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The Impact of Digital Financial Inclusion on Common Wealth: An Empirical Analysis Based on the Spatial Lag Model and Threshold Effect Model

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Abstract. Drawing on balanced panel data for 31 Chinese provincial-level units from 2011 to 2023, this paper combines a spatial lag model with a panel threshold model to examine how digital financial inclusion affects common wealth through three routes: spatial spillover, a transmission channel, and regime-dependent nonlinearity. The estimates show that a one-unit increase in the digital financial inclusion index raises the local common-wealth index by 0.725 units in net terms, but at the same time exerts a negative siphon effect of −0.203 on neighboring provinces. Industrial structure upgrading is found to be the main mediating channel, and its first-stage coefficient is 0.853. The direct effect declines from east to centre to west, and for all three sub-dimensions—coverage breadth, usage depth, and digitalization degree—local empowerment goes together with cross-regional suppression. With respect to marketization, a double-threshold pattern emerges: the promotion coefficient rises from 0.298 in the low regime to 0.475 in the high regime, so the marginal effect grows as institutional frictions ease. This study makes three advances. First, spatial spillovers and direct effects are identified within a single framework instead of treating them separately. Second, industrial upgrading is shown to be the channel through which digital finance affects common wealth. Third, the threshold-dependent pattern tied to marketization provides a concrete basis for region-specific policy design.

Keywords: Digital Financial Inclusion, Common Wealth, Spatial Lag Model, Threshold Effect, Industrial Structure Upgrading

1. Introduction

China's digital financial inclusion index expanded roughly eight-fold between 2011 and 2023, yet the spread between the most advanced eastern province and the least developed western province still hovers around a 3.2-fold gap—a coexistence of rapid aggregate catch-up and persistent regional cleavage that has emerged as a tangible obstacle to the realization of common prosperity. Leveraging low marginal cost, broad spatial reach, and high transactional efficiency, digital financial inclusion is capable of overriding the locational and admittance constraints embedded in the physical branch network of conventional banking, channeling capital toward credit-rationed households and remote territories [1-3]. Whether this developmental dividend is fully internalized, however, depends on the

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absorptive capacity of the receiving region: advantaged provinces, equipped with denser digital infrastructure and thicker financial markets, tend to attract capital, talent and innovation away from neighboring jurisdictions, generating a siphon rather than a diffusion outcome [4, 5]. A further complication is institutional. Where market-oriented reforms remain shallow, transactional frictions and information asymmetry blunt the empowering effect of digital finance, implying that its influence on common wealth is unlikely to be either linear or homogeneous across institutional regimes.

Against this backdrop, several gaps remain. Most empirical studies still treat provinces as independent, ignoring the spatial dependence that digital finance clearly implies. Meanwhile, industrial upgrading is often conjectured to be a mediator, but formal mediation tests within a spatial framework are scarce. Finally, the nonlinear role of marketization has received little empirical scrutiny, leaving policymakers unsure of when digital finance generates accelerating versus diminishing returns. This paper addresses the three gaps through a unified spatial-and-threshold strategy. Three marginal contributions follow: spatial spillovers and direct effects are jointly identified within a single econometric framework; industrial structure upgrading is endogenized as a verifiable mediation channel; and aggregate marketization is treated as a threshold variable that captures regime-dependent effects, supplying the empirical scaffolding for spatially differentiated policy design.

2. Literature review

2.1. Multidimensional impacts of digital financial inclusion

A growing body of work has examined digital financial inclusion at different levels. Household studies, such as Yi and Zhou [6] and Gong et al. [7], find that it helps smooth consumption and raises farm incomes, mainly via mobile payments and small-scale credit. Moving up, Gong and He [8] show that the same mechanism feeds into rural revitalization by fostering innovation in county-level industries. At the macro level, digital inclusion is also linked to more sustainable, higherquality growth [9]. Its social externalities, however, are decidedly mixed: urban-rural income gaps tend to narrow [10] and basic public services become more accessible [11], yet the very digitalization that enables inclusion can simultaneously magnify the difficulty of containing systemic risk [12]. On the environmental margin, the technological-upgrading effects embedded in digital finance facilitate carbon-reduction trajectories [13, 14].

2.2. Realization pathways of common wealth

On the realization of common wealth, three institutional layers have been examined sequentially. Government-side contributions hinge on the equalization of basic public services and on the build-out of digital infrastructure, both of which raise the floor of inclusive development [15]. Enterprise-side responses divide along ownership lines: state-owned firms expand the aggregate productive base through socially oriented strategic adjustments [16], whereas private firms reshape primary distribution by absorbing employment and upgrading the industrial mix [17]. At the societal layer, the construction of a spiritual dimension of common wealth supplies the cultural underpinning that material policies alone cannot deliver [18].

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2.3. The association mechanism between digital financial inclusion and common wealth

Studies bridging digital financial inclusion and common wealth have produced both convergent and divergent findings. On the positive side, Han et al. [2] report rising marginal contributions of digital finance to common prosperity, with entrepreneurial activity acting as the mediating channel. The spatial picture is more contested: Li and Zhou [3] find significant cross-province spillovers in rural consumption working through mobile payment, which suggests a diffusion pattern, whereas Chen and Pan [4] identify the opposite—an innovation siphon that benefits the focal city while suppressing its neighbors. This divergence implies that the spatial signature of digital finance need not be uniform across outcome variables, and that specifications that ignore inter-provincial dependence may be misspecified. With respect to the transmission mechanism, the digital economy is generally thought to drive industrial structure upgrading through technological innovation, yet the further link from such upgrading to common wealth has not been tested within the same framework. Three gaps therefore remain: spatial dependence is rarely modelled formally, marketization-driven nonlinearity has not been mapped onto a threshold structure, and industrial structure upgrading has not been empirically validated as a mediator between digital finance and common wealth. This paper closes these three gaps within a single empirical framework.

3. Methodology

3.1. Model specification

Spatial interdependence among Chinese provinces is incorporated through a spatial lag model (SLM); the choice of SLM over a spatial error counterpart is empirically grounded—the LM diagnostics reported in Section 4.3.1 reject independence through the lag channel at the 1% level while leaving the error counterpart non-significant, indicating that dependence enters via the dependent variable rather than the residual covariance structure. The baseline specification is $CP_{it} = \alpha_0 + \rho_0 W_{ij} CP_{jt} + \beta_1 DIF_{it} + \beta_2 control_{it} + \mu_i + \eta_t + \varepsilon_{it}$, where CP_{it} denotes the common wealth index, W_{ij} represents the spatial weight matrix, ρ_0 captures the spatial autoregressive parameter, DIF_{it} is the digital financial inclusion index, $control_{it}$ includes a set of control variables, and μ_i and η_t denote individual and time fixed effects, respectively. The spatial weight matrix is constructed as a geoeconomic nested matrix: $W_{ij}^{de} = \alpha W_{ij}^{d} + \left(1-\alpha\right) W_{ij}^{e}$ for $i \neq j$, and zero otherwise, where W_{ij}^{d} is the inverse geographical distance matrix and W_{ij}^{e} is the economic distance matrix, with row standardization applied.

To probe regime-switching nonlinearity, a Hansen-type panel threshold model is estimated with the aggregate marketization index serving as the threshold variable; the double-threshold specification reads $CP_{it} = \alpha_0 + \beta_1 DIF_{it} \cdot I(MKT_{it} < \gamma_1) + \beta_2 DIF_{it} \cdot I(\gamma_1 \leq MKT_{it} < \gamma_2) + \beta_3 DIF_{it} \cdot I(MKT_{it} \geq \gamma_2) + \delta control_{it} + \mu_i + \eta_t + \varepsilon_{it}$, where $I(\cdot)$ is the indicator function, γ_1, γ_2 are thresholds, and $\beta_1, \beta_2, \beta_3$ capture the marginal effects of digital financial inclusion under low, intermediate, and high marketization regimes, respectively.

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3.2. Variable measurement and description

The dependent variable—the common wealth index (CP)—is constructed from a hierarchical evaluation system comprising three first-level pillars (development, sharedness, sustainability), ten second-level constructs, and 21 third-level indicators, drawing on the frameworks of Han et al. [2] and Chen and Yan [11]. The entropy weight method is preferred over subjective weighting schemes such as the analytic hierarchy process because it derives weights directly from the dispersion structure of the data, reducing researcher discretion and improving cross-province comparability. The core regressor, the digital financial inclusion index (DIF), follows the Peking University series [1], spanning coverage breadth, usage depth and digitalization, and is rescaled by a factor of 1/1000 so that estimated coefficients remain directly readable. Four controls enter the specification: trade openness (imports plus exports relative to GDP), foreign direct investment (actually utilized FDI relative to GDP), science-and-education expenditure (the combined fiscal share of education, science and technology in general budgetary outlays), and education status, proxied by the number of regular senior high schools per province as a measure of the stock of basic education resources.

3.3. Data sources and descriptive statistics

The empirical sample is a balanced panel of 31 Chinese provincial-level units spanning 2011 through 2023, yielding 403 province-year observations. Digital financial inclusion is sourced from the Peking University Digital Financial Inclusion Index; the remaining variables are compiled from the Wind database and the China Statistical Yearbook, with residual gaps reconciled against provincial statistical yearbooks. All price-denominated variables are deflated to 2011 constant prices to remove the influence of inflation on cross-year comparisons. Descriptive statistics show a mean common wealth index of 0.239 with a standard deviation of 0.076; notably, the cross-sectional range of digital financial inclusion (0.458) is markedly larger than that of common wealth (0.385), pointing to wider geographic dispersion in digital finance and providing the empirical motivation for the regional heterogeneity decomposition reported below.

4. Results and discussion

4.1. Multicollinearity test

The variance inflation factors range from 1.020 to 2.280, with a mean of 1.670. Because all of these values are far below the usual cutoff of 10, multicollinearity is not a concern for the estimates that follow.

4.2. Spatial autocorrelation test

Throughout the sample period, the Global Moran's I for both the common wealth index and the digital financial inclusion index is significantly positive, which points to a stable spatial clustering of the high-high and low-low types. Eastern coastal provinces fall mostly in the high-high quadrant, while central and western provinces gather in the low-low quadrant. Since this pattern holds steady from year to year, a regional decomposition of the effects is warranted, and we report it below.

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Table 1. Comprehensive evaluation indicator system for common wealth

First-Level Indicators	Second-Level Indicators	Third-Level Indicators	Indicator Attribute
Development	Affluence	Per capita disposable income of residents (yuan/person)	+
		Per capita consumption expenditure of residents (yuan/person)	+
		Engel coefficient	-
	Commonality	Gini coefficient	-
		Urban-rural income ratio	-
		Urbanization rate (%)	+
Sharedness	Culture and Education	Public library collections (per capita)	+
		Average years of schooling(years/person)	+
	Healthcare	Licensed (assistant) physicians (per 10,000 persons)	+
		Hospital beds (per 10,000 persons)	+
	Infrastructure	Public transport vehicles (per 10,000 persons)	+
		Public toilets (per 10,000 persons)	+
	Informatization	Internet broadband subscribers (per 100 persons)	+
		Mobile phone subscribers (per 100 persons)	+
	Social Security	Social security expenditure (% of GDP)	+
Sustainability	Scientific and Technological Innovation	R&D intensity (%)	+
		Patents granted per 10,000 persons	+
	Ecological Environment	Forest coverage rate (%)	+
		Carbon emission intensity (million tons / billion yuan)	-
	Development Quality	GDP per capita (yuan/person)	+
		Overall labor productivity (yuan/person)	+

Note: + denotes a positive indicator, and − denotes a negative indicator. Data are sourced from the China Statistical Yearbook and provincial statistical yearbooks.

Table 2. Descriptive statistics of variables

Variable	Symbol	Obs	Mean	Std. Dev.	Max	Min
Common Wealth Index	*CP*	403	0.2386	0.0758	0.1139	0.4992
Digital Financial Inclusion	*DIF*	403	0.2545	0.1113	0.0162	0.4738
Trade Openness	*Open*	403	0.2642	0.2749	0.0076	1.4638
Foreign Direct Investment	*Fdi*	403	0.1267	0.7632	0.0048	9.6787
Science and Education Expenditure	*Se*	403	0.1834	0.0346	0.1058	0.2691
Education Status	*Edu*	403	0.1342	0.0235	0.0741	0.1902

Note: Variable symbols are presented in parentheses; all economic indicators are deflated using 2011 as the base year.

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Table 3. Test of Global Moran's *I* Index for common wealth and digital financial inclusion

Years	*CP*			*DIF*		
	Moran's *I*	*Z*-value	*P*-value	Moran's *I*	*Z*-value	*P*-value
2011	0.3561	5.3687	0.0000	0.4303	6.2310	0.0000
2012	0.3198	4.7908	0.0000	0.4303	6.2902	0.0000
2013	0.3184	4.7627	0.0000	0.4355	6.3943	0.0000
2014	0.3233	4.8415	0.0000	0.4441	6.5135	0.0000
2015	0.2864	4.3079	0.0000	0.4538	6.6574	0.0000
2016	0.2646	4.0056	0.0001	0.4397	6.4806	0.0000
2017	0.2452	3.7621	0.0002	0.4138	6.1357	0.0000
2018	0.2106	3.3070	0.0009	0.3827	5.6659	0.0000
2019	0.2011	3.1731	0.0015	0.3890	5.7442	0.0000
2020	0.1806	2.8988	0.0037	0.3827	5.6534	0.0000
2021	0.1978	3.1246	0.0018	0.3876	5.7071	0.0000
2022	0.1678	2.7108	0.0067	0.3830	5.5971	0.0000
2023	0.1626	2.6332	0.0085	0.4132	6.0176	0.0000

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The spatial weight matrix employed is the geo-economic nested matrix.

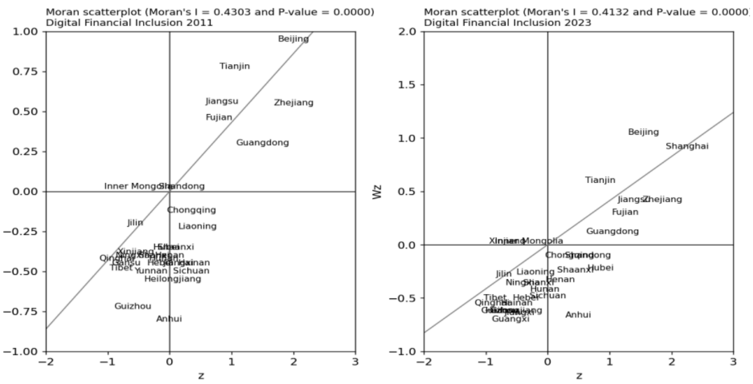

Figure 1. Local Moran scatter plot of digital financial inclusion, 2011 and 2023

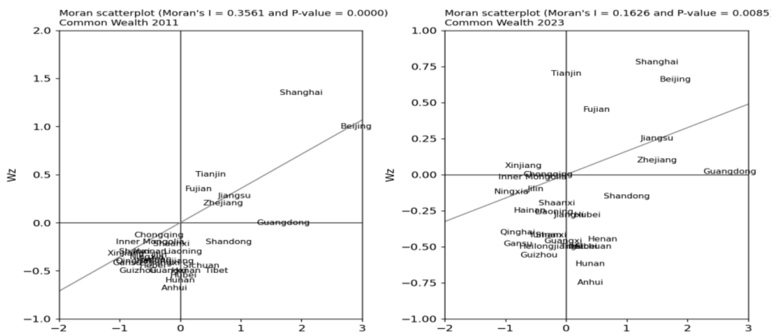

Figure 2. Local Moran scatter plot of common wealth, 2011 and 2023

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4.3. Spatial model selection

4.3.1. LM test (lagrange multiplier test)

The LM-Lag statistic (13.597) and the robust LM-Lag statistic (12.978) both reject the null of no spatial dependence at the 1% level, whereas neither the LM-Error nor its robust version reaches conventional significance. In line with the diagnostic approach of Anselin [19], we therefore choose the SLM over the SEM, because the dependence works through the dependent variable rather than through the residual covariance structure. The Hausman test yields a statistic of 111.14 ($p = 0.000$), which clearly favors fixed effects over random effects.

Table 4. LM Test and Hausman test results

Test Type	Statistic	P-value
LM-Error Test	0.6800	0.4100
Robust LM-Error Test	0.0600	0.8060
LM-Lag Test	13.5970	0.0000
Robust LM-Lag Test	12.9780	0.0000
Hausman Test	111.1400	0.0000

Note: The LM tests are based on residuals from ordinary OLS regression, using the geo-economic nested matrix.

4.3.2. LR test (likelihood ratio test)

Likelihood ratio tests reject the restricted specifications: the two-way fixed effects model is significantly superior to one with only individual fixed effects ($\chi^2(8) = 776.09$, $p = 0.000$) and to one with only time fixed effects ($\chi^2(8) = 134.88$, $p = 0.000$). The two-way fixed effects spatial lag model is therefore retained for estimation.

Table 5. LR test results

Test Combination	LR Statistic	*P*-value
Individual Fixed Effects vs. Two-Way Fixed Effects	776.09 (df=8)	0.000
Time Fixed Effects vs. Two-Way Fixed Effects	134.88 (df=8)	0.000

Note: df denotes degrees of freedom.

4.4. Baseline regression results

The spatial autoregressive coefficient ρ is estimated at −0.285 and is significant at the 1% level. A one-unit increase in a province's common wealth is thus associated with a 0.285-unit fall in that of its neighbors, which is the typical sign of a siphon pattern. With an R^2 of 0.5911, the model fits the data reasonably well. Since the SAR specification contains a spatial lag, we separate the total effect into direct and indirect components using the LeSage and Pace procedure. The direct effect of digital financial inclusion on local common wealth is 0.928 ($p < 0.01$); holding other factors constant, a one-unit increase in DIF raises the local common wealth index by 0.928 units. The indirect effect is −0.203 ($p < 0.01$), representing the negative spillover onto adjacent provinces, and the net total

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effect of 0.725 ($p < 0.01$) shows that local empowerment clearly dominates the cross-border drag. These results are in line with Chen and Pan [4] and Li and Zhou [3], and they extend the earlier innovation- and consumption-spillover findings to common wealth more broadly. Among the controls, trade openness has a positive direct effect (0.023) and a slightly negative indirect effect (−0.005), which fits the idea of a local trade dividend that does not spread to neighboring areas. Foreign direct investment has significantly negative direct and total effects, possibly because capital agglomeration brings short-term distributive distortions before productivity gains spread. Science and education expenditure has positive direct (0.285) and total (0.223) effects, so fiscal spending on human capital and innovation provides a lasting lever for common wealth. Education status, by contrast, is not statistically different from zero, which suggests that the sheer quantity of upper-secondary schooling does not immediately raise household welfare, perhaps because the returns to education appear with a lag and depend on how well the labor market absorbs graduates.

Table 6. Baseline regression results

Variable	Coefficient	Standard Error
DIF	0.9191***	(0.0979)
Open	0.0237**	(0.0100)
Fdi	-0.0028***	(0.0009)
Se	0.2776***	(0.0589)
Edu	-0.0026	(0.0869)
ρ	-0.2850***	(0.1075)
$sigma^2\_e$	0.0002***	(0.0000)
N	403	
R^2	0.5911	

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Clustered standard errors at the provincial level are reported in parentheses.

Table 7. Spatial effect decomposition results

Variable	Direct Effect	Indirect Effect	Total Effect
DIF	0.9284*** (0.0990)	-0.2032*** (0.0681)	0.7252*** (0.1020)
Open	0.0230*** (0.0088)	-0.0050* (0.0026)	0.0180** (0.0071)
Fdi	-0.0028*** (0.0010)	0.0006* (0.0003)	-0.0021*** (0.0008)
Se	0.2848*** (0.0637)	-0.0623** (0.0242)	0.2225*** (0.0551)
Edu	-0.0208 (0.1020)	0.0025 (0.0219)	-0.0182 (0.0816)

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses.

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4.5. Robustness tests

We carry out two robustness checks. The first re-estimates the baseline model after replacing the geo-economic nested matrix with an inverse-squared-distance matrix and then with a pure economic-distance matrix; under both, the core coefficient on digital financial inclusion stays positive and significant. The second follows Li et al. [5] and drops the 2020 observations so that the estimates are not distorted by the unusual shock of the COVID-19 pandemic; here too the main findings hold. The baseline conclusions are therefore not an artifact of a particular spatial weight matrix or of the pandemic-year outlier.

4.6. Mechanism analysis

Industrial structure upgrading is the channel we expect to carry the effect of digital financial inclusion through to common wealth. Two sub-pathways work at the same time. First, digital finance steers financial resources toward sectors with higher value added and so improves allocative efficiency. Second, by reducing the financing premium that small and micro firms face, it lowers entry barriers, encourages entrepreneurship, and speeds the movement of labor into more productive sectors. As the industrial structure upgrades, employment grows and the wage share of national income rises, which narrows income gaps between groups. Taking the aggregate industrial structure upgrading index (IS) as the mediator, the coefficient of digital financial inclusion on IS is 0.853 ($p < 0.1$), a significant first-stage effect, while the second-stage coefficient of IS on common wealth is 0.113 ($p < 0.05$). The mediation chain is thus complete.

Table 8. Robustness test results

	Direct Effect			Indirect Effect			Total Effect		
Variable	W_{ij}^{d}	W_{ij}^{e}	Sample Adjustment	W_{ij}^{d}	W_{ij}^{e}	Sample Adjustment	W_{ij}^{d}	W_{ij}^{e}	Sample Adjustment
DIF	0.8146*** (0.1093)	0.9284*** (0.0990)	0.4773*** (0.1132)	0.2365** (0.1184)	−0.2032** (0.0681)	−0.1003* (0.0502)	1.0511*** (0.1507)	0.7252*** (0.1020)	0.3771*** (0.1013)
Open	0.0256*** (0.0087)	0.0230** (0.0088)	0.0170* (0.0099)	0.0074* (0.0044)	−0.0050* (0.0026)	−0.0036 (0.0029)	0.0330*** (0.1112)	0.0180** (0.0071)	0.0134* (0.0078)
Fdi	-0.0028*** (0.0010)	−0.0028** (0.0010)	0.1036 (0.0698)	-0.0009 (0.0006)	0.0006* (0.0003)	−0.0225 (0.0198)	-0.0037** (0.0014)	−0.0021** (0.0008)	0.0811 (0.0547)
Se	0.2891*** (0.0637)	0.2848*** (0.0637)	0.2045*** (0.0675)	0.0849* (0.0461)	−0.0623** (0.0242)	−0.0429* (0.0243)	0.3740*** (0.0903)	0.2225*** (0.0551)	0.1617*** (0.0598)
Edu	-0.0662 (0.1013)	−0.0208 (0.1020)	0.0501 (0.1152)	-0.0223 (0.0405)	0.0025 (0.0219)	−0.0113 (0.0264)	-0.088 5(0.1383)	−0.0182 (0.0816)	0.0388 (0.0937)
ρ	0.2199** (0.0986)	−0.2850*** (0.1075)	−0.2759** (0.1392)						
sigma²_e	0.00015*** (0.00001)	0.00015*** (0.00001)	0.00010*** (0.00001)						
N	403	403	279						
R^2	0.5305	0.5911	0.5583						

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors are reported in parentheses.

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Table 9. Mechanism analysis results

	Model (1)	Model (2)
Variable	IS	CP
DIF	0.8533* (0.4717)	—
IS	—	0.1132** (0.0499)
Open	0.1293*** (0.0295)	-0.0097 (0.0415)
Fdi	0.0019 (0.0034)	-0.0036*** (0.0010)
Se	0.0307 (0.3739)	0.4473** (0.1725)
Edu	-0.0327 (0.3699)	0.1178 (0.2089)
Constant	2.1356*** (0.1323)	-0.1265 (0.1090)
N	403	403
R^2	0.9522	0.9685

4.7. Heterogeneity analysis

4.7.1. Regional heterogeneity analysis

The regional decomposition shows that the direct empowerment effect weakens clearly from east to west: it is 0.629 in the east, 0.549 in the centre and 0.274 in the west, and all three are significantly positive. This gradient matches the more developed digital-financial environment of the eastern coast, where wider digital infrastructure, higher smartphone use and stronger financial literacy together raise the efficiency with which inclusive finance is transmitted [2]. The siphon effect, by contrast, is strongest in the centre (−0.331) rather than in the east, with the east (−0.192) and the west (−0.080) behind it. One reading is that the central region acts as a corridor for factor mobility between the coast and the interior; its location in between leaves it especially open to the outflow of capital and talent toward more developed neighbors, which is in line with the innovation-suppression effect reported by Chen and Pan [4]. Total effects stay positive in every region but follow the same east-leading, west-lagging pattern.

Table 10. Regional heterogeneity analysis results

Region	Variable	Direct Effect	Indirect Effect	Total Effect
Eastern	*DIF*	0.6289*** (0.1857)	-0.1923*** (0.0716)	0.4366*** (0.1385)
Central	*DIF*	0.5493*** (0.1433)	-0.3309*** (0.0833)	0.2184*** (0.0660)
Western	*DIF*	0.2735* (0.1419)	-0.0799* (0.0464)	0.1936* (0.1025)

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Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses.

When the digital financial inclusion index is split into its three sub-dimensions—coverage breadth (CB), usage depth (UD) and digitalization degree (DD)—each shows a positive direct effect together with a negative indirect effect, which again reflects the pairing of local empowerment and cross-regional suppression [4]. By total effect, CB comes first (0.315), followed closely by UD (0.310) and DD (0.285). Because the direct coefficients of CB and UD are close to one another, at around 0.393, it appears that at the current stage of China's digital-finance development, widening the reach of financial services and deepening their use bring broadly similar gains to local common wealth, though coverage breadth keeps a small lead once spillovers are netted out.

Table 11. Dimensional heterogeneity analysis results

Dimension	Direct Effect	Indirect Effect	Total Effect
Coverage breadth (CB)	0.3920*** (0.1309)	-0.0772* (0.0403)	0.3147*** (0.1105)
Usage depth (UD)	0.3929*** (0.0585)	-0.0833*** (0.0310)	0.3096*** (0.0549)
Digitalization degree (DD)	0.3662*** (0.0372)	-0.0808*** (0.0266)	0.2854*** (0.0389)

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses. CB denotes coverage breadth, UD denotes usage depth, and DD denotes digitalization degree.

4.8. Threshold effect: The nonlinear moderation of marketization level

With the aggregate marketization index as the threshold variable, the data support a double-threshold structure: the single-threshold ($F = 116.00$, $p = 0.000$) and double-threshold ($F = 95.09$, $p = 0.000$) tests are highly significant, while the triple-threshold test is not. The two thresholds are estimated at 8.368 (95% CI: [8.299, 8.490]) and 10.597 (95% CI: [10.560, 10.733]), which divide the sample into low-, intermediate- and high-marketization regimes. Across these regimes the promotion coefficient of digital financial inclusion on common wealth is 0.298, 0.379 and 0.475, rising monotonically and each significant at the 1% level, which indicates accelerating marginal returns. As marketization deepens, transaction costs fall, information asymmetry lessens and factors are allocated more efficiently, and all of this raises the efficiency with which digital finance is transmitted into household welfare [5]; the pattern reinforces the increasing-marginal-effect mechanism reported by Han et al. [2]. The likelihood-ratio profile confirms that the two estimated thresholds are statistically reliable.

Table 12. Threshold effect significance test results

Threshold Type	F-statistic	P-value	10% Crit	5% Crit	1% Crit
Single threshold	116.00	0.0000	48.3684	60.7236	74.8133
Double threshold	95.09	0.0000	33.4667	37.9826	46.9667
Triple threshold	36.10	0.8400	88.1576	1000.1949	136.3340

Note: Crit10%, Crit5%, and Crit1% denote the critical values at the corresponding significance levels. The number of bootstrap replications is 300.

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Table 13. Threshold estimates and 95% confidence intervals

Threshold Type	Threshold Estimate	95% Confidence Interval
Threshold 1(γ_1)	8.3680	[8.2990, 8.4900]
Threshold 2(γ_2)	10.5970	[10.5600, 10.7330]

Note: The threshold variable is the aggregate marketization index (source: Wang et al., Marketization Index of China's Provinces: Annual Report).

Table 14. Threshold regression results

Variable	Coefficient	Standard Error
DIF(MKT < 8.368)	0.2979***	(0.0129)
DIF(8.368 ≤ MKT < 10.597)	0.3794***	(0.0111)
DIF(MKT ≥ 10.597)	0.4745***	(0.0114)
Control variables	Yes	
N	403	
Adjusted R²	0.924	

Note: *** denotes statistical significance at the 1% level. Standard errors are reported in parentheses. The control variables are identical to those in the baseline regression.

To check the reliability of the threshold estimates, we report the likelihood-ratio profile in Figure 3. At both thresholds the LR statistic lies well below the 7.35 critical value for the 95% confidence level, which gives further support to the double-threshold specification.

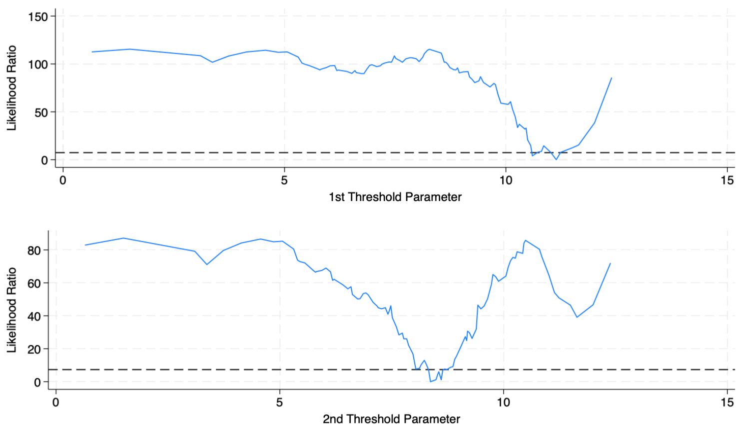

Figure 3. LR statistic plot for the threshold effect based on marketization level

5. Conclusion

5.1. Research conclusions

Using provincial panel data for 2011–2023, this paper applies spatial lag and panel threshold models to study the spatial, mediating and nonlinear effects of digital financial inclusion on common wealth. Four main findings stand out. First, digital financial inclusion raises local common wealth markedly

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(direct effect = 0.928, total effect = 0.725, $p < 0.01$) but produces a negative siphon effect (−0.203) on neighboring provinces, which extends the findings of Chen and Pan [4] and Li and Zhou [3] to the area of common wealth. Second, industrial structure upgrading is the main mediating channel. Third, the effects are heterogeneous: the direct effect follows an east > centre > west gradient, and all three dimensions of digital financial inclusion combine local empowerment with cross-regional suppression, with coverage breadth showing the strongest net effect. Fourth, marketization has a double-threshold moderating effect, with the promotion coefficient rising from 0.298 to 0.475 and exhibiting increasing marginal returns [2]. By moving beyond the conventional aspatial, linear framework, these results offer empirical support for coordinated regional development and common prosperity.

5.2. Policy recommendations

Drawing on these results, the paper offers four policy recommendations. First, give priority to digital financial inclusion infrastructure in the central and western provinces, and pair it with financial literacy programs aimed at rural residents, low-income households and MSMEs, so as to remove last-mile barriers and realize the benefits of wider coverage. Second, set up an inter-provincial coordination mechanism for digital finance to ease the siphon effect and help technology and talent spread from the coast to the interior. Third, align digital financial inclusion policy with industrial upgrading by directing financial resources to technology-intensive sectors, which strengthens the finance–employment–income chain. Fourth, push forward institutional reforms—property rights protection, factor marketization and a better business environment—in provinces where marketization is low; crossing the estimated threshold of 10.597 would bring the marginal effect of digital finance to its highest. Finally, this study works at the provincial level, and future research could draw on prefecture- or county-level data to examine these mechanisms in finer detail.

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