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Retraction

Retracted: Digital Inclusive Finance Data Mining and Model-Driven Analysis of the Impact of Urban-Rural Income Gap

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] C. Peng, "Digital Inclusive Finance Data Mining and Model-Driven Analysis of the Impact of Urban-Rural Income Gap," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 5820145, 8 pages, 2022.

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Research Article

Digital Inclusive Finance Data Mining and Model-Driven Analysis of the Impact of Urban-Rural Income Gap

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Digital inclusive finance, rural human capital, and agricultural green total factor productivity are simultaneously incorporated into the framework of urban-rural income gap analysis. Based on digital inclusive finance indices from several provincial panel data in China, a systematic generalized moment estimation method is used to the moderating effect of rural human capital and the mediating role of agricultural green total factor productivity. Annual time series data of foreign trade indicators and urban-rural income gap indicators are estimated by building a state-space model and applying Kalman filter to investigate the effects of these factors on the urban-rural income gap. The results show that the impact of urban-rural fixed asset investment ratio and foreign trade indicator on the urban-rural income gap in China tends to increase gradually, while the impact of rural financial development indicator is decreasing but still positive. The study finds that the development of digital inclusive finance significantly contributes to the reduction of the income gap between urban and rural residents; the breadth of coverage of digital inclusive finance and the degree of digitalization help to suppress the widening of the income gap between urban and rural residents; and rural health-based human capital, education and training-based human capital, and migration-based human capital not only have a convergence effect on the income gap between urban and rural residents themselves.

1. Introduction

In recent years, the "financialization" of Internet enterprises and the "internetization" of traditional financial services have promoted the deep integration of financial technology and inclusive finance, enabling China's digital inclusive finance to achieve extraordinary development [1]. With the initial improvement of digital technology infrastructure in rural areas and the further increase of national policy support for the development of digital inclusive finance in rural areas, digital inclusive finance has gradually penetrated into the "three rural areas," making an important contribution to the country's poverty eradication efforts and the complete elimination of absolute poverty [2]. At present, China has started a new journey of relative poverty alleviation, and the relative poverty, mainly characterized by the income disparity between urban and rural residents, has become a major practical issue of great concern to the government and academia. Regarding the mechanism of income dispersion between urban and rural residents, many scholars have extensively discussed it from the perspective of "financial exclusion" or "financial disincentives" [3–5].

Financial disincentives and bifurcation of credit distribution are common in development calculations, which exacerbate the unequal distribution of wealth in the country and create a vicious circle; relatively disadvantaged households and SMEs have difficulties in obtaining financial resources from formal financial channels such as banks on an equal footing due to internal artificial barriers and differences in the ability of different individuals to access financial resources, thus leading to unequal distribution of wealth. Farmers and SMEs generally face higher financing cost constraints, and coupled with credit discrimination in the financial sector, farmers and SMEs are excluded from the formal financial market, leading to a widening income gap between urban and rural residents; conditional exclusion and geographic and marketing exclusion of rural finance significantly widen the income gap between urban and rural

residents, and its cumulative contribution to the widening income gap between urban and rural residents is as high as 26.1% [6, 7].

So there is not much research on these issues in the academic field. A few papers have empirically examined the wealth distribution effect of digital inclusive finance in China and its convergence effect on the income gap between urban and rural residents and carefully examined the moderating role of rural human capital and the mediating role of agricultural green total factor productivity [8–11].

The marginal contributions of this paper are as follows: Firstly, unlike the income gap between urban and rural residents in the literature, this study, based on the perspective of financial disincentives, thoroughly explains the theoretical logic of digital inclusive finance affecting the income gap between urban and rural residents at four levels: transaction costs, risk control, market expansion, and financial supply system [12]. On this basis, we empirically test the convergence effect of digital inclusive finance on the income gap between urban and rural residents in China and reveal the heterogeneous effects of coverage breadth, usage depth, and digitization degree breakdown indices on the income gap between urban and rural residents. It is to include rural health human capital, education and training human capital, and migration human capital into the analysis framework of the relationship between digital inclusive finance and the income gap between urban and rural residents, to explain the moderating role of the three types of human capital in it, and to conduct empirical tests and discuss heterogeneity [13]. Third, we try to incorporate agricultural green total factor productivity into the analytical framework of the relationship between digital inclusive finance and the income gap between urban and rural residents and discuss the mediating role of agricultural green total factor productivity through a combination of theoretical explanation and empirical testing [14].

2. Related Work

Digital inclusive finance can reduce the difficulty of employment by alleviating the financial constraints of the rural labor force and providing financial support for the accumulation of its human capital and the bearing of transfer costs. This provides an important channel to promote the nonfarm transfer of rural labor, which in turn leads to more farmers enjoying economic development dividends and advances the realization of the rural revitalization strategy concept, for example, Riva Sanseverino et al. [15] studies on the industrial structure upgrading, Myeong et al. [16] meso level studies on enterprise financing constraints and innovation upgrading, and Echebarria et al. [17] level studies and microlevel studies on urban and rural residents' income, entrepreneurship, consumption, and employment. And the transfer of rural labor from the agricultural sector to the nonagricultural sector, as a major symbol of the present era, plays a crucial role in optimizing labor allocation, achieving economic development, and promoting social harmony and puts forward many ideas with academic value and policy guidance for the rational guidance of the nonagricultural transfer of rural labor, and the existing researches have been relatively mature and perfect.

The literature [18] found that the establishment and development of enterprises released a large number of jobs and increased farmers' opportunities for nonfarm employment. In addition, digital inclusive finance can provide financial and credit support for rural laborers to enhance their employability, which facilitates laborers to meet the hiring needs of nonfarm jobs, and thus increases the probability of successful matching of rural laborers with nonfarm jobs. The study of [19] shows that in the process of transferring rural labor to nonfarm jobs, there are costs, such as employment information acquisition costs, transportation costs, and accommodation and food costs, and many rural laborers with limited economic power cannot afford the transfer costs and thus cannot achieve nonfarm employment.

3. Theoretical Analysis and Formulation of Research Hypothesis

3.1. Income Gap between Urban and Rural Residents. Financial inhibition or financial exclusion exists in rural areas of China. At the supply level, due to the country's long-term unbalanced development strategy of "industrial priority and urban bias" and financial market reform, traditional financial institutions allocate limited financial resources to nonagricultural sectors in urban areas and take measures such as closing rural outlets to reduce operating costs in order to maximize profits. In the vast rural areas, due to the noncollection of rural residents and the difficulty of obtaining comprehensive credit information, it is more costly and risky for financial institutions to expand the rural market. In addition, the inherent "weak" characteristics of agriculture, such as long production cycle, high natural and market risks, and low returns, make financial resources with profit-seeking nature exclude rural areas or agriculture, and rural areas or agriculture faces long-term financial inhibition. In terms of financial demand, farmers and modern agricultural operators have a strong demand for financing [20]. In the process of reallocation of rural land resources and promotion of agricultural industrialization, farmers face a large credit gap in land transfer and moderate scale operation. Against the background of the deepening of the rural revitalization strategy, the integration of three rural industries and multifunctional expansion of agriculture and rural environmental management have put forward more and higher requirements for rural finance. Rural financial services need to explore new models and new paths.

3.2. Rural Human Capital. Since Schultz proposed the concept of human capital, human capital has become an important perspective for the new growth theory to interpret the source of economic growth and the formation of income disparity. The development of digital inclusive finance and its extensive penetration into the "three rural areas" have provided a greater possibility for farmers or households to access financial services, which can be used to develop production and increase income. However, whether digital inclusive finance can be successfully accessed and whether

it can be optimally allocated with other factors of production, such as labor and land, depends on the level of human capital of farmers and their households.

4. Variable Description and Model Construction

4.1. Variable Description

(1) All indicators are deducted the price factor, which is continuous and comparable

(2) Rural financial development indicators (FIR): there are many types of indicators on financial development, mainly including financial structure indicators, financial efficiency indicators, and financial relevance rate. From the data availability and the reality of China's rural financial development, this paper adopts the stock and flow indicators proposed by Goldsmith (1969) to measure the level of financial development of a country FIR, FIR = total financial assets/GDP [1]. Among them, the total amount of rural deposits (including the sum of deposits of farmers and township enterprises) and rural loans (including the sum of agricultural loans and loans of township enterprises) is used as indicator of total rural financial assets; the total output value of township enterprises is used as indicators of rural GDP

(3) Foreign trade (MY): this paper mainly adopts the flow of goods and services in the international economy to measure the degree of economic openness and specifically uses the ratio of total imports and exports to GDP to measure it

4.2. Building a State Space Model. The state space model consists the measurement equation can be expressed as

$$y_t = Z_t a_t + d_t + u_t \quad t = 1, 2 \cdots \cdots T, \tag{1}$$

where T denotes the sample length and y_t denotes a $k \times 1$ – dimensional observable vector containing k economic variables that are related to an $m \times 1$ – dimensional vectora_t, where a_t is referred to as the state vector. In general, the elements of a_t are unobservable, which in this paper are time-varying parameters to be estimated and can be expressed as a first-order Markov process, which is defined as the following state equation:

$$a_t = T_t a_{t-1} + c_t + R_t \varepsilon_t \quad t = 1, 2 \cdots \cdots T. \tag{2}$$

Z_t and d_t in the measurement equation and T_t, c_t, and R_t in the state equation are collectively referred to as the system matrix. They are assumed to be nonrandom if not otherwise specified. u_t and ε_t are the perturbation terms with mean 0 continuous uncorrelated in the measurement and state equations, respectively.

The system matrix Z_t uses the Kalman filter method to estimate the state vector a_t, and a_t is the dynamic development, urban and rural fixed asset investment, opening to the outside world, and China's urban-rural income gap that we hope to find.

Table 1: ADF unit root test results.

Variable	τ statistic	Inspection type	Critical value (significance level)	Conclusion
CJ	-1.3367	(C,0,1)	-2.9604 (5%)	Nonstationary
ΔCJ	-3.5860	(C,0,2)	-2.9678 (5%)	Stable
FIR	-1.094	(C,0,0)	-2.9571 (5%)	Nonstationary
ΔFIR	-4.071	(C,0,1)	-2.9640 (5%)	Stable
GT	-1.603	(C,0,2)	-2.9678 (5%)	Nonstationary
ΔGT	-7.1571	(C,0,2)	-0.9624 (5%)	Stable
MY	-1.341	(C,0,0)	-2.9571 (5%)	Nonstationary
ΔMY	-4.387	(C,0,0)	-2.9601 (5%)	Stable

4.3. Unit Root Test. Table 1 shows the results of the unit root test.

In this paper, the commonly used ADF test is selected to test the unit root of each variable. Since the indicators selected in this paper are the ratios of different time series, the test pattern is chosen to contain only the intercept term, not the trend term, and the lag order is determined according to the AIC criterion, and the specific unit root test pattern of each variable is expressed by the following formula:

$$\Delta \mathrm{CJ}_t = c + \delta \mathrm{CJ}_{t-1} + \sum_{j=1}^{p} \Delta \mathrm{CJ}_{t-j} + \mu_t, \tag{3}$$

$$\Delta \mathrm{FIR}_t = c + \delta \mathrm{FIR}_{t-1} + \sum_{j=1}^{p} \Delta \mathrm{FIR}_{t-j} + \mu_t, \tag{4}$$

$$\Delta \mathrm{GT}_t = c + \delta \mathrm{GT}_{t-1} + \sum_{j=1}^{p} \Delta \mathrm{GT}_{t-j} + \mu_t, \tag{5}$$

$$\Delta \mathrm{MY}_t = c + \delta \mathrm{MY}_{t-1} + \sum_{j=1}^{p} \Delta \mathrm{MY}_{t-j} + \mu_t t = 1, 2 \cdots \cdots \cdots T. \tag{6}$$

The results of the unit root test are shown in Table 1. According to the unit root test results in Table 1, each series is first-order differentially smooth at 5% significance level, i.e., CJ, FIR, GT, and MY are I (1) sequences.

4.4. Johansen Cointegration Test. The CJ, FIR, GT, and MY are known to be homogeneous single integer smooth series through unit root test, and the cointegration test is needed to determine. The E-G two-step method is a univariate test for two variables, and the principle is to test the smoothness of the residuals of the regression equation, if the residuals are smooth, then there is cointegration between the two variables; otherwise, the opposite. The Johansen test is a cointegration test based on regression coefficients in the

framework of VAR analysis. It is a cointegration test applicable to multiple variables. Therefore, Johansen cointegration test is used in this paper. Before conducting Johansen cointegration test, the VAR model between variables must be established first and the VAR must be stationary before Johansen cointegration test can be performed. In order to ensure the smoothness of the model, the VAR (2) model is established in this paper by the logarithm of each variable, and the numbers in parentheses indicate the lag order of the model, which is determined according to the AIC criterion. As shown in Figure 1, the inverse of the mode of all roots of this VAR (2) model is within the unit circle, indicating that the established VAR (2) model is stable and can be Johansen's cointegration test is performed.

Johansen cointegration test has five different forms of cointegrating equations, and according to the previous assumptions, we use the second form, i.e., there is no deterministic trend in each time series, but the cointegrating equation has an intercept term, and the test results are shown in Table 2. As can be seen from Table 2, there are three cointegration relationships among the four variables according to the trace statistic test; according to the maximum eigenvalue test method, there are only two cointegration relationships among the four variables. Therefore, a model can be constructed for these four variables to examine the quantitative relationships among them, which provides a basis for the establishment of the state-space model in the later section.

4.5. Modeling the State Space of Urban-Rural Income Gap. This paper utilizes this favorable feature of the state space model to analyze the dynamic paths of the impact of China's rural financial development, urban-rural fixed asset investment, and foreign opening on China's urban-rural income gap with the changes of China's economic structure and economic environment since the reform and opening up by establishing a variable parameter state space model of CJ on FIR, GT, and MY. The state-space model of this paper is established as follows.

The measurement equation:

$$\begin{aligned} \mathrm{LNCJ}_t &= c(1) + sv1 \times \mathrm{LNFIR}_t + sv2 \\ &\quad \times \mathrm{LNGT}_t + sv3\mathrm{LNMY}_t + \mu_t \\ &\quad t = 1, 2 \cdots \cdots T. \end{aligned} \tag{7}$$

Equation of state:

$$\begin{aligned} \mathrm{sv1} &= \mathrm{sv1}(-1) + \varepsilon_{1t}, \\ \mathrm{sv2} &= \mathrm{sv2}(-1) + \varepsilon_{2t}, \\ \mathrm{sv3} &= \mathrm{sv3}(-1) + \varepsilon_{3t}, \\ (u_t, \varepsilon_t)' &\sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \delta^2 g & \\ g & Q \end{pmatrix}\right), \end{aligned} \tag{8}$$

where sv1, sv2, and sv3 are the state vectors of the model, which are LNFIR_t, LNGT_t, and LNMY, respectively, and sv1, sv2, and sv3 are the time-varying parameters of the model. sv1, sv2, and sv3 are unobservable variables, which need to be estimated using the observable LNFIR_t, LNGT_t, LNMY_t, and LNCJ_t, and the state vectors are assumed to obey the AR (1) model in this paper. μ_t and ε_t are the random perturbation terms of the measurement and state equations, and they are assumed to obey a normal distribution with mean 0, variance δ_2, and covariance matrix Q, and cov $(\mu_t\, t) = g$. The state space model is analyzed using Kalman filter, and the results are shown in Table 3, from which it can be seen that the estimates of the variable parameter state space model pass the test and the model is set correctly.

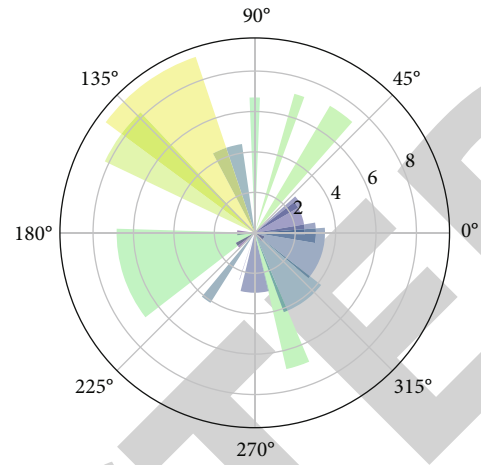

Figure 1: Inverse of the root of the VAR (2) model.

After the estimation of the state space model, the residuals of the model need to be tested by unit root test. If the residual vector is smooth, the estimation result of the model is credible; otherwise, the phenomenon of "pseudoregression" may occur, resulting in the wrong estimation of the regression result. The results of the unit root test of the residuals are shown in Table 4, which shows that the residual vector is smooth and the Kalman filter estimation of the model is valid.

4.6. Data Description. The model is constructed taking into account the possible inertia or path dependence of the urban-rural income gap, and here, the lags of the urban-rural income gap are included in the explanatory variables, which can not only serve as a proxy variable for some of the omitted variables but also reflect the inertia and persistent influence of the urban-rural income gap itself. Thus, a dynamic panel model is developed.

$$\mathrm{gap}_{i,t} = \alpha_0 + \alpha_1 \mathrm{gap}_{i,t-1} + \beta_0 \mathrm{dif} i_{i,t} + \beta_1 X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}. \tag{9}$$

$\mathrm{gap}_{i,t}$ represents the urban-rural income gap, which is the explanatory variable of this paper; d represents digital inclusive finance, which is the core explanatory variable of this paper, and its coefficient $\mathrm{difi}_{i,t}$ represents the net effect of urban-rural income gap; $X_{i,t}$ is the set of control variables, which are described later; 1 is the regional dummy variable, which is used to control the individual effect of each

Table 2: Johansen cointegration test results.

Original hypothesis	Characteristic value	Trace statistics	P value (signature test)	Maximum eigenvalue	P value (eigenvalue statistics)
0 cointegration vectors	0.8356	97.258	0	54.1550	0
At most one cointegration vector	0.5277	43.103	0.0057	22.5037	0.047
At most 2 cointegration vectors	03313	20.601	0.045	12.075	0.172
At most 3 cointegration vectors	0.2473	8.5240	0.0661	8.5240	0.0661

Table 3: Estimates and statistics of the state space model.

State vector	Final state	Root mean square error	Z value	P value
sv1	0.1270	0.0414	3.0664	0.002
sv2	0.4223	0.2207	19.139	0
sv3	0.2331	0.0210	11.1169	0

province; μ_i is the year dummy variable, which controls for fixed effects in all years; and $\varepsilon_{i,t}$ is the random disturbance term.

This study not only aims to portray the impact and effect of digital inclusive finance on the income gap between urban and rural residents but also further discusses whether rural human capital has a moderating effect on the above impact and effect. To this end, we draw on the research idea of Gong Ping8 and divide the measurement dimensions of rural human capital into three types: health, education and training, and migration, and add the interaction terms of digital inclusive finance and health human capital $\mathrm{hh}_{i,t}$, digital inclusive finance and education and training human capital $(\mathrm{difi}_{i,t} \times \mathrm{hh}_{i,t})$, $(\mathrm{difi}_{i,t} \times \mathrm{eh}_{i,t})$ and digital inclusive finance and migration human capital $\mathrm{mh}_{i,t}$ to equations (2)–(6), respectively. $(\mathrm{difi}_{i_+} \times \mathrm{mh}_{i,t})$ to obtain

$$g^{\mathrm{gap}_{i,t}} = \alpha_0 + \alpha_1 \mathrm{gap}_{it-1} + \beta_0 \mathrm{dif}i_{i,t} + \beta_1 \mathrm{hh}_{i,t} + \beta_2(\mathrm{dif}i_{i,t} \times \mathrm{hh}_{i,t}) + \beta_1 X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}, \quad (10)$$

$$\mathrm{gap}_{i,t} = \alpha_0 + \alpha_1 \mathrm{gap}_{i,t-1} + \beta_0 \mathrm{difi}_{i,t} + \beta_1 \mathrm{eh}_{i,t} + \beta_2(\mathrm{dif}i_{i,t} \times \mathrm{eh}_{i,t}) + \beta_1 X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}, \quad (11)$$

$$\mathrm{gap}_{i,} = \alpha_0 + \alpha_1 \mathrm{gap}_{i,t-1} + \beta_0 \mathrm{dif}_{i+} + \beta_1 \mathrm{mh}_{i_+} + \beta_2(\mathrm{difi}_{i_+} \times \mathrm{mh}_{i,t}) + \beta_1 X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}. \quad (12)$$

the following regression model:

$$\mathrm{gap}_{i,t} = c_1 + a_1 \mathrm{dii}_{i,t} + \beta_1 X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}, \quad (13)$$

$$\mathrm{gtfp}p_{i,t} = c_2 + a_2 \mathrm{dif}i_{i,t} + \beta_2 X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}, \quad (14)$$

$$\mathrm{gap}_{i,t} = c_3 + a_3 \mathrm{dii}_{i,t} + a_4 g_t fp_{i,t} + \beta_3 X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}. \quad (15)$$

The coefficient of α_3 is fully mediated if it is not significant and partially mediated if it is not. In order to deal with the inherent endogeneity problem of the model 2, this paper adopts the System Generalized Method GMM of moment system to estimate the parameters of the model, borrowing from [21–23].

The Thayer index of income disparity between urban and rural residents can not only portray the dynamic characteristics of the income disparity between urban and rural residents but also mitigate the possible effects of urban and rural demographic changes on the income disparity between urban and rural residents. Therefore, this study adopts the Thiel index to measure the income gap between urban and rural residents, which is defined by the following formula:

$$\mathrm{gap} = \sum_{i=1}^{2} \left(\frac{Y_{i,l}}{Y_t}\right) \times \ln\left[\frac{Y_{i,l}/Y}{X_{i,l}/X_t}\right], \quad (16)$$

where $i = 1$ denotes urban and $i = 2$ denotes rural.

5. Basic Regression Analysis

To explore the impact of digital inclusive finance on the nonfarm transfer of rural labor, the model is set up as Equation (17).

$$Y_{ijt}{}^* = \beta_1 + \beta_2 X_{ijt} + \beta_3 Z_{ijt} + \varphi_i + \theta_t + \varepsilon_{ijt}, \quad (17)$$

$$Y_{ijt}{}^* = \begin{cases} 0, & \text{if } Y_{ijt}{}^* \le \alpha_1, \\ 1, & \text{if } \alpha_1 \le Y_{ijt}{}^* \le \alpha_2, \\ 2, & \text{if } Y_{ijt}{}^* \ge \alpha_2, \end{cases} \quad (18)$$

where $Y_{ijt}{}^*$ denotes the degree of nonfarm transfer of rural labor in the explanatory variable, which represents the degree of transfer of the unobservable individual j in province i in year t. $X_{ijt}{}^*$ denotes the explanatory variable digital inclusion finance. $\beta$is the parameter to be estimated, where$\beta_1$is the intercept term, and$\beta_2$denotes the effect of digital inclusion finance on the nonfarm transfer of rural labor, all else being equal, and if it is greater than 0, it indicates the digital inclusion finance. If it is greater than 0, it indicates that the development of digital inclusive finance contributes to the nonfarm transfer of rural labor, i.e., hypothesis 1 is valid and the opposite is not valid; Z_{ijt} denotes control variables. φ_i denotes province fixed effects to control for province differences, and θ_t denotes year fixed effects to control for year differences. ε_{ijt} denotes a random disturbance term that measures a set of unobservable factors [24–26].

Based on the basic model, the quadratic term of digital inclusive finance was added to the basic regression model with reference to Wang et al. [12] 1 in order to examine

Table 4: Unit root test results for residuals of the state space model.

Variable	τ statistic	Inspection type (C, T, L)	Critical value (significance level)	Conclusion
Residual sequence	-5.083	(C,0,1)	-2.9640	Stable

Table 5: Income gap between urban and rural residents.

	1	2	3	4
$ga_{i,t-1}$	0.52	0.50	0.40	0.46
difi	-0.9	0.13	-0.03	-0.10
Urban	0.13	0.09		
fe	0.12	0.37	0.45	0.10
lnpgdp	0.15	0.12	0.10	0.8
fdi	-0.091	0.11	0.07	0.04
Control variable	Control	—	Control	Control
Time effect	Control	—	Control	Control
AR (1)	—	—	—	0.1
AR (2)	—	—	—	0.45
Sargan	—	—	—	0.35
Obs	270	270	270	270

Table 6: The effect of coverage and depth of use on the income gap between urban and rural residents.

	1	2	3
$ga_{i,t-1}$	0.64	0.73	0.69
difi	-0.12		
cov		0.01	
bre			0.40
dig			0.41
Control variable	Control	Control	Control
Regional effect	Control	Control	Control
Time effect	Control	Control	Control
AR (1)	0.19	0.04	0.02
AR (2)	0.42	0.43	0.32
Sargan	0.56	0.62	0.66
Obs	270	270	270

the characteristics of the effect of digital inclusive finance on rural labor. The model is set up as

$$Y_{ijt}^{*} = \delta_1 + \delta_2 X_{ijt} + \delta_3 Xsq_{ijt} + \delta_4 Z_{ijt} + \varphi_i + \theta_t + \nu_{ijt}, \quad (19)$$

where Y_{ijt}^{*} denotes the explanatory variable nonfarm transfer of rural labor, X_{ijt} denotes the explanatory variable digital financial inclusion, Xsq_{ijt} is the quadratic term of the explanatory variable, Z_{ijt} denotes the control variable, φ_t denotes the province fixed effect, θ_t denotes the year fixed effect, and ν_{ijt} denotes the random disturbance term.

6. Results and Discussion

The baseline regression results were estimated using the systematic GMM for the model parameters, and the estimated results are presented in column (4) of Table 5. For comparison with the system GMM estimation results, Table 5 also reports the results of estimation using mixed least multiplication (POIS), random effect model (RE), and fixed effect model (FE), which are presented in columns (1), (2), and (3), respectively. As a consistent estimation, the systematic GMM requires that the instrumental variables are exogenous and that there is no autocorrelation in the nuisance terms and no second-order autocorrelation in the differenced nuisance terms, for which the Hansen or Sargan instrumental variable validity tests and the ArellanoBond serial correlation tests are required. The Hansen test does not reject the validity of the instrumental variables. The above tests indicate that the systematic GMM estimation for model (1) is reliable, and the results are used as the baseline regression for discussion in this paper.

The coefficient of the one-period lagged term of the explanatory variable $ga_{i,t-1}$ is positive and passes the 1% significance level, indicating that there is inertia and path dependence in the time dimension of the income gap between urban and rural residents in China. This result is consistent with the findings of Ye and Chen. The coefficient of the core explanatory variable digital inclusive finance dj is negative at the 1% significance level. The possible reasons are that the development of digital inclusive finance effectively alleviates the financial disincentives and financial exclusion that exist in rural China, and more rural residents or households have improved their income levels through access to digital inclusive financial services. While digital inclusive finance can benefit urban residents or households, the narrowing of the income gap between urban and rural residents suggests that rural residents or households benefit more [27–30].

From the regression results of other control variables in column (4), the coefficient of urbanization is significantly positive, indicating that the traditional urbanization path of increasing the proportion of urban resident population by promoting the transfer of surplus rural labor to the urban sector does not help to promote the reduction of the income gap between urban and rural residents. Therefore, a new type of urbanization should be promoted with the citizenship of the rural migrant population as the key meaning and give full play to the role of cities and towns in driving agriculture or rural areas.

To examine the possible heterogeneous effects of different segmentation indices on the income gap between urban and rural residents, we selected three indicators of coverage breadth (con), usage depth (bre), and digitization degree (dig) as explanatory variables and conducted a systematic GMM estimation on the income gap between urban and rural residents, respectively, and the regression results are shown in Table 6.

Table 7: Robustness tests.

	1	2	3	4
$ga_{i,t-1}$	0.65	0.71	0.61	0.63
difi	-0.15			
cov		0.09		
bre			0.81	
dig				0.71
Control variable	Control	Control	Control	Control
Regional effect	Control	Control	Control	Control
Time effect	Control	Control	Control	Control
AR(1)	0.19	0.09	0.02	0
AR(2)	0.52	0.23	0.32	0.37
Sargan	0.36	0.32	0.25	0.35
Obs	270	270	270	270

The empirical results show that the impact of different segmentation indices is heterogeneous and show the coefficients of the between urban and rural residents. The possible reason is that expanding the coverage of digital inclusive finance helps to include more rural households or families and modern agricultural business organizations such as large farmers, farmers' cooperatives, and family farms into the service targets of inclusive finance, while increasing the degree of digitalization provides a quick and effective way for the abovementioned rural people or agricultural business entities to obtain financial support through "online" means. The increase in digitalization has provided a quick, convenient, and low-cost channel for the abovementioned rural people or agricultural business entities to obtain financial inclusion support through "online" means.

In this paper, we replace the Thiel index with the income gap between urban and rural residents (gu) based on the income ratio of urban and rural residents and use the systematic GMM estimation method to conduct the robustness test, and the results are shown in Table 7. It can be seen that after replacing the measures of the explanatory variables, the sign direction of the regression coefficients of the main explanatory variables in columns (1)–(4) did not change, and only the sign of individual explanatory variables changed but remained insignificant, which to some extent indicates that the results of this paper are robust.

In order to test the hypothesis whether agricultural green total factor productivity growth is a mediating variable of digital inclusive finance affecting the income gap between urban and rural residents, we report the estimation results of the mediating effect model of equations (7)–(9) in Table 8.

The empirical results show that the impact of different segmentation indices is heterogeneous and the coefficients differ for urban and rural residents. The possible reason is that expanding the coverage of digital inclusive finance helps to include more rural households or families and modern agricultural business organizations such as large farmers, farmers' cooperatives, and family farms into the target of inclusive financial services, while increasing the degree of digitalization, which provides a fast and effective way for the above rural population or agricultural business entities to obtain financial support, "online" means. The increase of digitalization provides a fast, convenient, and low-cost channel for the abovementioned rural people or agricultural business entities to obtain financial support through the "online" method.

Table 8: Analysis of the mediating effect of green total factor productivity in agriculture on the income gap between urban and rural residents.

	1. gap	2. gtfp	3. gap
difi	0.09	0.26	0.06
gtfp	—	—	0.032
Control variable	Control	Control	Control
Regional effect	Control	Control	Control
Time effect	Control	Control	Control
Obs	270	270	270

In this paper, based on the income ratio between urban and rural residents, the income gap between urban and rural residents (gu) is used to replace the Thiel index, and a systematic GMM estimation method is used to conduct robustness tests, and the results are shown in Table 8. It can be seen that after replacing the measures of the explanatory variables, the sign direction of the regression c-efficiency of the main explanatory variables in columns (1)–(4) does not change, and only the sign of a single explanatory variable changes, but it is still insignificant, which indicates to some extent that the results of this paper are robust.

7. Conclusions

It is suggested that China has successfully eradicated poverty from the rural poor under the current standards and entered the "postpoverty alleviation era," which makes the issue of relative poverty, mainly characterized by the income gap between urban and rural residents, a major historical issue facing the government in the long run. This study attempts to incorporate digital inclusive finance and rural human capital into the framework of urban-rural income gap analysis. Based on the panel data digital inclusive finance index, the moderating effects of rural residents and rural human capital are evaluated using a systematic generalized moment estimation method. The study finds that the development of digital inclusive finance makes a significant contribution to rural residents; it can contribute to the reduction of total factor productivity.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declared no conflicts of interest regarding this work.

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