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Research on the impact of digital inclusive finance development on carbon emissions—Based on the double fixed effects model

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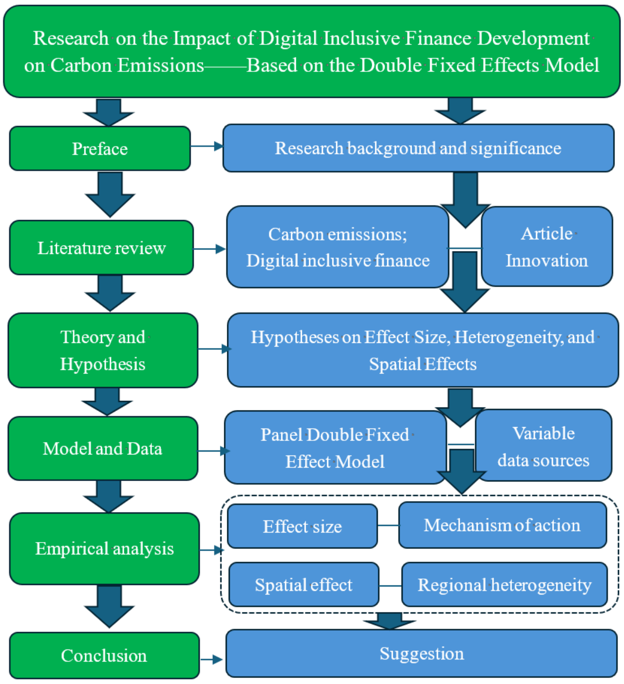
Graphical abstract



Abstract

With the accelerated global warming and the continuous rise of sea level, drastically reducing carbon emissions has gradually become a necessary action for major industrialized countries. Based on the panel data of Chinese cities from 2011 to 2022, this paper empirically examines the heterogeneous impact, mechanism and spatial externality of the development of digital inclusive finance on carbon emissions from the perspective of digital finance by applying the panel double fixed effects model. The study shows that: (1) China's digital inclusive finance index has shown a significant upward trend since 2011, and although there are obvious differences among regions, the regional differences are shrinking. As of 2022, the average carbon emissions per 10000 yuan of GDP in each province are 0.326 tons, with 11 provinces having carbon emissions exceeding this standard, mainly distributed in the underdeveloped central and western regions. (2) The development of digital inclusive finance can significantly reduce carbon emissions, and every 1% increase in the digital inclusive finance index will prompt a 0.311% decrease in carbon emissions. There is some regional heterogeneity in this effect, and for the backward central and western regions, carbon emissions can be reduced by 0.342% and 0.457%. (3) Optimizing regional industrial structure and promoting green technological innovation are important transmission mechanisms for digital inclusive finance to reduce regional carbon emissions. (4) There are also significant spatial positive externalities of digital inclusive finance, which can not only reduce local carbon emissions, but also effectively reduce the carbon emissions of neighboring regions. Finally, corresponding countermeasures are proposed based on the findings of the study.

Keywords: carbon emissions, digital finance, industrial structure, technological innovation

1. Introduction

Since the 1950s, climate issues such as global warming, accelerated melting of very low sea ice, and rising sea levels have received widespread attention from all sectors of society. In March 2024, the International Energy Agency (IEA) released its *Carbon Emissions Report 2023*. The report pointed out that global energy-related carbon dioxide emissions increase by 1.1% in 2023, increasing by 410 million tons to a record high of 37.4 billion tons. In 2023, China's emissions grew by about 565 million tons, the largest increase in the world to date. Currently, China's per capita emissions are 15 percent higher than those of developed economies. In September 2020, China announced at the seventy-fifth session of the United Nations General Assembly that it is striving to achieve a dual carbon target, that is, to peak carbon dioxide emissions by 2030 and to work towards carbon neutrality by 2060. In 2021, the Central Committee of the Communist Party of China (CPC) and the State Council jointly issued *a report on the complete, accurate and comprehensive Opinions on Carbon Peaking and Carbon Neutrality through the Implementation of the New Development Concept*, a document that clarifies the key tasks that China needed to accomplish in order to achieve its dual-carbon goals.

In 2013, the Third Plenary Session of the 18th Central Committee of the CPC formally put forward the concept of digital finance and regarded the development of digital inclusive finance as an important initiative to promote the construction of financial market system. Therefore, 2013 is also known as "the first year of digital finance in China". Since then, digital inclusive finance has shown rapid development in terms of both breadth and depth. Considering the low cost, high efficiency and wide coverage of digital inclusive finance, digital inclusive finance has a great impact on all aspects of production and life. An obvious question is, does the development of digital inclusive finance help to reduce regional carbon emissions? If the answer is yes, what are the mechanisms and pathways?

Are there regional heterogeneity and spatial positive externalities in this impact? Answering these questions will, on the one hand, help academics and practitioners to gain a comprehensive and in-depth understanding of the positive impact of digital inclusive finance. On the other hand, it also provides a feasible way of thinking about the realization of the dual-carbon goal, and is therefore of great practical significance.

2. Literature review

In this paper, we conduct a literature review from two aspects, one of which is the impact of digital inclusive finance, and the other is the influencing factors of urban carbon emissions. First, in terms of the impact of digital inclusive finance, Lee & Wang (2022) argued that digital inclusive finance can promote inclusive economic growth, can promote the entrepreneurial behavior of rural residents, and brings about equalization of entrepreneurial opportunities. Wang & Chen (2023) found that digital inclusive finance can alleviate the financing constraints of enterprises, thus reducing the cost of enterprise innovation. Therefore, it can promote enterprise innovation. This facilitating effect is stronger for SMEs and private enterprises. Zhang *et al*. (2024) found that digital inclusive finance has a greater role in enhancing the income of the poor. Therefore, the development of digital inclusive finance can reduce the gap between the rich and the poor and realize common wealth, which is again proved by the study. In addition to this, digital inclusive finance also has a significant contributing effect on the allocation efficiency of innovation factors, urban carbon emissions, total factor productivity, green technological innovation and ecological environment harmonization (Wen *et al*, Zhang *et al*, 2024). Huang *et al* (2024) found that tax incentives for key employees can help companies increase their R&D investment by increasing human capital of enterprises. Will digital inclusive finance also optimize the income of managers in small businesses, further promoting green technology innovation and reducing carbon emissions?

In terms of the influencing factors of regional carbon emissions, Liu's (2018) research found that the spatial agglomeration of productive service industries had a very limited effect on the reduction of urban carbon emission. The test based on the spatial Durbin model found that the agglomeration of productive service industries instead increased the carbon emissions of the neighboring areas. There is significant industry heterogeneity in the impact of spatial agglomeration of different service industries on carbon emissions. Wang *et al* (2023) used the double-difference method to study the effect of China's low-carbon city pilot policy on carbon emissions, and found that the policy led to a 1.05 percentage point reduction in urban carbon emissions. This effect was greater in western and backward cities. Pan *et al*. (2023) found that the sustainable development policy for resource-based cities can reduce urban carbon emissions through three ways: optimizing technology choices, enhancing financial support and improving quality of life. Using network analysis and exponential random graph modelling, Guo *et al*. (2022) found that the Chinese government's smart city construction plan helps to improve carbon emission efficiency. In addition, the peer effect of environmental policies, fiscal decentralization, regional innovation and reform policies, green technological innovation, and the Belt and Road Initiative all contribute to the reduction of regional carbon emissions (Tan *et al*., 2022; Martínez-Vázquez *et al*., 2017; Deng *et al*., 2019; Han *et al*., 2020). Li *et al* (2024) found that the presence of female executives in listed companies helps to reduce the energy consumption intensity of enterprises by encouraging an increase in the quantity and quality of green technology innovation; In addition, this impact has significant industry heterogeneity.

It can be seen that the current academic research on the impact mechanism of digital inclusive finance on carbon emissions is still relatively scarce. Different from the existing related literature, the expansion of this paper lies in the following. First, in terms of research perspective, based on the requirements of the era of carbon peak and carbon neutrality, it assesses the impact of digital inclusive finance based on the perspective of carbon emissions, which enriches the research on carbon emissions and ecological protection. Second, in terms of research content, it explores the possible mechanisms, heterogeneous impacts, and spatial positive externality spillovers of digital inclusive finance to reduce carbon emissions, which to a certain extent makes up for the lack of current research in these areas.

3. Theoretical analysis and research hypotheses

Digital inclusive finance is a concrete realization of “Internet + finance”. The effective combination of the Internet and traditional finance has lowered the transaction costs of both financing parties, and a large number of lending and borrowing transactions can be realized through communication networks and cell phone apps. With the help of the Internet, frequent online transactions have also expanded the scale of deposits and loans. Digital inclusive finance can also reduce the risks involved in traditional financial transactions. The reason for this is that digital inclusive finance leverages the power of big data. Internet technology companies and trading platforms provide financial enterprises with a large amount of data including transaction size, transaction time, transaction frequency, types of traded commodities, default records, integrity levels, customer satisfaction and other aspects (Li *et al.*, 2022). These data help financial enterprises to accurately build customer profiles, calculate customer default probability and and reasonable credit limits. Therefore, digital inclusive finance is characterized by low cost, low risk and wide coverage.

Considering information asymmetry and risk issues, traditional financial enterprises are often reluctant to provide credit services to individuals or individual businessmen with small assets. However, the characteristics of digital inclusive finance can precisely make up for this shortcoming. Digital inclusive finance makes it possible for individuals with smaller assets to have access to credit funds, increasing the supply of funds and lowering the cost of using them. As a result, it eases the financing constraints faced by individuals, thus promoting the development of the service industry, especially the living service industry. Ultimately, the industrial structure of the region is optimized, and the proportion of the secondary industry continues to decline, thus regional carbon emissions decline year by year. Digital inclusive finance expands the scale of the capital market and increases the supply of capital, thus reducing the cost of capital utilization. The link of financing constraints makes it possible for enterprises to carry out R&D activities of green technology or directly purchase green technology patents through credit funds, which ultimately reduces the carbon emissions of enterprises. Summarizing the above analysis, hypothesis H1 is proposed.

Hypothesis 1: Digital inclusive finance can reduce regional carbon emissions by optimizing regional industrial structure and promoting green technological innovation.

Compared to China's eastern seaboard, the central and western regions, which are landlocked, have weaker economic development, lower per capita incomes and smaller capital markets. Therefore, the central and western regions face tighter financing constraints. A large number of micro and small enterprises and self-employed businessmen are unable to obtain sufficient credit capital because of their small size. As a result, they are unable to expand their production scale and invest in R&D. The development of digital inclusive finance enables these enterprises to obtain credit funds and gain development opportunities. Summarizing the above analysis, hypothesis H2 is proposed.

Hypothesis 2: The development of digital inclusive finance has a greater dampening effect on carbon emissions in the backward regions of central and western China than on the developed regions in the east.

One of the main features of digital inclusive finance compared to traditional financial firms is that it is not limited by administrative boundaries or market barriers. When an enterprise is too small to obtain financial support from traditional financial enterprises locally, it is equally unable to obtain support from financial enterprises in neighboring regions. However, in the Internet era, enterprises can raise funds through national Internet financial companies or financial platforms without the restrictions of administrative divisions. The development of local digital inclusive finance can not only promote the development of local service industry and green technological innovation, but also provide financial support for neighboring regions through the Internet, thus promoting the development of service industry and green technological innovation in neighboring regions. existing literature has proven (Gu *et al*, 2023; Tang *et al*,2023; Zhu *et al*,2022) The digital economy, including digital inclusive finance, has a wide range of spatial spillover effects. The scope of influence of the digital economy will not be limited by administrative divisions. For example, if the first city has a high level of development in digital inclusive finance, it will attract nearby entrepreneurs, innovators, skilled and unskilled labor to work in the city. In addition, there may be competition among local governments. Within the same province, leaders of different prefecture level cities will continue to monitor the carbon reduction situation of other prefecture level cities in order to obtain the only political promotion opportunities. If other prefecture level cities have a significant reduction in carbon emissions, they will also have to increase their efforts to reduce their own city's carbon emissions. Therefore, based on existing literature and the competitive relationship between local governments, we believe that spatial models should be used for analysis. Summarizing the above analysis, hypothesis H3 is proposed (Figure 1).

Hypothesis 3: The development of digital inclusive finance has a spatial positive externality that reduces carbon emissions not only locally but also in neighboring regions.

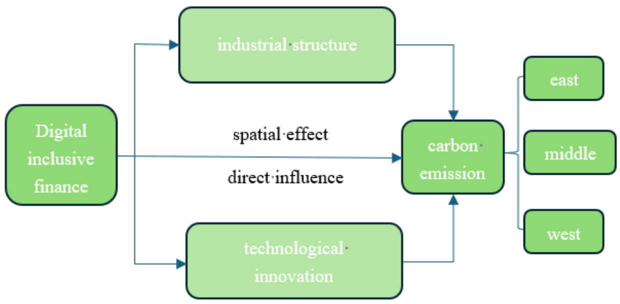


Figure 1. Diagram of the theoretical model

4. Models, variables and data

4.1. Modeling

In this paper, we mainly test the degree of influence, heterogeneity, spatial effect and its mechanism of digital inclusive finance development on regional carbon emissions, and the benchmark model set up is a panel regression model with double fixation of region and year, and the expression is shown in Equation (1).

$$co2_{it} = \alpha + \beta dfin_{it} + \gamma X_{it} + \delta_i + \theta_t + \varepsilon_{it} \quad (1)$$

Where co2 represents the carbon emissions corresponding to the regional GDP of 10,000 yuan. dfin represents the digital inclusive finance development index, and the data are from the Digital Finance Research Center of Peking University. I represents the region; T represents the year. X represents a series of control variables, specifically including the level of regional economic development (pgdp), the degree of regional openness to the outside world (export), the intensity of regional fiscal expenditure (fiscal), the degree of regional industrialization (sec), regional urbanization level (urban) and regional transportation accessibility (transp), etc. The basis for the selection of control variables is described below. θ and δ denote year fixed effects and regional fixed effects, respectively. ε denotes the random interference term. α, β and γ are parameters to be estimated. The method of defining each variable is detailed below. To mitigate estimation bias due to heteroskedasticity, all variables are taken as natural logarithms in the regression.

4.2. Variable definition and handling

First is the explanatory variable. The dependent variable is the amount of carbon dioxide (CO2) emitted per 10000 yuan of GDP, measured in tons per 10000 yuan. From Figure 2, it can be seen that the average weight of each province is 0.326 tons. There are 11 provinces above the mean. Among them, except for Tianjin, the other 10 provinces are all underdeveloped provinces in the central and western regions. Chongqing, Sichuan, and Hunan have the lowest carbon emissions, with carbon emissions per 10000 yuan of GDP of 0.108, 0.120, and 0.122 tons, respectively. Heilongjiang, Ningxia, and Inner Mongolia have the highest carbon emissions, producing 0.836, 0.834, and 0.744 tons of carbon emissions per 10000 yuan of GDP, respectively.

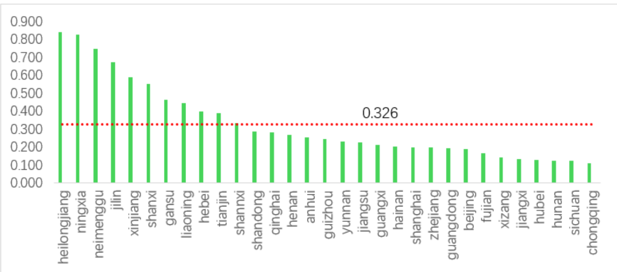


Figure 2. Carbon emissions per 10000 yuan of GDP in various provinces of China in 2022

The second is the core explanatory variable. The core explanatory variable is the Internet Comprehensive Development Index (dfin). Drawing on existing literature, the digital inclusive finance index compiled by the Digital Finance Research Center of Peking University is usually adopted (Lu *et al.*, 2023). The index system consists of three first-level indicators: the breadth of digital financial coverage, the depth of digital financial use, and the degree of digitization of inclusive finance. The breadth of digital financial coverage indicator contains one secondary indicator and three tertiary indicators. The depth of use of digital finance contains seven secondary indicators and 20 tertiary indicators. The degree of digitization consists of four secondary indicators and 10 tertiary indicators. Figure 3 reports the digital inclusive finance index and coefficient of variation for various years in China from 2011 to 2020. It can be seen that with the development of the digital economy, China's digital inclusive finance has achieved rapid development, rising from 49.4 in 2011 to 253.31 in 2020, with an average annual growth rate of 19.92%. At the same time, the coefficient of variation of the Digital Inclusive Finance Index is rapidly decreasing, from 0.32 in 2011 to 0.10 in 2020, indicating that the differences in the development level of digital inclusive finance among prefecture level cities are continuously narrowing. The development speed of digital inclusive finance in underdeveloped areas is faster than that of economically developed cities in the eastern region. Figure 3 reports a scatter plot of the Digital Inclusive Finance Index and carbon emissions (Figure 4).

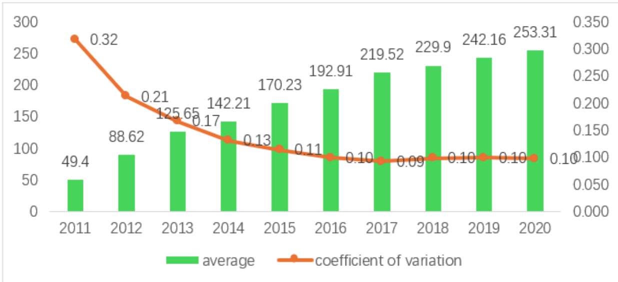


Figure 3. China Digital Inclusive Finance Index and Coefficient of Variation from 2011 to 2020

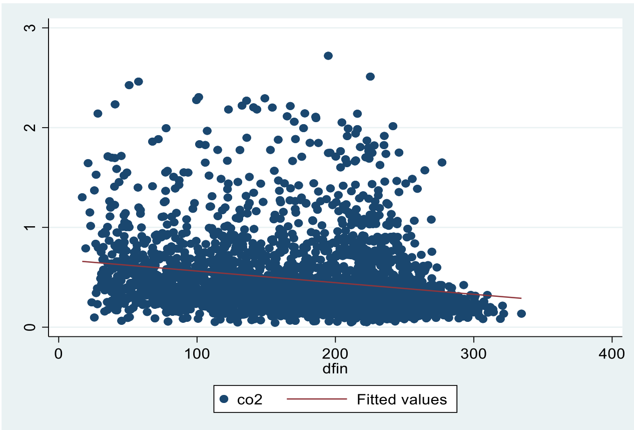


Figure 4. Scatter plot of digital inclusive finance and carbon emissions

Finally, there are the control variables. In order to avoid selectivity bias based on observable variables, it is necessary to select key control variables, which need to be related to the core explanatory variable (digital inclusive finance index). At the same time, must be an important influencing factor of the explanatory variable (carbon emissions). Based on this principle, while drawing on the research results of related literature, this paper selects the following control variables. (1) Regional economic development level (pgdp), measured by regional GDP per capita. (2) Degree of openness to the outside world (export), measured by the ratio of total regional imports and exports to GDP. (3) Government financial expenditure (fiscal), measured by the ratio of government financial expenditure to GDP. (4) Transportation accessibility (trans), measured by the per capita highway business mileage to measure. (5) Urbanization level (urban), using the proportion of urban population in the total population to measure. (6) Industrialization level (sec). The value added of the secondary industry as a share of GDP was used to measure it. The descriptive statistics of all relevant variables are shown in Table 1.

Table 1. Descriptive statistics of variables

Variable name	Sample size	Average value	Standard deviation	Minimum value	Maximum values
co2	3300	0.48	0.37	0.04	2.72
dfin	2750	171.26	68.34	11.30	334.38
pgdp	3300	31127.95	20281.56	3685.96	126000.00
export	3300	1.85	10.3	0.01	144.11
fiscal	3300	0.26	0.20	0.09	1.39
trans	3300	3.38	0.74	1.46	5.8
urban	3300	0.44	0.09	0.16	0.66
serv	3300	0.44	0.10	0.27	0.84
inno	3300	4770	3213	0	275774

Table 2. Benchmark regression results

Model	Model 1	Model 2	Model 3	Model 4
Lndfin	-0.483***	0.112***	-0.423**	-0.311**
	(0.117)	(0.033)	(0.183)	(0.135)
lndfin2		0.032		
		(0.007)		
Constant	1.267***	1.388***	1.405**	1.980**
	(0.033)	(0.037)	(0.034)	(0.897)
Control variable	No	No	No	Yes
Area fixed effect	No	No	Yes	Yes
Year fixed effects	No	No	Yes	Yes
N	3300	3300	3300	3300
R^2	0.509	0.532	0.706	0.755

*Note: *** p<0.01, ** p<0.05, * p<0.1; data in parentheses are heteroskedasticity robust standard errors.*

The data structure of this paper is a panel structure, with a time horizon of 12 years from 2011-2022, and the regions are 275 prefecture-level cities in mainland China. GDP and income data are converted to comparable values in 2011 using the GDP deflator and the consumer price index, respectively. Import and export data are converted according to the exchange rate of the RMB against the US dollar as published in the China Statistical Yearbook. The data sources used in this paper include the China Statistical Yearbook, China Population Statistical Yearbook, China Financial Statistical Yearbook, China Internet Network Information Center's (CNNIC) Statistical Report on the Development of the Internet in China for all years, and the CNRDS statistical database.

5. Empirical results and analysis

5.1. Benchmark regression

Benchmark regression was conducted according to equation (1) using stata17.0 software, and the estimation results are detailed in Table 2. In order to obtain data for 2021 and 2022, we calculated the indicator scores for 2021 and 2022 according to the average annual growth rate from 2011 to 2020. The estimated coefficient in Model 1 of Table 3 is -0.483 and passes the 1% significance level test. This indicates that there is a significant negative correlation between digital inclusive finance and carbon emissions. Model 2 adds the squared term of the digital inclusive finance index, and the squared term does not pass the significance test, which indicates that there is no significant positive U or inverted U type of relationship between the level of development of digital inclusive finance and carbon emissions. Model 3 adds double fixed effects on the basis of model 2, and the goodness of fit (R^2) increases, which indicates that the regional characteristics factor and the year trend factor explain part of the variation of carbon emissions, so double fixed effects should be added to the model. In order to further reduce the endogeneity bias and satisfy the identification assumptions required for causal inference as much as possible, key control variables are added to model 3, and the estimated coefficient of the digital inclusive finance index is obtained to be -0.311, and it passes the test at the 5% significance level. This suggests that an increase in the level of digital inclusive finance development can significantly reduce carbon emissions; the absolute value of the estimated coefficient decreases from 0.423 to 0.311, indicating that the addition of control variables eliminates some of the endogeneity bias based on observable variables. In addition, the goodness of fit improves, making the inclusion of these control variables necessary. In terms of economic significance, -0.311 implies that every 1% increase in the Digital Inclusion Development Index contributes to a 0.311% decrease in carbon emissions.

5.2. Instrumental variable tests

To mitigate endogeneity bias due to the omission of unobservable key control variables and measurement error, this paper employs an instrumental variable approach to estimation. Drawing on Wang and Shao (2024), the number of landline telephones per 100 people in 1984 is used as the instrumental variable for digital inclusive finance. Drawing on Nunn and Qian (2014), the number of fixed-line telephones per 100 people in 1984 is cross-multiplied with the cell phone penetration rate in the previous year to obtain an instrumental variable that varies over time by region (iv1). This paper also attempts to use the number of post offices (offices) in each region in 1984 (iv2) as an instrumental variable.

Table 3 reports the regression results using instrumental variables and the 2SLS estimation method, with Model 5 and Model 6 differing in the use of different instrumental variables. In both Model 5-Model 6, the first-stage regression results show that the significant positive correlation between the endogenous variable, dfin, and the instrumental variable, iv, remains after the inclusion of control variables and double fixed effects. In the second stage regression, the Kleibergen-Paap rk LM statistic corresponds to p-values less than 0.05. Therefore, the original hypothesis that the instrumental variable is under-identified is rejected, and the Kleibergen-Paap rk Wald F statistic is all greater than the critical value of 16.38 at the 10% level of significance. Therefore, the original hypothesis that the instrumental variable is a weak instrumental variable can be rejected. The results of the second-stage regression show that the parameter estimates of the digital inclusive finance index are all negative. The results of Model 5 and Model 6 indicate that the increase in the development level of digital inclusive finance can effectively reduce carbon emissions.

Table 3. Instrumental variable regression results

Model	Model 5	Model 6
Explained variable: *lntt*		
Second-stage regression		
lndfin	-0.277***	-0.249***
	(0.008)	(0.057)
Control variable	Yes	Yes
Area fixed effectS	Yes	Yes
Year fixed effects	Yes	Yes
Kleibergen-Paap rk LM	51.269	77.432
Kleibergen-Paap rk Wald F	62.101	59.483
N	3300	3300
R^2	0.603	0.673
Explained variable: *lnttr*		
Instrumental variable	*iv1*	*iv2*
First-stage regression		
lniv	0.615***	0.615***
	(0.082)	(0.082)
Control variable	Yes	Yes
Area fixed effect	Yes	Yes
Year fixed effects	Yes	Yes

Note: Data in parentheses are the corresponding p-values. The control variables for the first and second stage regressions are the same.

5.3. Other robustness tests

In order to enhance the credibility of the article's findings, the paper also designs five robustness tests, using regressions with panel data from 2011-2020 (Model 7). One period lagged for all explanatory variables (Model 8), two periods lagged for all explanatory variables (Model 9), remove the samples with the smallest and largest dependent variable values of 3% each (Model 10), and remove the samples with the smallest and largest digital inclusive finance values of 3% each (Model 11). The reason for constructing Model 7 is that the 2011 and 2022 digital inclusive finance indices used in Table 3 were calculated using the average annual growth rate method, which may be biased. The reason for constructing models 8 and 9 is that the reduction in carbon emissions caused by digital inclusive finance is achieved through accelerating the development of the service industry and encouraging research and development investment and technological innovation. Among them, the impact of R&D investment and technological innovation on carbon emissions is unlikely to occur in that year. Digital inclusive finance has promoted technological innovation, but it will take some time from technological innovation to applying technology to enterprises. Therefore, we believe that the development of digital inclusive finance will reduce carbon emissions for the next year or two. The purpose of constructing models 10 and 11 is to eliminate the influence of extreme values of variables on regression results. The empirical results are detailed in Table 4, Model 7- Model 11. The estimated coefficients in all three models are significantly negative and pass the significance level test at least 10%. This indicates that for every 1% increase in the Digital Inclusive Finance Index, it will significantly promote a 0.117% and 0.200% reduction in carbon emissions per 10000 yuan of GDP.

5.4. Tests for regional heterogeneity

Table 5 reports the results of the heterogeneity test. Model 12-Model 14 are regressions for the eastern, central and western regions, respectively. It can be seen that in the eastern region, the coefficient estimate of *lndfin* is only -0.199. However, in the central and western regions, the coefficient estimates are -0.342 and -0.457 respectively, and they pass the test at the 1% significance level. This indicates that the development of digital inclusive finance can reduce carbon emissions to a greater extent in the central and western less developed regions. The possible reason is that the impact of digital inclusive finance on carbon emissions is not linear. For developed cities in the eastern region, the proportion of the service industry is relatively high, the size of the capital market is large, and enterprises invest heavily in research and development. Therefore, the promotion effect of digital inclusive finance on the service industry and research and development intensity is not significant, and its impact on carbon emissions is relatively small. On the contrary, in the central and western regions, the proportion of the service industry in the economy is relatively low, the size of the capital market is small, and the investment in research and development by enterprises is relatively small. Therefore, the impact on carbon emissions is significant. So far, hypothesis 2 is verified.

Table 4. Robustness test results

Model	Model 7	Model 8	Model 9	Model 10	Model 11
lndfin	-0.289***			-0.117**	-0.200*
	(0.035)			(0.058)	(0.111)
L.lndfin		-0.276*			
		(0.145)			
L2.lndfin			-0.293*		
			(0.154)		
Control variable	Yes	Yes	Yes	Yes	Yes
Area fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N	2475	3025	2750	3102	3102
R^2	0.800	0.732	0.758	0.723	0.711

Table 5. Results of heterogeneity test and mechanism test

Model	Model 12	Model 13	Model 14	Model 15	Model 16
Shore	East	Central	Western	lnserv	lninno
lndfin	-0.199*	-0.342***	-0.457***	0.017***	0.125***
	(0.105)	(0.027)	(0.019)	(0.000)	(0.000)
Control variable	Yes	Yes	Yes	Yes	Yes
Area fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N	1260	1080	960	3300	3300
R^2	0.812	0.735	0.628	0.579	0.429

5.5. Analysis of impact mechanisms

In order to further reveal the impact mechanism of digital inclusive finance on carbon emissions, the following impact mechanism tests are conducted for the theoretical mechanism analysis and hypothesis 2. Drawing on the test method of Tan *et al* (2023), the following regression equations are constructed, such as equations (2) and (3).

$$serv_{it} = \alpha + \beta_2 dfin_{it} + \gamma X_{it} + \delta_i + \theta_t + \varepsilon_{it} \quad (2)$$

$$inno_{it} = \alpha + \beta_1 dfin_{it} + \gamma X_{it} + \delta_i + \theta_t + \varepsilon_{it} \quad (3)$$

Where inno denotes the number of patent applications in the region, and serv is the share of tertiary industry in GDP in the region. Other variable meanings are consistent with equation (1). For formal regression, all variables are taken as natural logarithms.

After combining the regression results of Model 15 and Model 16, it can be found that digital inclusive finance can promote the development of the service industry and optimize the regional industrial structure, as well as alleviate financing constraints and encourage R&D investment. Hypothesis 2 is verified to some extent.

5.6. Analysis of spatial effects

In order to test the spatial effects of digital inclusive finance development, it is necessary to set up a spatial weight matrix, test the spatial correlation of key variables, and perform spatial econometric regression.

First, the spatial weight matrix is constructed. Considering that the factor flow and resource optimization and allocation brought about by digital inclusive finance occur more often between spatially adjacent districts, the 0-1 spatial matrix is used. At the same time, this paper also uses the reciprocal of the highway distance between two district government locations as the weight matrix. In the 0-1 method, if there is a common boundary between two prefecture level cities, they are considered adjacent, and the weight in the spatial weight matrix is 1; On the contrary, the weight in the spatial weight matrix is 0. In the distance method, if the distance between two prefecture level cities is X kilometers, then the weight in the spatial weight matrix is 1/X. This means that the farther the distance between two prefecture level cities, the smaller the weight in the spatial weight matrix, and the smaller the mutual influence between the two cities. This is also the most commonly used method for constructing spatial weight matrices in existing literature.

Second, the spatial correlation of key variables is tested. This paper tests the global Moran index for carbon emissions and digital inclusive finance (*dfin*). The results show that the Moran index is significantly positive in most years.

Finally, a spatial econometric model is established to test the spatial spillover effect. A spatial Durbin model is established for spatial econometric analysis, and the model is shown in equation (4).

$$co2_{it} = \alpha + \rho Wco2_{it} + \beta ndfint_{it} + \sigma Wdfin_{it} + \gamma X_{it} + \delta_i + \theta_t + \varepsilon_{it} \quad (4)$$

Where W denotes the spatial weight matrix, Wco2 is the spatial lag term, ρ denotes the spatial autoregressive coefficient, reflecting the spatial autocorrelation of carbon emissions in different regions, $Wdfin_{it}$ denotes the spatial lag term of the development level of digital inclusive finance. The meanings of other variables are consistent with equation (1).

Drawing on Lesage and Pace (2009), the impact of digital inclusive finance development on carbon emissions is decomposed into direct, indirect and total effects. The estimation results of the spatial Durbin model are reported in Table 6 Model 17-Model 20.

Table 6. Results of spatial measurement regression

Model	Model 17	Model 18	Model 19	Model 20
Spatial weighting matrix	0-1 matrix	Intergovernmental distance matrix		
Direct effect	-0.188***	-0.152***	-0.199***	-0.178***
	(0.017)	(0.013)	(0.012)	(0.016)
Indirect effect	-0.137*	-0.125*	-0.014	-0.022*
	(0.072)	(0.065)	(0.052)	(0.012)
Aggregate effect	-0.325***	-0.277***	-0.213***	-0.199***
	(0.024)	(0.015)	(0.045)	(0.011)
Control variable	Yes	Yes	Yes	Yes
Area fixed effect	Yes	Yes	Yes	Yes
Year fixed effects	be	be	be	be
N	3300	2475	3300	2475
R^2	0.746	0.616	0.541	0.543
Log-likeihood	659.4	620.9	579.1	549.9

As shown in Table 6, the direct, indirect and total effects of digital inclusive financial development on carbon emissions are all significantly negative. This indicates that the increase in the development level of local digital inclusive finance not only effectively reduces local carbon emissions, but also helps to shrink the carbon emissions of neighboring regions. The development of local digital inclusive finance has a significant positive spatial externality, and Hypothesis 3 is verified.

6. Research findings, policy recommendations and research prospects

6.1. Research findings

This paper empirically examines the heterogeneous impacts, enabling mechanisms and spatial effects of the development of digital inclusive finance on carbon emissions using Chinese urban panel data from 2011 to 2022. The following conclusions are obtained: First, China's digital inclusive finance index has shown a significant upward trend since 2011, and although there are obvious differences in the development of various regions, the inter-regional differences are shrinking. China's digital inclusive finance index has shown a significant upward trend since 2011, and although there are obvious differences among regions, the regional differences are shrinking. As of 2022, the average carbon emissions per 10000 yuan of GDP in each province are 0.326 tons, with 11 provinces having carbon emissions exceeding this standard, mainly distributed in the underdeveloped central and western regions. Second, the development of digital inclusive finance can significantly reduce carbon emissions, and every 1% increase in the digital inclusive finance index will prompt a 0.311% decrease in carbon emissions. There is a certain regional heterogeneity in this effect, which can reduce carbon emissions by 0.199% for the developed eastern coastal region. However, it can reduce carbon emissions by 0.342% and 0.457% for the lagging central and western regions, respectively. Third, optimizing regional industrial structure and promoting green technology innovation are important transmission mechanisms for digital inclusive finance to reduce regional carbon emissions. Fourth, digital inclusive finance also has significant positive spatial externalities, which can not only reduce local carbon emissions, but also effectively reduce carbon emissions in neighboring regions.

6.2. Policy recommendations

The findings of this paper have the following policy implications.

First, the government should encourage the development of the digital inclusive finance industry. On the one hand, it should encourage traditional State-owned commercial banks to accelerate their digital and intelligent transformation and reduce transaction costs for both banks and consumers. On the other hand, it should encourage competent technology companies and Internet retail enterprises to utilize the big data obtained through their retail activities to carry out inclusive, consumer and supply chain finance, and to alleviate the problems of difficult and expensive financing caused by the underdevelopment of the capital market.

Second, the regional heterogeneity of digital inclusive finance in reducing carbon emissions is taken into account The central and western provinces and resource cities that are lagging behind in economic development should take advantage of the development opportunities of the digital economy to vigorously develop digital inclusive finance. Through the development of digital inclusive finance, on the one hand, they can upgrade the industrial structure and raise the income level. On the other hand, they can reduce carbon emissions and contribute to the realization of the goals of carbon peaking and carbon neutrality.

Third, neighboring local governments should strengthen the regional coordination of digital inclusive finance development planning. The development of digital inclusive finance has a strong positive spatial externality, so it needs to be jointly planned by neighboring local governments, comprehensively studied and coordinated. Avoid over-investment and waste of resources.

6.3. Limitations and research prospects

Although digital inclusive finance has a significant inhibitory effect on carbon emissions, our empirical research still has three limitations: firstly, we only found two intermediary paths: industrial structure upgrading and green technology innovation. In fact, there are still many channels through which digital inclusive finance affects carbon emissions, and more literature is needed to further explore. Secondly, why is the carbon reduction effect of digital inclusive finance weaker in the eastern region and stronger in the central and western regions? There is currently no consensus. According to existing empirical results, there is a moderating variable for the carbon reduction effect of digital inclusive finance, but what is this moderating variable? It cannot be determined yet. Thirdly, the panel double fixed effects model has flaws in determining causal relationships, as the fixed effects of year and city can only eliminate urban characteristics that do not change over time and macroeconomic trends that do not change with the city. In this case, there is still endogeneity bias in the model.

This research can be expanded from three aspects: firstly, further explore the inherent mechanism and nonlinear impact of digital inclusive finance on carbon emissions. If there are non-linear effects, then government departments can use digital inclusive finance more rationally to reduce carbon emissions. Secondly, there are differences in the development level of digital inclusive finance in different regions. Why do these differences exist? How much development space does digital inclusive finance have in the future? How to further promote the development of digital inclusive finance? This is a topic that policymakers and academia need to focus on. Thirdly, in order to avoid endogeneity bias, scholars need to seek new research designs such as natural experiments, quasi natural experiments, and panel IV estimation to verify the carbon reduction effects of digital inclusive finance.

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