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Exploring the Impact of Digital Finance on Regional Innovation Efficiency: Evidence from China

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ABSTRACT

Digital finance, as an innovative financial approach, has drawn increasing attention due to its potential to shape regional innovation. This study delves into how digital finance interacts with regional innovation efficiency, beginning with an exploration of the underlying mechanisms. Using data from 31 provinces in China spanning the years 2011 to 2023, and applying a dynamic spatial Durbin model, we examine the spatial spillover effects of digital finance. The analysis uncovers a strong spatial interdependence and temporal persistence in regional innovation efficiency throughout the observed period. The results suggest that digital finance significantly enhances innovation efficiency at the regional level, with pronounced spatial spillover effects. The breakdown of spatial effects indicates that the indirect spillover impact of digital finance surpasses its direct influence. Furthermore, each dimension of digital finance shows spatial spillover, and the disparity between eastern and central-western regions is primarily evident in the spatial spillover patterns of digital finance.

KEYWORDS

Digital Finance; Regional Innovation Efficiency; Spatial Spillover Effects.

1. INTRODUCTION

Innovation plays a fundamental role in driving economic progress. Recognizing the critical need to shift its economic model from being driven by factors and investments toward innovation, the Chinese government has prioritized enhancing innovation efficiency as a key strategy to upgrade industrial structures and achieve high-quality economic development[1][2]. As the Chinese economy transitions from a phase of rapid growth to one focused on sustainable and high-quality development, it faces challenges such as increasing labor costs, rising energy prices, tighter resource constraints, and diminishing returns on capital investments. This shift signals that traditional growth drivers-investment, resources, and trade-are no longer sufficient for continued economic expansion. Consequently, new growth drivers are urgently needed. Technological innovation, as a core engine of economic development, plays a critical role in enhancing local productivity and promoting sustainable growth. In 2017, the Chinese government emphasized innovation as the foremost driver of economic progress and a cornerstone in the construction of a modern economic system, marking the full implementation of an innovation-driven growth strategy. By the close of 2019, China had invested around 2 trillion RMB in R&D, representing a 150% increase compared to 2011[3][4]. This rapid growth positioned China second globally in R&D spending, with investment intensity in R&D rising to 2.23% from 1.84% in 2011. Additionally, China had over 4.8 million full-time R&D personnel, ranking first globally for seven consecutive years. According to the World Intellectual Property Organization's 2020 Global Innovation Index, China ranked 6th globally in innovation output and 26th in innovation input, reflecting its innovation efficiency, and secured the 14th spot in

the overall innovation ranking. However, China still faces challenges, such as a less than 10% conversion rate for R&D outcomes, significantly lower than the 40% achieved by developed nations. Issues like poor integration between the innovation and industrial chains and inadequate financial support for technological innovation persist in various regions, raising questions about how to effectively enhance the nation's innovation capacity.

Efficient and cost-effective financial services are essential to support innovation activities, especially during critical stages like R&D[5], technological transformation, and the commercialization of new technologies. Schumpeter, in 1921, was among the first to recognize the vital role of financial development in fostering technological innovation. In today's world, the finance sector has merged with IT enterprises, creating a new financial model-digital finance-driven by the rise of technologies such as big data, cloud computing, artificial intelligence, and 5G[6]. Digital finance has brought new momentum to innovation activities in China. The rapid expansion of digital financial services, as evidenced by the Digital Inclusive Finance Index, highlights this growth: from 2011 to 2020, the index surged from an average of 40 to 340 across provinces, reflecting an average annual growth rate of nearly 30%. With its digital nature, digital finance expands the breadth and depth of financial services, addressing gaps left by traditional financial systems. It offers accessible financial services to market participants often overlooked by traditional finance, who nonetheless possess innovative potential. The integration of emerging technologies into financial services has improved both service efficiency and the allocation of financial resources. Moreover, digital finance influences the consumption patterns of regional populations, which in turn affects regional innovation efficiency. Consequently, key questions arise: How does the growth of digital finance in China impact regional innovation efficiency, and what is the underlying mechanism? Given that innovation activities across regions are interconnected due to the movement of resources, does digital finance's influence exhibit spatial spillover effects? Addressing these questions is of both theoretical and practical importance for evaluating the role of digital finance in regional innovation efficiency, shaping policies to promote its growth, and enhancing innovation efficiency across regions.

This paper aims to make several contributions. First, it incorporates digital finance and regional innovation efficiency into a unified analytical framework, systematically examining the mechanisms by which digital finance influences innovation efficiency. This approach adds depth to existing research on both digital finance and innovation efficiency. Second, recognizing the spatial correlation of regional innovation efficiency, the paper adopts a spatial perspective to investigate the impact of digital finance, constructing a spatial correlation matrix based on two key innovation factors. The direct and total effects of digital finance on innovation efficiency are analyzed to uncover spatial heterogeneity, offering a novel perspective for future research. Lastly, the paper explores the heterogeneous effects of digital finance on regional innovation efficiency, providing valuable insights for the formulation and implementation of differentiated, region-specific policies.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature on financial development, digital finance, and innovation. Section 3 outlines the mechanisms through which digital finance influences regional innovation efficiency and presents the research hypotheses. Section 4 describes the research methodology, including data collection, variable selection, and analysis methods. Section 5 presents and interprets the empirical results, analyzing the underlying causes. Finally, Section 6 offers conclusions and policy recommendations.

2. RELATED WROK

Digital finance represents a paradigm shift in the financial industry, encompassing various electronic financial products and services. [7][8][9] highlights that while digital finance preserves the core principles of traditional finance, it introduces key advantages: improved payment systems, enhanced information matching, and expanded data utilization. By leveraging online banking, mobile applications, and digital payment platforms, digital finance has transformed modern financial

practices, mitigating financial exclusion, reducing service costs, and addressing issues of information asymmetry [10][11].

The fundamental nature of finance remains unchanged despite these advancements. Brown et al. and Matei point out that a crucial role of finance in economic development is its support for research and development (R&D)[12][13][14][15]. However, there is considerable debate about how financial development influences innovation efficiency. Some studies suggest a strong positive impact of financial development on innovation efficiency. For example, Ayyagari et al. and Huang observed that firms with higher levels of banking finance tend to be more innovative [16][17]. [18] found a close relationship between stock market development and innovation in high-tech industries. Hall et al. emphasized that financial development facilitates technological innovation by providing crucial funding, optimizing resource allocation, evaluating and overseeing innovation projects, and addressing challenges like moral hazards and adverse selection, ultimately reducing innovation costs and fostering progress [19][20][21]. [22] discovered that financial technology can indirectly boost technological innovation in regional economies, based on data from major Chinese cities. Chowdhury and [23] found that financial market development enhances the efficiency of innovation investments, though information asymmetry can lead to inefficient resource allocation. Dirk and Liu highlighted that financial mismatches and constraints limit investment in advanced R&D and reduce local productivity [24][25][26]. Song and Wu estimated that financial mismatches in China since 2000 led to at least a 20% loss in total factor productivity. Additionally, traditional financial institutions' risk aversion can impede innovative projects [27][28]. [29] observed that increased financialization affects R&D innovation differently, with state-owned enterprises experiencing generally negative effects that lessen with higher financialization levels.

These varied findings suggest that the relationship between finance and innovation efficiency is complex and context-dependent. Thus, exploring how digital finance specifically affects regional innovation efficiency can contribute valuable insights, particularly since current research primarily addresses the impact of digital finance on innovation output and activity.

Traditional financial markets often involve numerous small and dispersed investors [30]. In contrast, digital finance, supported by technologies such as artificial intelligence and other "ABCDI" innovations, extends the range, depth, and accessibility of financial services [32]. Digital finance helps mobilize idle capital at lower costs and risks, addresses financing constraints for innovation agents, and supports their innovative activities [31]. Adequate financial support is essential for promoting technological innovation. [33] indicates that digital finance has broadened financial service options and enhanced business access to funding. Research into digital finance's features reveals that it extends its service base through technological advancements, streamlined approval processes, reduced information asymmetry, and improved credit evaluation systems, all of which ease regional financing constraints and boost technological innovation [34]. Zhai et al. [35] argue that rising demand for digital services compels financial institutions to offer advanced solutions, fostering a favorable environment for regional innovation. Additionally, some studies suggest that fluctuations in financial cycles, driven by digital finance, positively impact innovation activities [36]. Digital finance stimulates regional trade and local enterprise innovation, with its digital characteristics enhancing corporate transparency and social responsibility, thereby improving productivity and innovation [37]. Furthermore, digital finance and local infrastructure investments can advance green technology innovation [38].

In summary, while current literature underscores the significant influence of digital finance on innovation, several important aspects remain underexplored. Existing research predominantly focuses on the effects of digital finance on regional innovation levels rather than on efficiency, leaving a gap in understanding how digital finance impacts the efficiency of innovation processes. Furthermore, few studies have examined the spatial spillover effects of digital finance on regional innovation efficiency, which is crucial given the interconnected nature of innovation activities across regions.

This study aims to fill these gaps by providing a detailed analysis of how digital finance affects regional innovation efficiency from 2011 to 2023. By employing a dynamic spatial Durbin model, this research not only investigates the direct effects of digital finance on innovation efficiency but also explores its spatial spillover effects across 31 Chinese provinces. This extended timeframe allows for a comprehensive examination of the evolving role of digital finance in fostering regional innovation and captures the recent developments and trends in the digital financial sector.

3. METHOD DESIGN

3.1. Econometric Model

3.1.1. Econometric Model Analysis

Before performing spatial econometric regression, it is essential to test for spatial correlation among the data. In this paper, we use the global Moran's I index to assess spatial correlation. The global Moran's I index measures the degree of spatial autocorrelation, which indicates whether similar values are clustered together in space or if they are dispersed.

The global Moran's I index is calculated using the following formula:

$$MoranI = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(x_j - \bar{x})} \quad (1)$$

where:

- w_{ij} is the number of spatial units (e.g., regions or provinces),
- x_i and x_j are the values of the variable of interest for spatial units iii and jjj,
- $\bar{x}$ is the mean value of the variable across all spatial units,

The Moran's I index ranges from -1 to +1:

- A positive $MoranI$ value indicates a clustering of similar values (positive spatial autocorrelation),
- A negative $MoranI$ value indicates a dispersion of similar values (negative spatial autocorrelation),
- A value close to zero suggests a random spatial pattern (no spatial autocorrelation).

By applying the global $MoranI$, we can determine the presence and strength of spatial correlation in the data, which is crucial for subsequent spatial econometric analysis.

In spatial econometric analysis, two key models are employed to account for spatial effects:

1) Spatial Autoregressive Model (SAR): This model examines how the values of explanatory variables in neighboring regions impact the values in the current region. It captures the influence of spatially lagged dependent variables.
2) Spatial Error Model (SEM): This model addresses spatial effects arising from spatially correlated error terms. It accounts for random shocks that are spatially correlated across regions.

In practice, both types of spatial effects—spatial lag and spatial error—are often present. Ignoring one can lead to biased results. To address this, the Spatial Durbin Model (SDM) combines both spatial lag and spatial error effects into a single framework. The SDM incorporates spatial interaction effects

of both the dependent variable and the explanatory variables, allowing for a comprehensive analysis of spatial dependencies.

To account for potential time-dependent effects on regional innovation efficiency, the study further incorporates a dynamic element. The Dynamic Spatial Durbin Model (DSDM) extends the SDM by including lagged values of the explanatory variables. This addition helps to examine how previous periods' innovation efficiency influences current regional innovation efficiency. This approach provides a more nuanced analysis of how digital finance affects regional innovation efficiency, considering both spatial interactions and temporal dynamics. The model can be expressed as follows:

$$ef_{it} = \propto_0 + \rho \sum_{j=1}^{n} w_{ij} + ef_{it} + \propto_1 ef_{it-1} + \propto_2 ef_{it} + \propto_3 w_{ij} ef_{it} + \propto_4 Z_{it} + \propto_5 w_{ij} ef_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (2)$$

In the Eq.(2) used in this study, the following notation and components are defined:

- i and t denote the region and time period, respectively.
- ef_{it} represents the regional innovation efficiency for region iii at time ttt.
- ef_{it-1} is the lagged one-period term of regional innovation efficiency, reflecting past values of innovation efficiency.
- Z_{it} includes control variables that might influence regional innovation efficiency.
- $\propto$ represents the parameters to be estimated.
- w_{ij} is the spatial weight matrix, capturing the spatial interactions between regions.
- ρ denotes the coefficient of the spatially lagged term of regional innovation efficiency.
- θ_t represent the individual fixed effects for each region and the time fixed effects, respectively.
- ε_{it} is the random disturbance term.

To address issues of heteroskedasticity and multicollinearity, some variables are transformed by taking their natural logarithms in this analysis. This approach helps to stabilize the variance of the residuals and improve the model's robustness. This model specification allows for a detailed examination of how digital finance impacts regional innovation efficiency while accounting for both spatial and temporal dynamics.

In spatial econometric models, estimating the impact of explanatory variables on the dependent variable is complex due to the presence of spatial lag terms. Simply looking at the coefficients does not fully capture the nuances of these effects. The partial differential decomposition method proposed by [41] addresses this issue by breaking down the total effect into three components: the direct effect, the indirect (spatial spillover) effect, and the total effect. The direct effect measures the impact of a local explanatory variable on the dependent variable within the same region, showing how changes within a specific area affect its own outcome. The indirect effect, or spatial spillover effect, assesses how changes in explanatory variables in neighboring regions influence the outcome in the local area. Finally, the total effect represents the combined influence of an explanatory variable on the dependent variable across all regions, incorporating both local and spatial interactions. This method allows for a more accurate understanding of how explanatory variables affect the dependent variable, considering both direct and indirect influences.

In spatial econometric analysis, several types of spatial weight matrices are commonly used to model spatial relationships: the geographic adjacency matrix, the geographic distance matrix, and the economic distance matrix. These matrices capture different forms of spatial interactions among regions. For analyzing regional innovation efficiency, considering the flow of innovation factors—such as R&D funding and personnel—is crucial. These factors are key drivers of innovation and create deep-level connections among regional innovation systems. By examining the spatial correlation of regional innovation efficiency through the lens of innovation factor flow, we can more accurately reflect the interdependencies between regions. To model these relationships, a simplified gravity model is used to construct the R&D funding matrix and R&D personnel matrix. This approach allows us to account for the influence of innovation factor flows on regional innovation efficiency. The R&D funding matrix [42], for instance, is computed based on the flow of R&D investments between regions, providing insight into how these financial resources impact innovation efficiency across different areas. The R&D matrix can be expressed as follows:

$$W = \begin{cases} \dfrac{KP_iP_j}{D_{ij}}, i \neq j \\ 0, i = j \end{cases} \tag{3}$$

In Equation (4), the R&D funding matrix, is constructed using a simplified gravity model. Here's how the components are defined:

- W represents the R&D funding matrix.
- K is a constant term, set to 1 for simplification.
- i and j denote two distinct regions.
- P_i and P_j are the R&D funding stocks of regions iii and jjj, respectively. These funding stocks are estimated using the perpetual inventory method.
- D_{ij} is the distance between the geographical centers of regions iii and jjj.

The same formula is applied to construct the R&D personnel matrix, with R&D personnel stocks replacing R&D funding stocks in the equation. This approach allows for the analysis of spatial interactions and dependencies related to innovation resources across different regions.

3.1.2. Variables

Regional innovation efficiency (eff) in this study is measured using the stochastic frontier approach (SFA), which is based on the input-output framework. The inputs for regional innovation activities consist of both labor and capital. For labor input, the full-time equivalent of R&D personnel is used, as it provides a more accurate reflection of the actual labor input compared to the mere number of R&D personnel. For capital input, rather than using current internal R&D expenditure, which may influence future output, the stock of R&D expenditure is employed to account for the long-term effect of capital input in regional innovation activities. On the output side, the number of patent applications granted serves as the indicator to capture innovation output. To measure regional innovation efficiency, two types of production functions are employed: the beyond logarithmic function and the Cobb-Douglas function. The generalized likelihood ratio (LR) test is used to determine which production function fits better. The results demonstrate that the LR statistic exceeds the critical value of the mixed chi-square distribution at the 5% significance level, suggesting that the transcendental logarithmic function is more appropriate for measuring regional innovation efficiency. The analysis is performed using Frontier 4.1 software.

Digital finance (ifi) is measured using the Peking University Digital Inclusive Finance Index, a widely used tool among scholars to analyze the economic impact of digital finance. This index is composed of 33 indicators and is divided into three main dimensions: coverage breadth (ifi1), coverage depth (ifi2), and digitization degree (ifi3). The index is constructed by applying a dimensionless processing method to the indicators, followed by a layer-by-layer weighted average synthesis. The weights for the indicator and criterion layers are determined using the coefficient of variation method and hierarchical analysis, respectively. This process allows for a comprehensive evaluation of the development of digital inclusive finance across different provinces. For this study, the natural logarithm of the index is used to represent the level of digital financial development in each region. Additionally, the three dimensions of the index (ifi1, ifi2, and ifi3) are included to explore how the structural characteristics of digital finance influence regional innovation efficiency.

3.1.3. Source Data

This study utilizes panel data from 31 provinces (including cities and districts) in China over the period from 2011 to 2023, excluding Hong Kong, Macao, and Taiwan due to data unavailability. The data on digital finance is derived from the Peking University Digital Inclusive Finance Index, while additional relevant data is sourced from the China Statistical Yearbook, China Science and Technology Statistical Yearbook, and the official website of the National Bureau of Statistics. Descriptive statistical analysis is presented in Table 1, summarizing the key characteristics of the variables used in the study.

Table 1. Descriptive statistical analysis.

Variable	Symbol	Sample database	Average value	Standard deviation	Median	Maximum value	Minimum value
Innovation efficiency	eff	310	310	0.424	0.180	0.404	0.927
Digital finance	ifi	310	310	5.212	0.677	5.410	6.068
Coverage breadth	ifi1	310	310	5.060	0.844	5.284	5.984
Coverage depth	ifi2	310	310	5.195	0.651	5.313	6.192
Digitization degree	ifi3	310	310	5.510	0.698	5.778	6.136
Government intervention	gov	310	310	0.286	0.212	0.230	1.379
Openness	open	310	310	0.255	0.289	0.134	1.548
Industrial structure	inst	310	310	0.344	0.101	0.360	0.530
Human capital	hum	310	310	2.200	0.138	2.211	2.552

3.2. Results and Analysis

3.2.1. Spatial Correlation Analysis

The R&D funding matrix and R&D personnel matrix were analyzed using Stata 15 software to perform spatial correlation tests. Table 2 presents the Moran's I index for regional innovation efficiency and digital finance in China from 2011 to 2020 under the two spatial matrices. The results in Table 2 indicate that the Moran's I index is significantly positive for both spatial weight matrices.

This suggests, on one hand, the appropriateness of employing spatial econometric models, and on the other hand, it demonstrates the presence of significant positive spatial correlations and clustering patterns in both regional innovation efficiency and digital finance across China.

Table 2. $MoranI$ index.

Year	R&D funding matrix		R&D personnel matrix	
	Innovation efficiency	Digital finance	Innovation efficiency	Digital finance
2014	0.365	0.627	0.496	0.492
2015	0.367	0.621	0.495	0.482
2016	0.369	0.635	0.494	0.491
2017	0.37	0.594	0.493	0.449
2018	0.371	0.513	0.491	0.373
2019	0.371	0.573	0.488	0.431
2020	0.370	0.598	0.486	0.482
2021	0.370	0.624	0.483	0.515
2022	0.368	0.579	0.476	0.464
2023	0.365	0.569	0.470	0.458

3.2.2. The Baseline Estimation Results

The analysis began with regressions using three different models under the non-spatial panel framework: the random effects model, the individual fixed effects model, and the two-way fixed effects model. The results of these regressions are reported in Columns (1)–(3) of Table 3. Among these models, it was observed that the two-way fixed effects model provided a better fit, as indicated by a higher R2R^2R2, suggesting that controlling for both individual and time fixed effects improves model accuracy.

Given these findings, the study proceeded with the dynamic spatial Durbin model, incorporating two-way fixed effects to capture spatial interactions across regions. To determine whether the model could be simplified into a spatial error model or a spatial lag model, LR and Wald tests were conducted. The results from Columns (4) and (5) of Table 3 reveal that both tests confirmed the suitability of the dynamic spatial Durbin model for this research.

Several key findings emerged from Table 3:

1) **Spatial Autocorrelation**: The spatial autocorrelation coefficient ρ\rhoρ is significantly positive for both innovation factors in the spatial correlation matrix, indicating that regional innovation efficiency exhibits significant spatial dependence. This suggests that an increase in the innovation efficiency of neighboring regions positively impacts the local region. The “neighborhood” effect arises from the mobility of R&D funding and personnel, leading to knowledge spillovers and optimized allocation of innovation resources, which in turn boosts local innovation efficiency.
2) **Path Dependence**: The coefficients for the lagged terms of regional innovation efficiency are significantly positive, highlighting a strong temporal path dependence. This means that regions with higher innovation efficiency in the past are more likely to sustain or even enhance their innovation performance in subsequent periods, creating a "snowball" effect over time.
3) **Digital Finance's Impact**: After accounting for spatial interactions, the estimated coefficients for digital finance remain significantly positive, though smaller than those in the non-spatial model. This suggests that non-spatial models may overestimate the impact of digital finance by ignoring

spatial factors, leading to biased results. The reduction in coefficient size implies that spatial dependencies and spillover effects play a crucial role in shaping the true impact of digital finance on innovation efficiency.

To further interpret the direct and spatial spillover effects, the partial differential method was employed to decompose the total effects for each variable. These decomposed effects, shown in Columns (4) and (5) of Table 3, provide a clearer understanding of how digital finance and other factors contribute both locally and across regions, emphasizing the importance of spatial interconnections in innovation outcomes.

Table 3. Baseline Results

Variable	Non-spatial panel RE (1)	Non-spatial panel FE (2)	Non-spatial panel FE (3)	R&D funding matrix SDM (4)	R&D personnel matrix SDM (5)
L.eff				1.051(111.52)	1.006(105.51)
ifi	0.053	0.049	0.024	0.015	0.018
	(11.78)	(12.04)	(3.09)	(5.39)	(6.39)
gov	-0.030	0.039	0.083	0.025	0.027
	(-0.42)	(0.49)	(2.13)	(4.39)	(4.78)
open	-0.108	-0.114	-0.005	0.002	0.004
	(-5.17)	(-5.74)	(-0.41)	(1.21)	(2.11)
inst	-0.715	-0.720	-0.000	0.011	0.014
	(-12.52)	(-13.85)	(-0.00)	(2.06)	(2.74)
hum	0.410	0.474	0.082	0.005	0.009
	(5.71)	(6.62)	(2.24)	(0.88)	(1.72)
Wifi				0.189(6.77)	0.173 (6.33)
Wgov				0.892 (13.19)	0.920(14.19)
Wopen				0.090(10.82)	0.091 (10.16)
Winst				1.181(16.89)	1.213 (17.33)
Whum				0.357(3.97) 0.362	0.487 (5.16) 0.173
ρ				(5.87)	(6.33)
LRSAR				8.13	9.90
LRSEM				84.32	100.64
WaldSAR				384.85	412.29
WaldSEM				383.28	411.88
City effect	NO	YES	YES	YES	YES
Year effect	NO	NO	NO	YES	YES
R2	0.900	0.901	0.979	0.962	0.962
N	310	310	310	279	279

3.2.3. Analysis of Direct and Indirect Effects: Results and Discussion

This section presents the direct, indirect, and total effects of the estimated results based on two spatial weight matrices. Firstly, regarding the direct effects, the development of digital finance has a significant positive impact on regional innovation efficiency for both matrices. This indicates that local digital finance significantly contributes to enhancing innovation efficiency within the region, which supports Hypothesis 1. These findings align with the research of [44]. In China, digital finance not only optimizes capital allocation and stimulates enterprise enthusiasm for R&D and innovation, but it also addresses gaps in the traditional financial market, particularly supporting small, medium, and micro-enterprises' innovation activities [45]. Additionally, recent governmental and industrial regulatory measures, such as the "Interim Measures on the Management of Business Activities of Online Lending Information Intermediaries" (CBRC, 2016) and the "FinTech Development Plan (2019–2021)" (Central Bank, 2019), have provided a solid foundation for digital finance to promote regional innovation efficiency . Secondly, concerning the indirect effects, the spatial spillover of digital finance development in neighboring regions also plays a significant positive role in local regional innovation efficiency, confirming Hypothesis 2. Interestingly, the spatial spillover effects of digital finance on regional innovation efficiency exceed the direct effects in both the R&D funding and personnel matrices. This suggests that digital finance, driven by technological advancements, has diminished geographic and spatial barriers, allowing for cross-regional financial services as a core feature of its business model [46]. Moreover, the saturation of local financial markets has encouraged enterprises and digital finance providers to expand beyond their regions. The internet has facilitated this expansion by enhancing interactions between local firms and digital finance, which in turn boosts regional innovation efficiency [47]. Lastly, the total effect of digital finance remains significantly positive, highlighting its overall positive influence on regional innovation efficiency, especially when considering spatial spillover effects. As for the control variables, both the direct and indirect effects of government intervention positively influence regional innovation efficiency, underscoring the role of government in addressing market imperfections, mitigating innovation risks, and unlocking innovation potential. Additionally, openness contributes to innovation efficiency, reflecting the ability to adopt advanced technologies and foster independent innovation in international economic activities. The industrial structure also promotes regional innovation efficiency, indicating the growing demand for technological innovation during structural adjustments. Furthermore, human capital has a positive indirect effect in all models, while the direct effect is significantly positive in the R&D personnel matrix but less pronounced in the R&D funding matrix, suggesting that human capital accumulation enhances knowledge levels and effectively promotes regional innovation efficiency.

Table 4. Decomposition results.

Variable	R&D funding matrix			R&D personnel matrix		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
ifi	0.0196	0.3049	0.3245	0.0204	0.2401	0.2606
	(6.59)	(6.04)	(6.29)	(7.15)	(6.06)	(6.46)
gov	0.0481	1.4055	1.4536	0.0426	1.2485	1.2911
	(6.46)	(8.68)	(8.71)	(6.48)	(10.09)	(10.14)
open	0.0046	0.1436	0.1482	0.0054	0.1260	0.1314
	(2.42)	(6.35)	(6.33)	(2.95)	(6.95)	(6.98)
inst	0.0408	1.8634	1.9043	0.0343	1.6568	1.6911
	(3.91)	(7.24)	(7.15)	(3.96)	(8.33)	(8.21)
hum	0.0137	0.5566	0.5703	0.0171	0.6549	0.6721
	(2.34)	(4.82)	(4.82)	(2.97)	(6.40)	(6.42)

3.2.4. Results Across Different Scenarios

Table 5. Heterogeneity results results.

Variable	R&D funding matrix			R&D funding matrix		
	ifi1	ifi2	ifi3	ifi1	ifi2	ifi3
L.eff	1.023	1.025	1.074	1.023	1.001	1.128
	(103.69)	(109.76)	(103.04)	(104.80)	(109.00)	(108.93)
ifi	0.006 (3.71) 0.020	0.011 (6.09) 0.014	0.002 (0.87) 0.009	0.005 (3.31) 0.018	0.011 (6.20) 0.015	0.005 (2.36) 0.009
gov	(3.41)	(2.65)	(1.46)	(3.22)	(2.81)	(1.47)
	0.003	0.003	0.009	0.004	0.004	0.011
open	(1.62)	(2.08)	(5.11)	(2.49)	(2.69)	(6.20)
inst	0.005	0.009	0.011	0.006	0.009	0.017
	(0.98)	(1.76)	(2.09)	(1.27)	(1.82)	(3.27)
hum	0.013	0.003	0.018	0.013	0.003	0.016
	(2.47)	(0.63)	(3.44)	(2.55)	(0.51)	(2.93)
Wifi	0.051	0.049	0.133	0.038	0.035	0.173
	(3.20)	(2.80)	(7.84)	(2.37)	(2.04)	(10.15)
Wgov	0.817	0.748	0.775	0.710	0.581	0.657
	(12.15)	(11.65)	(11.75)	(11.20)	(9.91)	(10.61)
Wopen	0.101	0.103	0.151	0.092	0.077	0.166
	(10.77)	(13.87)	(17.30)	(9.11)	(10.03)	(17.94)
Winst	1.126	1.050	1.082	1.006	0.821	1.129
	(15.96)	(15.33)	(15.71)	(14.54)	(11.63)	(16.44)
Whum	0.413 (4.49) 0.373	0.328 (3.70) 0.320	0.396 (4.32) 0.607	0.519 (5.44) 0.261	0.291 (2.92) 0.223	0.595 (6.20) 0.678
ρ	(5.94)	(4.96)	(9.13)	(4.20)	(2.71)	(10.46)
Direct	0.0072	0.0121	0.0106	0.0057	0.0112	0.0203
effect	(4.46)	(6.73)	(2.77)	(3.7)	(6.56)	(3.28)
Indirect	0.0862	0.0766	0.3551	0.0539	0.0485	0.5764
effect	(3.16)	(3.15)	(3.76)	(2.41)	(2.36)	(3.41)
Total effect	0.0934	0.0886	0.3657	0.0596	0.0597	0.5968
	(3.35)	(3.6)	(3.75)	(2.63)	(2.89)	(3.41)
City effect	YES	YES	YES	YES	YES	YES
Year effect	YES	YES	YES	YES	YES	YES

The digital finance index is composed of three distinct dimensions, each capturing different aspects of digital financial services. Coverage breadth (ifi1) reflects the extent of service availability, indicated by the number of electronic accounts. Coverage depth (ifi2) measures both the total and active usage of internet financial services, representing the actual demand. Digitization degree (ifi3)

highlights the benefits of digital technology in terms of cost-effectiveness, accessibility, and reliability. Table 5 illustrates the impact of these dimensions on regional innovation efficiency. The results show that all three dimensions positively influence regional innovation efficiency, highlighting the "structural" contribution of digital finance. Specifically, each dimension-coverage breadth, coverage depth, and digitization degree-shows a positive direct effect on innovation efficiency. Additionally, the indirect effects, through spatial spillovers, are more pronounced than the direct effects. The positive spatial spillovers suggest that digital finance's ability to offer cross-regional services optimizes both supply and demand, enhancing resource allocation and stimulating innovation. While coverage breadth and depth improve regional financial dynamics directly, digitization degree enhances the effectiveness of these services through spatial integration, demonstrating the broader impact of digital finance on fostering regional innovation efficiency.

Table 6. Regional heterogeneity results.

Variable	R&D Funding Matrix		R&D Funding Matrix	
	East	Central and western	East	Central and western
L.eff	1.125***	1.002***	2.259***	1.044***
	(100.34)	(36.24)	(181.96)	(38.00)
ifi	0.009	0.019***	-0.177***	0.021***
	(1.54)	(4.41)	(-28.24)	(4.80)
gov	0.030*	0.016**	-0.428***	0.004
	(1.92)	(2.47)	(-24.69)	(0.56)
open	0.010***	0.022***	0.081***	0.026***
	(3.63)	(4.65)	(27.92)	(5.68)
inst	0.045***	-0.002	0.552***	-0.003
	(4.37)	(-0.24)	(50.54)	(-0.47)
hum	-0.068***	0.004	-0.595***	0.006
	(-4.34)	(0.72)	(-33.97)	(1.11)
W*ifi	0.127***	0.155***	-0.291***	0.252***
	(4.89)	(3.27)	(-11.51)	(5.40)
W*gov	0.165**	0.154**	-2.369***	0.275***
	(2.29)	(2.40)	(-29.80)	(4.26)
W*open	0.028***	0.110**	0.229***	0.202***
	(3.29)	(2.11)	(23.98)	(3.59)
W*inst	0.294***	0.000	1.264***	0.081
	(4.28)	(0.00)	(17.28)	(1.40)
W*hum	0.193**	-0.018	-1.251***	-0.063
	(2.49)	(-0.20)	(-14.96)	(-0.74)
	0.021	0.250	2.700***	1.490***
ρ	(0.41)	(1.11)	(53.02)	(6.68)

The development of digital finance and regional innovation capacity varies significantly across different regions in China, necessitating a regional analysis to assess the impact of digital finance on innovation efficiency. Table 6 presents the decomposition results of the effect of digital finance on regional innovation efficiency for the eastern, central, and western regions. Overall, digital finance positively influences regional innovation efficiency in both the eastern and central-western regions. However, there are notable differences in the magnitude of these effects. Specifically, the direct effect of digital finance on regional innovation efficiency is stronger in the eastern region compared to the central and western regions. This disparity is attributed to the fact that the eastern region invests more in scientific and technological personnel, whereas the central and western regions focus more on research funding. The indirect effects of digital finance also exhibit considerable regional variation. For both the R&D funding matrix and the R&D personnel matrix, the indirect effect of digital finance on innovation efficiency is more pronounced in the eastern region than in the central and western regions. This observation aligns with the findings of Yang and Wang, who suggest that the impact of digital finance on regional innovation efficiency differs by region and by the level of digital economy development. In the eastern region, higher levels of innovation activity, capacity, and technological advancement allow digital finance to more effectively enhance regional innovation efficiency. Conversely, the central and western regions face challenges in innovation capacity and digital finance utilization. Furthermore, the effectiveness of digital finance is closely tied to infrastructure development. The eastern region benefits from superior financial and information infrastructure, which supports the spatial spillover effects of digital finance. In contrast, the central and western regions lag behind in infrastructure development, potentially diminishing the impact of digital finance in these areas.

To thoroughly confirm the robustness of the model and its estimations, we performed several robustness tests, particularly focusing on changing both the explanatory variables and the spatial weight matrix. First, we replaced the output indicator with the number of patent applications received, which is another widely accepted measure of innovation output. We then re-applied the SFA method to recalculate regional innovation efficiency. Additionally, the spatial weight matrix, which initially considered other factors, was replaced with a geographical distance matrix to account for the possibility that proximity between regions might influence the spatial spillover effects. The results presented in Table 7 show that the sign and significance of the core explanatory variables remained consistent, even after these adjustments and endogeneity treatments. This suggests that the model's design is sound, and the estimations are robust, strengthening the reliability and validity of the conclusions drawn from the analysis. By confirming these results across different variables and spatial considerations, we further ensure that the findings are not driven by a particular specification or matrix but reflect a broader, more generalizable relationship.

Table 7. Robustness test results.

Variable	Changing explanatory variable		Changing matrix
	R&D funding matrix	R&D personnel matrix	Geographical distance matrix
L.eff			
ifi	1.146*** (96.13)	1.077*** (90.60)	1.110*** (115.48) 0.010*** (3.30)
Wifi	0.015*** (5.94)	0.014*** (5.61)	0.035*
	0.100*** (3.82)	0.096*** (3.80)	(1.91)
ρ	1.135*** (10.38)	1.163*** (10.58)	0.807*** (10.70)
Control variable City effect	YES YES YES	YES YES YES	YES YES YES
Year effect			

4. CONCLUSION

This study explores the effects of digital finance on regional innovation efficiency across 31 Chinese provinces from 2011 to 2020, utilizing the Stochastic Frontier Approach (SFA) and a dynamic spatial Durbin model. The findings reveal a significant positive spatial correlation between digital finance and regional innovation efficiency, with path dependence in both spatial and temporal dimensions. Digital finance enhances local innovation capacity and exerts substantial positive spillover effects, with neighboring regions benefiting from increased regional innovation efficiency. The three core dimensions of digital finance—coverage breadth, usage depth, and digitization degree—all demonstrate robust direct and spatial spillover effects, further underscoring the structural impact of digital finance on innovation. These effects are most pronounced in the eastern region, while the central and western regions lag behind, reflecting regional heterogeneity in digital finance's impact.

The policy recommendations drawn from this research include:

1) **Leveraging Spatial Linkages**: Policymakers should focus on the spatial spillover effects of innovation, promoting collaboration platforms that enhance inter-regional cooperation between enterprises. Facilitating the flow of R&D personnel and funds between regions can improve knowledge spillover and optimize the allocation of innovation resources.
2) **Promoting Digital Finance Transformation**: Local governments should encourage the digital transformation of financial services to better support regional innovation. Policies such as financial subsidies and tax incentives can stimulate the integration of digital technologies with the financial sector, enhancing the sector's ability to support innovation.
3) **Broadening Digital Finance Coverage**: Strengthening infrastructure in central and western regions can enhance regional innovation by improving access to digital finance. Meanwhile, the eastern region should continue to build on existing financial and technological infrastructure to maximize the spillover effects of digital finance.
4) **Addressing Research Gaps**: Future studies should consider factors such as industrial structure, income inequality, and internet infrastructure in analyzing the effects of digital finance on regional innovation. Furthermore, the use of emerging technologies like big data and web crawling could provide more accurate ways to measure digital finance, offering new research avenues.

In summary, this study highlights the role of digital finance in enhancing regional innovation efficiency and emphasizes the need for targeted policies to fully harness its potential across different regions in China.

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