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Use of Theil for a Specific Duality Economy: Assessing the Impact of Digital Inclusive Finance on Urban-Rural Income Gap in Chongqing

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Abstract: This study uses panel data from 2016 to 2020 to examine the impact of digital financial inclusion on income inequality in the urban-rural divide of Chongqing, China. The results suggest that increasing access to digital financial services could help narrow the income gap between urban and rural areas. However, the impact becomes significantly positive when controlling for other variables with the Random Effects regression model. Among the control variables, the urbanization rate and government expenditure are found to be significant determinants of income inequality in Chongqing. These findings offer insights for policymakers on the potential benefits of targeted interventions to promote financial inclusion and sustainable urbanization, while ensuring effective allocation of government spending to reduce income inequality.

Keywords: Theil index; digital inclusive finance; urban-rural income gap

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1. Introduction

Fintech (refers to the use of innovative digital technology to deliver financial services) has revolutionized the financial industry by making it more efficient, convenient, and accessible to consumers [1] (pp. 119–129). One of the key areas where Fintech has made a significant impact is in financial inclusion [2]. Financial inclusion refers to the provision of affordable financial services such as banking, loans, payment systems, and insurance, to underserved populations who have been excluded from the traditional financial system [3,4]. According to the 2021 report of the Global Findex Database, approximately 1.4 billion adults worldwide do not have access to these financial services. However, the digital revolution has opened up new opportunities for traditional banks and non-bank institutions to reach currently financially excluded populations [3,4].

From 1981 to 2021, China's gross domestic product (GDP) grew at an average annual rate of 9.27 percent [5], leading to a remarkable increase in average annual per capita disposable income of households from 904 yuan in 1990 to 32,189 yuan in 2020 [6]. Despite a swift expansion of China's economy, the issue of income disparity between urban and rural areas remains a persistent challenge. In 2000, the income gap between urban and rural areas was 2.74 times, while in 2022, it decreased to 2.45 times [7]. Despite some progress made in reducing the income gap in recent years, achieving balanced economic growth in China is still a major concern.

With its remarkable GDP growth in recent years, Chongqing has emerged as a first-tier city and secured the fourth spot in China's GDP ranking for 2022. Compared to other first-tier cities like Beijing and Shanghai that have more diversified economies, Chongqing's economy is characterized by a typical urban-rural dual structure with a higher dependency on agriculture and manufacturing concentrated in rural areas. This heavy reliance on rural-based traditional industries has led to a notable disparity in income between urban and rural areas.

A comparison of the disposable incomes of urban and rural residents in Chongqing between 2011 and 2020 is presented in Table 1. During this period, the average annual growth rate for rural incomes was 147.7 percent, while for urban incomes, it was 116 percent. The higher income growth rate for rural residents suggests that efforts to alleviate income inequality have yielded some positive results. However, the urban-rural income ratio has only gradually decreased from 2.80 in 2011 to 2.45 in 2020, indicating that the income disparity is gradually narrowing but progress has been relatively slow. Further analysis of the data reveals that the absolute difference between the average income of urban and rural residents has remained notably significant over the past decade, peaking at 23,644.84 yuan in 2020 (which is only 41 percent of the urban income). These findings highlight that the progress towards narrowing the income gap in Chongqing has been relatively sluggish, and substantial income inequality persists. It is crucial to tackle this issue for sustainable growth in Chongqing.

Table 1. Chongqing's urban-rural income and related indicators (2011–2020).

Year	Urban Resident Income (Yuan)	Rural Resident Income (Yuan)	Absolute Difference (Yuan)	Urban-Rural Income Ratio
2011	18,516.80	6605.30	11,911.51	2.80
2012	21,002.61	7525.60	13,477.01	2.79
2013	23,058.22	8492.55	14,565.67	2.72
2014	25,147.23	9489.82	15,657.41	2.65
2015	27,238.84	10,504.71	16,734.13	2.59
2016	29,609.96	11,548.79	18,061.17	2.56
2017	32,193.23	12,637.91	19,555.32	2.55
2018	34,889.30	13,781.22	21,108.08	2.53
2019	37,938.59	15,133.27	22,805.33	2.51
2020	40,006.22	16,361.37	23,644.84	2.45

Data source: Chongqing Statistics Bureau.

China's historical urban-rural dual structure has resulted in an imbalance of development and a significant urban-rural digital divide. The growth of the digital finance industry since the introduction of Alipay in 2004 has provided opportunities for people in rural areas to access financial services that were previously unavailable to them. The subsequent integration of advanced technologies like cloud computing, blockchain, and 5G has significantly fueled the rapid growth of digital finance in China, providing an opportunity to tackle the issue of income inequality. This study aims to examine the impact of digital inclusive finance on income inequality within an economy characterized by a pronounced duality in its economic structure. The significance of this study lies in two aspects. First, it focuses on the specific duality present in the economy rather than analyzing the entire economic landscape. Secondly, it employs Theil coefficient as a measure of income inequality instead of relying on the conventional Gini coefficient. The findings of the study are expected to yield valuable insights into the potential of digital inclusive finance in narrowing the urban-rural income gap in Chongqing, thereby making a meaningful contribution to the existing literature on income inequality. These insights can serve as essential guidance for policymakers and practitioners in developing effective strategies to address income inequality issues.

2. Literature Review

Inclusive finance was first proposed in 2005 by the United Nations (UN) aimed to attain sustainable economic growth as embodied in the UN Sustainable Development Goals (SDGs) [8,9]. Financial inclusion is a prerequisite in achieving inclusive economic development [10]. The fundamental concept of financial inclusion is to provide affordable financial services that are accessible to all segments of society, economic activities, and geographical regions [11] (pp. 89–115), [12]. The relationship between financial inclusion and income inequality originated from the ability of formal financial services to ease investment and liquidity constraints, leading to increased economic growth and reduced inequality [13,14]. A growing number of cross-country studies suggested that greater levels of financial inclusion are linked to reduced levels of income inequality [15–17]. Ref. [18] examined the link between financial inclusion, poverty reduction, and income inequality in 116 developing countries using a novel financial inclusion index and panel data from 2004 to 2016. Their study supports that financial inclusion reduces poverty rates and promoting formal financial services to underprivileged populations can improve income inequality.

Digital inclusive finance, which involves the use of mobile banking, digital wallets, and online payment systems, has made financial services more accessible and affordable, particularly to those who are unbanked or underbanked [19] (pp. 229–238). With the new financial technologies, digital inclusive finance presents an opportunity to reduce financial exclusion and income inequality which are prevalent due to financial market imperfections that limit access to formal financial services [20–22]. These imperfections include information asymmetries, market segregation, and transaction costs [23,24]. Ref. [25] explored the impact of information and communication technologies (ICT) on reducing poverty and inequality through financial inclusion in 62 countries between 2001 and 2012. Their results suggest that the use of ICT as instruments for financial inclusion can promote economic growth and reduce poverty and inequality. Ref. [23] analyzed the relationship between Fintech, financial inclusion, and income inequality in 140 countries using Global Findex survey data from 2011 to 2017. Their findings indicate that Fintech can reduce income inequality at all quantiles through financial inclusion, but the effects are more significant in higher-income countries.

The urban-rural income gap is a significant challenge in income inequality, with rural populations often having limited access to financial services, which can lead to lower incomes and reduced economic opportunities. The growth of the digital finance industry has provided opportunities for people in rural areas to access financial services that were previously unavailable to them. Ref. [26] conducted a systematic literature review on digital financial inclusion across countries and found that developing countries, particularly Asian countries, are adopting and improving digital financial inclusion to reduce poverty. According to recent studies, digital financial inclusion in China reduces the income gap between urban and rural areas. Ref. [27] found that digital inclusive finance promotes entrepreneurship, alleviates financial exclusion, and broadens financing channels, reducing the income gap significantly. Ref. [28] found that digital inclusive finance has a positive effect on narrowing the urban-rural income gap in primary distribution and redistribution, albeit with regional differences, while ref. [29] found that it reduces the wage income gap.

Although digital inclusive finance has the potential to bridge the income gap by providing financial services to rural areas that may have been previously underserved, it is not the only factor contributing to the income gap. There are several other factors that contribute to the income gap between urban and rural areas. One such factor is economic development. Ref. [30] examined the relationship between inequality, growth, and redistribution in China, Japan, South Korea, and the United States. They found that there is a positive causal relationship between inequality and economic growth in China, Japan, and the United States. Ref. [31] employed wavelet analysis to examine the relationship between U.S. per capita real GDP and six income inequality measures from 1917 to 2012. They found a positive correlation between economic growth and inequality across frequencies, but the causality directions varied across frequencies and evolved over time. Based on a panel of 28 European Union (EU) countries from 2005 to 2016, the results of [32] support the Kuznets hypothesis, and emerging EU countries experience increasing income inequality with positive economic growth, while highly developed EU countries experience the opposite. According to [33], the digital economy's rapid growth has made it a vital driver of economic development, capable of reshaping the relationship between urban and rural areas, promoting equitable progress, and altering income distribution patterns. Ref. [34] based on panel data of 31 China provinces from 2013 to 2019 show that the digital economy positively impacts high-quality economic development, and promoting coordinated development between urban and rural areas, ultimately boosting sustainable development of the region.

Another factor that contributes to the income gap between urban and rural areas is urbanization. Generally, empirical studies found that urbanization narrows the urban-rural income gap [35,36]. Ref. [37] analyzed income inequality in China by studying provincial-level data from 1987 to 2010 and revealed an inverted-U relationship between income inequality and urbanization. Their results indicate that provinces above a threshold urbanization rate experience a decrease in income inequality. Ref. [38] used an unbalanced panel dataset for 48 countries from 1996 to 2016 and found evidence of a positive association between urbanization and income inequality in Sub-Saharan Africa. In Vietnam, ref. [39] based on panel data from 63 provinces between 2006 to 2016 confirmed the inverted-U-shaped relationship that urbanization has a reducing impact on income inequality in the long term but not for the short term.

Industrial structure is also one of the factors affecting urban-rural income inequality. In China, ref. [40] found a positive relationship between industrial structure upgrading and reducing income gaps between urban and rural areas, with the urbanization rate playing an intermediary role, and there are regional differences in the threshold effect. Similarly, ref. [41] found that balancing and upgrading industries leads to rising wage income and declining property income, thereby reducing income inequality. However, ref. [42] discovered that industrial structure upgrades exert varying effects on income gaps across different regions. In their findings, the upgraded industrial structures reduce the income gap in central China but increase the gap in western China.

In addition, increased government investment in infrastructure, education, and healthcare plays a significant role in enhancing economic opportunities and living standards in rural regions. Ref. [43] (pp. 23–25) conducted a study using panel data from 31 provinces in China from 2011 to 2015 to examine the factors that contribute to the income gap between urban and rural residents. They found that the development of digital financial inclusion significantly reduces the income gap, along with factors such as urbanization and industrial progress. However, uneven distribution of financial expenditure to urban and rural areas widened the income gap, while the opening-up policy had a positive impact on reducing the income gap. Recently, ref. [44] developed an analytical framework to assess the distribution effect of urbanization on the income gap between urban and rural areas. They recommended increasing fiscal expenditure on urban-rural affairs to significantly reduce the gap. However, they also cautioned that if government spending is biased towards urban areas, it can worsen the income disparity between urban and rural regions.

To summarize, these factors have the potential to influence the income disparity between urban and rural areas, with their effects further influenced by the advancement of digital financial inclusion.

3. Methodology

Following China implemented the Plan for Promoting the Development of Inclusive Finance (2016–2020) and the G20 High-Level Principles on Digital Inclusive Finance in 2016, the sample of this study includes 26 municipal districts and 12 counties in Chongqing from 2016 to 2020. The data are collected primarily from the Peking University Digital Financial Inclusion Index of China (PKU-DFIIC) and the Chongqing Statistics Bureau. Following [45], the basic regression model is as follows:

$$Theil_{it} = \alpha_0 + \alpha_1 DIFI_{it} + \varepsilon_{it} \quad (1)$$

In the Equation (1), α_0 is the constant, ε_{it} is the error term, $Theil_{it}$ is the explained variable measures the urban-rural income gap, while $DIFI_{it}$ refers to the index of the digital financial inclusion which is the core explanatory variable. The Theil index is a widely accepted measure of income inequality introduced by [46] that accounts for both the relative differences between different income groups and the distribution of income within each group. In contrast, the Gini coefficient (which is another commonly used inequality measure) based on the Lorenz curve neglects the differences in population structure between urban and rural residents and it is overly sensitive to income differences among middle-income populations [47–49].

The Theil index from information theory measures the entropy or inequality in the distribution of income among individuals in a population. It ranges between 0 (perfect equality) and 1 (perfect inequality), with higher values indicating greater inequality of income. An increasing value of the index indicates a widening income gap and vice versa. Following [50], the Theil index is calculated as follows:

$$Theil_t = \sum_{i=1}^{2} \left(\frac{Y_{i,t}}{Y_t} \right) \ln \left[\frac{Y_{i,t}}{Y_t} / \frac{X_{i,t}}{X_t} \right] \tag{2}$$

where, i stands for urban (i = 1) or rural (i = 2) area, $X_{i,t}$ is the population in urban or rural area in year t, X_t is the total population in year t, $Y_{i,t}$ is the income of urban or rural area in year t, Y_t is the total income in year t [46].

The selected control variables should be related to the dependent variable but have little or no correlation with the independent variables. Specifically, the control variables included in the present study are the level of economic development (PGDP), the urbanization rate (UR), the industrial structure (IS), and government fiscal expenditures (GOV). The following regression model incorporates these control variables:

$$Theil_{it} = \beta_0 + \beta_1 DIFI_{it} + \beta_2 PGDP_{it} + \beta_3 UR_{it} + \beta_4 IS_{it} + \beta_5 GOV_{it} + \varepsilon_{it} \tag{3}$$

In the Equation (2), β_0 is the constant, the gross domestic product (GDP) per capita (PGDP) is used to measure the economic growth [51], while the urbanization rate (UR) which is the ratio of urban population to total population measures the percentage of people who live in urban areas compared to those who live in rural areas [52]. Industrial structure (IS) is the added value of secondary and tertiary industry divided by GDP. This variable is used to measure the level of industrialization in a given region or country, by taking into account the contribution of secondary and tertiary industries to the overall GDP [41,53]. Government expenditure (GOV) is the regional government expenditure divided by GDP. This variable measures the level of government spending in a given region or country, by taking into account the total amount of money spent by the government in that region or country to the overall GDP [54]. All variables are defined in Table 2.

Table 2. Variable description.

Variables	Code	Variable Description
Explained Variable		
Income gap	Theil	Theil index
Explanatory Variable		
Digital inclusive finance	DIFI	Digital inclusive finance index
Control Variables		
Economic growth	PGDP	Gross domestic product (GDP) per capita
Urbanization rate	UR	Urban population/total population
Industrial structure	IS	Added value of secondary and tertiary industry/GDP
Government expenditure	GOV	Regional government expenditure/GDP

4. Results and Discussion

The Peking University Digital Inclusive Finance Index consists of 33 indicators grouped into three categories: breadth of digital financial coverage, depth of digital financial usage, and level of digitalization of inclusive finance. As of the third update in 2021, the index covers a time span of 2011–2020 and includes 31 provinces, 337 cities at or above the prefectural level, and about 2800 counties in China. Figure 1 portrays that the overall and sub-indices for Chongqing have been increasing steadily from 2011 to 2020, suggesting an improvement in digital financial inclusion in Chongqing over the past decade. Particularly in recent years, the growth of the digitalization level of the financial industry is a more than fourfold increase over the ten years.

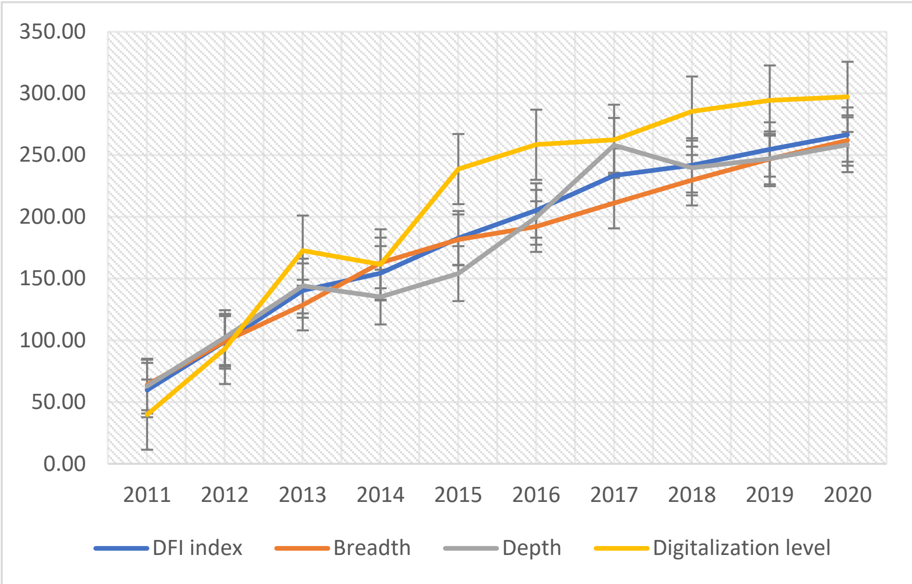

Figure 1. The digital inclusive financial index for Chongqing (2011–2020). Source: PKU-DFIIC.

In addition, the Figure 2 shows a downward trend of income inequality from 2011 to 2020 in Chongqing. The trend indicates an improvement in income distribution over this period. Nevertheless, the Theil index is still relatively high with a value of 0.0628 in 2020. Furthermore, the rate of decrease in the Theil index has slowed down in recent years suggesting efforts to reduce income inequality may have been effective only in the earlier years.

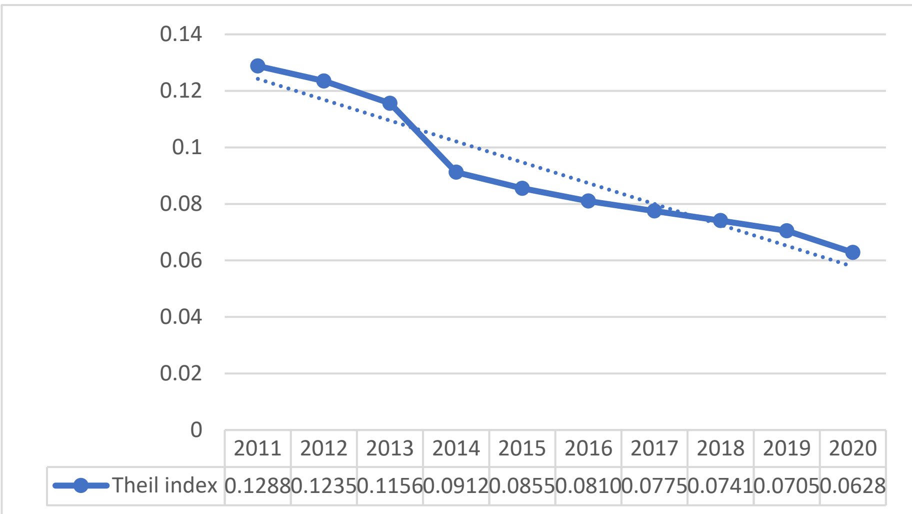

Figure 2. The Theil index for Chongqing from 2011 to 2020.

Table 3 presents the results of the descriptive statistics for six variables with 190 observations each. The mean value of 1.06 for DIFI suggest that on average there is a high level of access to financial services through digital means. It is worth nothing that the minimum and maximum values of 0 and 0.1482 for THEIL suggest that the inequality measure ranges from perfect equality to a relatively high level of inequality, which may be indicative of disparities in income distribution within the sample. Furthermore, the results show that the economic growth variable has the highest level of dispersion, suggesting that there are significant differences in economic performance across the sample. The median and mean values of most variables are closely aligned, indicating that the distribution of data is relatively unaffected by any outliers.

Table 3. Descriptive statistics for the tested variables.

Variable	N	Mean	Median	Std. Dev.	Minimum	Maximum
THEIL	190	0.0695	0.0700	0.0402	0.0000	0.1482
DIFI	190	1.0627	1.0754	0.1087	0.8354	1.2962
PGDP	190	6.1208	5.5901	3.0478	1.6836	22.9588
UR	190	0.6089	0.5760	0.2008	0.3091	1.0000
IS	190	0.8934	0.8862	0.0652	0.7575	1.0000
GOV	190	0.2039	0.1590	0.1322	0.0517	0.8353

Table 4 shows the correlation of all variables employed in this study and reveals that THEIL and GOV are positively correlated, as well as DIFI and PGDP, UR, and IS. In contrast, negative correlations were found between THEIL and DIFI, PGDP, UR, and IS, as well as DIFI and GOV, PGDP and GOV, UR and GOV, and IS and GOV. These correlations suggest that as income inequality increases, government expenditure tends to increase, while a higher level of digital financial inclusion, economic growth, urbanization rate, and industrial structure are associated with a lower level of inequality. The results also suggest that as these explanatory and control variables increase, they tend to positively impact each other, but negatively impact the government expenditure. To completely comprehend the implications of these correlations, further analysis and context-specific interpretation are necessary.

Table 4. Correlation matrix for the full sample.

Variable	THEIL	DIFI	PGDP	UR	IS	GOV
THEIL	1.0000					
DIFI	−0.5639	1.0000				
PGDP	−0.6756	0.6217	1.0000			
UR	−0.9256	0.6555	0.7228	1.0000		
IS	−0.8489	0.6143	0.7457	0.9133	1.0000	
GOV	0.7240	−0.4717	−0.6503	−0.6806	−0.7425	1.0000

Multicollinearity in a regression model arises when there is a strong correlation between independent variables. Detecting multicollinearity is crucial for ensuring the reliability of regression results and coefficient estimates. The variance inflation factor (VIF) is a metric used to gauge the extent to which a variable can be explained by other variables in the model. A VIF of 1 indicates no multicollinearity, while values above 1 suggest increasing levels of multicollinearity. A common threshold for identifying problematic multicollinearity is a VIF value of 5 or greater. The VIFs in Table 5 are less than 5 suggest that there is no severe collinearity problem for the model.

Table 5. Variance inflation factor (VIF) results.

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
Constant	0.001259	1192.197	NA
DIFI	0.000172	185.5291	1.912027
PGDP	3.01×10^{-7}	13.30354	2.632062
UR	0.000087	33.99279	3.317514
IS	0.000940	714.3805	3.768004
GOV	0.000142	7.943569	2.342818

To avoid spurious regressions, it is necessary to test for stationarity in panel data. The Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test in Table 6 show that null hypothesis of a unit root is rejected for all variables at the 5 percent significant level. The results indicate that all the variables are at stationarity in their level forms.

Table 6. Unit root test.

	THEIL	DIFI	PGDP	UR	IS	GOV
ADF statistics						
Level I(0)	−4.2789	−3.5674	−5.5404	−4.1261	−3.7946	−6.2953
p-values	0.0042	0.0355	0.0000	0.0069	0.0189	0.0000
PP statistics						
Level I(0)	−4.0073	−13.2898	−8.5944	−4.0847	−4.36706	−6.1719
p-values	0.0084	0.0000	0.0000	0.0079	0.0031	0.0000

Furthermore, the Breusch-Godfrey LM test is performed to ascertain the residual is not correlated with lagged values of itself which is not desirable. In panel A of Table 7, the *p*-value of 0.2297 did not support the rejection of the null hypothesis, suggesting that there is no significant serial correlation among the residuals. In terms of the residual variance inequality between the observations, the Breusch-Pagan-Godfrey (BPG) test and ARCH test are used to examine the presence of heteroskedasticity. The *p*-values of BPG test and ARCH test in panel B of Table 7 have failed to reject the null hypothesis of homoscedasticity, indicating that the residual have constant variance which is desirable.

Table 7. Serial correlation test and Heteroskedasticity test.

Panel A: Breusch-Godfrey Serial Correlation LM Test			
F-statistic	1.483542	Prob. F (2, 182)	0.2297
Obs*R-squared	3.050994	Prob. Chi-Square(2)	0.2175
Panel B: Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	1.687059	Prob. F (5, 184)	0.1548
Obs*R-squared	6.686709	Prob. Chi-Square (5)	0.1534
Scaled explained SS	8.920300	Prob. Chi-Square (5)	0.0631
Heteroskedasticity Test: ARCH			
F-statistic	2.103436	Prob. F (1, 187)	0.1251
Obs*R-squared	4.178698	Prob. Chi-Square (1)	0.1238

A panel data regression is employed for data analysis in this study. To determine the appropriate model from pooled ordinary least square (POLS), fixed effect model (FEM), and random effect model (REM), relevant diagnostic tests for models were used. The result of Chow Test in Table 8 shows that null hypothesis of POLS is appropriate than FEM is rejected, suggesting the FEM is accepted. Following that, the examinations of Hausman Test and Bresuch Pagan Lagrange Multiplier (LM) Test both supported the REM is a significant and appropriate panel model over the FEM and POLS.

The analysis presented in Table 9 suggests that even when explanatory and all control variables are set to zero, income inequality still persists at a significant level. The negative and statistically significant coefficient of DIFI (−0.2086) in the univariate analysis implies that higher levels of digital financial inclusion are associated with lower levels of income inequality. The results are consistent with the findings of [27,55]. However, it is important to note that the model only explains a small proportion of the variance in Theil index as indicated by the relatively low coefficient of determination (R-squared) of 0.3180. This highlights that other factors beyond DIFI could also be important determinants of income inequality in Chongqing.

Table 8. Model specification test results.

Chow Test **H0: POLS is appropriate than FEM**	**Statistic**	**d.f.**	**Prob.**
Cross-section F	15.4572	(37,147)	0.0000
Cross-section Chi-square	301.5894	37	0.0000
Hausman Test **H0: REM is appropriate than FEM**	**Chi-Sq. Stat**	**Chi-Sq. d.f.**	**Prob.**
Cross-section random	7.0062	5	0.2202
Bresuch Pagan LM Test **H0: POLS is appropriate than REM**	**Cross-section**	**Test hypothesis time**	**Both**
Breusch-Pagan	191.5708 (0.0000)	1.6492 (0.1991)	193.2201 (0.0000)

Table 9. Regression results for the full sample.

Variables	**Univariate**	**REM**
Constant	0.2912 * (12.2358)	0.1939 * (5.3417)
DIFI	−0.2086 * (−9.3625)	0.0212 * (2.6797)
PGDP		0.0005 (1.2352)
UR		−0.1604 * (−11.2636)
IS		−0.0657 (−1.5444)
GOV		0.0309 * (2.3497)
R-squared	0.3180	0.6773
Adjusted R-squared	0.3144	0.6685
F-statistic	87.6555	77.2323
Prob (F-statistic)	0.0000	0.0000
Durbin-Watson stat	0.3710	1.4251

t-statistic in parenthesis, * $p < 0.05$.

The results of REM reveal that the coefficient for DIFI is significantly positive (0.0212), which suggests that increased access to digital financial services could result in higher income inequality. This result is similar to [56] who found that financial inclusion and Fintech exacerbated income inequality across 39 African countries. This is in line with the "Matthew effect" that those who are already wealthy and have access to digital financial services may have more opportunities to invest and grow their wealth, thus widening the income gap [57]. This creates a digital divide that reinforces existing inequalities in Chongqing. The government expenditure also has a significant positive coefficient (0.0309), which indicates that higher government spending is associated with greater income inequality. The results are similar to the findings of [58]. It is plausible that government expenditure may not be targeted towards reducing income inequality, and instead allocate resources towards certain sectors or groups in Chongqing.

In contrast, the urbanization rate has a significant negative coefficient (−0.1604), which implies that more urbanization can lead to less income inequality. This result suggests that urbanization may create more employment opportunities, which could lead to a more even distribution of income in Chongqing. The finding is consistent with [59] that the urbanization rate is the key factor for the digital inclusive finance to narrow the urban-rural income gap in China, and [50] that the effect of urbanization in reducing the income gap between urban and rural areas is more significant than that of inclusive finance.

Both economic growth and industrial structure have a positive coefficient, but no statistical evidence suggests that they have a significant effect on income inequality. The adjusted R-squared value of 0.6685 suggests that REM is a good fit for the data, while the F-statistic of 77.2323 with a p-value of 0.0000 confirms that this model is statistically significant and has a goodness of fit. The Durbin-Watson statistic of 1.4251, being close to 2, indicates no significant autocorrelation problem.

In summary, this study reveals that digital financial inclusion has a significant negative impact on income inequality, while controlling for other variables. It implies that increasing access to digital financial services can play a role in narrowing the income gap between urban and rural areas in Chongqing. However, the presence of control variables amplifies the effect of digital financial inclusion. The impact becomes significantly positive when these variables are considered. Of all the control variables, the urbanization rate and government expenditure are significant determinants of income inequality in Chongqing. On the other hand, economic growth and industrial structure do not appear to have a statistically significant impact on income inequality.

5. Conclusions

The findings of this study demonstrate that digital financial inclusion is a significant determinant of income inequality in Chongqing, China. Univariate analysis indicates that digital financial inclusion has a negative and statistically significant relationship with income inequality, suggesting that increased access to digital financial services could help reduce income inequality. However, the limited explanatory power of the model highlights the need to consider other factors beyond digital financial inclusion in understanding income inequality in the region. The findings of Random Effect Model show that increased access to digital financial services could result in higher income inequality. The model further reveals that while higher government expenditure is associated with greater income inequality, urbanization is negatively correlated with income inequality, suggesting that more urbanization can lead to a more equitable distribution of income. The positive coefficient of economic growth and industrial structure does not provide sufficient evidence of their impact on income inequality. The robustness of REM is confirmed by its high adjusted R-squared value and significant F-statistic. Policymakers in Chongqing could leverage these findings to implement specific interventions aimed at promoting financial inclusion and sustainable urbanization while ensuring that government spending is effectively allocated towards reducing income inequality. Possible interventions include increasing the availability of digital financial services to marginalized populations, improving infrastructure in low-income areas, promoting financial literacy and education programs, and stimulating employment opportunities and entrepreneurship in urban areas. Additionally, future research could further explore the interaction between digital financial inclusion and other socioeconomic factors that impact income inequality.

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