Data-Driven Modeling of the Impact of Internet Inclusive Finance on the Urban-Rural Income Gap in the E-Commerce Era

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Abstract

In modern society, in which e-commerce is advancing rapidly, conventional finance has begun to adopt the internet, and digital inclusive finance activity has emerged. In the e-commerce era, the use of massive data to digitally evaluate important issues remains promising. Against this background, this paper proposes a data-driven modeling framework for the impact of inclusive internet finance on the urban-rural income gap in the e-commerce era. Specifically, using 2011-2017 panel data on 204 prefecture-level cities in China, this paper visualizes statistical features needed to evaluate the rationality of the initial data samples. Then, the study sets up five basic explanatory variables and five control variables and establishes two regression models to map the relationship between the feature variables and the urban-rural income gap. Using several parameter estimation methods to fit the model parameters, the paper examines the impact of inclusive finance on the urban-rural income gap from multiple perspectives. Finally, based on the data-level analysis results, the paper proposes policy suggestions.

Keywords: E-commerce, Urban-rural income gap, Internet inclusive finance, Data-driven modeling, Multivariant regression

1 Introduction

With the growth of mobile computing, artificial intelligence and other digital technologies, inclusive internet finance driven by digital technology is increasingly used worldwide [1-2]. This phenomenon has lead to the provision of diversified financial services, such as payments, savings and money management, to more people, especially those who have suffered "financial exclusion" [3-4]. Thus, practically anyone accessing the internet can obtain financial services at low cost [5-6].

One important indicator of relative poverty is the urban-rural income gap. This gap has become an economic and social issue that governments and academics follow closely while seeking methods to alleviate it [7-8]. Many scholars have extensively discussed the formation mechanism of the (urban-rural) income gap from the angle of "financial exclusion" or "financial repression" [9-10]. Polarized financial repression and credit allocation are pervasive in developing countries, and this phenomenon will aggravate national wealth inequality and create a vicious circle [11-12]. In light of the internal man-made obstacles and differing ability of different people to obtain financial resources, it is difficult for families and small and medium-sized businesses (SMBs) who are relatively disadvantaged to obtain financial resources from a bank or through other formal financial channels on equal terms, thus resulting in an unequal distribution of wealth [13-14]. Constrained by higher financing costs and credit discrimination by the financial sector, farm households and SMBs are often excluded from the formal financial market; as a result, the income gap has further widened [15-16]; the condition exclusion as well as the geographic and marketing exclusion of rural finance has markedly expanded the urban-rural income gap, with a cumulative contribution up to 26.1% [17-18].

In recent years, scholars have turned their attention to the relationship between digital inclusive finance and wealth distribution. Digital inclusive finance stimulates entrepreneurial activities among rural residents, thereby increasing household income, especially that of rural low-income families [19]. To an extent, the development of digital inclusive finance has eased the long-standing financial exclusion or financial repression in China's formal financial market, thus enabling relatively disadvantaged groups, such as rural residents, previously excluded from the formal financial market to obtain financial resources for self-development or to increase their incomes. This phenomenon has helped decrease the urban-rural income gap [20-23].

Compared with the literature, the main innovations of this paper are as follows. In terms of its theoretical analysis, the paper uses the dynamic panel model to examine the impact of digital inclusive finance on the urban-rural income gap. Considering the lag characteristics, the paper introduces data on digital inclusive finance in the current period, one lag period and two lag periods into a model to investigate the dynamic relationship between digital inclusive finance and the urban-rural income gap. In addition, based on previous studies, this paper makes full use of massive business data in the era of e-commerce and sets up two data-driven analytical models to map several feature variables onto income gap results. By estimating model parameters that adopt multiple algorithms, the impact of

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digital inclusive finance on the urban-rural income gap is visualized from multiple viewpoints.

The empirical research results reveal that internet inclusive finance can greatly inhibit the expansion of the urban-rural income gap and that there is regional heterogeneity. The inhibition effect in the eastern and western regions of China is greater than in the central regions. Additionally, by subdividing the digital inclusive finance index, we find that insurance and credit in coverage and depth of use can effectively narrow the income gap between urban and rural areas. However, the degree of e-payment and digitization has significantly widened the income gap between urban and rural areas.

2 Related Research

At present, academics mainly hold the following two views on the relationship between digital inclusive finance and the urban-rural income gap. The first is that the development of digital inclusive finance will narrow the income gap and that the "digital dividend" will become more significant. This view is usually based on the inclusiveness of digital inclusive finance. Such finance is considered to play a greater role in improving the income of rural populations and low-income groups so as to significantly narrow the income gap between urban and rural areas. The second view is that the relationship between the development of digital finance and the urban-rural income gap display a Kuznets effect. Several representative papers are surveyed in this section.

Song et al. [3] used data on 31 provinces in China from 2011 to 2015 to construct a balanced panel data model and showed that digital inclusive finance has significantly narrowed the income gap between urban and rural areas.

Based on quantile regression, Zhou et al. [24] found that digital inclusive finance is conducive to narrowing the urban-rural income gap, and its marginal effect is greater at the low quantile.

C. He et al. [25] found that inclusive finance mainly reduces the urban-rural income gap by improving the financial environment. However, urbanization is more effective than inclusive finance in narrowing the urban-rural income gap.

Using the statistical data on 280 prefecture-level cities in China from 2011 to 2020, Yao et al. [26] found that there is a Kuznets effect of digital finance development on the income gap in China. This outcome indicates that most regions in China have not crossed the inflection point of the bell-shaped curve, and the income gap will continue to expand with the development of digital finance.

3 Data Preprocessing

3.1 Data Collection

The statistical data used in this article mainly come from the China City Statistical Yearbook and the EBS global statistical database. Considering data availability and sample integrity, certain data have been supplemented according to the local statistical yearbooks of the provinces and cities concerned, and missing data have been addressing using the interpolation method. The data related to digital inclusive finance come from the Peking University Digital Inclusive Financial Index (2011-2015) and the Peking University Digital Inclusive Financial Index (2016-2018) compiled by the Institute of Digital Finance, Peking University. This article adopts the data of 2011-2017 and the panel data on 204 Chinese cities above the prefecture level.

3.2 Index System

On the one hand, the Theil index reflects dynamic change in the urban-rural income gap; on the other, it weakens the impact of population structure change on the urban-rural income gap [27]. Therefore, the index is used here to measure the urban-rural income gap and defined by the following formula:

$$GAP = \sum_{i=1}^{2} \left(\frac{Y(i,t)}{Yt}\right) \times Ln\left[\left(\frac{Y(i,t)}{Yt}\right)/\left(\frac{X(i,t)}{Xt}\right)\right], \quad \textbf{(1)}$$

where $i = 1$ stands for city and town, $i = 2$ refers to rural area, $Y(i,t)$ is the urban and rural disposable income in the tth year, Yt is the total urban and rural disposable income in the tth year, $X(i,t)$ stands for the urban or rural population in the tth year, and Xt stands for the total population in the t-th year.

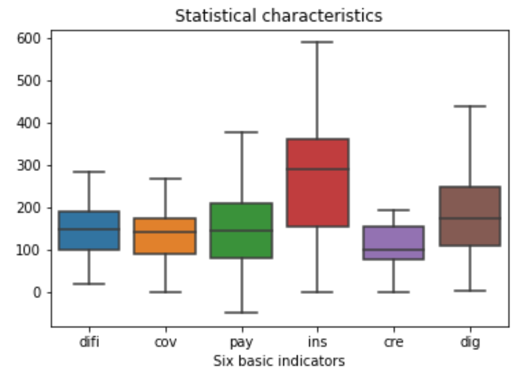
The digital inclusive financial index of 204 China's prefecture-level cities in this article comes from the Peking University Digital Inclusive Financial Index (2011-2015) and the Peking University Digital Inclusive Financial Index (2016-2018) compiled by the Institute of Digital Finance, Peking University. Since the index value is too large for the other index selected in this article and the two indices do not have the same dimensions, up to 100% of the index was used as the primary data. The five variables include the following:

- breadth of coverage: cov;
- payment: pay;
- insurance: ins;
- credit: cre;
- level of digitalization: dig.

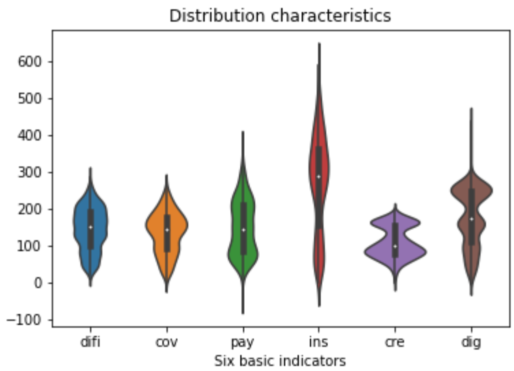
3.3 Visualization of Initial Data

Before modeling, we visualize the statistical characteristics of the initial research data to analyze their distribution reasonability. First, the six basic indices (cov, pay, ins, cre, dig and $difi$) are integrated to inspect their own statistical distribution characteristics. Figure 1 utilizes two types of diagram to present this information. As shown in the images, the distribution of ins is located in a higher interval compared with the other five indicators, and the other five indicators possess relatively similar distribution features.

The statistical characteristics of the six basic indicators are visualized in Figure 2. The figure consists of six subfigures that correspond to the statistical characteristics of six basic indicators. These subfigures reveal that the six basic indicators are nearly drawn from normal distributions, showing the reasonability of the initially collected research samples. In addition to the statistical characteristics of single variables, the relationship between pairwise variables also requires investigation. The indicator $difi$ is highly related to digital finance status. With this indicator as the baseline, the relationship between it and the other five indicators is illustrated in Figure 3. This figure contains five subfigures that correspond to five groups of relationships. In each subfigure, the X-axis denotes the range interval of $difi$, and the Y-axis denotes the range interval of the comparison indicators. As clearly shown in these five subfigures, there is a linear relationship between $difi$ and the other five indicators, indicating positive correlations.

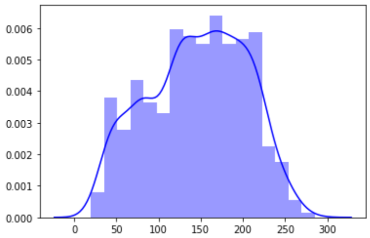


(a) Box-type diagram

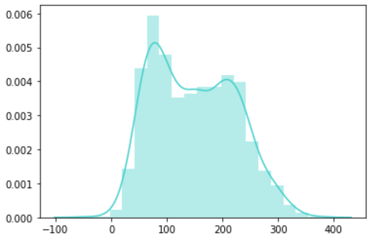


(b) Piano-type diagram

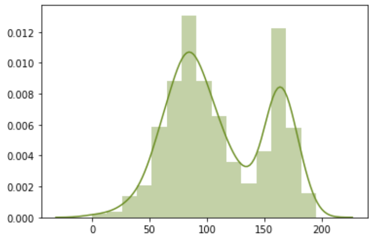
Figure 1. Distribution of six basic indicators in the initial research data



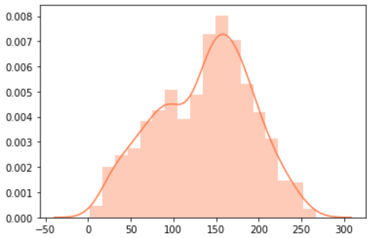
(a) $difi$



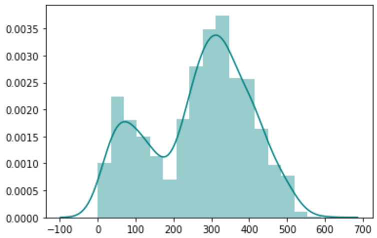
(b) cov



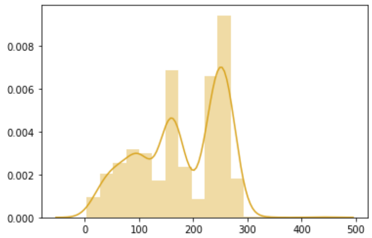
(c) pay



(d) ins

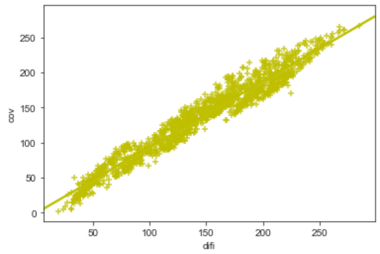


(e) cre

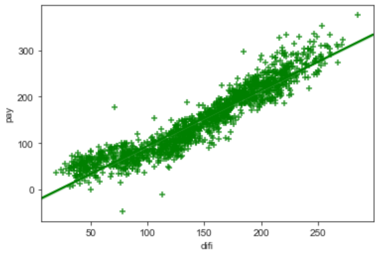


(f) dig

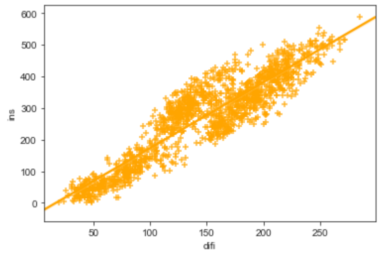
Figure 2. Independent distribution for six basic indicators



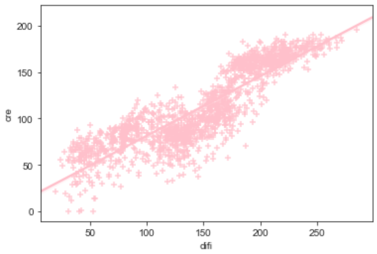
(a) cov



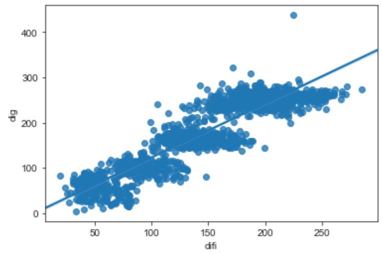
(b) pay



(c) ins



(d) cre



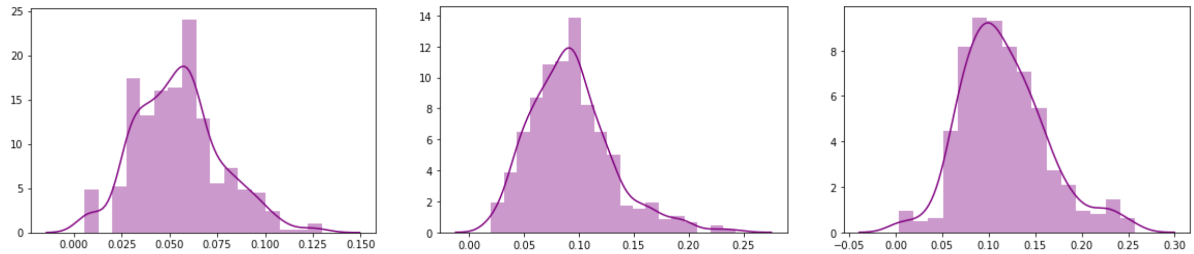
(e) dig

Figure 3. Relationship between indicator $difi$ and the other five indicators

3.4 Preliminary Analysis of the Estimated Gap

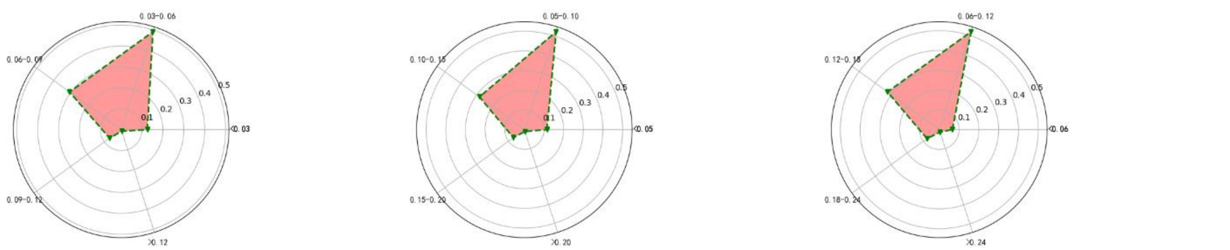
As the urban-rural income gap can be preliminarily estimated by Eq. (1), one can expect to investigate gap characteristics with respect to three different regions of China: the eastern area, central area and western area. The results are shown in Figure 4, in which the three subfigures represent the distribution of gap values in the three different areas. It can be observed from these subfigures that the gap in the eastern area is within the range of (-0.02,0.15), that the gap in the central area is within the range of (-0.02,0.3), and that the gap in the western area is within the range of (-0.05,0.3). These numerical results indicate that the urban-rural income gap in the eastern area is smaller than in the central and western areas. This finding corresponds to actual circumstances as the eastern area of China is regarded as more developed than the central and western areas.

In addition, the numerical interval distributions for the gap values of the three areas are presented using three radar charts, which correspond to the three subfigures in Figure 5. For each area, the entire numerical interval is divided into five small intervals. In the polar coordinate system of radar diagrams, a higher depth at a polar point indicates that more gaps are located in the corresponding interval. It can again be observed from the three radar charts that the gap values in each area exhibit features of normal distribution. Additionally, the joint distribution of gap values between three pairs of area combinations is shown in Figure 6, in which the three subfigures correspond to three combinations. These graphical results reveal that gap values of pairwise relations can exhibit characteristics of uniform distribution inside the sample space.



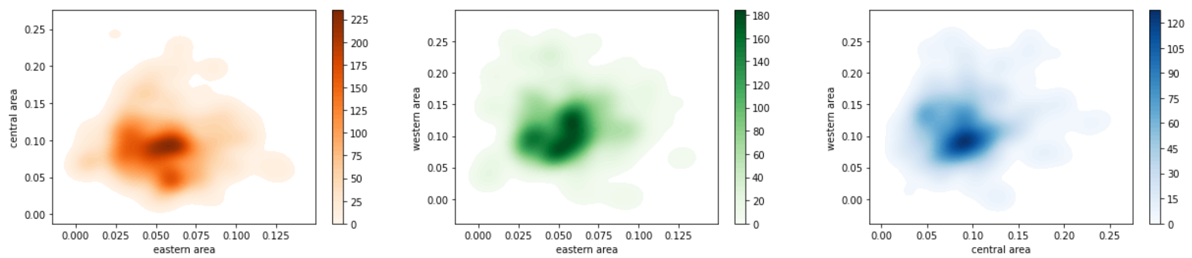
(a) Eastern area (b) Central area (c) Western area

Figure 4. Distribution of gap values with respect to the eastern area, central area and western area



(a) Eastern area (b) Central area (c) Western area

Figure 5. Numerical interval distribution for the gap values of three areas



(a) Between eastern area and central area (b) Between eastern area and western area (c) Between central area and western area

Figure 6. Joint distribution of gap values between three pairs of area combinations

4 Model Formulation

4.1 Control Variable

This paper's control variables are introduced as follows:

- industrial structure: is;
- economic growth: $rgdp$;
- urbanization rate: urb;
- government economic behavior: geb;
- formal finance development: ff.

Financial development, ff, is represented by the proportion of the year-end deposit-loan balance in the local and foreign currency of financial institutions to GDP. It can be calculated using the following formula:

$$ff = Q/gdp, \quad \textbf{(2)}$$

where Q denotes the year-end deposit-loan balance in the local and foreign currency of financial institutions.

Fiscal expenditure, geb, is expressed by the proportion of local fiscal expenditure to each city's GDP. It can be calculated using the following formula:

$$geb = W/gdp, \quad \textbf{(3)}$$

where W denotes local fiscal expenditure.

Industrial structure, is, is represented by the proportion of added value of the secondary and tertiary industries to GDP. It can be calculated using the following formula:

$$is = E/gdp, \quad \textbf{(4)}$$

where E denotes the added value of the secondary and tertiary industries.

The urbanization rate, urb, is expressed by the proportion of each city's year-end population to the total regional population. It can be calculated using the following formula:

$$urb = R/popu, \quad \textbf{(5)}$$

where R denotes the urban year-end population and $popu$ denotes the total regional population.

The economic growth rate, $rgdp$, is expressed by the natural logarithm of the per capita GDP of each city. It can be calculated using the following formula:

$$rgdp = \ln gdp/popu. \quad \textbf{(6)}$$

The five control variables are visualized in Figure 7, which includes 25 small figures. Of these 25 images, 20 represent all 20 groups of pairwise relations among the five variables, whereas the 5 images along the diagonal represent the numerical distributions of the five variables. It can be observed from the 20 scatter charts that the joint distributions of all the pairwise relations exhibit relatively uniform characteristics, which indicates the reasonability of the five control variables to a certain extent.

Integrating the six basic indicators, gap values and five control variables, Table 1 lists the statistical characteristics of the 12 variables. These statistical characteristics include mean values, standard deviations, minimum values and maximum values. As shown in Table 1, the values of the 12 variables are located in stable intervals, without obvious fluctuation. Figure 8 provides the correlation heatmap for the five control variables, in which color depth represents correlation degree. The color change from blue to red denotes that the correlation degree ranges from 0 to 1. It can be noted from the figure that most of the correlation values are within the range of $(0.3,0.8)$. Therefore, the five control variables are suitable for establishing data models.

4.2 Regression-based Gap Assessment

With a view to possible inertia or "path dependence" in the evolution of the urban-rural income gap, we included the one-period lagged variable of the urban-rural income gap as an explanatory variable. Thus, we constructed a dynamic panel model:

$$gap_{it} = \alpha_i + B_{it} + u_{it}, \quad \textbf{(7)}$$

where i stands for city, t stands for year, α_i stands for unobservable regional effect, u_{it} is a stochastic disturbance term, and B_{it} is represented as the following formula:

$$B_{it} = \beta_0 gap_{it-1} + \beta_1 difi_{it} + \beta_2 X_{it}, \quad \textbf{(8)}$$

where gap_{it} is an explanatory variable representing the urban-rural income gap among prefecture-level cities, $difi_{it}$ is the digital inclusive financial index and a core explanatory variable, and gap_{it-1} is the one-period lagged variable of the urban-rural income gap.

The digital inclusive financial index provided by the Internet Development Research Center of Peking University includes three dimensions: breadth of coverage (account coverage rate), depth of usage (payment, credit, insurance, investment and credit investigation) and level of digitalization (convenience and financial service cost). To investigate the heterogeneous impact of different indicators on the urban-rural income gap, this study further selected breadth of coverage (cov), payment (pay), insurance (ins), credit (cre) and level of digitalization (dig) as explanatory variables, with data integrity, to investigate their impacts on the urban-rural income gap. The model is as follows:

$$gap_{it} = \alpha_i + C_{it} + u_{it}, \quad \textbf{(9)}$$

where C_{it} is represented by the following formula:

$$C_{it} = C_{it}^{(1)} + C_{it}^{(2)}, \quad \textbf{(10)}$$

where C_{it} is represented by the following formula:

$$C_{it}^{(1)} = \beta_0 gap_{it-1} + \beta_1 lncov_{it} + \beta_2 lnpay_{it} + \beta_3 lnins_{it}. \quad \textbf{(11)}$$

$$C_{it}^{(2)} = \beta_4 lncre_{it} + \beta_5 lndig_{it} + \beta_6 X_{it}. \quad \textbf{(12)}$$

Table 1. Total statistics for 12 variables from 204 cities

Variable	Sample size	Mean value	Standard deviation	Minimum value	Maximum value
gap	1428	0.0839	0.0438	0.0030	0.2576
difi	1428	1.4551	0.5785	0.1953	2.8543
rgdp	1428	10.6304	0.5538	8.8416	12.5792
is	1428	0.8918	0.0685	0.6777	1.0714
urb	1428	0.5300	0.1371	0.2126	0.9797
geb	1428	0.1916	0.1342	0.0012	1.4857
ff	1428	2.2706	1.1609	0.6293	12.5079
cov	1428	1.3608	0.5571	0.0188	2.6713
pay	1428	1.4896	0.7411	-0.4697	3.7599
ins	1428	2.6801	1.3159	0	5.8819
cre	1428	1.1068	0.4237	0	1.9526
dig	1428	1.7722	0.7666	0.0364	4.3791

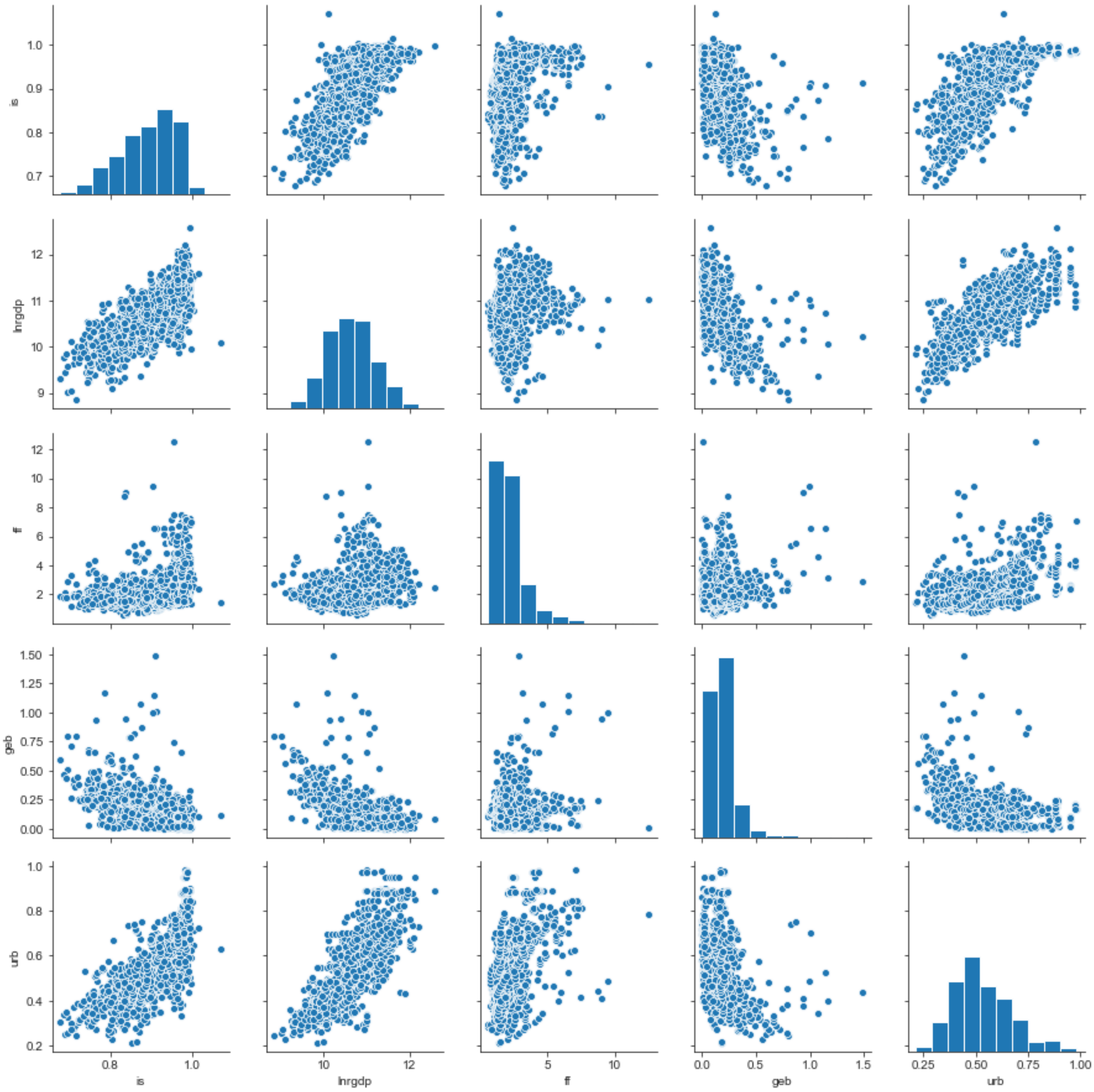


Figure 7. Joint distribution of pairwise relationships among five control variables

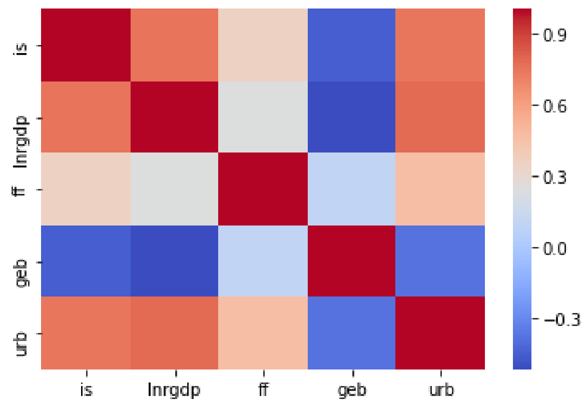


Figure 8. Correlation heatmap for the five control variables

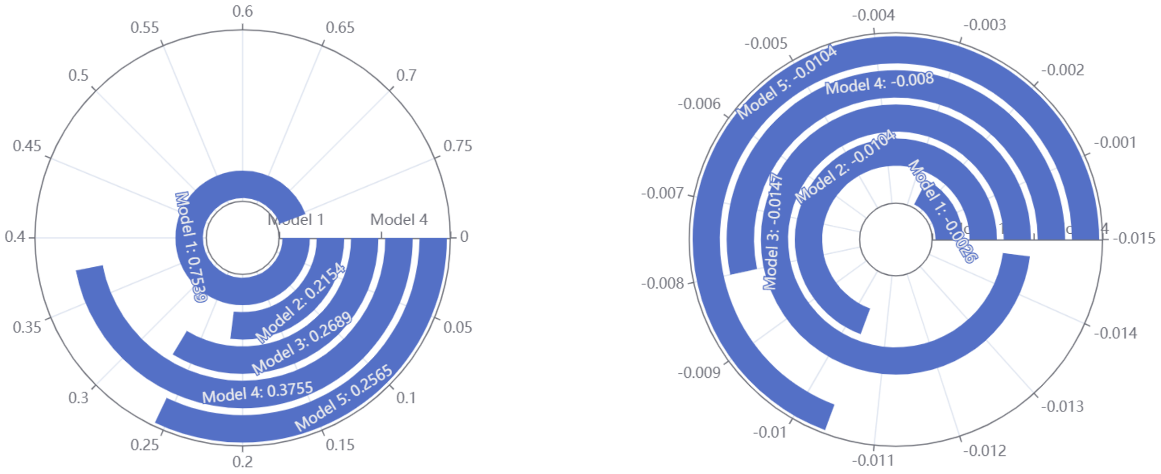
5 Results of Numerical Analytics

5.1 Baseline Regression

To address the model's inherent endogeneity problem [28-29], we performed a parameter estimation of Model (1) using the system generalized method of moments (system GMM), and the results are reported in Column (3) of Table 2 as a baseline regression result for discussion. Columns (4) and (5) report the regression results of the one and two lag periods of Digital Inclusive Finance, respectively. In addition, Table 2 presents the results of the estimation that adopted pooled OLS (POLS) and a fixed-effects model (FE), as shown in Columns (1) and (2), to further check the robustness of system GMM estimation. Since there is no control over the regional effect, mixed estimation typically overestimates the coefficient of the lag term of the dependent variable. Although the fixed effect estimation has a fixed effect in the control area, the fixed effect estimation will underestimate the coefficient of the lag term due to the relatively small period. Only through system GMM estimation can a consistent and unbiased estimation be obtained.

Table 2. Impact of digital inclusive finance on urban-rural income gap

Explanatory variable	(1)	(2)	(3)	(4)	(5)
gap_{it-1}	0.7539*** (0.0273)	0.2154*** (0.0584)	0.2689* (0.1466)	0.3755*** (0.1224)	0.2565* (0.1428)
$difi$	-0.0026*** (0.0009)	-0.0104*** (0.0033)	-0.0147*** (0.0046)		-
$difi_{it-1}$				-0.008*** (0.0023)	-
$difi_{it-2}$					-0.0104*** (0.0037)
is	0.0266* (0.0146)	-0.0179 (0.0152)	0.0506** (0.0206)	0.0488*** (0.0168)	0.0554*** (0.0176)
rgdp	-0.0030* (0.0017)	-0.0112** (0.0047)	0.0169*** (0.0052)	0.0137 (0.0117)	0.0102 (0.0188)
ff	0.0011*** (0.0004)	0.0006 (0.0007)	0.0152** (0.0064)	0.0063* (0.0036)	0.0066 (0.0065)
geb	0.0043 (0.0028)	-0.0006 (0.0030)	-0.0373*** (0.0143)	-0.0187* （0.0098）	-0.0097 (0.0138)
urb	-0.0408*** (0.0075)	-0.03145 (0.0462)	-0.3194*** (0.0881)	-0.2542*** (0.0785)	-0.2470** (0.1109)
Year		Yes	Yes	Yes	Yes
area		Yes	Yes	Yes	Yes
AR(1)	—	—	0.001	0.000	0.005
AR(2)	—	—	0.417	0.064	0.151
Sargan	—	—	0.125	0.522	0.538
Obs	1224	1224	1224	1224	1020



(a) Value of gap_{it-1} (b) Value of $difi$

Figure 9. Values of two important indicators in five different regression models

Let us first examine the regression result of the baseline model in Column (3). The endogenous variables in the model are the one lag period of the urban-rural income gap and the digital inclusive finance index, and the three lag periods of the two variables are the instrumental variables. The AR(1) and AR(2) tests show that although the residual sequence of the difference equation cannot reject the first-order serial correlation, it can significantly reject the second-order serial correlation. This outcome suggests that the model specification is practicable. The Hansen test cannot reject the valid null hypothesis of an instrumental variable, which indicates that the instrumental variable is valid. These tests demonstrate that the system GMM estimation for Model (1) is reliable.

As shown in Figure 9(a), the coefficient of the one-period lagged variable $gap_{(i_t-1)}$ for the explained variable is positive and passes the significance level of 10%, which indicates that the urban-rural income gap in China features inertia and "path dependence" in the time dimension. This finding is consistent with the conclusion drawn by Ye et al. [30]. As shown in Figure 9(b), the coefficient of digital inclusive finance $difi$, and the core explanatory variable is negative at the level of approximately 1%, which indicates that the development of digital inclusive finance is conducive to decreasing the urban-rural income gap. This may be because of the development of digital inclusive finance, which effectively mitigates financial repression or financial exclusion in Chinese rural areas. More rural residents are increasing their incomes through access to digital inclusive financial services. Although digital inclusive finance also benefits urban residents, the reduction of the urban-rural income gap demonstrates that rural residents reap more benefits.

We continue to focus on the regression result of other control variables in Column (3). The coefficient of industrial structure "is" is distinctly positive, which reveals that the urban-rural income gap increases as a result of industrial structure change. The reason is that the rapid development of industrialization has an absorption effect on rural land, capital and other production factors, which worsens the agricultural production environment and then affects the growth of rural income. This phenomenon widens the urban-rural income gap. The RGDP coefficient of the economic growth rate is significantly positive, which indicates that compared with urban residents, rural residents do not effectively receive the dividends of economic growth. As explained by Kuznets's inverted U-shaped hypothesis, the income gap of a country or region will initially increase and then decrease with economic growth. The urban-rural income gap increase is due to a growing economy. Thus, China has not yet successfully passed the critical point of the Kuznets inverted U-shaped curve.

The coefficient of formal finance development ff is distinctly positive, which indicates that the improvement of formal finance increases the urban-rural income gap. To maximize revenue, formal financial institutions, such as banks and insurance companies, may allocate more financial resources to urban areas, making it difficult for rural residents to obtain financial services. The coefficient of fiscal expenditure geb is distinctly negative. This outcome indicates that government expenditure helps decrease the urban-rural income gap. In recent years, China has increased the allocation percentage of the rural or agricultural sector, consolidated the construction of infrastructure (such as rural water facilities, electric power facilities, traffic facilities and internet infrastructure and public services for medical health and elementary education) and optimized agricultural production and environment as well as the conditions for the improvement of rural welfare. This effort has effectively brought fiscal expenditure into play to adjust the urban-rural income distribution. The coefficient of urbanization rate urb is distinctly negative. This outcome indicates that promoting the transfer of the rural surplus labor force and promoting urbanization are conducive to narrowing the urban-rural income gap.

5.2 Urban-Rural Income Gap Impact Factors

The inclusive financial index jointly released by Peking University and Alibaba includes breadth of coverage, depth of usage and level of digitalization. Depth of usage comprises payment, insurance and credit. To investigate the possible heterogeneous impact of different subindices on the urban-rural income gap, we adopted breadth of coverage (cov), depth of usage (including payment (pay), insurance (ins) and credit (cre)) and level of digitalization (dig) as explanatory variables to perform regression analysis of the urban-rural income gap. The regression results are shown in Table 3. Columns 1 and 2 present the results obtained by pooled OLS (POLS) and a fixed-effects model (FE), whereas the results in Columns 3, 4, and 5 were obtained by system GMM estimation. The discussion was based on these results.

Table 3. Impact of breadth of coverage, depth of usage and level of digitalization on urban-rural income gap

Explanatory variable	(1)	(2)	(3)	(4)	(5)
gap_{it-1}	0.7451*** (0.0162)	0.1955*** (0.0585)	0.4553*** (0.1730)	0.2927* (0.1716)	0.3154** (0.1422)
cov	-0.0063 (0.0044)	-0.0309*** (0.0066)	-0.0893*** (0.0287)	-	-
cov_{it-1}				-0.0278 (0.0195)	-
cov_{it-2}				-	0.0219 (0.0232)
pay	-0.0019 (0.0029)	0.0142*** (0.0037)	0.0461** (0.0192)	-	-
pay_{it-1}				0.0178 (0.0125)	-
pay_{it-2}				-	-0.0124 (0.0160)
ins	-0.0006 (0.0009)	0.0006 (0.0007)	-0.0035** (0.0017)	-	-
ins_{it-1}				-0.0019 (0.0017)	-
ins_{it-2}				-	-0.0085*** (0.0027)
cre	-0.0019 (0.0031)	-0.0117*** (0.0036)	-0.0403** (0.0165)	-	-
cre_{it-1}				-0.0242** (0.0100)	-
cre_{it-2}				-	-0.0302*** (0.0068)
dig	0.0053*** (0.0017)	0.0019 (0.0023)	0.0206*** (0.0055)	-	-
dig_{it-1}				0.0090** (0.0046)	-
dig_{it-2}				-	0.0120*** (0.0040)
Control variable	Yes	Yes	Yes	Yes	Yes
AR (1)	——	——	0.001	0.002	0.002
AR (2)	——	——	0.166	0.112	0.086
Sargan	——	——	0.081	0.170	0.969
Obs	1224	1224	1224	1224	1020

The empirical results suggest that different subindices of digital inclusive finance have heterogeneous impacts on the urban-rural income gap. The coefficients insurance (ins) and credit (cre) under breadth of coverage and depth of usage are negative and reach a significance level of at least 5%. This outcome shows that broad coverage of digital inclusive finance and increasing depth of usage of insurance and credit can effectively help decrease the urban-rural income gap. It should be noted that e-payment (pay) under depth of usage and level of digitalization (dig) have dramatically widened the urban-rural income gap. This is probably because of the low level of digitalization in rural areas and rural residents' poorer awareness of mobile payment and ability to use digital services compared to urban residents. Additionally, because many rural residents have doubts regarding the payment, they are reluctant to use e-payment, which leads to them only being able to receive limited benefits from e-payment.

5.3 Regional Heterogeneity Test

Eastern, central and western China obviously differ in the marketization, factor and resource endowment conditions and industrial bases, which is why digital inclusive finance and its subindices may have heterogeneous impacts on the urban-rural income gap. In response to this circumstance, we divided the 204 sample cities into eastern, central and western cities according to their locations for separate parameter estimation. The results are presented in Table 4.

Table 4. Regional heterogeneity test

Explanatory variable	Eastern China		Central China		Western China	
gap_{it-1}	0.4598*** (0.0613)	0.6556*** (0．0895)	0.1202 (0.1636)	0.1258 (0.3207)	0.7390*** (0.0076)	0.7322*** (0.0417)
$difi$	-0.0454*** (0.0079)		-0.0035 (0.0050)		-0.0012*** (0.0002)	
cov		-0.0135*** (0.0039)		-0.1569** (0.0654)		-0.0440*** (0.094)
pay		-0.0149*** (0.0038)		0.1027** (0.0412)		0.0123*** (0.0040)
ins		0.0015* (0.0008)		-0.0049 (0.0041)		0.0022 (0.0014)
cre		0.0197*** (0.0040)		-0.0902*** (0.0322)		0.0151*** (0.0038)
dig		0.0073*** (0.0022)		0.0306* (0.0157)		0.0203*** (0.0029)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
AR (1)	0.001	0.001	0.002	0.035	0.025	0.020
AR (2)	0.601	0.145	0.483	0.308	0.098	0.090
Sargan	0.575	0.951	0.243	0.416	0.129	0.789
Obs	432	432	456	456	336	336

The empirical results suggest that the development of digital inclusive finance can markedly curb the widening urban-rural income gap in eastern and western China, but the effect is not obvious in central China. In terms of breadth of coverage and level of digitalization, both have marked impacts on the urban-rural income gap in different regions. However, their effects are exactly opposite. Breadth of coverage significantly suppressed the urban-rural income gap, while digital level increased the gap.

The subindicators under the depth indicators, such as pay, ins and cre, and their impact on the urban-rural income gap exhibit obvious regional heterogeneity. The regression coefficient of payment is distinctly positive in central and western China but distinctly negative in eastern China. This finding suggests that increasing the payment level of digital inclusive finance will widen the urban-rural income gap in central and western China but help decrease it in eastern China. This is probably because central and western China are less developed than eastern China, and the cultural competence and digital payment awareness of urban and rural residents vary greatly. The payment level of rural residents or families lags far behind that of urban residents or families. Therefore, digital payments have a more obvious effect on the income growth of urban residents. However, in economically highly developed eastern China, the income growth effect of digital payments will benefit rural residents more because to their strong awareness and high acceptance of digital payments. The use and availability of digital insurance significantly increases the urban-rural income gap in eastern China, but the effect is not obvious in central and western China. In eastern and western China, digital credit dramatically widens the urban-rural income gap but exerts a strong convergence effect in central China.

6 Conclusion

Based on 2011-2017 panel data for 204 prefecture-level cities in China and the digital inclusive financial index issued by the Institute of Digital Finance, Peking University, this study attempted to incorporate digital inclusive finance into an analytical framework for the income gap between urban and rural residents using system generalized method of moments (GMM). In addition, it evaluated the impact of digital inclusive finance on the urban-rural income gap in a systematic manner. In sum, the development of digital inclusive finance can markedly curb the widening urban-rural income gap in eastern and western China. However, the effect is not obvious in central China. After decomposing the digital inclusive financial index into breadth of coverage, depth of usage and level of digitalization, we found that insurance and credit offerings under breadth of coverage and depth of usage can effectively help decrease the urban-rural income gap, while e-payment under depth of usage and level of digitalization observably increase the gap.

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