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DIGITAL FINANCIAL INCLUSION AND URBAN CARBON EMISSIONS: AN EMPIRICAL STUDY BASED ON NONLINEAR CHARACTERISTICS AND MECHANISM TESTING

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ABSTRACT

Purpose- This study intends to investigate the nonlinear relationship between Digital Financial Inclusion (DFI) and carbon emission intensity in Chinese cities. It seeks to uncover the potential "U-shaped" pattern of DFI's environmental effects and examine the underlying mechanisms, including technological innovation and urbanization, while considering variations across different city types.
Methodology- Applying balanced panel data from 270 Chinese cities spanning 2012 to 2022, the study employs a two-way fixed effects model and the system Generalized Method of Moments (GMM) for empirical analysis. The research examines the nonlinear impact of DFI on carbon emission intensity and explores the mediating role of technological innovation and the moderating effect of urbanization.
Findings- The results indicate that DFI significantly reduces carbon emission intensity, but this effect follows a distinct "U-shaped" pattern, with a turning point at an index value of 137, revealing diminishing marginal returns in emission reduction benefits. Technological innovation is identified as a key mediating channel. Urbanization negatively moderates the emission reduction effect, reflecting an "inclusive compensation" characteristic of DFI in less developed areas. Furthermore, resource-based cities exhibit a stronger initial emission reduction effect but face more severe U-shaped rebound risks.
Conclusion- We provide empirical evidence supporting the design of differentiated emission reduction strategies. It highlights the importance of considering the nonlinear dynamics of DFI and local characteristics—such as urbanization and city type—in formulating effective environmental policies.

Keywords: Digital financial inclusion, carbon emission intensity, U-shaped curve, resource endowment, carbon lock-in
JEL Codes: Q56, O13, O33

1. INTRODUCTION

In the macro context of the global response to climate change and China's comprehensive promotion of the "dual carbon" (carbon peak and carbon neutrality) goals, exploring new drivers that balance economic growth with carbon emission reduction has become a core issue in achieving high-quality development (Gao & Li, 2024). In recent years, Digital Financial Inclusion (DFI), with its advantages of low cost and wide coverage, has effectively broken the geographical and class barriers of traditional finance, and is widely regarded as a "new engine" for optimizing resource allocation and driving green transformation (Zheng et al., 2025). However, digital technology itself exhibits a significant dual nature regarding its environmental effects: on the one hand, it can reduce carbon emissions by improving total factor productivity and promoting industrial structure upgrading; on the other hand, the high energy consumption characteristics of underlying infrastructures such as data centers, coupled with the expansion of economic activities triggered by the popularization of digital finance, can easily trigger a "rebound effect" in energy consumption, leading to a local or overall increase in carbon emissions (Li, 2025). Therefore, an in-depth exploration of nonlinear effect of DFI on carbon emissions as well as its boundary conditions holds high academic value and practical significance.

A review of existing literature reveals that although research on the relationship between the digital economy and environmental pollution is increasingly abundant, most studies are still limited to exploring their linear relationship. Although some scholars have begun to reorganize the nonlinear or U-shaped characteristics within this relationship, there is still a lack of sufficient empirical precision in measuring the specific "turning point" of DFI's emission reduction effect, making it difficult to provide micro-level guidance for policy implementation. Furthermore, existing research often treats all cities as homogeneous when exploring this issue, ignoring urban regional heterogeneity under the context of the "resource curse" , as well as the deep constraints on the implementation of green finance policies caused by the "carbon lock-in" effect formed through long-term reliance on fossil fuels.

In view of this, based on the balanced panel data of 270 prefecture-level and above cities in China from 2012 to 2022, this paper conducts a systematic empirical test using two-way fixed effects and system GMM models. The marginal contributions of current paper are mainly reflected as follows: (1) Revising the linear perspective: Breaking through the traditional linear assumption, this study confirms a significant "first decline and then rise" U-shaped relationship between DFI and carbon emission intensity, and precisely calculates that the turning point is located near the index value of 137, profoundly revealing the "diminishing marginal returns" rule of emission reduction dividends. (2) Expanding the heterogeneity perspective: By incorporating resource endowments into the analytical framework for the first time, it finds that resource-based cities exhibit stronger emission reduction "penetration" in the initial stage, but face a more severe rebound risk after crossing the turning point; meanwhile, it confirms that the urbanization level plays a "negative moderating" role in the emission reduction process. (3) Clarifying the mechanism of action: Through a mediation effect model, it rigorously verifies the core transmission pathway of DFI in "alleviating financing constraints and thereby promoting green technological innovation."

2.LITERATURE REVIEW

2.1. The Environmental Duality of Digital Finance

Regarding the environmental impact of DFI and its underlying technologies, existing literature primarily presents two contrasting views. The mainstream perspective, based on the financial function viewpoint, supports the "emission reduction hypothesis" of digital finance. For instance, Le et al. (2020), using evidence from emerging Asian economies, pointed out that financial inclusion effectively suppresses carbon dioxide emissions by reducing transaction costs (Le et al., 2020). Wan et al. (2022), utilizing data from Chinese cities, further confirmed how digital finance substantially curbs pollution intensity by driving industrial structure upgrades. Recent research also found that a robust digital financial sector can effectively promote carbon emission reductions in traditional real sectors by lowering the financing costs of green development.However, another group of scholars emphasizes the "energy rebound" risk associated with Information and Communication Technology . The classic study by Sadorsky (2012) showed that the universal application of communication technology and information is often accompanied by surges in electricity demand. Recently, Li (2025) provided new empirical evidence based on micro-level household data in emerging countries, confirming that while DFI promotes survival- and development-oriented consumption upgrades, it significantly increases both direct and indirect carbon emissions, suggesting that the negative environmental externalities of digital finance may gradually intensify as it develops. However, recent empirical studies emphasize the "energy rebound" risk associated with large-scale digital infrastructure. Pu et al. (2025) warned that while digital technology innovation greatly decreases carbon intensity over the near term, the widespread deployment of new digital technologies inevitably triggers a long-term carbon rebound effect, potentially offsetting the initial efficiency gains.

2.2. Nonlinear Characteristics of the Digital Economy and Carbon Emissions

Based on the aforementioned contradictions, recent studies have begun to focus on nonlinear characteristics. Li & Wang (2022) were the first to find that the relationship within the carbon emissions and digital economy may exhibit a 'first decline and then rise' U-shaped pattern. Concurrently, recent research by Kang et al. (2025) indicates that the emission reduction impact of DFI demonstrates notable heterogeneity depending on city type, alongside cross-regional spatial spillover effects. However, the measurement of the exact turning point in this regard remains imprecise. Further clarifying the specific turning point of DFI's emission reduction effect and its intrinsic driving mechanisms is of great significance for grasping the optimal environmental window for digital finance development, which is exactly the direction this paper seeks to explore deeply.

2.3. Resource Endowments and the "Carbon Lock-in" Effect

Furthermore, when exploring the emission reduction effects of digital finance, existing research has overlooked the heterogeneity under the context of the 'resource curse'. As noted by Badeeb, Lean, & Clark (2017), resource-based economies face severe transformation deadlocks. Unruh (2000) defined this as the 'carbon lock-in' effect, where fossil-fuel-dependent infrastructures and institutions create systematic barriers to green transitions. Therefore, exploring the role of DFI in breaking the "high-carbon lock-in" of resource-based cities, as well as the potential rebound risks it may trigger, is a critical gap that urgently needs to be addressed in the current literature.

3. THEORETICAL ANALYSIS AND RESEARCH DESIGN

3.1. Theoretical Mechanism and Research Hypothesis

The interplay of DFI on urban carbon emissions is complex. The present paper establishes a theoretical framework from three dimensions: direct effects, nonlinear characteristics, and transmission channels.

3.1.1. Direct Emission Reduction Effect

From a financial function perspective, DFI achieves carbon emission reduction through two pathways. First, it mitigates information asymmetry. Traditional financial institutions often allocate credit to green small and medium sized enterprises because of high-risk control costs. Through leveraging big data to refine credit profiles, DFI reduces the cost of financial service access, directing funds to low-energy, high-efficiency green industries and optimizing resource allocation (Stiglitz & Weiss, 1981). Second, it replaces physical services with contactless alternatives. Micro-level evidence indicates that smartphone banking and digital financial platforms significantly reduce the need for physical travel and offline branch operations, which directly lowers the household and corporate carbon footprints (Li, 2025).

Hypothesis 1 (H1): The development of Digital Financial Inclusion can generally reduce urban carbon emission intensity.

3.1.2. U-shaped Nonlinear Characteristics

Recent literature increasingly corroborates this nonlinear dynamic. For instance, studies examining G20 countries have identified curvilinear or N-shaped relationships between financial inclusion and CO2 emissions, emphasizing that emission reduction effects often stabilize or reverse at advanced levels of financial development (Shaheen, 2025). Furthermore, recent empirical evidence from Chinese cities verifies a U-shaped relationship between digital finance and carbon emission efficiency, primarily driven by the escalating energy demands of digital infrastructure in later stages (Chen, n.d.).

While DFI inherently reduces emissions, its emission reduction benefits may follow the law of diminishing marginal utility and be constrained by the Jevons Paradox. In the early development phase, DFI adoption drives the elimination of outdated production capacity through technology spillover effects, yielding extremely high marginal emission reductions (Lange et al., 2020). However, as development enters deeper waters, two factors may weaken or even reverse emission reduction effects: First, the high energy consumption lock-in of infrastructure. Data centers, 5G base stations, and blockchain computing power are inherently energy-intensive industries, and their scaled-up electricity consumption cannot be ignored. Second, the rebound effect from scale expansion. Financial facilitation reduces production and consumption costs, potentially stimulating excessive expansion of total output and consumption, thereby offsetting the emission reduction benefits from improved energy efficiency per unit.

Hypothesis 2 (H2): The impact of Digital Financial Inclusion on carbon emission intensity follows a U-shaped pattern, initially suppressing emissions before gradually recovering.

3.1.3. The Mediating Mechanism of Technological Innovation

The endogenous growth theory asserts that technological progress serves as the fundamental driver to overcome environmental constraints (Romer, 1990). Green technology innovation, characterized by its long development cycles, high risks, and limited collateral, faces severe external financing constraints (Feng et al., 2022). DFI provides stable funding for enterprises to upgrade clean production equipment and develop green processes by expanding financing channels and reducing costs, thereby curbing carbon emissions at the source.This mechanism is strongly supported by recent international and regional evidence, which highlights that technological innovation acts as a crucial moderating and mediating variable. By alleviating corporate financial constraints, digital finance bridges the gap between financial inclusion and environmental sustainability, directly stimulating investments in cleaner technologies and reducing regional CO2 emissions (He & Jiang, 2024).

Hypothesis 3 (H3): Investment in technological innovation serves as the key intermediary channel for Digital Financial Inclusion to achieve emission reduction effects.

3.2. Data Sources and Variable Selection

This paper employs balanced panel data on 270 prefecture-level and above cities in China for the years 2012–2022. Carbon emission figures are rooted in the China Carbon Accounting Database—a source based on nighttime light inversion with proven high accuracy—and DFI Index is obtained from Peking University's Digital Finance Research Center. The main variables are defined as follows:

Dependent variable: Urban carbon emission intensity (Carbon), measured by carbon dioxide emissions per unit of GDP, mirroring the green efficiency of economic growth.

Core explanatory variables: Digital Financial Inclusion Index (Carbon) and its squared term ($\ln DIF^2$). To eliminate heteroscedasticity, the index was log-transformed.

Mediating variable: Technology investment ($\ln Tech$), measured by local fiscal expenditure on science and technology. Moderating variable: Urbanization rate (Urb), calculated as the percentage of the population that are urban permanent residents.

Control variables: To eliminate confounding factors, industrial structure (Ind, proportion of the secondary industry) and foreign direct investment ($\ln FDI$) were selected as control variables.

Table 1 presents descriptive statistics of primary variables. The dependent variable, carbon emission intensity (Carbon), has a mean of 3.361 with a large standard deviation, indicating significant disparities in low-carbon development levels across cities. DFI Index (($\ln DIF$), which is primary explanatory variable, ranges from 4.017 to 5.375, reflecting the exponential growth of digital finance during the study period. Furthermore, all control variables exhibit statistical characteristics within reasonable ranges, with no outliers detected, thus meeting the fundamental requirements for subsequent regression analysis.

Table 1: Descriptive Statistics of Primary Variables

Variable quantity	Observed number	Mean value	Standard deviation	Minimum	Median	Maximum
Carbon	2,970	3.361	3.254	0.064	2.461	28.852
ln_DIF	2,970	5.274	0.365	4.017	5.375	5.889
ln_DIF_sq	2,970	27.949	3.741	16.134	28.894	34.681
Industrial structure	2,970	44.468	10.720	11.700	44.985	81.820
Urbanization rate	2,970	0.539	0.166	0.112	0.531	1.000
ln_FDI	2,970	-4.949	1.455	-9.197	-4.637	-2.185
ln_Tech	2,970	-4.417	0.936	-7.390	-4.395	-1.575

3.3. Model Specification

For a more comprehensive verification of the aforementioned hypothesis, we construct a multi-level econometric model system based on York et al., 2003 and Balli & Sørensen, 2013.

3.3.1. Benchmark and Nonlinear Models

To test H1 and H2, we utilize a bidirectional fixed effects model containing quadratic terms:

$$Carbon_{it} = \alpha_0 + \alpha_1 \ln DIF_{it} + \alpha_2(\ln DIF_{it})^2 + \lambda Controls_{it} + \mu_i + \delta_t + \varepsilon_{it.} \tag{1}$$

Here, μ_i represents the city-specific fixed effect, and δ_t indicates the time-specific fixed effect. If α_1<0 and α_2>0, it confirms the U-shaped characteristic. Based on the coefficient, we can calculate the inflection point value $K = -\alpha_1/(2\alpha_2)$.

3.3.2. Mechanism and Regulatory Effect Model

To validate H3, a mediation effect model was constructed using the stepwise regression method:

$$\ln Tech_{it} = \beta_0 + \beta_1 \ln DIF_{it} + \lambda Controls_{it} + \mu_i + \delta_t + \varepsilon_{it}. \tag{2}$$

To examine the moderating effect of urbanization, an interaction term is introduced into equation (1):

$$Carbon_{it} = \cdots + \gamma(\ln DIF_{it} \times Urb_{it}) + \cdots \tag{3}$$

3.3.3. Dynamic Panel Model

To account for the carbon lock-in inertia in emissions, the dynamic panel model incorporates a lagged first-period dependent variable, thereby constructing the dynamic panel model:

$$Carbon_{it} = \rho Carbon_{it-1} + \theta_1 \ln DIF_{it} + \theta_2(\ln DIF_{it})^2 + \cdots + \varepsilon_{it}. \tag{4}$$

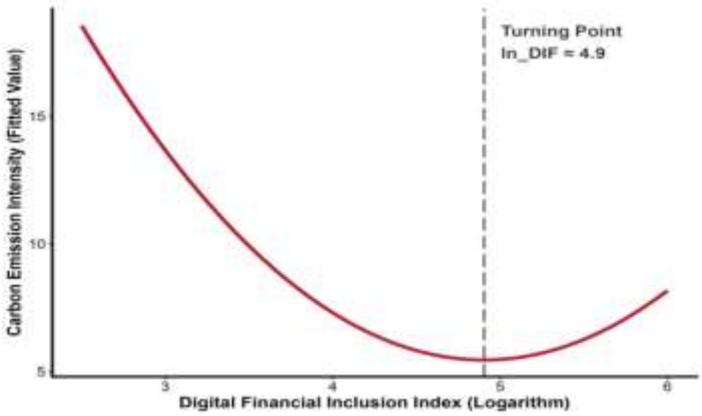
The two-step System-GMM approach is used to estimate equation (4) to address the potential endogeneity issue.

4. EMPIRICAL RESULTS AND ANALYSIS

4.1. The Analysis of Nonlinear Characteristics of Regression

Table 2 shows the core empirical results. Column (1) indicates that without the squared term, the regression coefficient of $\ln DIF$ is -2.594, statistically meaningful at the 1% level. It means that, from the perspective of overall average effects, a 1% increase in digital finance reduces carbon emission intensity by approximately 2.59%, validating H1. After introducing the square term in column (2), the coefficient of the first-order term is -22.245 and the coefficient of the second-order term is 2.268, both of which are significant and have opposite signs (negative, positive). This confirms that the relationship between DFI and carbon emissions follows a significant "U-shaped" pattern rather than a simple linear one (see Fig. 1). This finding aligns with Zhou et al. (2024), who similarly discovered a nonlinear effect of digital finance on carbon performance characterized by initial suppression followed by promotion (Zhou & Wang, 2024). This suggests that as digital finance development deepens, its marginal emission reduction effect gradually diminishes. Calculations indicate the inflection point of the curve occurs at ln DIF ≈ 4.92 (corresponding to an original index of approximately 137).

Figure 1: U-shaped Fitting Curve Graph



Using the inflection point value of 4.92 as a threshold, the sample was divided into "early development" and "mature phase" for grouped regression analysis (Table 2, columns 3-4). The results were highly enlightening: In the early development phase (ln DIF ≤4.92), the regression coefficient reached -2.381 ($p<0.01$), indicating that DFI effectively filled the gap in traditional finance during the initial stage, demonstrating strong emission reduction momentum. In the mature phase (ln DIF>4.92), the regression coefficient plummeted to -0.580 and lost statistical significance. This strongly demonstrates that after crossing the inflection point, relying solely on digital finance expansion faces emission reduction bottlenecks, with potential rebound risks triggered by infrastructure energy consumption.

Table 2: Baseline Regression and Stage-based Heterogeneity Results

Variables	(1) Baseline(Linear)	(2) Non-linear(U-Shape)	(3) Early Stage(Left of Turn)	(4) Mature Stage(Right of Turn)
ln_DIF	-2.594***	-22.245***	-2.381***	-0.58
	-0.29	-1.913	-0.776	-0.548
ln_DIF²		2.268***		
		-0.218		
Ind	-0.061***	-0.068***	-0.059***	-0.042***
	-0.003	-0.003	-0.004	-0.009
Urb	-0.584**	-0.473*	-0.612**	-0.115
	-0.21	-0.217	-0.231	-0.402
ln_FDI	0.023	0.008	0.015	0.033
	-0.015	-0.015	-0.019	-0.024
ln_Tech	-0.124***	-0.192***	-0.155***	-0.201***
	-0.028	-0.03	-0.035	-0.051
Constant	8.452***	45.320***	9.102***	3.220*
	-1.201	-3.55	-1.54	-1.89
Observations	2970	2970	1450	1520
R-squared	0.145	0.184	0.152	0.098
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.2. Transmission Mechanism and Regulatory Effects

The mechanism test results (detailed tables omitted due to space constraints) demonstrate that in the regression with technological input ($\ln \mathrm{Tech}$) as the dependent variable, the coefficient of $\ln \mathrm{DIF}$is dramatically positive (0.352, $p < 0.01$). Combined with the considerable negative influence of $\ln \mathrm{Tech}$ on carbon emissions in the baseline regression (-0.192, Table 2, Column 1), the mediation effect criterion confirms that "promoting green technological innovation" serves as a crucial channel for DFI to exert its emission reduction effects, thereby validating Hypothesis H3. The moderating effect analysis (Table 3, Column 1) implies that the coefficient of the interaction term $\ln \mathrm{DIF} \times \mathrm{Urb}$ is 1.777 ($p < 0.01$), opposite in sign to the main effect, indicating that urbanization exerts a negative moderating effect on emission reduction. This finding highlights DFI's "inclusive compensation" characteristic: in underdeveloped regions with low urbanization rates where financial exclusion is severe, the introduction of DFI effectively fills the financial service gap, providing critical support for local low-carbon development with higher marginal emission reduction benefits. In highly urbanized areas, however, the emission reduction dividends of DFI are partially diluted due to crowding effects and energy demand rigidity.

4.3. Heterogeneity and Robustness Analysis

Considering the spatial differences in China's resource endowment, we further disaggregated the sample into resource-based and non-resource-based cities, with the results shown in Table 3, columns 2–3. For resource-based cities, the absolute value of the first-order coefficient is 38.416, substantially larger than the corresponding figure of 7.365 for non-resource-based cities. It demonstrates that DFI has a stronger structural correction effect in breaking the "high-carbon lock-in" of resource-based cities (Sachs & Warner, 2001). However, its second-order coefficient is also larger (3.928), suggesting that although resource-based cities achieve significant initial emission reductions, they also face a steeper U-shaped rebound risk, necessitating vigilance against energy rebound during the digitalization process (Wang et al., 2024). Finally, to address endogeneity and verify the robustness of the results, we employ the systematic GMM method (Table 3, column 4). The results reveal that the one-period lagged carbon emission coefficient ($\mathrm{L.Carbon}$) is as high as 0.930 ($p < 0.01$), confirming the strong path dependence of carbon emissions. After controlling for this dynamic inertia and endogeneity, the U-shaped characteristics of the core explanatory variables remain robust. Additionally, robustness tests using one-period lagged explanatory variables and excluding municipal samples all support the above conclusions.

Table 3: Mechanism, Moderation, and Advanced Heterogeneity Analysis

Variables	(1) Moderation(Interaction)	(2) ResourceCities	(3) Non-ResourceCities	(4) Dynamic(System GMM)
L.Carbon(Lagged 1)				0.930***
				-0.001
ln_DIF	-2.084***	-38.416***	-7.365	4.674***
	-0.313	-4.034	-1.924	-0.223
ln_DIF^2		3.928***	0.690*	-0.495***
		-0.445	-0.22	-0.022
ln_DIF × Urb	1.777***			
	-0.275			
Controls	YES	YES	YES	YES
Constant	6.551***	89.201***	15.332***	-
	-1.502	-8.12	-4.33	-
Observations	2970	1265	1705	2700
R-squared / AR(2)	0.164	0.235	0.157	0.45 (p-val)
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. "Controls" include Ind, Urb, ln_FDI, ln_Tech.

5. CONCLUSIONS

5.1. Main Conclusions

This study systematically investigates the nonlinear impact and underlying mechanisms of DFI on carbon emission intensity, utilizing balanced panel data from 270 Chinese cities spanning 2012 to 2022. The main empirical findings are fourfold:

(1) Nonlinear Duality: A significant "U-shaped" relationship exists between DFI and carbon emission intensity, with the inflection point occurring at a digital finance index of approximately 137. This indicates that while digital finance significantly curbs emissions initially, its marginal emission reduction dividend follows the law of "diminishing returns." This finding aligns with recent literature indicating that the fast growth of digital infrastructure and data centers eventually introduces severe energy-intensive burdens that can offset early emission reduction gains (Dong et al., 2025).

(2) Transmission Mechanism: Alleviating financing constraints to promote green technological innovation acts as the critical intermediary channel. Digital finance effectively bridges the funding gap for environmental sustainability, accelerating the clean transformation of enterprises and directly lowering carbon intensity (Jiang et al., 2024).

(3) Heterogeneity and Moderation: The urbanization rate exerts a negative moderating effect on emission reductions, confirming the "inclusive compensation" feature of DFI. Furthermore, resource-based cities exhibit a stronger structural correction effect in the early stages but face a much steeper U-shaped rebound risk subsequently (Kang et al., 2025).

(4) Dynamic Characteristics: Urban carbon emissions demonstrate significant path dependence and a robust "carbon lock-in" effect, emphasizing the immense inertia of historical high-carbon development models.

5.2. Policy Implications

Based on the empirical findings and the urgent requirements of the global "dual carbon" goals, we propose the differentiated policy recommendations as follows:

(1) Implement Stage-Specific Digital Finance Strategies: Policymakers must abandon "one-size-fits-all" approaches and adopt threshold-based governance. For regions with a DFI index below 137, local governments should accelerate the deployment of digital financial infrastructure to fully unleash its "inclusive compensation" dividend and lower regional carbon abatement costs. Conversely, for mature regions that have crossed the inflection point, policies must pivot from scale expansion to quality enhancement. This involves strictly regulating the energy consumption of new digital infrastructure (e.g. 5G base stations and data centers) to flatten the U-shaped rebound curve.

(2) Construct Targeted "Digital-Green" Financial Conduits: Given that green technological innovation is the core mediator, financial institutions should design specialized digital credit products that strictly ring-fence funds for green R&D and clean production. By utilizing big data and blockchain for end-to-end capital tracking, policymakers can accelerate the market exit of high-pollution and high-emission enterprises while preventing digital funds from flowing into the scale-expansion of carbon-intensive activities.

(3) Design Asymmetric Low-Carbon Transitions for Resource-Based Cities: Recognizing their steep rebound risks, resource-based cities must capitalize on the early "structural correction" window provided by digital finance. Local governments in these areas should mandate strict renewable energy purchasing quotas for newly established digital platforms and couple digital integration directly with industrial decarbonization metrics to permanently break the "carbon lock-in."

(4)Foster Spatially Synergistic Governance: Because highly urbanized areas experience crowding effects that dilute emission reduction benefits, national digital economy strategies should intentionally direct digital financial resources toward less developed, lower-urbanization regions where the marginal emission reduction effects are strongest. Cultivating this spatial spillover effect will maximize the marginal carbon productivity of digital finance at a macroeconomic level.

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