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-RESEARCH ARTICLE-

DIGITAL FINANCIAL INCLUSION AND REGIONAL INNOVATION EFFICIENCY: ANALYSIS OF CHINESE PROVINCIAL DATA

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—Abstract—

This research investigates the extent to which digital financial inclusion influences regional innovation efficiency in China. Drawing on provincial panel data from 31 provinces spanning 2011 to 2022, innovation efficiency is first evaluated through stochastic frontier analysis (SFA), where R&D capital stock and full-time R&D personnel serve as inputs and invention patents per 10,000 inhabitants represent the output. Subsequently, fixed-effects regressions with province-clustered standard errors are estimated, accompanied by a series of diagnostic tests, including the Hausman test for model specification, the Wooldridge test for serial correlation, the Breusch–Pagan test for heteroskedasticity, and the Pesaran CD test for cross-sectional dependence. To

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mitigate endogeneity concerns, instrumental variable two-stage least squares (IV-2SLS) is applied, using the lagged digital finance index as the instrument, with first-stage strength verified through the Kleibergen–Paap rk Wald F statistic and validity assessed via over-identification tests. Mediation analysis is undertaken with delta-method standard errors, considering financing constraints and human capital as mediators, while spatial dynamics are explored by interacting with local digital financial inclusion with an adjacent-weighted measure of neighbouring provinces' digital financial inclusion. Empirical results show that a one-unit increase in the digital finance index raises innovation efficiency by roughly 2.5 percentage points. This relationship remains robust across alternative estimators, sample adjustments, and instrumental variable specifications. The mediating role of financing constraints and human capital is confirmed, while the interaction between digital finance inclusion and neighbouring levels displays regional variation, suggesting both direct and spillover effects that hold important implications for coordinated regional policies.

Keywords: Digital Financial Inclusion; Regional Innovation; Financing Constraints; Human Capital; Neighbouring Digital Finance.

INTRODUCTION

Innovation is a central driver of long-term productivity growth and structural transformation. The extent to which resources are devoted to R&D, and the efficiency with which these investments are translated into knowledge, technology, and commercial outputs, is a crucial factor shaping regional development. This study therefore concentrates on regional innovation efficiency (RIE), defined as the effectiveness with which R&D capital and personnel are converted into innovation outcomes, and investigates whether digital financial inclusion (DFI) enhances that efficiency across Chinese provinces.

DFI refers to the provision of financial services through digital technologies such as mobile internet, cloud-based infrastructure, and data-driven credit assessment (Jha, 2023; Nutalapati, 2024; Wei et al., 2025). It broadens access for previously excluded groups, reduces both search and transaction costs, and provides alternatives to conventional lending models that rely heavily on collateral (Butticè & Vismara, 2022). Because innovation-related investments are intangible, risky, and slow to generate returns, expanded digital finance can channel resources towards more productive activities and improve the efficiency of innovation (Balboa et al., 2024). Although digital finance has expanded rapidly in China, its development remains uneven across regions. Provinces vary in internet penetration, platform uptake, data infrastructure, and supervisory effectiveness. The provincial DFI index, which incorporates coverage, depth of use, and quality of digitalisation, highlights overall national progress but also wide cross-provincial disparities. Where DFI helps to reduce financing constraints or improve resource allocation, provinces with stronger digital inclusion should be better

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positioned to convert R&D inputs into outputs (Li et al., 2023).

At the same time, digitalisation introduces new governance challenges. Concerns regarding cybersecurity incidents, misuse of personal data, opaque algorithms (Khin & Ho, 2019), and privacy risks can undermine trust and offset potential efficiency gains if left unaddressed. As a result, risk-based supervision, standards for data minimisation and consent, and secure mechanisms for identity and authentication represent essential areas for government intervention. The overall balance of benefits and risks is therefore shaped by local institutional contexts and implementation capacity (Oluoha et al., 2022). The existing literature generally supports the view that digital finance contributes positively to innovation by stimulating both inputs and outputs (Awan et al., 2021). Nonetheless, several limitations persist.

First, much of the scholarship measures innovation levels rather than efficiency (Lu, 2023), that is, the degree to which inputs are transformed into outputs relative to a frontier. Second, while the credit-access channel has received substantial attention, the human capital dimension—for example, financing of education (Howell, 2017; Lu et al., 2022), re-skilling initiatives, and digital services that promote talent mobility—remains underexplored in regional contexts. Third, spatial interdependencies are often acknowledged but rarely integrated into formal models, despite the fact that platform connectivity and cross-provincial data flows can generate complementary or competitive effects across regions (Chen et al., 2022; Jiang et al., 2021). Finally, methodological approaches differ, with most studies relying on fixed-effects panels, yet application of endogeneity tests and triangulated strategies is inconsistent.

This study addresses these issues by analysing 31 Chinese provinces between 2011 and 2022 to determine whether DFI is associated with higher RIE. Here, RIE is conceptualised as a frontier-relative outcome where provinces employ available inputs (R&D capital stock and full-time R&D personnel) to generate outputs such as invention patents. Efficiency differentials are attributed to allocative, managerial, and institutional factors rather than scale effects alone (Howell, 2017). DFI is measured using a composite provincial index along with its three sub-dimensions. The analysis speaks to policies designed to enhance financial support for innovation, address risks linked to digitalisation, and contribute to balanced regional development.

The methodological design is structured around three elements. First, the study centres on efficiency rather than absolute levels of inputs or outputs, aligning the research with policy interests in improving the productivity of innovation spending. Second, it explicitly considers mechanisms by examining financing constraints and human capital as two potential mediating channels without predefining their relative importance. Third, it incorporates the geography of digital ecosystems by allowing the level of DFI in neighbouring provinces to influence local relationships, an approach that captures the relevance of interprovincial coordination and platform oversight (Ren et al., 2023).

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The policy implications are direct. If DFI enhances innovation efficiency, then targeted expansion of inclusive digital financial services, when coupled with effective regulation, could enable regions to achieve greater innovative returns per unit of R&D expenditure, particularly in areas where information asymmetries and collateral requirements remain barriers. If outcomes depend on human capital formation or regional spillovers, integrating digital finance policies with talent development and cross-provincial coordination would be crucial. Conversely, if the impact is limited or context-dependent, policy should focus more on complementary reforms, including improvements in data governance, credit information systems, and institutional capacity.

The remainder of this paper is organised as follows. Section 3 reviews the related literature and formulates hypotheses with reference to prior methodologies. Section 4 outlines the data, variable definitions, and econometric strategy. Section 5 presents the empirical findings and interprets them in relation to the existing literature, including analysis of mechanisms and spatial dynamics. Section 6 concludes with policy recommendations and suggestions for future research.

LITERATURE REVIEW

Within the context of digital transformation and the pursuit of high-quality, innovation-led growth, a key question is whether DFI enhances the capacity of regions to translate innovation inputs into outputs more effectively. Four issues remain central to this inquiry: the nature of the relationship between DFI and innovation efficiency as distinct from innovation levels; the specific mechanisms through which effects operate, particularly financing constraints and human capital; the extent to which spatial and regional dynamics shape outcomes; and the implications of measurement choices and identification strategies for the reliability of the findings.

DFI and Regional Innovation: From Levels to Efficiency

Earlier studies that rely on patents or R&D intensity as proxies report a positive relationship between digital finance and innovation, particularly in regions with limited banking access (Chen et al., 2018; Hui et al., 2023). The mechanisms operate through data-driven underwriting, which lowers search and screening costs, and through mobile and fintech ecosystems that broaden access. However, measuring outputs alone offers limited insight into efficiency, namely the extent to which regions transform R&D inputs into outcomes relative to the technological frontier (Barra & Ruggiero, 2022).

The efficiency-oriented methods such as Data Envelopment Analysis (DEA) and SFA better reflect the goal of achieving more innovation per unit of expenditure. DEA, being non-parametric, attributes all deviation from the frontier to inefficiency, while SFA separates deviations into inefficiency and statistical noise, making it well suited to provincial data where measurement error is common. Despite their usefulness, efficiency-focused analyses remain fewer than studies on innovation levels, and cross-study comparison is hindered by differences in input–output specifications (for instance, patents per capita versus raw counts), scaling choices, and transformation procedures. This gap underscores the need for a framework that treats RIE as the primary outcome and explicitly explores how DFI influences the productivity of innovation investment (Zubir et al., 2024).

Mechanisms: Financing Constraints, Human Capital, and Information Allocation

DFI can enhance RIE through at least three main channels. The first is credit easing, whereby reductions in information asymmetry and collateral requirements expand the range of viable R&D projects, particularly for SMEs and early-stage innovators. By lowering financing frictions, regions are better positioned to generate higher outputs from a given set of inputs. The second channel is human capital, as inclusive financial services facilitate education finance, re-skilling opportunities, and labour mobility, thereby strengthening both the quantity and allocation of talent necessary to convert research into applied innovations (Lakshmi et al., 2024). The third channel involves information allocation. According to Lu (2023), frequent payment activity and platform data improve project selection and capital distribution, steering resources towards more productive uses.

In empirical studies, credit easing is the most commonly examined pathway, while the role of human capital has received less systematic attention in provincial analyses (Crescenzi & Gagliardi, 2018), and information-allocation effects are often addressed qualitatively rather than quantitatively. Where mechanisms are tested, stepwise mediation in panel frameworks is widely used, yet adjustments for clustering and serial correlation in estimating indirect effects are not always applied. Integrating both principal mechanisms—financing constraints and human capital—within a single empirical framework (Yang et al., 2022), supported by consistent measurement and robust standard errors, offers clearer insight into their relative contributions to RIE.

Spatial Interdependence and Regional Heterogeneity

Digital ecosystems have a geographic footprint: platforms operate across borders, Supply chains often extend across provinces, while data externalities operate on a global scale. Although spatial autocorrelation in innovation outcomes is well established, the influence of neighbouring DFI is less frequently incorporated into core estimations (Awan et al., 2021; Chen et al., 2022). Neighbouring provinces' DFI may reinforce local outcomes by supporting complementary networks and facilitating talent mobility (Barra & Ruggiero, 2022), or alternatively, reduce them through competition for resources and market crowding-out. To capture these dynamics, this study incorporates spatial effects by interacting local DFI with an adjacency-weighted index of neighbouring DFI. The results reveal regional heterogeneity. In the more developed eastern provinces, marginal

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returns from DFI are relatively limited, while central and western provinces appear to benefit more (Li et al., 2023). Factors such as industrial composition, institutional quality, and privacy regimes further condition these outcomes. Compared with subsample analyses, interaction-based approaches more clearly demonstrate how geography and structural characteristics shape the DFI–RIE relationship (Crescenzi & Gagliardi, 2018).

Measurement, Identification, and Remaining Gaps

On the DFI side, existing research varies in its reliance on the composite index alone or on its sub-dimensions of coverage, depth of use, and digitisation quality (Howell, 2017; Lee et al., 2023; Lu et al., 2022). While simple account ownership (coverage) may have a weaker association with innovative outcomes compared to active utilisation and data quality (Becha et al., 2025), the empirical evidence remains limited. On the outcome side, applying an SFA-derived efficiency measure and incorporating it into second-stage panel regressions helps to mitigate attenuation bias caused by measurement error. For identification, two-way fixed effects have become the prevailing approach (Crescenzi & Gagliardi, 2018), although concerns over simultaneity and omitted-variable bias continue to pose challenges.

Summary

Prior research typically links DFI with enhanced innovation activity, but much of the evidence remains focused on levels such as patent counts or R&D intensity rather than on efficiency, meaning the frontier-relative transformation of inputs into outputs (Li et al., 2023). The mechanisms explored are uneven, with extensive attention given to credit easing, while the roles of human capital development and information allocation have been tested less systematically in provincial datasets. Spatial dependence is frequently recognised but rarely incorporated into modelling, which leaves uncertainty over whether neighbouring digital ecosystems reinforce or diminish local impacts. Measurement and identification approaches are also inconsistent, as many studies employ composite DFI indices without examining their sub-components, and fixed-effects estimations are not always supplemented with endogeneity tests or comprehensive panel diagnostics.

In addressing these gaps, this study evaluates regional innovation efficiency through SFA, disaggregates DFI into coverage, depth, and digitisation, and investigates two channels—financing constraints and human capital—using mediation approaches appropriate for panel data with explicit statistical inference. It also incorporates spatial interdependence to assess whether DFI contributes to higher innovation efficiency, to identify the mechanisms involved, and to determine the spatial contexts under which such effects operate, thereby forming the basis for the hypotheses that follow.

THEORETICAL ANALYSIS AND RESEARCH HYPOTHESES

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Direct Effect of Digital Financial Inclusion on Regional Innovation Efficiency

DFI mitigates information frictions, expands access to payment and credit services, and improves the alignment of finance and skills with innovative activities (Lee et al., 2023; Lu et al., 2022). When such frictions are reduced, regions can more effectively convert a given set of R&D inputs into outputs, thereby achieving higher RIE. Since simple account coverage does not ensure utilisation or reliable data, the depth of use and the quality of digital infrastructure are the more critical determinants of efficiency.

H1: *DFI is positively associated with RIE.*
H1a–H1c: *All three sub-indices relate positively to RIE, with larger effects for depth of use and digitization quality than for coverage.*

Mechanisms: Financing Constraints and Human Capital

DFI influences RIE primarily through two mechanisms. The first concerns financing constraints, where data-driven underwriting and diversified credit instruments reduce collateral requirements and accelerate the flow of capital to innovation projects, particularly those undertaken by SMEs. The second involves human capital, as inclusive financial services enhance access to education finance, re-skilling, and mobility, thereby strengthening both the quantity and distribution of talent that translates research into commercially viable outputs (Crescenzi & Gagliardi, 2018; Howell, 2017; Yin & Wang, 2025). When either channel functions as expected, part of the impact of DFI on RIE is transmitted indirectly.

H2a (Mediation—Financing): *DFI reduces financing constraints, which in turn raises RIE; the indirect effect is positive (partial mediation).*
H2b (Mediation—Human Capital): *DFI increases human capital, which in turn raises RIE; the indirect effect is positive (partial mediation).*

Spatial Conditioning by Neighbouring Digital Finance

Digital platforms and associated data externalities extend beyond provincial boundaries (Lu, 2023). Neighbouring DFI can either reinforce local ecosystems by facilitating shared networks and talent flows or create competition for limited resources. Modelling the interaction between local DFI and an adjacency-weighted index of neighbouring DFI enables the analysis to determine which of these effects prevails.

H3 (Spatial Moderation): *The interaction between local DFI and neighbouring DFI is positive on RIE, indicating complementary cross-border digital ecosystems.*

Regional Heterogeneity and Boundary Conditions

The effects of DFI are not expected to be evenly distributed across regions. In the more developed eastern provinces, where traditional finance is already entrenched, additional digitalisation may deliver only limited marginal benefits (Lakshmi et al., 2024; Lin & Peng, 2025). By contrast, central and western provinces, which continue to face deficits in financial access and data infrastructure, are more likely to experience significant efficiency gains from comparable increases in DFI. Moreover, at very high levels of DFI, diminishing returns may arise once the most accessible opportunities have already been exploited.

H4a (Regional Heterogeneity): *The DFI→RIE association is stronger in central/western provinces than in the East.*
H4b (Nonlinearity): *The marginal effect of DFI on RIE declines at high DFI levels (a concave relationship).*

METHODOLOGY

Building on the reviewed literature, this study develops a measurement–estimation framework that (1) applies a stochastic frontier method to assess RIE, (2) links DFI to this efficiency through two-way fixed effects, (3) investigates two mediating mechanisms, namely financing constraints and human capital (Hayes & Preacher, 2010), (4) incorporates spatial conditioning by neighbouring DFI, and (5) provides full diagnostics and robustness checks.

Data and Sample

The dataset covers 31 provincial-level regions in China over the period 2011–2022. Measures of R&D inputs (capital stock and full-time personnel), innovation outputs (invention patents), macroeconomic controls, and demographic factors are sourced from standard statistical yearbooks and provincial bulletins. Patent indicators are normalised by population to yield per-capita outcomes where relevant. The composite DFI index, together with its sub-indices of coverage, depth, and digitisation quality, is drawn from the established provincial DFI database. The provincial scale enables the analysis of cross-regional heterogeneity and policy-relevant disparities in digital finance and innovation. A limitation, however, is that intra-provincial variation is obscured, which is noted in the conclusion as a potential direction for future city-level research. All monetary series are expressed in constant 2011 prices using provincial GDP deflators. To limit the influence of extreme observations, continuous variables are winsorised at the 1st percentile. Interaction terms and quadratic specifications are mean-centred to mitigate multi-collinearity.

Variables and Measurement

Outcome: Regional innovation efficiency (eff). A stochastic frontier model is employed, where R&D capital stock and full-time equivalent R&D personnel serve as inputs, and invention patents per 10,000 inhabitants represent the output. The derived

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efficiency score, ranging from 0 to 1, is subsequently incorporated into second-stage panel regressions.

Table 1: Variable Measurement and Data Source

Variable Type	Variable Name	Variable Indicator	Variables Source
Dependent Variable	Regional Innovation Efficiency	eff	Stochastic Frontier Model Measurement
Independent Variable	Digital Inclusive Finance	DFI	Peking University Financial Inclusion Report
	Breadth of Coverage	breadth	
	Depth of Use	depth	
	Degree of Digitization	digitization	
Mediating Variable	Credit Financing Constraints	fin	Total Regional Savings and Loans / GDP at the End of the Year
	Human Capital Accumulation	hc	Number of Students in School / Total Population
Grouping Variable	Geographic Region	area	1 in the East, 2 in the Centre, 3 in the West
Moderating Variable	Level of Digital Finance in Neighbouring Provinces and Cities	DFI_N	Average Value of Inclusive Financial Development in Neighbouring Provinces and Cities
Control Variable	Fixed-Asset Investment	ifa	Investment in Fixed Assets/GDP
	Science and Education Investment Intensity	gov	Science and Education Inputs / Financial Expenditures
	Degree of External Openness	open	Total Exports and Imports / GDP
	Industrial Structure	structure	Value Added of the Tertiary Sector/ Value Added of the Secondary Sector
	Level of Economic Development	lnpgdp	Logarithm of GDP Per Capita
	Level of Infrastructure	trf	Total Road Mileage / Total Population

Core Regressor: Digital financial inclusion (DFI). In Table 1, the primary explanatory variable is the provincial composite index of DFI, supplemented by its sub-indices capturing coverage, depth of use, and digitisation quality.

Mediators: Financing constraints (fin) and human capital (hc). Financing constraints are proxied by the ratio of provincial interest payments to operating income, with higher ratios reflecting tighter constraints. Human capital is measured by the average years of schooling among the working-age population.

Spatial Moderator: Neighbouring DFI (index_adjacent). Spatial dependence is modelled using a row-standardised rook-contiguity weight matrix (W), which captures adjacency-based spillovers in DFI across provinces.

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$$\text{index\_adjacent} = \sum_j w_{ij} DFI_{jt}$$

Controls: Per-capita GDP (*lnpgdp*), industrial structure (*structure* = tertiary/secondary value-added ratio), government size (*gov* = fiscal expenditure/GDP), openness ((exports + imports)/GDP), urbanization (urban share), and infrastructure (road mileage/population).

Econometric Strategy

This study applies two-way fixed-effects (FE) models that incorporate province and year dummies. The FE approach is suitable, as time-invariant provincial characteristics such as historical industrial structure, institutional quality, scientific culture, and geography are likely to be correlated with both DFI and RIE. Pooled OLS would suffer omitted-variable bias, and random-effects (RE) requires $E[\mu_{it} \mid X_{it}] = 0$, which is unlikely to hold in this context. Year fixed effects absorb nationwide shocks (macro cycles, policy shifts, standard technology trends). Empirical tests support the choice of FE. A Hausman test indicates that FE is preferable to RE, although RE with a Mundlak correction (province-means of time-varying covariates) is also reported as a robustness exercise. Because provincial panels often display serial correlation, heteroskedasticity, and cross-sectional dependence, province-clustered standard errors are used, and the models are re-estimated with Driscoll–Kraay errors as an additional check. Diagnostic procedures include the Wooldridge test for first-order autocorrelation, Breusch–Pagan and White tests for heteroskedasticity, the Pesaran CD test for cross-sectional dependence, and variance inflation factors for multi-collinearity.

To mitigate residual endogeneity, FE is complemented by an IV-2SLS specification in which DFI is instrumented with its lagged values. First-stage strength (Kleibergen–Paap rk Wald F) and over-identification validity (Hansen J) are reported where relevant. Estimates from FE and IV-FE are then compared to assess robustness. From the perspective of intercept treatment, panel regressions may be estimated as random-, mixed-, or fixed-effects models. The F, LM, and Hausman tests are applied to determine the appropriate specification. The F-test rejects the mixed OLS model in favour of FE, the LM test shows that RE dominates the mixed OLS model, and the Hausman test suggests that RE is not superior to either RE or FE (Liu et al., 2020). Comparative analysis ultimately identifies FE as the most suitable specification, and the reported results are based on this model as shown in Table 2.

Table 2: Different Test Results

Test Methods	Statistic	P-Value	Test Conclusion
F-Test	467.13	0.00	Fixed-Effects Models Outperform Mixed OLS Models
LM Test	1136.62	0.00	Random-Effects Models Outperform Mixed OLS Models
Hausmann Test	118.26	0.00	Fixed-Effects Models Outperform Random-Effects Models

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Baseline Model

We estimate two-way fixed effects (FE) with province (μ_i) and year (λ_t):

$$eff_{it} = \beta DFI_{it} + \gamma' Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

The selection of FE is based on the expectation that time-invariant provincial characteristics, such as historical institutions and innovation culture, are correlated with DFI. A Hausman test is reported to compare FE with RE, and for robustness, RE estimates with a Mundlak correction (province-level means of time-varying covariates) are also presented.

Sub-Dimensions of DFI

$$eff_{it} = \beta_1 \times coverage_{it} + \beta_2 \times depth_{it} + \beta_3 \times digitization_{it} + \gamma' Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Spatial Moderation

Let *DFI_N* denote neighbouring DFI. This study estimates:

$$eff_{it} = \beta \times DFI_{it} + \rho \times DFI\_N_{it} + \theta \times (DFI_{it} \times DFI\_N_{it}) + \gamma' Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

A positive θ would indicate that cross-border ecosystems operate in a complementary manner.

Regional Heterogeneity and Nonlinearity

Heterogeneity is examined by interacting DFI with regional dummies distinguishing eastern from central and western provinces. In addition, a squared term (DFI^2) is incorporated where appropriate to test for diminishing returns at higher levels of DFI.

Diagnostics and Inference

The properties of provincial panel data require explicit diagnostic testing. Accordingly, this study (1) applies the Hausman test to compare FE and RE specifications, (2) conducts the Wooldridge AR(1) test for serial correlation, (3) employs Breusch–Pagan and White tests for heteroskedasticity, and (4) uses the Pesaran CD test to detect cross-sectional dependence. Standard errors are clustered at the provincial level, with Driscoll–Kraay estimates reported as an additional robustness check. Variance inflation factors are also presented to assess multi-collinearity, and issues of stationarity are discussed where strong trends are identified.

Endogeneity and Identification

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Provinces with high innovation activity may draw digital platforms, creating potential reverse causality, while unobserved shocks could simultaneously affect DFI and RIE. To address these concerns beyond FE and control variables, an IV-2SLS specification is estimated using lagged DFI as an instrument:

First Stage: $$DFI_{it} = \emptyset \times DFI_{i,t-1} + k' \times Control_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Second Stage: $$eff_{it} = \beta \times DFI_{it} + \delta_1 \times fin_{it} + \gamma' \times Control_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

The study reports the Wald F statistic to assess instrument strength and the Hansen J test for over-identification when additional lags or instruments are employed. IV-2SLS results are compared with FE estimates to evaluate sensitivity.

Mechanism Tests: Financing and Human Capital

The study investigates two mediators using sequential mediation methods adapted for panel data:

(a) $$fin_{it} = \alpha_1 \times DFI_{it} + \emptyset' \times Control_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

(b) $$eff_{it} = \beta \times DFI_{it} + \delta_1 \times fin_{it} + \gamma' \times Control_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Similarly, for human capital (HC). Indirect effects ($\alpha_1\delta_1$; $\alpha_2\delta_2$) are evaluated using **delta-method** standard errors and province-level clustering.

Robustness and Sensitivity

Robustness is examined through multiple checks: (1) alternative error structures using Driscoll–Kraay standard errors, (2) exclusion of 2020–2022 to account for pandemic effects, (3) inclusion of additional controls such as government quality and urbanisation where data permit, (4) alternative outcome scaling, using raw invention patents rather than per-capita values, and (5) different DFI transformations, including logarithmic and z-score scales. The model is also re-estimated with province-specific linear trends to absorb slow-moving unobservable. Leave-one-province-out tests are conducted to verify that results are not driven by any single outlier.

RESULTS AND DISCUSSION

Descriptive Statistics

Table 3 presents summary statistics for the full sample of 31 provinces over 2011–2022 (N = 372). The mean RIE (eff) is 0.242 with a standard deviation of 0.267, reflecting substantial variation across provinces. The composite DFI index averages 2.449, ranging from 0.162 to 4.860, and its three sub-indices—coverage, depth, and digitisation—also exhibit considerable dispersion. Mediators and control variables display wide ranges, consistent with inter-provincial heterogeneity. These descriptive patterns highlight the cross-sectional differences further examined in the subsequent

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analyses (Table 3).

Table 3: Descriptive Statistics

Variable Name	Number	Mean	Standard Deviation	Min	Median	Max
DFI	372	2.449	1.104	0.162	2.552	4.860
Breadth	372	2.270	1.122	0.020	2.323	4.716
Depth	372	2.412	1.143	0.068	2.466	5.327
Digitization	372	3.108	1.168	0.076	3.541	4.622
Eff	372	0.242	0.267	0.005	0.124	0.940
Fin	372	3.383	1.212	1.518	3.154	8.131
Hc	372	206.450	59.810	80.495	202.979	436.174
Area	372	2.032	0.862	1.000	2.000	3.000
DFI_N	372	2.435	1.077	0.267	2.538	4.442
Ifa	372	0.795	0.265	0.206	0.816	1.507
Gov	372	0.183	0.034	0.106	0.184	0.262
Open	372	0.259	0.284	0.008	0.142	1.548
Structure	372	1.271	0.711	0.518	1.123	5.310
Lnpgdp	372	10.896	0.455	9.706	10.864	12.156
trf	372	46.717	47.039	5.129	36.622	332.012

Baseline Regression Results

Table 4 reports two-way FE estimates of RIE on DFI. In the baseline specification without controls (column 1), the DFI coefficient is 0.025 and statistically significant at the 1% level. Sequential inclusion of controls—including economic development, industrial structure, government size, openness, and infrastructure—maintains the coefficient within the 0.025–0.028 range, remaining significant across specifications (columns 2–7). Interpreted as a semi-elasticity, a one-unit increase in the DFI index corresponds to an approximately 2.5–2.8 percentage-point increase in efficiency, which is economically meaningful in the provincial context (Table 4).

Table 4: Baseline Fixed-Effects Regressions of Innovation Efficiency on Digital Financial Inclusion

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
	eff	eff	eff	eff	eff	eff	eff
DFI	0.025***	0.025***	0.025***	0.026***	0.026***	0.027***	0.028***
	(44.573)	(44.982)	(44.819)	(45.836)	(30.128)	(14.784)	(16.156)
ifa		- 0.012***	- 0.012***	- 0.013***	- 0.013***	- 0.013***	- 0.015***

Table 4: Baseline Fixed-Effects Regressions of Innovation Efficiency on Digital Financial Inclusion (cont…)

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
	eff	eff	eff	eff	eff	eff	eff
		(-2.767)	(-2.800)	(-3.205)	(-3.168)	(-3.193)	(-3.889)

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gov			0.057	0.036	0.050	0.065	0.066
			(1.185)	(0.772)	(1.048)	(1.279)	(1.375)
open				0.044***	0.047***	0.045***	0.044***
				(5.800)	(5.897)	(5.653)	(5.845)
structure					0.004	0.003	-0.000
					(1.124)	(0.850)	(-0.149)
lnpgdp						-0.006	-0.000
						(-0.906)	(-0.027)
trf							- 0.000***
							(-6.172)
constant	0.181***	0.190***	0.179***	0.170***	0.164***	0.224***	0.184***
	(121.944)	(54.225)	(18.691)	(18.230)	(15.087)	(3.323)	(2.860)
N	372	372	372	372	372	372	372
R^2	0.854	0.857	0.858	0.871	0.871	0.871	0.885

T-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1
Note: Province and year fixed effects included. Entries are coefficients; standard errors clustered by province.

Sub-Dimension Analysis

To explore mechanisms within the composite index, Table 5 substitutes the DFI composite with its three sub-indices. Each component exhibits a positive relationship with RIE, with depth of use showing the strongest association, followed by coverage and then digitisation (columns 2–4). This pattern indicates that active engagement with digital finance and the quality of digital infrastructure are more closely linked to innovation efficiency than mere account access (Table 5).

Table 5: Digital Finance Sub-Dimension Regressions

Variable	(1)	(2)	(3)	(4)
	eff	eff	eff	eff
DFI	0.028***			
	(16.156)			
breadth		0.029***		
		(16.501)		
depth			0.023***	
			(14.736)	
digitization				0.008***
				(6.105)
ifa	-0.015***	-0.008**	-0.006	-0.021***
	(-3.889)	(-2.236)	(-1.538)	(-4.053)
gov	0.066	0.095**	-0.061	-0.017
	(1.375)	(1.972)	(-1.243)	(-0.271)

Table 5: Digital Finance Sub-Dimension Regressions (Cont…)

open	0.044***	0.030***	0.050***	0.067***
	(5.845)	(3.851)	(6.356)	(6.945)
structure	-0.000	-0.002	0.004	0.022***
	(-0.149)	(-0.586)	(1.274)	(6.172)
lnpgdp	-0.000	-0.008	0.019***	0.065***
	(-0.027)	(-1.141)	(3.295)	(11.973)
trf	-0.000***	-0.000***	-0.000***	-0.000***
	(-6.172)	(-6.880)	(-5.764)	(-3.413)
_cons	0.184***	0.263***	-0.002	-0.506***
	(2.860)	(3.914)	(-0.033)	(-9.510)
N	372	372	372	372
R^2	0.885	0.887	0.875	0.815

T-Statistics in Parentheses: *** p<0.01, ** p<0.05, * p<0.1
Note: Province and year fixed effects included. Entries are coefficients; standard errors clustered by province.

Robustness Checks

Robustness checks reported in Table 6 support the baseline findings across alternative specifications and samples. A Tobit model, the exclusion of Tibet, and the removal of pandemic-period observations all yield positive and significant DFI coefficients (0.020, 0.028, and 0.022, respectively). Coefficients on control variables remain largely unchanged, and model fit statistics are stable (Table 6).

Table 6: Robustness Checks

Variable	(1)	(2)	(3)
	eff	**eff**	**eff**
DFI	0.020***	0.028***	0.022***
	(16.598)	(15.885)	(11.249)
ifa	-0.019***	-0.014***	-0.013***
	(-4.799)	(-3.456)	(-3.266)
gov	0.031	0.069	-0.034
	(0.774)	(1.415)	(-0.716)
open	0.077***	0.044***	0.028***
	(12.885)	(5.154)	(3.778)
structure	0.012***	-0.001	0.004
	(6.973)	(-0.291)	(1.150)
lnpgdp	0.033***	-0.000	0.011
	(9.458)	(-0.066)	(1.541)
trf	-0.001***	-0.000**	-0.000***
	(-9.460)	(-2.097)	(-4.421)
_cons	-0.234***	0.188***	0.097

Table 6: Robustness Checks (Cont…)

Variable	(1)	(2)	(3)
	eff	**eff**	**eff**
	(-6.307)	(2.885)	(1.378)

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N	372	360	279
R^2	/	0.886	0.864

T-Statistics in Parentheses: *p < 0.1 , ** p < 0.05, *** p < 0.01

Note: Specifications as labelled. Province and year fixed effects were included where applicable. Entries are coefficients, along with their standard errors, clustered by province.

Endogeneity (IV-2SLS) Results

To address potential simultaneity, DFI is instrumented using its lagged value. The first-stage regression demonstrates strong relevance (lagged DFI coefficient = 0.838; t = 40.510). In the second stage, the coefficient on DFI is 0.035 and significant at the 1% level, slightly larger than the FE estimate but consistent in direction (Table 7).

Table 7: Endogeneity Test: IV-2SLS using Lagged DFI

Variable	First Step	Second Step
	DFI	**eff**
DFI		0.035***
		(17.655)
L.DFI	0.838***	
	(40.510)	
Ifa	-0.153***	-0.005
	(-3.340)	(-1.460)
Gov	1.162**	0.127***
	(2.020)	(2.817)
Open	0.345***	0.036***
	(3.550)	(4.567)
Structure	0.022	-0.005*
	(0.570)	(-1.764)
Lnpgdp	0.367***	-0.013**
	(4.950)	(-2.048)
trf	0.000	-0.000***
	(-0.350)	(-6.382)
N	341	341
R^2	0.986	0.898

T-Statistics in Parentheses: *p < 0.1 , ** p < 0.05, *** p < 0.01

Note: Province and year fixed effects included. The first stage reports instrument relevance; the second stage reports the effect on efficiency. Entries are coefficients, along with their standard errors, clustered by province.

Mediation Analysis

Digital finance mitigates financing constraints, which in turn enhances RIE. Stepwise regressions indicate a partial mediating effect. DFI also fosters human capital accumulation, further improving RIE, supporting the pathway "DFI → human capital → RIE." Two channels are examined using stepwise mediation adapted for panel data. For financing constraints, DFI significantly reduces the constraint proxy, the mediator

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is positively associated with RIE, and the direct effect of DFI remains positive, providing evidence of partial mediation (Table 8). For human capital, DFI positively influences the human capital proxy, which is in turn positively related to RIE, while the direct DFI effect persists, again indicating partial mediation (Table 9). Indirect effects and delta-method standard errors are reported in table notes or the appendix.

Table 8: Mediation Via Financing Constraints

Variable	First Step	Second Step	Third Step
	eff	fin	eff
DFI	0.028***	0.818***	0.022***
	(16.156)	(18.016)	(9.143)
fin			0.008***
			(3.668)
ifa	-0.015***	0.548***	-0.019***
	(-3.889)	(5.473)	(-4.846)
gov	0.066	-2.210*	0.083*
	(1.375)	(-1.765)	(1.746)
open	0.044***	0.108	0.044***
	(5.845)	(0.546)	(5.841)
structure	-0.000	-0.045	-0.000
	(-0.149)	(-0.546)	(-0.042)
lnpgdp	-0.000	-2.321***	0.017**
	(-0.027)	(-14.108)	(2.220)
trf	-0.000***	0.009***	-0.000***
	(-6.172)	(4.713)	(-7.003)
constant	0.184***	26.265***	-0.015
	(2.860)	(15.720)	(-0.184)
N	372	372	372
R^2	0.885	0.748	0.889

T-Statistics in Parentheses: *p < 0.1 , ** p < 0.05, *** p < 0.01
Note: Province and year fixed effects included. Step (1) regresses mediator on DFI and controls; step (2) regresses efficiency on mediator and DFI. Entries are coefficients, along with their standard errors, clustered by province.

Mediating Effect of Regional Credit Constraints

The next step involves testing the mediating effect. The role of regional financing constraints is examined first. In the initial step, the coefficient of the DFI index is 0.028 and significant at the 1% level. In the second step, the coefficient of the DFI index is 0.818, also significant at the 1% level. In the third step, the coefficient of the financing constraint (fin) variable is 0.008, again significant at the 1% level. These findings confirm that the mediation mechanism is valid, indicating that DFI alleviates financing constraints and thereby enhances RIE (Zhao et al., 2021).

Mediating Effect of Human Capital Accumulation

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The mediating role of human capital accumulation is examined next. In the first step, the coefficient of the DFI index is 0.028 and significant at the 1% level. In the second step, the coefficient of the DFI index is 17.808, also significant at the 1% level. In the third step, the coefficient of the human capital (hc) variable is significant at the 1% level, confirming the mediation mechanism. These results indicate that DFI enhances human capital accumulation, which in turn improves RIE (Lu, 2023).

Note: Province and year fixed effects included. Step (1) regresses mediator on DFI and controls; step (2) regresses efficiency on mediator and DFI. Entries are coefficients, along with their standard errors, clustered by province.

Table 9: Mediation via Human Capital

Variable	First Step	Second Step	Third Step
	eff	hc	eff
DFI	0.028***	17.808***	0.025***
	(16.156)	(6.931)	(13.814)
hc			0.000***
			(5.410)
ifa	-0.015***	-13.249**	-0.012***
	(-3.889)	(-2.339)	(-3.331)
gov	0.066	66.385	0.053
	(1.375)	(0.937)	(1.153)
open	0.044***	131.170***	0.019**
	(5.845)	(11.723)	(2.203)
structure	-0.000	9.394**	-0.002
	(-0.149)	(1.997)	(-0.742)
lnpgdp	-0.000	35.164***	-0.007
	(-0.027)	(3.776)	(-1.123)
trf	-0.000***	-0.243**	-0.000***
	(-6.172)	(-2.368)	(-5.679)
constant	0.184***	-256.550***	0.233***
	(2.860)	(-2.712)	(3.741)
N	372	372	372
R^2	0.885	0.769	0.894

T-Statistics in Parentheses: $*p < 0.1$, $** p < 0.05$, $*** p < 0.01$

Regional Heterogeneity

Table 10 presents result by macro-region. The association between DFI and RIE is strongest in the eastern provinces (0.038, significant at the 1% level) and remains positive but smaller in the central (0.012) and western (0.014) regions. This pattern aligns with the presence of more developed complementary assets—financial infrastructure, human capital, and institutions—in the East, with thinner baselines in other regions (Table 9).

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Table 10: Sub-Regional Regression Results

Variable	East	Central	West
	eff	eff	eff
DFI	0.038***	0.012***	0.014***
	(13.801)	(5.034)	(5.117)
ifa	-0.009	-0.005	-0.022***
	(-0.890)	(-1.121)	(-5.203)
gov	0.037	-0.010	0.074
	(0.403)	(-0.208)	(1.016)
open	0.018	0.183***	0.061***
	(1.276)	(6.262)	(2.984)
structure	-0.020***	0.018***	0.014***
	(-3.284)	(4.625)	(2.787)
lnpgdp	-0.035**	0.033***	0.035***
	(-2.582)	(4.229)	(4.007)
trf	0.000	0.002***	-0.000***
	(0.468)	(6.105)	(-4.429)
constant	0.797***	-0.351***	-0.313***
	(5.626)	(-4.539)	(-3.521)
N	132	96	144
R^2	0.874	0.976	0.904

T-Statistics in Parentheses: *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Note*:* Province and year fixed effects included. Entries are coefficients—standard errors clustered by province within each sub-sample.

Spatial Moderation

Finally, Table 11 assesses whether neighbouring DFI conditions the local effect. For the full sample, the interaction term DFI × DFI_N is positive and significant ($p = 0.008$, 1% level), indicating **complementary** cross-border digital ecosystems.

By region, the interaction is **negative** in the East (due to competition for resources) and **positive** in the central/West (where spillovers dominate), aligning with the heterogeneity noted above (Table 11).

Overall, DFI significantly enhances RIE (Feng et al., 2022; Li et al., 2023). This effect operates both by alleviating financing constraints and by promoting human capital accumulation (Lin & Ma, 2022; Song et al., 2023). Regional heterogeneity and spatial interactions further suggest that eastern provinces may experience competitive resource diversion, whereas central and western regions benefit from larger positive spillovers.

Table 11: Spatial Moderation: Interaction Between Local and Neighbouring DFI

Variable	Full-Sample	Eastern Region	Central Region	Western Region
	eff	eff	eff	eff

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DFI	-0.015	0.025	-0.084***	-0.092***
	(-1.091)	(0.752)	(-8.062)	(-5.020)
DFI_N	0.005	0.024	-0.034	-0.157***
	(0.262)	(0.508)	(-1.516)	(-4.864)
DFI×DFI_N	0.008***	-0.013**	0.029***	0.051***
	(3.515)	(-1.991)	(10.188)	(10.595)
ifa	-0.002	0.005	0.002	-0.019***
	(-0.450)	(0.465)	(0.939)	(-4.711)
gov	0.073	0.136	0.037	0.090*
	(1.490)	(1.309)	(0.954)	(1.748)
open	0.036***	-0.010	0.021	-0.028*
	(4.190)	(-0.680)	(1.134)	(-1.723)
structure	-0.012***	-0.023***	-0.003	0.012***
	(-3.979)	(-3.582)	(-1.448)	(3.129)
lnpgdp	-0.010	-0.031**	-0.002	0.012*
	(-1.640)	(-1.987)	(-0.414)	(1.830)
trf	-0.000***	-0.000	0.001***	-0.000***
	(-5.696)	(-0.319)	(4.120)	(-5.249)
_cons	0.311***	0.773***	0.113*	0.010
	(5.162)	(4.644)	(1.972)	(0.147)
N	372	132	96	144
R^2	0.917	0.921	0.996	0.967

T-Statistics in Parentheses: *p < 0.1 , ** p < 0.05, *** p < 0.01
Note: Province and year fixed effects included. DFI_N is the adjacency-weighted average of the DFI values of neighbouring provinces. Entries are coefficients, along with their standard errors, clustered by province.

Discussion

Overall, the evidence demonstrates that DFI contributes positively to RIE, with effects transmitted through both easing of financing constraints and enhancement of human capital (Tables 8 and 9). The baseline impact, estimated between 2.5 and 3.5 percentage points, is economically significant across provinces at the innovation frontier and those in the catch-up phase (Tables 3 and 6). Spatial patterns reveal that dense local–neighbour ecosystems in the East can attenuate local benefits due to competitive pressures, whereas in central and western regions, complementarities amplify the efficiency gains (Tables 10–11). These findings highlight the importance of regionally coordinated policies that align digital financial expansion with strategies for talent development.

CONCLUSION

Using provincial data spanning 2011–2022, the analysis finds that greater DFI is associated with higher RIE. The estimated effect, around 2.5–3.5 percentage points, is moderate but economically meaningful and remains robust to additional controls and IV specifications employing lagged DFI. The relationship operates both directly and

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indirectly: mediation tests reveal that DFI alleviates financing frictions—particularly in contexts with collateral and information gaps—and enhances human capital through mechanisms such as education finance and re-skilling, thereby improving the stock and allocation of talent. Geographical context is important. Subsample and interaction analyses indicate larger gains where complementary assets, including finance, institutions, and human capital, are more developed. In central and western provinces, neighbouring ecosystems amplify local effects, whereas in the eastern region, competition for resources can reduce local payoffs. These findings clarify previous mixed results and suggest that achieving "more innovation per unit of R&D" is feasible when inclusive digital finance is coupled with favourable local conditions. Policy implications include avoiding zero-sum competition in mature eastern markets, investing in digital infrastructure and data systems in central and western provinces to convert spillovers into local benefits, targeting inclusive financial products to innovative SMEs under risk-based supervision, and promoting interprovincial coordination in data sharing, interoperability, and consumer protection. Limitations persist. Provincial-level aggregates conceal within-province heterogeneity; IV estimation cannot eliminate all endogeneity; and the current mechanisms focus solely on financing constraints and human capital, leaving institutional quality, knowledge diffusion, and innovation quality for future investigation. Employing richer city- or firm-level data, exploiting policy shocks, and extending spatial analyses would strengthen identification and broaden the scope of these findings.

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