JOURNAL OF ECONOMICS AND SUSTAINABILITY
https://e-journal.uum.edu.my/index.php/jes

How to cite this article:
Guo, X. & Gao, X. (2024). The impact and heterogeneity of digital inclusive finance development on poverty alleviation: based on county-level panel data in Jing-Jin-Ji Region. *Journal of Economics and Sustainability, 6*(1), 20-40. https://doi.org./ 10.32890/jes2024.6.1.2

THE IMPACT AND HETEROGENEITY OF DIGITAL INCLUSIVE FINANCE DEVELOPMENT ON POVERTY ALLEVIATION: BASED ON COUNTY-LEVEL PANEL DATA IN JING-JIN-JI REGION

[1]Xiaohui Guo, [2]Xiaokun Gao
[1,2] *School of Economics, Hebei University*

Corresponding author: nlmh6@126.com

Received: 15/11/2021 Revised: 21/12/2022 Accepted: 17/9/2023 Published: 31/1/2024

ABSTRACT

Based on county-level panel data from 2014 to 2017 in Jing-Jin-Ji region, this paper employs SDEM model to analyze the impact and heterogeneity of digital inclusive finance on poverty alleviation. The results show that, first, digital inclusive finance exerts significant poverty alleviation effect, and this effect focuses on local region, having no apparent spillover effects on neighborhood counties. Second, the poverty alleviation effects of digital inclusive finance are heterogeneous, the effects of index of Coverage and Usage, and basic, upgraded and supported digital finance service are different in Jing-Jin-Ji, Hebei and Poverty Area Samples. Third, digital inclusive finance exerts bigger poverty alleviation effect on the less developed region and poverty region, showing the effect of Corner Overtaking.

Keywords: Jing-Jin-Ji; digital inclusive finance; poverty alleviation; Heterogeneity.

INTRODUCTION

The complete eradication of absolute poverty requires substantial financial support, and the stabilization of poverty eradication and the alleviation of relative poverty need even more sustained financial support.In contrast,the sustainability of China's existing financial instruments for poverty reduction is generally inadequate. At the heart of the issue, vulnerable groups such as people emerging from poverty, low-income classes, and micro and small businesses have low and volatile incomes, missing or insufficient property that can be used as collateral and security, and irregular finances, resulting in more significant risks and higher risk identification costs. Financial institutions have adequate incentives to reduce poverty due to the high costs, risks, and low returns of investing financial resources.

Financial poverty alleviation is based on financial support to the poor. Financial subsidies partially subsidize the cost to leverage financial resources to participate in poverty alleviation, which has achieved good results in poverty alleviation. However, the method of financial subsidies does not significantly solve the problem of high costs of financial poverty alleviation. Without the support of government financial funds, the financial poverty alleviation would not be sustainable. (Zhou Mengliang, 2018; Guo et. al., 2020) Without government funding, the sustainability of the financial poverty reduction strategy is uncertain. Inclusive finance seeks to provide appropriate and effective financial services to disadvantaged groups and micro and small businesses at a reasonable cost to reduce financial exclusion and increase financial inclusion. Inclusive finance has anti-poverty properties, but under the traditional financial model of implementing inclusive finance through physical branch, institutional, and personnel expansion, it is extremely difficult to reduce costs on the supply side, and the endogenous motivation of financial institutions to reduce poverty remains insufficient (Ding Jie, 2015; HeDexu and Miao Wenlong, 2015; Song Xiaoling, 2017; Xing Yan, 2016; Dong Yufeng et al., 2020) Reducing costs on the supply side is challenging, and financial institutions currently lack significant endogenous capacity to eliminate poverty. Lulei(2014) have proposed the "paradox of inclusive finance" to illustrate the contradiction between conventional financial development and inclusive finance. (Lulei，2014), from the perspective of the market mechanism alone, the traditional financial model for the developing inclusive finance is not necessarily the best course of action.

In recent years, digital finance and fintech have flourished, exploring a possible path for the growth of inclusive finance. Digital finance aims to use digital technologies such as big data, cloud computing, blockchain, and artificial intelligence to expand inclusive finance. The sharing, convenience, low cost, and low threshold characteristics of digital finance give it a natural advantage in the development of inclusive finance. First, digital inclusive finance is powered by digital technology, employs smart devices such as mobile phones as carriers, and depends on mobile internet to give financial services to the poor at any time and place. (Song Xiaoling, 2017; Dong Yufeng and Zhao Xiaoming, 2020) Second, the integration of digital finance with various scenarios, aided by digital technologies such as big data, cloud computing, and blockchain, fully exploits the realization value of data from e-commerce, social networking, and payment, big data risk control reduces credit costs and risk costs. (Qiu Zhaoxiang and Xiang Xiaojian, 2018; Huang Hao, 2017). It is evident that digital inclusive finance relies on digital technology to successfully reduce costs on the supply side of inclusive finance, greatly enhancing the sustainability of financial poverty reduction.

Digital finance has profoundly altered how users access financial services. Smartphone owners proficient with mobile internet have access to digital banking services. With the use of digital technology, digital financial inclusion expands the reach of services to remote and impoverished communities, and other places where traditional financial services are lacking. Developing output can help farmers increase their income and better their own lives, fulfilling the goals of reducing poverty and boosting revenue. Digital finance simultaneously improves the convenience of financial transactions, reduces the cost of banknote wastage and financial transaction fees, and helps to improve the user experience and generate user income. Consequently, this study presents hypothesis 1: Digital financial inclusion development can reduce poverty by enhancing the use and ease of financial services for consumers and expanding financial services coverage.

Financial inclusion is predicated on ensuring that all socioeconomic classes have equal access to and enjoyment of financial services. (Li Jianjun et al，2020）. On the supply side, digital inclusive finance enables equal access to financial services for individuals who have been pulled out of poverty and farmers in rural locations.Still their ability to grab the opportunity and accomplish poverty reduction and income development is contingent on their financial capability. Access to digital financial services still needs farmers to possess a minimum level of financial literacy, although the rise of digital finance has drastically lowered the financial barrier. Different regions have different levels of economic development and financial ecosystems, and the digital infrastructure and financial literacy of farmers vary greatly, which inevitably leads to differences in the extent to which farmers use digital financial services in different regions, and thus differences in the effectiveness of different types of digital financial services in reducing poverty in different regions. Consequently, this study presents hypothesis 2: There is variation in the efficiency of various dimensions and types of digital financial services in reducing poverty in multiple locations.

As long as they have mobile internet and smart devices, farmers in distant places have the same access to digital financial services as those living in major cities. However, digital finance cannot be formed out of thin air, and its development is still contingent on the economic and financial development state of the local community (Guo et al. 2020). Different regions are at various stages of economic and financial development, and there are gaps in the level of development of digital inclusive finance; however, these gaps are gradually closing because the good geographical penetration of digital inclusive finance enables backward regions to enjoy relatively more financial services (Guo et al., 2020). This study claims that digital financial inclusion is the most efficient means of achieving this objective. Consequently, this research suggests hypothesis 3: digitally inclusive financial development contributes more significantly to poverty reduction in formerly impoverished regions than in wealthier regions.

The majority of China's poverty-reduction regions are distinct hardship zones with vastly different geographical locations and poverty-reduction characteristics. Therefore, it is more pertinent to examine the topic of sustainable poverty eradication from a regional standpoint. As one of the most important regional development engines in China, the Beijing-Tianjin-Hebei region has two special hardship areas intersecting within its jurisdiction, the Yanshan-Taihang Mountains and Heilonggang, and has been affected by the capital's siphoning effect for many years, forming an anti-poverty belt around Beijing. There is less literature on digital inclusion and financial poverty reduction using counties as the basic unit, with most literature using provinces as the unit (Liu Jinyi and Liu Chunyang, 2020; song Xiaoling, 2017; Li Muchen et al., 2020; Chen Huiqing et al., 2021; Huang Qian et al., 2019), and the averaged provincial data obscures the actual situation in counties. The Peking University Digital Financial Inclusion Index of China employs the county as the smallest unit, and there is a mismatch between county data and microdata. The possible marginal contributions of this paper are: firstly, from a regional perspective, combining counties with spatial factors such as spatial distance and geographical location, and using counties as the basic unit to explore the relationship between digital inclusive finance development and poverty reduction in the Beijing-Tianjin-Hebei region, providing more practical county evidence for the study of the relationship; secondly, this paper argues that the "contagion effect" is the driving force behind the relationship between digital inclusive finance development and poverty reduction in the Beijing-T Therefore, error correlation effects are more acceptable than dependent variable interaction effects for inclusion in the empirical model.

EMPIRICAL RESEARCH DESIGN

Model Setting and Selection of Variables

The first law of geography argues that everything is interconnected, with closer things being more connected than distant ones. (Tobler，1970) There is typically a high geographical association between surrounding counties with the same economy, and the sample data looks comparable. The sample is now more suited for spatial econometric models. This paper uses sample data from 129 county units in the Beijing-Tianjin-Hebei region from 2014 to 2017 to construct a spatial panel model (including 124 counties in Hebei province and 5 districts in Beijing-Tianjin) to examine the relationship between digital inclusive finance and poverty reduction. Following Lee and Yu (2010), the spatial panel model was constructed as follows.

$$y_{it} = \lambda W y_{it} + X_{it}\beta + c_i + u_{it} \qquad (1)$$

$$u_{it} = \rho M u_{it} + v_{it} \qquad i = 1,2,\dots,n \qquad t = 1,2,\dots,T \qquad (2)$$

W and M are n× n space weight matrices, while and λ, β ,and ρ are unknown coefficients. yit is the interpreted variable, while Xit is the interpreted variable that may contain both the general interpreted variable and the space-lagged solved variable WZit. Ci for individual effect, uit, and vit for spatial lag error term and residual vector under the assumption that vit is independent and identifiably distributed (i.i.d.) with variance Σ2. In the spatial econometric model, the spatially lagged dependent variable WY and the independent variable WX describe the impact of the surrounding area's dependent variable and the independent variable on the local area, the spatial lag error. Wu represents the impact of unobservable elements or causes on the region. SAR, SEM, and SLX models contain just one spatial lag term (WY, Wu, and WX), but SDM, SAC, and SDEM models have two (WY and WX, WY and Wu, WX and Wu) ,and the GNSM model contains all three terms simultaneously. This research, the spatial panel model is estimated using QML (Quasi-Maximum Likelihood, Maximum Likelihood approach) (Lee and Yu, 2010a, 2010b).

In this paper, the per capita disposable income of rural residents in counties is used to measure the explanatory variable county poverty, and the Peking University Digital Inclusive Finance Index is selected to represent the core explanatory variable county digital inclusive finance development level, which is compiled using data from Ant Financial Services and comprises 24 indicators across three dimensions: breadth of coverage, depth of use, and degree of digitalization. In addition, it measures digital payment, digital finance, digital credit, digital investment, and digital insurance. (Guo et. al., 2020)

This study provides economic growth factors, government behavior factors, and human capital factors as control variables based on economic growth poverty reduction, developmental poverty alleviation, and human capital theory. (Xu Yuebin et al. , 2007; Wang Sangui, 2018; he Xuefeng, 2018）. The economic growth factor is determined by the per capita gross domestic product, the degree of opening up to the outside world, the industrial structure, and the urbanization level. The governmental behavior component is reflected by the county's amount of financial assistance for agriculture and digital infrastructure development. The human capital element is determined by the level of educational advancement and social security. Table 1 provides detailed variable explanations and descriptive data. All of the statistics in this report come from the Beijing, Tianjin, and Hebei statistical yearbooks, the rural statistical yearbook, and the China county statistical yearbook.

Table 1

Description of variables and descriptive statistics

Variable name	Variable symbols	Measurement indicators	N	Avg. Value	Standard dev.	Min	Median	Max
Poverty	Income	Per capita disposable income of rural residents by county (in logarithms)	516	9.241	0.326	8.414	9.295	10.026
Digital inclusive finance index	Index	County Digital Financial Inclusion Index (Original Index/100)	516	0.736	0.215	0.152	0.805	1.161
Level of economic growth	GDP	GDP per capita by county (in logarithms)	516	10.284	0.503	9.251	10.238	11.782
Level of openness to the outside world	Open	Total exports/GDP by county (converted at current year exchange rate)	516	0.051	0.078	0.000	0.026	0.698
Industrial structure	Agriculture	Value added in agriculture/GDP by county	516	0.183	0.093	0.024	0.172	0.459
Level of urbanisation	Urban	Number of urban population in each county/total population	516	0.428	0.077	0.220	0.424	0.638
Level of financial expenditure	Expend	Public budget expenditure/GDP by county	516	0.203	0.114	0.049	0.182	0.893

Level of infrastructure development	Mobile	Number of mobile phones per capita by county	516	0.750	0.252	0.137	0.744	1.894
Level of educational development	Education	Number of students per 100 population in general secondary and secondary vocational schools	516	4.288	1.206	1.011	4.285	13.474
Social security1	Medical	Basic health insurance participation rates by county	516	0.884	0.072	0.619	0.888	1.221
Social security Level 2	Insurance	Basic pension insurance participation rates by county	516	0.593	0.084	0.275	0.591	0.877

Spatial Weighting Matrix Setting

In the spatial econometric model, the spatial weight matrix is utilized to determine the spatial position of cross-sectional individuals to reflect the degree of the spatial relationship between persons. The central diagonal element of the spatial weight matrix is assumed to be 0 for the purposes of this paper. The spatial adjacency matrix assigns a value of 1 if two items are adjacent and 0 otherwise. According to the spatial distance matrix, the intensity of spatial dependence between persons relies on their physical separation. In this study, the matrix elements are determined by the reciprocal of the square of the centroid distance between two people. Most spatial weight matrices adopt row standardization to better explain the model, but row standardization causes the matrix to lose its original economic meaning, and because the matrix is no longer symmetric after row standardization, the sum of any spatial units affected by their neighbors is 1, which is excessively powerful. According to Elhorst (2001) and Kelejian and Prucha (2010), the use of the greatest eigenvalue of a matrix for Standardization does not alter the interaction between spatial elements and. It maintains the original spatial weight matrix's economic consequences.

This research proposes using the maximum eigenvalue approach to normalize the spatial weight matrix and five spatial matrices to assess the results' stability. W1 and W2 are the spatial neighborhood and distance matrices, W3 is the row normalized neighborhood matrix, and W4 is the second order neighborhood matrix, where the elements of the first order neighborhood matrix are set to 1 and.The elements of the second order neighborhood matrix are set to 0.5. w5 is the threshold distance matrix, and the threshold distance is set to 50 km. The elements of the matrix and within 50 km of the threshold distance. In this research, W1 serves as the baseline spatial weight matrix, while W2-W5 is employed for robustness testing.

Direct, Indirect and Aggregate Effects of Spatial Panel Models

The spatial econometric model contains spatially lagged terms for the explanatory or explained variables; therefore, the model coefficients do not accurately estimate the effect of the explanatory variables on the defined variables. LeSage and Pace (2009) suggest employing a biased estimation approach and decomposing the effect into direct and indirect effects. Since the spatially lagged error component does not influence on the direct and indirect effects, substituting ui in Equation (1) with the residual term vit produces the following result:

$$y_{it} = (I - \lambda W)^{-1}(X_{it}\beta + c_i + v_{it}) \quad (3)$$

Define y_{it}^* as the spatial spillover effect of yit minus the individual effect of

$$y_{it}^* = y_{it} - (I - \lambda W)^{-1}c_i \ = (I - \lambda W)^{-1}(X_{it}\beta + v_{it}) \quad (4)$$

For individual fixed effects, theyy_{it}^* The conditional expectations relative to Xit and W are

$$E(y_{it}^*|X_{it}, W) = (I - \lambda W)^{-1}(X_{it}\beta) \quad (5)$$

Taking the partial derivative of (5), and thus the spatial effect of the explanatory variables on the explanatory variable is

$$\text{aggregate effects} = \frac{1}{n^2T}\sum_{t=1}^{T}\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{\partial E(y_{it}^*|X_{it}, W)}{\partial X_{jt}} \quad (6)$$

$$\text{direct effects} = \frac{1}{nT}\sum_{t=1}^{T}\sum_{i=1}^{n}\frac{\partial E(y_{it}^*|X_{it}, W)}{\partial X_{it}} \quad (7)$$

$$\text{indirect effects} = \frac{1}{nT(n-1)}\sum_{t=1}^{T}\sum_{i=1}^{n}\sum_{j=1, j\neq i}^{n}\frac{\partial E(y_{it}^*|X_{it}, W)}{\partial X_{jt}} \quad (8)$$

The direct effect is the mean of the diagonal components of the bias matrix. It represents the average effect of changes in other region-specific independent variables on the region-specific dependent variable. The indirect impact is the row average of the nondiagonal members of the skew matrix, which represents the average influence of changes in other region-specific independent variables on the region-specific dependent variable. The total effect is the sum of the two or the average effect of all the region-specific independent variables on the region-specific dependent variable.

ANALYSIS OF THE EMPIRICAL RESULTS

Table 2 displays the spatial panel Moran'I and Geary'C indices for the four core variables of poverty status, digital inclusive finance index, GDP per capita and urbanization rate in Beijing, Tianjin ,and Hebei counties from 2014-2017, with the Moran'I index for the four variables being significantly greater than 0 and The Geary'C index being significantly less than 1, indicating a significant spatial positive relationship between poverty status, digital inclusive finance index, GDP per capita and urbanization rate.

Table 2

Spatial correlation index statistics for core variables in the Beijing-Tianjin County, 2014-2017

	Poverty	Digital Inclusive Finance Index	GDP per capita	Urbanization rate
Moran'I	0.525^{***}	0.896^{***}	0.436^{***}	0.305^{***}
	(17.280)	(29.414)	(14.365)	(10.076)
Geary'C	0.458^{***}	0.101^{***}	0.537^{***}	0.688^{***}
	(-17.232)	(-28.810)	(-14.601)	(-9.833)

Note: Spatial weight matrix is unnormalised W1, z-values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The tables 3 and 4 display the regression outcomes and impact effect breakdown for the four spatial panels fixed effects models, respectively. Empirical findings indicate that the coefficients on WY, WU, and a portion of WX are statistically significant. The spatial model with two spatial lags beats the geographic model with one spatial lag. (Tables 3 and 4 do not contain the regression findings for the SAR, SEM, and SLX models). According to Elhorst (2014), the ratio of indirect to direct impacts of the explanatory variables in the SAC model is fixed, making it too rigid and potentially leading to erroneous spillover effects. (Elhorst，2014) Gibbons and Overman (2012) contend that endogenous interaction effects and error-related effects can only be weakly identified and compete with one another when coexisting in GNSM models, thereby reinforcing the problem and leading to over-parameterisation of the model, thereby reducing the significance level of the parameter estimates. (Gibbons and Overman，2012) This causes the model to be over-parameterized, decreasing the parameter estimates’ significance level . The final model was selected between the SDM and SDEM models, with the AIC and BIC criterion and LR test results favoring SDEM.

Table 3

Spatial panel fixed effects model regression results

Income	SAC		SDM		SDEM		GNSM	
Index	0.167^{***}	(7.991)	0.175^{***}	(7.945)	0.163^{***}	(7.764)	0.163^{***}	(7.710)
GDP	0.087^{***}	(3.611)	0.089^{***}	(3.759)	0.088^{***}	(3.730)	0.088^{***}	(3.736)
Agriculture	-0.110	(-1.305)	-0.095	(-1.144)	-0.054	(-0.616)	-0.056	(-0.639)
Open	-0.068	(-0.816)	-0.091	(-1.111)	-0.106	(-1.269)	-0.104	(-1.253)
Urban	1.241^{***}	(9.533)	1.243^{***}	(9.760)	1.369^{***}	(10.661)	1.361^{***}	(9.985)
Expend	0.206^{***}	(3.518)	0.182^{***}	(3.144)	0.201^{***}	(3.448)	0.199^{***}	(3.352)
Mobile	0.082^{***}	(3.194)	0.083^{***}	(3.214)	0.090^{***}	(3.371)	0.090^{***}	(3.368)
Education	0.014^{***}	(3.947)	0.013^{***}	(3.783)	0.012^{***}	(3.194)	0.012^{***}	(3.205)
Medical	-0.189^{***}	(-3.879)	-0.171^{***}	(-3.386)	-0.170^{***}	(-3.404)	-0.169^{***}	(-3.367)
Insurance	0.232^{***}	(3.677)	0.262^{***}	(4.167)	0.278^{***}	(4.344)	0.277^{***}	(4.313)
W1								
Income	0.211^{***}	(4.523)	0.542^{***}	(7.685)			0.031	(0.182)
e.Income	0.438^{***}	(5.011)			0.619^{***}	(9.159)	0.601^{***}	(4.943)
Index			-0.183^{***}	(-4.159)	-0.114^{**}	(-2.380)	-0.119^{**}	(-2.174)
Gdp			-0.027	(-0.405)	-0.002	(-0.022)	-0.004	(-0.051)
Agriculture			0.377^{*}	(1.859)	0.440^{*}	(1.721)	0.437^{*}	(1.720)
Open			0.148	(0.796)	0.028	(0.119)	0.035	(0.148)
Urban			0.622^{*}	(1.827)	1.919^{***}	(4.947)	1.858^{***}	(3.640)

Expend		0.085	(0.651)	0.336**	(2.084)	0.323*	(1.867)
Mobile		-0.060	(-0.829)	-0.021	(-0.244)	-0.023	(-0.271)
Education		-0.017*	(-1.888)	-0.017	(-1.460)	-0.017	(-1.479)
Medical		0.133	(1.217)	-0.073	(-0.529)	-0.062	(-0.418)
Insurance		-0.172	(-1.179)	0.077	(0.416)	0.065	(0.328)
Pseudo R^2	0.308	0.025		0.169		0.161	
AIC	-1502.104	-1502.449		-1514.768		-1512.801	
BIC	-1446.905	-1409.035		-1421.353		-1415.140	
Log Lik.	764.052	773.224		779.384		779.400	
Wald Test	68.33***	106.95***		117.48***		113.57***	
N	516	516		516		516	

Note: Z values are in parentheses, * p < 0.10,** p < 0.05,*** p < 0.01, Wald Test focuses on the spatial lag term, Log Lik. is the log likelihood of the model and the constant term is ignored. Regression results for the SAR, SEM and SLX models are omitted from Table 3 and are available from the authors on request.

Individual fixed effects control for individual heterogeneity of spatial units in the spatial panel selected effects model. Still, individuals in close geographical proximity are also influenced by some common factors, creating some similarities between neighboring spatial units. In other words, the nearby county units in Beijing, Tianjin, and Hebei exhibit higher 'poverty similarities' due to the error correlation effect as opposed to the endogenous interaction effect. Therefore, WU is more suitable than WY for the model. Additionally, the endogenous interaction effect indicates a worldwide impact, and it is hard to think that the development of digital inclusive finance in Huai'an County, Zhangjiakou, will affect all other counties in Hebei Province. An endogenous interaction effect not entering the model implies a local product; a spatially lagged explanatory variable entering the model then means that only neighboring regions (first- or second-order neighbours) can have an impact SDEM is therefore selected as the final model for this article.

As shown in Table 4, the effects of different model choices do not differ significantly on the direct effects of the explanatory variables, but the effects on indirect effects are more significant. In order to assess the stability of the spillover effects of the explanatory variables, this research uses the matrices W2-W5 to do so. Tables 5 and 6 display the regression outcomes and the decomposition of the impact effects of the SDEM model under various spatial weight matrices. As demonstrated in Tables 5 and 6, there is slight variation in the direct impacts of the explanatory variables of the SDEM model under different spatial weight matrices, showing the resilience of the direct effects of the explanatory variables on the explained variables. However, only the indirect effect of the variable Urban is significant in all models, and the magnitude difference is not statistically significant. The core explanatory variable Index has a significantly negative indirect effect under W1 and a very positive indirect effect under W2, both in opposing directions. When the matrices are W3 and W4, the spillover effect is in the other direction but small, and it is negative and insignificant when the matrix is W5. In conclusion, the results of the indirect influence of the core explanatory variable index lack adequate robustness. Therefore, this research contends that the growth of digitally inclusive finance primarily impacts local poverty reduction and has little influence on poverty reduction in neighboring regions. Based on the above concept, this research indicates that, except the Urban variable, none of the explanatory variables have spillover effects.

Table 4

Decomposition of the effect of different model explanatory variables on the explained variables (W1)

Effects	SAC		SDM		SDEM		GNSM	
	dy/dx	Z-value	dy/dx	Z-value	dy/dx	Z-value	dy/dx	Z-value
Direct effects								
Index	0.168***	8.12	0.165***	7.88	0.163***	7.76	0.163***	7.76
GDP	0.088***	3.61	0.092***	3.75	0.088***	3.73	0.088***	3.72
Agriculture	-0.111	-1.31	-0.060	-0.68	-0.054	-0.62	-0.054	-0.62
Open	-0.069	-0.82	-0.081	-0.96	-0.106	-1.27	-0.104	-1.25
Urban	1.249***	9.57	1.383***	10.48	1.369***	10.66	1.370***	10.64
Expend	0.208***	3.52	0.202***	3.43	0.201***	3.45	0.201***	3.43
Mobile	0.083***	3.2	0.081***	2.91	0.090***	3.37	0.090***	3.34
Education	0.014***	3.95	0.012***	3.16	0.012***	3.19	0.012***	3.18
Medical	-0.190***	-3.88	-0.166***	-3.28	-0.170***	-3.4	-0.169***	-3.38
Insurance	0.234***	3.68	0.259***	3.99	0.278***	4.34	0.277***	4.31
Indirect effects								
Index	0.034***	4.61	-0.134**	-2.31	-0.093**	-2.38	-0.095**	-2.31
GDP	0.018***	2.65	0.033	0.33	-0.001	-0.02	-0.001	-0.02
Agriculture	-0.023	-1.26	0.495	1.59	0.360*	1.72	0.365*	1.7
Open	-0.014	-0.8	0.150	0.55	0.023	0.12	0.027	0.14
Urban	0.256***	3.67	1.975***	3.77	1.570***	4.95	1.592***	4.59
Expend	0.043**	2.51	0.280	1.45	0.275**	2.08	0.276**	2.06
Mobile	0.017**	2.48	-0.023	-0.21	-0.017	-0.24	-0.017	-0.24
Education	0.003***	2.82	-0.015	-1.07	-0.014	-1.46	-0.014	-1.44
Medical	-0.039***	-2.76	0.061	0.39	-0.060	-0.53	-0.057	-0.49
Insurance	0.048***	2.68	-0.046	-0.21	0.063	0.42	0.061	0.4
Total effect								
Index	0.202***	9.63	0.031	0.53	0.070*	1.77	0.068	1.62
GDP	0.106***	3.58	0.124	1.17	0.087	1.21	0.087	1.19
Agriculture	-0.134	-1.31	0.435	1.23	0.306	1.19	0.310	1.18
Open	-0.083	-0.82	0.070	0.23	-0.083	-0.36	-0.077	-0.33
Urban	1.505***	9.17	3.358***	5.84	2.939***	7.86	2.962***	7.38
Expend	0.251***	3.44	0.482**	2.28	0.476***	3.05	0.477***	3
Mobile	0.100***	3.18	0.058	0.47	0.073	0.87	0.072	0.85
Education	0.017***	3.93	-0.003	-0.19	-0.002	-0.14	-0.002	-0.14
Medical	-0.229***	-3.85	-0.105	-0.61	-0.229*	-1.77	-0.225*	-1.69
Insurance	0.282***	3.65	0.212	0.88	0.341*	1.89	0.339*	1.84

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5

Regression results of SDEM model with different spatial weight matrices

Income	SDEM (W2)		SDEM (W3)		SDEM (W4)		SDEM (W5)	
Index	0.099***	(4.651)	0.090***	(3.532)	0.139***	(5.780)	0.140***	(7.536)
GDP	0.100***	(4.239)	0.077***	(3.445)	0.086***	(3.477)	0.092***	(3.767)
Agriculture	0.009	(0.107)	0.043	(0.519)	-0.074	(-0.823)	-0.002	(-0.025)
Open	-0.072	(-0.872)	-0.105	(-1.369)	-0.093	(-1.088)	-0.097	(-1.121)
Urban	1.413***	(10.737)	1.197***	(9.996)	1.360***	(10.194)	1.628***	(11.728)
Expend	0.265***	(4.483)	0.152***	(2.745)	0.235***	(3.956)	0.277***	(4.616)
Mobile	0.068**	(2.537)	0.091***	(3.587)	0.086***	(3.064)	0.076***	(2.745)
Education	0.014***	(3.769)	0.015***	(4.257)	0.012***	(3.091)	0.010**	(2.555)
Medical	-0.157***	(-3.193)	-0.153***	(-3.228)	-0.164***	(-3.151)	-0.175***	(-3.463)
Insurance	0.263***	(4.178)	0.244***	(4.101)	0.261***	(4.035)	0.279***	(4.270)
	W2		W3		W4		W5	
e.Income	0.960***	(49.797)	0.513***	(9.796)	0.716***	(7.900)	0.901***	(17.751)
Index	0.259**	(2.209)	0.040	(1.085)	-0.073	(-0.896)	-0.069	(-0.735)
GDP	0.009	(0.049)	-0.001	(-0.029)	-0.117	(-0.758)	0.006	(0.041)
Agriculture	1.328**	(2.288)	0.131	(0.744)	-0.405	(-0.799)	0.824	(1.559)
Open	-0.224	(-0.435)	0.046	(0.257)	0.050	(0.114)	-0.146	(-0.348)
Urban	3.068***	(4.212)	1.177***	(4.464)	2.207***	(2.974)	3.493***	(4.559)
Expend	0.073	(0.209)	0.231**	(2.102)	0.507	(1.642)	0.137	(0.396)
Mobile	-0.048	(-0.249)	0.016	(0.317)	0.113	(0.652)	-0.000	(-0.002)
Education	-0.023	(-1.295)	-0.005	(-0.640)	-0.046*	(-1.905)	-0.057***	(-2.794)
Medical	-0.104	(-0.338)	-0.072	(-0.743)	0.173	(0.689)	0.052	(0.191)
Insurance	0.110	(0.317)	0.001	(0.008)	-0.415	(-1.176)	0.278	(0.824)
Pseudo R^2	0.104		0.399		0.310		0.101	
AIC	-1502.328		-1569.087		-1486.560		-1480.718	
BIC	-1408.914		-1475.672		-1393.146		-1387.303	
Log Lik.	773.164		806.543		765.280		762.359	
Wald Test	3027.067***		207.611***		77.926***		414.396***	
N	516		516		516		516	

Note: Z values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, Wald Test focuses on the spatial lag term, Log Lik. is the log likelihood of the model and the constant term is ignored.

Table 6

Decomposition of SDEM model impact effects under different spatial weight matrices

Effects	SDEM (W2)		SDEM (W3)		SDEM (W4)		SDEM (W5)	
	dy/dx	Z-value	dy/dx	Z-value	dy/dx	Z-value	dy/dx	Z-value
Direct effects								
Index	0.099***	4.65	0.090***	3.53	0.139***	5.78	0.140***	7.54
GDP	0.100***	4.24	0.077***	3.44	0.086***	3.48	0.092***	3.77
Agriculture	0.009	0.11	0.043	0.52	-0.074	-0.82	-0.002	-0.03
Open	-0.072	-0.87	-0.105	-1.37	-0.093	-1.09	-0.097	-1.12
Urban	1.413***	10.74	1.197***	10	1.360***	10.19	1.628***	11.73
Expend	0.265***	4.48	0.152***	2.74	0.235***	3.96	0.277***	4.62
Mobile	0.068**	2.54	0.091***	3.59	0.086***	3.06	0.076***	2.75

Education	0.014***	3.77	0.015***	4.26	0.012***	3.09	0.010**	2.56
Medical	-0.157***	-3.19	-0.153***	-3.23	-0.164***	-3.15	-0.175***	-3.46
Insurance	0.263***	4.18	0.244***	4.1	0.261***	4.03	0.279***	4.27
Indirect effects								
Index	0.186**	2.21	0.040	1.08	-0.058	-0.9	-0.038	-0.74
GDP	0.007	0.05	-0.001	-0.03	-0.093	-0.76	0.003	0.04
Agriculture	0.953**	2.29	0.131	0.74	-0.322	-0.8	0.455	1.56
Open	-0.161	-0.44	0.046	0.26	0.039	0.11	-0.080	-0.35
Urban	2.203***	4.21	1.177***	4.46	1.756***	2.97	1.927***	4.56
Expend	0.052	0.21	0.231**	2.1	0.403	1.64	0.075	0.4
Mobile	-0.034	-0.25	0.016	0.32	0.090	0.65	0.000	0
Education	-0.017	-1.3	-0.005	-0.64	-0.036*	-1.9	-0.031***	-2.79
Medical	-0.074	-0.34	-0.072	-0.74	0.138	0.69	0.029	0.19
Insurance	0.079	0.32	0.001	0.01	-0.330	-1.18	0.153	0.82
Total effect								
Index	0.284***	3.7	0.130***	3.91	0.081	1.26	0.102*	1.87
GDP	0.106	0.74	0.076	1.31	-0.007	-0.06	0.096	1.04
Agriculture	0.963**	2.15	0.174	0.79	-0.396	-0.9	0.452	1.37
Open	-0.232	-0.61	-0.059	-0.28	-0.054	-0.15	-0.177	-0.68
Urban	3.616***	6.24	2.374***	7.48	3.116***	4.9	3.555***	7.15
Expend	0.317	1.18	0.384***	2.86	0.639**	2.46	0.352*	1.68
Mobile	0.033	0.22	0.107	1.62	0.176	1.16	0.076	0.73
Education	-0.003	-0.22	0.010	1	-0.024	-1.16	-0.021	-1.62
Medical	-0.232	-1	-0.225**	-2	-0.026	-0.12	-0.146	-0.87
Insurance	0.342	1.25	0.245	1.58	-0.069	-0.23	0.432**	1.99

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Therefore, in this paper, the SDEM model is reformulated to include only Urban as the spatially lagged explanatory variable, i.e. the explanatory variable Urban has an impact on poverty reduction in both the region and neighboring regions. In contrast the other explanatory variables only have an impact on poverty reduction in the region. To fully examine the poverty reduction effect of digital inclusive finance development, the secondary indicators of digital inclusive finance are the breadth of coverage (Coverage), depth of usage (Usage), digitization (Digitization) ,and the sub-indicators of the depth of usage indicator Digital Payment (Payment), Digital Money (Monetary), Digital Credit (Credit), Digital Insurance (Insecurity) Credit, Insur-index, Investment,and Credit-invest are included in the SDEM model. In addition, this paper also conducts a comparative analysis of the regression results for the total Beijing-Tianjin-Hebei sample, the sub-sample of Hebei Province, and the sub-sample of poverty-removing counties (44 poverty-removing counties, all belonging to Hebei Province) to examine the heterogeneity of digital financial inclusion for poverty reduction in different regions.

Table 7

Regression results of the baseline SDEM model for the total sample in Beijing, Tianjin and Hebei

Income	SDEM1		SDEM2		SDEM3		SDEM4	
Index	0.158***	(7.747)						
Coverage			0.094***	(5.364)				
Usage					0.121***	(7.061)		
Digitization							0.074***	(5.684)
GDP	0.087***	(3.649)	0.088***	(3.581)	0.103***	(4.324)	0.100***	(4.074)
Agriculture	-0.100	(-1.214)	-0.138	(-1.625)	-0.062	(-0.740)	-0.067	(-0.779)
Open	-0.077	(-0.942)	-0.063	(-0.748)	-0.094	(-1.134)	-0.095	(-1.120)
Urban	1.279***	(10.335)	1.425***	(11.437)	1.331***	(10.748)	1.382***	(10.913)
Expend	0.189***	(3.271)	0.219***	(3.676)	0.184***	(3.121)	0.225***	(3.737)
Mobile	0.079***	(3.174)	0.083***	(3.215)	0.097***	(3.842)	0.084***	(3.224)
Education	0.014***	(4.041)	0.014***	(4.045)	0.014***	(4.007)	0.015***	(4.245)
Medical	-0.184***	(-3.804)	-0.170***	(-3.381)	-0.209***	(-4.254)	-0.206***	(-4.115)
Insurance	0.243***	(3.922)	0.256***	(4.013)	0.237***	(3.754)	0.285***	(4.446)
W1								
Urban	1.048***	(5.324)	1.490***	(7.912)	1.057***	(5.192)	1.411***	(7.630)
e.Income	0.587***	(8.346)	0.607***	(8.982)	0.607***	(8.829)	0.560***	(7.692)
Pseudo R^2	0.325		0.256		0.340		0.255	
Wald test	86.779***		124.436***		100.231***		104.546***	
N	516		516		516		516	

Note: Z values in parentheses, *p < 0.10,** p < 0.05,*** p < 0.01, Wald Test focuses on spatially lagged terms, constant terms are ignored.

Table 8

Regression results of the SDEM model for the Hebei sub-sample

Income	**SDEM5**		**SDEM6**		**SDEM7**		**SDEM8**	
Index	0.175***	(8.432)						
Coverage			0.118***	(6.355)				
Usage					0.126***	(7.257)		
Digitization							0.073***	(5.529)
GDP	0.091***	(3.683)	0.093***	(3.611)	0.110***	(4.387)	0.111***	(4.308)
Agriculture	-0.071	(-0.851)	-0.112	(-1.298)	-0.031	(-0.364)	-0.038	(-0.433)
Open	-0.096	(-1.148)	-0.082	(-0.954)	-0.106	(-1.245)	-0.109	(-1.248)
Urban	1.322***	(10.485)	1.468***	(11.557)	1.397***	(11.007)	1.447***	(11.036)
Expend	0.174***	(2.905)	0.204***	(3.310)	0.186***	(3.026)	0.236***	(3.748)
Mobile	0.083***	(3.197)	0.084***	(3.129)	0.097***	(3.681)	0.083***	(3.031)
Education	0.015***	(4.340)	0.015***	(4.371)	0.015***	(4.214)	0.016***	(4.337)
Medical	-0.175***	(-3.578)	-0.156***	(-3.058)	-0.207***	(-4.149)	-0.208***	(-4.060)
Insurance	0.198***	(3.109)	0.210***	(3.201)	0.191***	(2.906)	0.252***	(3.751)
W1*								
Urban	0.786***	(4.087)	1.200***	(6.499)	0.885***	(4.429)	1.290***	(7.108)
e.Income	0.515***	(6.857)	0.529***	(7.246)	0.549***	(7.441)	0.504***	(6.507)
Pseudo R^2	0.390		0.330		0.381		0.298	
Wald test	59.758***		84.814***		75.661***		86.088***	
N	496		496		496		496	

Note: Z values in parentheses, * p < 0.10,** p < 0.05,*** p < 0.01, Wald Test focuses on spatially lagged terms, constant terms are ignored.

Tables 7-9 show the regression results of the SDEM model for the full digital inclusive finance index and secondary indicators for the total Beijing-Tianjin-Hebei sample, the Hebei sub-sample ,and the sub-sample of poverty-removing counties, respectively.The empirical results indicate that the growth of digital inclusive finance has the potential to increase significantly the per capita disposable income of rural residents in the counties of Beijing, Tianjin, and Hebei, hence reducing poverty dramatically. Regarding secondary indicators, the overall Beijing-Tianjin-Hebei sample and the subsample from Hebei show that the depth indicator has the most significant impact on poverty reduction, followed by the range of coverage and digitalization. In the subsample of counties that eliminated poverty, however, the breadth of coverage indicator had the highest effect on poverty reduction, followed by the depth of use and digitalization ranked third.

Table 9

Regression results of the SDEM model for the sub-sample of out-of-poverty counties

Income	SDEM9	SDEM10	SDEM11	SDEM12
Index	0.186^{***}			
	(6.856)			
Coverage		0.177^{***}		
		(6.918)		
Usage			0.138^{***}	
			(5.366)	
Digitization				0.082^{***}
				(4.177)
Control variables	Control	Control	Control	Control
$W1^{**}$				
Urban	0.573^{*}	0.604^{*}	0.833^{**}	0.973^{***}
	(1.723)	(1.880)	(2.317)	(2.935)
e.Income	0.590^{***}	0.569^{***}	0.624^{***}	0.376^{**}
	(5.100)	(4.945)	(5.169)	(2.381)
Pseudo R^2	0.232	0.215	0.172	0.142
Wald test	26.634^{***}	26.052^{***}	27.785^{***}	10.364^{***}
N	176	176	176	176

Note: Z values in parentheses, * $p < 0.10$,** $p < 0.05$,*** $p < 0.01$, Wald Test mainly for spatial lag terms, control variables and constant terms are ignored.

Comparing the regression findings of the three samples reveals that the development of the total digital inclusive finance index and its secondary indicators has a larger effect on poverty reduction and income growth in the backward region (Hebei Province) and the out-of-poverty area(out-of-poverty counties). It can be shown that the growth of digital inclusive finance has an "overtaking" effect and can contribute to the synergistic development of Beijing, Tianjin, and Hebei by reducing the excessive economic gap between the three cities. Farmers have had limited or no access to financial services for a long time in out-of-poverty or remote places. The rapid development of digital inclusive finance has substantially aided in reducing the financial exclusion of agricultural households in places where poverty is being eradicated and has increased the reach of digital financial services. Consequently, the breadth of coverage indicator has the most significant on poverty reduction in the sub-sample of poverty-removal zones.It is significantly superior to the complete sample of Beijing, Tianjin, and Hebei Province and the sub-sample of Hebei Province.

The depth of use indicator represents the amount to which digital financial services ease users' usage-based financial exclusion, have a slightly higher financial threshold and spread and develops more slowly in anti-poverty areas than the breadth of coverage indicator. The effects of the depth of use indicator on poverty reduction and income improvement won't be completely realized until digital financial inclusion has surpassed a certain threshold. The digitization indicator assesses the ease of access to digital inclusion, user happiness, and the extent to which digital inclusion is "inclusive" and is more rigorous than the previous two indicators. Consequently, the breadth of coverage indicator is most successful at reducing poverty in counties that have escaped poverty, but the depth of use indicator is most effective in the subsample of Beijing-Tianjin-Hebei and Hebei Province. Comparatively, the poverty reduction effect of the breadth of coverage indicator is significantly greater in the subsample of deprived counties than in the other two samples, and the poverty reduction advantage of using the depth indicator is also more pronounced in deprived areas. In contrast, the disparity between the digitization indicators is smaller in the three samples.

Table 10

SDEM model regression results for the total sample of digital financial products in Beijing, Tianjin and Hebei

Income	SDEM13	SDEM14	SDEM15	SDEM16	SDEM17	SDEM18
Digital payments	0.017					
	(1.080)					
Digital Insurance		0.035^{**}				
		(2.439)				
Digital Money Management			0.039^{**}			
			(2.526)			
Digital Investment				0.063^{***}		
				(5.721)		
Digital Credit					0.103^{***}	
					(7.097)	
Digital Credit						0.001
						(0.066)
Control variables	Control	Control	Control	Control	Control	Control
W1						
Urban	1.828^{***}	1.696^{***}	1.758^{***}	1.238^{***}	1.245^{***}	1.302^{***}
	(10.019)	(8.858)	(9.551)	(6.228)	(6.457)	(2.688)
e. Income	0.602^{***}	0.606^{***}	0.610^{***}	0.552^{***}	0.633^{***}	0.711^{***}
	(8.891)	(8.928)	(9.144)	(7.755)	(9.483)	(6.340)
Pseudo R^2	0.221	0.233	0.231	0.302	0.311	0.204
Wald test	161.677^{***}	144.158^{***}	156.922^{***}	86.913^{***}	130.060^{***}	40.905^{***}
N	516	516	516	516	516	258

Note: Z values in parentheses, * $p < 0.10$,** $p < 0.05$,*** $p < 0.01$, Wald Test mainly for spatial lag terms, control variables and constant terms are ignored.

Table 11

SDEM model regression results for a sub-sample of digital financial products in Hebei Province

Income	SDEM19	SDEM20	SDEM21	SDEM22	SDEM23	SDEM24
Digital payments	0.036**					
	(1.969)					
Digital Insurance		0.046***				
		(3.105)				
Digital Money Management			0.049***			
			(2.931)			
Digital Investment				0.066***		
				(5.996)		
Digital Credit					0.102***	
					(6.793)	
Digital Credit						-0.003
						(-0.190)
Control variables	Control	Control	Control	Control	Control	Control
W1*						
Urban	1.616***	1.497***	1.560***	1.077***	1.116***	0.881*
	(8.916)	(7.967)	(8.596)	(5.550)	(5.879)	(1.930)
e.Income	0.533***	0.548***	0.541***	0.492***	0.573***	0.656***
	(7.306)	(7.489)	(7.535)	(6.509)	(7.876)	(5.783)
Pseudo R^2	0.276	0.283	0.282	0.347	0.348	0.296
Wald test	120.877***	111.784***	120.090***	66.779***	100.549***	36.056***
N	496	496	496	496	496	248

Note: Z values in parentheses,* $p < 0.10$,** $p < 0.05$,*** $p < 0.01$, Wald Test mainly for spatial lag terms, control variables and constant terms are ignored.

The regression results for the depth of digital financial inclusion utilizing sub-indicators for the overall Beijing-Tianjin-Hebei sample, the Hebei sub-sample, and the impoverished county sub-sample are presented in Tables 10-12. The empirical findings indicate that introducing digital financial services has dramatically reduced absolute poverty and increased agricultural households' disposable income per capita. Among the six digital financial products or services, digital credit services had the most significant impact on reducing poverty and raising income, however ,the effect on poverty reduction was not statistically significant. Upgraded digital financial services (credit, investment, and wealth management) were the most effective at reducing poverty and increasing income in both the Beijing-Tianjin-Hebei total sample and the Hebei subsample, followed by protection digital financial services (insurance) and essential digital financial services (payment). In the overall sample of Beijing, Tianjin, and Hebei, the effects of digital payments on poverty reduction and income generation were not statistically significant. In the subsample of counties where poverty was eliminated, the impacts of basic, improved, and protection-based digital financial services on poverty reduction were substantial, but the differences were not.

Table 12

SDEM Model Regression Results For Digital Financial Products In The Sub-Sample Of Deprived Counties

Income	SDEM25	SDEM26	SDEM27	SDEM28	SDEM29	SDEM30
Digital payments	0.080**					
	(2.398)					
Digital Insurance		0.079***				
		(3.084)				
Digital Money Management			0.068**			
			(2.546)			
Digital Investment				0.070***		
				(5.034)		
Digital Credit					0.094***	
					(3.692)	
Digital Credit						-0.006
						(-0.331)
Control variables	Control	Control	Control	Control	Control	Control
W1**						
Urban	1.329***	1.147***	1.252***	1.026***	1.041***	0.795
	(3.957)	(3.222)	(3.664)	(3.081)	(2.844)	(1.373)
e.Income	0.473***	0.526***	0.463***	0.530***	0.572***	0.776***
	(3.282)	(3.609)	(3.182)	(4.048)	(3.991)	(5.659)
Pseudo R^2	0.086	0.112	0.097	0.131	0.132	0.084
Wald test	20.190***	17.954***	17.655***	20.245***	18.747***	41.132***
N	176	176	176	176	176	88

Note: Z values in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, Wald Test mainly for spatial lag terms, control variables and constant terms are ignored.

Among the five types of digital financial services, digital credit, investment, and finance can increase users' income directly, whereas digital insurance helps reduce fluctuations in users' income, and digital payments increase users' income primarily through more convenient payments and lower transaction costs. Basic digital financial services (digital payments) have the lowest barrier to entry; consequently, they develop the quickest and have the greatest impact on reducing poverty and increasing income in regions where poverty is being addressed. In the total sample of Beijing, Tianjin, and Hebei, the effect of digital payments on poverty reduction is insignificant, indicating that after digital payments have reached a certain stage of development, it is more difficult to further increase farmers' income.The financial thresholds for investment and credit in the upgraded digital financial services are higher, and the difference in poverty reduction effect between them is not statistically significant across the three samples, with digital credit performing marginally better than the other two samples of poverty reduction and income growth. The financial thresholds for digital finance and digital insurance are in the middle, and their poverty-reduction benefits are more apparent in the subsample of poverty-reduction regions. Overall, the popularity and use of the five types of digital inclusive financial services have a greater impact on reducing poverty and increasing income in backward regions and regions emerging from poverty, again demonstrating the "overtaking" effect of the development of digital inclusive finance. Its good geographical penetration has allowed backward regions to enjoy relatively more financial services.

In terms of the control variables, as shown in Table 7, growth in GDP per capita has a significant poverty-reducing and income-raising effect among the economic growth factors, whereas increases in agricultural output and openness to the outside world do not have a significant poverty-reducing effect. From the perspective of income growth, an increase in agriculture's share of the industrial structure does not significantly contribute to the income growth of rural residents. According to the sample data, the proportion of exports in most Beijing, Tianjin, and Hebei counties was low. It fluctuated during the sample period, with no correlation to poverty reduction. Urbanization has the most significant impact on poverty reduction.An increase in urbanization in a county not only has a significant positive effect on local poverty reduction but also has a significant positive effect on the reduction of poverty in neighboring counties. In terms of government action factors, the increase in financial support for agriculture and the construction of digital infrastructure both have significant effects on poverty reduction. Because counties that have escaped poverty have received significantly more financial resources from higher levels of government during the poverty reduction phase, the actual poverty reduction financial effect assistance may be greater than the model estimates. As part of the "new infrastructure," the construction of digital infrastructure can support the growth of e-commerce, social media, self-media, live streaming, and other new businesses, and there is room for future growth.

Regarding human capital factors, increases in the county's education level and basic rural pension insurance can significantly reduce absolute poverty. Contrary to expectations, an increase in the level of basic medical insurance has a significant negative relationship with the income of rural residents. In 2016, Hebei Province integrated urban residents' basic medical insurance and new rural cooperative medical insurance into urban and rural residents' basic medical insurance. The change in the statistical caliber caused the participation rate of basic medical insurance to decline in most counties in Hebei Province during the sample period, resulting in a distorted estimate of this factor's poverty-reduction effect.

CONCLUSION

This paper analyzes the effect of digital inclusive finance on poverty reduction and its heterogeneity using the SDEM model and spatial panel data from 2014-2017 in Beijing, Tianjin, and Hebei, with the following findings:

First, digital financial inclusion development significantly affects poverty reduction, with the poverty reduction effect acting primarily within the region, with no significant spillover effect on poverty reduction in neighboring counties, and with some heterogeneity in the poverty reduction effect. In the total Beijing-Tianjin-Hebei sample and the Hebei subsample, depth indicators have the greatest effect on reducing poverty, followed by range of coverage and digitalization. In the subsample of counties where poverty was eliminated, the breadth of coverage indicator had the greatest effect on reducing poverty, followed by the depth of use and digitalization.

Second, the effect of various types of digital financial services on poverty reduction is significant and heterogeneous. Digital credit services have the greatest effects on poverty reduction and income enhancement, whereas digital credit services have negligible effects on poverty reduction. The poverty reduction effect of upgraded digital financial services is greatest in the total sample and the subsample from Hebei, followed by guaranteed digital financial services and basic digital financial services. The poverty reduction and income enhancement effects of digital payment in the total sample are not significant. In the subsample of counties where poverty was eliminated, the effects of basic, upgraded, and guaranteed digital financial services on poverty reduction were significant, but the differences were not.

Thirdly, the development of digital inclusive finance has a certain "overtaking" effect, and its development has a greater influence on poverty reduction and income growth in developing and emerging economies. The effect of the breadth of coverage indicator on poverty reduction is significantly greater in the sample of areas emerging from poverty than in the other two samples, whereas the total index and depth of use indicators have a more pronounced advantage in poverty reduction in areas emerging from poverty.

Digital inclusive finance development not only plays an important role in reducing poverty during the period of poverty eradication, but it will also play an important role in sustaining rural residents' income growth and enrichment during the stable poverty eradication and rural revitalization phases. Therefore, the government should continue to improve the construction of digital infrastructure in counties, strengthen financial literacy publicity and education for rural residents, continuously improve farmers' financial literacy, prioritize the construction of a rural digital credit system and the protection of digital financial consumers' rights and interests, and promote the healthy and sustainable development of digital inclusive finance in rural areas.

ACKNOWLEDGMENT

The study is supported by the 2020 Youth Talent Support Program of High Learning Institution in Hebei Province (Program Number: BJ2021077)

REFERENCE

Kai-ming, C. (2011). Aggregation or diffusion: theoretical and empirical analysis on urban size and urban-rural income gap. *Economic Theory and Business Management*, (8), 14. Dong Yufeng & Zhao Xiaoming. (2020). Responsible Digital Financial Inclusion: Origin, Connotation and Construction. South China Finance, 215(01), 50-56.

Guo, F., Wang, J., Wang, F., Kong, T., Zhang, X., & Cheng, Z. (2020). Measuring China's digital financial inclusion: Index compilation and spatial characteristics. *China Economic Quarterly*, *19*(4), 1401-1418.

Kelejian, H. H., & Prucha, I. R. (2010). Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances. *Journal of econometrics*, *157*(1), 53-67.

He, X. F. (2018). The policy of poverty alleviation and social security in the anti-poverty strategy of China's rural areas. *Wuhan Univ. J*, *71*, 147-153.

Huang, Y., & Huang, Z. (2018). The development of digital finance in China: Present and future. *China Economic Quarterly*, *17*(4), 205-218.

Huang, H. (2018). Formation and challenges of digital financial ecosystem—Experience from China. *Economist*, *4*, 80-85.

Huang Q., Hu Z. & Liu Y. (2017). Development level of China's inclusive finance and its poverty reduction effect. *Financial Economics Research*,*32*(06),75-84.

Huang Yiping. (2017). The opportunity and the risk of digital inclusive finance. *New Finance*, (08), 4 -7.

Elhorst, J. P. (2010). Applied spatial econometrics: raising the bar. *Spatial economic analysis*, *5*(1), 9-28.

LeSage, J., & Pace, R. K. (2009). *Introduction to spatial econometrics*. Chapman and Hall/CRC.

Ming, L., & Zhao, C. (2004). Urbanization, urban-biased economic policies and urban-rural inequality. *Economic Research Journal*, *6*, 50-58.

Lee, L. F., & Yu, J. (2010). Estimation of spatial autoregressive panel data models with fixed effects. *Journal of econometrics*, *154*(2), 165-185.

Lee, L. F., & Yu, J. (2010). Some recent developments in spatial panel data models. *Regional Science and Urban Economics*, *40*(5), 255-271.

Mengliang Zhou. (2018). Research on path innovation for coordinating digital inclusive finance and precise poverty alleviation. *Journal of Nanjing Agricultural University (Social Sciences Edition),18*(02), 149-156.

Qiu Zhaoxiang & Xiang Xiaojian (2018). Research on problems and counter measures faced in the development of digital inclusive finance. *Financial Theory & Practice*, 5-9.

Shao, H., & Wang, K. (2017). Poverty reduction effect and the mechanism of action in inclusive finance: empirical analysis based on cross-national panel data. *Financial Economics Research*, *32*(6), 65-74.

Song, X. (2017). Empirical analysis of digital inclusive finance bridging the urban-rural residents' income gap. *Finance & Economics*, *6*, 14-25.

Gibbons, S., & Overman, H. G. (2012). Mostly pointless spatial econometrics? *Journal of regional Science*, *52*(2), 172-191.

Tan, Y. Z., & Peng, Q. R. (2018). Inclusive financial development and poverty alleviation: direct impact and spatial spillover effect. *Contemporary Finance & Economics*, (03), 154.

Wang, S. G., & Zeng, X. X. (2018). From regional poverty alleviation and development to precision poverty alleviation: The evolution of poverty alleviation policies in China during the 40 Years of reform and opening-up and the current difficulties and countermeasures for poverty alleviation. *Issues in Agricultural Economy*, *8*, 40-50.

Sangui, W. (2018). China□ s Large□ scale Poverty Reduction: Main Driving Forces and Institutional Foundation# br. *Journal of Renmin University of China*, *32*(6), 1.

Wei, W. & Yi-ming, Z. (2018). Inclusive finance and county capital outflow: poverty alleviation or worsen——Evidence from 592 Poverty Counties in China. *Economic Theory and Business Management*, *37*(1), 98.

Fu, Q. Z., & Huang, Y. P. (2018). Digital finance's heterogeneous effects on rural financial demand: evidence from China household finance survey and inclusive digital finance index. *J. Financ. Res*, *11*, 68-84.

Wu, B., Mao, N. & Guo, L. (2017). The inclusive effect of internet finance in rural areas under "Double Exclusion", *Journal of South China Normal University (Social science edition)*. 94-100.

Wu Lijuan & Xu Zhongyang. (2018).research on poverty alleviation and rural economy growth of inclusive finance in China: based on survey data of 4023 rural households via rd. regression. *South China Journal of Economics*. 104-127.

Xu, Y., Liu, F., & Zhang, X. (2007). Reflection on China's rural anti-poverty policies: transition from social assistance to social protection. *Social Sciences in China*, *3*, 40-53.

YanXing. (2015). The effectiveness and realization of inclusive of finance: review and enlightenment. *Global Finance*, 24-36.

Yi, X., & Zhou, L. (2018). Does digital financial inclusion significantly influence household consumption? Evidence from household survey data in China. *Journal of Financial Research*, *11*(461), 47-67.

He, Z., & Qinxian, B. (2018). Has digital financial inclusion reduced the urban-rural income gap?- A panel threshold regression analysis based on provincial data in China. *Inquiry into Economic Issues*, *39*(10), 122.

Zhang, Y., Wan, G. H., & Shi, Q. H. (2013). Chronic poverty and transient poverty in rural China: decomposition and their determinants. *Economic Research Journal (in Chinese)*, *4*, 119-129.

Zhang Zihao & Tan Yanzhi. (2018). Digital inclusive finance and the urban- rural income gap in China——Empirical Analysis Based on spatial econometric model. *Financial Theory & Practice*, 1-7.

Yiming, Z., & Wei, W. (2017). How Does Inclusive Finance Achieve Precise Poverty Alleviation? *Journal of Finance and Economics*, *43*(10), 43-54.