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Economies

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Suggested Citation: Chen, Liuwu; Zhang, Guimei (2025) : Exploring the impact of digital inclusive finance and industrial structure upgrading on high-quality economic development: Evidence from a Spatial Durbin Model, *Economies*, ISSN 2227-7099, MDPI, Basel, Vol. 13, Iss. 8, pp. 1-32, <https://doi.org/10.3390/economies13080212>

This Version is available at:

<https://hdl.handle.net/10419/329492>

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Article

Exploring the Impact of Digital Inclusive Finance and Industrial Structure Upgrading on High-Quality Economic Development: Evidence from a Spatial Durbin Model

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Abstract

This study investigates the impact and mechanisms of digital inclusive finance (DIF) on high-quality economic development in China. Drawing on panel data from 281 prefecture-level cities between 2011 and 2021, we employ a Spatial Durbin Model (SDM) to analyze both the direct effects and spatial spillovers of DIF. The results indicate that (1) DIF has a significantly positive effect on high-quality development, which remains robust after conducting various stability and endogeneity tests; (2) DIF strongly contributes to economic upgrading in eastern regions, while its impact is weaker or even negative in central and western regions, revealing notable regional disparities exist; (3) a key finding is the identification of a double-threshold effect, suggesting that the positive influence of DIF only emerges when financial and industrial development surpass certain thresholds; (4) results from the two-regime SDM further show that spillover effects are more prominent in non-central cities than in central ones; and (5) mechanism analysis reveals that DIF facilitates high-quality growth primarily by promoting industrial structure upgrading. These findings underscore the importance of region-specific policy strategies to enhance the role of DIF and reduce spatial disparities in development across China.



Academic Editor: Nuno Carlos Leitão

Received: 24 June 2025

Revised: 10 July 2025

Accepted: 16 July 2025

Published: 24 July 2025

Keywords: digital inclusive finance (DIF); high-quality economic development; spatial Durbin model (SDM); two-regime system

Citation: Chen, L., & Zhang, G. (2025). Exploring the Impact of Digital Inclusive Finance and Industrial Structure Upgrading on High-Quality Economic Development: Evidence from a Spatial Durbin Model. *Economics*, 13(8), 212. <https://doi.org/10.3390/economics13080212>

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1. Introduction

High-quality economic development has become the core objective of China's current national strategy (2024; Zhao et al., 2020). As emphasized in the 20th National Congress of the Communist Party of China, future development should prioritize quality improvement alongside moderate growth in scale. Unlike traditional quantity-driven models, high-quality development emphasizes innovation, green transformation, coordinated growth, openness, and inclusiveness (Zheng et al., 2025).

In the context of accelerating digital transformation, DIF has emerged as a key driver of financial innovation. Since 2016, under strong policy support, DIF has rapidly expanded across all 31 provinces, 337 cities, and nearly 2800 counties in China. By leveraging advanced technologies such as big data, artificial intelligence, and blockchain, DIF has broadened financial accessibility while enhancing the efficiency, transparency, and inclusiveness of financial services (H. Lin & Peng, 2025).

These developments raise several critical research questions: Can DIF significantly promote high-quality economic development in China? Through what mechanisms does

this influence operate? Are the effects spatially heterogeneous across regions? Do they exhibit spatial spillover characteristics?

Addressing these questions is both theoretically meaningful and practically urgent. Existing studies on DIF and economic growth are often constrained to linear models or provincial-level data, limiting their capacity to capture spatial interdependence and nonlinear dynamics (e.g., [M. Xu et al., 2021](#); [Z. H. Zhang & Yang, 2022](#)). In contrast, this study introduces a spatial econometric perspective, utilizing the SDM to uncover both direct and spillover effects of DIF among 281 prefecture-level cities. Furthermore, we integrate a multidimensional mechanism analysis—combining mediating effects (e.g., industrial structure upgrading) and threshold effects—to provide a more comprehensive understanding of how DIF influences high-quality development.

This paper proceeds by first outlining the theoretical mechanisms through which DIF may affect high-quality economic development and proposing corresponding hypotheses. We then apply the SDM to empirically test these hypotheses. Our analysis includes tests of regional heterogeneity, spatial spillover, mediating effects, and double-threshold effects. Based on the results, we propose differentiated policy recommendations tailored to varying regional conditions.

This study contributes to the existing literature in several key ways:

- (1) It extends DIF research by adopting a spatial econometric approach, capturing both local and neighboring effects while introducing industrial structure upgrading as a mediating mechanism;
- (2) It utilizes prefecture-level panel data across 281 cities from 2011 to 2021, addressing regional heterogeneity and distinguishing the impact between central and non-central cities through a two-regime SDM;
- (3) It applies a threshold regression model to reveal the nonlinear characteristics of the relationship between DIF and high-quality development, identifying the conditions under which DIF becomes most effective.

2. Literature Review

2.1. DIF Promotes High-Quality Economic Development

Previous studies have confirmed the positive impact of DIF on high-quality economic development. For example, [Zhan \(2018\)](#), [Y. H. Yang and Zhang \(2022\)](#), and [S. Jiang and Zhou \(2021\)](#) demonstrated through panel data analysis that DIF significantly contributes to improvements in economic quality. However, [M. Xu et al. \(2021\)](#) observed that this effect tends to diminish over time, while [Y. P. Xu et al. \(2023\)](#) further suggested that the level of marketization moderates the relationship between DIF and economic development. [Z. H. Zhang and Yang \(2022\)](#) identified a nonlinear, inverted U-shaped relationship, implying diminishing returns at higher levels of DIF. [R. Z. Wang and Zhan \(2023\)](#) emphasized the joint role of DIF and green finance in promoting high-quality growth. In addition, [Du et al. \(2023\)](#), [Shang and Liu \(2024\)](#), and [Z. Wang and Chen \(2025\)](#) found that DIF enhances economic resilience, primarily through broader coverage and deeper usage, with the effect becoming stronger over time.

Internationally, empirical evidence from Kenya supports these findings. [Wachira and Njuguna \(2023\)](#) reported that mobile financial payments had a significant positive impact on productivity and output growth. [Tiony \(2023\)](#) found that digital financial services improved financial resilience, enhanced livelihoods, and reduced poverty and inequality. Early studies such as [Suri and Jack \(2016\)](#) showed that mobile money lifted approximately 2 percent of Kenyans out of poverty. However, as digital financial services have continued to expand, concerns have emerged regarding their potential to exacerbate financial risks and exclusion. As emphasized by [Sommer et al. \(2025\)](#), promoting financial inclusion requires

careful risk management to ensure that digital financial services sustainably contribute to economic development.

2.2. *Exploring the Mechanisms Linking DIF and High-Quality Economic Development*

According to Bing (2022), DIF contributes to high-quality economic development by enhancing accessibility, operational efficiency, and the inclusiveness of financial services. L. Zhang et al. (2023) found that DIF promotes growth through improved financial resource allocation, technological innovation, and increased consumer spending. N. Y. Wang et al. (2023), using panel data, demonstrated that digital finance enhances urban economic quality by stimulating innovation, entrepreneurship, and household consumption. C. Zhou and Huang (2021), based on provincial-level empirical analysis, identified market development as a key mediating factor. Y. Sun and Tang (2022) concluded that DIF supports sustainable economic growth by expanding institutional lending, household savings, and consumption. T. H. Liu et al. (2022) emphasized that digital finance facilitates industrial upgrading, thereby improving the quality of economic development. Dong and Pan (2024) noted that DIF significantly boosts regional innovation output, which in turn acts as a crucial driver of high-quality growth. Meanwhile, W. Li et al. (2023) highlighted that to fully leverage the positive spillover effects of DIF across regions, it is essential to stimulate consumer demand and optimize the consumption structure. Gao et al. (2025) further argued that encouraging and safeguarding entrepreneurial activities can also play a vital role in fostering high-quality economic development.

2.3. *A Threshold Analysis of the Impact of DIF on High-Quality Economic Development*

Drawing on 10 years of panel data from 30 provinces, J. He and Zhang (2020) employed a threshold regression approach and confirmed the existence of a single-threshold effect in the relationship between DIF and high-quality economic development. However, using data from 2011 to 2021, E. Li et al. (2024) identified a double-threshold effect, suggesting a more complex nonlinear relationship. C. L. Jiang and Jiang (2020), based on data from 258 prefecture-level cities, observed a “convergence threshold” in large cities and an “acceleration threshold” in smaller ones. Z. J. Zhou et al. (2022), focusing on the Yangtze River Delta, found that when the inclusive finance index is below 0.358, it hinders high-quality development, but when it exceeds 0.522, it significantly promotes it. Cheng and Duan (2022), studying 79 cities in the central region, also reported a single-threshold effect specific to central cities. Similarly, Abdelghaffar et al. (2023) revealed a nonlinear relationship between financial inclusion and economic growth, where the marginal effect declines once a certain threshold is surpassed. In contrast, Becha et al. (2025) found an initial inhibitory effect, with DIF contributing positively only when it exceeds a threshold of 4.594.

2.4. *Research on the Spatial Effect Between DIF and High-Quality Economic Development*

Zhao et al. (2020) demonstrated that DIF exerts a notable spatial spillover effect on high-quality economic development while also highlighting mass entrepreneurship as a crucial mediating mechanism. Ge and Wu (2022), using SDM and panel data from 31 provinces over 10 years, found that DIF exerts a markedly positive direct influence on the development of the private economy, while its spatial spillover effect is negative. Their study further revealed notable regional disparities: DIF has a stronger promotive impact in northern, eastern, and central-southern China but exhibits a significant suppressive effect in the western region.

Niu (2023) confirmed the existence of spatial spillover effects of digital finance on high-quality development. Drawing on national provincial-level panel data, W. Li et al. (2023) employed a spatial econometric approach to demonstrate that the combined effects

of digital finance, household consumption, and economic development contribute to enhanced high-quality growth. Furthermore, their analysis using a semi-parametric spatial lag model revealed an inverted U-shaped nonlinear relationship between DIF and high-quality economic development. Similarly, [W. J. Zhang and Jia \(2024\)](#), using 10 years of provincial panel data, found a significant direct effect, while the spatial spillover effect was not significant.

2.5. Literature Review and Comments

Although existing studies generally agree that DIF promotes high-quality economic development, several limitations remain. Firstly, most mechanism analyses focus on direct effects and overlook spatial pathways through which DIF may influence development. Secondly, existing studies are mostly based on provincial-level empirical analyses, lacking in-depth exploration at the city level. Moreover, when considering spatial heterogeneity, many studies fail to incorporate spatial factors and mainly rely on traditional panel data models. Finally, most of the literature does not examine the role of industrial structure upgrading in the process through which digital inclusive finance promotes high-quality economic development.

3. Mechanism Analysis and Hypotheses

3.1. Impact Mechanisms of DIF on High-Quality Economic Development

3.1.1. Impact Mechanisms of DIF on the High-Quality Economic Development of the Local Region

DIF, characterized by digitalization, convenience, and inclusiveness, injects new vitality into regional economic development.

1. Expanding financial access. DIF significantly broadens the accessibility of financial services by utilizing mobile payment systems and internet-based platforms ([Nanda, 2025](#); [Adebayo, 2025](#)). These digital tools help overcome the traditional geographical and infrastructural constraints of brick-and-mortar banking, thereby enabling financially underserved populations—particularly those in remote or underdeveloped regions—to gain access to essential financial services ([Mulili, 2022](#)). By narrowing the urban–rural and regional financial service gaps, DIF enhances financial inclusion and contributes to the advancement of high-quality economic development at the local level.
2. Improving service accessibility and precision. DIF leverages big data analytics and AI to improve the accuracy of customer identification and credit risk assessment at the local level. These technologies allow financial institutions to develop detailed user profiles based on transactional behavior, consumption patterns, and social data ([Q. Wang, 2024](#)). As a result, financial products and services can be precisely tailored to individual needs, creditworthiness, and repayment capacity. This customization reduces information asymmetry and improves resource allocation efficiency. Moreover, it enables a larger number of micro, small, and medium-sized enterprises (MSMEs), as well as low-income and previously unbanked populations, to access essential financial resources. Empirical studies have shown that such precision lending mechanisms significantly increase loan approval rates and reduce default risks in underserved areas. In turn, this expanded and efficient access to finance supports a more resilient financial ecosystem and drives high-quality, inclusive economic growth.
3. Reducing service costs. Traditional financial services are heavily dependent on physical infrastructure and labor-intensive processes, which result in high fixed and operational costs. DIF, by contrast, reduces these costs significantly by leveraging virtual platforms, automating service delivery, and removing geographic constraints. Ac-

According to Ozili (2017), digital financial channels such as mobile banking and online lending platforms enable users—especially those in rural or underserved areas—to access services at a fraction of the cost of traditional banking. Lower service delivery costs not only improve the cost efficiency of financial institutions but also allow for more competitive interest rates and transaction fees. This encourages broader market participation, stimulates household and business consumption, and enhances firm productivity. Collectively, these outcomes contribute to a more dynamic local economy and support the broader goal of high-quality, inclusive regional development.

In summary, DIF strengthens the foundation for high-quality development within local regions by enhancing financial accessibility, precision, and cost efficiency. These mechanisms promote greater financial inclusion and economic participation, particularly in underserved areas. To capture these effects, this paper proposes Hypothesis H1a: DIF significantly promotes high-quality economic development at the local level by expanding financial access, improving service efficiency, and lowering transaction costs.

3.1.2. Spillover Mechanisms of DIF in Promoting High-Quality Growth Across Neighboring Regions

1. Enhancing regional financial inclusion. DIF promotes the interregional flow of financial resources, effectively narrowing spatial disparities in capital access. Through online platforms and digital lending systems, urban investors and financial institutions can allocate funds across administrative boundaries to support rural and underdeveloped areas. This cross-regional capital reallocation improves the efficiency of resource distribution and mitigates regional financing constraints. Empirical research (e.g., Chen & Li, 2025) shows that such capital flows significantly increase credit availability for micro and small enterprises (MSEs) and agricultural households in adjacent regions. By unlocking new sources of external financing, DIF stimulates local entrepreneurship, supports employment, and enhances the financial resilience of economically disadvantaged areas. Ultimately, this inclusive growth pattern contributes to more balanced and high-quality economic development across regions.
2. Promoting technology diffusion and innovation-driven growth. DIF supports innovation by encouraging financial institutions to invest in high-tech, specialized, and innovative industries, as well as new business models. This helps address financing barriers for enterprises (Kolesar et al., 2023), supports their innovation efforts, accelerates the growth of emerging sectors, and contributes to high-quality economic development. Furthermore, DIF itself stems from technological innovation. It enables information sharing, reduces access costs, and lowers barriers to digital infrastructure. These features facilitate cross-regional technology transfer and knowledge spillovers, which in turn drive innovation and growth in neighboring regions.
3. Fostering interregional economic coordination. DIF reduces barriers to accessing financial services across administrative boundaries, thereby promoting greater interregional economic integration. Neighboring areas can share digital financial infrastructure—such as cloud-based platforms and payment systems—and benefit from economies of scale in service provision. This fosters complementary specialization, where urban areas serve as financial and technological hubs, while adjacent rural areas provide labor and resource inputs, enabling mutually reinforcing development. Moreover, urban financial institutions can extend both technical support (e.g., fintech tools, risk assessment models) and financial resources (e.g., rural microloans, agricultural credit) to surrounding areas, promoting integrated regional growth. DIF also enhances supply chain collaboration by facilitating smoother transactions and financing between upstream and downstream enterprises across regions. Such strengthened

economic linkages improve regional coordination, reduce development imbalances, and collectively advance high-quality growth on a broader spatial scale.

These spillover effects suggest that DIF not only boosts local development but also drives regional convergence through financial connectivity, technology diffusion, and cross-regional cooperation. However, these mechanisms remain underexplored in the spatial econometric literature. To address this gap, this study proposes Hypothesis H1b: DIF generates significant positive spillover effects on high-quality economic development in neighboring regions through capital flows, technological diffusion, and regional coordination.

3.2. Impact Mechanisms of DIF on High-Quality Economic Development via Industrial Structure Upgrading

3.2.1. Impact on the Local Regions

1. Optimizing resource allocation through industrial upgrading. Emerging industries such as artificial intelligence, big data, and new energy are high-risk, capital-intensive, and long-cycle but offer strong growth potential. Due to information asymmetry and risk aversion, traditional financial institutions often underserve these sectors. DIF, powered by technologies like big data and AI, enables more accurate risk assessment and credit profiling, making financing more accessible to emerging industries (Y. Li et al., 2022). Traditional industries, meanwhile, face mounting pressure to transform. DIF provides targeted products—such as industrial funds and supply chain finance—that support their shift toward high-end, intelligent, and green production (Erundu et al., 2025). As industries upgrade, resources are reallocated toward more efficient sectors, improving the overall quality and productivity of the economy.
2. Advancing technological innovation through industrial upgrading. Industrial upgrading is inherently linked to technological progress. Both emerging industries and modernized traditional sectors depend on new technologies, processes, and management models. In pursuit of competitiveness, firms increase investment in R&D, which drives continuous innovation. In turn, these innovations feed back into further industrial upgrading, creating a self-reinforcing cycle of technological and structural advancement (F. Li et al., 2022; Z. Li et al., 2025).
3. Driving green transformation through industrial upgrading. As environmental awareness rises and sustainability gains traction, green industries have become a central focus of industrial restructuring. DIF channels financial resources into strategic sectors such as green enterprises, environmental protection, and resource recycling, thereby fostering their sustainable development (Y. Sun & Tang, 2022; R. Sun et al., 2025). Meanwhile, traditional industries increasingly adopt green practices—such as energy conservation and emissions reduction—during their transformation. This dual shift supports ecological sustainability while advancing high-quality development.
4. Industrial upgrading reshapes labor demand by accelerating the transition toward a more knowledge-intensive economy. Emerging sectors—such as artificial intelligence, green manufacturing, and digital services—require a workforce with advanced technical competencies, digital literacy, and adaptive learning capacity. Consequently, DIF indirectly promotes the accumulation of human capital by encouraging individuals to invest in education, vocational training, and lifelong learning. Furthermore, the expansion of digital finance itself creates new employment opportunities (e.g., fintech services, data governance, cybersecurity), driving demand for highly skilled professionals. These changes not only raise income levels but also contribute to a more efficient and innovation-ready labor market, thereby reinforcing the human capital base essential for high-quality development (E. Li et al., 2024).

3.2.2. Impact on Neighboring Regions

1. Expand and stabilize the industrial chain. DIF fosters tighter collaboration among upstream and downstream enterprises by offering flexible financing solutions. With improved access to capital, firms can expand production capacity and upgrade technologies (P. Zhang et al., 2025). This, in turn, drives the growth of supporting enterprises along the supply chain, promotes coordinated development across related industries, and enhances the overall competitiveness of the industrial chain. As a result, it supports industrial structure optimization and contributes to regional high-quality economic development.
2. The demonstration–learning effect reflects the process through which regions emulate successful policy models and institutional innovations observed in neighboring areas. In the context of DIF, technologically advanced or policy-innovative regions often serve as demonstration zones by piloting inclusive digital finance strategies, regulatory sandboxes, and incentive mechanisms. Neighboring regions, especially those with institutional proximity or economic ties, tend to adopt and adapt these practices based on localized conditions—a phenomenon aligned with the theory of policy diffusion and spatial learning (Berry & Baybeck, 2005). Empirical studies have shown that such horizontal learning fosters financial innovation spillovers and reduces policy uncertainty, thereby enhancing regional governance capacity and stimulating industrial transformation (T. H. Liu et al., 2022).

In summary, industrial structure upgrading serves as a key mechanism through which DIF promotes high-quality economic development, operating both locally and across neighboring regions (see Figure 1). At the local level, DIF supports industrial upgrading by enhancing resource allocation efficiency, stimulating technological innovation, advancing green transformation, and optimizing the employment structure. Simultaneously, it contributes to regional development by strengthening industrial chains and fostering demonstration–learning spillover effects. However, prior studies have rarely leveraged city-level spatially disaggregated data to examine these mechanisms in depth.

To address this gap, we propose Hypothesis H2: DIF promotes high-quality economic development through the spatial mediating effect of industrial structure upgrading.

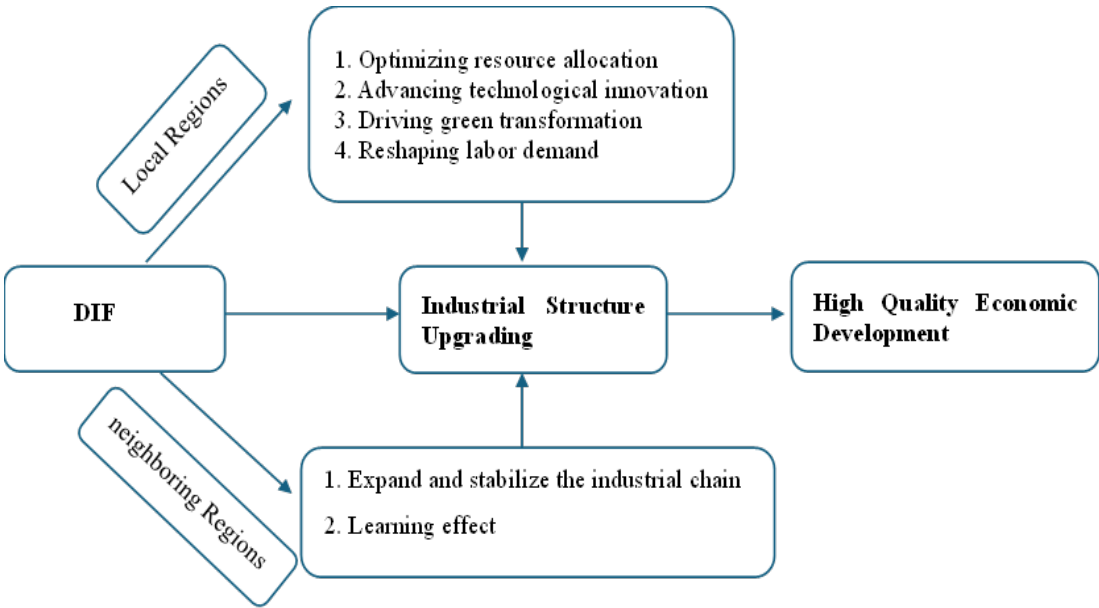


Figure 1. Mediation mechanism.

3.3. Threshold Effect Analysis of DIF on High-Quality Economic Development

1. **Technical Threshold.** The effectiveness of DIF is fundamentally dependent on the availability and quality of information and communication technology (ICT) infrastructure. In many underdeveloped or remote regions, weak digital foundations—such as limited broadband coverage, unstable network connections, and inadequate access to digital devices—substantially constrain the implementation and utilization of digital financial services. Without sufficient ICT support, even well-designed financial products cannot be effectively delivered or adopted, leading to a digital divide that excludes certain regions from the benefits of financial innovation. This suggests the existence of a technical threshold: only when a minimum level of digital infrastructure is met can DIF exert a meaningful impact on local economic development. Regions below this threshold are likely to experience weaker or negligible benefits from DIF interventions.
2. **Financial Literacy.** The effective use of DIF presupposes a basic level of financial literacy and digital competency among users (Fang & Qian, 2024). However, many individuals—particularly those from low-income households, elderly populations, and rural communities—lack the foundational knowledge and skills needed to navigate digital financial platforms, interpret financial products, or make informed economic decisions. This limitation significantly reduces their ability to engage with and benefit from DIF services. Consequently, a threshold of financial literacy and digital proficiency is necessary for DIF to translate into meaningful economic outcomes. Regions or groups falling below this threshold may experience marginal or even adverse effects, as insufficient understanding can lead to financial exclusion, misuse of digital tools, or increased vulnerability to fraud. Thus, user capability emerges as a critical bottleneck in realizing the full potential of digital finance for high-quality economic development.

In summary, both technical infrastructure and user financial literacy serve as critical preconditions for the effective functioning of DIF. In areas where these foundational conditions are lacking, the positive effects of DIF on economic development may be severely limited or delayed. Prior studies have suggested that digital finance exhibits diminishing returns or nonlinear behavior under different development levels, yet empirical evidence at the city level remains scarce.

Therefore, we propose Hypothesis H3: The impact of DIF on high-quality economic development is subject to threshold effects, reflecting the conditional nature of its effectiveness in different regional contexts.

4. Research Design

4.1. Kernel Density Estimation Method

To analyze the distribution characteristics of the DIF and High-Quality Economic Development, this study employs Kernel Density Estimation (KDE), a non-parametric method for estimating the probability density function of a random variable. The general formula is as follows:

$$f(x) = \left(\frac{1}{nh} \right) \sum_{i=1}^n k \left(\frac{x - x_i}{h} \right) \quad (1)$$

where $f(x)$ is the estimated density value at point x ; n is the number of observations; x_i is the i th observation; h is the bandwidth parameter that controls the smoothness of the density curve; and $K(\cdot)$ is the kernel function—commonly used ones include the Gaussian kernel, Uniform kernel, and Epanechnikov kernel.

KDE does not rely on any specific distributional assumptions and thus provides a flexible way to reflect the actual distribution of the data. In empirical analysis, the proper selection of the bandwidth h and the kernel function $K(\cdot)$ is crucial for the accuracy of the estimation.

4.2. Model Specification

(1) SDM Design

High-quality economic development demonstrates strong spatial correlation and dependence (Z. H. Zhang & Yang, 2022). Traditional econometric models fail to account for spatial spillover effects between regions, often resulting in biased estimates. To address this limitation, this study adopts a spatial econometric model for empirical analysis. Drawing on the work of (W. Li et al., 2023; E. Li et al., 2024), the model is specified as follows:

$$H_{it} = \rho W \times H_{it} + \beta_1 DIF_{it} + \beta_2 W \times DIF_{it} + \gamma Controls_{it} + \varepsilon_{it} + v_i + u_t \quad (2)$$

In this model, i and t represent prefecture-level cities and years, respectively. The spatial weight matrix w captures intercity spatial relationships and is primarily specified using the adjacency matrix, with the inverse distance matrix employed for robustness checks. The dependent variable H denotes high-quality economic development. DIF refers to the digital inclusive finance index, which reflects the extent of DIF across cities. $Controls$ encompass a series of control variables. The error term is denoted by ε , while λ_t and μ_i account for time-fixed and individual-fixed effects, respectively.

(2) Two-Regime SDM Design

In order to consider the heterogeneity among different regions and the spatial dependence between regions in a more refined manner, and simultaneously incorporate various variables into one model, based on SDM, this paper draws on the works of Elhorst and Frère (2009) and designs the two-regime SDM as follows:

$$high_{it} = p_1 d_{it} W * high_{it} + p_2 (1 - d_{it}) W * high_{it} + \beta_1 DIF_{it} + \beta_2 W * DIF_{it} + \gamma Controls_{it} + \varepsilon_{it} + v_i + u_t \quad (3)$$

In this model, i denotes the prefecture-level city, t denotes the year, and w represents the spatial weight matrix. This study adopts the inverse geographical distance matrix for empirical analysis. Parameters p_1 , p_2 , β_1 , and β_2 are the estimated coefficients.

The variable d_{it} is a dummy variable. Following W. J. He et al. (2021), central cities—including sub-provincial cities, provincial capitals, and municipalities directly under the central government—are assigned a value of 1, while all other cities are assigned 0.

The dependent variable $high$ represents high-quality economic development. DIF denotes the Digital Inclusive Finance Index. $Controls$ is a set of control variables. ε_{it} is the error term, u_t captures time-fixed effects, and v_i captures individual-fixed effects.

(3) Mediation Effect Model Design

The aforementioned theoretical analysis part has expounded the mechanism by which DIF affects “ $high$ ” through the channel of industrial structure upgrading. Referring to the studies of Y. H. Zhang and Hao (2022), as well as Wen and Ye (2014), this paper conducts an empirical test on this mechanism and sets up the SDM mediating effect model of panel data as follows:

$$high_{it} = \beta_0 + \rho_1 W \times high_{it} + \beta_1 DIF_{it} + \beta_2 W \times DIF_{it} + \gamma Controls_{it} + \varepsilon_{it} + V_{it} + u_i \quad (4)$$

$$I_{it} = \alpha_0 + p_2 W \times I_{it} + \alpha_1 DIF_{it} + \alpha_2 W \times DIF_{it} + \gamma Controls_{it} + \varepsilon_{it} + V_{it} + u_i \quad (5)$$

$$high_{it} = \gamma_0 + p_3 W \times high_{it} + \gamma_1 I_{it} + \gamma_2 W \times I_{it} + \gamma_3 DIF_{it} + \gamma_4 W \times DIF_{it} + \gamma Controls_{it} + \varepsilon_{it} + v_i + u_t \quad (6)$$

Among them, p_1 , p_2 , and p_3 represent the spatial lag coefficients (of the explained variable); w represents the spatial weight matrix of inverse geographical distance; $DIFI$ represents the Digital Inclusive Finance Index; $Controls$ represents the control variables; I represents the upgrading of industrial structure (the mediating variable); β_0 , α_0 , and γ_0 are estimated constants; β_1 , β_2 , α_1 , α_2 , γ_1 , γ_2 , γ_3 , and γ_4 are the parameters to be estimated in the model; and ε_{it} , v_i , and u_t represent the random error term, regional effect, and time effect, respectively.

(4) Threshold Effect Model Design

To examine potential nonlinearities in the relationship between DIF and economic development, this study applies Hansen's (1999) threshold regression model. DIF is used as threshold variables. Estimations are performed using Stata 17 under single, double, and triple threshold settings, with 300 bootstrap replications.

$$high_{it} = \beta_0 + \beta_1 DIF_{it} \times I(DIF_{it} \leq \chi_1) + \beta_2 DIF_{it} \times I(\chi_1 < DIF_{it} < \chi_2) + \beta_3 DIF_{it} \times I(DIF_{it} \geq \chi_2) + \gamma Controls_{it} + \varepsilon_{it} + V_{it} + u_i \quad (7)$$

The meanings of the variables and letters are the same as in (1).

4.3. Explanation of Variables and Data

1. This study follows the methodology of J. Liu et al. (2021) to construct a comprehensive index of high-quality economic development covering five dimensions: innovation, coordination, green development, openness, and sharing. Specific details are shown in Table 1. The tertiary indicators under each dimension are weighted and aggregated using the entropy method. This approach aligns with China's strategic goals and captures key aspects such as innovation and sustainability. While entropy weighting improves sensitivity by emphasizing indicators with greater variability, it also presents some limitations. Specifically, the selection of indicators may be constrained by data availability, and the data-driven nature of entropy weights may overemphasize volatile but less critical metrics. Moreover, as a synthetic index, it may obscure the performance of individual components, limiting interpretability for policy applications.

Processing steps of the entropy method:

- (1) Dimensionless treatment:

$$\text{Positive indicators: } X_{ij} = \frac{X_{ij} - \min\{X_j\}}{\max\{X_j\} - \min\{X_j\}} \quad (8)$$

$$\text{Negative indicators: } X_{ij} = \frac{\max\{X_j\} - X_{ij}}{\max\{X_j\} - \min\{X_j\}} \quad (9)$$

The process of calculating the weight of each indicator value is as follows:

- (2) Calculate the proportion P of the indicator value of the i -th project under the j -th indicator.

$$p_{ij} = r_{ij} / \sum_{i=1}^n r_{ij} \quad (10)$$

(3) Calculate the entropy value e_j of the j -th indicator.

$$e_j = -k \sum_{i=1}^m P_{ij} \times \ln p_{ij} \quad (11)$$

including:

$$K = 1/\ln m \quad (12)$$

(4) The entropy weight of the j -th indicator is derived as follows:

$$W_j = (1 - e_j) / \sum_{j=1}^n (1 - e_j) \quad (13)$$

(5) Calculate the evaluation scores of indicators:

$$S_{ij} = W_i \times X_{ij} \quad (14)$$

Table 1. Indicators for measuring high.

Category Indicator	Secondary Indicator	Specific Indicator	Unit of Measurement	Indicator Attribute		
				Positive	Moderate	Negative
Innovation Development	Investment in Science and Technology	Science and Tech Expenditure/Fiscal Expenditure	%	✓		
		Education Expenditure/Fiscal Expenditure	%	✓		
	Patent Level	Number of Patents Granted	Count	✓		
Coordinated Development	Financial Development	Financial Deposits/Financial Loans	%		✓	
	People's Livelihood	Per Capita Income	CNY	✓		
		Non-Real Estate Investment/Fixed Asset Investment	%	✓		
Open Development	Industrial Structure	Proportion of Tertiary Industry	%	✓		
	Foreign Investment Overview Foreign Enterprises Overview	Utilized Foreign Capital	Billion USD	✓		
		Assets of Foreign Enterprises	Billion CNY	✓		
		Number of Foreign Enterprises	Count	✓		
Green Development	Three Wastes Emissions	Industrial Wastewater Emissions/Industrial Output Value	Ton/CNY 10,000			✓
		Industrial SO ₂ Emissions/Industrial Output Value	Ton/CNY 10,000			✓
		Industrial Smoke (Dust) Emissions/Industrial Output Value	Ton/CNY 10,000			✓
	Waste Treatment	Comprehensive Utilization Rate of General Industrial Solid Waste	%	✓		
		Sewage Treatment Rate	%	✓		
		Harmless Treatment Rate of Domestic Waste	%	✓		

Table 1. Cont.

Category Indicator	Secondary Indicator	Specific Indicator	Unit of Measurement	Indicator Attribute		
				Positive	Moderate	Negative
Shared Development	Social Welfare	Number of Doctors/Population	Per 10,000 People	✓		
		Wages of On-the-Job Employees	CNY	✓		
		Urban Greening Rate	%	✓		
	Consumption Level	Retail Sales of Consumer Goods/GDP	%	✓		
	Government Burden	Fiscal Expenditure/Fiscal Revenue	%			✓

Note: Table sourced from J. Liu et al. (2021).

To visualize the data distribution, this study uses high-quality urban economic development data from 2011 to 2021 and applies kernel density estimation through MATLAB R2016b. The results are shown in Figures 2 and 3. The kernel density curves exhibit a unimodal pattern, indicating the absence of polarization in high across cities. The main peak shifts upward and becomes narrower over time, suggesting a gradual convergence and narrowing gap in development levels among cities.

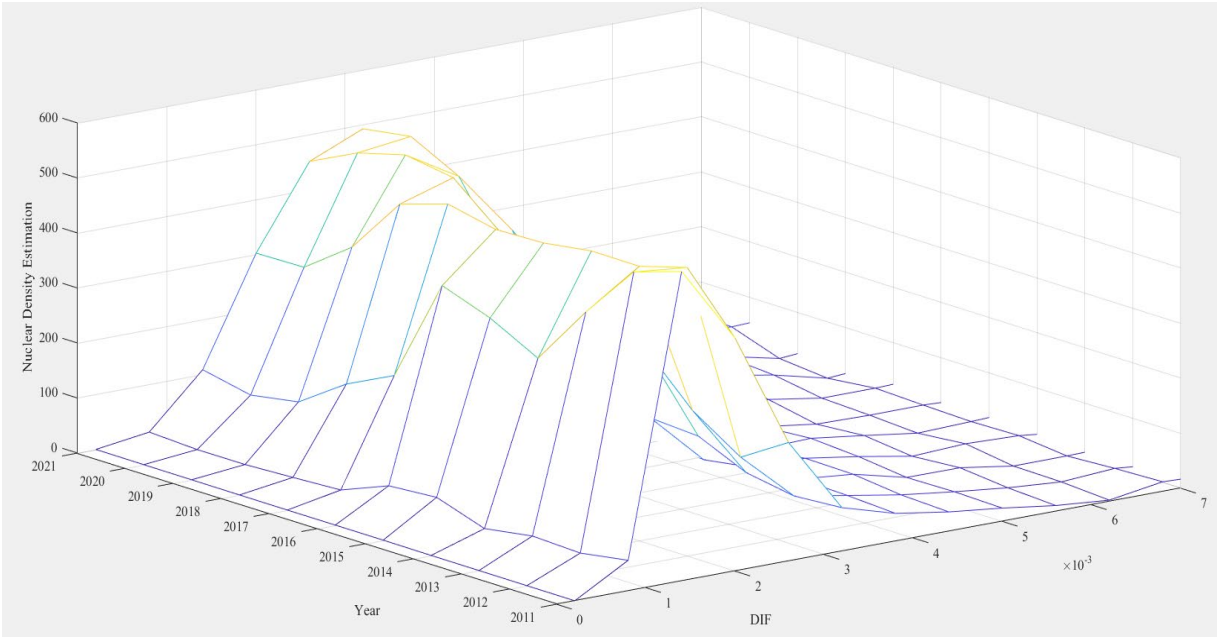


Figure 2. Three-dimensional kernel density map of high.

2.
- Explanatory variable: DIF. This study employs the Digital Inclusive Finance Index developed by the Digital Finance Research Center at Peking University. The index construction is based on the methodology proposed by X. Zhang et al. (2019) and Guo et al. (2020), and it comprises three primary dimensions: breadth of coverage, depth of usage, and degree of digitization. A higher index value indicates a more advanced level of digital inclusive finance (DIF) development. Detailed indicators are presented in Table 2.

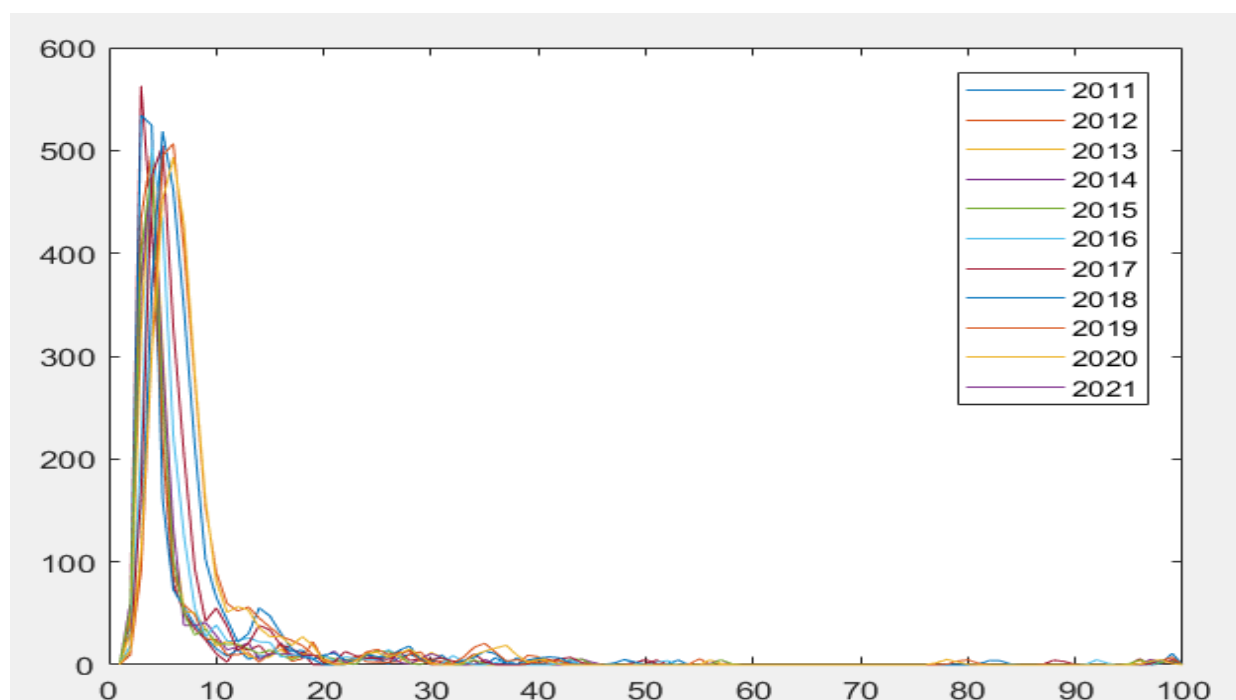


Figure 3. Two-dimensional kernel density map of high.

Table 2. Indicators for measuring DIF.

Overall Index	Primary Dimension	Secondary Dimension	Specific Indicator
Digital Inclusive Finance Index	Breadth of Coverage	Account Coverage Rate	Number of Alipay accounts per 10,000 people
			Proportion of Alipay users with linked bank cards
			Average number of bank cards linked per Alipay account
	Depth of Use	Payment Services	Number of payments per capita
			Payment amount per capita
			Ratio of high-frequency users (≥ 50 active days/year) to total active users
		Money Market Fund Services	Average number of Yu'e Bao purchases per person
			Average amount of Yu'e Bao purchases per person
			Number of Yu'e Bao buyers per 10,000 Alipay users
		Credit Services	Number of internet consumer loan users per 10,000 adult Alipay users
			Average number of loans per capita
			Average loan amount per capita
			Number of SME loan users per 10,000 adult Alipay users
			Small and Micro Business Operators
			Small and Micro Business Operators
		Insurance Services	Number of insured users per 10,000 Alipay users
			Average number of insurance policies per capita
			Average insurance amount per capita
		Investment Services	Number of online wealth management participants per 10,000 Alipay users
			Average number of investments per capita
			Average investment amount per capita
		Credit-Based Services	Average number of credit inquiries per natural person
			Number of users utilizing credit-based services (finance, housing, travel, social, etc.) per 10,000 Alipay users

Table 2. Cont.

Overall Index	Primary Dimension	Secondary Dimension	Specific Indicator
Digital Inclusive Finance Index	Degree of Digitalization	Mobile Services	Proportion of mobile payment transactions
			Proportion of mobile payment amount
			Proportion of Huabei payment transactions
		Creditization	Proportion of Huabei payment amount
			Proportion of Sesame Credit deposit-free transactions (compared to all requiring deposits)
			Proportion of Sesame Credit deposit-free amount (compared to all requiring deposits)
		Convenience	Proportion of QR code payment transactions
			Proportion of QR code payment amount

Note: Table sourced from [Guo et al. \(2020\)](#).

Figures 4 and 5 present the kernel density plots of the DIF. The distributions consistently exhibit a unimodal pattern, with no signs of polarization across cities. Over time, the main peak shifts upward and becomes narrower, suggesting a gradual reduction in absolute differences among cities. In most years, the distribution displays a clear peak with high concentration and declines smoothly on both sides, resembling a normal or near-normal pattern. No significant tailing is observed.

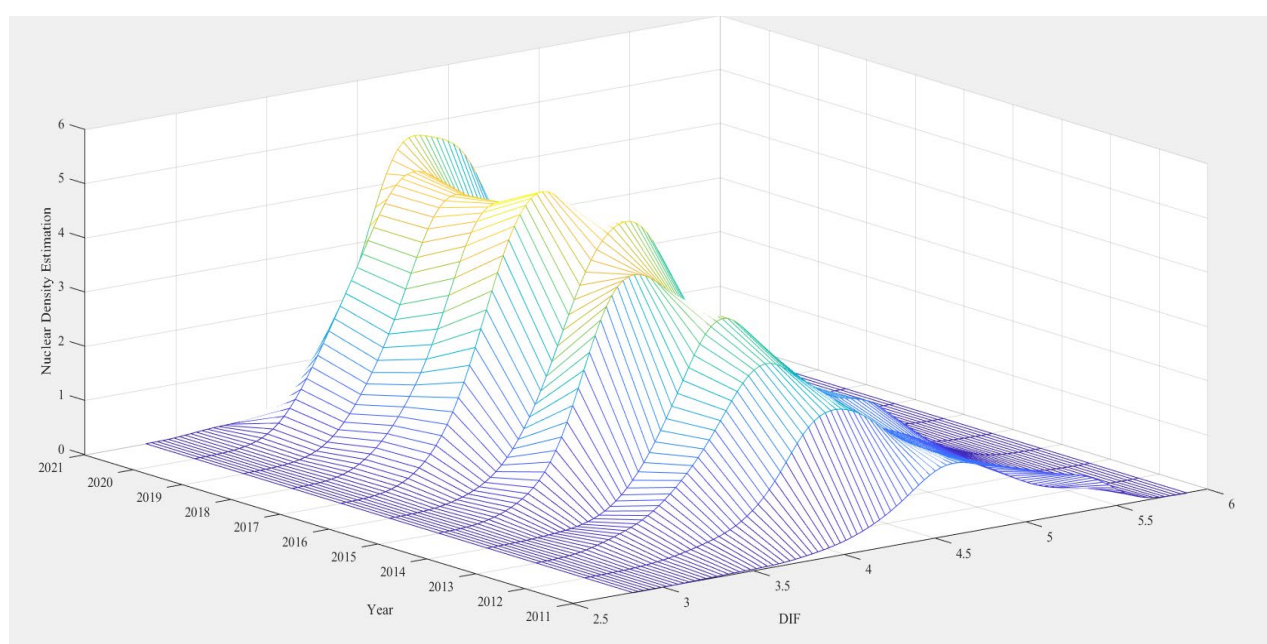


Figure 4. Three-dimensional kernel density plot of DIF.

3. **Intermediate Variable.** This paper employs industrial structure upgrading as the mediating variable, quantified by the output ratio of the tertiary-to-secondary industries.
4. **Control Variables.** Drawing on the prior literature, this study incorporates the following control variables that may influence high: (1) Urbanization level (CT): measured by the proportion of the urban population to the total population. (2) Human capital level (HM): proxied by the average years of education. (3) Financial development level (FA): represented by total bank deposits. (4) Consumption level (Con): measured by the ratio of total retail sales of consumer goods to regional GDP.

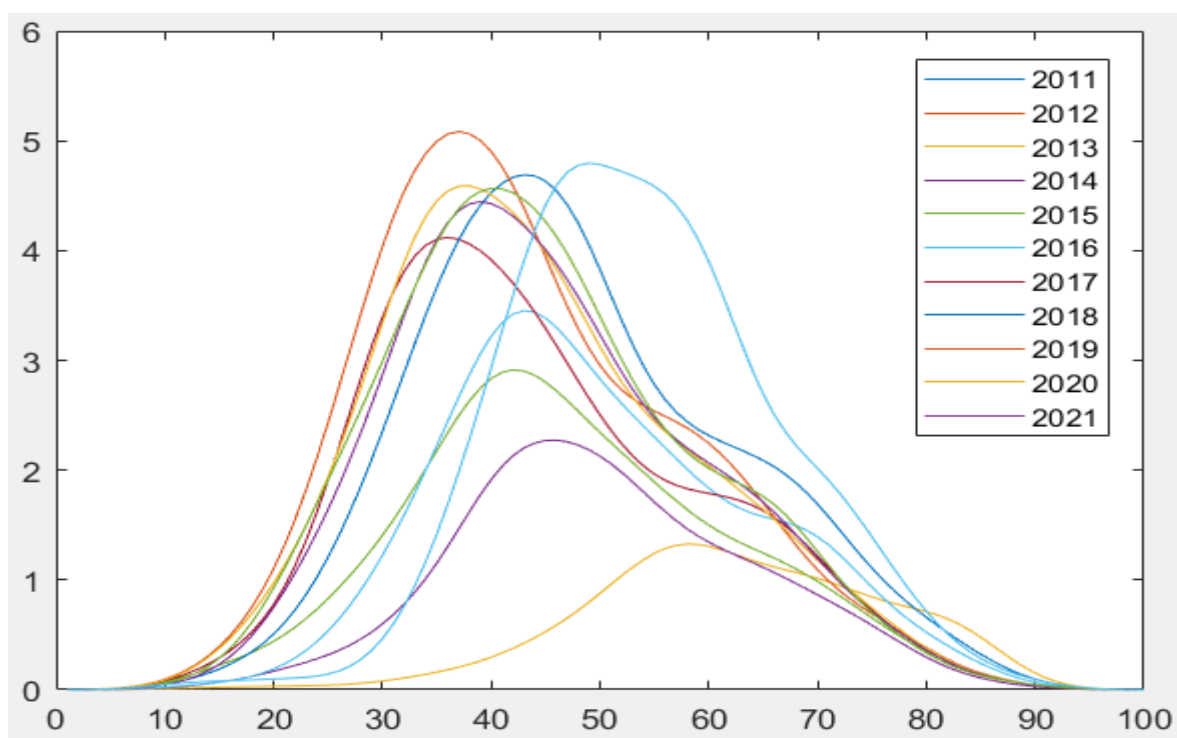


Figure 5. Two-dimensional kernel density plot of DIF.

The specific meanings and names of the aforementioned variables are shown in Table 3, and the descriptive statistics of each variable are shown in Table 4. In Table 4, the variables are highly variable, with extreme values, and the overall distribution is right skewed.

5. **Data Description:** Owing to limitations in data availability, Taiwan Province, as well as the Hong Kong and Macao Special Administrative Regions, are excluded from the sample. To ensure the reliability and consistency of the dataset, this study utilizes panel data covering 281 prefecture-level cities in mainland China from 2011 to 2021. The original data are sourced from the China Urban Statistical Yearbook and the Wind database. A small number of missing values are supplemented using interpolation.

Table 3. Names of variables.

Variable Nature	Variable Name	Variable Measurement	Symbol
Dependent variable	High-quality economic development	Measured by the entropy method	high
Independent variable	Digital Inclusive Finance	Take the logarithm of the Digital Inclusive Finance Index	DIF
Intermediate variable	Upgrading of industrial structure	Output value of the tertiary industry/Output value of the secondary industry	I
Control variables	Urbanization level	Urban population/Total population	CT
	Human capital level	Average years of education	
	Level of financial development	Take the logarithm of bank deposits	FIA
	Consumption level	Retail sales of consumer goods in the whole society/GDP	Con

Note: Self-organized findings.

Table 4. Descriptive statistics.

Variable	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
high	3091	0.003	0.005	0.0001	0.060
DIF	3091	5.112	0.519	2.834	5.885
CT	3091	0.564	0.149	0.181	1.000
I	3091	1.071	0.603	0.114	5.350
HM	3091	0.020	0.026	0.00001	0.140
FA	3091	2.529	1.226	0.588	21.302
Con	3091	0.351	0.152	0.00003	0.996

Note: Self-organized findings.

6. Construction of Spatial Weights

(1) Spatial distance matrix and calculation formula:

$$W_d = \begin{cases} \frac{1}{d_{ij}}, & i \neq j \\ 0, & i = j \end{cases} \quad (15)$$

The variable d is derived from the geographic coordinates (longitude and latitude) of each prefecture-level city.

(2) Adjacency matrix:

$$W_{ij} = \begin{cases} 1, & \text{region } i \text{ is adjacent to region } j. \\ 0, & \text{region } i \text{ and region } j \text{ are not adjacent.} \end{cases} \quad (16)$$

4.4. Spatial Autocorrelation Test of DIF and High

Tables 5 and 6 list the global and local Moran's I and Geary's C indices of DIF under the inverse geographical distance weight matrix. The results show that both the global and local Moran's I indices are greater than 0 and significant at the 1% significance level, indicating the existence of spatial autocorrelation in DIF. Meanwhile, both the global and local Geary's C indices are less than 1 and also significant at the 1% level. These two findings suggest the existence of high–high and low–low agglomeration effects in DIF. The local Moran's I has exhibited a steady increase, whereas the local Geary's C has gradually declined, suggesting a strengthening trend in spatial dependence.

Table 5. Global Moran's I and Geary's C indices of DIF under the inverse geographical distance matrix.

DIF	Value	E(I)	sd(I)	z	p-Value
Moran's I	0.388	−0.004	0.038	10.391	0.000
Geary's C	0.548	1.000	0.051	−8.816	0.000
Getis and Ord's G	0.017	0.017	0.000	−1.691	0.091

Note: Self-organized findings.

Table 6. Local Moran's I and Geary's C indices of DIF under the inverse geographical distance matrix.

Year	Moran's I	p-Value	Geary's C	p-Value
2011	0.4127	0.0000	0.548	0.000
2012	0.4573	0.0000	0.524	0.000
2013	0.4777	0.0000	0.523	0.000
2014	0.4983	0.0000	0.555	0.000
2015	0.5105	0.0000	0.546	0.000
2016	0.4773	0.0000	0.569	0.000

Table 6. *Cont.*

Year	Moran's <i>I</i>	<i>p</i> -Value	Geary's <i>C</i>	<i>p</i> -Value
2017	0.4731	0.0000	0.524	0.000
2018	0.4457	0.0000	0.468	0.000
2019	0.4332	0.0000	0.460	0.000
2020	0.4216	0.0000	0.435	0.000
2021	0.3711	0.0000	0.421	0.000

Note: Self-organized findings.

Tables 7 and 8 list the global and local Moran's *I* and Geary's *C* indices of “high” (assuming “high” represents a certain variable related to high-quality economic development) under the inverse geographical distance matrix. The empirical results indicate that both the global and local Moran's *I* indices are positive and statistically significant at the 10% level, confirming the presence of spatial autocorrelation in “high”. Meanwhile, the Moran's *I* value shows an increasing trend, which also indicates that the spatial correlation is strengthening.

Table 7. Global Moran's *I* and Geary's *C* indices of “high” under the inverse geographical distance matrix.

High	Value	E(I)	sd(I)	z	<i>p</i> -Value
Moran's <i>I</i>	0.345	−0.004	0.034	10.152	0.000
Geary's <i>C</i>	0.566	1.000	0.170	−2.559	0.000
Getis and Ord's <i>G</i>	0.041	0.017	0.003	8.172	0.000

Note: Self-organized findings.

Table 8. Local Moran's *I* and Geary's *C* indices of “high” under the inverse geographical distance matrix.

Year	Moran's <i>I</i>	<i>p</i> -Value	Geary's <i>C</i>	<i>p</i> -Value
2011	0.1942	0.0000	0.566	0.011
2012	0.2005	0.0000	0.579	0.013
2013	0.2035	0.0000	0.595	0.015
2014	0.2122	0.0000	0.594	0.011
2015	0.2125	0.0000	0.595	0.011
2016	0.2076	0.0000	0.609	0.015
2017	0.2205	0.0000	0.604	0.011
2018	0.2236	0.0000	0.608	0.010
2019	0.2297	0.0000	0.617	0.011
2020	0.2064	0.0000	0.609	0.014
2021	0.2095	0.0000	0.615	0.014

Note: Self-organized findings.

Using Stata 17.0, local Moran scatter plots and LISA (Local Indicators of Spatial Association) maps were generated for the years 2011, 2014, 2017, and 2021 to examine the spatial distribution of “high”. In Figure 6, the majority of observations fall within the first and third quadrants of the Moran scatter plots, indicating strong spatial clustering. Specifically, regions with high development levels are adjacent to similarly high-performing areas (“high–high” agglomeration), while regions with low development levels tend to cluster together as well (“low–low” agglomeration). A smaller number of cities fall within the second and fourth quadrants, reflecting spatial outliers and indicating persistent disparities in development across regions.

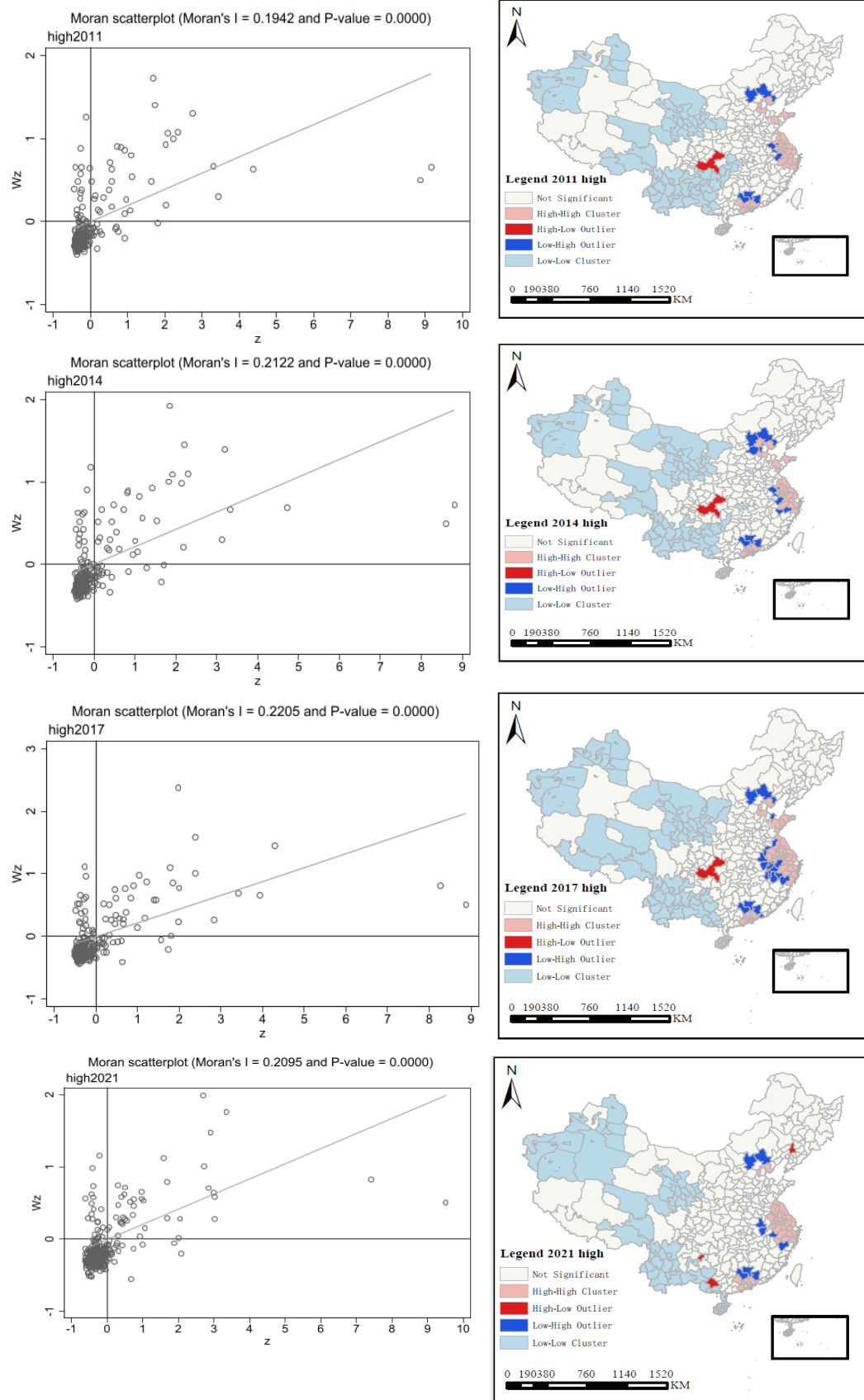


Figure 6. Local Moran scatter plots and LISA maps of "high" for the years 2011, 2014, 2017, and 2021. Base map source: Standard Map Service of the Ministry of Natural Resources (<http://bzdt.ch.mnr.gov.cn/index.jsp>) (accessed on 17 June 2025), Approval No.: GS(2020)4630.

LISA cluster maps, generated using ArcGIS 10.8, further illustrate these patterns. “High–High” agglomeration areas are primarily located in the eastern region, including the Guangdong–Hong Kong–Macao Greater Bay Area, the Yangtze River Delta, and the Beijing–Tianjin–Hebei region. These areas and their neighbors exhibit relatively high levels of “high” and strong positive spatial correlation. In contrast, “low–low” agglomeration is concentrated in the southwestern and northwestern regions, where both central and surrounding areas show persistently low development levels, also with significant positive spatial correlation.

4.5. Model Selection

In order to verify the reliability of the spatial model established in the article (1), relevant tests need to be conducted. Table 9 reports the diagnostic test results based on the inverse geographical distance matrix. The Lagrange Multiplier (LM) test for spatial error is significant, but the Robust LM test is not. In contrast, the LM test for spatial lag is significant, and both the Likelihood Ratio (LR) test and Wald test for SDM confirm the suitability of the SDM specification. The Hausman test yields statistically significant results, supporting the use of a fixed-effects specification; accordingly, the fixed-effects SDM is adopted for the empirical analysis. The above results also confirm the correctness of model (1).

Table 9. Test results for the applicability of SDM.

Spatial error	LM-error	65.138 ***
	R-LM-error	0.590
Spatial lag	LM-lag	81.191 ***
	R-LM-lag	16.642 **
Can the SDM Degenerate	LR-lrtest sdm sar	24.86 ***
	LR-lrtest sdm sem	41.48 ***
Wald-sdm	9.98 *	
Hausman	31.98 ***	

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively; the values represent standard errors.

5. Analysis of Empirical Results

5.1. SDM Results and Discussions

Table 10 reports the estimation results of the SDM based on an inverse geographical distance spatial weight matrix. The significantly positive ρ (rho) confirms the presence of spatial spillover effects in the relationship between DIF and “high”. Both the coefficient of DIF in the local region and its spatial lag term are significantly positive, with the latter being larger. Specifically, a 1% increase in DIF improves local “high” by 0.001%, while the effect from neighboring regions reaches 0.002%, indicating strong spatial spillover.

To further decompose these effects, the SDM is estimated using the maximum likelihood method (ML) proposed by Elhorst (2014), and the partial–differential decomposition results are reported in Tables 3–5. The direct effect estimates confirm that DIF significantly promotes local economic quality. The indirect effects—capturing spatial spillovers—are also significantly positive and notably larger than the direct effects. Overall, the total effect indicates that DIF plays a substantial role in enhancing “high” across regions. These findings support Hypothesis H1.

Table 10. Regression results of SDM.

Variable	(1) Main	(2) WX	(3) Direct Effect	(4) Indirect Effect	(5) Total Effect
DIF	0.001 ** (2.20)	0.002 *** (2.68)	0.001 *** (2.87)	0.006 *** (3.97)	0.007 *** (4.88)
CT	0.004 *** (5.62)	0.004 ** (2.46)	0.004 *** (6.05)	0.013 *** (3.31)	0.017 *** (4.03)
HM	0.005 (0.98)	−0.026 (−1.55)	0.003 (0.58)	−0.050 (−1.41)	−0.047 (−1.25)
FA	−0.000 ** (−2.28)	0.000 (1.04)	−0.000 * (−1.87)	0.000 (0.80)	0.000 (0.50)
Con	−0.000 (−0.46)	0.002 (1.59)	−0.000 (−0.09)	0.003 (1.50)	0.003 (1.37)
rho			0.546 *** (18.01)		
sigma2_e			0.000 *** (38.23)		
Observations			3091		
R ²			0.011		
Number of Cities			281		
Time Fixed			Yes		
Individual Fixed			Yes		

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively; values in parentheses indicate Z-values.

5.2. Analysis of Spatial Heterogeneity

Existing studies underscore pronounced regional disparities in China's "high". This pattern is further validated by the local Moran's *I* index and LISA cluster maps, which reveal evident spatial differentiation. In line with the methodology of [J. Xu and Li \(2023\)](#), the present study classifies 281 prefecture-level cities into three macro-regions for spatial consistency analysis: 100 cities in the eastern region, 99 in the central region, and 82 in the western region. The corresponding regression results are reported in [Table 11](#).

As indicated in the results, the spatial autocorrelation coefficient (ρ) is 0.504 and statistically significant, confirming the existence of spatial dependence and spillover effects. Columns (3), (4), and (5) present the estimated direct, indirect, and total effects, respectively, all of which are statistically significant. In the eastern region, DIF substantially enhances "high" at both the local and neighboring levels. Notably, the spillover (indirect) effect surpasses the direct effect, highlighting the pivotal role of interregional dynamics in amplifying the benefits of digital finance.

[Table 12](#) reports the SDM estimation results for 99 cities in the central region. The spatial lag coefficient (ρ) is 0.052 and statistically insignificant, implying the absence of spatial spillover effects. Furthermore, the estimated direct, indirect, and total effects indicate that DIF exerts a suppressive impact on "high" both within the region and across neighboring areas.

Several factors may explain this negative outcome: (1) Weak Digital Financial Infrastructure. The central region may suffer from underdeveloped digital financial infrastructure, including low internet penetration, limited payment networks, and inadequate data processing capacity. Although DIF is being promoted, these infrastructural weaknesses reduce its effectiveness, limit its reach to intended beneficiaries, and may lead to inefficient resource allocation and low financial efficiency. (2) Underdeveloped Industrial Structure. Compared with the eastern coastal region, central cities tend to have less mature industrial systems and lower levels of economic development. DIF typically performs better in regions with more advanced economies and diverse entrepreneurial activity, particularly among SMEs. If the

central region remains dominated by traditional industries, DIF may struggle to find sufficient application scenarios, diminishing its effectiveness or even causing adverse effects. (3) Risk of Over-Financialization. DIF may also contribute to “over-financialization”—the excessive expansion of financial services and credit (Z. X. Li & Chen, 2023). For traditional industries in the central region, increased access to credit without corresponding gains in productivity may result in a heavier debt burden. Given the limited competitiveness and profitability of these sectors, this can lead to resource misallocation and rising financial risks. Under such conditions, DIF may harm rather than help “high”.

Table 11. Regression results of the SDM for eastern cities.

Variable	(1) Main	(2) WX	(3) Direct Effect	(4) Indirect Effect	(5) Total Effect
DIF	0.002 (1.58)	0.004 * (1.81)	0.003 ** (2.00)	0.011 *** (2.86)	0.014 *** (3.71)
CT	0.006 *** (3.50)	0.006 (1.64)	0.006 *** (3.73)	0.016 ** (2.16)	0.023 *** (2.67)
HM	−0.003 (−0.31)	−0.015 (−0.42)	−0.004 (−0.34)	−0.032 (−0.49)	−0.036 (−0.51)
FA	−0.000 (−1.18)	0.001 ** (2.44)	−0.000 (−0.57)	0.002 ** (2.31)	0.001 ** (1.99)
Con	−0.003 *** (−2.91)	−0.001 (−0.32)	−0.003 *** (−3.19)	−0.004 (−1.12)	−0.007 * (−1.84)
rho			0.504 *** (11.07)		
sigma2_e			0.000 *** (23.00)		
Observations			1100		
R ²			0.014		
Number of Cities			100		
Time Fixed			Yes		
Individual Fixed			Yes		

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; values in parentheses indicate Z-values.

Table 12. Regression results of the SDM for central cities.

Variable	(1) Main	(2) WX	(4) Indirect Effect	(5) Total Effect
DIF	−0.000 ** (−2.26)	−0.001 *** (−2.93)	−0.001 *** (−2.93)	−0.002 *** (−4.10)
CT	0.002 *** (5.03)	0.003 *** (3.04)	0.003 *** (2.87)	0.005 *** (4.18)
HM	−0.003 (−1.39)	−0.044 *** (−4.79)	−0.046 *** (−4.90)	−0.049 *** (−5.09)
FA	−0.000 * (−1.73)	0.000 (0.97)	0.000 (1.05)	0.000 (0.47)
Con	−0.000 (−0.96)	−0.000 (−0.65)	−0.000 (−0.65)	−0.001 (−0.93)
rho			0.052 (0.95)	
sigma2_e			0.000 *** (23.58)	
Observations			1089	
R ²			0.057	
Number of Cities			99	
Time Fixed			Yes	
Individual Fixed			Yes	

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively; values in parentheses indicate Z-values.

Table 13 presents the SDM estimation results for 82 cities in the western region. The spatial lag coefficient (ρ) is -0.038 and statistically insignificant, suggesting the potential existence of a negative spatial spillover effect, often described as a “siphon effect”. Columns (5), (6), and (7) report significantly negative direct, indirect, and total effects, respectively, indicating that DIF suppresses “high” both locally and in surrounding areas.

Several factors may contribute to these findings: (1) Weak Economic Base and Simplified Industrial Structure. The western region is characterized by a relatively weak economic foundation and a high dependence on traditional industries. High-tech and service industries account for a small proportion of the economy (H. D. Liu & Ji, 2023). Even with some development in DIF, its capacity to support high-value-added industries is limited. Inefficient capital use and low returns on investment may further dampen economic dynamism. (2) Insufficient Human Capital and Technological Capacity. DIF depends heavily on the availability of skilled technical and managerial talent. However, the western region lacks sufficient high-quality human capital and has relatively low levels of technological development and innovation capacity. This hampers the effective implementation of digital financial services and may even lead to misdirected investments and inefficient resource use, ultimately undermining high-quality development. (3) Unfavorable Socioeconomic Conditions. High poverty rates, low education levels, and wide urban–rural disparities limit the adoption of digital finance in the western region. Low levels of financial and digital literacy among residents hinder the effective use of digital financial services, resulting in suboptimal resource allocation and limited contribution to economic growth. (4) Outflow of Resources and Negative Spillovers. Due to the large developmental gap between the western and more advanced regions, DIF may inadvertently facilitate the outflow of capital and resources toward more developed areas. This negative externality can worsen interregional disparities, contribute to resource depletion, and intensify brain drain, further impeding local economic development. (5) Potential Data Limitations. The sample size for cities in the western region—particularly in areas such as Xinjiang and Tibet—may be relatively small. This could reduce the model’s ability to accurately capture spatial dependence and may affect the reliability of the results (Anselin, 1988).

Table 13. Regression results of the SDM for western cities.

Variable	(1) Main	(2) WX	(3) Direct Effect	(4) Indirect Effect	(5) Total Effect
DIF	-0.000^{**} (-2.36)	-0.001^{***} (-4.02)	-0.001^{**} (-2.22)	-0.001^{***} (-3.95)	-0.002^{***} (-5.66)
CT	0.001^{**} (2.32)	0.002 (1.52)	0.001^{**} (2.32)	0.002 (1.42)	0.003^{**} (1.97)
HM	-0.009^{***} (-3.89)	-0.011 (-1.03)	-0.009^{***} (-3.96)	-0.010 (-0.99)	-0.019^{*} (-1.80)
FA	-0.000^{**} (-2.30)	0.000 (0.90)	-0.000^{**} (-2.39)	0.000 (1.02)	0.000 (0.21)
Con	-0.000 (-0.19)	0.000 (0.01)	-0.000 (-0.19)	0.000 (0.04)	-0.000 (-0.02)
ρ			-0.038 (-0.58)		
σ^2_e			0.000^{***} (21.47)		
Observations			902		
R^2			0.005		
Number of Cities			82		
Time Fixed			Yes		
Individual Fixed			Yes		

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively; values in parentheses indicate Z-values.

5.3. Analysis of the Two-Regime SDM

Table 14 reports the regression results based on two spatial matrices. In the model, p_1 and p_2 represent the spatial lag coefficients of DIF on “high” in central and non-central cities, respectively. Under the inverse geographical distance matrix, the coefficient for central cities (p_1) is 0.4761 and for non-central cities (p_2) is 1.404, both statistically significant. Under the economic–geographic weight matrix, p_1 is 0.234, and p_2 is 1.302, also both significant. The differences in coefficients between non-central and central cities are -0.928 and -1.068 under the two matrices, respectively, both significant at the 10% level. These results suggest that the spatial spillover effect of DIF is stronger in non-central cities than in central cities.

Possible explanations include (1) Greater Marginal Gains from Service Expansion.

In non-central cities, DIF is still in the growth stage. It often fills the gap left by traditional financial institutions, expanding access for SMEs and underserved populations (Ge & Wu, 2022). This expansion enhances local economic activity and innovation, driving high-quality development with strong spillover to neighboring areas. (2) Diminishing Returns in Central Cities. In contrast, DIF in central cities is relatively mature. Financial needs are largely met, which reduces the marginal gains from further expansion. As a result, its spatial spillover effect is less pronounced. (3) Weaker Economic Base in Non-Central Cities. Non-central cities typically have weaker economic foundations and simpler industrial structures (Z. Zhang et al., 2021). The development of DIF injects new momentum into these areas, improving local development while also stimulating growth in surrounding regions through economic linkage effects.

Table 14. Regression results of the two-regime model.

Variable	Results of Inverse Distance Matrix	Results of Economic Geography Weight Matrix
DIF	0.0065 *** (6.619)	0.011 *** (12.02)
CT	0.0022 *** (2.7313)	0.004 *** (5.761)
HM	−0.0361 *** (−7.729)	−0.04 *** (−8.131)
FA	0.0002 *** (3.050)	0.0002 *** (2.334)
Con	−0.0001 *** (6.84)	−0.0018 *** (−2.239)
p_1	0.4761 *** (18.55)	0.234 *** (7.323)
p_2	1.404 *** (32.47)	1.302 *** (21.23)
$p_1 - p_2$	−0.928 *** (−19.24)	−1.068 *** (−15.99)
$W \times \text{DIF}$	−0.002 * (−1.704)	−0.011 *** (−5.656)
$W \times \text{CT}$	0.0067 (−1.430)	0.004 *** (2.52)
$W \times \text{HM}$	0.006 *** (3.573)	0.04 *** (3.276)
$W \times \text{FA}$	−0.0001 (−0.698)	−0.519 (−0.467)
$W \times \text{Con}$	−0.0019 (−1.09)	−0.0001 *** (−3.453)
Individual Fixed		Yes
Time Fixed		Yes
R^2	0.5463	0.4762
Sample Size		3091

* and *** represent significance at the 10% and 1% levels, respectively; values in parentheses indicate t -values.

5.4. Analysis of the Mediating Effect

Tables 15–17 present the regression results of the SDM with the upgrading of industrial structure as the mediating variable. According to the testing rules for the mediating effect in spatial econometrics, in Table 13, for the model's β_1 value, columns (3), (4), and (5) in this table indicate that, respectively, the direct effect, indirect effect, and total effect all pass the significance test. There are no opposite signs in the regression results of (3, 4, 5). The total effect coefficient of 0.007 is taken as one of the core parameters of the equation (Yin & Chen, 2023). In Table 14, for the regression results of model (3, 4, 5), the value of α_1 is significant. Both the direct effect and the total effect pass the significance test and are positive. The indirect effect is positive but fails to pass the significance test. The total effect coefficient of 0.107 is taken as one of the core parameters of the equation. In the model of Table 15, the regression coefficients of the value of γ_1 in the direct effect, indirect effect, and total effect in the regression results (3, 4, 5) are positive, and all pass the significance test; the regression coefficient of the total effect, 0.02, is taken as one of the core parameters of the equation. As can be seen from the above, the signs of β_1 , α_1 , and γ_1 are all positive, indicating a partial mediating effect. The proportion of the mediating effect to the total effect is $0.107 \times 0.02 / 0.007 = 0.3057$. In conclusion, Hypothesis H2 in this paper holds.

Table 15. Regression results of the SDM for “high” with the inverse geographical distance matrix.

Variable	(1) Main	(2) WX	(3) Direct Effect	(4) Indirect Effect	(5) Total Effect
DIF	0.001 ** (2.20)	0.002 *** (2.68)	0.001 *** (2.87)	0.006 *** (3.97)	0.007 *** (4.88)
CT	0.004 *** (5.62)	0.004 ** (2.46)	0.004 *** (6.05)	0.013 *** (3.31)	0.017 *** (4.03)
HM	0.005 (0.98)	−0.026 (−1.55)	0.003 (0.58)	−0.050 (−1.41)	−0.047 (−1.25)
FA	−0.000 ** (−2.28)	0.000 (1.04)	−0.000 * (−1.87)	0.000 (0.80)	0.000 (0.50)
Con	−0.000 (−0.46)	0.002 (1.59)	−0.000 (−0.09)	0.003 (1.50)	0.003 (1.37)
rho			0.546 *** (18.01)		
sigma2_e			0.000 *** (38.23)		
Observations			3091		
R ²			0.011		
Number of Cities			281		
Time Fixed			Yes		
Individual Fixed			Yes		

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively; values in parentheses indicate *t*-values.

Table 16. Regression results of the SDM for “industrial structure upgrading” with the inverse geographical distance matrix.

Variable	(1) Main	(2) WX	(3) Direct Effect	(4) Indirect Effect	(5) Total Effect
DIF	0.089 *** (3.69)	0.022 (0.47)	0.090 *** (3.59)	0.017 (0.39)	0.107 *** (3.07)
CT	0.079 ** (1.98)	0.127 (1.29)	0.076 ** (1.98)	0.116 (1.18)	0.192 * (1.79)
HM	−0.139 (−0.51)	0.880 (0.89)	−0.117 (−0.45)	0.826 (0.89)	0.709 (0.74)

Table 16. Cont.

Variable	(1) Main	(2) WX	(3) Direct Effect	(4) Indirect Effect	(5) Total Effect
FA	0.003 (1.19)	0.001 (0.15)	0.003 (1.21)	0.002 (0.22)	0.005 (0.54)
Con	0.094 *** (4.01)	0.043 (0.69)	0.093 *** (4.12)	0.038 (0.63)	0.131 ** (2.10)
rho			0.0561 * (8.35)		
sigma2_e			0.006 *** (39.30)		
Observations			3091		
R ²			0.320		
Number of Cities			281		
Time Fixed			Yes		
Individual Fixed			Yes		

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively; values in parentheses indicate Z-values.

Table 17. Regression results of the SDM with the inverse geographical distance matrix.

Variable	(1) Main	(2) WX	(3) Direct Effect	(4) Indirect Effect	(5) Total Effect
DIF	0.001 (1.52)	0.002 ** (2.03)	0.001 ** (1.99)	0.004 *** (2.75)	0.005 *** (3.36)
I	0.003 *** (11.43)	0.006 *** (4.55)	0.004 *** (12.56)	0.016 *** (5.88)	0.020 *** (6.93)
CT	0.003 *** (5.17)	0.002 (1.43)	0.004 *** (5.70)	0.009 ** (2.57)	0.013 *** (3.38)
HM	0.005 (1.02)	−0.022 (−1.34)	0.003 (0.61)	−0.039 (−1.16)	−0.036 (−1.01)
FA	−0.000 ** (−2.56)	0.000 (1.25)	−0.000 ** (−2.14)	0.000 (0.87)	0.000 (0.52)
Con	−0.001 (−1.36)	0.001 (0.97)	−0.000 (−1.02)	0.002 (0.74)	0.001 (0.51)
rho			0.525 *** (17.03)		
sigma2_e			0.000 *** (38.32)		
Observations			3091		
R ²			0.034		
Number of Cities			281		
Time Fixed			Yes		
Individual Fixed			Yes		

, and * represent significance at the 5%, and 1% levels, respectively; values in parentheses indicate Z-values.

5.5. Analysis of the Threshold Effect

The results are presented in Table 18 and Figure 7. The findings confirm the existence of a threshold effect, specifically, a double-threshold structure, in the impact of DIF on industrial structure upgrading.

Table 19 provides the regression estimates across the three threshold intervals. When the DIF index exceeds 5.6945, its effect on industrial structure upgrading is positive but not statistically significant. In the intermediate range (5.5371–5.6945), the effect becomes significantly negative, indicating an inhibitory impact. When the index falls below 5.5371, the negative effect is also significant and more pronounced. These results suggest that digital inclusive finance must exceed a critical threshold of 5.6945 to support industrial

upgrading and contribute positively to “high”. In conclusion, the evidence supports Hypothesis H3.

Table 18. Results of the threshold test.

Variable	Number of Thresholds	<i>p</i> -Value	Threshold Value	Critical Value		
				10%	5%	1%
DIF	2	0.0000	5.6945	25.6142	29.5870	42.4237
			5.5371	62.8270	68.8782	89.0653

Note: Self-organized findings.

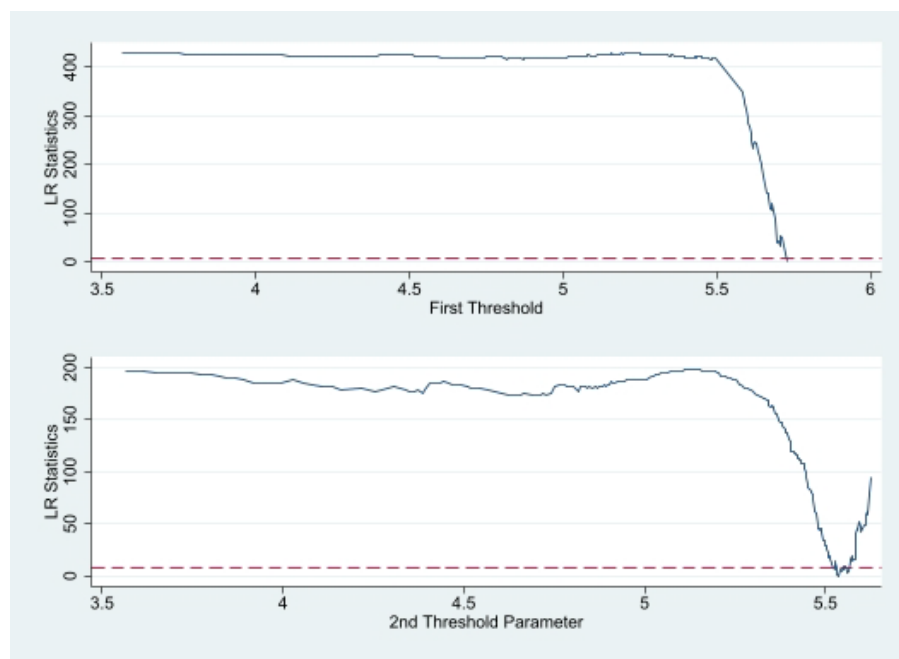


Figure 7. Graph of the threshold regression results.

Table 19. Results of the threshold regression.

Variables	(1)
	High
CT	0.002 *** (2.68)
HM	0.004 (0.92)
FA	−0.000 *** (−3.52)
Con	−0.002 *** (−9.85)
DIF > 5.6945	0.0001 (1.48)
5.6945 ≤ DIF < 5.5371	−0.0001 * (−1.78)
DIF ≤ 5.5371	−0.001 *** (−10.30)
Constant	0.003 *** (9.01)
Observations	3091
Number of id	281
R-squared	0.210

*** indicates $p < 0.01$, * indicates $p < 0.1$, and the values in () indicate *t*-values.

5.6. Robustness Test and Endogeneity Test

5.6.1. Robustness Test

To ensure the consistency of the empirical results, robustness checks were performed, with the outcomes reported in Table 20. The significance levels and the direction (positive or negative) of the core variable—DIF—remain unchanged, indicating stability in the estimation results.

Table 20. Results of the robustness regression.

Variable	(1) Main	(2) WX	(3) Direct Effect	(4) Indirect Effect	(5) Total Effect
DIF	0.001 * (1.91)	0.002 ** (2.05)	0.001 ** (2.13)	0.006 ** (2.20)	0.007 ** (2.32)
CT	0.004 ** (2.13)	0.004 * (1.67)	0.004 ** (2.28)	0.013 ** (2.12)	0.017 ** (2.29)
HM	0.005 (0.60)	−0.026 (−0.85)	0.003 (0.34)	−0.056 (−0.84)	−0.053 (−0.74)
FA	−0.000 (−1.21)	0.000 (1.17)	−0.000 (−1.10)	0.000 (0.89)	0.000 (0.54)
Con	−0.000 (−0.38)	0.002 * (1.86)	−0.000 (−0.08)	0.003 * (1.80)	0.003 (1.64)
rho			0.546 *** (8.00)		
sigma2_e			0.000 ** (2.42)		
Observations			3091		
R ²			0.011		
Number of Cities			281		
Time Fixed			Yes		
Individual Fixed			Yes		

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively; values in parentheses indicate Z-values.

Following the method of [Y. Li et al. \(2022\)](#), this study performed robustness testing using the SDM with an economic–geographical spatial weight matrix. In Table 21, most results are consistent with those of the baseline study, further confirming the robustness and reliability of the previous conclusions.

Table 21. Regression results of the SDM with the economic geographical matrix.

Variable	(1) Main	(2) WX	(3) Direct Effect	(4) Indirect Effect	(5) Total Effect
DIF	0.001 *** (3.09)	0.009 *** (3.23)	0.002 *** (3.85)	0.103 * (1.95)	0.105 ** (1.98)
CT	0.004 *** (6.12)	−0.009 (−1.59)	0.004 *** (5.75)	−0.056 (−0.76)	−0.052 (−0.71)
HM	−0.002 (−0.41)	0.192 ** (2.42)	0.006 (0.85)	1.920 (1.64)	1.926 (1.64)
FA	0.000 (0.15)	−0.000 (−0.45)	0.000 (0.06)	−0.001 (−0.34)	−0.001 (−0.34)
Con	−0.000 (−0.48)	0.002 (0.64)	−0.000 (−0.36)	0.017 (0.56)	0.017 (0.55)
rho			0.893 *** (28.34)		
sigma2_e			0.000 *** (39.17)		
Observations			3091		
R ²			0.001		
Number of Cities			281		
Time Fixed			Yes		
Individual Fixed			Yes		

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively; values in parentheses indicate Z-values.

5.6.2. Endogeneity Test

Following the approach of [Shi and Sun \(2023\)](#), this study addresses potential endogeneity by using the first lag of the dependent variable as an instrumental variable. Table 22 reports the results of the two-stage least squares (2SLS) estimation.

The coefficient of the core explanatory variable, DIF_1, is 0.023 and statistically significant at the 1% level, confirming a robust and positive impact on “high”. All control variables also pass the significance tests.

Table 22. Results of the endogeneity test.

Variable	High
DIF_1	0.023 *** (5.81)
Con	0.004 *** (3.23)
HM	0.109 *** (6.19)
CT	−0.020 *** (−3.50)
FA	−0.003 *** (−5.26)
Constant	−0.101 *** (−5.98)
Number of Observations	3091
F-statistic	(5.3085) = 145.59

*** represent significance at the 1% levels, respectively; values in parentheses indicate *t*-values.

6. Conclusions and Countermeasures

6.1. Conclusions

This paper employs SDM and panel data from 281 prefecture-level cities in China spanning 2011 to 2021 to empirically examine the impact of DIF on “high”. The main findings are as follows:

First, the Moran’s *I* index of “high” shows a significant positive spatial correlation. LISA maps reveal distinct patterns of “high–high” and “low–low” agglomeration, confirming spatial clustering effects.

Second, SDM estimations based on both the inverse geographical distance matrix and the economic–geographic weight matrix demonstrate that DIF exerts a significant promotive effect on “high” in both local and adjacent regions, thereby corroborating the existence of spatial spillover effects.

Third, spatial heterogeneity is evident. In the eastern region, DIF significantly contributes to “high”. However, in the central and western regions, it exerts a negative impact. This may be attributed to underdeveloped industrial and financial infrastructure, as well as the presence of a “siphon effect”, where resources are drawn toward more developed areas, weakening local development potential. Results from the two-regime SDM further show that non-central cities exhibit stronger spillover effects than central cities.

Fourth, threshold analysis confirms a double-threshold effect, indicating a nonlinear relationship. The impact of DIF varies across development stages, and only when it surpasses a certain level does it exert a significantly positive influence on “high”.

6.2. Countermeasures

1. Enhance Digital Financial Infrastructure in Central and Western Regions

Given the infrastructure gaps that hinder DIF's effectiveness in central and western regions, governments should prioritize targeted investments to expand internet access, stabilize digital payment systems, and promote fintech adoption. Improving infrastructure will reduce regional disparities; improve financial accessibility; and foster inclusive, high-quality economic growth.

2. Promote Financial Innovation in the Eastern Region

Empirical results confirm that DIF has a stronger impact in the eastern region. To sustain this advantage, policymakers should support innovation in technologies such as blockchain, AI-based risk control, and digital identity systems. These advancements can improve service precision, security, and user experience, further strengthening the eastern region's role in leading economic transformation.

3. Mitigate Risks and Prevent Digital Exclusion

Acknowledging threshold effects and potential siphon risks, regulatory improvements are essential. Rapid DIF expansion in low-literacy or fragile areas may exacerbate inequality or digital exclusion. Policymakers should balance innovation with safeguards, including investments in digital literacy, consumer protection, and inclusive policies to ensure that vulnerable groups are not left behind. A sound regulatory environment will support sustainable DIF development nationwide.

4. Preventing Digital Exclusion and Inequality

In addition to emphasizing differentiated regional strategies, it is also important to acknowledge potential risks associated with rapid DIF expansion. In regions with fragile infrastructure or low financial literacy, aggressive digitalization may exacerbate digital exclusion, leaving vulnerable groups further behind. Moreover, over-reliance on digital channels without adequate safeguards could increase exposure to financial fraud or deepen inequalities. Therefore, while promoting DIF, policymakers should ensure parallel investments in digital literacy, infrastructure, and regulatory frameworks to mitigate these unintended consequences and promote inclusive, sustainable development.

7. Future Research Directions

7.1. City-Level Microdata and Household Surveys

Future research could incorporate micro-level data—such as firm- or household-level surveys—to gain a deeper understanding of how DIF affects different stakeholders. Examining the heterogeneity of effects among low-income groups, SMEs, or specific industry sectors could help uncover more nuanced impacts of DIF and reveal micro-level transmission mechanisms.

7.2. Cross-Country Comparative Studies

Most current studies, including this one, are China-focused. Cross-country comparative studies in emerging markets or among BRI (Belt and Road Initiative) partner countries could provide broader insights into how institutional contexts, regulatory frameworks, and digital infrastructure moderate the effects of DIF on economic quality.

7.3. Improvements to the Synthetic Index

Although the entropy method provides an objective weighting scheme, its reliance on data dispersion may overlook indicators of high theoretical relevance. Future research

could explore alternative composite index methods that better capture the multidimensional nature of high-quality development.

7.4. Expanding Future Research Horizons in Digital Financial Tools

This study mainly focuses on DIF as measured by the Peking University Index, which emphasizes platforms like Alipay. However, it does not consider tools such as the digital CNY. The digital CNY, as a CBDC, may enhance inclusion by improving access and security, especially in underserved areas. Future research could explore how different tools—DIF platforms, CBDCs, and even cryptocurrencies—compare in promoting inclusive and sustainable development. This would broaden the global relevance of the analysis.

Author Contributions: Conceptualization, L.C. and G.Z.; methodology, L.C.; software, L.C.; validation, L.C. and G.Z.; formal analysis, L.C. and G.Z.; resources, L.C. and G.Z.; data curation, L.C.; writing—original draft preparation, L.C. and G.Z.; writing—review and editing, L.C. and G.Z.; visualization, L.C.; supervision, L.C. and G.Z.; project administration, L.C. and G.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

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