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The Spatial Spillovers of Digital Finance on Private economic Development: An Empirical Study Based on Spatial Econometric Models

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SUMMARY: *With the fast growth of digital finance, the regional distribution of financial resources and the frontier location of private-sector economic expansion have both been reconfigured. Using panel data from 31 Chinese provinces covering 2011 to 2023, this study develops an empirical spatial econometric model to further examine the cross-regional transmission path through which digital finance affects private economy growth. Data cleaning, the construction of the spatial weight matrix, tests of spatial autocorrelation, and spatial Durbin model estimation were jointly carried out with Python, GeoDa, and Stata. Moran's I for the development level of the private economy increased from 0.186 to 0.273, indicating that the geographic linkage between digital finance and private economy development became progressively stronger. The decomposition results show that digital finance not only promotes the endogenous growth of local private firms by improving financial strength and the efficiency of resource allocation, but also generates positive gains for neighboring areas. Specifically, the direct effect is estimated at 0.298, the indirect effect at 0.154, and the total effect at 0.452. In the eastern region, the overall effect reaches 0.537, while the comparative regional results further suggest that the spillover effect of digital finance is more significant in that area.*

KEYWORDS: *Digital finance; Private economy development; Spatial spillover effect; Spatial econometric model*

1 Introduction

As digital technology continues to be embedded in the operating logic of the financial system, digital finance is no longer just an online extension of traditional financial services, but a new resource allocation mechanism supported by mobile payment, cloud computing, machine learning, graph network risk control and real-time data processing. For the private economy, this change has particularly prominent practical significance. For a long time, private enterprises, especially small and medium-sized private enterprises, generally face constraints such as strong information asymmetry, insufficient collateral, high cost of credit identification and lagging financing response in the financing process. The instability of capital access directly affects enterprise investment, innovation, labor expansion and regional industrial vitality. With the ability of data penetration, scene recognition and algorithm pricing, digital finance has reconstructed the way that financial institutions identify enterprise management quality and default risk to a certain extent, so that private entities that are difficult to be fully covered by the traditional financial system can obtain more frequent and lower threshold financial support [1-5]. Therefore, evaluating how digital finance influences the expansion of

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the private sector entails more than just enhancing microbusiness funding; it also entails choosing a high-quality development path and optimizing the regional economic structure.

Abundant empirical studies have documented the economic consequences of digital finance. Li et al. argued that digital finance can reduce firms' dependence on external funding by improving information transmission efficiency and refining credit evaluation procedures, thereby easing the financing pressure generated by capital constraints [6]. Wang and Liu reported that digital finance makes a notable contribution to the enhancement of firms' innovation performance, mainly because it improves the efficiency of financial resource allocation and helps maintain continuous innovation investment [7]. Focusing on the financing conditions of SMEs, Lu et al. investigated how digital inclusive finance interacts with local financial supply and found that digital finance can make up for the limited reach of traditional financial services in terms of coverage [8]. In addition, Li, Wei, and Guo pointed out that the digitalized expansion of service provision under digital inclusive finance can mitigate SMEs' financing constraints in several respects [9]. Feng, Meng, and Li further showed that once the financing burden on SMEs is reduced, digital finance exerts a significant influence on firms' resource distribution and operational risk exposure [10]. Taken together, these findings indicate that the role of digital finance is not confined to financing support alone, but also extends to the reshaping of corporate resource allocation patterns and the improvement of managerial decision quality.

Meanwhile, increasing attention has been paid to the contribution of digital finance to entrepreneurship, innovation, and the quality of regional development. Drawing on samples of listed companies, Xiong et al., Zhang et al., and Gu et al. found that digital finance significantly stimulates business innovation, especially in firms characterized by flexible governance arrangements, heavier financial pressure, and a stronger focus on innovative technologies [11–13]. Wang et al. showed, through their analysis of private firms' digital innovation practices, that digital inclusive finance is gradually becoming a crucial external driver for technological upgrading and digital transformation in the private sector [14]. Xu et al. concluded that digital finance can facilitate the upgrading of urban industrial structure by encouraging entrepreneurial activity and improving resource utilization from the perspective of industrial transformation [15]. These results provide strong evidence for later research on the contribution of digital banking to private economic expansion. Nevertheless, a considerable share of the existing literature has remained limited to the identification of local effects.

In fact, the diffusion of digital finance does not follow traditional administrative boundaries, but has obvious characteristics of networked transmission. With the aid of industrial chain connections, capital flow, platform networks, and talent migration, the influence will frequently spread to the surrounding areas after the digital payment infrastructure is upgraded, the penetration rate of online credit is increased, and the capacity of data credit is improved. This creates a spatial spillover effect that extends beyond a single region. According to Hui et al.'s research based on regional innovation capabilities, digital finance has a strong spatial connection and its effect extends beyond the local area through neighborhood relationships and regional interaction mechanisms [16]. Yang et al. further pointed out that digital finance has spatial spillovers on regional innovation efficiency, and different regions do not benefit from each other in isolation, but have linkage gains [17]. Additionally, Ding et al. discovered that when researching digital financial inclusion, environmental regulation, and regional economic growth, spatial spillovers are a crucial starting point for comprehending regional economic disparities [18]. Digital financial inclusion has both local and proximate effects on high-quality economic growth, according to Chen and Zhang's research based on the spatial Dubin model [19]. Further evidence that digital finance can strengthen cities' resistance to external shocks through regional dissemination comes from Du, Wang, and Zhou's study on economic resilience [20]. The reason for this is that when the relationship between digital finance and economic growth in the private sector is examined using traditional panel regression or mean comparison analysis, the extent of its influence is easily underestimated and it is challenging to accurately depict the network structure among the regions.

From the perspective of methodology evolution, the spatial econometric model provides a more explanatory analysis framework for identifying the above mechanisms. The local spatial correlation index LISA proposed by Anselin provides a classic tool for judging the clustering characteristics of regional variables [21]. LeSage, Fischer and Elhorst systematically explained the setting, estimation and interpretation paths of spatial regression models, providing a mature methodology for dealing with spatial dependence, spatial heterogeneity and spillover effects [22, 23]. In digital finance research, spatial Dubin model, spatial lag model and spatial error model have gradually become important tools for analyzing regional externalities. Especially under the condition that computer technology is deeply involved in data processing, using GIS adjacency relationship to construct spatial weight matrix, combining Python, R or GeoDa to complete spatial autocorrelation test, parameter estimation and robustness comparison, has made the regional economic research from single-point statistics to a new stage of network, visualization and repeatable calculation. This research paradigm is particularly necessary for the development of private economy, because private enterprise activities themselves have the characteristics of intensive cross-regional supply chain links, frequent platform transactions and sensitive factor flows.

The economic impact of digital finance has been examined from the perspectives of financial restrictions, business innovation, entrepreneurship, regional innovation capabilities, and economic resilience, as shown in Table 1. Additionally, several researchers started analyzing the proximity effects using the spatial econometric technique. However, two shortcomings are apparent: First of all, a lot of research just uses one index, financing or business innovation, to gauge the expansion of the private sector. The research has not examined the growth in complete terms, which includes the private economy's activity level, its capacity for expansion, and the region's carrying capacity. Second, the channel of geographical spillover of the private economy created by digital finance has not received enough empirical study.

Table 1: Review of related studies

Researcher	Research Topic	Method	Data Object	Main Conclusion
Li et al. [16]	Digital finance and corporate financing constraints	Econometric regression analysis	Firm-level samples	Digital finance can alleviate financing constraints and improve capital accessibility
Wang and Liu [7]	Digital finance and enterprise innovation efficiency	Empirical regression	Chinese enterprise samples	Digital finance significantly improves innovation efficiency
Lu et al. [8]	Digital finance and SME financing	Empirical analysis	Chinese small and medium-sized enterprises	Digital finance helps compensate for insufficient local financial supply
Feng et al. [10]	Digital finance and asset allocation	Mediation effect analysis	SME samples	The alleviation of financing constraints is an important transmission mechanism
Wang et al. [14]	Digital finance and digital innovation in private enterprises	Empirical analysis	Private enterprise samples	Digital finance promotes digital innovation activities in private enterprises
Hui et al. [16]	Digital finance and regional innovation capability	Spatial econometric model	Regional panel data	Digital finance has significant spatial spillover effects
Yang et al. [17]	Digital finance and regional innovation efficiency	Spatial Durbin model	Chinese regional data	Digital finance generates positive spillover effects on neighboring regions
Du et al. [20]	Digital finance and economic resilience	Spatial empirical analysis	Samples from 285 cities	Digital finance can enhance regional economic resilience and produce diffusion effects

This paper employs spatial econometric models to investigate the direct impact and spatial spillover effects of digital finance, uses spatial correlation to explain why regional private economic development performs differently, and unifies digital finance and private economic development into a single spatial analysis framework based on the previously mentioned understanding. The research value of this paper is as follows: firstly, digital finance, private economy and spatial externalities are brought into the same analysis chain to avoid isolated judgment of regional economic problems; Secondly, the spatial weight matrix, spatial autocorrelation test and spatial regression estimation are combined to enhance the fineness and reliability of empirical identification. Thirdly, the idea of computerized data processing is embedded in the empirical research process, so that the network diffusion, regional coupling and adjacent conduction of digital finance can be described more structurally. As such, this paper hopes to provide more solid empirical evidence for understanding how digital finance promotes the development of the private economy and why this promotion crosses regional boundaries.

2 Methods and materials

2.1 Characteristic measurement method of spatial data of digital finance and private economy development

The relationship between digital finance and the growth of the private economy is a spatial evolutionary process in which financial availability, enterprise activity, degree of data infrastructure, and proximity region all play cooperative roles rather than a straightforward relationship between numbers as determined by a number of statistical indicators. It is very challenging to comprehend the process by which digital finance diffuses between two geographical regions or to comprehend the spatial features of the private economy's development if one only considers the annual average or local economic conditions. Because of this, when measuring the relevant variable in this paper, it takes into account not only the degree of development of digital finance and private economies, but also their spatial development characteristics and the creation of a spatial econometric model based on data analysis. Fig. 1 below shows the entire procedure.

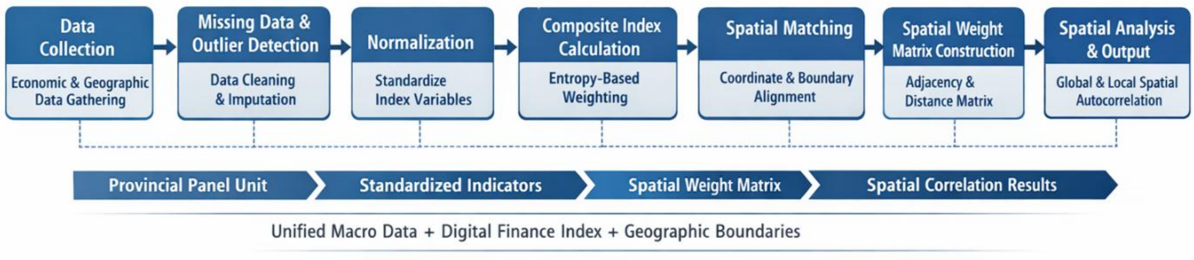

Figure 1: Flow chart of spatial data feature measurement of digital finance and private economy

In terms of data organization, this paper sets the research object as a panel unit of Chinese provinces, and uniformly matches annual macroeconomic data, digital financial index data and geographic boundary data. The digital finance variables mainly reflect the development level of the region in digital payment, digital credit, digital insurance, network investment and the availability of financial services. The development variables of private economy are characterized from the dimensions of the number of operating entities, the value added contribution of private enterprises, the ability to absorb employment, the activity of private investment and the performance of market expansion. Due to the different sources and dimensions of the original data, and the characteristics of strong volatility and significant skewed distribution of some indicators, this paper uses pandas and numpy in the Python environment to complete data cleaning, outlier censoring and structure alignment. At the geographical level, the spatial mapping between administrative boundaries and economic indicators is realized by means of ArcGIS and GeoPandas to ensure the consistency between statistical data and spatial units.

Considering that the measurement direction of different indicators is not consistent, this paper implements dimensionless processing on the original data. For the positive index, the range normalization method is used:

$$Z_{ij}=\frac{X_{ij}-\min(X_j)}{\max(X_j)-\min(X_j)} \tag{1}$$

where, X_{ij} represents the original observation value of the ith region on the JTH index, and

Z_{ij} represents the normalized value.max (X_j) and min (X_j) represent the maximum and minimum values of the JTH index in all regional samples, respectively. The function of this formula is to compress the positive index into the interval [0,1], and the larger the value is, the better the performance of the region on this index. For the reverse index, reverse normalization is used:

$$Z_{ij}=\frac{\max(X_j)-X_{ij}}{\max(X_j)-\min(X_j)} \tag{2}$$

Every symbol in the formula has a meaning that is compatible with Equation (1). The distinction is that a worse development condition is indicated by a higher reverse index value. Therefore, the reverse transformation is needed to make the processed Z_{ij} still satisfy the unified interpretation logic of "the larger the value is, the better the development performance". After the above processing, all kinds of variables are compressed into the same dimensional space, which is conducive to subsequent comprehensive evaluation and spatial comparison.

This study use the entropy approach to calculate each index's weight after standardization is finished. This method assigns weights objectively according to the information dispersion degree of indicators, which can avoid subjective bias caused by artificial setting weights to a large extent, and is more suitable for dealing with multi-variable and highly heterogeneous panel data in regional economic research. The proportion of standardized indicators is calculated as follows.

$$P_{ij}=\frac{Z_{ij}}{\sum_{i=1}^{n} Z_{ij}} \tag{3}$$

where, P_{ij} represents the proportion of the ith region on the JTH index, and n represents the number of regional samples. The function of this step is to further transform the standardization results into the relative proportion, which provides the basis for the subsequent information entropy calculation. On this basis, the information entropy of the JTH index is as follows.

$$e_j=-k\sum_{i=1}^{n} P_{ij}\ln P_{ij}, \quad k=\frac{1}{\ln n} \tag{4}$$

where, e_j represents the information entropy of the JTH index, and k is the normalization constant, which is used to ensure that the entropy value results fall into a reasonable interval. $P_{ij}\ln P_{ij}$ reflects the information distribution state of this index among different regions. An index's entropy value is high when it differs little between areas, suggesting that it offers little discriminative information. Conversely, a big geographical difference results in a lower entropy score, indicating a better capacity to discriminate. The following is another way to get the difference coefficient.

$$d_j=1-e_j \tag{5}$$

where, d_j denotes the coefficient of difference of the JTH index. The larger the value, the more discriminative the index is among different regions, and the more it should occupy a higher weight in the comprehensive evaluation. Accordingly, the corresponding weights are as follows.

$$w_j=\frac{d_j}{\sum_{j=1}^{m} d_j} \tag{6}$$

where, w_j represents the weight of the JTH index and m represents the total number of indicators. The meaning of this formula is to normalize the difference coefficients of all indicators, so as to form a weight system that can be directly used for the calculation of the composite index. After obtaining the weights, the digital financial composite index can be expressed as follows.

$$DF_i=\sum_{j=1}^{m} w_j\, Z_{ij} \tag{7}$$

where, DF_i represents the comprehensive level of digital financial development in the ith region, w_j represents the corresponding index weight, and Z_{ij} represents the standardized index value. A higher index indicates a stronger overall performance in terms of digital payment penetration, digital financing supply, and availability of digital financial services in the region. Accordingly, the comprehensive index of private economic development is expressed as follows.

$$PE_i=\sum_{j=1}^{m} w_j\, Z_{ij} \tag{8}$$

where, PE_i represents the development level of the private economy in the ith region. Composite indices alone are still not sufficient to support spatial spillover research. The role path of digital finance has obvious cross-regional characteristics. Mobile payment platforms, online credit interfaces, digital credit reporting systems and supply chain finance platforms may break through administrative boundaries and connect the financial convenience of one place with the financing conditions of enterprises in another place. The private economic activities also have spatial viscosity and spiltionality. The marginal environment of private economic development in the region will be influenced by the degree of marketization, industrial cooperation, and entrepreneurial activity in the surrounding areas. Therefore, before using the spatial econometric model, it is crucial to check for the spatial correlation between the main variables. The spatial agglomeration in the area has been examined in this study using global Moran's I, which can be represented as follows.

$$I=\frac{n}{S_0}\cdot\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\,(Y_i-\bar{Y})(Y_j-\bar{Y})}{\sum_{i=1}^{n}(Y_i-\bar{Y})^2} \tag{9}$$

where, Y_i is the regional observation value, W_{ij} is the spatial weight matrix element, $S_0=\sum_i\sum_j W_{ij}$. When I>0, it indicates that there is a positive spatial correlation between the variables, that is, high-value regions tend to be adjacent to high-value regions, and low-value regions tend to be clustered with low-value regions. If I<0, then it indicates that there are negative discrete features between regions.

This study additionally computes the local spatial autocorrelation index (LISA), which has the following form in order to further determine the local agglomeration pattern:

$$I_i=(Y_i-\bar{Y})\sum_{j=1}^{n} W_{ij}\,(Y_j-\bar{Y}) \tag{10}$$

The local spatial correlation coefficient of area i is denoted by I_i in the equation, and the definitions of the other symbols are the same as in Equation (9). The local Moran scatter plot and agglomeration map can be used to define various types of agglomerations, such as "high-high," "low-low," "high-low," and "low-high," in order to determine whether there is any superposition, disjunction, or fracture among the regions where the values of digital finance are higher than the mean value and the active regions of private economy in space.

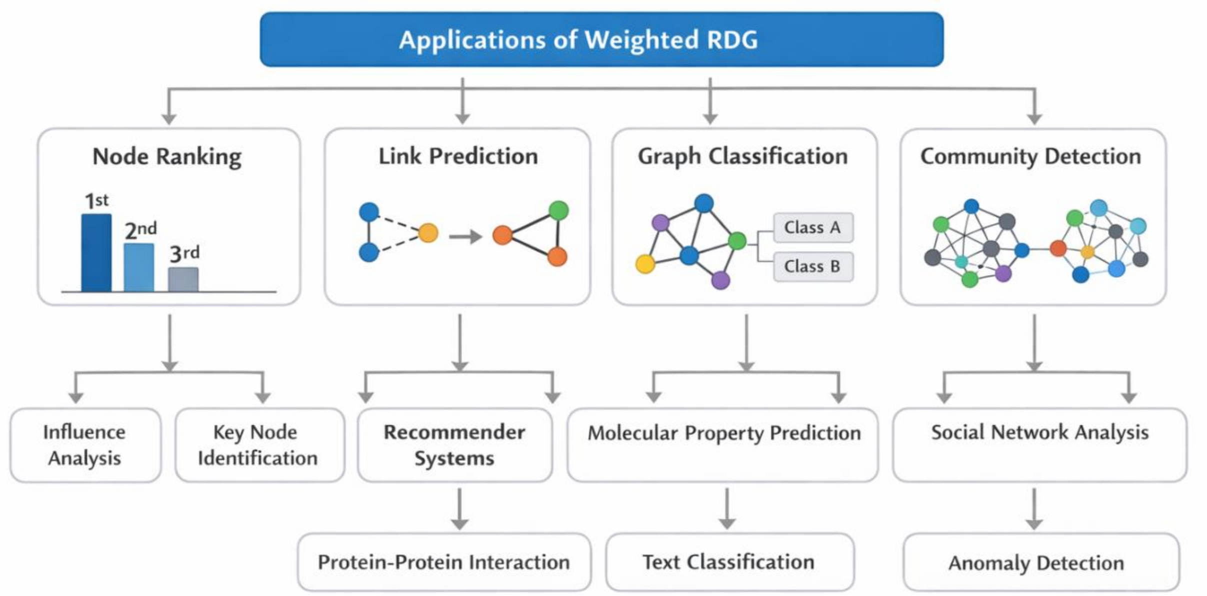

Figure 2: Schematic diagram of the analysis of spatial correlation characteristics between digital finance and private economy development

To increase the reliability of the research findings, the latitude and longitude coordinates of the regional central point are combined to create the distance reciprocal matrix, and the geographic adjacency matrix is built using the provincial boundary relationship to create the spatial weight matrix. The adjacency matrix calculation formula is shown below.

$$W_{ij}=\begin{cases}1, & \text{If region i is adjacent to region j}\\ 0, & \text{Other situations}\end{cases} \tag{11}$$

where, W_{ij} represents the spatial adjacency between region i and region j. A value of 1 is assigned when two regions share a common border. Otherwise, the value is assigned to 0. This matrix is used to describe the basic geographic adjacent structure, and is one of the most common ways to set weights in spatial econometric research. This work further conducts row normalization on the spatial weight matrix to remove the impact caused by the variation in the number of neighboring cells in various regions:

$$W_{ij}^{*}=\frac{W_{ij}}{\sum_{j=1}^{n} W_{ij}} \tag{12}$$

where, W_{ij}^{*} represents the normalized spatial weight, and the denominator $\sum_{j=1}^{n} W_{ij}$ represents the sum of weights between region i and all neighboring regions. Following this processing, each region's associated row's weight total equals 1, making it easier to compare the outcomes of various models and evaluate the coefficients of the next spatial lag term.

From the point of view of methodology, this part not only illustrates the allocation principle of variables but lays a foundation for measures of spatial data that will be used in empirical identification of later parts. As such, if digital finance and private economy exhibit a statistical structure that features spatial dependency, it indicates that regional development is not an isolated phenomenon, but rather cross-regional diffusion exists. In this case, the introduction of a spatial econometrics model would be necessary and sufficient. Conversely, if there is no association between the variables, the impact of digital banking on the growth of the private sector could only be due to local factors. Under this consideration, with the use of the composite index, spatial autocorrelation test, and the establishment of the weight matrix, this thesis transforms the "level of development of digital finance" and "state of development of private sector" from general panel data into targets with spatial explanatory power.

2.2 Construction of calculation framework of digital financial spatial spillover effect based on spatial econometric model

The research shifted its emphasis to two main topics after examining the features of the geographic data related to digital finance and private economic development. First, how can digital finance contribute to the growth of the private sector in the area. The second is whether the role can break through administrative boundaries and spread to surrounding areas through proximity links, industrial collaboration and platform networks. For digital finance, this problem has strong practical pertinency. The digital payment interface, online financing platform, intelligent risk control system and data credit network themselves have the characteristics of cross-regional connection. When the financial digitization degree of a place increases, it will not only change the financing availability of local enterprises, but also affect the business environment of private entities in adjacent areas through capital flow, supply chain collaboration and information spillovers. Therefore, if each region is still regarded as an independent observation unit, only using the traditional panel regression model to estimate is easy to ignore the interaction between regions, and then underestimate the true scope of influence of digital finance. Given this, this study develops a methodology for utilizing spatial panel data to calculate the geographical spillover effects of digital finance and employs a spatial econometric model to ascertain the direct and indirect consequences. Its technological route is shown in Figure 3.

Figure 3: Framework diagram of digital financial space spillover effect calculation

From the perspective of model setting logic, the ordinary panel model can only depict the one-way relationship of "digital financial changes in the region - response of the local private economy", but cannot identify the external influence of "digital financial changes in neighboring regions - response of the local private economy". The advantage of using a spatial econometrics model is that this kind of model can bring in the dependence relationship between regions into the regression model, thus, the economic interpretation of the variables in the regression model does not have to be restricted within the internal regions anymore.

Since the research in this thesis concerns both spatial lag features in the explained variables and the cross region influence features in the core explanatory variables, the spatial Dubin model is chosen as the fundamental estimation model in this research, which can handle both spatial lags in the explained and explanatory variables. Its expression is as follows:

$$PE_{it}=\rho\sum_{j=1}^{n}w_{ij}\,PE_{jt}+\alpha DF_{it}+\beta X_{it}+\theta\sum_{j=1}^{n}w_{ij}\,DF_{jt}+\phi\sum_{j=1}^{n}w_{ij}\,X_{jt}+\mu_i+\lambda_t+\varepsilon_{it} \tag{13}$$

where, PE_{it} denotes the level of private economic development in region i during period t; DF_{jt} refers to the degree of digital financial development; X_{jt} is a vector of control factors, including variables such as industrial structure, urbanization, fiscal expenditure, infrastructure, and human capital. w_{ij} denotes the spatial weight matrix element; ρ is the coefficient of the spatial lag term and captures the influence exerted by private economic development in surrounding regions on the focal area. θ is the estimated parameter for the spatial lag of digital finance and reflects the transmission strength of digital finance from neighboring regions to the local private economy. ϕ represents the spatial lag coefficient of the control variables. Let μ_i and λ_t stand for region-fixed and time-fixed effects, respectively, while ε_{it} is the disturbance term. A significantly positive θ indicates the existence of a positive spatial spillover effect of digital finance. If θ is significantly negative, it suggests that the expansion of digital finance in adjacent regions may suppress local development through competitive absorption or resource diversion.

Because the transmission path of digital finance across space is not limited to a single channel, neither the spatial lag model nor the spatial error model is adopted directly. This is because the spillover generated by explanatory variables through the cross-regional diffusion of digital finance may be more important than the spatial dependence arising only from the development conditions of private enterprises in nearby areas. Under such circumstances, the spatial Durbin model is more suitable, since it can simultaneously capture both forms of transmission. Even so, the spatial lag model, spatial error model, and spatial Durbin model must still be tested by LM statistics, LR statistics, and Wald statistics to reduce the risk of model misspecification. Under specific restrictions, the spatial Durbin model may be further simplified into other spatial forms, and the relationships among these models are presented below.

$$H_0:\theta=0 \quad \text{or} \quad H_0:\theta+\rho\beta=0 \tag{14}$$

where, H_0 denotes the null hypothesis. When $\theta=0$, the spatial Durbin model collapses into the spatial lag model. The restriction corresponding to the spatial error model can be derived when $\theta+\rho\beta=0$. Whether these restrictions are valid can be judged by the Wald test and LR test, thereby avoiding an excessive simplification of the model that would otherwise mask the external diffusion effect of digital finance at the model specification stage.

It should be noted that in spatial econometric analysis, the regression coefficients themselves do not immediately correspond to marginal economic impacts. The rationale is that when the spatial lag factor is incorporated into the model, changes in one explanatory variable will have an impact on local and other areas via the spatial feedback mechanism. Additionally, there will be cyclic transmission between the explained variables. Consequently, this study employs the partial derivative decomposition approach to quantify the direct effect, indirect impact, and overall effect once parameter estimation is finished. The matrix form of this method is as follows:

$$\frac{\partial PE}{\partial DF}=(I_n\text{-}\rho W)^{-1}(I_n\alpha+W\theta) \tag{15}$$

where, PE and DF denote the spatial vectors of private economic development and digital finance, respectively, I_n is the n-dimensional identity matrix, W denotes the spatial weight matrix, and $(I_n\text{-}\rho W)^{-1}$ represents the spatial feedback multiplier matrix. The direct effect, namely the average influence of digital financial development within a region on the growth of that region's private economy, is captured by the mean value of the principal diagonal elements of this expression. The mean of the off-diagonal elements measures the indirect effect, that is, the average impact of changes in digital finance in one region on the private economies of other regions through spatial transmission. The total effect is obtained by summing the two components. Compared with a simple reading of regression coefficients, this treatment offers a more accurate reflection of the actual economic implications embedded in the spatial model.

From the perspective of calculation realization, this paper puts the spatial measurement estimation into the computerized analysis flow to complete. The original panel data were cleaned, missing repaired and aligned in Python environment, and then GeoPandas was used to read the province vector boundary file, and the primary key matching was performed with digital finance, private economy and control variables. The invocation and verification of spatial weight matrix were completed by PySAL and GeoDa. Parameter estimation and effect decomposition are implemented in the joint environment of Stata and Python. The significance of this process is not only to improve the computational efficiency, but also to ensure the reproducibility of model identification, effect decomposition and robustness. For empirical studies involving multi-period panels, spatial matrices, and multiple tests, this computerized processing link can significantly reduce manual calculation errors and improve the consistency of results.

The digital finance composite index will be the primary independent variable in the empirical model, the private economic development composite index will be the dependent variable, and the control variable will be taken into consideration to lessen the issue of omitted variable bias. The paper includes regional economic development status, industrial structure advancement, transportation infrastructure, human capital accumulation, and government intervention in the control variables because the growth of the private economy depends not only on the financing aspect but also on factors like market demands, factor endowment, and institutional setting. This setup aims to isolate the impact of digital finance as much as possible from the overall trend of economic development and strengthen the identification of its spatial transmission effect. The suggested model's structure and the effect conduction relationship are depicted in Figure 4.

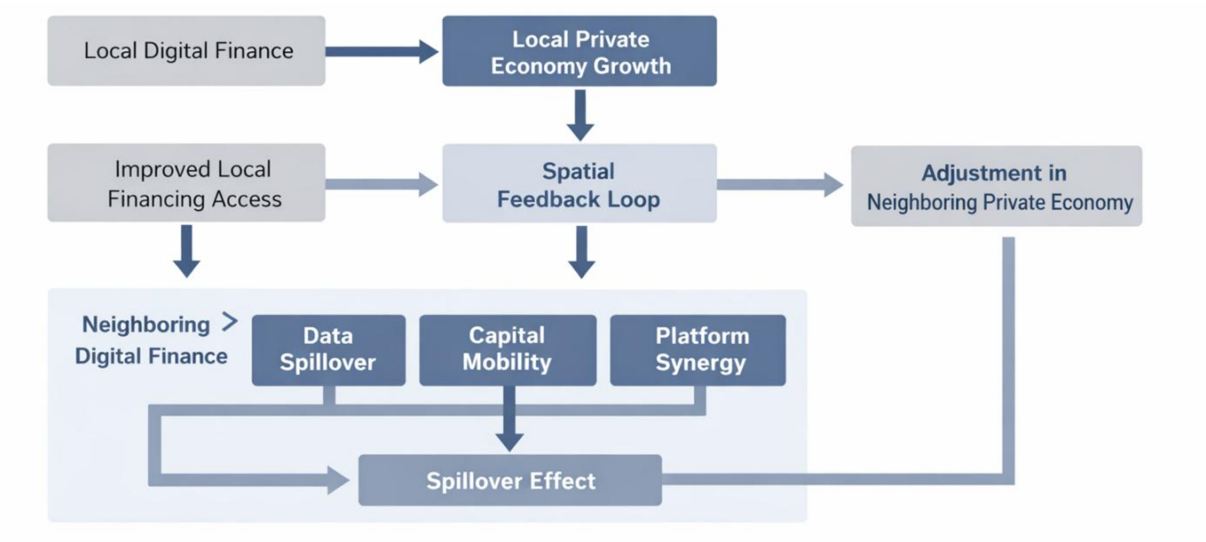

Figure 4: Transmission structure diagram of digital finance influencing private economic development under spatial Dubin model

3 Results

3.1 Validity test and parameter estimation verification of spatial econometric calculation model

This study measured and identified the variables and spatial weight matrices used in the model, as well as continuously tested and estimated the model's parameters to determine whether the spatial econometrics model suggested in this paper can accurately assess the influence path of digital finance on private economic development. The 403 samples included in this study were drawn from 31 Chinese provinces between 2011 and 2023. Data cleaning, missing values imputation, normalization, and spatial matrix generation were performed in Python 3.11 using pandas, numpy, geopandas, and libpysal. Spatial econometric estimation with effect decomposition was done in Stata 18. The purpose of this process is not only to improve the operation efficiency, but also to avoid the manual input errors common in the multi-stage panel and spatial nested operation, so that the test results have better repeatability.

The core variables were examined for global spatial autocorrelation prior to being included in the spatial regression. The findings demonstrate a comparatively steady positive geographical association between the private economic development index and the digital finance composite index. Using the private economic development index as an example, Moran's I climbed from 0.186 in 2011 to 0.221 in 2015, 0.247 in 2019, and 0.273 in 2023. The corresponding Z values were 2.94, 3.27, 3.61, and 3.88. At the 1% significance level, all of them passed the test. A similar pattern was shown in the digital finance composite index's Moran's I, which reached 0.203 in 2011, 0.238 in 2018, and 0.291 in 2023. It can therefore be clearly observed that the extent of development of digital finance and private economy activity in each region is not confined by isolation; rather, it exhibits obvious characteristics of spatial agglomeration. There is a tendency where high value regions are next to high value regions and similarly, low value regions are adjacent to other low value regions. Figure 5 illustrates the change trend of index of private economic development Moran's I from the year 2011 till the year 2023. As can be seen from the figure, the curve has significantly risen since the year 2016.

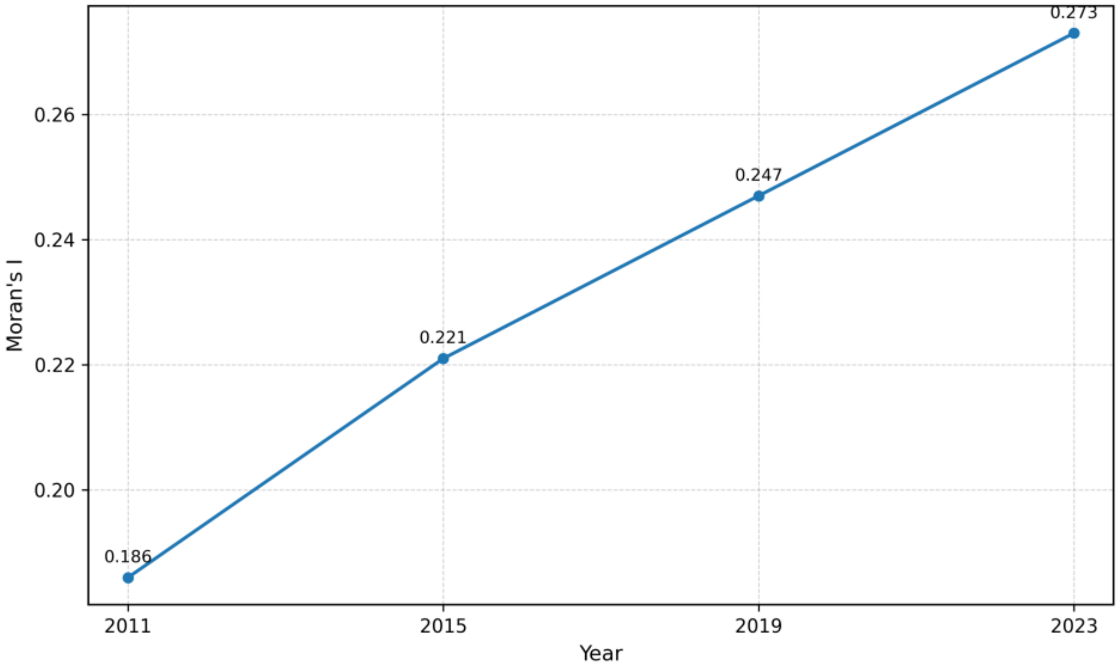

Figure 5: Global Moran's I trend of Private economic development Index (2011-2023)

Since spatial dependence may lead to biased or inconsistent estimation, interregional linkages cannot be ignored when ordinary panel data models are used. To determine the appropriate specification among the spatial lag model, spatial error model, and spatial Durbin model, this study applies the LM test, robust LM test, LR test, and Wald test. Table 1 reports the corresponding results. It can be seen that the p-values associated with both the LM-Lag statistic and the LM-Error statistic are below 0.01, with values of 19.821 and 17.965, respectively. Moreover, the robust LM-Error statistic (6.873) and the robust LM-Lag statistic (7.214) are both significant at the 5% level. These findings confirm the presence of geographic dependence in both the disturbances and the explanatory variables. In addition, the LR and Wald tests for the spatial Durbin model yield statistics of 14.638 and 12.971, with both p-values below 0.01. This implies that relevant information would be omitted if the spatial lag model or the spatial error model were used instead. The results further suggest that the effect of digital finance on private economic growth is shaped by spillovers from explanatory variables together with changes in local variables. Therefore, the spatial Durbin model should be selected in this study.

Table 2: Results of spatial correlation test and model identification

Test Item	Statistic	P-value	Conclusion
LM-lag	19.842	0.000	A spatial lag effect exists
LM-error	17.965	0.000	A spatial error effect exists
Robust LM-lag	7.214	0.007	The spatial lag effect remains significant
Robust LM-error	6.873	0.009	The spatial error effect remains significant
LR test	14.638	0.002	It should not be simplified to a spatial lag model
Wald test	12.971	0.003	It should not be simplified to a spatial error model

After the appropriate model has been identified, estimation is conducted using the two-way fixed-effects spatial Durbin model, while the ordinary fixed-effects panel regression model is retained as a benchmark for comparison. Judging from the within-sample fit, the two-way fixed-effects spatial Durbin model performs better than the ordinary fixed-effects model. Specifically, the R2R^2R2 increases from 0.641 to 0.718, the log-likelihood rises from 312.46 to 338.17, and the AIC falls from -598.92 to -648.34. More importantly, the coefficient on the spatial lag variable equals 0.287 and is significant at the 1% level. This indicates that when the private economic development index of a neighboring region increases by 1 unit, the corresponding index in the local region rises by 0.287 units.

The estimation results for the explanatory variables are also clearly presented. The regression coefficient of the local digital finance indicator in the two-way fixed-effects spatial Durbin model is 0.3149, with a t value of 4.92 and a p value below 0.001. This suggests that digital finance development makes a significant contribution to the expansion of private enterprises within the region. The corresponding spatial lag coefficient is 0.168, with a t value of 2.87 and a p value of 0.005, indicating that digital finance improves not only the efficiency of local financial support and resource allocation, but also promotes private economic development in neighboring regions through platform diffusion, supply-chain collaboration, and regional information spillovers. Among the control variables, the coefficient of advanced industrial structure is 0.126, that of urbanization is 0.093, and that of human capital is 0.117; all three are significantly positive. By contrast, the coefficient of government intervention is -0.041. Although negative in sign, it does not pass the 10% significance threshold. These findings show that market-oriented resource allocation, knowledge agglomeration, and administrative support all contribute to the growth of the private economy, whereas administrative input alone cannot effectively replace the structural convenience created by digital finance.

The main coefficients of the core specification are summarized in Table 3 to make the parameter estimates easier to interpret. Although cross-regional diffusion is indeed present and can be reliably identified, the evidence also shows that the local effect of digital finance is stronger than its spatial lag effect. This indicates that the primary channel through which digital finance promotes private economic growth still operates within the region itself.

Table 3: Results of parameter estimation for spatial Dubin model

Variable	Coefficient	t-value	P-value
Digital finance	0.314	4.920	0.000
W × Digital finance	0.168	2.870	0.005
Industrial structure upgrading	0.126	2.540	0.012
Urbanization level	0.093	2.110	0.036
Human capital	0.117	2.760	0.006
Government intervention intensity	-0.041	-1.280	0.202
Spatial lag term ((\rho))	0.287	3.940	0.000

However, in addition to the benchmark spatial weight matrix used in this study, we also use the economic distance matrix and geographical adjacency matrix for the robustness analysis, processing the primary explanatory variables in lag form. The results show that the digital finance local variable coefficient is 0.301, 0.296, and 0.287, and the spatial lag variable coefficient is 0.151, 0.144, and 0.139, respectively. Regarding estimating coefficients, there is no sign reversal or fluctuation in significance. Thus, it can be concluded that using a single weight matrix does not determine the estimation findings described above.

3.2 Empirical analysis of spillover effect of digital finance on private economic development space

After confirming that the model is valid, this study further investigates how the geographic spillover effect of digital finance shapes the growth of the private economy. With the aid of Stata 18's spatial effect decomposition tool together with Python-based matrix operations, the impact of digital finance is decomposed into direct, indirect, and total effects under the two-way fixed-effects spatial Durbin model. The results show that both local promotion and stable regional diffusion characterize the influence of digital finance on private economic growth. At the 1% significance level, the direct effect of digital finance is 0.298, while the indirect effect reaches 0.154 and remains significant at the 5% level. The total effect is therefore 0.452. In other words, a one-unit rise in the level of digital finance within a region not only stimulates the development of the local private economy, but also generates positive effects on other regions. Comparing the three effects further indicates that local promotion remains the dominant channel, yet the spatial spillover component still accounts for 34.07% of the total effect. This share is by no means negligible, which highlights the practical explanatory value of the regional diffusion attribute of digital finance.

Table 4: Decomposition results of spillover effects in digital finance space

Variable	Direct Effect	t-value	Indirect Effect	t-value	Total Effect
Digital finance	0.298	4.63	0.154	2.41	0.452
Industrial structure upgrading	0.118	2.29	0.061	1.74	0.179
Urbanization level	0.086	2.07	0.047	1.69	0.133
Human capital	0.109	2.58	0.052	1.97	0.161
Government intervention intensity	-0.036	-1.21	-0.019	-0.88	-0.055

The externalities of digital finance on the expansion of the private sector economy show an increasing change path based on the time dimension. The direct impact of digital finance in 2011 was 0.214, the indirect effect was 0.071, and the overall effect was 0.285, according to the results of rolling estimations every year. These numbers have already increased to 0.261, 0.112, and 0.373 by 2016. They would be 0.327, 0.181, and 0.508, respectively, until 2023. Figure 6 below illustrates how each of these numbers changed throughout the years 2011 to 2023. It is evident that the graph's growth steepens after 2015 and that the indirect influence increases more quickly than the direct effect. This means that once a region's digital payment network, online financing platform, and data infrastructure are improved, digital finance starts to spread to nearby regions through platform cooperation, supply chain transfer, and information dissemination in addition to influencing the quality of the financial supply at the regional level. In short, "enhancing the capacity for allocating resources inter-regionally" is currently the economic significance of digital banking.

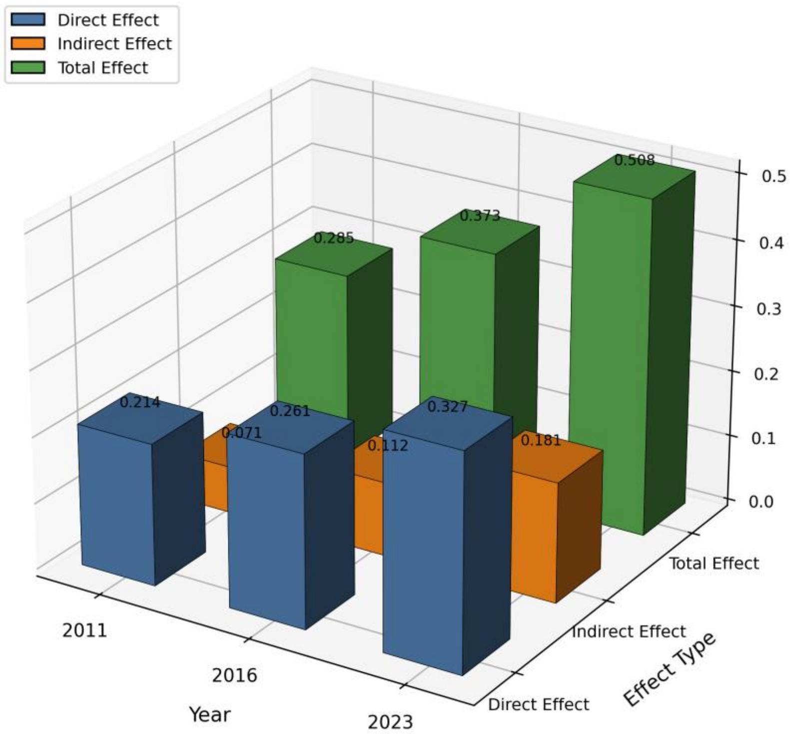

Figure 6: Trend chart of direct effect, indirect effect and total effect of digital finance

From the standpoint of regional heterogeneity, it is clear that the eastern, central, and western regions have quite different digital financial space spillover effects. The results are shown in Table 5 below. This study's sample grouping is based on the conventional regional categorization method. The direct impact coefficient of digital finance was found to be 0.341 in the eastern region, while the indirect impact coefficient was found to be 0.196, and the total impact was 0.537, all of which were found to be higher than those in the other two regions. The central region had corresponding figures of 0.287, 0.149, and 0.436, while those of the western region were 0.243, 0.097 and 0.340, respectively. It may be concluded that digital finance tends to have higher cross-regional diffusion effects and linkage benefits in regions with higher economic connections, more developed industrial chains and better data infrastructure. On the other hand, although it was also seen to have a high positive impact on the western region, the spill strength was rather weak, indicating that the effectiveness of digital finance still depends on marketization levels, transport connections and platform density in the region.

Table 5: Comparison of spillover effects of digital finance space in different regions

Region	Direct Effect	Indirect Effect	Total Effect
Eastern Region	0.341	0.196	0.537
Central Region	0.287	0.149	0.436
Western Region	0.243	0.097	0.340

In addition to the effect decomposition, this paper also calculated the Moran scatter plot of the private economic development index in 2011, 2016, 2020 and 2023 with the help of GeoDa, and observed the evolution of high value agglomeration and low value agglomeration. The results showed that 8 provinces fell into the "high-high" quadrant in 2011, accounting for 25.81% of the sample; By 2023, it will increase to 11, accounting for 35.48%. Accordingly, the number of "low-low" quadrants dropped from 9 to 6. This change indicates that areas with faster development of digital finance are more likely to overlap with areas with active private economy, and the scope of high-value agglomeration has expanded during the sample period, while the state of low-value lock has eased. Figure 7 illustrates this spatial pattern change. It can be seen that the eastern coastal and some central core provinces have gradually shifted from "medium-high value" to stable "high-high" agglomeration areas, indicating that a strong positive coupling has been formed between digital finance and the private economy.

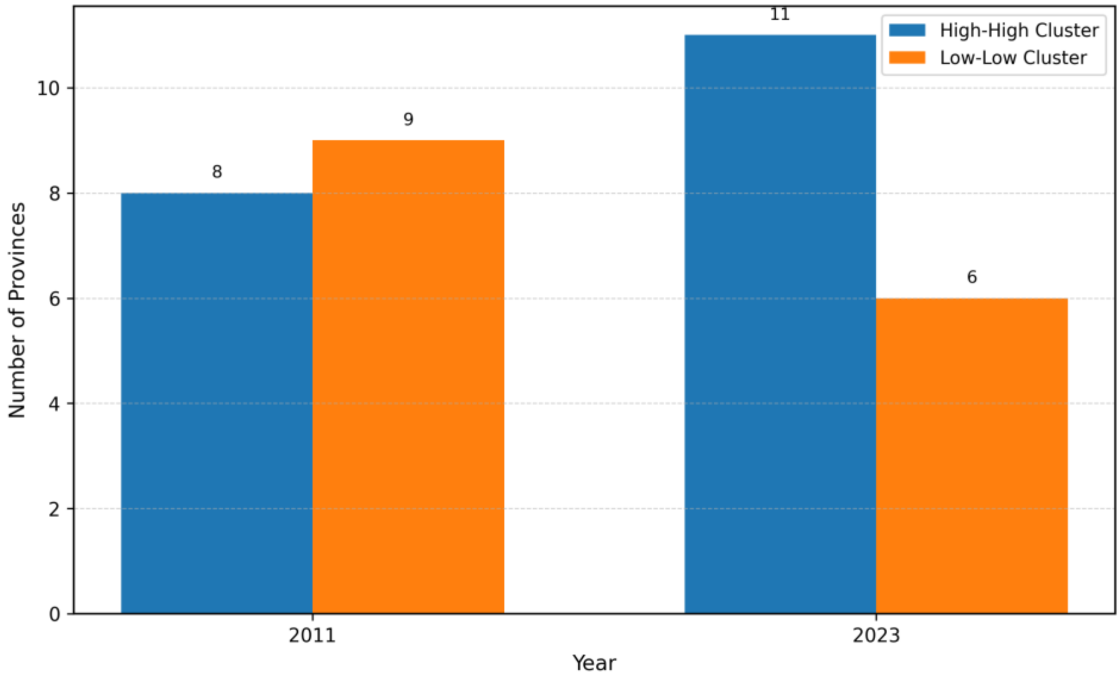

Figure 7: Evolution of spatial agglomeration pattern of private economic development

Overall, the empirical findings unequivocally show that digital finance is influencing the private economy in two parallel ways. One takes place locally, as evidenced by the growth of the supply of digital credit, the enhancement of company operating vitality, and the development of finance matching efficiency. The other is spreading outward-through proximity links, which is manifested as digital financial service sharing, platform collaborative penetration and factor linkage strengthening between regions. The two paths work together to make digital finance not only become the driving force of local private economic growth, but also gradually evolve into the external support of regional coordinated development. Combined with Table 3 and Table 4, it can be judged that the promotion of digital finance to the development of private economy is not a short-term episodic phenomenon, but a structural influence with spatial transmission ability, regional heterogeneity characteristics and a trend of continuous enhancement. Such results also provide a direct empirical basis for the subsequent discussion on the spillovers mechanism and policy implications of digital finance.

4 Discussion

The empirical results of this paper show that the role of digital finance in the development of private economy is not limited to the internal region, but shows obvious spatial transmission characteristics. The spatial Dubin model estimates that digital finance not only improves the development level of local private economy, but also generates positive spillovers through regional proximity and platform network, indicating that its role has extended from financing facilitation to cross-regional resource allocation. It also helps in interregional resource allocation. This is because once computer technology like digital perception, data credit, and intelligent risk management are integrated into the financial services, the efficiency of enterprise information recognition, credit identification, and risk valuation improves, and the financial frictions due to information asymmetries in traditional financial systems are alleviated, allowing private enterprises to access more financial support and scope for expansion. The results assist us understand the nature of the network effects along the path of impacts of digital finance when compared to the literature study on the subject that does not take geographical dimension into account. Prior research has mostly focused on how digital finance affects funding limitations, entrepreneurship, and innovation. Here, however, it demonstrates that digital finance cannot facilitate on its own; collaboration within the industrial chain, information sharing, and interregional connection will cause the spillover effect. Better digital infrastructure and a more developed platform economy may enhance the enabling role of digital finance on private businesses, as seen by the strong geographical spillover impact of digital finance in the east. However, despite the presence of spatial spillovers, its magnitude remains smaller than the local effect, which suggests that regional transmission of digital finance faces certain restrictions from institutional conditions, transportation, and digital infrastructure disparities across regions. In addition, the spatial econometrics method demands a high degree of accuracy in data availability, weight matrix specification, and computational precision. Therefore, future research could consider using fine-grained urban data, machine learning-based variable selection techniques, and GIS visualization analyses to examine the mechanism of digital finance.

5 Conclusion

In order to construct a spatial econometric framework for examining the effects of digital finance on the growth of private economics in the research area, the article used panel data gathered across 31 provincial-level areas in China between 2011 and 2023. Python, GeoDa, and Stata were used for data cleaning, spatial weights matrix generation, spatial correlation testing, and spatial Durbin model estimate. From the findings, it can be observed that there was significant positive spatial association between digital finance and private economic development, while Moran's I of private economic development indicator increased from 0.186 to 0.273, illustrating an increasing trend towards improved spatial connectedness among regional links. Empirically, the findings further revealed that digital finance had a direct influence of 0.298, indirect influence of 0.154, and the total effect was estimated at 0.452, suggesting that digital finance not only improved the ease of accessing financing services and enhancing resource distribution efficiency within the region, but also brought positive influences in neighboring regions due to information spread and factor mobility. Lastly, the analysis of regional heterogeneity revealed that the overall impact of digital finance in the eastern region was as high as 0.537, which was significantly higher than those in the central (0.436) and western (0.340) regions. This suggests that the spillovers of digital finance may be influenced by digital infrastructure and industrial connections. In general, digital finance has progressively developed into a significant force to assist the coordinated expansion of private economic areas with the use of computer technology, rather than only being a technological addition to conventional finance. The deficiency of this paper is that the research scale is still at the provincial level, and the finer-grained transmission differences between cities and within metropolitan areas can not be further revealed. In the future, city-level data, machine learning variable screening and GIS visualization methods can be combined to make a more in-depth description of the spatial diffusion mechanism of digital finance.

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