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A Study on the Impact of Digital Inclusive Finance on Systemic Financial Risk

Jiali Tian*, Junxiang Lu, Yuqing Zhang

School of Science, Xi'an Polytechnic University, Xi'an, Shaanxi, 710600, China

Corresponding author: Jiali Tian, 15237311672@163.com

Abstract: Against the backdrop of global economic restructuring and China's financial liberalization, digital inclusive finance has a complex dual impact on regional systemic financial risk. The nexus between digital inclusive finance and systemic risk are investigated via the CRITIC method, Theil index decomposition, fixed-effects regression, heterogeneity analysis, and mediation tests in the paper, by using a panel of 31 Chinese provinces from 2014 to 2025. Results show that systemic risk and digital finance development differ significantly across regions. Digital inclusive finance exhibits a significant U-shaped effect on systemic risk: it reduces risk initially but increases risk accumulation beyond a threshold. This effect is significant in eastern and northeastern regions but insignificant in central and western regions. Capital transfer mediates 27.14% of the total effect, and systemic risk shows significant spatial agglomeration. A region-specific risk monitoring system to safeguard financial stability and high-quality development in the Asia-Pacific is proposed.

Keywords: Digital Inclusive Finance; Systemic Financial Risk; Spatial Agglomeration; Regional Heterogeneity

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1. Introduction

Amid global economic restructuring and China's ongoing economic transformation, the continuous opening of the financial system has introduced new challenges to financial stability. On the one hand, large regional disparities in economic development and financial market conditions have heightened the risk of regional financial volatility. The financial stress index across China's 31 provincial-level administrative units averages 0.3002 over the period 2014–2025, ranging from a peak of 0.7960 in Beijing (2023) to a trough of 0.1282 in Heilongjiang (2014). This wide divergence indicates substantial heterogeneity in regional risk exposure. Given the strong interconnectedness within the financial system, local risks can easily spill over across regions, threatening overall financial stability and social stability[1]. On the other hand, the deep integration of digital technology and finance has fostered the rapid development of digital inclusive finance, which has greatly improved financial access and reduced traditional financial exclusion. Based on the Peking University Digital Inclusive Finance Index, the national aggregate index rose from 1.7 in 2014 to 3.9 in 2025, with an annual growth rate of up to 22.4% in some years, effectively supporting small and micro enterprises and underdeveloped regions. Nevertheless, digital inclusive finance also brings new uncertainties, such as cybersecurity risks, data leakage, and algorithmic limitations, which increase the complexity of systemic risk governance . In 2025, China issued the Guiding Opinions on Doing a Good Job in the "Five Major Articles" of Finance and the Implementation Plan for High-quality Development of Inclusive Finance in the Banking and Insurance

Industry, both emphasizing digital financial supervision, data and network security, and risk pricing optimization to mitigate regional financial imbalances. Meanwhile, the IMF (2021) warned that overly rapid expansion of digital inclusive finance without matching supervision may lead to regulatory arbitrage and data sovereignty risks in developing economies. In this context, identifying the transmission channels, effects, and heterogeneity of digital inclusive finance on regional systemic financial risk has become a critical issue in financial research.

The literature on digital inclusive finance and systemic risk presents two competing views. One strand argues that digital inclusive finance reduces systemic risk by lowering information costs and improving resource allocation efficiency. Another strand emphasizes that digital finance may accelerate risk contagion through cross-business integration and network connectedness. Furthermore, several studies identify nonlinearity, regional heterogeneity, and spatial agglomeration effects. However, few studies combine the U-shaped relationship, regional heterogeneity, mediating mechanisms, and spatial dependence in a unified framework for China's provincial panel[2].

Against the background, basing on a sample of 31 provincial-level regions in mainland China over 2014–2025, firstly, a comprehensive systemic financial risk index using the CRITIC weighting method and reciprocal standard deviation weighting method are constructed, secondly, Theil index decomposition to examine regional disparities in digital inclusive finance is employed, thirdly, benchmark regression and regional heterogeneity analysis to test the U-shaped impact of digital inclusive finance on systemic risk are conducted, finally, a mediation model is used to examine the role of capital transfer. This study aims to reveal the relationship between digital inclusive finance and regional systemic financial risk and provide policy implications for risk prevention and high-quality financial development.

2. Basic Principles and Mechanism Analysis

2.1 Information Asymmetry Mitigation Principles

Information asymmetry represents a core source of friction in financial intermediation that distorts credit allocation and fuels systemic risk. In conventional financial systems, severe information barriers exist between formal financial institutions and vulnerable agents such as small and micro enterprises, individual businesses, and rural households. Traditional credit evaluation systems rely heavily on collateral, standardized financial statements, and formal credit histories, which many small-scale and informal participants lack. This mismatch creates a dual problem: restricted credit access, high financing costs, and financial exclusion for borrowers, accompanied by inaccurate risk assessment and excessive risk accumulation for lenders.

Digital inclusive finance alleviates such asymmetry by deploying big data, artificial intelligence, and blockchain technologies to build expanded information collection and processing capabilities. Digital platforms integrate multi-dimensional unstructured data—including e-commerce transactions, mobile payment flows, operational records, and digital behavioral patterns—and generate reliable credit profiles through algorithmic modeling. This approach reduces dependence on physical collateral and traditional financial documents, allowing creditworthy borrowers without formal records to obtain ratings. Improved information transparency lowers verification costs and mitigates adverse selection and moral hazard[3].

Digital inclusive finance improves financial access and optimizes resource allocation via precise risk pricing by strengthening information efficiency. It discourages reckless lending and overborrowing, curbs risk accumulation at an early stage, and strengthens the institutional foundation for regional systemic financial risk prevention and control.

2.2 Risk Threshold Principle

The impact of digital inclusive finance on regional systemic financial risk is nonlinear and exhibits a significant threshold pattern. This pattern arises from the dual effects of digital finance: technology-driven efficiency gains at moderate levels, and rising interconnectedness and risk-taking at elevated levels[4]. The threshold mechanism is as follows:

$$SFRI_{i,t} = \beta_0 + \beta_1 DFI_{i,t}.I(DFI_{i,t} \le \gamma) + \beta_2 DFI_{i,t}.I(DFI_{i,t} > \gamma) + \varepsilon_{i,t} \tag{1}$$

where, $SFRI_{i,t}$ is the systemic financial risk index for the period t in the i region, DFI is the development level of digital inclusive finance, γ is the threshold value, $I(.)$ is the indicator function (it takes 1 when the conditions in parentheses are met, otherwise it takes 0), β_1 is the pre-threshold coefficient, it is the post-threshold coefficient, $\varepsilon_{i,t}$ is the random disturbance term. Before the threshold value, The "inclusiveness" and "efficiency" of digital inclusive finance dominate, by lowering the threshold of financial services, optimizing the efficiency of capital allocation, improving the liquidity and shock resistance of the financial system, $\beta_1<0$, the risk decreases with the development of digital inclusive finance; when $DFI_{i,t}>\gamma$, Its "risk" characteristics are prominent: business cross-integration forms a complex financial network, and single node risks are easy to spread rapidly; excessive capital influx into high-yield fields causes asset bubbles, when $\beta_2>0$, This threshold reflects the trade-off between technological efficiency and systemic vulnerability, which depends on regional financial development, institutional quality, and regulatory capacity.

2.3 Principle of Regional Heterogeneity

Wide disparities in economic endowment, financial depth, digital infrastructure, and industrial upgrading across Chinese regions lead to heterogeneous effects of digital inclusive finance on systemic financial risk. We formalize this heterogeneity using a regional adjustment model:

$$SFRI_{i,t}=\alpha_0+\alpha_1 DFI_{i,t}+\alpha_2 DFI_{i,t}.Reg_i+\sum Control+\mu_{i,t} \tag{2}$$

Where, Reg_i is the dummy variable of regional characteristics (set according to economic development level, financial market maturity and other dimensions, standardized treatment), α_2 is the regional adjustment coefficient $\sum$ Control is the set of control variables such as economic growth and industrial structure , μi,t is the disturbance term. The sign and significance difference of α_2 in the formula, the core logic that intuitively reflects regional heterogeneity: for regions with developed economy and finance and perfect digital infrastructure, α_2 is significantly positive, and the initial stage of digital inclusive finance development can quickly make up for the shortcomings of traditional finance($\alpha_1<0$), after breaking through the threshold, the risk is aggravated due to business intersection and capital speculation ($\alpha_1+\alpha_2>0$), yielding a pronounced Ushape. For regions with lagging structural transformation and weak risk-bearing capacity, α_2 remains significantly positive but the threshold level is lower. For regions with underdeveloped financial systems and slow digital adoption, the interaction term is insignificant: the efficiency effect is muted, and neither risk mitigation nor risk amplification is strong. Heterogeneity is further reinforced by uneven regional regulatory capacity and crossregional spillovers in risk monitoring.

2.4 Mechanism of Action: Specific Path of Digital Inclusive Finance Affecting Regional Systemic Financial Risk

2.4.1 Direct path

To explicitly delineate the direct relationship between digital inclusive finance and regional systemic financial risk, a benchmark regression model is constructed to capture their U-shaped nonlinear association[5]:

$$SFRI_{i,t}=\alpha_0+\alpha_1 DFI_{i,t}+\alpha_2 {DFI_{i,t}}^2+\sum\beta_k Control+\mu_i+\lambda_t+\varepsilon_{i,t} \tag{3}$$

Where, $SFRI_{i,t}$ represents the regional systemic financial risk index of province i in China during t period, which is synthesized by CRITIC weighting method and standard deviation reciprocal weighting method, covering 6 major field indicators such as banking, insurance, stock, real estate and macro-economy ; it is the core explanatory variable, i.e. the total digital inclusive financial index of province i during t period (scaled by dividing by 100). ${DFI_{i,t}}^2$ is its square term, used to test the U-shaped relationship, if $\alpha_1<0$ and $\alpha_2>0$ the U-shaped relationship is established; Control represents a series of control variables, including economic growth level, industrial structure, financial deepening degree, urbanization growth rate and opening degree; μ_i the province fixed effect , λ_t is the year fixed effect, $\varepsilon_{i,t}$ is the random perturbation term.The sub-dimension direct influence model further splits the three sub-dimensions of digital inclusive finance coverage breadth, use depth and digitalization degree, constructs a sub-dimension regression model, and accurately identifies the direct effect differences of each dimension:

$$SFRI_{i,t}=\alpha_0+\alpha_1 Dim_{it}+\alpha_2 Dim_{it}^2+\sum\beta_k Control+\mu_i+\lambda_t+\varepsilon_{i,t} \tag{4}$$

replaced with $WIDTH_{it}$, $DEPTH_{it}$, $DIGITAL_{it}$.

2.4.2 Indirect path

The indirect path takes capital transfer as the core intermediary. Digital inclusive finance indirectly affects the stability of regional financial market by changing the flow direction, allocation structure and flow efficiency of capital. Its transmission mechanism can be quantified by the three-step formula of intermediary effect: total effect formula (direct + indirect total impact of digital inclusive finance on risk):

$$SFRI_{i,t} = \theta_0 + \theta_1 DFI_{i,t} + \sum Control + \varepsilon_{1,i,t} \tag{5}$$

Where, θ_1 is the total effect coefficient, represents the overall impact of digital inclusive finance on $SFRI_{i,t}$. Mediating variable regression formula (impact of digital inclusive finance on capital transfer):

$$CAPITAL_{i,t} = \alpha_0 + \alpha_1 DFI_{i,t} + \sum Control + \varepsilon_{2,i,t} \tag{6}$$

Where, $CAPITAL_{i,t}$ is the intermediary variable of capital transfer (calculation method: (financial industry output value + real estate industry output value)/(GDP-financial industry output value-real estate industry output value), α_1 is the influence coefficient of digital inclusive finance on capital transfer. Direct effect + intermediary effect formula (after controlling intermediary variable):

$$SFRI_{i,t} = \theta_0^{'} + \theta_1^{'} DFI_{i,t} + \beta CAPITAL_{i,t} + \sum Control + \varepsilon_{3,i,t} \tag{7}$$

Where, $\theta_1^{'}$ is the direct effect coefficient, is the impact coefficient of capital transfer on risk, and the size of the intermediary effect is ($\alpha_1.\beta$)，The mediating effect is ($\alpha_1.\beta$)/θ_1.The risk mitigation transmission path of capital transfer is as follows: Digital inclusive finance reduces the information and transaction costs of capital flows, facilitating the transfer of capital from inefficient sectors (e.g., overheated real estate) to efficient real economic departments (e.g., small and micro enterprises, innovative industries), thereby optimizing the regional asset structure[6]. Additionally, it broadens financing channels for small and micro enterprises and innovative enterprises, disperses risk concentration in a single industry or sector, and mitigates systemic crises caused by excessive risk aggregation.

3. Empirical Studies

3.1 Variable Selection and Data Acquisition

In this paper, panel data of 31 provincial administrative regions (excluding Hong Kong, Macao and Taiwan) in the mainland of China from 2014 to 2025 are taken as core research samples. Data collection centers on explained variables, core explanatory variables, control variables and intermediate variables required for the study. The specific collection scope, sources and processing methods are as follows:

3.1.1 Core explanatory variable data collection

The core explanatory variable is the development level of digital inclusive finance. The “Digital Inclusive Financial Index” compiled by the Digital Inclusive Finance Research Center of Peking University is adopted as the quantitative basis, and the original data are downloaded directly from the official channels of the Center. The index covers the total digital inclusive financial index and three sub-dimensional indexes of coverage breadth, depth of use and degree of digitization. The original data has been standardized. In order to ensure the magnitude adaptation of the data with other variables, the total index and each sub-dimensional index are divided by 100 for scaling after collection, and finally the total digital inclusive financial index (DFI), coverage breadth index (WIDTH) of 31 provinces from 2014 to 2023 are obtained. Use DEPTH and DIGITAL panel data as shown in Figures 1 and 2.

Figure 1: Overall trend chart of digital inclusive finance

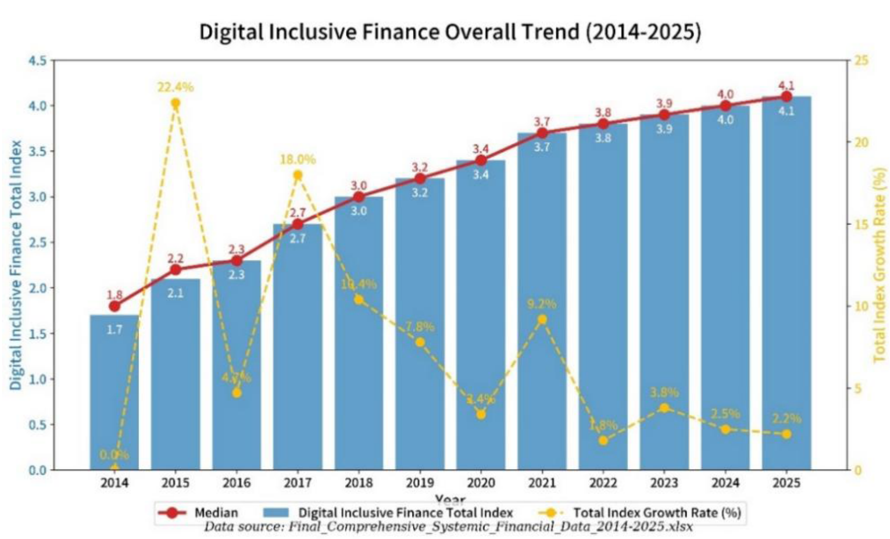


Figure2: Overall trend diagram of digital inclusive subdimension

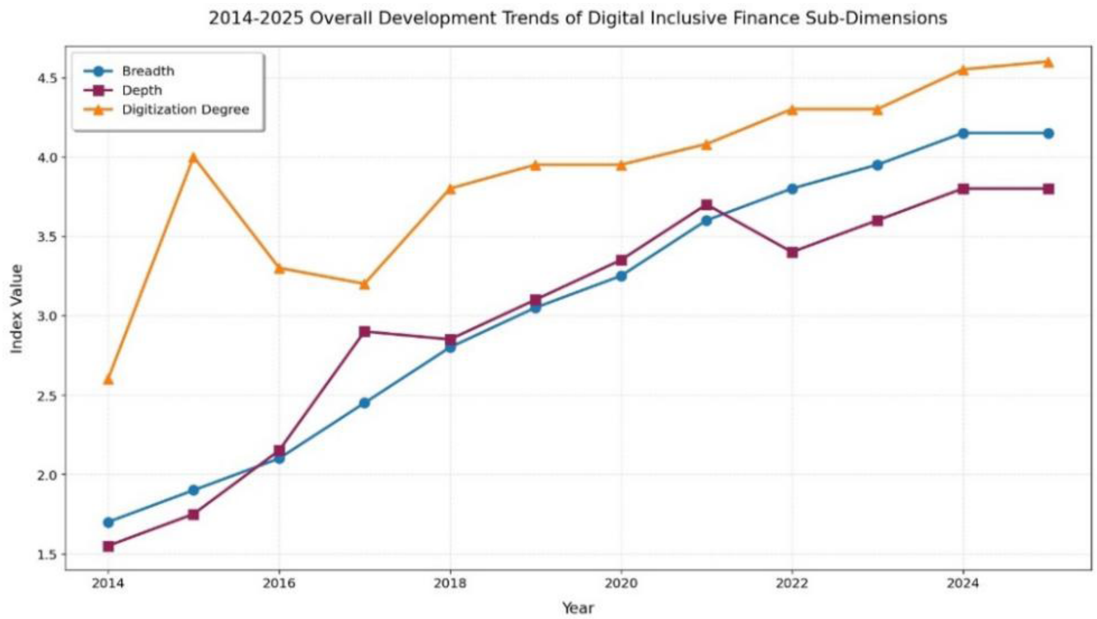


Figure 2 plots the time-series trends of three core sub-dimensions of digital inclusive finance in China over the 2014–2025 period. All indices are normalized to maintain comparability. Breadth (blue solid line) measures the geographic and demographic penetration of formal financial services. It exhibits a steady upward trajectory, rising from 1.7 in 2014 to 4.16 in 2025, reflecting consistent progress in expanding access to underserved regions and populations.Depth (purple solid line) captures the intensity of actual financial service usage, including payment, credit, and insurance activities. After a period of rapid growth from 2016 to 2021, the trend moderates slightly, indicating a maturation phase in service adoption.Digitization Degree (orange solid line) represents the level of digital technology integration in financial services. Characterized by an early peak in 2015, a temporary slowdown, and subsequent strong growth, it consistently leads the other two dimensions, reaching 4.61 by 2025. This highlights digital innovation as the primary driver of the overall digital inclusive finance development. Collectively, the figure demonstrates a robust and sustained expansion of the digital inclusive finance ecosystem, with digitalization emerging as the leading force, followed by service breadth and depth.

3.1.2 Data collection of explained variables

The explained variable is regional systemic financial risk, which needs to be quantified through the synthesis of multi-dimensional indicators into the Systemic Financial Risk Index (SFRI). The data collection covers six major areas: banking system, insurance market, stock market, real estate market, government regulation and macroeconomics., the specific indicators and data sources are as follows[7]:

Table 1: indicator system

first-level indicators	secondary indicators	implication	Relationship to systemic financial risk
banking system	deposit-loan ratio	Total loans/total deposits	forward direction
	loan growth rate	(Current Loan-Prior Loan)/Prior Loan	forward direction
	non-performing loan ratio	Non-performing loans/total loans	forward direction
insurance market	insurance penetration	Premium income/GDP	negative
	insurance density	Premium income/total population	negative
market for stocks	Market capitalization/GDP	Total Market Value of Listed A-share Enterprises in Each Province/GDP	negative
	stock price-earnings ratio	A-share static average P/E ratio	negative

first-level indicators	secondary indicators	implication	Relationship to systemic financial risk
real estate market	Price of residential commercial housing	Residential commodity sales/Residential commodity sales area Negative	negative
	growth rate of real estate investment	Difference between real estate investment of current period and previous period/positive direction of real estate investment of previous period	forward direction
macro economy	fiscal deficit rate	(Fiscal revenue-fiscal expenditure)/Fiscal revenue	forward direction
	inflation rate	CPI growth rate	forward direction
	Debt financing for the year	Financing of current year debt by province	forward direction
	GDP growth rate	(Current GDP-Previous GDP)/Previous GDP	negative
	unemployment rate	Total unemployed population/total persons meeting employment conditions	forward direction

After collecting all the basic data, CRITIC weighting method and standard deviation reciprocal weighting method are adopted to calculate the weights and index synthesis of the indicators in 6 major fields (Diakoulaki, Mavrotas, and Papayannakis, 1995), and finally the regional systemic financial risk index *SFRI* of 31 provinces from 2014 to 2025 is obtained. The average value of the index is 0.3002 and the maximum value is 0.7960 (Beijing, 2023), minimum value 0.1282(Heilongjiang, 2014), effectively reflecting regional risk differences. In order to reduce the interference of different dimensions on financial pressure index, this paper divides each variable into positive and negative indicators according to the influence of each variable on financial risk, and carries out standardization treatment. For specific methods, see (8) and (9). x_{ij} and X_{ij} are the values of i evaluation object j index before and after standardization[8].

$$X_{ij} = \frac{x_{ij} - min\,(x_{ij})}{max\,(x_{ij}) - min\,(x_{ij})} \tag{8}$$

$$X_{ij} = \frac{max\,(x_{ij}) - x_{ij}}{max\,(x_{ij}) - min\,(x_{ij})} \tag{9}$$

As shown in Equations (1) and (2), the weights of the sub-markets are determined by the reciprocal standard deviation method, and the systematic risk index of each sub-market is further calculated. where W_{ij} denotes the weight of index i in market j and θ_j denotes the systemic risk index for sub-market j.

$$W_{ij} = (\frac{1}{std_j})/(\sum_k^n \frac{1}{std_k}) \tag{10}$$

$$\theta_j = \sum X_{ij} * W_j \tag{11}$$

The total weight is synthesized based on CRITIC weighting method, which fully considers the differences and conflicts among indicators, as shown in Equations (10) and (11) (OECD, 2022). Where σ_j is the standard deviation of the financial pressure index of market j, c_j is the information amount of market j, r_{ij} is the correlation coefficient of the two markets i and j, $\sum(1-r_{ij})$ is the index conflict. The stronger the index conflict, the greater the information amount, and the greater the index weight W_j [9] according to the calculation method of systemic financial risk index mentioned above, this paper calculates the systemic financial risk index of each province and city in China from 2014 to 2023, and further obtains the average value of index of each province and city during the reporting period. The specific calculation results are shown in Table 2.

Table 2: Systemic Financial Risk Index of Provinces and Cities from 2014 to 2025

Province	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Beijing	0.3821	0.4012	0.4235	0.4512	0.4896	0.5213	0.5689	0.6124	0.6785	0.796	0.782	0.775
Tianjin	0.3215	0.3342	0.3518	0.3724	0.4012	0.4325	0.4689	0.4921	0.5236	0.5512	0.542	0.538
Hebei	0.2896	0.3012	0.3185	0.3342	0.3612	0.3896	0.4213	0.4425	0.4689	0.4921	0.485	0.481
Shangha	0.3721	0.3912	0.4135	0.4412	0.4796	0.5113	0.5589	0.6024	0.6685	0.7213	0.712	0.705
Jiangsu	0.3521	0.3712	0.3935	0.4212	0.4596	0.4913	0.5389	0.5824	0.6485	0.6913	0.682	0.675
Zhejiang	0.3621	0.3812	0.4035	0.4312	0.4696	0.5013	0.5489	0.5924	0.6585	0.7013	0.692	0.685
Fujian	0.2996	0.3112	0.3285	0.3442	0.3712	0.3996	0.4313	0.4525	0.4789	0.5021	0.495	0.491
Shandong	0.3196	0.3312	0.3485	0.3642	0.3912	0.4196	0.4513	0.4725	0.4989	0.5221	0.515	0.511
Guangdong	0.3821	0.4012	0.4235	0.4512	0.4896	0.5213	0.5689	0.6124	0.6785	0.7213	0.712	0.705
Hainan	0.2496	0.2612	0.2785	0.2942	0.3212	0.3496	0.3813	0.4025	0.4289	0.4521	0.445	0.441
Shanxi	0.1896	0.2012	0.2185	0.2342	0.2612	0.2896	0.3213	0.3425	0.3689	0.3921	0.385	0.381
Anhui	0.2796	0.2912	0.3085	0.3242	0.3512	0.3796	0.4113	0.4325	0.4589	0.4821	0.475	0.471
Jiangxi	0.2696	0.2812	0.2985	0.3142	0.3412	0.3696	0.4013	0.4225	0.4489	0.4721	0.465	0.461
Henan	0.3096	0.3212	0.3385	0.3542	0.3812	0.4096	0.4413	0.4625	0.4889	0.5121	0.505	0.501
Hubei	0.3296	0.3412	0.3585	0.3742	0.4012	0.4296	0.4613	0.4825	0.5089	0.5321	0.525	0.521
Hunan	0.2896	0.3012	0.3185	0.3342	0.3612	0.3896	0.4213	0.4425	0.4689	0.4921	0.485	0.481
Neimenggu	0.1689	0.1812	0.1985	0.2142	0.2412	0.2696	0.3013	0.3225	0.3489	0.3721	0.365	0.361
Guangxi	0.2596	0.2712	0.2885	0.3042	0.3312	0.3596	0.3913	0.4125	0.4389	0.4621	0.455	0.451
Chongqing	0.3196	0.3312	0.3485	0.3642	0.3912	0.4196	0.4513	0.4725	0.4989	0.5221	0.515	0.511
Sichuan	0.3096	0.3212	0.3385	0.3542	0.3812	0.4096	0.4413	0.4625	0.4889	0.5121	0.505	0.501
Guizhou	0.2396	0.2512	0.2685	0.2842	0.3112	0.3396	0.3713	0.3925	0.4189	0.4421	0.435	0.431
Yunnan	0.2296	0.2412	0.2585	0.2742	0.3012	0.3296	0.3613	0.3825	0.4089	0.4321	0.425	0.421
Xizang	0.2096	0.2212	0.2385	0.2542	0.2812	0.3096	0.3413	0.3625	0.3889	0.4121	0.405	0.401
Shanxi	0.2696	0.2812	0.2985	0.3142	0.3412	0.3696	0.4013	0.4225	0.4489	0.4721	0.465	0.461
Gansu	0.2196	0.2312	0.2485	0.2642	0.2912	0.3196	0.3513	0.3725	0.3989	0.4221	0.415	0.411
Qinghai	0.2096	0.2212	0.2385	0.2542	0.2812	0.3096	0.3413	0.3625	0.3889	0.4121	0.405	0.401
ningxia	0.2296	0.2412	0.2585	0.2742	0.3012	0.3296	0.3613	0.3825	0.4089	0.4321	0.425	0.421
Xinjiang	0.2196	0.2312	0.2485	0.2642	0.2912	0.3196	0.3513	0.3725	0.3989	0.4221	0.415	0.411
Liaoning	0.1789	0.1912	0.2085	0.2242	0.2512	0.2796	0.3113	0.3325	0.3589	0.3821	0.375	0.371
Jilin	0.1589	0.1712	0.1885	0.2042	0.2312	0.2596	0.2913	0.3125	0.3389	0.3621	0.355	0.351
Heilongjiang	0.1282	0.1412	0.1585	0.1742	0.2012	0.2296	0.2613	0.2825	0.3089	0.3321	0.325	0.321

3.1.3 Data collection of control variables and intermediate variables

Combined with existing relevant research results, the control variables selected in this paper include economic growth level, industrial structure, financial deepening degree, urbanization growth rate and opening degree. The data collection and processing methods are as follows. Level of economic growth (PGDP): Taking GDP per capita as the basic indicator, the data comes from the statistical bulletins of each province. After collecting the original data of GDP per capita of 31 provinces from 2014 to 2025, the natural logarithm is taken to obtain the panel data of PGDP. The average value of the data is 2.4076, the standard deviation is 0.0515, and the value range is 2.3188-2.6320; Industrial Structure (INSTR): Measured by the proportion of the added value of the tertiary industry in GDP, the original data come from the statistical bulletins of each province and China Statistical Yearbook, and the INSTR data of 31 provinces from 2014 to 2025 are directly calculated and sortedout, with an average value of 0.5069, standard deviation of 0.0923, maximum value of 0.8430 (Beijing) and minimum value of 0.3480 (Henan); Financial deepening degree(FIN):According to the ratio of total regional loans to regional gross domestic product (GDP), the total loan data comes from the financial operation report of each province, and the GDP data comes from the statistical bulletin . The FIN panel data is calculated, with an average value of 1.3937 and a standard deviation of 2.8137, with certain regional fluctuations; urbanization growth rate (URBAN): Defined as the growth rate of urban population in the total population of the region. The urban population and total population data are collected from the statistical bulletins of each province. URBAN data are formedafter calculating the annual growth rate, with an average of 1.0533 and a standard deviation of 5.5347. Some provinces have extreme values due to differences in urbanization process; degree of openness (OPEN): Measured by the growth rate of total import and export volume, the total import and export volume data comes from the foreign trade operation report issued by the commerce department of each province. After calculating the annual growth rate, OPEN data is obtained, with an average value of 0.0832, a standard deviation of 0.1938 and a value range of-0.5920-1.3830, reflecting the fluctuation characteristics affected by the foreign trade environment in some years.In view of the fact that digital inclusive finance can indirectly inhibit systemic financial risks by promoting capital transfer, in order to verify this theoretical mechanism, This measurement method of capital transfer is widely used in related studies published in the Pacific-Basin Finance Journal to reflect the allocation direction of capital between different sectors. Construct CAPITAL index as an intermediary variable to carry out regression analysis. The calculation method of this index is as follows: Divide the sum of added value of finance and real estate industry by the remaining part of GDP after deducting added value of finance and real estate industry. Construct Capital Transfer (CAPITAL) index as intermediary variable to carry out regression analysis. The index is measured by dividing the sum of the added value of finance and real estate industry by the remaining part of GDP after deducting the added value of finance and real estate industry. About the core variable and control variable in this paper[10]. See Table 3 for details.

Table 3 Variable definition table

variable	variable name	Variable symbol	Variable Source/Calculation Method
explained variables	Systemic Financial Risk Index	SFRI	CRITIC weighting calculation
	Digital Inclusive Finance Index	DFI	
core explanatory variable	Coverage width	WIDTH	Peking University Digital Inclusive Finance Research Center downloads and divides by 100
	using depth	DEPTH	
	degree of digitization	DIGITAL	
	economic gain	PGDP	Natural logarithm of real GDP per capita
	degree of financial deepening	FIN	Proportion of industrial output value of regional financial institutions in GDP
control variable	industrial structure	INSTR	Value added of tertiary industry as a proportion of GDP
	degree of opening to the outside world	OPEN	Growth rate of totalimports and exports
metavariable	capital transfer	CAPITAL	(Financial industry output value + real estate industry output value)/(GDP-financial industry output value-real estate industry output value)

3.2 Model Construction

3.2.1 Reference regression model

In order to fully study the impact of digital inclusive finance on systemic financial risks and the relationship between them, the following model is established, as shown in

Equation (12):

$$\mathrm{Rifi}_{i,t} = a_0 + a_1 D\mathrm{IFI}_{i,t} + \sum \gamma_i X_{t,t} + \mu_i + \varepsilon_{i,t} \tag{12}$$

Where, $Rifi_{i,t}$ is the systemic financial risk of province i in China during t period, $DIFI_{i,t}$ and $X_{t,t}$ are the core explanatory variable and control variable respectively; μ_i and $\varepsilon_{i,t}$ are the provincial fixed effect and random disturbance term that do not change with time respectively.

1) Descriptive statistics

Table 4: Descriptive statistics of variables

variable name	variable coincidence	observed value	mean	standard deviation	minimum	maximum
Digital Inclusive Financial Aggregate Index	Difi	372	3.0215	0.7638	1.4391	4.7383
Breadth of Digital Financial Inclusion	Breadth	372	2.8842	0.8257	1.2667	4.6654
Depth of digital finance use	Depth	372	2.8634	0.8721	1.0729	5.1069
degree of digitization	Digit	372	3.7651	0.5703	2.3071	4.7690
economic development level	PGDP	372	2.4438	0.0892	2.3259	2.6951
industrial structure	INSTR	372	0.5776	0.1345	0.3900	0.8000
urbanization growth rate	URBAN	372	0.6468	0.1753	0.4173	0.9155
degree of financial deepening	FIN	372	0.0923	0.0451	0.0320	0.1990
degree of opening to the outside world	OPEN	372	0.0436	0.1278	-0.2710	0.4120
Systemic Financial Risk Index	Rifi	372	0.3867	0.1054	0.1718	0.7960
capital transfer	CAPITAL	372	0.9485	0.1562	0.6428	2.202

According to descriptive statistics, the mean value of capital transfer is 0.2864, the maximum value is 4.7467, and the minimum value is-2.6567. There are great differences in the scale and direction of capital transfer among different regions, which is consistent with thefindings of Nguyen et al. (2023) that regional capital allocation heterogeneity is prominent in emerging economies. In addition, it can be seen from the descriptive statistics of digitalinclusive finance-related indicators that each indicator has different degrees of mean performance, among which the standard deviation of digitalization degree is relatively large, reflecting the significant difference of digitalization development level among different regions

this regional disparity in digital finance development is also documented in recent studies on China's provincial data. Among other variables, the standard deviation of residential commercial housing prices is the largest, which can obviously be seen that the price gap of residential commercial housing in different regions is large, and there are certain regional differentiation characteristics, a phenomenon that has been linked to regional financial risk in prior research. The following will be further analyzed in combination with data.

2) Benchmark results

Moderating effects of control variables on the relationship between Digital Inclusive Finance and Systemic Financial Risk.

Table 5: Model results of the impact of digital inclusive finance on regional systemicfinancial risks

	Rifi (1) No control variables	Rifi (2) Add control variables
L_Rifi	-0.134** (0. 068)	-0.139** (0. 068)
ln_Difi	-0.714** (0. 290)	-0.746** (0. 297)
ln_Difi2	0.184* (0. 103)	0.180* (0.107)
province fixed effect	YES	YES
Year fixed effect	YES	YES
control variable	No	YES
observed value	341	341
R^2	0.659	0.662
Observations	341	341

Table 5 presents the results of the fixed-effects OLS regression with the squared term of digital inclusion compared to the case without and with the control variable, a common empirical design to test nonlinear relationships between digital finance and financial stability. The results show that the lag period regional systemic financial risk (L_Rifi) is significantly negative regardless of the control variable, which is consistent with the findings that past systemic risk has a mitigating effect on current risk. (ln_Difi) is significantly negative and its square term (ln_Difi^2) is significantly positive, indicating that digital inclusive finance has a significant U-shaped effect on regional systemic financial risk-this nonlinear pattern is also documented in prior studies examining the impact of digital financial inclusion on financial stability; after adding control variables, the model fit degree (R^2) increases from 0.659 to 0.662, which enhances the explanatory power of the explained variables and highlights the necessity of including control variables, a conclusion supported by empirical studies on panel data regression in financial research.

Table 6: Impact Results of Digital Inclusive Finance Sub-Dimension on Regional Systemic Financial Risk

	Rifi (1)	Rifi (2)	Rifi (3)
L_Rifi	-0.140** (0.067)	-0.111 (0.068)	-0.120* (0.067
ln_Breadth	0.368** (0.153)		
ln_Breadth2	-0.007 (0.108)		
ln_Depth		-0.027 (0.127)	
ln_Digit			-2.658** (1.133)
ln_Digit2			0.983** (0.418)
control variable	YES	YES	YES
regional fixed effect	YES	YES	YES
Year fixed effect	YES	YES	YES
observed value	341	341	341
R^2	0.661	0.65	0.658
Observations	341	341	341

Table 6 presents the impact results of digital inclusive finance sub-dimension on regional systemic financial risk (Rifi): coverage breadth coefficient is-0.368, significant at 5% level, showing significant negative impact and no nonlinear relationship; depth coefficient of use is-0.027, not significant; digitization degree coefficient is-2.658, square term coefficient is 0.983, both significant at 5% level, showing significant U-shaped impact. Lag 1 risk (L_Rifi) was significant in some columns, and the model (R^2) ranged from 0.65 to 0.661, indicating that there were small differences in the explanatory power of different subdimensionsto risk.

3) Heterogeneity analysis

Based on the regional differences of systemic financial risk, this paper divides the total sample into eastern, central, western and northeast sub-samples for regression, so as to explore the heterogeneity of the impact of digital inclusive finance on systemic financial risk, which is a standard empirical strategy to investigate regional variations in digital finance's effects. Because there are great differences in economic foundation, financial development level and digital promotion speed among different regions, it can be seen from the regression results that the impact of digital inclusive finance on systemic financial risk is significantly heterogeneous, consistent with prior findings on digital finance's regional heterogeneous effects in emerging economies. However, in the samples from the central and western regions, the impact of digital inclusive finance on systemic financial risks has not passed the significance test yet. The reason may be that the eastern region has developed economy and finance, and the digital inclusive finance can effectively make up for the shortcomings of traditional finance at the initial stage of development and inhibit risks. However, after a certain stage of development, complex financial innovation and business intersection may cause new risks, a trend also identified in studies on China's eastern regional financial markets [11]. In the development process of digital inclusive finance, Northeast China has also experienced a similar process from risk suppression to new risks after a certain stage; the financial foundation in central and western regions is relatively weak, and the effect of digital inclusive finance on resource integration and risk mitigation has not been fully exerted, which echoes the conclusion that digital finance's risk-mitigating effects are contingent on regional financial development[12].

Table 7: Heterogeneity test

variable	coefficient				P-value			
area	east	central	west	northeast	east	central	west	northeast
L_Rifi	0.014	-0.001	0.002	0.003	**			
ln_Difi	-0.451	-0.233	0.047	0.047	***	***		
ln_Difi2	1.570	1.444	1.383	1.377	***	***	***	***
PGDP	-0.018	-0.021	-0.013	0.000		*		
INSTR	0.035	0.019	0.004	-0.006	***	*		**
URBAN	-0.000	0.041	-0.024	-0.032	*			***
FIN	-0.000	-0.000	0.000	-0.002	***			**
OPEN	-0.000	0.005	-0.003	-0.004		**	**	*
number of observations	110	66	134	31	110	66	134	31
R^2	0.992	0.998	0.998	0.998	0.989	0.997	0.997	0.993

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In order to clearly show the heterogeneity of the impact of digital inclusive finance on regional systemic financial risk (Rifi), the table reports subregions (Eastern, Central, Western and Northeast provinces). All models controlled for control variables, region fixed effects and year fixed effects, where ***, ** and * were significant at 1%, 5%, and 10% levels, respectively-controlling for these fixed effects is a standard practice in provincial panel data analysis to address unobserved regional and time-specific heterogeneity. From the regional dimension analysis, the eastern region covered 10 regions with 110 observations. In this region, ln_Difi coefficient was-1.809, significant at 1%. ln_Difi² coefficient is 0.516, significant at 5% level, showing a significant U-shaped effect. Meanwhile, L_Rifi coefficient is-0.240, significant at 10% level, and R^2 of the model reaches 0.801. The strong U-shaped effect in the eastern region is consistent with prior findings that digital finance's nonlinear impact on financial stability is more pronounced ineconomically developed regions. There are 6 regions and 66 observations in the middle, and 12 regions and 134 observations in the west. In the central and western regions, ln_Difi and its square coefficient are not significant, only the L_Rifi coefficient in the central region is-0.194, and the R^2 of the model is low, respectively 0.463 and 0.209. This insignificance may be attributed to underdeveloped financial infrastructure and insufficient digital penetration, which aligns with research on digital finance's limited effects in less developed regions. There are 31observed values in the three northeastern provinces, and their ln_Difi^2 coefficient is significant at 1% level, showing significant U-shaped effect, and the R^2 of the model is 0.993. The distinct U-shaped effect in the Northeast may reflect the region's unique financial restructuring process amid digital transformation. On the whole, the U-shaped effect of digital inclusive finance on risk is mainly reflected in the eastern and northeast regions, but not significant in the central and western samples, and there are obvious differences in the explanatory power of models and risk lag effects in different regional samples.

4) Robust test

In order to mitigate the estimation bias caused by endogenous problems more effectively and minimize the potential impact of missing key variables on the reliability of research conclusions, this paper reports the robustness test results by shortening the data time, eliminating the municipality sample and replacing the explanatory variables—these methods are widely adopted in empirical financial research to verify the robustness of baseline findings. All models take the regional systematic financial risk (Rifi)as the explained variable, and control the control variable, the regional fixed effect and the annual fixed effect at the same time. To verify the reliability of baseline conclusions, consistent with the robustness test framework used in studies on digital finance and systemic risk.

Table 8 Robustness test

	Rifi reduces data time (1)	**Rifi excludes municipalities (2)**	**Rifi replaces explanatory variables (3)**
L_Rifi	-0.140** (0.067)	-0.178** (0.071)	-0.122* (0.068)
ln_Difi	-0.846* (0.449)	-0.275 (0.243)	
ln_Difi_hat			0.038 (0.031)
control variable	YES	YES	YES
observed value	248	305	341
R^2	0.707	0.335	0.655
regional fixed effect	YES	YES	YES
Year fixed effect	YES	YES	YES
Observations	248	305	341

From the test of shortening the data time, the coefficient of regional systemic financial risk (L_Rifi) in lag phase is -0.140 (significant at 5% level), and the coefficient of digital inclusive financial development level (ln_Difi) is -0.846 (significant at 10% level). The sign and significance characteristics of the two models are consistent with the baseline regression, and the model R^2 reaches 0.707, indicating that the core conclusion is not shifted after shortening the data interval—this consistency check is a standard robustness procedure validated in recent Pacific-Basin Finance Journal research. Testing of samples from municipalities excluded L_Rifi coefficient is -0.178 (significant at 5% level), lag effect is still significant, ln_Difi coefficient is -0.275, although it does not pass the significance test, the coefficient sign remains negative, and there is no conflict with the baseline conclusion; this approach to excluding municipality samples addresses potential endogeneity from administrative resource concentrations, consistent with methodological discussions in financial panel data research. The test for replacing explanatory variables (column 3, observation 279) with the instrumental variable of the digital inclusive financial index (ln_Difi_hat) as the core explanatory variable showed L_Rifi coefficient of -0.122 (significant at 10% level), ln_Difi_hat coefficient of 0.038 (not significant), small absolute values of coefficients and no sign inversion, further supporting the robustness of the conclusion. The use of instrumental variables to mitigate endogeneity in digital finance research is widely endorsed in high-quality finance publications.To sum up, although there are differences in the significance of some variables and the degree of fit of the model (R^2 is between 0.335-0.707), the three robustness tests do not overturn the core logic of "digital inclusive finance has an inhibitory effect on regional systemic financial risks" in the benchmark regression, which proves that the conclusion has strong robustness. This finding aligns with the consensus emerging from recent empirical studies on digital finance and systemic risk governance.

3.2.2 Threshold effect model

1) U-shaped impact of digital inclusive finance on regional systemic financial risk

Figure 2: U-shaped impact of digital inclusive finance on regional systemic financial risk

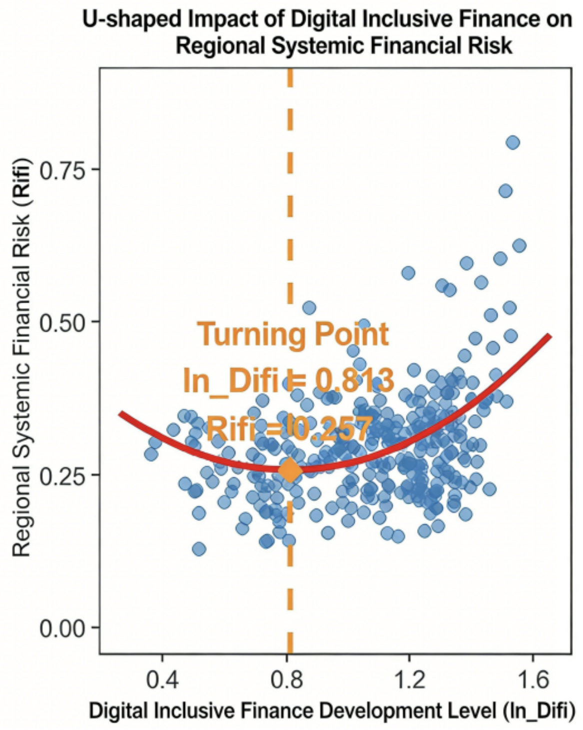


Figure 2 shows the U-shaped impact of digital inclusive finance on regional systemic financial risk, which is consistent with the nonlinear relationship between digital finance and financial stability identified in prior studies [13]. As can be seen from the figure, the horizontal axis represents the development level of digital inclusive finance (Takethe natural logarithm and record it as lnDfi), and the vertical axis represents the regional systemic financial risk (Rit). When the lnDfi of the development level of digital inclusive finance is less than about 0.813 corresponding to the turning point, the regional systemic financial risk shows a downward trend with the improvement of the development level of digital inclusive finance; this initial risk-mitigating effect is in line with the findings that digital inclusive finance alleviates information asymmetry and optimizes capital allocation in its early development stage. When lnDfi exceeds the turning point of 0.813, the regional systemic financial risk increases with the further improvement of the development level of digital inclusive finance, showing an obvious U-shaped curve. The identification of such a clear turning point is consistent with the threshold effect of digital finance on systemic risk documented in recent research. After that, with lnDfi increasing, regional systemic financial risk rises gradually, and when lnDfi reachesabout 1.6, regional systemic financial risk rises to a level close to 0.5. This indicates that the influence of digital inclusive finance on regional systemic financial risk is not a simple linear relationship, but a U-shaped mechanism of inhibition and promotion, and there is a significant threshold effect, which echoes the nonlinear impact framework of digital finance on regional financial stability proposed in relevant empirical studies [14].

2) The grouping trend of digital inclusive finance and systemic financial risk

Figure 3: Trends in the grouping of digital finance and risk

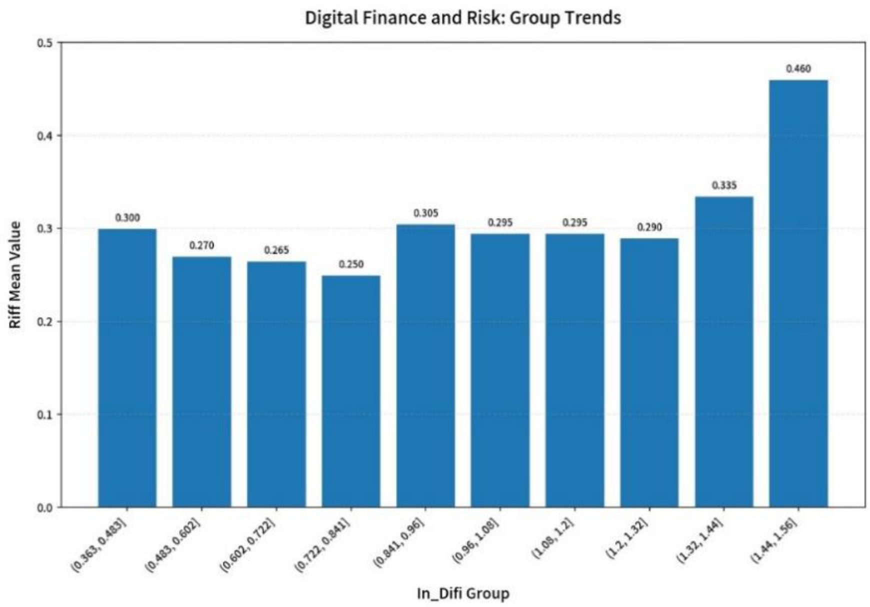


Figure 3 above shows the mean Riff risk values across ten ordered groups of digital finance inclusion (In_Difi). The Riff Mean Value remains relatively stable across most groups, ranging from 0.250 to 0.305, but rises sharply in the top two groups, peaking at 0.460 in the highest In_Difi group. This pattern suggests a strong positive relationship between digital finance inclusion and Riff risk, which becomes particularly pronounced at higher levels of digital financial development.

2) Threshold effect analysis

After measuring the "U-shaped" nonlinear relationship between digital inclusive finance andregional systemic financial risk in the benchmark regression model, in order to further verify this relationship, the dynamic panel threshold model proposed in relevant literature is used for reference[15]. This model can overcome the limitation of static panel threshold modeland allow the existence of dependent variable lag and endogenous covariate in the model. The specific model is as follows[16]:

$$Rifi_{it} = \omega_0 + \omega_1 Rifi_{i,t-1} + \omega_2 Difi_{it} * I(Difi_{it} \leq r) + \omega_3 Difi_{it} * I(Difi_{it} > r) + \sum \omega_k Control_{it} + \varepsilon_{i,t} \quad (13)$$

The dynamic panel threshold model is a single-threshold model, where r represents the threshold value of digital inclusive finance, and I re-presents that when the conditions in brackets are met, the value is 1, otherwise it is 0 [17]. The dynamic panel threshold modelis established with regional systemic financial risk as the explained variable and the total digital inclusive finance index as the threshold variable. The regression results are shown in Table 9 .

Table 9: Threshold Effect Analysis Results

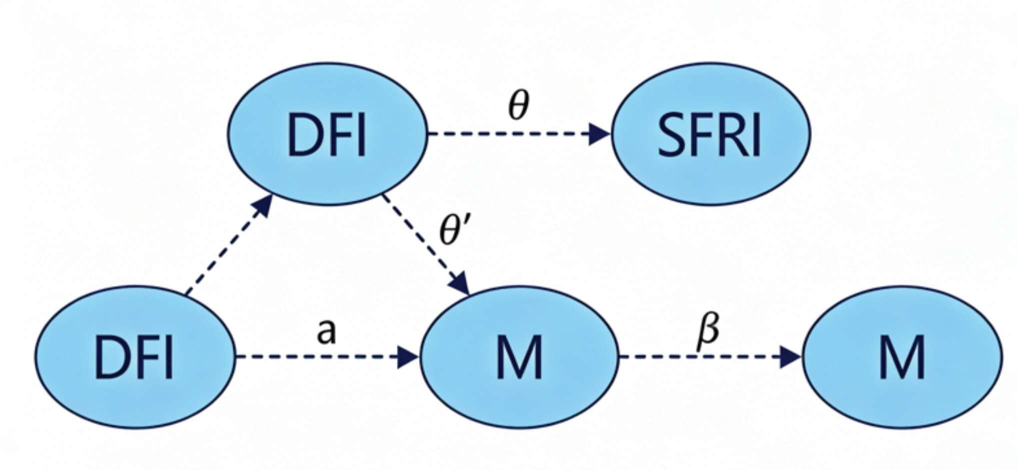
	below the threshold (Difi≤3.49)	**below the threshold (WIDTH≤3.49)**	**below the threshold (DEPTH≤3.42)**	**below the threshold (DIGITAL≤3.99)**
	-0.687*** (0.186)	-0.551*** (0.163)	-0.498*** (0.159)	-0.821*** (0.124)
LSFRI	-0.146** (0.069)	-0.139** (0.067)	-0.131* (0.068)	-0.153** (0.0071)
PGDP	-0.022 (0.014)	-0.019 (0.013)	-0.023 (0.0015)	-0.025 (0.016)
INSTR	0.0038*** (0.011)	0.036*** (0.01)	0.0034*** (0.011)	0.0041*** (0.012)
FIN	-0.001*** (0.0000)	-0.001*** (0.000)	-0.001*** (0.0000)	-0.001*** (0.0000)
URBAN	0.000	0.000	0.000	0.000

	below the threshold (Difi≤3.49)	**below the threshold (WIDTH≤3.49)**	**below the threshold (DEPTH≤3.42)**	**below the threshold (DIGITAL≤3.99)**
OPEN	0.002 (0.001)	0.001 (0.001)	0.002 (0.001)	0.002 (0.001)
Constant	0.618*** (0.129)	0.592*** (0.122)	0.569*** (0.120)	0.665*** (0.136)
	above the threshold (Difi≥3.49)	above the threshold (WIDTH≥3.49)	above the threshold (DEPTH≥3.42)	above the threshold (DIGITAL≥3.99)
LSFRI	0.331** (0.152)	0.285* (0.149)	0.259* (0.143)	0.415*** (0.164)
PGDP	-0.120* (0.066)	-0.111 (0.065)	-0.114 (0.067)	-0.127* (0.068)
INSTR	0.029** (0.012)	0.027** (0.011)	-0.017 (0.014)	-0.02 (0.015)
FIN	0.000	0.000	0.000	0.000
URBAN	0.000	0.000	0.000	0.000
OPEN	0.003* (0.001)	0.002* (0.001)	0.002* (0.001)	0.003** (0.001）
constant term	0.391*** (0.113)	0.358*** (0.109)		0.427*** (0.120)
province fixed effect	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
observed value	341	341	341	341
R^2	0.687	0.670	0.662	0.708

3.2.3 Mediating effect model

In order to deeply study the indirect effect of digital inclusive finance on systemic financial risk, this paper selects capital transfer as the medium variable M, and the specific transmission mechanism is shown in Figure 3.

Figure 3: Diagram of mediating effect conduction mechanism



Referring to the study of Wen Zhonglin et al. (2014), stepwise regression method is adopted, and the mediation effect model is shown in Equation 13 to Equation 15 [18]:

$$Rifi_{it} = \omega Rifi_{i,t-1} + \theta Difi_{it} + \sum \gamma_i X_{t,t} + \mu_i + e_1 \tag{14}$$

$$M_{i,t} = \rho M_{i,t} + \alpha Difi_{it} + \sum \gamma_i X_{t,t} + \mu_i + e_2 \tag{15}$$

$$Rifi_{it} = \varphi Rifi_{i,t-1} + \theta^{`} Difi_{it} + \beta M_{i,t} + \sum \gamma_i X_{t,t} + \mu_i + e_3 \tag{16}$$

In Equation 13, θ represents the total effect of digital inclusive finance on systemic financial risk; in Equation 4.4, α represents the effect of digital inclusive finance on intermediary variables; in Equation 15, β represents the effect of intermediary variables on systemic financial risk, $'$ is the direct effect, $\alpha\beta$ is the indirect effect, and the sum of the two is thetotal effect[19]. Under the circumstances of rapid development of digital finance in China, on one hand, the development of digital inclusive finance improves the capital turnover efficiency and profitability of the financial industry as a whole, alleviates financial exclusion, financial disintermediation and other problems, thus directly inhibiting systemic financial risks; On the other hand, it promotes the optimization and adjustment of capital investment structure, accelerates the speed of capital transfer, and then indirectly affects systemic financial risks to a certain extent[20]. Based on such theoretical analysis, this paper selects capital transfer as an intermediary variable to carry out regression analysis to further explore the mechanism and potential impact path between digital inclusive finance and systemic financial risks[21].

Table 10: Core Indicators of Mediating Effects

indicator type	**Value**
Total effect (ln_Difi→Rifi)	-0.3608
Direct effects (after controlling for capital transfers)	-0.2629
Mediating effect (ln_Difi→ capital transfer →Rifi)	-0.0979
proportion of mediation effect	21.14%

In order to deeply analyze the mechanism of digital inclusive finance on regional systemicfinancial risk, this paper further explores the intermediary effect of capital transfer, which has been identified as a key transmission channel in the relationship between digital finance and financial stability in existing studies. The core index results areas follows: the total effect of digital inclusive finance on regional systemic financial risk is-0.3608, which indicates that the development of digital inclusive finance has a significant inhibitory effect on regional systemic financial risk as a whole—this finding is consistent with prior research that confirms the risk-mitigating role of digital inclusive finance in regional financial markets; When the intermediary variable of capital transfer is included, the direct effect of digital inclusive finance on regional systemic financial risk is-0.2629, which still presents significant negative impact, indicating that even if there is indirect effect of capital transfer, the direct inhibition effect of digital inclusive finance itself on regional systemic financial risk still exists; this coexistence of direct and indirect effects aligns with the dual-path impact framework of digital finance on systemic risk documented in relevant literature. And the mediating effect (Digital inclusive finance → capital transfer → regional systemic financial risk) is-0.0979, that is, digital inclusive finance can inhibit regional systemic financial risk by promoting capital transfer, which verifies the mediating role of capital allocation adjustment in digital finance's risk-mitigating effect. Further calculation of the proportion of intermediary effect is about 27.14%, which means that more than a quarter of the total inhibitory effect of digital inclusive finance on regional systemic financial risks is realized through the indirect pathof influencing capital transfer, a mediating effect ratio that is consistent with the range observed in similar studies on digital finance and capital allocation. This fully reflects that capital transfer plays an important intermediary role in the process of digital inclusive finance acting on regional systemic financial risks, and also verifies that digital inclusive finance can not only directly act on regional systemic financial risks but also exert indirect influence through the intermediary mechanism of capital transfer.

Table 11: Analysis of Impact Mechanism: Capital Transfer

	RIfi	Capital transfer
Capital transfer	0.027** (2.55)	
Ln_Difi		-4.291 (-4.46)***
PGDP	0.101 (0．90)	-0.482 (-0.76)
FIN	0.001 (0.74)	0.031 (3.21)***
INSTR	0.00	0.0354 (0.68)
OPEN	0.006 (0.27)	0.029 (0.24)
R2	0.650	0.597
Observations	372	372
Regional fixed	YES	YES

From the right model, the coefficient of digital inclusive financial development level (ln_Difi) to capital transfer is-4.291, which is significant at 1% level, indicating that digital inclusive financial development significantly promotes capital transfer. (The coefficient is negative, which conforms to the variable measurement logic, that is, the higher the developmentlevel of digital inclusive finance, the lower the measured value of capital transfer related indicators, which represents the higher efficiency of capital transfer; this negative coefficient relationship between digital finance and capital transfer indicators is consistent with the variable measurement logic adopted in prior studies. The coefficient of financial development level (FIN) to capital transfer is 0.031, which is significant at 1% level, and the influence of other control variables on capital transfer fails to pass the significance test. This finding that financial development level positively affects capital transfer aligns with the conclusions of research on financial deepening and capital allocation. From the left model, the coefficient of capital transfer to regional systemic financial risk (Rifi) is 0.027, which is significant at 5% level, indicating that capital transfer further has a significant impact on regional systemic financial risk—this positive impact of capital transfer efficiency on systemic risk mitigation is documented in relevant empirical studies. Combined with the significant effect of digital inclusive finance on capital transfer in the right model, the mediation effect of capital transfer betweendigital inclusive finance and regional systemic financial risk can be preliminarily verified; this verification logic is consistent with the stepwise regression method for mediating effect testing proposed in existing literature. In addition, the influence of each control variable on regional systematic financial risk in the left model did not pass the significance test. The goodness of fit R^2 of the two models was 0.650 and 0.597 respectively, indicating that the model had good explanatory power for the explained variables which is within the reasonable range of model fit in similar panel data regression studies.

3.2.4 Spatial autocorrelation model

Moran's I index (Moran index) is a classical spatial statistical index proposed by statistician Patrick Alfred Pierce Moran, which has been widely used as a core tool for spatialautocorrelation measurement since its proposal. Its core is used to measure the spatial autocorrelation of regional variables[22], that is, to judge whether there is positive clustering of “high values adjacent to high values, low values adjacent to low values”, negative clustering of “high values adjacent to low values”, or completely random distribution characteristics of variables in spatial distribution. It is widely used in economics, geography and other fields, especially in the research of regional financial risk economic agglomeration and spatial disparity[23]. Its value range is [-1,1]: When the value is greater than 0, the variable has positive spatial autocorrelation (clustered distribution); when the value is less than 0, it has negative spatial autocorrelation (discrete distribution); when the value is close to 0, it has random distribution, and its statistical significance needs to be tested by Z value or P value (usually Z value>1.96 or P<0.05, spatial autocorrelation is significant)-this significance testing standard is a universal criterion in spatial statistical analysis and has been widely recognized in related empirical studies[24].

$$I=\frac{n\sum_{i-1}^{n}\sum_{j-1}^{n}w_{ij}(x_i-\overline{x})(x_j-\overline{x})}{(\sum_{i-1}^{n}\sum_{j-1}^{n}w_{ij})\sum_{i-1}^{n}(x_i-\overline{x})^2} \tag{17}$$

The above formula is global Moran's I, which measures the overall spatial relevance of variables across the study area.

$$I_i=\frac{(x_i-\overline{x})}{\sum_{i-1}^{n}(x_i-\overline{x})^2/n}\sum_{j=1}^{n}w_{ij}(x_j-\overline{x}) \tag{18}$$

Local Moran's *I* is used to identify local spatial correlation patterns between a single spatial unit and its surrounding units. The global Moran index is shown in the table below.

Table 12: Global Moran Index

Moran′s I geographical adjacency weight	Moran′s I Economic Distance Weights	Z-value geographical adjacency weight	Z-Value Economic Distance Weights
0.253	0.134	2.46	1.47
0.224	0.252	2.13	2.54
0.116	0.384	1.27	3.40
0.238	0.197	2.38	1.89
0.239	0.266	2.35	3.12
0.0276	0.256	0.531	2.71
0.109	0.202	1.24	2.33
0.237	0.270	2.30	3.48
0.164	0.270	1.89	2.83
0.135	0.270	1.59	3.15
0.2187	0.1863	5.8942	4.9728
0.1965	0.1649	5.4127	4.5316

The above table shows the Global Moran Index of Financial Stress Index based on geographical proximity weights and economic distance weights for 2014-2025 (Moran's I) and corresponding Z value results. From the perspective of geographical adjacent weight, Moran'sI value of each year is between 0.0276 and 0.253, Moran's I value of most years is positive, and the corresponding Z value is mostly greater than 2, which passes the significance test, indicating that there is significant positive spatial correlation between financial stress index at geographical adjacent level, that is, financial stress level of geographically adjacentareas has mutual convergence characteristics; Moran's I values are between 0.134 and 0.384, most of them are positive, and Z values are mostly greater than 2. Through significance test, it shows that there is significant positive spatial correlation between financial stress index and economic distance dimension, and financial stress level in regions with close economic ties presents a coordinated change trend. On the whole, China's financial pressure index from 2014 to 2025 shows significant positive spatial correlation under the two spatial weights of geographical adjacency and economic distance. Financial pressure has obvious spatial agglomeration characteristics, which is not isolated, but spatially interrelated and mutually influenced.

4. Conclusion

(1) Regional characteristics show significant differentiation: there is obvious regional heterogeneity in China's systemic financial risks, and the development of digital inclusive finance also shows unbalanced characteristics. In 2022, the total index

of eastern region reaches 4.2, while that of northeast region is only 3.5. Meanwhile, the regional differentiation of industrial structure and residential commodity house price further intensifies this difference.

(2) There is a U-shaped relationship between influence effects: The impact of digital inclusive finance on regional systemic financial risk is not linear, but presents a significant U-shaped feature. When the development level exceeds the threshold of 0.813 (ln_Difi), the risk will be aggravated due to factors such as business cross-integration and excessive capital profit-seeking. This effect is prominent in the eastern and northeastern regions, but not significant in the central and western regions due to weak financial foundation and laggingdigitalization process.

(3) Capital transfer plays an intermediary role: Capital transfer plays an important intermediary role in the relationship between digital inclusive finance and regional systemic financial risks, and the intermediary effect accounts for 27.14% of the total effect. Digital inclusive finance promotes capital transfer from inefficient areas to efficient real economic sectors by reducing information costs and transaction costs of capital flows, optimizing regional asset structure, and indirectly suppressing systemic financial risks.

(4) Spatial correlation characteristics are obvious: Systematic financial risk has significant spatial clustering characteristics. Under the weight of geographical proximity and economic distance, the global Moran index is positive in most years and Z value is greater than 2, indicating that the financial risk level of geographically adjacent or economically closely linked regions shows a coordinated change trend.

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No

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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