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Digital Finance, Capital Misallocation, and Urban Carbon Emission Intensity

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Abstract: *With the development of the digital economy and the proposal of the 'dual carbon' goals, digital finance and carbon emissions have become hot topics in related fields of research. However, existing studies lack exploration of the mechanism of capital misallocation. This paper utilises data from 280 cities in China from 2011 to 2021 to conduct research on this issue. The results indicate that digital finance markedly lowers the intensity of urban carbon emissions, with capital misallocation serving as a mediating factor. Digital finance has an inhibitory effect on carbon emission intensity in non-old industrial base cities, eastern and central regions, but its impact on carbon emission intensity in traditional industrial base cities and western regions is not significant.*

Keywords: *Digital Finance; Capital Misallocation; Urban Carbon Emission Intensity; Financial Friction, Non-Old Industrial*

1. Introduction

How digital finance influences carbon emissions has become a major focus in the field of finance and carbon emissions research. Some scholars argue urban carbon emission efficiency can be elevated by digital finance through green technological innovation, the development of the tertiary sector, and economic growth effects [1-3], reduce regional carbon emission intensity by low-carbon technological innovation, economic growth effects, and industrial structure effects [2, 4], supporting the industrialisation of digital technology and the digital transformation of traditional industries [5]. Other scholars argue that digital finance increases household consumption carbon emissions through two mechanisms: expanded consumption scale and upgraded consumption preferences driven by payment convenience and wage premiums. In this context, residents' environmental awareness and social environmental governance play a moderating role [6]. Additionally, some literature suggests that the coverage breadth and usage depth of digital finance have a non-linear impact on manufacturing carbon intensity, initially promoting increases before later inhibiting them. The emission reduction effects depend on the combined influence of scale effects and technology effects [7]. Currently, academic conclusions on the impact of digital finance on carbon emissions are inconsistent, and limited research has explored how capital misallocation influences the link between digital finance and urban carbon emissions.

Can digital finance reduce urban carbon emissions? Does capital misallocation act as a transmission mechanism linking digital finance to carbon emissions? Researches on these questions holds significant theoretical and practical implications. This paper takes urban carbon emission intensity as its research object, uses data from 281 Chinese cities between 2011 and 2017. It analyses the impact of digital finance and capital misallocation on urban carbon emission intensity from both theoretical and empirical perspectives, aiming to address gaps in existing research. The study seeks to provide empirical support and policy recommendations for China's ongoing efforts to explore and improve its urban carbon emission governance system, leverage the enabling role of digital finance, and achieve its dual carbon strategic goals.

2. Theoretical Analysis and Research Hypothesis

2.1 Digital Finance and Carbon Emission Intensity

This paper argues that digital finance influences urban carbon emission intensity in the following ways: First, digital inclusive finance promotes green consumption, green payments, and second-hand platform transactions, thereby fostering green production and lifestyle patterns and reducing resource consumption [8, 9]. Through online credit transaction platforms, digital inclusive finance accelerates the cross-temporal and spatial flow of funds, enhancing the convenience of corporate financing channels [10]. This reduces corporate operational costs and the carbon emissions generated by businesses travelling to and from financial institutions.

Furthermore, digital finance can provide credit support for corporate green transformation. Energy consumption is the primary source of carbon emissions. Whether it is the renovation and upgrading of energy systems, the development and utilisation of new energy sources, or the establishment and improvement of resource recycling systems, all require green technological innovation. The implementation of green technological innovation necessitates the support of the financial system [11]. The long-term shortage of traditional financial services has severely constrained the development of technological innovation. Digital finance can overcome the shortcomings of traditional finance and directly provide more abundant financing support to innovative entities such as enterprises and research institutions, thereby promoting regional innovation. As regional innovation levels improve, digital finance can effectively leverage the promotional role of scientific and technological progress and innovation in enhancing energy efficiency. Additionally, digital finance can make carbon financial products more inclusive and accessible, driving the expansion of carbon trading markets, thereby benefiting urban carbon emissions reduction.

The synergistic development of digital finance and low-carbon finance can serve China's high-quality development. Financial institutions can use digital platforms to screen enterprises, eliminate high-energy-consuming and high-polluting enterprises, and guide financial resources toward environmentally friendly enterprises. Thus, a green-oriented financial resource allocation and management system can be formed through digital platforms [12]. Accordingly, this study puts forward the following hypothesis:

H1: Digital finance contributes to lowering the intensity of urban carbon emissions.

2.2 The Mediating Role of Capital Misallocation

Capital misallocation refers to a state where the actual efficiency of capital allocation deviates from the optimal allocation efficiency. The primary factors influencing capital misallocation include financial frictions, credit constraints, and the development of formal and informal financial systems. From the perspective of financial frictions, financial frictions can explain 30% of capital misallocation in China [13], while digital finance can reduce financial frictions caused by information asymmetry and incomplete contracts [14]. From the perspective of credit constraints, the inclusiveness and universality of digital finance enable previously financially excluded borrowers to access credit funds, influencing corporate financial asset allocation, alleviating credit constraints [15], and reducing capital misallocation. For example, digital finance increases the total supply of rural credit, reduces financing constraints for vulnerable farmers [16], and increases the scale of high-risk financial asset allocation for rural households [17]. Internet finance and fintech can alleviate credit rationing for small and medium-sized enterprises [18, 19].

This paper argues that capital misallocation affects environmental pollution through the following channels. On the one hand, China's industrial policies, such as its heavy chemical industry development strategy, and the fixed asset mortgage credit system of financial institutions have led to the heavy chemical industry occupying a large amount of credit resources. As a result, the current basic situation of China's financial resource allocation is concentrated in capital-intensive, high-energy-consuming, and high-value-added key industries and popular industries [20]. Credit investments have driven the development of these industries, exerting adverse effects on the environment [21] and exacerbating carbon dioxide emissions. Additionally, the allocation of credit resources has increased the share of fixed assets in the heavy chemical industry, further enhancing its credit capacity and stimulating its scale expansion [22], while pollution emissions are positively correlated with the share of fixed assets. Therefore, this further exacerbates carbon emissions. Recently, although the growth rate of financial resources flowing into heavy industries has slowed due to industrial policies, a significant portion of credit resources remains in traditional pillar industries such as steel, coal, and petrochemicals due to long-standing business relationships and 'lifeline' support for various reasons. The proportion of resource allocation in these sectors remains high [20], leading to the solidification of high carbon emissions and path dependence in China. This indicates that there is severe capital misallocation between industries in China, and capital misallocation exacerbates carbon emissions. On the other hand, capital misallocation can suppress energy efficiency and low-carbon technological progress. Factor distortions can hinder improvements in China's energy efficiency through pathways such as locking in

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extensive growth models, encouraging rent-seeking, and restricting inter-regional specialisation and division of labour [23]. Elemental distortions and capital misallocation primarily exert adverse environmental impacts by inhibiting technological progress and low-carbon productivity improvements [24, 25]. Therefore, this paper puts forward the following hypothesis:

H2: Digital finance reduces urban carbon emission intensity by mitigating capital misallocation.

3. Research Design

3.1 Variable Selection and Data Sources

3.1.1 Dependent Variable: Carbon Emission Intensity

The dependent variable in this paper is urban carbon emission intensity, which is calculated as the ratio of total urban carbon emissions to urban gross domestic product (GDP) using data from EDGAR.

3.1.2 Core Explanatory Variable: Digital Finance

The level of digital finance in cities (index) is represented by the city-level ‘Digital Inclusive Finance Index’ compiled by Peking University.

3.1.3 Mechanism Variable: Capital Misallocation

The steps for calculating the capital misallocation index in this paper are as follows:

(1) Calculate the labour and capital inputs of cities. This paper uses 2011 as the base period to calculate the actual GDP of each city, and uses the number of employed persons in each city to represent the labour input. The capital input is calculated using the perpetual inventory method, with the formula as follows:

$$K_{it} = I_{it} \ / P_{it} + \left(1-\delta\right) K_{it-1} \tag{1}$$

Among these, I_{it} is the total fixed asset investment for city i in year t, and P_{it} is the fixed asset price index for city i in year t. Due to the lack of city-level fixed asset price indices, this paper uses provincial fixed asset price indices as a substitute. The asset depreciation rate is set at 9.6%.

(2) Calculating capital output elasticity and labour output elasticity. This paper calculates capital output elasticity and labour output elasticity based on the method used by Zhao et al. (2006) [26]. Assuming constant returns to scale, the Solow residual method is used for calculation, i.e.:

$$Y_{it} = AK_{it}^{\theta_{ki}} L_{it}^{1-\theta_{ki}} \tag{2}$$

In this equation, Y is total output, A is total factor productivity, K is capital input, and L is labour input. We take the logarithm of both sides of the equation, which yields:

$$ln\left(Y_{it} / L_{it}\right) = ln\ A + \theta_{Ki} ln\left(K_{it} / L_{it}\right) + \lambda_i + \ \nu_t + \varepsilon_{it} \tag{3}$$

Among them, ε_{it} is the random disturbance term for city i in year t, Y_{it} ,K_{it} and L_{it} are the actual GDP, capital investment, and labour input for city i in year t, respectively.

(3) Calculation of the relative capital distortion coefficient. This paper borrows the method of Bai and Liu (2018) [27] to calculate the relative capital distortion coefficient.

$$\gamma_{Ki} = \left(\frac{K_i}{K}\right) / \left(\frac{s_i \beta_{Ki}}{\beta_K}\right) \tag{4}$$

Among them, s_i represents the share of city i's actual GDP in the total actual GDP. (K_i/K) represents the proportion of city i's capital in the total capital. β_{Ki} is the capital-output elasticity of city i. ($s_i\beta_{Ki}$)/β_K represents the proportion of capital used by city i when capital is effectively allocated.

(4) Calculate the capital mismatch index, i.e. $kmis_i=1/\gamma_{Ki}$. Considering that the index may have negative values, it is generally recommended to refer to the method described in the existing literature [28] and take the absolute value to obtain the capital misallocation index, i.e. $abstauk = | kmis_i |$

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3.1.4 Control variables

The control variables are as follows: 1) Economic development level (lngdp): measured using the logarithm of regional GDP; 2) Urban population size (lnp): measured using the logarithm of the total urban population at the end of the year; 3) Tertiary industry share (structure): tertiary industry value added / GDP; 4) Forest area (forests): measured using provincial forest area; 5) Per capita road area (road): measured using per capita urban road area; 6) Energy structure (coal): measured using Proportion of coal in overall energy use (million tonnes of standard coal).

3.1.5 Data Sources

The data sources are: EDGAR, the Digital Finance Index released by the Digital Finance Research Centre of Peking University, the China Urban Statistical Yearbook, provincial statistical yearbooks, and some incomplete data were processed using interpolation methods. The descriptive statistics for all variables are shown in Table 1.

Table 1 Descriptive statistics of variables

Variable	Observation	Mean	Standard deviation	Minimum	Maximum
egdp	3,080	4.6728	5.7292	0.0002	91.7109
index	3,080	185.0113	72.9619	17.0200	359.6825
lngdp	3,080	4.6809	0.0269	4.5539	4.7570
lnp	3,080	5.8952	0.6839	3.0057	8.1421
structure	3,080	0.4257	0.1010	0.1436	0.8387
forests	3,080	861.1504	618.6707	6.8100	2614.8500
road	3,080	17.0692	4.3218	4.0400	26.7800
coal	3,080	0.9240	0.4439	0.0010	2.5369

3.2 Measurement Model Specification

This paper specifies the following linear regression model:

$$egdp_{it} = \alpha_0 + \alpha_1 \, index_{it} + \sum \alpha X_{it} + u_i + v_t + \mu_{it} \tag{5}$$

Where: i and t represent the city and the year; *egdp* represents the dependent variable, i.e., urban carbon emission intensity; *index* represents digital finance; X, u, v and μ represent a set of control variables, individual effects, time effects and random errors.

The digital finance may affect urban carbon emission intensity by improving capital misallocation. This study explores the intermediary mechanism of capital misallocation. The following mechanism analysis model is designed:

$$abstauk_{it} = \alpha_0 + \alpha_1 \, index_{it} + \sum \alpha X_{it} + u_i + v_t + \mu_{it} \tag{6}$$

$$cgdp_{it} = \alpha_0 + \alpha_1 abstauk_{it} + \alpha_2 index_{it} + \sum \alpha X_{it} + u_i + v_t + \mu_{it} \tag{7}$$

In the equation, the core variable in the mechanism test is capital misallocation (*abstauk*); other symbols are consistent with the above equation.

4. Empirical Results

4.1 Baseline Regression Results

According to the model specification, the baseline regression results of the impact of digital finance on urban carbon emission intensity are shown in Table 2. Columns (1) to (7) present the benchmark regression results with control variables added stepwise. In column (7), the regression coefficient for urban digital finance (index) is -0.044 and significant. The benchmark regression indicates that urban digital finance is inversely associated with urban carbon emission intensity.

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Table 2 Benchmark regression results

	(1) egdp	(2) egdp	(3) egdp	(4) egdp	(5) egdp	(6) egdp	(7) egdp
index	-0.056***	-0.054***	-0.048**	-0.045**	-0.045**	-0.044**	-0.044**
	(-2.736)	(-2.647)	(-2.273)	(-2.212)	(-2.190)	(-2.095)	(-2.106)
lngdp		-10.024**	-8.681*	-6.819	-6.825	-5.767	-4.843
		(-1.992)	(-1.744)	(-1.262)	(-1.296)	(-1.111)	(-0.949)
lnp			-3.638***	-3.477***	-3.477***	-3.459***	-3.694***
			(-3.373)	(-3.219)	(-3.218)	(-3.214)	(-3.338)
structure				4.096	4.096	3.933	4.041
				(1.058)	(1.060)	(1.014)	(1.044)
forests					-0.000	-0.001	-0.002
					(-0.010)	(-0.275)	(-0.771)
road						0.108**	0.110**
						(2.187)	(2.219)
coal							-1.354**
							(-2.059)
_cons	14.984***	61.636***	75.573***	63.762**	63.815**	57.337**	56.776**
	(3.951)	(2.692)	(3.225)	(2.409)	(2.511)	(2.292)	(2.297)
N	3080	3080	3080	3080	3080	3080	3080
r2_a	0.7286	0.7289	0.7302	0.7306	0.7305	0.7310	0.7322

Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The same applies to the following table.

4.2 Robustness Testing

First, this paper employs a replacement model for robustness testing. Since urban carbon emission intensity cannot be less than zero, using the OLS method for estimation may fail to yield consistent estimates. To address this, Tobin proposed an estimation method for constrained dependent variables, namely, using the maximum likelihood estimation method to ensure consistent results from the reviewed data. For panel data, this paper employs a mixed Tobit regression for robustness testing. The results in Column (1) of Table 3 show that the coefficient for digital finance (index) in the mixed Tobit regression is -0.044 and significant. This result indicates that after applying the replacement model, digital finance still reduces urban carbon emission intensity.

This study measures the level of the digital economy in cities using the principal component method (dec), based on indicators such as the share of internet users, the share of mobile phone users, the proportion of employees in the information transmission and technology services sector, per capita telecommunications service volume, and the urban digital financial inclusion index. For robustness checks, digital finance is employed as a proxy for the digital economy. As shown in column (2) of Table 3, the coefficient for the digital economy is negative and statistically significant.

Column (3) of Table 3 shows that after excluding samples from municipalities, the regression results indicate that the coefficient of digital finance (index) is -0.043, significant at the 5% level. Considering that many scholars regard the launch of Yu'e Bao in 2013 as the beginning of China's digital finance era, Column (4) presents a robustness check using data from this period onward. The results reveal that the coefficient of digital finance (index) is -0.068, also significant at the 5% level.

Table 3 Robustness test

	(1) egdp	(2) egdp	(3) egdp	(4) egdp	(5) egdp	(6) egdp	(7) index	(8) egdp
index	-0.044***		-0.043**	-0.068**	-0.059***			-0.192***
	(-4.619)		(-2.012)	(-2.496)	(-3.710)			(-8.160)
dec		-0.812***						
		(-5.786)						
index_1						-0.099***		
						(-3.044)		
iv							-0.676***	
							(-15.278)	
_cons	50.866**	42.193*	63.207**	52.270*	34.429	63.516**	313.909***	52.489**
	(2.262)	(1.703)	(2.506)	(1.824)	(1.009)	(2.345)	(7.598)	(2.249)
Control FE	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	3080	3080	3036	2520	2429	2800	3080	3080
r2_a		0.7325	0.7332	0.7630	0.6632	0.7563	0.9952	0.7115

Finally, this paper considers the treatment of endogeneity issues. 1) Omitted variables. To reduce the impact of omitted variables on the regression results, this paper gradually adds four variables that affect urban carbon emissions—urban human capital (human), urban social security level (isa), private economic vitality (entr), and foreign direct investment (fdi)—as control variables in the baseline regression model for testing. The regression results in Column (5) of Table 3 confirm that, even after accounting for omitted variables, digital finance still significantly reduces urban carbon emission intensity. 2) Reverse causality. To mitigate endogeneity issues caused by reverse causality, this paper uses a lagged one-period digital finance variable as the explanatory variable and re-runs the regression. The results in column (6) show that the coefficient for digital finance is -0.099, which is significant at the 1% significance level, indicating that digital finance has an inhibitory effect on urban carbon emission intensity. This result remains consistent with the benchmark regression results. 3) This study uses the distance between a city and Hangzhou, multiplied by the average level of digital finance development in cities other than the city in question, as the instrumental variable. The rationality of constructing this instrumental variable lies in the following: first, the average level of digital finance development in other cities excluding the city itself is strongly correlated with the city's own level of digital finance development. Referring to previous literature, it is believed that Hangzhou has a high level of digital finance development, and the farther a city is from Hangzhou, the poorer its digital finance development. Therefore, this instrumental variable meets the correlation requirement. Second, this instrumental variable excludes the digital financial development level of the city itself, so it does not affect the city's carbon emission intensity, satisfying the exclusivity requirement. Additionally, the results in Column (7) of Table 3 show that this instrumental variable passed the over-identification test and the weak instrumental variable test (Anderson canonical correlation LM statistic Chi-sq (1) = 549.422***; Cragg-Donald Wald F statistic = 604.226 > 16.38). The first-stage outcomes of the two-stage least squares (2SLS) estimation reveal that the coefficient of the instrumental variable (IV) is -0.676 and statistically significant. This finding suggests a strong negative association between local digital finance and the instrumental variable. As shown in column (8), the coefficient of digital finance (index) is -0.192, also significant at the 1% level. These results confirm that the 2SLS estimates continue to support Hypothesis 1, indicating that digital finance can effectively reduce urban carbon emission intensity.

4.3 Results of the Mediating Mechanism

To examine whether digital finance mitigates urban carbon emission intensity by alleviating capital misallocation and improving capital allocation, this study constructs a mediating effect model. As shown in column (1) of Table 4, the coefficient of digital finance is -0.011, indicating a significant reduction in capital misallocation at the 1% level. Column (2) shows that the coefficients for digital finance and capital misallocation are -0.049 and -0.458, respectively, both significant at the 5% level. Taken together, these results suggest that digital finance can lower urban carbon emission intensity by reducing capital misallocation.

Table 4 Mechanism Testing and Heterogeneity Analysis

	(1) abstauk1	(2) egdp	(3) egdp	(4) egdp	(5) egdp	(6) egdp	(7) egdp
index	-0.011***	-0.049**	-0.004	-0.096***	-0.075***	-0.084***	0.113
	(-7.312)	(-2.260)	(-0.113)	(-5.705)	(-4.852)	(-5.120)	(1.250)
abstauk1		-0.458**					
		(-2.531)					
_cons	9.500***	61.131**	15.783	128.797***	41.277	-6.465	-26.688
	(4.530)	(2.466)	(0.395)	(3.361)	(1.043)	(-0.246)	(-0.234)
Control FE	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
N	3080	3080	1309	1771	1243	1177	660
r2_a	0.8587	0.7326	0.7745	0.6789	0.5170	0.6629	0.8325

4.4 Heterogeneity Analysis

Old industrial base cities typically exhibit high energy consumption, severe environmental pollution, and elevated carbon emissions, making them critical yet challenging targets for energy conservation, emission reduction, and ecological protection. This study investigates whether the effect of digital finance on urban carbon emission intensity differs between old industrial base cities and other cities. Based on the National Plan for the Adjustment and Transformation of Old Industrial Bases (2013–2022) (State Council Document [2013] No. 46), the sample cities are classified into old industrial base cities and non-old industrial base cities. The empirical results, shown in columns (3) and (4) of Table 4, reveal that digital finance significantly lowers carbon emission intensity in non-old industrial base cities, whereas its effect is not statistically significant in old industrial base cities.

This study categorizes the sampled cities into eastern, central, and western regions to investigate the effect of digital finance on urban carbon emission intensity. The empirical findings are presented in columns (5) through (7) of Table 4. The results indicate that digital finance significantly reduces carbon emission intensity in eastern and central cities, whereas no significant effect is observed in western cities. This suggests that the western region lags behind the eastern and central regions in digital finance development, and therefore, the mitigating effect of digital finance on carbon emissions has not yet materialized in the west.

5. Conclusions and Recommendations

Can digital finance reduce urban carbon emissions? Does capital misallocation play a mechanism role between digital finance and carbon emissions? Research on these issues holds significant theoretical and practical implications. To this end, this paper conducts theoretical and empirical research on the issue using data from 280 Chinese cities from 2011 to 2021. The research findings and related recommendations are as follows:

First, this paper argues that digital finance can significantly reduce urban carbon emission intensity, with capital misallocation playing an intermediary role. Based on this, the paper recommends that the emission reduction effects of digital finance should be better leveraged. To this end, efforts should be made to accelerate the deep integration of digital finance with the real economy, guide credit funds toward green and low-carbon economies, and increase support for resource-efficient and environmentally friendly enterprises and projects. Additionally, urban low-carbon and high-quality development should be promoted through pathways such as energy system upgrades and green technology innovation. Furthermore, digital technology should be utilised to vigorously develop green finance and low-carbon finance, advance climate finance and investment initiatives, and emphasise the financial attributes of carbon markets.

Second, the paper divides cities into old industrial base and non-old industrial base cities for heterogeneous analysis. The findings show that digital finance significantly reduces carbon emission intensity in non-old industrial base cities, while its effect in old industrial base cities is not significant. Accordingly, efforts should be directed toward identifying ways to reduce capital misallocation in both types of cities, thereby improving the efficiency of financial resource allocation.

Finally, the results indicate that digital finance lowers carbon emission intensity in eastern and central regions, but its impact in western regions is negligible. Therefore, policies should focus on advancing digital finance development in the western region to alleviate local financing constraints.

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