometric methods such as two-way fixed effects model (Li et al., 2023; Wu et al., 2023), difference-in-difference model (Cao et al., 2021; Zhong et al., 2023), quantile regression model (Xu et al., 2023), non-linear threshold model (Bai et al., 2023), and spatial econometric model

(Wang and Guo, 2022; Zhao et al., 2023). Considering that the two-way fixed effects model can control for unobservable individual differences and time trends, reduce omitted variable bias, and facilitate accurately identifying the causal relationship between DF and CMAC, this method is used in the paper for the benchmark regression analysis. Based on the advantages that the spatial econometric model can capture interregional spatial spillover effects (e.g. technology diffusion, pollution transfer, etc.), make up for the inadequacy of the traditional model in ignoring geographic correlation, and facilitate revealing the indirect impact of DF on CMAC in neighboring regions, so the paper adopts this method to further analyze the spatial impact of DF on CMAC.

The contributions are summarized as follows. Firstly, existing studies have mainly concerned the influence of DF on environmental performance (Cao et al., 2021), green economic growth (Razzaq and Yang, 2023), carbon emissions (Zhao et al., 2023), energy transition (Li et al., 2023), industrial green transition (Zhong et al., 2023), green technological innovation (Hao et al., 2023), and other related green development impacts. However, these studies have not yet established a framework for linking DF with green development costs. Therefore, the paper incorporates DF and carbon reduction costs into the same analytical framework for the first time and innovatively examines the relationship between DF and urban CMAC, which can fill the gaps in the existing studies. Secondly, existing studies have mainly discussed the role of policy preferences (Cui et al., 2022), environmental regulation (Xu et al., 2022), regional integration (He et al., 2018), energy efficiency (Wang et al., 2017), energy consumption (Wang et al., 2024), carbon productivity (Wang et al., 2020), and differences in geographic location (He, 2015) on CMAC. However, these studies ignored the impact of financial development on CMAC. Consequently, the paper systematically reveals the mechanism of the role of DF on urban CMAC to improve the theoretical system of the influencing factors of CMAC, which can provide path references for the effective reduction of CMAC. Thirdly, the paper extends the heterogeneity analysis of the impact of DF on CMAC and captures the spatial spillover effects of DF on CMAC, thus providing differentiated guidance for lowering CMAC in cities with different characteristics. Given these, the paper takes 264 Chinese cities as samples from 2011 to 2021. It adopts two-way fixed effects and spatial econometric models for studying the nexus between DF and CMAC, exploring the mechanism through which DF can act on CMAC. Then, the paper examines whether there exists a remarkable asymmetry in the influence of DF on CMAC from three major dimensions: geographic location, resource endowment, and scale of cities.

The remaining sections are arranged as follows. Section 2 introduces the theoretical analysis and research hypotheses. Section 3 shows the research design. Section 4 reports the empirical results and analyses. Section 5 presents the research conclusions and policy implications.

2. Theoretical analysis and research hypothesis

In the digital era, DF has gradually become the core of financial development, which is the major form of providing financial services. It can contribute to overcoming the severe challenges of economic low-carbon transformation, thus providing opportunities for the faster realization of the “dual carbon goals”. On the one hand, DF can optimize all aspects of production, distribution, living, consumption, and investment, which is beneficial for increasing the matching degree of demand and supply for financial services and reducing resource mismatch problems. This can create good conditions for enhancing the quality of urban innovation, help optimize resource allocation and use efficiency, and thus improve environmental performance (Cao et al., 2021), which in turn helps reduce CMAC. On the other hand, DF supports the digital reform of corporates (Razzaq and Yang, 2023), which facilitates the smashing of boundaries between industries and sectors and promotes the achievement of integrated and coordinated development between industries. This can encourage corporates in cities to disclose environmental information and technological progress actively (Liu et al., 2024), thus promoting the transformation of urban industries into knowledge-intensive and technology-intensive types, which consequently help to reduce CMAC. In summary, DF can create a favorable financial environment and promote economic growth. Specifically, DF can affect CMAC through the following three channels.

Firstly, based on the circular economy theory, resources can be recycled, which helps to reduce pollution emissions (Huang et al., 2018). DF can promote industrial upgrading on the supply side and cultivate a low-carbon market on the demand side by reorganizing the direction of economic factor flows, thus forming a systematic carbon reduction pathway. Specifically, DF can use digital technologies to alleviate the problem of information asymmetry within and between industries, improve the ratio of the internal structure of primary, secondary, and tertiary sectors, enhance the quality of inter-industry aggregation, and contribute to the optimization of the industrial structure (Ren et al., 2023). This will improve the production efficiency of the whole society and lower the pollution control cost per unit of output. Meanwhile, DF can leverage big data and intelligent algorithms to allocate resources optimally (Zhao et al., 2023) and precisely match the financing needs of green projects. Thus, limited financial resources can be invested more in industries with high output benefits through tools such as data-based risk assessment models, intelligent matching platforms for climate investment and financing, and full carbon emission traceability systems. This can bring advantages such as lowering the transaction costs of information matching (Wang and Ma, 2024), reducing the proportion of high energy-consuming industries, and improving energy utilization (Li et al., 2023), thus making carbon reduction less difficult. Furthermore, DF can scientifically assess industries' risks (Zeng et al., 2025), innovate risk management tools, and enable environmental constraints to be imposed on upstream and downstream corporates through supply chain finance, thereby promoting the high-end, intelligent, and greening of industries. This can promote the dynamic adjustment of industrial structure (Zhang et al., 2025), enhance the resilience of the industrial chain, and help form the synergistic effect of emission reduction of the whole industrial chain, etc., which can help reduce the pollution emission per unit of output and decrease CMAC.

Secondly, based on endogenous growth theory, technological progress can drive economic growth. Regarding technological progress, DF can effectively lower the financing threshold of the urban research and development (R&D) sector, which can help it overcome the financing difficulties previously constrained by the long R&D cycle and high investment risks (Cao et al., 2021). It will support the continuous R&D of technologies and promote the large-scale application of photovoltaic and energy storage technologies, thereby reducing the cost of technological innovation and enhancing urban innovation capacity. This will lower the difficulty of mitigating carbon emissions (Zou et al., 2024) and help to create diminishing marginal cost effects. Meanwhile, DF can increase the active degree of the carbon trading market, expand the financing channels of corporates, reduce the distortion of capital allocation (Wang and Guo, 2022), and help guide the flow of capital to low-carbon and environment-friendly corporates. Thus, it provides sustainable emission reduction power for corporates. This will stimulate the willingness of corporates to innovate and promote various types of corporates to increase capital investment in green technological innovation activities (Wen et al., 2025), which will improve environmental performance, increase the efficiency of emission reduction investment, and promote the urban energy and low-carbon transition (Li et al., 2023). Moreover, DF can assist carbon accounting through digital payments, smart contracts, AI algorithms, etc., thereby improving the financial position of urban corporates by reducing labor inputs, lowering overheads, and increasing sales revenues. This can support corporates in adopting low-carbon technologies to increase green innovation outputs and encourage them to invest in energy-saving equipment, thereby spreading business risks and compressing intermediate costs, generating long-term cost savings (Lu et al., 2023).

Thirdly, based on the long-tail theory, the long-tail group is featured as small, numerous, and dispersed, with unique and more challenging needs to satisfy. DF can use digital platforms to expand the scope of its customer base, transform the original long-tail group into potential subjects, and absorb small amounts of funds from long-tail investors. Then, these funds are aggregated into a vast capital flow and applied to corporate development (Wang and Guo, 2022). This will generate more economic benefits while driving the expansion of the corporate production scale, thus making more funds available for investment in green production. Ultimately, this can help reduce the scale of resource consumption, balance the relationship between ecological environment and economic development (Wang et al., 2025), etc., which in turn reduces the CMAC. Meanwhile, DF can reduce consumers' purchasing costs and payment difficulties, which contributes to improving the experience of consumer services. This can accelerate residents' consumption decisions and tap their consumption potential, thus triggering an increase in the scale of consumption (Cheng et al., 2024). In recent years, increased consumer awareness of environmental protection has increased demand for green and low-carbon products, increasing green production scale. This can trigger urban corporates' green and low-carbon initiatives, further reducing CMAC. Besides, based on the optimal allocation of resources theory, DF can use digital technologies to accurately identify green and low-carbon projects and play the guiding, incentive, and supervisory roles of green credits to invest financial resources in green projects with potential. This can expand the scope of economic activities, reduce the waste of resources, and improve the efficiency of resource utilization, thus contributing to the expansion of the economic scale (Guo and Tu, 2023) and the improvement of high-quality economic development (Wu et al., 2024). It then benefits to reduce CMAC.

Accordingly, the following hypotheses are formulated in the paper.

H1: DF can reduce CMAC in Chinese cities.

H2: DF can reduce CMAC in Chinese cities by exerting a structural effect.

H3: DF can reduce CMAC in Chinese cities by exerting a technological effect.

H4: DF can reduce CMAC in Chinese cities by exerting a green productivity improvement effect.

3. Research design

3.1 Measurement of CMAC

The paper estimates the CMAC using the non-radial and non-oriented SBM model. There are three main steps.

Firstly, let x, y, and b respectively denote factor inputs, expected outputs, and unexpected outputs. Nonparametric linear programming for the sample containing K decision-making units (DMU_o) is designed in equation (1).

$$(\theta^*) = min\frac{1-\frac{1}{M}\sum_{m=1}^{M}\frac{s_{mo}^{x}}{x_{mo}}}{1+\frac{1}{Z+J}(\sum_{z=1}^{Z}\frac{s_{zo}^{y}}{y_{zo}}+\sum_{j=1}^{J}\frac{s_{jo}^{b}}{b_{jo}})} \quad (1)$$

$$s.t.\begin{cases} x_{mo} \geq \sum_{k=1}^{K} \lambda_k x_{mk} + s_{mo}^{x} \\ y_{zo} \leq \sum_{k=1}^{K} \lambda_k y_{zk} - s_{zo}^{y} \\ b_{jo} = \sum_{k=1}^{K} \lambda_k y_{jk} + s_{jo}^{b} \\ s_{mo}^{x} \geq 0, s_{zo}^{x} \geq 0, s_{jo}^{x} \geq 0, \lambda_k \geq 0 \end{cases}$$

M, Z, and J respectively denote the numbers of x, y, and b. θ^* ($0 < \theta^* \leq 1$) represents the efficiency value of DMU_o. s_{mo}^{x}, s_{jo}^{b} respectively represent potential reductions in input and unexpected output. s_{zo}^{y} means potential increase in expected output. λ_k denotes intensity variable, $\lambda_k \geq 0$ represents a constant return to scale production technologies.

Secondly, the paper applies the Charnes-Cooper transformation (Wang and Feng, 2015; Wei et al., 2012) on equation (1) to obtain equation (2).

$$\max u^{y} y_o - u^{x} x_o - u^{b} b_0 \tag{2}$$

$$s.t.\begin{cases} \sum_{z=1}^{Z} u_z^{y} y_{zo} - \sum_{m=1}^{M} u_m^{x} x_{mo} - \sum_{j=1}^{J} u_j^{b} b_{jo} \leq 0 \\ u^{x} \geq \frac{1}{M}(1/x_o) \\ u^{y} \geq \frac{1 - u^{x} x_o - u^{b} b_o + u^{y} y_o}{Z+J}(1/y_o) \\ u^{b} \geq \frac{1 - u^{x} x_o - u^{b} b_o + u^{y} y_o}{Z+J}(1/b_o) \end{cases}$$

Where u_m^{x}, u_z^{y} and u_j^{b} respectively denote virtual prices of x, y, and b.

Finally, the paper assumes that the shadow price of expected output is equal to its market price (Cheng et al., 2022). Letting p^{y}, p^{b} respectively be the shadow prices of Gross Domestic Product (GDP) and CO_2. p^{b} is shown in equation (3).

$$p^{b} = p^{y} \times \frac{u^{b}}{u^{y}} \tag{3}$$

3.2 Model construction

The paper constructs equation (4) using a two-way fixed effects model to investigate the nexus between DF and CMAC.

$$LCMAC_{it} = \mu_1 + \alpha_1 L.LDF_{it} + \varphi_1 Control_{it} + \sigma_i + \sigma_t + \varepsilon_{it} \tag{4}$$

Where $LCMAC_{it}$ denotes CMAC. $L.LDF_{it}$ indicates DF. $Control_{it}$ represents control variables. μ_1 denotes the constant term, σ_i indicates city fixed effect, σ_t represents year fixed effect, and ε_{it} is the random error term. Besides, i and t respectively stand for city and year.

To explore the transmission mechanism of DF affecting CMAC. The paper combines the previous analyses, focuses on the mechanism test that DF can exert structural, technological, and green productivity improvement effects, and constructs equations (5)-(6).

$$LSTRU_{it}(LTECH_{it}, LGPE_{it}) = \mu_2 + \alpha_2 L.LDF_{it} + \varphi_2 Control_{it} + \sigma_i + \sigma_t + \varepsilon_{it} \tag{5}$$

$$LCMAC_{it} = \mu_3 + \alpha_3 LSTRU_{it}(LTECH_{it}, LGPE_{it}) + \varphi_3 Control_{fit} + \delta_i + \delta_t + \varepsilon_{it} \tag{6}$$

Among them, $LSTRU_{it}$ represents industrial structure upgrading. $LTECH_{it}$ indicates green technology innovation. $LGPE_{it}$ means green production efficiency.

3.3 Variables selection

(1) Explained variable. $LCMAC$: the paper first selects input and output indicators (see Table 1

for specific measurements), then estimates CMAC using the SBM model, and finally takes the logarithm of the estimated value to obtain *LCMAC*.

(2) Explanatory variable. *LDF*: the paper refers to the practice of most studies and selects the "Peking University Digital Finance Index" compiled by Guo et al. (2020) as the value of DF, then takes the logarithm of it to get the *LDF*. Considering that the impact of DF on CMAC is usually lagged, the paper uses one-period-lagged *LDF* (*L.LDF*) to represent the explanatory variable in the following regression analyses.

(3) Mechanism variables. Industrial structure upgrading *(LSTRU*): the paper adopts the entropy method to process the indicator data containing industrial structure rationalization (*INDR*) and industrial structure heightening (*INDH*) and then takes the logarithm to get *LSTRU*. Green technological innovation (*LTECH*): the paper selects the number of green patent applications (*LTECH1*) and the number of green patent authorizations (*LTECH2*) to represent it. Green production efficiency (*LGPE*): the paper uses the logarithm of green total factor productivity (GTFP) to measure it.

(4) Control variables. Setting control variables is also essential to more thoroughly analyze the nexus between DF and CMAC. They specifically include fiscal decentralization (*FI*), foreign investment (*FDI*), urbanization (*UR*), trade openness (*TR*), human capital (*HR*), and financial development (*FD*).

Table 1

Variable definitions

Variables	Name	Description
Explained variable	*LCMAC*	Labor x: Annual total number of employees (unit: 10000 people) Energy x: Annual electricity consumption (unit: 10000 kWh) Capital x: Fixed asset capital stock (unit: 10000 yuan), it is calculated by perpetual inventory method y: Regional GDP (unit: 10000 yuan). b: Carbon emissions (unit: 10000 tons) are calculated based on the consumption of electricity, natural gas, liquefied petroleum gas, and thermal energy
Explanatory variable	*LDF*	The logarithm of the Peking University Digital Finance Index
Mechanism variables	*LSTRU*	After processing the index data of *INDR* and *INDH* using the entropy method, the logarithm is taken to obtain *LSTRU*. Among them, $INDR = 1-\frac{1}{3}\sum_{n=1}^{3}\left\|S_n^y - S_n^l\right\|$. $INDH = \sum_{n=1}^{3} S_n^y \times n$. S_n^y=Y_n/Y, denoting the share of value added of the nth industry in GDP. S_n^l=S_n/S, indicating the share of actual employment in the nth industry to total employment.
	LTECH1	The logarithm of the total number of green patent applications
	LTECH2	The logarithm of the total number of green patent authorizations
	LGPE	The logarithm of GTFP (the Super-SBM model is used to measure GTFP. Notably, the input and output variables are measured using the same indicators as those used to calculate CMAC, except for non-expected outputs, which are measured using industrial sulfur dioxide, wastewater, and soot emissions)

	FI	Fiscal budget revenues/fiscal budget expenditures
	FDI	Amount of foreign capital used/regional GDP
Control variables	*UR*	The logarithm of population density
	TR	Total trade exports and imports/regional GDP
	HR	Number of employees/total population
	FD	Balance of deposits and loans of financial institutions/regional GDP

3.4 Data sources

The paper selects Chinese cities as the sample. The research period is 2011-2021. The data on carbon emission and control variables are mainly from the EPS database and the National Bureau of Statistics. The data of mechanism variables are mainly from the EPS database and the State Intellectual Property Office of China. For severely missing data, the paper deletes them. For the small part of missing data, the paper applies the interpolation method to supplement them. For all continuous variables, the paper takes the logarithm of them. Finally, the relevant data for 264 cities in China are obtained, totaling 2,904 observations. Moreover, the paper winsorizes all continuous variables at the 1% and 99% quantiles to prevent outliers from interfering with the empirical results.

Table 2

Descriptive statistics

Variable	N	mean	sd	max	min
LCMAC	2,904	9.257	0.805	13.790	5.431
LDF	2,904	5.109	0.507	5.728	3.567
LSTRU	2,904	-0.732	0.447	0	-9.210
LTECH1	2,904	5.069	1.618	9.289	1.609
LTECH2	2,904	4.590	1.612	8.654	1.099
LGPE	2,904	-1.448	0.552	0.041	-2.551
FI	2,904	0.556	0.230	1.218	0.114
FDI	2,904	0.006	0.007	0.038	0.000
UR	2,904	6.336	1.117	8.242	2.573
TR	2,904	0.378	0.572	3.469	0.000
HR	2,904	0.199	0.108	0.611	0.041
FD	2,904	1.418	0.711	3.768	0.356

4. Empirical results and analysis

4.1 Measurement results of CMAC

Fig.1 shows the measurement results of the average annual CMAC of Chinese cities. It is shown that the average yearly CMAC increases from 12838.95 in 2011 to 15057.92 in 2021, with a minimum value of 12838.95 and a maximum value of 18677.57. Previously, many studies estimated China's CMAC, but the values varied due to the measurement methodology, study level selection, and study year interval. For instance, Wang et al. (2020) measured the CMAC for 30 provinces in China from 2011 to 2020 and found that the CMAC ranged within the interval [15, 20274]. Ji and Zhou (2020) evaluated the CMAC for 105 cities in China during 2006-2014. They found the CMAC ranged within the interval [1.2, 70359.46]. Wang et al. (2022b) calculated the CMAC for industries in China from 2005 to 2016 and discovered that CMAC ranged within the interval of [6300, 54040]. Xu et al. (2022) estimated the CMAC of 282 cities in China from 2003 to 2018 and revealed that the CMAC ranged within the interval of [6860, 7790]. Overall, the CMAC calculated in the paper is within the range of existing studies. It indicates that the CMAC computed in the paper is reasonable.

Additionally, as for the magnitude of change in CMAC, CMAC generally shows an upward trend, explicitly showing an N-shaped trend of first increasing, then decreasing, and finally increasing. At the beginning stage of carbon reduction, the resource input of carbon reduction tends to be larger than its green output benefits. Thus, CMAC is increasing. As green and low-carbon technologies mature, the resulting green innovation spillover effect is noticeable, and the carbon production efficiency is high, so the CMAC is getting smaller. Notably, CMAC is the lowest and declines the fastest in 2017, which corresponds with the research of Wang et al. (2022a). The reason is that in 2017, the Chinese government released policies such as the Strategy for Energy Production and Consumption Revolution (2016-2030) and the National Carbon Emission Trading Market Construction Scheme (Power Generation Sector). These policies can stimulate economic activities to be more inclined to low-carbon emission reduction by price signaling, which contributes to reducing energy use and pollutant output. It leads to the substitution costs of low-carbon technologies for high-carbon technologies being lower than the emissions costs, effectively decreasing the CMAC. Nevertheless, as the work on carbon reduction progresses, it gets harder to mitigate carbon, and the costs of inputs are higher, so CMAC is increasing again.

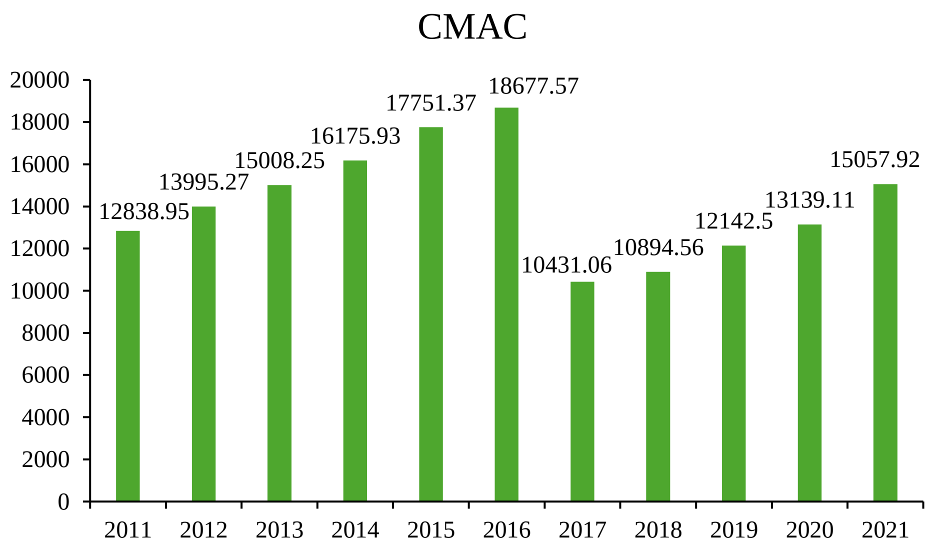


Fig. 1. Average annual CMAC measurement results for Chinese cities from 2011 to 2021 (unit: yuan/ton)

4.2 Benchmark model results

Table 3 shows the benchmark regression results. In column (1), only city-fixed and year-fixed effects are controlled. It is found that DF significantly reduces CMAC. In column (2), the above finding remains the same after including the relevant control variables. This may be because DF can reduce the difficulty of carbon reduction in many ways. For instance, promoting the optimization of economic structure, improving the efficiency of financial services, promoting technological innovation, inducing the rationalization of market competition, and supporting the implementation of green policies. Thus, it is favorable to reduce CMAC in Chinese cities.

Next, the paper analyzes the influence of control variables on CMAC. *FI* and *FDI* significantly increase the CMAC. *UR*, *TR*, *HR*, and *FD* significantly decrease the CMAC. The reasons for the results are as follows. For one thing, fiscal decentralization and foreign investment are both oriented to economic growth and tend to improve economic efficiency by sacrificing the environment, which is unfavorable for improving carbon emission efficiency. Thus, CMAC will increase. For another, increased levels of urbanization, trade openness, human capital, and financial development are beneficial for optimizing production methods, resource allocation efficiency, and industrial structure. They can hasten the development of low-carbon technologies. Their contributing rate to urban economic growth is larger than the increased rate in energy consumption, which can improve the efficiency of carbon emissions so that CMAC will decrease.

Table 3

Benchmark regression results

Variables	(1)	(2)
	LCMAC	*LCMAC*
L.LDF	-0.8432***	-0.7421***
	(0.1462)	(0.1399)
FI		0.1868*
		(0.0968)
FDI		8.8603***
		(3.1806)
UR		-0.0687***
		(0.0112)
TR		-0.1347***
		(0.0362)
HR		-0.5466***
		(0.1862)
FD		-0.3029***
		(0.0457)
_cons	13.5234***	13.8847***
	(0.7404)	(0.7111)
City	Yes	Yes
Year	Yes	Yes
N	2640	2640
R^2	0.7723	0.7891

Note: *, **, *** mean significant at 10%, 5%, and 1%, respectively. Values in parentheses are heteroskedasticity-robust standard errors. The same as below.

4.3 Robustness test

Firstly, the time width test. The sample time factor may affect the accuracy of the benchmark regression results. Therefore, the first and last year's sample data are excluded from the paper. Secondly, replacing the explanatory variable. The measures to reduce carbon emissions (e.g., technological inputs, policy implementation, etc.) usually take time to show their effects. As a result, the paper adopts the one-period-lagged *LCMAC* (*L.LCMAC*) to replace the explanatory variables that can be more consistent with the dynamic adjustment process of the actual economic activities. Thirdly, adding control variables. Omitted variables can cause large errors in the statistical results. Given that carbon intensity (*CI*), consumption scale (*CS*), and economic scale (*ES*) may affect the difficulty of carbon emission abatement by changing the demand side (consumption pattern) and the supply side (economic aggregate). Consequently, the paper adds three more control variables (*CI*, *CS*, and *ES*) to the existing control variables and then re-runs the regression. The three variables are measured as follows. *CI*: the logarithm of the ratio of carbon emissions to GDP. *CS*: the logarithm of total social retail consumption per capita. *ES*: the logarithm of per capita regional GDP. Fourthly, the endogeneity test. When using a two-way fixed effects model for benchmark regression, problems such as omitted variable bias and bi-directional causality of variables may result in falsely significant empirical results. Accordingly, to verify the sensitivity of the empirical results to the methodological assumptions, the paper uses the instrumental variable method to test the possible endogeneity problem with the help of two-stage least squares (2SLS). Based on the two principles of relevance and exclusivity that need to be satisfied in the selection of instrumental variables, the paper uses the interaction term between the spherical distance of prefecture-level cities to Hangzhou and the mean *L.LDF* of other Chinese cities as an instrumental variable for *L.LDF*. Since there is multicollinearity between the spherical distance from prefecture-level cities to Hangzhou and the regional dummy variable, the paper does not control for the city-fixed effect here. Unidentifiable tests and weak instrumental variable tests are also conducted. In Table 4, the coefficients of *L.LDF* are significantly negative. It suggests that DF indeed reduces CMAC in Chinese cities.

Table 4

Various robustness tests

Variables	(1) *LCMAC*	(2) *L.LCMAC*	(3) *LCMAC*	(4) *LCMAC*
L.LDF	-1.4081***	-0.4093***	-0.8267***	-0.4868***
	(0.2153)	(0.1446)	(0.1287)	(0.0500)
CI			-0.5656***	
			(0.0450)	
CS			0.0205	
			(0.0553)	
ES			0.1973***	
			(0.0493)	
Control	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	No
Year	Yes	Yes	Yes	Yes
Kleibergen-Paap rk LM statistic				459.547***
Cragg-Donald Wald F statistic				1506.195
Kleibergen-Paap rk Wald F statistic				970.334
N	2112	2640	2640	2640
R^2	0.8153	0.7620	0.8207	0.1129

4.4 Mechanism test

(1) Structural effect

From Table 5, the coefficients of *L.LDF* and *LSTRU* are significantly positive, suggesting that the promotion of upgrading industrial structure is a channel through which DF reduces CMAC. It is because, firstly, DF helps raise financial resource allocation efficiency, effectively reduces information asymmetry (Hao et al., 2023), and guides capital flow to high-tech and green industries. This will accelerate the industrial restructuring of cities and prompt corporates to increase the green energy usage ratio and decrease carbon emissions, thus reducing the difficulties and costs of carbon emission reduction. Secondly, DF lowers financial service thresholds, expands financing channels for corporates, meets the diversified financing needs of corporates, and contributes to easing the difficulties in financing faced by corporates (Wang and Guo, 2022). This will provide powerful guarantees for optimizing industrial structure, effectively reducing the waste of resources and energy, and help corporates decrease their operating costs and environmental governance costs, thus lowering the CMAC of cities. Thirdly, DF improves the financial structure and provides better financial support for the innovation activities of urban corporates, therefore enhancing the allocation of production factors and driving the low-carbon development of corporates (Wu et al., 2023). This will facilitate the development of the industrial structure of cities towards advanced and rationalized orientation and encourage corporates to enhance their innovation abilities. This will make the positive effects of increasing carbon productivity greater than the negative effects of carbon emissions, ultimately reducing the CMAC. Accordingly, hypothesis H2 is proved.

Table 5

Mechanism test: structural effect

Variables	(1) *LSTRU*	(2) *LCMAC*
L.LDF	0.7540***	
	(0.0957)	
LSTRU		-0.0564**
		(0.0259)
Control	Yes	Yes
City	Yes	Yes
Year	Yes	Yes
N	2640	2904
R^2	0.6839	0.7676

(2) Technological effect

From Table 6, the regression coefficients of *L.LDF*, *LTECH1*, and *LTECH2* are significantly positive, suggesting that DF's green technology innovation effect is a channel to lower CMAC. This is because, firstly, DF has the attributes of digital technologies, innovation, and greenness, which can provide R&D financial support for the innovation system of cities. It benefits urban innovators' green technological innovation activities (Wu et al., 2023), thereby facilitating the advancement of green technologies and decreasing carbon emissions. Secondly, DF can increase the penetration of digital technologies, which can help expand the supply of green financial products and reduce the affordable innovation costs for urban corporates. It can facilitate the development of carbon trading markets and improve the efficiency of carbon trading, thereby reducing CMAC. Thirdly, DF can improve the efficiency of green finance services. It will have a squeezing effect on industries with high pollution emissions. This will force highly polluting corporates of cities to carry out green reforms, thus prompting corporates to be more concerned about green technological innovations and saving energy consumption. Ultimately, it can help improve the green economic efficiency of cities and reduce CMAC. Accordingly, hypothesis H3 is demonstrated.

Table 6

Mechanism test: technological effect

Variables	(1) *LTECH1*	(2) *LCMAC*	(3) *LTECH2*	(4) *LCMAC*
L.LDF	0.4049***		0.6176***	
	(0.1176)		(0.1179)	
LTECH1		-0.0921***		
		(0.0260)		
LTECH2				-0.1268***

				(0.0252)
Control	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	2640	2904	2640	2904
R^2	0.9611	0.7686	0.9622	0.7699

(3) Green productivity improvement effect

From Table 7, the coefficient of *L.LDF* is significantly positive, implying that DF can improve green productivity. The coefficient of *LGPE* is significantly negative, meaning that enhancing green production efficiency facilitates the reduction of CMAC. This is because, firstly, DF can integrate digital technologies into the financial services system, improving the coverage and efficiency of financial services and promoting an increase in consumption scale (Cheng et al., 2024). It will facilitate the efficient flow of capital and the rational allocation of factors. Consequently, it will break down industrial development boundaries and shift the focus of economic development to technology-intensive industries to improve the efficiency of green development (Liu et al., 2023) and thus reduce CMAC. Secondly, DF can satisfy the consumption needs of long-tail groups, such as low-income groups and rural residents, increasing consumer spending and triggering economic expansion (Guo and Tu, 2023). It will push the production sectors in cities to improve productivity through digital mindset shifts, digital ecology optimization, and enhanced digital facilities. As a result, cities can invest in carbon reduction more efficiently and sustainably, resulting in lowering CMAC. Thirdly, DF can improve environmental performance by supporting greener consumption patterns. As a result, the carbon reduction effect caused by the scale expansion triggered by DF is greater than the carbon increase effect, ultimately leading to a decrease in CMAC. Accordingly, hypothesis H4 is confirmed.

Table 7

Mechanism test: green productivity improvement effect

Variables	(1) *LPEG*	(2) *LCMAC*
L.LDF	0.1526***	
	(0.0180)	
LGPE		-0.2851***
		(0.0390)
Control	Yes	Yes
City	Yes	Yes
Year	Yes	Yes
N	2640	2904
R^2	0.8116	0.7331

4.5 Heterogeneity test

(1) Geographic location differences

Different regions of China have considerable distinctions in energy structure, industrial layout, trade development, and pollution emissions. It may cause the development environment, corporate entrepreneurship and innovation atmosphere, and ecological environment protection atmosphere in DF to differ (Cai et al., 2025; Cao et al., 2021; Guo et al., 2023). Consequently, the carbon emission reduction potentials of different regions may be heterogeneous (Wang et al., 2017). Accordingly, to examine whether the influence of DF on CMAC differs according to geographic location, the paper divides the regions into eastern, central, northeastern, and western cities.

In Table 8, DF has the most excellent inhibiting effect on CMAC in cities in central China, followed by the northeast, the east is the smallest, and the west is not significantly affected. It may be attributed to cities in the central and northeastern regions having factor cost advantages and a strong demand for financial services. They can fully utilize the characteristics and benefits of DF to empower innovative R&D and resource allocation and have great green development space, which can assist in effectively reducing CMAC. Secondly, eastern cities have the advantages of mature digital technologies, numerous financial institutions, well-developed financial services, and substantial economic vitality (Guo and Tu, 2023). Their industrial structure is superior, the atmosphere of innovation and entrepreneurship is intense, and energy production efficiency is high. In this case, the financial services provided by DF are more of a supplement to the original financial mode. Although it is also helpful for lowering CMAC, the effect is relatively weak. Thirdly, western cities have low levels of digital technologies and financial development (Zhao et al., 2023), and the construction of new infrastructures is in its infancy. Coupled with their disadvantages in human capital, R&D strength, market demand, trade openness, and so on, it is hard to exert DF's energy-saving and emission-reduction efficacy (Hao et al., 2023). Ultimately, it causes the influence of DF to decrease CMAC, which is not apparent.

Table 8

Regional heterogeneity test

Variables	(1) East *LCMAC*	(2) Northeast *LCMAC*	(3) Centre *LCMAC*	(4) West *LCMAC*
L.LDF	-0.6596***	-1.0449**	-1.1581***	-0.4623
	(0.2243)	(0.5058)	(0.2422)	(0.3555)
Control	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	990	270	760	620
R^2	0.7381	0.8304	0.8228	0.7674

(2) Resource endowment differences

Natural resources are the vital material basis of economic development. As an advanced form of finance that overlaps and integrates financial and technological innovations, DF will inevitably affect natural resource use. Notably, resource endowment affects resource consumption during changes in production, consumption, employment (Cai et al., 2024b), and industries, which can exacerbate carbon emissions. The heterogeneity of natural resource endowment and distinctions in carbon productivity across Chinese cities can affect the nexus between DF and CMAC. Thus, the paper tests whether the impact of DF on CMAC varies due to differences in urban resource endowment. According to the "National Sustainable Development Plan for Resource-Based Cities (2013-2020)"[1], the sample cities in the paper are categorized into resource-based cities and non-resource-based cities.

In Table 9, DF has a greater impact on CMAC in non-resource-based cities and no impact on CMAC in resource-based cities. It might be because, for one thing, resource-based cities usually rely on natural-resource-driven industries highly for their development, with lower levels of science and technology innovation development and higher carbon emission intensities (Xu et al., 2022). When this type of cities tries to utilize DF to realize low-carbon development, they can hardly take

[1] https://www.gov.cn/zhengce/content/2013-12/02/content_4549.htm

advantage of DF owing to its low level of technology, and they will continue to choose to sacrifice resources and the environment to promote economic development. Hence, DF has no apparent influence on the CMAC of this type of cities. For another, non-resource-based cities usually rely on facilitating technological progress, improving industrial structure, and enhancing energy use efficiency to foster economic growth. This type of cities can fully utilize DF's power to save energy and reduce emissions at lower costs and more efficiently. Accordingly, DF is good for lowering the CMAC of this type of cities.

Table 9

Resource endowment heterogeneity test

Variables	(1) Resource-based *LCMAC*	(2) Non- Resource-based *LCMAC*
L.LDF	-0.0438	-1.0251***
	(0.2511)	(0.1738)
Control	Yes	Yes
City	Yes	Yes
Year	Yes	Yes
N	1070	1570
R^2	0.7794	0.7713

(3) Urban scale differences

DF is closely related to the scale of the population using IT and can adjust the economic scale by affecting the stability of financial markets, the consumer behaviors of the population, and so on. It thus influences carbon emission intensity (Cheng et al., 2024) and subsequently affects the CMAC. Notably, China has so many cities that different scales of cities will vary in policies, scale of financial services, resource allocation, level of innovation, and infrastructure development, which will affect the nexus between DF and CMAC. Therefore, the paper explores whether the nexus between DF and CMAC varies because of the different urban scales. The paper classifies the sample cities into large cities and small-medium cities. Among them, cities with populations over 1 million are classified as large cities and conversely as small-medium cities.

In Table 10, compared to small-medium cities, DF has a greater impact on CMAC in large cities. It might be because, for one thing, the higher quality of economic development in large cities helps DF play active functions in expanding the scope of financial services, accurately controlling financial risks, enhancing the innovation output, and assisting the green transformation of industries. This can effectively reduce carbon emissions in large cities (Guo and Tu, 2023), and this can also help to reduce CMAC by further improving carbon productivity and reducing marginal energy consumption. For another, small-medium cities have a poor economic base, a singular industrial structure (Xu et al., 2022), and relatively backward IT infrastructure, and the extension of DF services is more difficult (Guo and Tu, 2023). This lowers the impact of DF on carbon reduction in small-medium cities, leading to its relatively weak effect on lowering CMAC.

Table 10

Urban scale heterogeneity test

Variables	(1) Big *LCMAC*	(2) Small-medium *LCMAC*
L.LDF	-0.5515**	-0.5405***

	(0.2264)	(0.1760)
Control	Yes	Yes
City	Yes	Yes
Year	Yes	Yes
N	1160	1480
R^2	0.7821	0.7476

4.6 Further analysis

According to the theory of cities' spatial structure, there is the risk of carbon emissions spreading to neighboring areas, which may affect the effectiveness of environmental governance in neighboring areas (Wang and Guo, 2022). DF can weaken the limitation of geographical location and strengthen the spatial linkage between the regional economy and environmental pollution. It will enable resource factors to achieve better cross-regional flows and cause the externalities of economic activities to affect the carbon reduction behaviors of local and neighboring cities. This can result in spatial spillovers from DF on economic development quality and energy use efficiency in cities (Zhao et al., 2023). Ultimately, the opportunity costs of carbon reduction in the local and neighboring cities are affected. Additionally, relevant studies have found that digital technologies have remarkable spatial spillover impacts on abating carbon emissions (Liu et al., 2022; Yang et al., 2024). It will also make the influence of DF on CMAC may have spatial spillover effects. Based on this, further systematic exploration of the impact of DF on CMAC from a spatial perspective is necessary. The paper develops a Spatial Durbin Model (SDM) to achieve this.

$$LCMAC_{it} = \mu_4 + \beta \sum_{j=1}^{264} W_{ij}\, LCMAC_{jt} + \alpha_4 L.LDF_{it} + \varphi_4 Control_{it} +$$

$$\theta_1 \sum_{j=1}^{264} W_{ij}\, LDF_{jt} + \theta_2 \sum_{j=1}^{264} W_{ij}\, Control_{jt} + \sigma_i + \sigma_t + \varepsilon_{it} \quad (7)$$

Where W_{ij} is the spatial weight matrix. α_4 denotes the degree of direct influence of DF on CMAC. θ_1 represents the intensity of spatial spillover influence of DF on CMAC. The other variables have been described in the aforementioned content, so they are not repeated here.

(1) Spatial correlation test

Before performing spatial regression, it is essential to test whether spatial autocorrelation exists in CMAC. The paper uses the geographic distance matrix to calculate the Moran's index for CMAC. From Table 11, Moran's index of CMAC from 2011 to 2020 is all significantly negative, proving the existence of spatial correlation.

Table 11

Spatial autocorrelation test

Year	Moran's I	E(I)	Sd(I)	Z	P
2011	-0.0322	-0.0038	0.0021	-13.5299	0.0000***
2012	-0.0390	-0.0038	0.0021	-16.7441	0.0000***
2013	-0.0398	-0.0038	0.0021	-17.1794	0.0000***
2014	-0.0563	-0.0038	0.0021	-25.0288	0.0000***
2015	-0.0811	-0.0038	0.0021	-36.9038	0.0000***
2016	-0.0897	-0.0038	0.0021	-41.0239	0.0000***
2017	-0.0559	-0.0038	0.0021	-24.8028	0.0000***
2018	-0.0606	-0.0038	0.0021	-27.0755	0.0000***
2019	-0.0681	-0.0038	0.0021	-30.6399	0.0000***
2020	-0.0625	-0.0038	0.0021	-28.0211	0.0000***

2021	-0.0596	-0.0038	0.0021	-26.6291	0.0000***

(2) SDM regression

In Table 12, the coefficients of *L.LDF* and *W*L.LDF* are significantly negative, which suggests that DF has negative spatial spillover effects on CMAC. This is because, for one thing, DF can break through spatial and temporal constraints, shorten the distance of financial services, and reduce information costs. It enhances the correlation and exchange of economic activities between cities and helps to push the cross-regional optimal allocation of production factors and the cross-regional flow of technological innovations, thus producing a negative spatial spillover influence on CMAC. For another, due to the external characteristics of carbon emissions and the existence of competition, demonstration, and economic linkage effects among cities, carbon emission performance shows an obvious spatial spillover function. This causes DF to have spatial spillover effects when lowering CMAC.

Table 12

SDM regression results

Variables	(1) *LCMAC*
L.LDF	-0.9920***
	(0.1345)
*W*L.LDF*	-19.1760***
	(3.7087)
Control	Yes
W* Control	Yes
rho	-1.7157***
	(0.3086)
sigma2_e	0.1333***
	(0.0037)
City	Yes
Year	Yes
N	2640
R^2	0.0361

(3) Spatial spillover decomposition

Table 13 reports the spatial spillover decomposition results. The results reveal that while DF suppresses local CMAC, it also reduces CMAC in neighboring cities. This is because, for one thing, DF can help inhibit CMAC by improving the coverage breadth, using depth, digitizing financial services, and promoting the development of the local economy in the trend of greening and decarbonization. For another, with the development of DF, corporates, governments, and other actors between neighboring cities can fully utilize digital technologies for cooperation and communication. This can enhance the positive effects of marketization, green technology innovation, industrial structure optimization, consumption upgrading, and other effects on carbon reduction, thus reducing CMAC.

Table 13

Decomposition results for spatial spillover effect

Variables	(1) Total *LCMAC*	(2) Direct *LCMAC*	(3) Indirect *LCMAC*

L.LDF	-7.5871***	-0.9133***	-6.6737***
	(1.7779)	(0.1354)	(1.7503)
Control	Yes	Yes	Yes

5. Research conclusions and policy implications

5.1 Conclusions

Firstly, from 2011 to 2021, the CMAC of Chinese cities generally shows an upward trend, specifically reflecting an N-shaped trend of rising, then falling, and finally rising. Secondly, DF can help reduce CMAC through three paths: promoting the rationalization and advancement of industrial structure, improving green technological innovation capacity, and enhancing green production efficiency. This means that relevant departments should make a more detailed layout when building the DF system to support the optimization of industrial structure, strengthen the green technology innovation platform for digitalization, and promote the digital transformation of the production system. Thirdly, the inhibitory role of DF on CMAC can be heterogeneous by geographical location, resource endowment, and urban scale. Particularly, compared to western, resource-based, and small-medium cities, DF has a stronger inhibitory role on CMAC in eastern, northeastern, central cities, non-resource-based cities, and large cities. This means that relevant departments should strengthen cooperation and exchange between different types of cities in resource allocation, energy use, technological reforms, human capital, etc., so as to reduce the differences in CMAC between different types of cities. Fourthly, DF has negative spatial spillover effects on CMAC and can suppress CMAC in both local and neighboring cities. This means relevant departments should establish more cross-regional DF cooperation platforms to promote low-carbon technology sharing and financial flows and amplify the spatial spillover effect.

5.2 Policy implications

Firstly, relevant departments should use policy tools or financial instruments to strengthen the awareness of carbon reduction in cities in all aspects. Specifically, they should improve cities' carbon emission statistics and accounting system, enhance carbon emission data quality, and increase carbon quotas paid allocation in due course to help decrease CMAC. Moreover, they should optimize cities' energy conservation and emission reduction work plans, improve carbon pricing, carbon market, and financial mechanism, scientifically regulate energy consumption's total amount and intensity, and effectively lower CMAC.

Secondly, relevant departments should promote the whole industry chain to optimize and upgrade various industries in cities. Specifically, they should guide social capital to invest in cities' low-carbon or zero-carbon industries, encourage corporates to actively reform and innovate low-carbon technologies, and urge them to improve energy use efficiency. Furthermore, they should continue to expand the depth and breadth of DF services, further advance the digitization process of urban green financial institutions, and scientifically adjust the optimization efforts of green credit resource allocation. Specifically, they should increase financial support for clean and environment-friendly corporates, guide highly polluting corporates to improve their environmental awareness, and encourage them to take the benign development path of innovation-driven, intelligent, green, and low-carbon.

Thirdly, relevant departments should implement dynamic, differentiated, and precise DF development strategies. Specifically, they should formulate targeted and operable low-carbon measures based on the actual development of different cities and fully tap the DF development potential and carbon reduction potential of different cities to narrow the differences in the CMAC of different cities. For example, central and northeastern cities should increase support for DF development, promote green technology R&D, optimize factor resource allocation, and magnify cost advantages. Eastern cities should further synergize DF and traditional finance, focus on green industry upgrading and energy efficiency improvement, and strengthen the effectiveness of emission reduction. Western cities should prioritize the improvement of digital infrastructure and financial infrastructure, strengthen the cultivation of human capital and the introduction of technology, and enhance the resilience of DF infrastructure. Resource-based cities should prioritize promoting the technological upgrading of traditional industries and strengthening DF infrastructure support. Non-resource-based cities should further promote the in-depth integration of DF and green technologies, and improve the green credit incentive mechanism and carbon emission trading mechanism to make CMAC lower. Large cities should establish cross-urban technology collaboration platforms to facilitate the diffusion of DF's experience in emission mitigation. Small-medium cities should increase investment in digital infrastructure, raise the coverage of inclusive financial services, and guide DF to target support for clean energy and circular economy projects.

Fourthly, relevant departments should deepen the exchanges between financial institutions and cities and encourage cooperation in carbon reduction. Specifically, they should further break down the spatial barriers to factor flows, reinforce the cross-city flows of DF innovations, and prompt the precise allocation of financial resources to key areas and weak links in the low-carbon transition. Besides, they should conduct multiple collaborative activities for urban carbon reduction, dynamically adjust the green financial risk prevention mechanism, stimulate the innovation and development of digital and high-carbon industries, and decrease the costs of resource depletion and reduction.

5.3 Limitations and future prospects

Although the paper has revealed the influence pattern of DF on CMAC from the multi-dimensional perspective, it still has a few limitations that require further breakthroughs in future studies. Firstly, the indicators for measuring DF should be improved. The methodology used in the paper to assess the level of DF development focuses mainly on the inclusiveness of DF, but it is inadequate in portraying the characteristics of DF, such as technological nature, security, and high efficiency. Future studies should adopt more comprehensive indicators to reflect these characteristics of DF. Secondly, the research perspective should be expanded. The paper examines the mechanism of the impact of DF on CMAC based on the perspective of Chinese cities. Future studies can explore the relationship between DF and CMAC globally. Thirdly, the time span of the research sample should be lengthened. The paper is limited by the availability of data and only uses data for the period 2011-2021 to test the impact of DF on CMAC. Future studies can use the latest available data.

Acknowledgments

The paper was funded by the National Social Science Fund Youth Project (Grant number: 23CJY028).

References

Bai, L., Guo, T., Xu, W., Liu, Y., Kuang, M., & Jiang, L. (2023). 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,* **183,** 113792.

Cai, Q., Chen, W., Wang, M., & Di, K. (2024a). How does green finance influence carbon emission intensity? A non-linear fsQCA-ANN approach. *Polish Journal of Environmental Studies*.

Cai, Q., Chen, W., Wang, M., & Di, K. (2024b). Optimizing resource allocation for regional employment governance: A dynamic fuzzy-set QCA analysis of low-carbon pilot cities in China. *Global NEST Journal,* **26(8)**.

Cai, Q., Chen, W., Wang, M., & Di, K. (2025). The impact of self-determined efficacy on university student's environmental conservation intentions: An SEM-ANN exploration. *Environment, Development and Sustainability*.

Cao, S., Nie, L., Sun, H., Sun, W., & Taghizadeh-Hesary, F. (2021). Digital finance, green technological innovation and energy-environmental performance: Evidence from China's regional economies. *Journal of Cleaner Production,* **327,** 129458.

Charnes, A., Cooper, W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research,* **2(6),** 429-444.

Cheng, J., Xu, L., Wang, H., Geng, Z., & Wang, Y. (2022). How does the marginal abatement cost of CO_2 emissions evolve in Chinese cities? An analysis from the perspective of urban agglomerations. *Sustainable Production and Consumption,* **32,** 147-159.

Cheng, Q., Zhao, X., Zhong, S., & Xing, Y. (2024). Digital financial inclusion, resident consumption, and urban carbon emissions in China: A transaction cost perspective. *Economic Analysis and Policy,* **81,** 1336-1352.

Cui, L., Dong, R., Mu, Y., Shen, Z., & Xu, J. (2022). How policy preferences affect the carbon shadow price in the OECD. *Applied Energy,* **311,** 118686.

Färe, R., Grosskopf, S., C., A. K. L., & Yaisawarng, S. (1993). Derivation of shadow prices for undesirable outputs: A distance function approach. *The Review of Economics and Statistics,* **75(2),** 374-380.

Färe, R., & Grosskopf, S. (2010). Directional distance functions and slacks-based measures of efficiency. *European Journal of Operational Research,* **200(1),** 320-322.

Guo, D., Qi, F., Wang, R., & Li, L. (2023). How does digital inclusive finance affect the ecological environment? Evidence from Chinese prefecture-level cities. *Journal of Environmental Management,* **342,** 118158.

Guo, F., Wang, J., Wang, F., Kong, T., Zhang, X., & Cheng, Z. (2020). Measuring China's digital financial inclusion: Index compilation and spatial characteristics. *China Economic Quarterly,* **19(04),** 1401-1418.

Guo, X., & Tu, Y. (2023). How digital finance affects carbon intensity-The moderating role of financial supervision. *Finance Research Letters,* **55**.

Hao, Y., Wang, C., Yan, G., Irfan, M., & Chang, C. (2023). Identifying the nexus among environmental performance, digital finance, and green innovation: New evidence from prefecture-level cities in China. *Journal of Environmental Management,* **335,** 117554.

He, W., Wang, B., Danish, & Wang, Z. (2018). Will regional economic integration influence carbon dioxide marginal abatement costs? Evidence from Chinese panel data. *Energy Economics,* **74,** 263-274.

He, X. (2015). Regional differences in China's CO_2 abatement cost. *Energy Policy,* **80,** 145-152.

Huang, Y., Li, L., & Yu, Y. (2018). Does urban cluster promote the increase of urban eco-efficiency? Evidence from Chinese cities. *Journal of Cleaner Production,* **197,** 957-971.

Ji, D. J., & Zhou, P. (2020). Marginal abatement cost, air pollution and economic growth: Evidence from Chinese cities. *Energy Economics,* **86,** 104658.

Lee, M. (2005). The shadow price of substitutable sulfur in the US electric power plant: A distance function approach. *Journal of Environmental Management,* **77(2),** 104-110.

Li, G., Wu, H., Jiang, J., & Zong, Q. (2023). Digital finance and the low-carbon energy transition (LCET) from the perspective of capital-biased technical progress. *Energy Economics,* **120,** 106623.

Liu, D., Li, Y., You, J., Balezentis, T., & Shen, Z. (2023). Digital inclusive finance and green total factor productivity growth in rural areas. *Journal of Cleaner Production,* **418,** 138159.

Liu, J., Yu, Q., Chen, Y., & Liu, J. (2022). The impact of digital technology development on carbon emissions: A spatial effect analysis for China. *Resources, Conservation and Recycling,* **185,** 106445.

Liu, M., Li, Y., & Hu, J. (2024). Does the Yangtze River Protection Strategy help heavily polluting corporates deleverage? Evidence from corporates in the Yangtze River Economic Belt. *Economic Change and Restructuring,* **57(2)**.

Lu, L., Liu, P., Yu, J., & Shi, X. (2023). Digital inclusive finance and energy transition towards carbon neutrality: Evidence from Chinese firms. *Energy Economics,* **127,** 107059.

Razzaq, A., & Yang, X. (2023). Digital finance and green growth in China: Appraising inclusive digital finance using web crawler technology and big data. *Technological Forecasting and Social Change,* **188,** 122262.

Ren, X., Zeng, G., & Gozgor, G. (2023). How does digital finance affect industrial structure upgrading? Evidence from Chinese prefecture-level cities. *Journal of Environmental Management,* **330,** 117125.

Sun, B., Li, J., Zhong, S., & Liang, T. (2023). Impact of digital finance on energy-based carbon intensity: Evidence from mediating effects perspective. *Journal of Environmental Management,* **327,** 116832.

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research,* **130(3),** 498-509.

Wang, F., Wang, R., & Nan, X. (2022b). Marginal abatement costs of industrial CO_2 emissions and their influence factors in China. *Sustainable Production and Consumption,* **30,** 930-945.

Wang, H., & Guo, J. (2022). Impacts of digital inclusive finance on CO_2 emissions from a spatial perspective: Evidence from 272 cities in China. *Journal of Cleaner Production,* **355,** 131618.

Wang, J., Li, Z., & Wang, Y. (2024). How does China's energy-consumption trading policy affect the carbon abatement costs? An analysis based on spatial difference-in-differences method. *Energy,* **294,** 130705.

Wang, J., Lv, K., Bian, Y., & Cheng, Y. (2017). Energy efficiency and marginal carbon dioxide emission abatement cost in urban China. *Energy Policy,* **105,** 246-255.

Wang, Z., Chen, H., Huo, R., Wang, B., & Zhang, B. (2020). Marginal abatement cost under the constraint of carbon emission reduction targets: An empirical analysis for different regions in China. *Journal of Cleaner Production,* **249,** 119362.

Wang, Z., Song, Y., & Shen, Z. (2022a). Global sustainability of carbon shadow pricing: The distance between observed and optimal abatement costs. *Energy Economics,* **110,** 106038.

Wang, Z., Wang, F., & Ma, S. (2025). Research on the coupled and coordinated relationship between ecological environment and economic development in China and its evolution in time and space. *Polish Journal of Environmental Studies,* **34(3),** 3333-3342.

Wang, Z., & Feng, C. (2015). Sources of production inefficiency and productivity growth in China: A global data envelopment analysis. *Energy Economics,* **49,** 380-389.

Wang, Z., & Ma, S. (2024). Research on the impact of digital inclusive finance development on carbon emissions-Based on the double fixed effects model. *Global NEST Journal*, **26(7)**.

Wei, C., Ni, J., & Du, L. (2012). Regional allocation of carbon dioxide abatement in China. *China Economic Review*, **23(3),** 552-565.

Wen, L., Ma, S., Zhao, G., & Liu, H. (2025). The impact of environmental regulation on the regional cross-border e-commerce green innovation: Based on system GMM and threshold effects modeling. *Polish Journal of Environmental Studies*, **34(2),** 1347-1362.

Wu, J., Zhao, R., & Sun, J. (2023). What role does digital finance play in low-carbon development? Evidence from five major urban agglomerations in China. *Journal of Environmental Management*, **341,** 118060.

Wu, Q., Jin, Y., & Ma, S. (2024). Impact of dual pilot policies for low-carbon and innovative cities on the high-quality development of urban economies. *Global NEST Journal*, **26(9)**.

Xu, J., Chen, F., Zhang, W., Liu, Y., & Li, T. (2023). Analysis of the carbon emission reduction effect of Fintech and the transmission channel of green finance. *Finance Research Letters*, **56,** 104127.

Xu, L., Yang, J., Cheng, J., & Dong, H. (2022). How has China's low-carbon city pilot policy influenced its CO_2 abatement costs? Analysis from the perspective of the shadow price. *Energy Economics*, **115,** 106353.

Yang, M., Pu, Z., Zhu, B., & Tavera, C. (2024). The threshold spatial effect of digital technology on carbon emissions. *Journal of Cleaner Production*, **442,** 140945.

Zeng, H., Abedin, M. Z., Lucey, B., & Ma, S. (2025). Tail risk contagion and multiscale spillovers in the green finance index and large US technology stocks. *International Review of Financial Analysis*, **97,** 103865.

Zhang, G., Ma, S., Zheng, M., Li, C., Chang, F., & Zhang, F. (2025). Impact of digitization and artificial intelligence on carbon emissions considering variable interaction and heterogeneity: An interpretable deep learning modeling framework. *Sustainable Cities and Society*, **125,** 106333.

Zhao, H., Chen, S., & Zhang, W. (2023). Does digital inclusive finance affect urban carbon emission intensity: Evidence from 285 cities in China. *Cities*, **142,** 104552.

Zhong, S., Peng, L., Li, J., Li, G., & Ma, C. (2023). Digital finance and the two-dimensional logic of industrial green transformation: Evidence from green transformation of efficiency and structure. *Journal of Cleaner Production*, **406,** 137078.

Zou, F., Ma, S., Liu, H., Gao, T., & Li, W. (2024). Do technological innovation and environmental regulation reduce carbon dioxide emissions? Evidence from China. *Global NEST Journal*, **26(7)**.