The Impact of Digital Finance on Regional Innovation: Evidence from China

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Abstract: Digital finance emerges as a rising financial paradigm that has a significant impact on regional innovation level. This paper analyzes digital finance's effect on regional innovation, based on China's provincial panel data from 2011 to 2019, and combines the spatial lag model and mediating effect model for the empirical analysis. The results show that digital finance can significantly promote regional innovation. In sub-regional analysis, it is found that there exists an obvious regional heterogeneity in the regional innovation level promoted by digital finance development. Compared with eastern regions, the role of digital finance in promoting innovation is more prominent in the central and western regions. Furthermore, taking the Theil index and consumption expenditure as mediators, digital finance is found to enhance regional innovation by narrowing the income gap and boosting household consumption.

1. Introduction

As China's economy enters a New Normal, the development of economy is increasingly driven by innovation instead of input and investment. In this paper, we intend to take China as an empirical lens to probe into the factors driving the further development of innovation level. Enterprises, as the key entities of China's innovation activities, will need a lot of financial support to carry out their innovation activities, thus the development of China's financial industry emerges as an important factor affecting the innovation level (Hsu et al., 2014; Tylecote,2007) [1,2].

With the development of digital technology, digital finance has also brought many innovations to traditional finance. Compared with the traditional financial industry, digital finance has three advantages in terms of business channels, information matching and credit data, enabling more diversified loan services with faster lending speed, thus helping to broaden the reach and service scope of financial services and providing new opportunities for innovative activities [3,4]. Furthermore, some scholars have conducted in-depth research on how digital finance affects innovation level. Bollaert et al. (2021) argue that digital finance positively affects innovation activities by alleviating corporate financing constraints [5]. In addition to the direct financing effects of digital finance, Xie et al. (2018) and Du and Zhang (2020) note that the new business models spawned by digital finance could present opportunities for regional innovation [6,7]. More scholars conclude that digital finance corrects the attribute mismatch, domain mismatch, and stage mismatch in the traditional financial industry as well as provides complete business system and business sustainability, which would dramatically optimize technological innovation [8,9].

Based on previous studies, it can be found that financial development undoubtedly plays a key and important role in innovation. Most scholars accepted that digital finance would improve innovation development by reducing the credit cost, expanding the breadth of financial services, and promote the consumption and industrial upgrading, which in turn drove innovation development. Some scholars believed that the mechanism of digital finance affecting innovation has not been fully illuminated. In existing studies less research has been conducted on the external

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channel mechanisms. To address the issue, we based on the perspective of innovation factor flow, control the spatial dependence of regional innovation at the level of factor flow at the basic end, and use spatial econometric methods to empirically test the impact of digital finance on regional innovation and identify its regional heterogeneity. Then we conduct a channel mechanism study to test whether there are other factors serve as channel mechanisms for digital finance to influence regional innovation.

2. Variables, data and empirical methodology

2.1. Spatial econometric modeling

2.1.1. Spatial correlation test

Before the spatial econometric regression, a spatial correlation test is required. In this paper, we adopt the Global Moran' I index to test the spatial correlation of regional innovation level. The formula is as follows:

$$\text{Moran's I} = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(x_i-\bar{x})^2} \quad (1)$$

where wij is spatial weight matrix, i and j refer to region, and x is regional innovation level.

2.1.2. Spatial econometric model

According to Anselin (1988), we construct a spatial econometric model of the impact of digital finance on regional innovation level [10]. The formulas are as follows:

$$lninno_{it} = \alpha_0 + \rho\sum_{j=1}^{n} w_{ij} lninno_{it} + \alpha_1\, ifi_{it} + \sum \beta Z_{it} + \varepsilon_{it} \quad (2)$$

$$lninno_{it} = \alpha_0 + \alpha_1 ifi_{it} + \sum \beta Z_{it} + \varphi_{it}\,, \qquad \varphi_{it} = \lambda\sum_{j=1}^{n} w_{ij}\,\varphi_{it} + \varepsilon_{it} \quad (3)$$

where formula (2) is Spatial Lag Model (SAR), formula (3) is Spatial Error Model (SEM). And lninno is regional innovation level, ifi is digital finance, Z are control variables, α0 is the intercept term, α1 and β are the coefficients to be estimated, ρ is the spatial lag term coefficient, λ is the spatial error term coefficient, wij is the spatial weight matrix, and ε it and Φ it are the random perturbation terms.

2.1.3. Spatial weight matrix modeling

The popular spatial weight matrices include the geographic adjacency matrix, the geographic distance matrix, and the economic distance matrix. Innovation factors are the carriers of innovation activities, and there are deep connections among regional innovation systems due to innovation factor flows. Therefore, studying the spatial correlation of regional innovation level in China from the perspective of innovation factors can rigorously reflect the innovation correlation degree among provinces. With reference to the study of Bai and Jiang (2015), we employ the simplified gravity model to construct the R&D funding matrix and R&D personnel matrix in China [11]. The R&D funding matrix is calculated as follows:

$$W = \begin{cases} \frac{KP_iP_j}{D_{ij}}, i \neq j \\ 0, i = j \end{cases} \quad (4)$$

where W is R&D funding matrix, K is a constant term taking the value of 1, i and j are regions; Pi and Pj denote the R&D funding stocks of regions i and j, and are calculated by the perpetual inventory method, according to the study of Han and Cheng (2020) [12]. Dij is the distance between the geographic center of region i and j. The same formula was used for the R&D personnel matrix.

2.2. Variables selection and description

2.2.1 Dependent variable

The dependent variable is regional innovation level (lninno). Nowadays, the regional innovation level is widely measured by the number of patents, new product sales revenue, and technology market turnover, among which the application of patent technology is rarely susceptible to external interference and is often used as an indicator of innovation output [13]. Therefore, the number of authorized patent applications is used to indicate the regional innovation level in this paper. Drawing on the method of Bai and Bian (2016) [14], we give values of 0.5, 0.3, and 0.2 to invention patents, utility models, and designs according to the innovation intensity, and calculate them by the weighted average method, then use the logarithm of these values as indicators of the regional innovation level of each province.

2.2.2. Explanatory variable

The explanatory variable is digital finance development level (ifi). The Peking University Digital Financial Inclusion Index of China has been used by many scholars to study the development of digital finance and its economic effects in recent years. The index system consists of three dimensions: coverage breadth, usage depth and digitization level with 33 indicators [15]. We use this index to measure the level of digital finance development in each region in this paper. Also, considering that the level of financial inclusion development contains multiple dimensions [16], three dimensions of the index are also collected and used to study the impact of structural characteristics of digital finance on regional innovation.

2.2.3. Control variable

The control variables include government support for science and technology, human capital, openness level, infrastructure level and industrial agglomeration. Government support for science and technology is measured by the percentage of local government fiscal science and technology expenditures to GDP; human capital is measured by the logarithm of the average number of years of schooling for the population aged 6 years and older; openness level is measured by the ratio of total imports and exports to GDP; infrastructure level (inf) is measured by the number of road miles per capita; and industrial agglomeration, drawing on the study by Xie (2019), is expressed as the agglomeration of productive service industries [17].

2.3. Data source

Table 1. Descriptive statistics for the main variables.

Variables	Variable Abbreviation	Obs	Mean	S.D.	Median	Max	Min
Regional innovation	lninno	279	8.694	1.605	8.850	11.929	3.651
Digital finance	ifi	279	2.023	0.916	2.124	4.103	0.162
Coverage breadth	ifi1	279	1.823	0.905	1.893	3.847	0.020
Usage depth	ifi2	279	1.970	0.915	1.898	4.399	0.068
Digitalization level	ifi3	279	2.784	1.177	3.136	4.622	0.076
Government support for science and technology	gov	279	0.450	0.264	0.362	1.325	0.136
Human capital	lnhum	279	2.193	0.137	2.204	2.548	1.440
Openness level	open	279	0.266	0.300	0.139	1.548	0.013
Infrastructure level	inf	279	4.470	4.374	3.507	29.650	0.515
Industrial agglomeration	agg	279	1.012	0.370	0.920	2.742	0.600

Note: Summary statistics are weighted. Digital finance, coverage breadth, usage depth and digitalization data come from The Peking University Digital Financial Inclusion Index (2019). Regional innovation data and other data comes from the China Statistical Yearbook, China Science and Technology Statistical Yearbook and the official website of the National Bureau of Statistics.

We select panel data for 31 provinces (cities and districts) in China spanning from 2011 to 2019, and based on data availability, Hong Kong, Macao, and Taiwan are not considered. The data of digital finance is from The Peking University Digital Financial Inclusion Index, and other data comes from the China Statistical Yearbook, China Science and Technology Statistical Yearbook and the official website of the National Bureau of Statistics. Table 1 presents descriptive statistics for the main variables used in the empirical analysis.

3. Results and discussion

3.1. Spatial correlation results and analysis

By testing the Moran' I index for regional innovation in China from 2011 to 2019 under both weights matrices, it is clear that the Moran' I index is significantly positive, indicating that the use of the spatial econometric model is appropriate.

3.2. Benchmark regression results

For whether to use the SAR model or the SEM model, it is usually judged with the help of the LM test and its robustness form test. Table 2 shows the relevant results. As can be seen in Table 2, the statistics of LM and its robustness form under the two types of spatial weight matrices both suggest that the SAR model is more appropriate than the SEM model.

Table 2. LM test and its robustness form test.

Years	LM-Lag	RLM-Lag	LM-Error	RLM-Error
R&D funding matrix	3.623*	4.225**	0.194	0.796
R&D personnel matrix	3.123*	3.690*	0.193	0.760

Note: *, **, and *** indicate passing the significance test at 10%, 5%, and 1% levels, respectively.

The Hausman test demonstrates that the null hypothesis of random effects is rejected and a fixed effect is more appropriate. Fixed effects include four categories: no fixed effects (nonF), individual fixed effects (sF), time fixed effects (tF), and two-way fixed effects model (stF). In this paper, the four types of fixed effects in the SAR model are estimated separately, and the results are shown in Table 3. Judging from the Maximum Likelihood Estimate (Log-L) and the goodness of fit (R^2), we finally use the individual fixed-effects model (sF) in the spatial lag model (SAR).

Table 3. Spatial econometric model estimation results of the impact of digital finance on regional innovation.

Variables	**R&D funding matrix**				**R&D personnel matrix**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
ifi	0.147***	0.133***	2.382***	-0.163	0.144***	0.130***	2.373***	-0.162
	(3.90)	(3.79)	(6.22)	(-0.97)	(3.73)	(3.61)	(6.17)	(-0.96)
gov	0.585***	0.597***	-0.362	0.604***	0.581***	0.593***	-0.366	0.602***
	(5.30)	(5.76)	(-1.24)	(5.78)	(5.26)	(5.71)	(-1.24)	(5.76)
lnhum	1.260***	0.760*	0.451	0.896**	1.266***	0.763*	0.469	0.896**
	(2.87)	(1.87)	(0.54)	(2.14)	(2.88)	(1.87)	(0.56)	(2.15)
open	0.367***	0.290**	1.443***	0.266*	0.365***	0.289**	1.448***	0.268*
	(2.72)	(2.30)	(4.43)	(1.93)	(2.70)	(2.28)	(4.43)	(1.94)
inf	0.099***	0.129***	-0.169***	0.126***	0.099***	0.129***	-0.168***	0.126***
	(4.90)	(7.03)	(-7.53)	(6.83)	(4.87)	(7.00)	(-7.47)	(6.82)
agg	-0.300**	-0.284**	-1.339***	-0.293**	-0.293**	-0.277**	-1.337***	-0.290**
	(-2.15)	(-2.15)	(-5.92)	(-2.20)	(-2.10)	(-2.09)	(-5.90)	(-2.17)
ρ	0.663***	0.685***	-0.059	0.300	0.654***	0.675***	-0.035	0.300
	(7.83)	(8.65)	(-0.26)	(1.61)	(7.69)	(8.46)	(-0.16)	(1.60)
R^2	0.875	0.879	0.824	0.331	0.877	0.880	0.824	0.315
Log-L	4.758	129.5	-329.0	132.8	4.548	129.1	-328.4	133.3
Fixed effects	nonF	sF	tF	stF	nonF	sF	tF	stF
N	279	279	279	279	279	279	279	279

Note: *, **, and *** indicate passing the significance test at 10%, 5%, and 1% levels, respectively.

From column (2) and (6) of Table 3 , it can be seen that the coefficients of the spatial lag term ρ , are significantly positive under both weight matrices, suggesting that there is a significant positive spatial correlation of regional innovation levels in China. It also verifies the conclusion of many scholars that the development of regional innovation level in innovation spatially connected regions will significantly enhance the local innovation level. The reason is that the flow of R&D funds and R&D personnel between regions improves the scale of regional innovation factors and the level of knowledge spillover, and optimizes the allocation of innovation factor resources, which provides strong conditions for the improvement of regional innovation.

The estimated coefficients of digital finance development levels are all significantly positive at the 1% level, which implies that the development of digital finance in China effectively improves regional innovation. As a matter of fact, digital finance has compensated for the shortcomings of the traditional financial market for the innovation market in China, especially supports the innovative activities of SMEs. Meanwhile, the government and market have strengthened the regulation of digital finance in recent years to provide a strong guarantee for digital finance to support regional innovation, such as the Interim Measures for the Management of Business Activities of Network Lending Information Intermediaries issued by the CBRC in 2016 and the Financial Technology (FinTech) Development Plan (2019~2021) issued by the Central Bank in 2019, which all set out requirements and plans for the regulation of digital finance.

Regarding control variables, the estimated coefficient of government support for science and technology is significantly positive. The government gives positive externalities to regional innovation activities in the form of science and technology subsidies, science and technology services and management, and science and technology development and application, which can actively compensate for market deficiencies and funding gaps, eliminate innovation risks, and stimulate innovation potential. A significantly positive estimated coefficient of human capital indicates that the improvement of human capital contributes to innovation. The estimated coefficient of infrastructure level is also significantly positive, indicating that infrastructure development facilitates the flow of innovation factors and plays a positive role in the improvement of regional innovation level. Industrial agglomeration has a significantly negative estimated coefficient, indicating that industrial agglomeration is not conducive to regional innovation in China, for the reason that Chinese industries are mostly clustered in industrial parks, which are prone to innovation imitation and innovation low-end “lock-in”, forming “innovation inertia”, which has a negative effect on the improvement of regional innovation level [18].

3.3. Regional heterogeneity analysis

Table 4. Estimation results of sub-regional spatial econometric model

Variables	R&D funding matrix			R&D personnel matrix		
	Eastern	**Central**	**Western**	**Eastern**	**Central**	**Western**
ifi	0.075*	0.354***	0.274***	0.077*	0.355***	0.270***
	(1.81)	(4.05)	(3.59)	(1.83)	(4.08)	(3.40)
gov	0.622***	0.407	0.784***	0.617***	0.407	0.789***
	(4.87)	(1.53)	(3.95)	(4.80)	(1.53)	(3.97)
lnhum	0.252	-3.810**	1.215**	0.233	-3.808**	1.203**
	(0.29)	(-2.56)	(2.57)	(0.27)	(-2.56)	(2.54)
open	-0.202	1.253	0.574	-0.200	1.254	0.560
	(-1.47)	(1.23)	(1.28)	(-1.45)	(1.23)	(1.25)
inf	0.301***	0.071	0.099***	0.302***	0.071	0.099***
	(3.29)	(0.53)	(4.19)	(3.29)	(0.53)	(4.19)
agg	0.365***	-1.705***	-0.865***	0.377***	-1.701***	-0.861***
	(2.73)	(-3.80)	(-3.07)	(2.80)	(-3.79)	(-3.05)
ρ	0.616***	0.226	0.384***	0.605***	0.224	0.383***
	(6.28)	(1.38)	(2.69)	(6.13)	(1.37)	(2.62)
R^2	0.879	0.887	0.923	0.884	0.887	0.923
Log-L	70.95	35.54	50.34	70.71	35.52	50.20
N	99	72	108	99	72	108

Note: *, **, and *** indicate passing the significance test at 10%, 5%, and 1% levels, respectively.

As shown in Table 4, there is a heterogeneous effect under both weights matrices. Although digital finance significantly contributes to the regional innovation in all three regions, the estimated coefficients rank from highest to lowest: central region, western region, and eastern region. The eastern region has frequent innovation activities, high innovation capacity and technology level compared to the central and western regions. It also has close ties with large commercial banks and venture capital firms, and more investment in innovation activities comes from these banks and firms, and their traditional finance behaves better than digital finance. The number of companies using digital finance to drive innovation is limited. In contrast, the positive and significant support of digital finance for regional innovation in the central and western regions precisely reflects the inclusiveness of digital finance, which makes up for the shortage of innovation financing in the central and western regions and strengthens their ability to catch up with the innovation level in eastern regions.

3.4. Mechanism test of digital finance to affect regional innovation

According to the previous analysis, digital finance can narrow income gap and boost consumption demand, which in turn drive the regional innovation level. We refer to the mediating effect model of Baron and Kenny (1986) and construct a recursive model to test the transmission mechanism of digital finance affecting regional innovation level [19]. The model is constructed as follows:

$$lninno_{it} = a_0 + \alpha_1 ifi_{it} + \sum \alpha_2 Z_{it} + \varepsilon_{it} \quad (5)$$

$$M_{it} = b_0 + b_1 ifi_{it} + \sum b_2 Z_{it} + \mu_i + \varepsilon_{it} \quad (6)$$

$$lninno_{it} = c_0 + c_1 ifi_{it} + c_2 M_{it} + \sum c_3 Z_{it} + \varepsilon_{it} \quad (7)$$

where M is the mediating variable and the remaining variables are as same as equation (2). Since the income gap in China is largely shown as the urban-rural income gap, we use the urban-rural income gap represented by the Theil index as the income gap (gap) indicator, and consumption demand (lnc) is measured by the logarithm of per capita consumption expenditure after eliminating the price trend. To test the mediating effect, we adopt the sequential test method, which first requires a1, b1, and c2 to be significant in turn, and then determine whether the effect is fully mediated or partially mediated according to the significance of c1, and finally calculate the mediating effect value. To be specific, if c1 is not significant, it means that the variable M holds a full mediating effect, namely, the promotion effect of digital finance on regional innovation is fully realized through channel M; if c1 is significant, it means that the variable M holds a partial mediating effect, and the mediating effect is b1c2, and then the ratio of the mediating effect is b1c2/a1.

Next, we adopted the income gap between urban and rural areas and the per capita consumption expenditure as intermediary variables for the mechanism examination. Columns (1) to (3) of Table 5 displays the test of mediating effects with income gap as the mediating variable. The estimated coefficient of digital finance development level in column (2) is negatively significant, which indicates that digital finance can narrow the income gap; while the estimated coefficient of income gap in column (3) is negatively significant, which indicates that narrowing income gap helps to improve the regional innovation level. Moreover, the significance of the estimated coefficients of each variable meets the criterion of partial mediating effect, which means that income gap plays a partial mediating effect in the impact of digital finance on regional innovation, with a mediating effect value of 0.066 and a mediating effect share of 16.36%. Therefore, digital finance promotes regional innovation through narrowing income gaps between urban and rural areas.

Columns (4) to (6) of Table 8 displays the test of mediating effects with per capita consumption expenditure as the mediating variable. The estimated coefficient of digital finance development level in column (5) is positively significant, which indicates that digital finance can increase consumption demand; the estimated coefficient of consumption demand in column (3) is positively significant, which indicates that the increase in consumption demand has a positive pulling effect on the regional innovation level. The significance of the estimated coefficients of other variables also meet the criterion of partial mediating effect, which means that consumption demand plays a partial mediating effect in the impact of digital finance on regional innovation, with a mediating effect value of 0.139 and a mediating effect share of 34.26%. Overall, the results in Table 5 suggest that digital finance development can enhance regional innovation by narrowing income gap and boosting consumption demand.

Table 5. Estimation results of mediating effect.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	lninno	gap	lninno	lninno	lnc	lninno
ifi	0.406***	-0.016***	0.338***	0.406***	0.217***	0.267***
	(22.38)	(-18.31)	(12.29)	(22.38)	(42.05)	(5.18)
gap			-4.152***			
			(-3.26)			
lnc						0.641***
						(2.88)
Control variables	YES	YES	YES	YES	YES	YES
Individual-fixed	YES	YES	YES	YES	YES	YES
R^2	0.877	0.724	0.882	0.877	0.949	0.881
N	279	279	279	279	279	279

Note: *, **, and *** indicate passing the significance test at 10%, 5%, and 1% levels, respectively.

4. Conclusions

Based on the analysis of direct effects and channel mechanisms of digital finance affecting regional innovation, this study uses data from 2011 to 2019 across 31 Chinese provinces (cities and districts) and adopts spatial lag model and mediating effect model to conduct empirical tests. Four findings emerged from our study. (ⅰ) China’s regional innovation level has a positive spatial correlation, and digital finance development has a significant contribution to regional innovation level. This conclusion still holds after endogeneity processing and robustness test. (ⅱ) There is significant regional heterogeneity with regard to the level of regional innovation influenced by digital finance, with the highest effect in the central region, followed by the western region and the smallest in the eastern region. (ⅲ) Digital finance can affect regional innovation through two channel mechanisms: narrowing income gap and increasing household consumption demand.

Our findings have essential implications. First of all, it is necessary to accelerate the digital transformation of the financial sector and improve the ability of digital financial services to the real economy so as to achieve better support for regional innovation by digital finance. Secondly, promote the comprehensive development of digital finance in all regions in order to achieve high-quality support of digital finance for regional innovation. For the eastern region, it is important to improve the flexibility of digital finance so that it can become a backing guarantee for innovative activities；while for the central and western regions, it is advisable to create a favorable market environment, strongly support the development of digital finance, and improve the utilization of digital finance for innovative projects with multi-channel, low-cost and high-efficiency financing, so as to further enhance the regional innovation level in the central and western regions. Thirdly, increasing the inclusiveness of digital finance is also required, which would further narrow the income gap and stimulate consumption demand, and thereby indirectly serve as a catalyst for regional innovation.

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