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Spatial effect of digital financial inclusion on the urban–rural income gap in China—analysis based on path dependence

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ABSTRACT
Digital financial inclusion (DFI) helps to narrow the income gap between urban and rural areas, but path dependence may lead to spatial agglomeration in the development of DFI, causing the spatial effect on the urban–rural income gap. This study mainly examines the mechanism and effect of DFI on the urban–rural income gap in China, including its spatial effect issues. Results show that China's DFI has different impacts on the urban–rural income gap in the east, central, and western regions, showing evident spatial heterogeneity. In addition, the development of DFI has spatial agglomeration, and its impact on China's urban–rural income gap also has a spatial spillover effect. Moreover, the spatial effect of DFI is mainly because of the path dependence on the development of traditional finance and digital technology. The spatial correlation between them is transmitted to DFI, and the impact of digital technology development is greater. Finally, corresponding policy recommendations are proposed based on the conclusions.

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1. Introduction

China's economy has shifted from a stage of rapid to high-quality development, and balanced income distribution should be one major subject of high-quality economic development. Since the reform and opening-up policy, China's urban–rural income gap has shown to continuously expand and then hover at a high level (Li & Zhu, 2018). Financial exclusion in rural areas has further exacerbated the problem of urban–rural dualism. Based on digital technology, digital financial inclusion (DFI) could alleviate the contradiction between the social and commercial goals of traditional financial inclusion (Sandhu & Arora, 2022). Moreover, DFI could provide a new direction for narrowing the urban–rural income gap.

DFI refers to all activities that promote financial inclusion through digital financial services. It provides a series of formal financial services by leveraging digital

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technology for groups that do not have or have minimal access to financial services. The financial services provided could meet their needs and are provided in a responsible and affordable manner. Such services simultaneously are sustainable for service providers.[1] Compared with traditional finance, DFI services mainly target disadvantaged groups who are financially excluded. Meanwhile, compared with traditional financial inclusion, the use of digital technology has broken the constraint of geographic distance. DFI uses online services to collect micro-data and uses big data, cloud computing, and other technologies to reduce the risk of information asymmetry (Gomber et al., 2017), lower the operating costs under controllable risks (Peterson, 2018), and enhance the sustainability of financial supply when providing financial support for rural residents (Jain & Gabor, 2020).

Some literature on DFI and urban–rural income gaps exists. For instance, Jiang et al. (2021) empirically found that the development of DFI has narrowed the income gap between urban and rural areas on the whole. Li et al. (2020) analyzed from the perspective of financial exclusion theory and financial function. They pointed out that the impact of DFI on the urban–rural income gap was structurally heterogeneous. Meanwhile, Zhang et al. (2020) confirmed that DFI could help rural residents start their own businesses, increase their income, and thereby achieve inclusive growth of the economy. Moreover, Wang et al. (2022) believed that DFI has different impacts on farmers' income through different financial channels. This case in general reduces the probability of rural formal credit demand for production but increases that for consumption.

Some studies also found that the development of DFI has a spatial effect. For example, Guo et al. (2017) found that the development of Internet finance shows spatial agglomeration. Moreover, Tian et al. (2020) discovered that the development of DFI has spatial differences. Regarding urban and rural incomes, Kong (2020) thought that DFI has a spatial spillover effect on urban and rural residents' incomes. Then, Liu et al. (2019) pointed out that DFI also has a spatial spillover effect on farmers' non-agricultural income.

In summary, the existing literature focused on the impact of DFI on the urban–rural income gap and recognized that the development of DFI is beneficial to narrowing the urban–rural income gap. However, relatively few studies have been conducted from the perspective of the spatial effect. The biggest advantage of using digital technology is to break the limitations of geography. However, if DFI still has a spatial effect on the urban–rural income gap, then what is the reason? Few studies have explored this notion. Moreover, most studies are based on provincial data. In contrast, in terms of the spatial effect, there is bound to be a big deviation between provincial and municipal data. Based on this, this article will select municipal data to study the impact of DFI on the urban–rural income gap from the perspective of the spatial effect. The study will further explain the spatial effect of DFI from the perspective of path dependence. The subsequent structure of this article is as follows: the second part proposes hypotheses through theoretical analysis; the third part sets up an empirical model and explains the selected variables and data; the fourth and fifth parts are empirical analysis; the last part summarizes the above research and proposes policy recommendations.

2. Theoretical analysis and hypothesis

With the vigorous development of the digital economy, it has become the fifth production factor after labor, capital, land, and technology (Ragnedda et al., 2020). This article draws on the methods of Barro (1990) and Sun (2012) to construct a two-sector model and incorporates digital technology into the framework to analyze the impact of DFI on the urban–rural income gap.

2.1. The impact of DFI on the urban–rural income gap

We assume that the economy has two sectors: the urban sector with better economic development (u) and the rural sector with relatively laggard economic development (r). There are many competing firms. In the context of capital financialization and economic digitization, output (Y), financial capital (F), digital technology capital (I), and labor capital (L) are used to construct the production function in the form of Cobb-Douglas, with the return to scale remaining unchanged. Let $y = Y/L, f = F/L,\ i = I/L$; thus, the intensive form of the two-sector production function could be obtained, where $y_u = f_u^{\alpha} i_u^{\beta}$ and $y_r = f_r^{\gamma} i_r^{\lambda}$, α, β, γ, and λ represent the financial and digital technology capital-output elasticities of firms in the urban and rural sectors, respectively, where $0 < \alpha < 1,\ 0 < \beta < 1,\ 0 < \gamma < 1,\ 0 < \lambda < 1,\ 0 < \alpha + \beta < 1,\ 0 < \gamma + \lambda < 1$. When $L = L_u + L_r$ and remains unchanged, the urbanization rate would be $\mu = L_u/(L_u + L_r)$. Then, let the financial inequality rate $\theta = F_r/(F_u + F_r)$ and the degree of financial development $\varphi = F/Y$. When a firm makes decisions based on the principle of profit maximization in a perfectly competitive market, the factor price is equal to its marginal output. Therefore, when the labor market is in equilibrium, the labor-capital price is the real wage: $w = \partial(y \cdot L)/\partial L = y + L \cdot y' \cdot \{[\partial(F/L)/\partial L]\} = y - y' \cdot f$. Assume the urban–rural income gap is the ratio of the real wages of urban and rural residents; the urban–rural income gap π is: $\pi = w_u/w_r = [(1-\alpha)y_u]/[(1-\gamma)y_\gamma]$.

Assuming that DFI is D, $D = D_u + D_r$. On the one hand, as a new financial format, DFI will promote the development of finance itself. Therefore, the degree of financial development is $\varphi' = (F + D)/Y$ and $\partial\varphi/\partial D > 0$. On the other hand, the inclusive nature determines that it focuses more on providing financial services for rural areas and easing the unbalance of financial development. In this case, the rate of financial inequality is $\theta' = (F_r + D_r)/(F_u + F_r + D)$ and $\partial\theta/\partial D > \partial\varphi/\partial D > 0$.

On this basis, we first sort out the degree of financial development:

$$\varphi = \frac{F}{Y} = \frac{F_u + F_r}{Y_u + Y_r} = \frac{F_u/(1-\theta)}{Y_u[(Y_r/Y_u) + 1]} = \frac{F_u}{(1-\theta)Y_u\left[\frac{(1-\alpha)}{(1-\gamma)} \cdot \frac{1}{\pi} \cdot \frac{1-\mu}{\mu} + 1\right]}.$$

We further sort out the following:

$$F_u/Y_u = \varphi(1-\theta)Y_u\{[(1-\alpha)/(1-\gamma)] \cdot (1/\pi) \cdot [(1/\mu) - 1] + 1\}.$$

We use the implicit function method to derive the difference between urban and rural income gap π and the degree of financial development φ :

$$\frac{\partial \pi}{\partial \varphi} = -\frac{\partial F_1/\partial \varphi}{\partial F_1/\partial \pi} = -\frac{(1-\theta)Y_u\left[\frac{(1-\alpha)}{(1-\gamma)}\cdot\frac{1}{\pi}\cdot\left(\frac{1}{\mu}-1\right)+1\right]}{-\varphi(1-\theta)Y_u\left[\frac{(1-\alpha)}{(1-\gamma)}\cdot\frac{1}{\pi^2}\cdot\left(\frac{1}{\mu}-1\right)+1\right]},$$

where $F_1 = \varphi(1-\theta)Y_u\{[(1-\alpha)/(1-\gamma)]\cdot(1/\pi)\cdot[(1/\mu)-1]+1\}-(F_u/Y_u)$, and then, we derive the urban and rural income gap π to financial inequality θ :

$$\frac{\partial \pi}{\partial \theta} = -\frac{\partial F_1/\partial \theta}{\partial F_1/\partial \pi} = -\frac{-\varphi Y_u\left[\frac{(1-\alpha)}{(1-\gamma)}\cdot\frac{1}{\pi}\cdot\left(\frac{1}{\mu}-1\right)+1\right]}{-\varphi(1-\theta)Y_u\left[\frac{(1-\alpha)}{(1-\gamma)}\cdot\frac{1}{\pi^2}\cdot\left(\frac{1}{\mu}-1\right)+1\right]}.$$

Further, the derivative of the urban–rural income gap π to the DFI D could be obtained:

$$\frac{\partial \pi}{\partial D} = \frac{\partial \pi}{\partial \varphi}\frac{\partial \varphi}{\partial D} + \frac{\partial \pi}{\partial \theta}\frac{\partial \theta}{\partial D} = \left[\frac{\partial \varphi}{\partial D}(1-\theta) - \frac{\partial \theta}{\partial D}\varphi\right]\cdot\frac{\left[\frac{(1-\alpha)}{(1-\gamma)}\cdot\frac{1}{\pi}\cdot\left(\frac{1}{\mu}-1\right)+1\right]}{\varphi(1-\theta)\left[\frac{(1-\alpha)}{(1-\gamma)}\cdot\frac{1}{\pi^2}\cdot\left(\frac{1}{\mu}-1\right)+1\right]}. \quad (1)$$

According to the hypothesis, when DFI reaches a certain level, $[(\partial\varphi/\partial D)(1-\theta)-(\partial\theta/\partial D)\varphi]<0$, and then, formula (1) becomes negative. This case indicates that the urban–rural income gap could be narrowed.

2.2. The spatial heterogeneity of the impact of DFI on the urban–rural income gap

In recent years, the spatial effect has received widespread attention in research and analysis, which has been divided into spatial heterogeneity and spatial correlation. That is, the parties distributed in the space are different but related to each other. The impact of DFI on the income gap between urban and rural areas should also be different among different regions, that is, spatial heterogeneity.

First, the degree of development of DFI is different. The development of DFI could be roughly summarized into two paths. One is that traditional financial institutions provide financial inclusion services through digital technology, that is, the digitization of financial inclusion. The other is that Internet companies carry out financial services called digital finance. Digital finance acquires customers through e-commerce or social media. Thus, they are inherently inclusive (i.e., the inclusiveness of digital finance). From the perspective of DFI, the strength of traditional financial institutions and the level of residents' digital technology use would both affect DFI. Considering the difference in the degree of development of the two drivers in different regions, the development of financial inclusion is also different. For example, the DFI index of China released by the Institute of Digital Finance of Peking University indicates that the development of DFI in provincial capital cities with well-developed TF is relatively good. Moreover, the DFI in Hangzhou, where the Internet giant Alibaba is located, leads the country (Guo et al., 2020). If the development of DFI is insufficient, then $\left[(\partial\varphi/\partial D)(1-\theta)-(\partial\theta/\partial D)\varphi\right]$ may not be negative. Thus, Eq. (1) shows different signs in different regions, indicating diversity.

Furthermore, the effect of DFI on the urban–rural income gap is different in different regions. DFI mainly improves the income of rural residents by alleviating financial exclusion in rural areas, thereby narrowing the income gap between urban and rural areas. However, the types and degrees of financial exclusion in various regions are not identical. Sarma (2012) classified financial exclusion into opportunity, condition, price, market, and self-exclusion. Rural residents in economically developed areas are mainly subjected to conditional and price exclusions because of high prices of financial services and insufficient assets. Rural residents in remote mountainous areas are mainly excluded from opportunities because of the long distance from financial institutions. In addition, the culture, education level, and customs of rural residents in different regions are different, leading to different attitudes toward digital technology and even refusal of digital finance, thereby forming different degrees of self-exclusion. The degree of mitigation of financial exclusion reflected by the impact of DFI on the degree of financial inequality $\partial\theta/\partial D$, would further affects the value of $\left[(\partial\varphi/\partial D)(1-\theta)-(\partial\theta/\partial D)\varphi\right]$. Thus, Eq. (1) shows regional differences. In addition, studies confirmed that the economic influence of DFI would be affected by macro and micro factors, such as physical capital (Lindell, 2020), digital infrastructure (Ren et al., 2018), and residents' age (Kirk et al., 2015), income (Li et al., 2020), and financial literacy (Moritz & Mietzner, 2020) in different regions. Again, the impact on the urban–rural income gap should also be different. Based on this, hypothesis 1 is proposed.

Hypothesis 1: The impact of DFI on the urban–rural income gap is spatially heterogeneous.

2.3. The spatial correlation of the impact of DFI on the urban–rural income gap

The impact of DFI on the urban–rural income gap may not be limited to the local area. According to the First Law of Geography, things are inter-related, and things that are closer are usually more relevant (Tobler, 1970). If the local DFI is well developed, it would be influential to the urban–rural income gap in local and neighboring areas, that is, spatial correlation.

First, a spatial agglomeration effect is observed in the development of DFI. The agglomeration effect refers to the spatial concentration of industrial and economic activities. From the supply side, the geographical concentration of DFI companies is conducive to sharing resources and increasing the utilization rate of various production factors, thereby forming economies of scale, reducing production costs, transmitting information, and strengthening ties with each other simultaneously. This event will, in turn, reduce transaction costs. From the demand side, DFI is a derivative of digital technology innovation, and penetration of new technologies often requires a gradual process and needs to be continuously spread in the daily use of residents. For example, the penetration of mobile payment began with individual merchants in several cities. Residents were increasingly accepting it owing to its convenience and safety, and then, more merchants deployed it, eventually forming the popularity in that city. Residents in neighboring cities would also apply it in their cities after the favorable experience, creating a spreading trend in the space. Guo et al. (2020) also found that the closer the city to Hangzhou, the better the development of DFI. Whether analyzed from the supply or the demand side, the spatial agglomeration effect of DFI has its reasons.

Second, the impact of DFI on the urban–rural income gap has a spatial spillover effect. The spatial spillover effect is manifested in that the development of DFI in the region would have an impact on the urban–rural income gap in neighboring areas. As neighboring cities communicate more closely and residents move more frequently, if the DFI in one city develops, it would have a demonstration effect, allowing residents of neighboring cities to learn in the process of communication and gradually master the DFI. The use of technology, knowledge, and human capital related to DFI would have a spillover effect, which will have an impact on the urban–rural income gap in neighboring cities. In addition, DFI mainly affects the urban–rural income gap through four channels: promoting consumption, increasing employment, alleviating credit constraints, and improving human capital (Li & Feng, 2020). Related studies have confirmed that DFI has an impact on the income gap. Moreover, the impact of DFI on consumption (Zou & Wang, 2020), entrepreneurship (Huang & Zeng, 2021), and poverty reduction (Wang & Chen, 2020) has a spatial spillover effect. Then, in terms of the urban–rural income gap, DFI should also have a spatial spillover effect. Based on this, hypothesis 2 is proposed.

Hypothesis 2: The impact of DFI on the urban–rural income gap is spatially correlated.

3. Model design and variable selection

3.1. Basic econometric model design

The basic econometric model is used to test the impact of DFI on the urban–rural income gap, so a panel regression model is constructed:

$$gap_{i,t} = \alpha_0 + \alpha_1 difi_{i,t} + \alpha_i control_{i,t} + \varepsilon_{i,t}. \qquad (2)$$

Among them, the subscripts i and t represent city and year, respectively. The dependent variable $gap_{i,t}$ is the urban–rural income gap; the independent variable $difi_{i,t}$ is the development level of DFI, and $control_{i,t}$ is the control variable. Economic development level $gdp_{i,t}$, development level of traditional financial $loan_{i,t}$, fiscal expenditure $fe_{i,t}$, industrial structure $is_{i,t}$, and degree of open-up $open_{i,t}$, $\varepsilon_{i,t}$ are random error terms.

3.2. Spatial econometric model design

When using a spatial econometric model, a spatial correlation test should be performed first, followed by correlation analysis. The test of spatial correlation often uses the Moran index (Moran's I) to measure whether a spatial agglomeration effect exists. The calculation formula is as follows:

$$Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(X_i - \overline{X}\right)\left(X_j - \overline{X}\right)}{S^2 \sum_{i-1}^{n}\sum_{j-1}^{n} W_{ij}}, \tag{3}$$

where $S^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2$, $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$, the observation value of city i is x_i, n is the number of sample cities (256 in this article), and W_{ij} is the spatial weight matrix. Then, the Euclidean distance was used to construct the geographic distance matrix. The value of the Moran index is between -1 and 1. When the Moran index is positive, a positive spatial correlation exists. That is, when a region has better development, neighboring areas also develop better, showing an agglomeration of regions with the same level of development. When the Moran index takes a negative value, a negative spatial correlation exists. That is, when the development of one area is better, the development of adjacent areas is less comparable, showing the agglomeration of regions with different development levels. Moreover, if the Moran index is 0, then no spatial correlation exists. The regional development level is randomly distributed.

With some improvement based on formula (2), a spatial econometric model could be constructed:

$$gap_{i,t} = \beta_0 + \rho\sum_{j=1}^{N} W_{ij}gap_{i,t} + \beta_1 difi_{i,t} + \sum_{j=1}^{N} W_{ij}difi_{i,t}\theta + \beta_i control_{i,t} + \mu_{i,t}, \tag{4}$$

$$\mu_{i,t} = \lambda\sum_{j=1}^{N} W_{ij}\mu_{i,t} + \nu_{i,t}. \tag{5}$$

Among them, ρ is the spatial autoregressive (SAR) coefficient, λ is the spatial autocorrelation coefficient, and θ is the spatial spillover effect coefficient. If $\rho \neq 0$, $\lambda = 0$, and $\theta = 0$, then it is a SAR model, which reflects the endogenous interaction effect of the urban–rural income gap in different regions. If $\rho = 0$, $\lambda \neq 0$, and $\theta = 0$, then it is the spatial error model (SEM), which reflects the spatial interaction effect of the error terms in different regions. Furthermore, if $\rho \neq 0$, $\lambda = 0$, and $\theta \neq 0$, then it is the spatial Doberman model (SDM), which reflects the endogenous and exogenous interaction effect in different regions. The exogenous interaction effect is the impact of DFI in one place on the urban–rural income gap of another place. Various tests are necessary to decide which model is most suitable.

3.3. Variable selection and description

The explained variable is the urban–rural income gap. Existing studies mostly used the ratio of urban to rural per capita disposable income, Gini coefficient, or Theil index to measure. The measurement of the Gini coefficient is more sensitive to the middle part, whereas the urban–rural income gap focuses on the two ends of income. Therefore, the Gini coefficient could not well reflect the changes in the urban–rural income gap. Although the Theil index could better reflect the changes at both ends, its calculation requires the use of historical data of urban and rural populations. However, the rural area of China does not have insufficient data, leading to a large number of gaps in the calculation of the Theil index. Finally, we choose the ratio of urban to rural per capita disposable income to measure the gap between urban and rural income, *gap*.

The core explanatory variable is the level of DFI. At present, most measurement methods of DFI in China use the DFI index released by the Institute of Digital Finance of Peking University. This index is based on the massive data of Ant Financial's DFI business and follows principles of comprehensiveness, balance, comparability, continuity, and feasibility. The index includes the DFI index (*difi*), which also includes the coverage breadth index (*breadth*), the depth of use index (*depth*), and the digitization degree index (*level*). Among them, the coverage breadth index considers the characteristics of not requiring a physical network and not being subject to geographical restrictions. This index also uses the number of digital accounts to measure the ability of DFI to reach customers. The depth of use index focuses on actual usage and considers different financial services, using the total actual usage (number of users per million people), usage dynamic (per capita transaction numbers), and usage intensity (per capita transaction amount) to examine the development depth of DFI. The digitization degree index measures the degree of convenience brought by DFI through the characteristics of mobilization, affordability, credibility, and facilitation.

This article also selects some control variables, including the following: (1) Economic development level: most existing studies noted that economic development could reduce the income gap between urban and rural areas (Lu et al., 2005). The current study uses real GDP per capita to measure the level of economic development, expressed in *gdp*. (2) TF development level: Guo et al. (2020) pointed out that DFI is closely related to the development of TF, and the influence of TF should be controlled to accurately measure the impact of DFI on the income gap between urban and rural areas. This study uses financial institution loan balance as a percentage of GDP to measure the development level of TF, expressed by *loan*. (3) Fiscal expenditure: related research posited that as fiscal expenditures prefer urban areas, the income gap between urban and rural areas widens (Hu, 2017). The present study uses fiscal expenditures as a percentage of GDP to measure fiscal expenditures, denoted by *fe*. (4) Industrial structure: Su et al. (2015) noted that the decline in the proportion of the primary industry has caused a large amount of resources to flow to non-agricultural industries, resulting in a larger divergence in efficiency between agriculture and non-agricultural industries. In addition, this case in turn widens the income gap between urban and rural areas. This study uses the proportion of the added value of the primary industry to GDP to measure the industrial structure, denoted by *is*. (5) Degree of open-up: foreign trade mostly occurs in urban areas, improving the urban economy and widening the income gap between urban and

Table 1. Variable names and calculation methods.

	Variable name	Calculation method
Explained variable	Urban–rural income gap (*gap*)	$\frac{\textit{Disposable income per capita in urban areas}}{\textit{disposable income per capita in rural areas}}$
Key explanatory variables	DFI (*difi*)	DFI Index (For details, see: Guo et al. (2020))
Control variable	Degree of economic development (*gdp*)	Real GDP per capita
	Degree of traditional financial development (*loan*)	Financial institution loan balance/GDP
	Financial expenditure (*fe*)	Fiscal expenditure/GDP
	Industrial structure (*is*)	Primary industry added value/GDP
	Degree of open-up (*open*)	Total import and export of goods/GDP

Source: Summarized from 3.3.

rural areas (Zhu et al., 2020). This study uses the local total value of import and export goods as a percentage of local GDP sorted by business units' location to measure the degree of opening up, expressed by *open*. Table 1 is a summary table of selected variables.

3.4. Data selection and statistical description

This article selects municipal data of China for research and analysis. Owing to the lack of data, Tibet, Hong Kong, Macao, and Taiwan regions are not included. We use the panel data of 256 municipalities in China from 2011 to 2017, mainly derived from the 2011–2018 China Statistical Yearbook and provincial statistical yearbooks. The remaining data come from the 'Peking University DFI Index (2011–2018)' and Wind database. Among them, the National Bureau of Statistics changed the statistical caliber in 2013, changing 'rural net income per capita' to 'rural disposable income per capita' to keep constant with 'urban disposable income per capita'. In this case, 'rural disposable income per capita' data are replaced by 'rural per capita net income' in 2011 and 2012. The original data of the total import and export value sorted according to business units' location are measured in US dollars and converted to RMB with the foreign exchange middle rate in the corresponding year. Table 2 shows the statistical description of each variable. Meanwhile, to visually inspect the development level differences among different regions, Table 3 shows a statistical description of China's eastern, central, and western regions.

From the statistical description of different regions, big differences can be observed in the development of China's eastern, central, and western regions, with the eastern region taking the lead in various aspects. From the perspective of the urban–rural income gap, the eastern region has the narrowest gap, followed by the central region, and the western region is the worst. Compared with the national average, the western region is the main cause of the national urban–rural income gap. From the perspective of the overall development level of DFI, a downward trend still exists in the east, central, and western regions. Moreover, the central and western regions lag behind the national average. However, from the perspective of sub-indexes, although the coverage and depth of use are similar to the overall index, the digitization degree index shows the opposite trend. In addition, the central and western regions are better than the eastern regions. The relevant statistical values of the control variables

Table 2. Statistical description.

Variable name	Number of samples	Average	Standard deviation	Minimum value	Maximum value
Urban–rural income gap	1792	2.404	0.476	1.318	4.29
DFI index	1792	145.147	57.632	21.26	285.432
Coverage breadth index	1792	136.342	54.92	4.49	267.129
Depth of use index	1792	143.32	61.037	12.49	325.679
Digitization degree index	1792	177.543	78.501	2.7	581.23
GDP per capita (RMB)	1792	49404.205	28780.09	10433	215488
The ratio of loan to GDP	1792	670.811	5049.515	13.218	69556.203
The ratio of fiscal expenditure to GDP	1792	83.098	546.36	4.523	7547.6
The ratio of primary industry to GDP	1792	11.998	7.674	0.301	49.891
The ratio of total import and export value to GDP	1792	264.544	2367.618	0.053	32151.801

Source: Authors' processing in Stata15.

Table 3. Statistical description by region.

	East		Middle		West	
Variable name	Average	Standard deviation	Average	Standard deviation	Average	Standard deviation
Urban–rural income gap	2.189	0.32	2.358	0.451	2.754	0.487
DFI index	155.235	57.997	139.684	56.796	138.557	56.403
Coverage breadth index	149.728	55.09	127.48	52.835	129.697	53.898
Depth of use index	155.975	61.313	140.883	59.858	129.313	58.804
Digitization degree index	172.079	76.665	177.81	78.581	184.611	80.42
GDP per capita (RMB)	61868.625	30657.408	40434.905	20990.547	44148.297	28993.863
The ratio of loan to GDP	1440.726	7946.185	79.945	45.322	394.053	2511.563
The ratio of fiscal expenditure to GDP	152.75	819.09	19.638	7.027	71.066	412.616
The ratio of primary industry to GDP	9.094	5.536	14.251	9.103	13.012	6.866
The ratio of total import and export value to GDP	654.325	3832.638	8.577	10.105	68.312	504.336
Number of samples	665		637		490	

Source: Authors' processing in Stata15.

may be affected by the extreme values of the municipalities directly under the central government and the 'survivor bias'. After excluding the data of these special municipalities, the eastern region is still leading, whereas the central and western regions have minimal differences. Considering the large differences among different regions and the wide range of indicators, we use the logarithm of the DFI index, GDP per capita, the proportion of financial institution loan balance to GDP, the proportion of fiscal expenditure to GDP, and the proportion of import and export value to GDP in the regression process.

4. Result and analysis

4.1. The spatial heterogeneity analysis of the impact of DFI on the urban–rural income gap

The statistical description Table 3 shows that differences exist in the development of DFI among the eastern, central, and western regions. However, in view of the spatial heterogeneity of its impact on the urban–rural income gap, we continue to analyze region by region. The samples are regressed and compared separately, and the national sample is also added for comparative analysis. Regression analysis is carried out with formula (2). Considering the influence of multicollinearity, the variance

Table 4. Impact of DFI on the urban–rural income gap.

Variable name	Nationwide	East	Middle	West
DFI	−0.357*** (0.077)	−0.424***(0.147)	−0.051(0.150)	−0.299***(0.090)
Economic development	−0.338***(0.085)	−0.376**(0.154)	−0.025**(0.172)	−0.502***(0.134)
TF development	0.156**(0.061)	0.222**(0.108)	0.147(0.116)	0.096(0.127)
Fiscal expenditure	−0.279***(0.072)	−0.472***(0.113)	−0.282**(0.137)	−0.181*(0.098)
Industrial structure	0.014***(0.005)	0.005(0.010)	0.035***(0.007)	0.005(0.006)
Foreign trade	−0.035(0.028)	−0.063(0.041)	−0.032(0.050)	0.001(0.042)
Constant term	7.513***(1.177)	8.468***(2.339)	2.719(2.168)	9.321***(1.747)
Time effect	Control	Control	Control	Control
Regional effect	Control	Control	Control	Control
R^2	0.458	0.421	0.477	0.577
Number of samples	1792	665	637	490

Note: The standard errors are in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%, respectively.
Source: Authors' processing in Stata15.

inflation factor (VIF) test is also conducted on the regression results, and we receive a VIF of 2.96 (VIF less than 10 indicates that no serious multicollinearity exists). Considering the influence of heteroscedasticity, the empirical regression in this study uses clustering robust standard errors. For the national and eastern, central, and western panels, the model regressions are performed with the Hausman test, and the results all show that the fixed-effect model should be selected. Table 4 shows the regression results.

The regression results in Table 4 show that from a national perspective, the coefficient of DFI is −0.357, which is significant at a significance level of 1%. This result indicates that DFI could significantly reduce the urban–rural income gap. However, after distinguishing the regions, different characteristics are observed. That is, DFI has a significant impact on the eastern and western regions, but the convergence effect in the central region is not evident, and the regression coefficient in the eastern region is −0.424, with an absolute value higher than the national average of 0.357. In comparison, the absolute value of the regression coefficient in the western region is 0.299, which is lower than the national average.

This finding indicates that the effect of DFI in reducing the urban–rural income gap is mainly led by the eastern region, and the central and western regions need improvement. Specifically, China's leading digital finance company Alibaba is located in Hangzhou, and Tencent is located in Shenzhen, both in the eastern region, where most cities enjoy well-developed economy and DFI. Second, the eastern region has rich educational resources and human capital, and economic development also brings more employment opportunities. Once rural residents ease their financial exclusion, they could quickly find entrepreneurial, investment opportunities and produce goods with sufficient consumption demand, thereby increasing income and alleviating the urban–rural income gap. By contrast, the western region is at a disadvantage in terms of economy and education. However, given that its urban–rural income gap is too large, DFI could still bring higher marginal benefits when easing rural financial exclusion. The central region is in a dilemma. On the one hand, economic and educational development is lagging, and the local development room is small, making it difficult to build strong DFI competitiveness. On the other hand, the income gap between urban and rural areas is mainly restricted by the industrial structure, and agriculture accounting for a relatively high proportion is the main reason for the low income of rural residents. The effectiveness of DFI has not yet been clearly demonstrated. In general, the effect of DFI in reducing the urban–rural income gap varies across the country and among the eastern, central, and western regions.

The regression results of the control variables also show regional differences. First, economic development provides more jobs for the society, helps the transfer of surplus rural labor to urban areas, reduces the supply of rural labor, and increases the income per capita of rural residents. Therefore, economic development could significantly reduce the urban–rural income gap, and this convergence effect is very evident in the east, middle, and west, but most apparent in the west. The western region has been underdeveloped for a long time, and the level of urbanization is not high, with great potential for development. Economic development could generate great impetus and promote farmers to increase their income. Second, fiscal expenditure has the effect of narrowing the income gap between urban and rural areas across the country and regions. Fiscal expenditures with policy targets could directly refer to the 'Three Rural' issues and provide designated financial support to rural areas to help farmers get rid of poverty and become rich. However, the convergence effect of fiscal expenditure gradually decreases from east to west, indicating that current fiscal expenditures are still leaning toward economically developed areas. Moreover, the financial support in undeveloped areas is either insufficient or inefficient, and targeted poverty alleviation policies need to be further deepened. Third, the regression results of TF development and industrial structure are more regional. On the whole, both would enlarge the income gap between urban and rural areas, and the effect is found to be evident only in certain areas after being analyzed region by region. TF 'despises the poor and curries favor with the rich' and mainly serves high-income groups, thereby widening the urban–rural income gap and the local income gap. The local income gap again has enabled the financial development of the eastern region to develop well and further widened the urban–rural income gap in the eastern region. This case could be observed from the fact that the coefficient of TF development is significant only in the eastern region. Forth, the industrial structure upgrade reflects the progress of social production. The high proportion of the primary industry means low production capacity and limited non-agricultural job opportunities, which restricts farmers' income. The high proportion of agriculture in the central region makes the income gap between urban and rural areas very significant. Last, the impact of foreign trade is not significant in the whole country or in any region.

The second-level indicators of DFI are further used to measure and analyze the urban–rural income gap, and Table 5 shows the results. The coverage breadth and depth of use of DFI across the country have a significant impact on the urban–rural income gap, and regionally speaking, only the breadth of coverage has an impact on the eastern and western regions. Moreover, the effect of the eastern region is better than that of the western region. The impact of the depth of use is not significant. However, the central region is still 'invulnerable'.

We can conclude that the effect of DFI in reducing the income gap between urban and rural areas is mainly brought by digital technology expanding the coverage of financial services. However, DFI is still in the early stage of development, and

Table 5. Impact of the DFI sub-index on the urban–rural income gap.

Variable name	Nationwide	East	Middle	West
Coverage breadth	−0.192*** (0.056)	−0.331*** (0.088)	−0.028 (0.084)	−0.136** (0.057)
Depth of use	−0.112** (0.053)	−0.032(0.087)	0.025(0.095)	−0.078 (0.066)
Digitization degree	0.0234(0.019)	0.104**(0.032)	−0.021(0.036)	−0.016(0.023)
Time effect	Control	Control	Control	Control
Regional effect	Control	Control	Control	Control
Number of samples	1792	665	637	490

Note: The standard errors are in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%, respectively.
Source: Authors' processing in Stata15.

Internet coverage is insufficient. Many remote areas have not yet received digital technology support, reflected by different impacts of the breadth of coverage in different regions. The penetration of DFI is even more lacking, resulting in an insufficient impact of the depth of use. In addition, many DFI products are complicated in design and have formed a certain threshold for residents' use. Those who could really enjoy the convenience of DFI are often high-income groups, opposite to the target groups. The degree of digitalization is only significant in the eastern region and is widening the income gap between urban and rural areas, indicating that DFI is currently only 'spreading' among the people but not yet 'benefiting' the people. In general, the convergence effect of DFI shows different characteristics across the country and different regions. The eastern, central, and western regions have greater differences in the performance of the two-dimensional index. The impact of DFI on the urban–rural income gap presents spatial heterogeneity. Hypothesis 1 is proved.

4.2. The spatial correlation analysis of the impact of DFI on the urban–rural income gap

First, the spatial correlation test is carried out. The Moran index for calculating urban–rural income gap, that is, the gap is 0.067, and the Moran index for calculating DFI *difi* is 0.905. Both are greater than 0 and pass the 1% significance level test. This result indicates that China's urban–rural income gap and the development of DFI have spatial agglomeration, and the spatial correlation is positive.

Then, the spatial econometric model is selected. Referring to Elhorst's (2014) test idea, we first choose between the SAR and SEM models, regress the non-spatial effect model, and perform the Lagrangian multiplier (LM) test. The results show that LM-SAR and LM-SEM can pass the test. Furthermore, we compare robust-LM and found that R-LM-SEM could pass the test, but R-LM-SAR has failed. Hence, we choose the SEM model. Next, we test whether the SDM model would degenerate into a SAR model or a SEM model, and we estimate the SDM model to conduct LR and WALD tests. The results show that the SDM model is the best. Meanwhile, the Hausman test shows that the fixed-effect model should be selected. According to the test, this study finally selects the SDM model of individual fixed effect. To obtain consistent parameter estimation results, the maximum likelihood method is used for estimation. Table 6 presents a summary of the regression results, and the regression results of the SAR and SEM models are provided for comparison.

Table 6. Spatial effect of DFI on the urban–rural income gap.

	SAR	SEM	SDM
DFI	−0.022(0.023)	−0.166**(0.081)	−0.355***(0.074)
DFI	−0.336***(0.081)	−0.303***(0.080)	−0.344***(0.088)
TF development	0.075(0.052)	0.134**(0.065)	0.155**(0.063)
Fiscal expenditure	−0.231***(0.067)	−0.247***(0.070)	−0.271***(0.073)
Industrial structure	0.017***(0.005)	0.017***(0.005)	0.013***(0.005)
Foreign trade	−0.031(0.028)	−0.030(0.028)	−0.035(0.028)
W × DFI			0.547***(0.103)
W × economic development			−1.241***(0.419)
W × TF development			−0.956***(0.248)
W × fiscal expenditure			0.646**(0.311)
W × industrial structure			−0.120***(0.022)
W × foreign trade			−0.522***(0.163)
Spatial autoregressive coefficient ρ	0.384***(0.112)		0.052(0.137)
Spatial autocorrelation coefficient λ		0.691***(0.148)	
R^2	0.414	0.411	0.457
Number of samples	1792	1792	1792
Likelihood	977.083	991.917	1026.668

Note: The standard errors are in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%, respectively.
Source: Authors' processing in Stata15.

The comparison of the coefficient of determination (R^2) and the value of the natural logarithmic function (likelihood) of the regression results shows that the SDM model is more suitable for this study. The SAR coefficient in the SAR model and the spatial autocorrelation coefficient in the SEM model are significant at a significance level of 1%, indicating that the urban–rural income gap among regions has a significant spatial interaction effect. By contrast, the spatial autocorrelation coefficient in the SDM model is not significant, indicating that ignoring the exogenous spatial interaction effects of explanatory variables would overestimate the endogenous interaction effect of the urban–rural income gap. Again, this result proves that the SDM model is more appropriate. In the regression of the SDM model, the regression results of the explanatory variables that do not consider the spatial effect are consistent with those in Table 3. In sum, we focus on analyzing the spatial explanatory variables.

The regression coefficients of all spatial explanatory variables could pass the significance level test of at least 5%, showing a strong spatial spillover effect. Second, the coefficient of the spatial effect of DFI on the urban–rural income gap is positive, indicating that the development of DFI has a positive spatial spillover effect. That is, the development of DFI would exacerbate the urban–rural income gap in neighboring areas. The wide income gap between China's urban and rural areas is mainly caused by the predicament of 'urbanizing land without urbanizing residents' in China's urbanization process. On the one hand, industrial upgrading has reduced agricultural income. On the other hand, the household registration system and other factors make it difficult for farmers to enter cities to earn a living (Zhang et al., 2018). Then, financial exclusion further hinders rural residents from entering non-agricultural industries to increase their income. DFI is to break the credit constraints of farmers, promote the flow of rural labor to cities, and provide opportunities for their entrepreneurship and employment. However, the flow of rural labor is cross-regional. Rural residents in areas with well-developed DFI are easy to break

Table 7. Effect decomposition of SDM regression results.

	Direct effect	Indirect effect	Total effect
DFI	−0.352***(0.076)	0.553***(0.101)	0.201**(0.081)
Economic development	−0.348***(0.085)	−1.322***(0.435)	−1.670***(0.428)
TF development	0.153**(0.061)	−0.988***(0.245)	−0.836***(0.234)
Fiscal expenditure	−0.275***(0.069)	0.670**(0.313)	0.395(0.297)
Industrial structure	0.013***(0.005)	−0.125***(0.019)	−0.112***(0.018)
Foreign trade	−0.034(0.028)	−0.552***(0.205)	−0.586***(0.204)

Note: The standard errors are in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%, respectively.
Source: Authors' processing in Stata15.

financing limits. They have an advantage over local farmers in the process of influx into neighboring cities, increasing the pressure on local farmers entering non-agricultural fields. It further exacerbates the urban–rural income gap in neighboring areas. Hypothesis 2 is proved.

However, the SDM model contains a global effect, and its regression coefficients could not capture all the influence of explanatory variables on the explained variables. Therefore, according to Lesage and Pace (2009), we further estimate the direct and indirect effects of each explanatory variable, to accurately measure the spatial impact on the urban–rural income gap. The direct effect is the influence of the explanatory variables of the local on the urban–rural income gap within the same region. Then, the indirect effect is the influence of the explanatory variables of the neighboring region on the local urban–rural income gap, that is, the spatial spillover effect. The total effect is the sum of the direct and indirect effects. Table 7 shows the results.

According to the decomposition results of the effect, DFI has a negative direct effect and positive indirect effect on the urban–rural income gap. Both are significant at the 1% significance level, indicating that local DFI could effectively alleviate the local urban–rural income gap, and DFI in neighboring areas would expand the local urban–rural income gap, which is consistent with the conclusions in Table 6. The other explanatory variables have similar results. However, the indirect effect of DFI is relatively more evident, even offsetting all the direct effects, and making the total effect positive and significant. As a whole, it aggravates the urban–rural income gap. This conclusion provides a new perspective for the development of DFI. Previous studies focused on local development and ignored the external influence on neighboring regions. If the development of DFI fails to form an overall plan across the regions, improper competition among regions may arise and enlarge the income gap between urban and rural areas, depleting digital premium.

4.3. Robustness test

The key to the above-mentioned spatial measurement is the introduction of a spatial matrix, but the selection of the spatial matrix may affect the robustness of the conclusions. Many studies believe that inter-regional dependence is not limited to geographical distance. With the frequent economic communication among regions, the spatial correlation caused by economic distance may be more evident. Therefore, we replace the geographic distance matrix with the economic distance matrix to test the

Table 8. Robustness test.

	SAR	SEM	SDM
DFI	−0.044* (0.026)	−0.096*** (0.035)	−0.314***(0.072)
W × DFI			0.400***(0.083)
W × economic development			−0.431*(0.225)
W × TF development			−0.248**(0.109)
W × fiscal expenditure			0.021(0.149)
W × industrial structure			−0.026**(0.013)
W × foreign trade			−0.034(0.053)
Spatial autoregressive coefficient ρ	0.189***(0.059)		0.186*** (0.050)
Spatial autoregressive coefficient λ		0.242***(0.059)	
R^2	0.417	0.417	0.443
Number of samples	1792	1792	1792
Likelihood	974.859	978.241	1009.808

Note: The standard errors are in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%, respectively.
Source: Authors' processing in Stata15.

robustness, and the economic distance is measured by the GDP difference. Table 8 shows the results.

The Moran index for calculating the urban–rural income gap *gap* and DFI *difi* is 0.029 and 0.904, respectively, and both passed the 1% significance level test, showing a positive spatial correlation. After the LM, LR, and WALD tests, the SDM model is still selected, and the R2 and likelihood statistics also show that the SDM model is the best. Significant SAR coefficients and spatial autocorrelation coefficients reflect an apparent spatial endogenous interaction effect, and DFI also presents an evident spatial spillover effect. The remaining results are generally consistent with the above research, proving the reliability of the conclusions of this study.

5. Further analysis: path dependence of DFI

DFI uses digital technology to provide financial services. Its distinctive feature is that it transforms geographic space into cyberspace, breaks the limitations of geographic distance, reduces costs, increases the availability of financial services, and provides sustainable financial inclusion services. If geographic distance is no longer a constraint and traditional financial geographic space would be reshaped (Tian, 2016), then the interactive effect on geographic space should gradually disappear. However, the above empirical results show that the spatial correlation of DFI is still evident. Why does the spatial effect that should have disappeared still exist? To solve this problem is very important for understanding the development of DFI.

From the above analysis of the empirical results of spatial correlation, we could conclude that economic development, traditional financial development, and other macro variables mainly attract surplus labor in rural areas by shaping a favorable employment environment and providing employment opportunities, thereby alleviating the urban–rural income gap. Meanwhile DFI provides impetus by improving the capability of rural residents, exposing them to employment opportunities to increase income. Compared with the attraction of the former, DFI plays a propelling role through the penetration among rural residents. In this case, the popularization and use of DFI have become a prerequisite for its effectiveness. If a spatial correlation exists in the penetration of DFI, then it may be passed on to the economic effect of

DFI. Furthermore, DFI relies on digital technology, and its essence is still financial services. Therefore, the development characteristics of digital technology and TF will be transferred to DFI. On the one hand, in areas where digital technology is deeply penetrated, residents could have more exposure to DFI services in their daily lives, thereby increasing their use. In areas with better financial development, residents are more familiar with financial services and could also increase the acceptance of DFI. Both could promote the popularization and application of DFI. On the other hand, a spatial correlation also exists between the development of digital technology and TF, which would lead to the spatial agglomeration effect of DFI. In general, the development of DFI has path dependence on the development of digital technology and TF,[2] reflecting the characteristics of spatial agglomeration.

First, the path dependence of the development of DFI has been examined. On the basis of formula (2), we take DFI as the explained variable and take one lagging period of the development of digital technology and TF as the explanatory variables. In addition, we perform the regression again. Among them, the development of digital technology is measured by the proportion of mobile phone users in the population, designated as *phone*. According to the '44th Statistical Report on Internet Development in China', the proportion of mobile internet users in China has reached 99.1%, and we believe that mobile phone penetration could properly measure the popularity degree of digital technology. One-period lagging variable reflects the influence by the established environment and the characteristics of path dependence. The regression results show that the lagging variable of digital technology development has a significant positive impact on DFI. That is, the increase in the penetration rate of digital technology could increase the popularization of DFI. In addition, the development of TF has a significant negative impact, and the possible reason is that regions with better traditional financial development have also developed better financial inclusion services, thereby squeezing the development space of DFI. However, the regression results all show that the development of DFI would have path dependence on the development of existing digital technology and the development of TF.

Second, we examine the path dependence of DFI concentration. The above study uses the Moran index calculated by panel data, and observing the dynamic changes of the Moran index is impossible. Therefore, we use annual cross-sectional data to calculate the Moran index, and Table 9 shows the results.

Table 9 shows that the Moran index of the urban–rural income gap shows a trend of increasing first and then decreasing, and significant spatial agglomeration still

Table 9. Trends of the Moran index.

	Urban–rural income gap	Digital technology development	TF development	DFI
2011	0.006	0.013**	0.017***	−0.002
2012	0.007*	0.019***	0.016***	0.005
2013	0.008*	0.011**	0.018***	0.013**
2014	0.018***	0.009*	0.019***	0.010**
2015	0.012**	0.004	0.022***	0.006
2016	0.013**	0.004	0.021***	0.009*
2017	0.011**	0.008*	0.020***	0.011**

Note: The standard errors are in parentheses. *, **, and *** indicate the significance levels of 10%, 5%, and 1%, respectively.
Source: Authors' processing in Stata15.

Table 10. Statistical comparison of Moran index.

	DFI	TF	Digital technology	The same number as TF	The same proportion as TF	The same number as digital technology	The same proportion as digital technology
2011	60	26	53	13	21.67%	35	58.33%
2012	55	28	45	14	25.46%	26	47.27%
2013	75	29	45	16	21.33%	31	41.33%
2014	76	32	49	17	22.37%	36	47.37%
2015	69	40	44	18	26.09%	28	40.57%
2016	79	37	58	17	21.52%	27	34.18%
2017	70	37	49	18	25.71%	28	40%

Source: Authors' summarize.

exists to date. Meanwhile, in addition to the sharp increase in 2012, the Moran index of digital technology has also shown a downward trend as a whole and has even tended to disappear in recent years. This case reflects that digital technology could breakthrough geographical distance restrictions. The Moran index of TF development is very significant and continues to increase, indicating that the development of TF has a high degree of financial agglomeration. The Moran index of DFI was not significant in 2011 and 2012 but rose sharply in 2013. This case may be because 2013 was recognized as the 'first year of digital finance', and DFI began to develop in an all-round way. The spatial agglomeration effect of DFI is showing a downward trend, which may also be the result of the breakthrough in digital technology. On the whole, the Moran index of DFI is more similar to that of digital technology, indicating that the spatial agglomeration effect of DFI may be more affected by the development of digital technology.

The above calculations are all global Moran indexes. We then compare the local Moran indexes calculated based on the cross-sectional data and summarize the results of the significant numbers of local Moran indexes in Table 10. When comparing the significant sample points of the Moran index of DFI with the rest two, the proportion consistent with TF development is relatively stable, with an average of 23.45%. That is, of all the municipalities where DFI is concentrated, 23.45% also have traditional financial clusters. The proportion consistent with the development of digital technology shows a continuous downward trend, but the average is still as high as 44.15%. That is, of all the municipalities where DFI is concentrated, nearly half still show the spatial agglomeration effect of digital technology development.

Consistent with the conclusions drawn in Table 9, the spatial agglomeration of digital technology development is transmitted to the application of digital technology and then to the spatial agglomeration of DFI. Although traditional financial agglomeration also has an impact, digital technology development imposes a dominant effect. The above analysis roughly shows that the spatial agglomeration of DFI would have path dependence on the development of TF and digital technology.

6. Conclusions

Is there a spatial effect on the impact of DFI on the urban–rural income gap? This study tests this question based on the panel data of 256 municipalities in China from

2011 to 2017 and analyzes it from the perspective of path dependence. The results show the following: (1) The development of DFI could effectively reduce the income gap between urban and rural areas but with spatial heterogeneity. The effect is highest in the eastern region and lower in the western region, which is also lower than the national average. In addition, the effect on the central region is the lowest; (2) The convergence effect of different dimensions of DFI is also spatially different. The effect of breadth development is consistent with the total index, and the depth of use development is generally effective, but it has no significant impact on each region. The development of digitalization has even expanded the urban–rural income gap in the eastern region; (3) DFI and urban–rural income gap show a significant positive spatial correlation; (4) The development of DFI also exhibits a spatial spillover effect and has widened the urban–rural income gap in neighboring areas when converging the local urban–rural income gap; (5) The development of DFI is path-dependent on the development of digital technology and TF, and its spatial agglomeration effect is also transmitted by the agglomeration of the two, with digital technology playing a dominant role.

7. Recommendations

Policy recommendations are proposed based on the above conclusions.

First, the development of DFI must pay attention to regional coordination. At present, the development of DFI focuses more on the impact on the local area. The development of DFI would have a spillover effect and influence the development of surrounding areas. Without coordination, the benefits brought by the development of DFI may be offset by competition from neighboring regions and even develop into a vicious circle. Therefore, it is necessary to provide regulatory insurance for the development of DFI, change the traditional thinking of fragmentations, break the constraints of the free flow of labor, build a regional overall development pattern based on the construction of urban agglomerations, and give full play to the concentration of resources, such as DFI. Promoting cross-regional economic development could help narrow the overall urban–rural and regional income gaps.

Second, the development of DFI must break the digital monopoly to benefit the people. The digital premium brought by DFI is mostly because of the increase in its coverage. In addition, the increase in the availability of financial services could alleviate financial exclusion problems to some extent. However, owing to the serious monopoly of Internet giants, DFI products are still priced highly, such as Ant Credit Pay, Ant Cash Now, and JD Baitiao. These representative products have interest rates much higher than the average bank rate, keeping low-income groups out of the door. The effect of the depth of use of financial services is not ideal. In addition, the relatively loose regulatory environment for digital finance has caused some DFI products to conceal some key information, accumulating high risks for users, and hindering the real implementation of DFI. The supervision of Internet monopoly should be strengthened to truly lower the threshold for the use of DFI, so that DFI is both 'universal' and 'beneficial'.

Finally, the development of DFI must focus on infrastructure. On the one hand, the popularization of digital technology is a prerequisite for the development of DFI services. However, China has not yet achieved full coverage of the Internet. A large gap exists in the construction of Internet infrastructure among various regions, with some remote rural areas still being excluded from the Internet world and the benefits brought by digital technology. We should take new infrastructure as the direction and vigorously carry out the construction of digital technology infrastructure, which would lay a solid foundation for the development of the digital economy while driving economic development. On the other hand, the incapability to use digital technology and financial services would also limit the use of DFI. Vulnerable groups often lack the related knowledge, resulting in an inability to take advantage of DFI, and even exclusion. While continuing the financial literacy, we should also carry out popular education activities on Internet knowledge to achieve soft guarantees for the development of DFI.

Notes

1. The definition comes from the 'G20 High-Level Principles for Digital Financial Inclusion.'
2. Path dependence refers to the inertia and self-reinforcing of technological progress and institutional change in human society.

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