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The Impact Mechanism of Digital Inclusive Finance on Regional Carbon Emission Intensity Based on Empirical Research

Xinyao Liu, Yun Chen * and Chuanmei Ge

School of Economics and Management, Communication University of China, Beijing, China

Abstract: Based on panel data from 30 provinces in China from 2011 to 2020, this study systematically examines the mechanisms by which digital inclusive finance influences regional carbon emission intensity. Empirical results demonstrate that digital inclusive finance significantly suppresses carbon emission intensity by promoting social financing, but this effect exhibits regional heterogeneity and threshold constraints. Emission reductions are evident in eastern and central regions, where digital infrastructure is well-developed. However, the transmission efficiency of emission reductions is inefficient in western regions, constrained by low fintech penetration and reliance on energy-intensive industries. The study further finds that the emission reduction effect diminishes when the market capitalization share of energy-intensive industries exceeds a threshold of 3.53%. Using the XGBoost model, carbon emission intensity is projected to show a divergent trend over the next decade: "eastern regions lead the decline, while western regions face pressure." Regions like Beijing and Hainan will continue to improve, while regions like Inner Mongolia and Ningxia will maintain high levels. Regionally differentiated policies are recommended to strengthen the synergy between digital infrastructure development and industrial restructuring in western China.

Keywords: Digital inclusive finance; Carbon emission intensity; Regional heterogeneity; Threshold effect; XGBoost model.

1. Introduction

Against the backdrop of global climate change, achieving carbon peak and neutrality has become a global consensus. China's 14th Five-Year Plan for Energy Conservation and Emission Reduction calls for building a green, low-carbon, circular economy to support these goals. As a key driver of sustainable development, finance plays a crucial role in the green transition. In the digital economy era, digital inclusive finance enhances access, affordability, and adaptability of financial services, expanding financing for small and micro enterprises and low-income groups. While it can promote clean technology investment, green innovation, and carbon reduction, it may also stimulate economic activity and increase energy consumption. Understanding its impact on regional carbon emission intensity is therefore essential for designing effective environmental and financial policies that balance growth with emission reduction.

In recent years, the role of digital inclusive finance in promoting high-quality economic development and green transformation has attracted widespread attention from the academic community. Existing studies have mainly explored the impact of digital inclusive finance on corporate digital transformation, technological innovation and carbon emissions. Guo et al. [1] pointed out that digital inclusive finance can promote corporate digital transformation, thereby improving resource allocation efficiency and green innovation capabilities. He and Jiang [2]'s research shows that digital inclusive finance can significantly reduce carbon emission intensity by promoting digital technology innovation, but its emission reduction effect has regional differences. Su and Cao [3] further verified the inhibitory effect of digital inclusive finance on urban carbon emission intensity from the perspective of green travel and clean energy, revealing its important role in promoting low-carbon transportation and energy structure optimization. In addition, Li et al. [4] found that digital inclusive finance also has a positive role in promoting high-quality agricultural development, but its impact degree shows significant regional heterogeneity. In terms of the interactive relationship between regional economic growth and environmental governance, Ding et al. [5] emphasized that the synergistic effect of digital inclusive finance and environmental regulation not only affects regional economic growth, but also has spatial spillover effects and threshold effects. Overall, existing research has made important progress in revealing the impact mechanism of digital inclusive finance on carbon emissions, but there is still room for further in-depth research in terms of regional heterogeneity, threshold characteristics and forecast trends.

2. Study Design

This article uses a balanced panel data set covering 30 provinces and municipalities in China (excluding Tibet) from 2011 to 2020. After screening, a total of 3,300 observations were selected. The original data for each variable were obtained from historical city statistical yearbooks and local statistical bureau websites. Variable definitions are shown in Table 1. The selection of control variables utilizes a multi-factor approach.

Table 1. Variable definition

Variable	Variable name	Measurement method	Data sources
Interpreted variable	Carbon intensity	The proportion of total carbon emissions to real GDP	China Carbon Accounting Database (CEADs), Peking University Digital Financial Inclusion Index, Peking University Digital Financial Inclusion Index, China Statistical Yearbook, National Bureau of Statistics website, etc
Core explanatory variables	Digital Financial Inclusion Index	Peking University Digital Inclusive Finance Index takes logarithms	
Mediating variables	Social financing scale	The scale of social financing is taken logarithmically	
Replace the explanatory variable	Digitization	The index of digitalization of inclusive finance is taken logarithmically	
Threshold variables	The proportion of market value of high-energy-consuming industries	The proportion of the market value of high-energy-consuming industries to the total market value of industries	
Control variables	Energy structure	Coal energy consumption accounts for total energy consumption	
	The degree of government intervention	The proportion of regional general budget expenditure to GDP	
	Industrial development level	The proportion of secondary industry added value to GDP	
	population density	The natural logarithm of the ratio of the population to the area of the administrative region at the end of the year	
	Economic development level	The level of economic development is taken logarithmically	

After selecting the variables, we conducted sample selection and descriptive statistics. Taking into account the statistical period of the Digital Inclusive Finance Index published by Peking University and the latest statistical period, the sample period is 2011–2020. Due to the significant lack of data on carbon emission intensity in Tibet, this article ultimately selected 30 provinces and municipalities for research. These 30 provinces and municipalities are Beijing, Tianjin, Hebei, Shanxi, Liaoning, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Xinjiang, Inner Mongolia, Jilin, Heilongjiang, Hainan, Gansu, Qinghai, and Ningxia. The descriptive statistics of the variables selected above are shown in Table 2 below.

Table 2. Descriptive statistics for each variable

VarName	Mean	SD	Min	Median	Max
Carbon intensity	0.6791	0.438	0.05	0.62	2.12
Digital Financial Inclusion Index	5.2193	0.668	2.91	5.41	6.07
Digitization logarithm	5.5103	0.698	2.03	5.78	6.14
The scale of social financing is logarithmic	8.3013	0.898	4.76	8.34	10.61
The level of technological innovation is the number of green patents granted	7.3246	1.378	2.89	7.42	10.45
Energy structure	0.8644	0.376	0.01	0.79	1.84
The degree of government intervention	0.0972	0.046	0.02	0.10	0.20
Industrial development level	0.1894	0.130	0.02	0.16	0.51
population density	0.0439	0.056	0.00	0.03	0.30
The proportion of market value of high-energy-consuming industries	0.2153	0.153	0.01	0.18	0.78

Correlation analysis of various variables was conducted to test the controllability of the sample. The results indicate that there should be a significant correlation between carbon emission intensity and the digital financial inclusion index. The results of this correlation analysis indicate that this relationship holds true in this sample, indicating that the sample is controllable.

3. Empirical Analysis and Results

3.1. Benchmark Regression

A baseline regression analysis was conducted to analyze the impact of the Digital Financial Inclusion Index on carbon emission intensity. As shown in Table 3 below, the results show that the logarithm of the Digital Financial Inclusion Index is significantly negatively correlated with carbon emission intensity across multiple models, indicating a significant reduction in carbon emission intensity. Furthermore, factors such as energy structure, government intervention, and industrial development level also significantly influence carbon emission intensity across different models. All models account for both individual and annual effects and exhibit high R^2 values, indicating a good model fit.

Table 3. Benchmark regression results

	(1) Carbon intensity	(2) Carbon intensity	(3) Carbon intensity	(4) Carbon intensity	(5) Carbon intensity	(6) Carbon intensity
Digital Financial Inclusion Index Logarithm		-0.223*** (-2.76)	-0.235*** (-3.23)	-0.228*** (-2.93)	-0.162** (-2.20)	-0.334*** (-4.18)
Energy structure	0.470*** (5.97)		0.637*** (7.43)	0.601*** (7.20)	0.505*** (6.56)	0.455*** (5.94)
The degree of government intervention	1.917*** (3.15)			2.653*** (4.31)	1.817*** (2.78)	2.053*** (3.44)
Industrial development level	3.748*** (9.42)				3.465*** (8.42)	3.606*** (9.29)
population density	-10.094** (-2.08)					-23.214*** (-5.18)
_cons	-0.247 (-1.16)	1.826*** (4.32)	1.338*** (3.53)	1.076*** (2.74)	0.245 (0.63)	2.035*** (3.97)
Individual effects	YES	YES	YES	YES	YES	YES
Annual effect	YES	YES	YES	YES	YES	YES
N	300	300	300	300	300	300
R2	0.9708	0.9471	0.9584	0.9617	0.9711	0.9739
F	55.56	7.63	30.39	29.14	47.14	51.31
***p<0.01", "**p<0.05", "*p<0.10 The t-value obtained based on the miscalculation of the robust standard in parentheses (the same below)						

3.2. Robustness Test and Heterogeneity Analysis

After adding the logarithm of economic development level to the regression model, the negative inhibitory effect of digital financial inclusion on carbon emissions intensity still passed the 1% significance test, confirming the robustness of this study's conclusions. However, its marginal effect is somewhat weaker than that of the baseline model, indicating that economic development level, as an important control variable, partially explains the emission reduction mechanism of financial digitalization.

In the regional heterogeneity analysis, samples from central and eastern China show a significant negative impact of the digital financial inclusion index on carbon emission intensity, indicating that financial digitalization in these regions can effectively curb carbon emissions. However, this effect is not significant in samples from western China. This disparity stems primarily from several factors: First, weak digital infrastructure and low financial technology penetration in western China result in inefficient transmission of digital emissions reductions; second, western industries are more reliant on energy-intensive heavy industries such as energy and metallurgy. According to 2012 data, industrial value-added energy consumption in western China was 1.8 times that of eastern China, resulting in structural lock-in effects that weaken financial regulation. These systemic differences make it difficult for digital financial inclusion in western China to replicate the emission reduction achievements of eastern China. In the future, tailored policies, such as targeted clean energy finance, will be needed to unleash the potential of technology empowerment.

3.3. Mediating Effect

Regarding the "three-step method" of the mediation effect model, some scholars have recently raised clear doubts. For example, in 2022, China Industrial Economy published Professor Jiang Ting's (2022) views on mechanism analysis, which this article calls "mechanism analysis method". Mechanism analysis method means that in empirical regression analysis, in order to explore the formation mechanism of the influence relationship between independent variables and dependent variables, we only need to analyze the influence relationship between independent variables and mechanism variables, and at the same time use existing theories or literature viewpoints to explain the influence relationship between mechanism variables and dependent variables, so as to achieve the above two-step regression analysis. Obviously, the most important step of this method is the influence relationship between independent variables and mechanism variables. This article draws on the mechanism analysis method to analyze the mediation effect.

The regression results are shown in Table 4, which shows that digital inclusive finance can promote social financing. Specifically, the coefficient of social financing scale in model (2) is -0.699, which is significant at the 1% significance level. The inhibitory effect of social financing scale on carbon emissions is also supported by existing literature. For example, Wang Jia (2021) empirically tested the inverted U-shaped relationship between social financing scale and carbon emission intensity, pointing out that within the threshold (when the financing scale in central and western China is moderate), carbon emissions are significantly suppressed. These research results further verify the important role of social financing scale in curbing carbon emissions.

Table 4. Mediating effect results

	Carbon intensity	The scale of social financing is logarithmic
Digital Financial Inclusion Index Logarithm	-0.334*** (-4.18)	0.663*** (2.78)
Energy structure	0.455*** (5.94)	-0.699*** (-2.65)
The degree of government intervention	2.053*** (3.44)	-0.610 (-0.37)
Industrial development level	3.606*** (9.29)	-5.203*** (-3.67)
population density	-23.214*** (-5.18)	57.541*** (3.29)
_cons	2.035*** (3.97)	4.266** (2.37)
Individual effects	YES	YES
Annual effect	YES	YES
N	300	300
R2	0.9739	0.9143

The threshold effect analysis aims to explore whether the impact of digital inclusive finance on carbon emission intensity exhibits nonlinear characteristics as the market capitalization share of high-energy-consuming industries changes. Based on the threshold regression results in the document, the main conclusions are as follows: First, the significance test shows that the single threshold effect is significant at the 5% level, while the double threshold effect is not significant. This suggests that the impact of digital inclusive finance on carbon emissions has a significant threshold point, but no multiple threshold structure. Second, the threshold regression results reveal nonlinear characteristics: when the market capitalization share of high-energy-consuming industries is below the threshold value of 0.0353, the logarithm of the digital inclusive finance index has a stronger effect on reducing carbon emission intensity (coefficient = -0.079, t-value = -3.50, significant at the 1% level); when the share reaches or exceeds the threshold, the effect weakens but remains significant (coefficient = -0.045, t-value = -2.60, significant at the 5% level). This means that the inhibitory effect of digital inclusive finance on carbon emissions is more significant in regions where the proportion of high-energy-consuming industries is low, which may be due to the higher efficiency of financial digitalization in promoting the diffusion of clean technologies; while in regions with a high proportion, the rigid structure of high-energy-consuming industries may weaken the emission reduction potential of financial support.

4. Carbon Emission Intensity Forecast

To further explore future trends in carbon emission intensity across provinces, this study constructed a time series forecasting model based on XGBoost. This model integrates historical carbon emission intensity data to create a multi-dimensional feature system, including lagged features, moving average features, and differential features. GridSearchCV was used for model training to optimize hyperparameters, and the optimal parameter combination was selected through 5-fold cross-validation to ensure robustness and accuracy of the forecast.

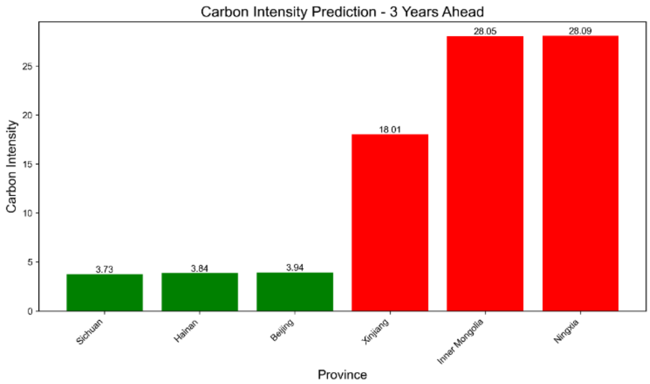

Figure 1. Carbon Intensity Prediction -3 Years Ahead

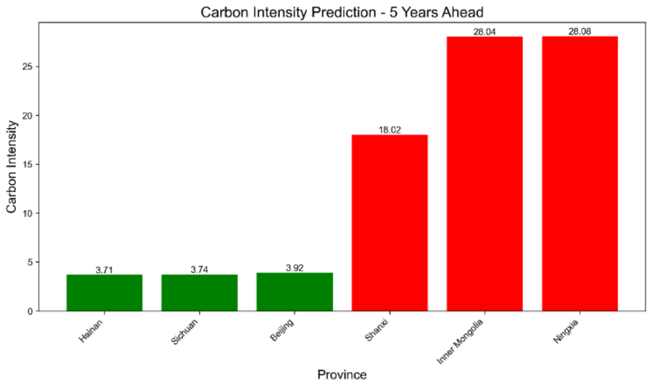

Figure 2. Carbon Intensity Prediction -5 Years Ahead

Forecast results for the next three, five, and ten years, as shown in Figures 1-3 below, show a clear trend of divergence in carbon emission intensity across provinces. The provinces with the lowest carbon emission intensities are primarily concentrated in economically developed regions and areas rich in clean energy resources: Beijing, Hainan, and Sichuan remain in the top three across all forecast periods. Beijing's carbon emission intensity is projected to decrease from 3.94 in three years to 3.74 in ten years, while Hainan's is projected to decrease from 3.84 to 3.74, indicating a trend of continuous improvement. In contrast, provinces with high carbon emission intensities are primarily energy- and resource-intensive regions: Inner Mongolia, Ningxia, Xinjiang, and Shanxi. Inner Mongolia's carbon emission intensity is projected to remain high at 28.04 in 10 years, while Ningxia's is projected to be 28.07. This indicates that these regions' economic growth models remain heavily reliant on high-energy-consuming and high-emission industries, posing a daunting challenge for economic restructuring.

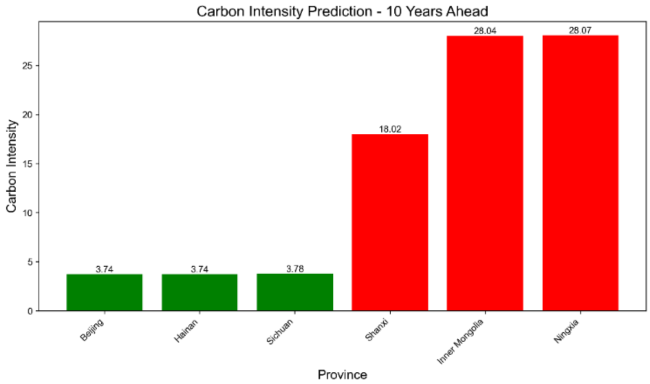

Figure 3. Carbon Intensity Prediction -10 Years Ahead

A feature importance analysis, as shown in Figure 4 below, shows that the previous year's carbon emission intensity (Lag 1) contributes most to the forecast, with an importance exceeding 0.55, followed by the three-year moving average (MA3) and the two-year lag (Lag 2). This indicates that carbon emission intensity exhibits strong path dependence. These forecast results provide important insights for developing differentiated regional carbon reduction policies and assessing the potential carbon reduction effects of digital financial inclusion.

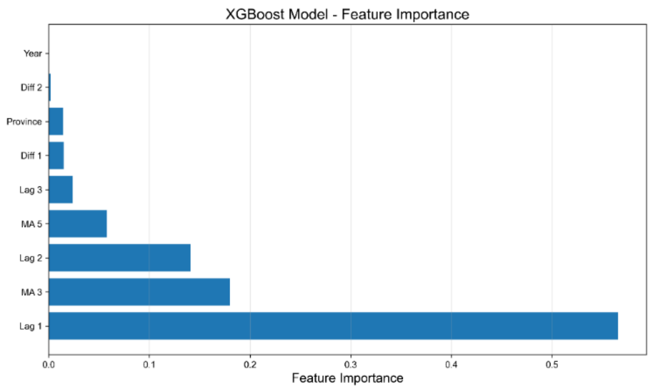

Figure 4. XGBoost Model -Feature Importance

5. Conclusion

Digital inclusive finance can significantly curb regional carbon emissions by promoting the expansion of social financing, but this effect exhibits significant regional heterogeneity. Central and eastern regions, thanks to well-developed digital infrastructure and high penetration of financial technology, have achieved significant emission reduction results. However, western regions, constrained by the digital divide and reliance on heavy industry, have yet to see significant effects. Time series forecasts also indicate that carbon emission intensity across Chinese provinces will exhibit a divergent trend: the eastern region will lead the way, the central region will follow, and the western region will face pressure. Eastern provinces will achieve deep emission reductions through emerging industries and electrification, while central provinces will accelerate their progress through industrial upgrading and energy transformation. Western energy bases, however, will need to address the responsibility for carbon emissions from exported electricity. Therefore, it is recommended to establish a differentiated regional policy framework: In the eastern and central regions, digital inclusive finance should be further expanded, with a focus on supporting financing for clean technology companies. In the western region, digital infrastructure such as 5G base stations and data centers should be prioritized. Financial institutions should be guided by fiscal subsidies to develop low-interest, green digital credit products to gradually unlock emission reduction potential.

As a core mediating variable, moderate growth in social financing can effectively reduce carbon emissions intensity, but overreliance on financing from traditional, energy-intensive industries can weaken this effect. Empirical evidence suggests that when the market capitalization of energy-intensive industries exceeds a threshold, the emission reduction impact of digital inclusive finance weakens. Therefore, a dynamic financing regulatory mechanism is necessary: on the one hand, accurately identify low-carbon projects through digital platforms and establish dedicated green finance funds; on the other hand, implement a carbon emission quota system for energy-intensive enterprises, linking their financing costs to their carbon reduction performance, and thus forcing industrial transformation. Furthermore, financial institutions should be encouraged to develop carbon footprint tracking technology to enhance financing transparency.

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