sustainability

Article

# How Does Digital Finance Contribute to Sustainable Wealth Growth: Perspective from Residents' Income

**Dan Luo [1,2], Feifan Wang [3], Yue Gu [2] and Jiamin Lv [2,*]**

[1] Alibaba Business School, Hangzhou Normal University, Hangzhou 310058, China; luodan@hznu.edu.cn
[2] Institute of Digital Finance, Hangzhou City University, Hangzhou 310015, China; guyue9401@zju.edu.cn
[3] School of Finance, Shanghai University of Finance and Economics, Shanghai 200433, China; feifanw@126.com
* Correspondence: jamielv@zju.edu.cn

**Abstract:** Sustainable growth relies on common prosperity, which is reflected in increasing total income and equitable income distribution. This study first proposes the theoretical mechanisms by which digital financial development affects residents' total income and income distribution. After that, a two-stage generalized method of moments estimation model with endogeneity treatment is constructed to investigate the impact of digital finance on residents' total income in 31 Chinese provinces. Moreover, Moran's *I* and a spatial autoregression model are used to explore the impact of digital finance on residents' income distribution. The results demonstrate that digital financial development can significantly contribute to the increase in residents' total income in both urban and rural areas, thus contributing to regional sustainable wealth growth. In addition, digital finance has a spatial direct effect and a spatial spillover effect on the optimization of residents' income distribution. This indicates that a region's digital financial development benefits regional sustainable wealth growth, as it not only can improve residents' income distribution within the same region but also can promote the income distribution of neighboring regions.

**Keywords:** digital finance; sustainable wealth growth; residents' total income; income distribution; spatial effect



**Citation:** Luo, D.; Wang, F.; Gu, Y.; Lv, J. How Does Digital Finance Contribute to Sustainable Wealth Growth: Perspective from Residents' Income. *Sustainability* **2024**, *16*, 8266. https://doi.org/10.3390/su16188266

Academic Editor: Ştefan Cristian Gherghina

Received: 30 July 2024
Revised: 5 September 2024
Accepted: 17 September 2024
Published: 23 September 2024



## 1. Introduction

One of the biggest problems facing the world today is how to pursue sustainable wealth growth. Poverty undermines sustainable wealth growth and even leads to structural conflicts within societies. That is why all the countries, especially developing countries, should make no concessions when it comes to eliminating poverty to pursue sustainable wealth growth. The United Nations estimated that 1.1 billion people in 110 countries were living in multidimensional poverty by 2023 [1]. Moreover, 65.3 percent of poor people (730 million) were living in middle-income countries rather than low-income countries, which highlighted the importance of looking at both total and disaggregated income data when pursuing sustainable wealth growth [1,2].

A consensus has emerged that sustainable wealth growth requires an increase in income and an optimal distribution of income, especially in developing countries. While economic growth may result in an overall increase in income, the issue of uneven income distribution remains serious, exemplified by the excessive rich-poor disparity. Since 1980, the global wealth gap has widened rapidly, and global income inequality has reached an all-time high. According to Credit Suisse [3], 10% of the global population owned 82% of the world's wealth, with the richest 1% owning 45%. As the world's largest developing country, China's income distribution is also disproportionately skewed, despite its overall income growth. The National Bureau of Statistics of China reported a Gini coefficient of 0.465 in 2019, which exceeds the internationally recognized alert line of 0.4. In the long run, this will negatively affect sustainable wealth growth. As a developing country trying to eliminate poverty, China is seeking to maintain a steady increase in income while optimizing income distribution and narrowing the income gap.

To this end, digital finance has become increasingly prominent in recent years. Throughout the world, digital finance has contributed to increasing financial inclusion, providing the means to alleviate poverty and income inequality, particularly in developing and emerging economies [4,5]. By leasing digital credit-related solar panels, the Solar Credit project in Kenya has enabled about 1 million African users without traditional financial accounts to establish digital credit files and further provided them with follow-up financial services [6]. This offers the users additional opportunities to expand their production and increase their income. Besides, a notable feature of China's digital financial applications is that they are among the most advanced in the world. For instance, the leading digital bank in China, WeBank, has created the Weilidai loans to help micro-, small-, and medium-sized enterprises (MSMEs) and individuals obtain credit and improve their income. Reportedly, by the end of 2023, more than 400 million users obtained Weilidai loans and contributed 2.3 billion CNY in value-added tax (VAT) to 47 impoverished counties in China. Clearly, digital finance has enabled long-tail users [7] to access financial services such as credit files and loans. This will allow users to expand their production and diversify sources of income [8], thus contributing to a better income distribution in society and achieving the mission of sustainable growth.

There have been numerous studies conducted on the impact of traditional financial development on residents' income, mainly indicating its positive effects on residents' total income and ambiguous effects on residents' income distribution [9,10]. As digital finance evolves at an accelerated pace, scholars have increasingly acknowledged its significance and have explored various aspects, including its definition, driving forces, and impacts [11–14]. However, the relatively short history of digital finance and the limited availability of data have resulted in a scarcity of research investigating the effects of digital financial development on residents' income. Furthermore, the existing studies exhibit three notable limitations. First, the majority of research tends to focus on the overall income of residents rather than on income distribution, with insufficient theoretical analysis regarding the underlying mechanisms. Second, many of these studies primarily adopt descriptive or case study methodologies [15,16], with only a small fraction offering empirical investigations [17,18]. Third, previous research has not addressed the spatial effect of digital finance on residents' income.

In light of the limitations in preceding research, the study aims to construct a theoretical model and examine the impact of digital finance on residents' total income and income distribution, in addition to addressing the spatial effect. Firstly, this study summarizes the theoretical mechanisms and illustrates that three key characteristics of digital finance make it a valuable tool for addressing traditional financial institutions' three pain points. That may enable digital finance to make good on residents' income growth while narrowing the income gap. This makes it natural for us to propose two major hypotheses with several sub-hypotheses, i.e., digital financial development has a positive impact on the increase in residents' total income and also on the optimization of residents' income distribution. In particular, digital finance may have a spatial direct effect and a spatial spillover effect on the optimization of residents' income distribution. That means that a region's digital financial development not only can improve residents' income distribution within the same region but also can contribute to the equitable income distribution among neighboring regions. After that, based on panel data of 31 Chinese provinces (including provinces, municipalities, and autonomous regions) between 2011 and 2019, a two-stage generalized method of moments (GMM) estimation model with endogeneity treatment is constructed to investigate the impact of digital finance on residents' total income. Last, the paper utilizes Moran's $I$ and a spatial autoregression (SAR) model to analyze the impact of digital finance on residents' income distribution. According to the results, both of these two major theoretical hypotheses are empirically confirmed.

There are four ways in which this study contributes to the literature: (i) It discusses the impact of digital finance on residents' income in a more comprehensive and systematic way by studying its impact on both residents' total income and income distribution. (ii) To the best of our understanding, this paper represents the first effort to explore the mechanisms through which digital finance enhances both residents' total income and income distribution. Additionally, it aims to develop a theoretical framework to elucidate the interrelationship between these two aspects. (iii) With the Moran's *I* and SAR model, this research presents novel evidence that there is a spatial direct effect as well as a spatial spillover effect of digital finance on the optimization of residents' income distribution. This fills a research gap in the spatial effect of digital finance on residents' income. (iv) The research provides policymakers and financial institutions with an important reference regarding digital finance and sustainable wealth growth.

The following provides an overview of the structure of the paper. Section 2 presents definitions and conducts a literature review. Section 3 formulates two major hypotheses along with several sub-hypotheses and outlines the data selection process and model specifications. Section 4 discusses the empirical findings, while Section 5 concludes the paper and includes policy recommendations.

## 2. Literature Review

To start with, the definition of three key concepts should be very clear: digital finance, residents' total income, and residents' income distribution. Firstly, digital finance is still contested in its definition, which was often used interchangeably with Fintech. Bettinger [19] originally coined the term Fintech to describe the use of electronic technology to process financial services [20], and this concept has evolved over time. As defined by the Financial Stability Board (FSB) in 2016, Fintech is "technology-enabled innovation in financial services". Contrary to Fintech, which covers various types of technological innovations, digital finance emphasizes the digitalization of the financial industry [21], and it is defined as providing new forms of financial services through the use of digital technology [8].

Residents' total income is often measured by residents' net income, residents' wages, residents' disposable income, etc. Among them, disposable income per capita, i.e., a resident's final consumption expenditures and savings, is the most commonly used indicator [22,23]. Furthermore, the macroenvironment differs greatly between rural and urban areas in China because of its unique urban-rural dichotomous system. This further leads to obvious differences in rural and urban residents' total income and income distribution. Therefore, to acquire more accurate results, the paper distinguishes between urban and rural areas when conducting the research [24–26].

Residents' income distribution refers to the income gap that exists between different types of residents, such as the gap between the rich and the poor, the urban-rural income gap. In view of the above, the residents' income gap in China is highlighted as the urban-rural income gap under its urban-rural dichotomous structure [23,27,28], and it is often measured as the gap in disposable income per capita between urban and rural residents in the same region [29].

Much research has been devoted to the impact of financial development on residents' income. In terms of residents' total income, many scholars argue that financial development can enable the residents to expand production and acquire additional sources of income through the provision of financial services such as loans and insurance, thereby increasing the total income of residents and reducing poverty [30,31]. In terms of residents' income distribution, the impact of financial development on it is controversial. Some scholars believe that financial services can reduce the urban-rural income gap, and this impact can be attributed to the trickle-down effect [32]. Other scholars argue that the characteristics of financial institutions, such as the strict profit target, expensive risk management, and homogeneous competition, make them tend to "provide umbrellas on sunny days and remove umbrellas on rainy days". As a result, users are often faced with a situation where the strong become stronger and the weak become weaker in the financial market. The trickle-down effect is limited and even leads to the deterioration of income distribution [33,34].

Currently, the global academia has been increasingly interested in digital finance as a result of its rapid development. Even though digital financial development is still at an early stage, there has been considerable research conducted on its connotations, enablers, impacts, and effects [35–37]. Among them, the studies on the impact of digital finance can be grouped into two strands of literature: put emphasis on the providers as well as the demanders of financial services. The first strand of literature emphasizes how digital finance affects financial institutions, particularly with regard to efficiency gains and cost reductions in digital finance [11,13,38]. The other stream of studies focuses on the impact of digital finance on the demanders of financial services (e.g., MSMEs, residents, and families), especially the impact on their development, entrepreneurship, and consumption. These studies suggest that digital finance benefits the development of users by changing the way users access financial services, overcoming geographical boundaries, and reducing the costs of financial services [12,14]. Furthermore, some researchers have examined the effects of digital finance on residents' income, especially pointing out that digital finance can attenuate the depth and intensity of poverty and eventually improve the income of poor households [39]. In contrast, there is little research on the impact of digital finance on income distribution [18]. The results suggest that digital finance can narrow the urban-rural income gap via increased financial accessibility.

In examining the methods used to assess the impact of digital finance, it is evident that the lack of sufficient data has constrained most existing research on digital finance and residents' income to qualitative approaches, such as descriptive analyses or case studies [15,16]. There has been minimal empirical research conducted in this area [17,18], and fewer scholars have investigated the theoretical mechanisms that explain how digital finance influences residents' income. In addition, despite the fact that some researchers have demonstrated the development and diffusion process of digital finance is influenced by spatial geography and spatial economic characteristics [17,18], research has been limited on the spatial effect of digital finance.

To summarize, a growing body of studies have explored the impact of financial development on residents' income, mainly indicating its positive effects on residents' total income and ambiguous effects on residents' income distribution. In recent years, while there has been a growing interest among scholars in digital finance, research examining its effects on residents' income, particularly regarding income distribution, remains scarce. Additionally, the limited availability of data has led most studies in this area to adopt qualitative methodologies, such as descriptive analyses or case studies, rather than pursuing empirical investigations. And digital finance has not been investigated in depth in terms of its spatial effect on residents' income.

There are three ways in which this study differs from the existing literature: (i) the paper examines the impact of digital finance on residents' income in a detailed manner by considering residents' total income and income distribution at the same time; (ii) the research establishes a theoretical framework to investigate the theoretical mechanism by which digital finance affects residents' income, and this can fill the theoretical research gap in previous studies; (iii) this paper innovatively explores the spatial effect brought by the instant cross-spatial information dissemination characteristic of digital finance. A Moran's $I$ and a SAR model are adopted to test the spatial correlation between digital finance and residents' income and study its spatial direct and spillover effects. The empirical research in this field can be enriched by all of these factors.

## 3. Empirical Research Methodology

### *3.1. Theoretical Mechanism and Research Hypotheses*

In light of the previous literature, this research proposes the theoretical mechanism for digital finance to raise residents' total income and optimize income distribution (see

Figure 1). We present a detailed description of the theoretical mechanism and two major hypotheses in the following section.

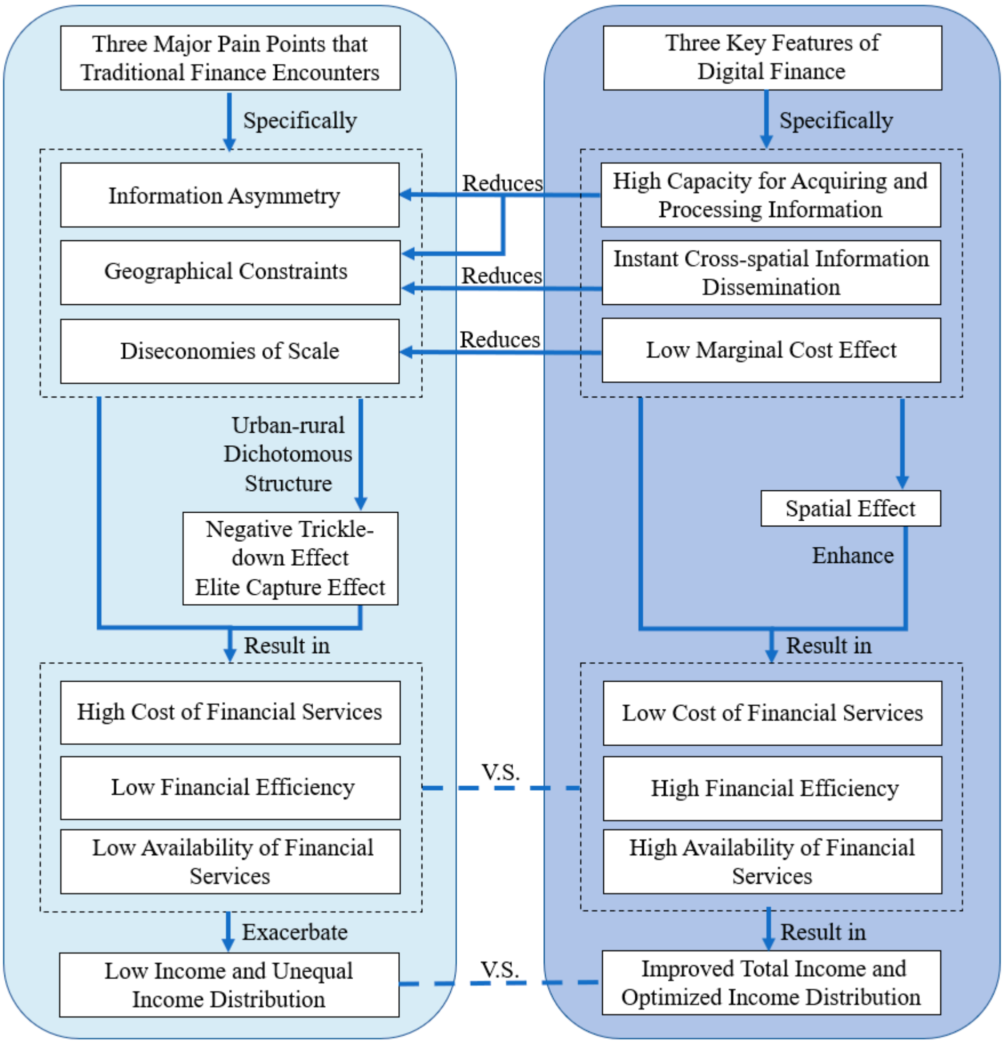


**Figure 1.** Framework of the theoretical mechanism for digital finance to raise residents' total income and optimize income distribution.

As mentioned previously, it has been demonstrated that financial services enable residents to increase their production and sources of income, thus raising their total income [9,10,40] and optimizing income distribution [32,41]. However, there are three pain points faced by traditional financial institutions when they offer services to users, especially long-tail users. The three pain points are illustrated on the left side of Figure 1.

First, information asymmetry. It is challenging for long-tail users to provide standardized and qualified information necessary for financial risk analysis or even just to open bank accounts. Therefore, financial institutions have difficulty collecting reliable information from these users and identifying real demanders. Thus, financial services are no longer provided to these users in order to avoid the issues of adverse selection and moral hazard.

Second, geographical constrains. Users are required to travel to the branches of financial institutions in order to obtain traditional financial services. Due to difficulties in transmitting information as well as transportation and time expenses, traditional financial institutions are hesitant or not able to serve their users in remote areas.

Third, diseconomies of scale. For traditional financial services, the reliance on paper credentials, a large number of workers, and cash transactions are all necessary, which result in high costs. Thus, there will be no economies of scale for financial institutions if the cost of providing these services is prohibitively high, even if the demand for financial services remains high.

These three pain points make traditional financial institutions' services less efficient and more expensive [42], thereby undermining their capacity to improve residents' income and income distribution.

Furthermore, the negative trickle-down effect and elite capture effect exacerbate these three pain points for traditional financial services. First, a negative trickle-down effect is often observed between urban and rural areas because the financial infrastructure in rural areas is far less developed than in urban areas [43]. Hence, residents in urban areas (or economically developed areas) and large- and medium-sized enterprises obtain access to increasing financial resources, while the financial resources of rural residents and MSMEs are gradually encroached upon. Second, similar to the negative trickle-down effect, residents in rural areas are often affected by the elite capture effect. The elite capture effect refers to the phenomenon in which elite farmers with certain power and relationship advantages in rural areas have more chances to access financial resources such as agricultural loans [44] and even tend to occupy the resources for themselves, which makes it more difficult for poor farmers to obtain financial services. Both the negative trickle-down effect and the elite capture effect lead to lower levels of financial accessibility, lower levels of financial efficiency, and higher costs for long-tail users. As a result, these long-tail users are not able to fulfill their own financial needs and improve their income.

Luckily, digital finance offers a solution to the three pain points. Three key characteristics of digital finance make it a valuable tool for addressing traditional financial institutions' three pain points: high capacity for acquiring and processing information, instant cross-spatial information dissemination, and a low marginal cost effect. They are illustrated on the right side of Figure 1.

First, digital finance technologies provide cost-effective and low-risk methods for acquiring large quantities of data [45]. Consequently, financial institutions can acquire and process information efficiently and construct massive databases through algorithms [35], thereby embedding massive information systems into financial services and enhancing the identification and selection of potential qualified users of financial services [46]. Consequently, information asymmetry between users and financial institutions can be reduced, thus enhancing the financial efficiency of financial institutions as well as financial accessibility for users. Particularly, this feature can also mitigate the elite capture effect.

Second, digital finance has the ability of instant cross-spatial information dissemination [47]. This can allow users to access a wide range of financial services online without visiting any branch; in other words, it can reduce geographical restrictions as well as regional and institution–user boundaries, thereby eliminating the negative trickle-down effect. Furthermore, it is worth noting that digital finance may have a spatial spillover effect when it comes to narrowing the geographical income gap (e.g., urban-rural income gap). Digital finance can eliminate geographical constraints, allowing financial institutions in one region to serve residents in its neighboring regions, which may directly contribute to narrowing income gaps within neighboring regions. In addition to the direct impact, the digital financial development in one region can also have an indirect impact on the income gaps within neighboring regions. The mechanism is that the digital financial development in one region first improves the digital financial development in its neighboring regions, and then the digital financial development in its neighboring regions will further narrow the income gaps within neighboring regions.

Third, due to the internet's ubiquitous nature, digital finance has a low marginal cost effect, i.e., through the application of digital technologies, long-tail users can be provided with financial services at a reduced marginal cost [48]. In this case, this group of users will also benefit from economies of scale. As a result of its extensive capabilities for acquiring and processing information, as well as its low marginal costs, digital finance can also be utilized by financial institutions as a means of integrating financial services into a variety of daily life scenarios. As a result, it may be possible to provide customized financial services tailored to the needs of particular individuals. Various financial services will be made available to consumers more frequently and efficiently in a more convenient manner, thereby improving residents' income.

Accordingly, it is natural for us to find the research purpose, which is to verify the impact of digital finance on residents' total income and income distribution, while considering its special effects. Thus, two major theoretical hypotheses are proposed as follows, including sub-hypotheses for each:

**Hypothesis 1 (H1).** *Digital financial development has a positive impact on the increase in residents' total income.*

**Hypothesis 1a (H1a).** *Digital financial development has a positive impact on the increase in urban residents' total income.*

**Hypothesis 1b (H1b).** *Digital financial development has a positive impact on the increase in rural residents' total income.*

**Hypothesis 2 (H2).** *Digital financial development has a positive impact on the optimization of residents' income distribution.*

**Hypothesis 2a (H2a).** *Digital financial development has a total spatial effect on the optimization of residents' income distribution.*

**Hypothesis 2b (H2b).** *Digital financial development has a spatial direct effect on the optimization of residents' income distribution.*

**Hypothesis 2c (H2c).** *Digital financial development has a spatial spillover effect on the optimization of residents' income distribution.*

### *3.2. Data Description*

Table 1 presents an overview of the variables utilized in this research. The dataset, which encompasses 31 provinces in China from 2011 to 2019, includes variables related to residents' total income, income distribution, digital financial development, and three types of control variables. The first type of control variables encompasses regional characteristics, such as the degree of opening-up, government expenditure, urbanization, industrial foundation, education, housing conditions, and population. The second type reflects residential characteristics, including household savings and consumption. The third type captures financial characteristics, specifically loan size and social financing scale. The sources of data are detailed below:

(i) The Peking University Digital Financial Inclusion Index of China (PKU-DFIIC) is used as a measurement of China's digital financial development in this paper. This index is derived from the underlying transaction account data provided by Ant Group, a globally renowned Chinese digital financial giant. Currently, it serves as the primary data source for scholars studying digital finance in China [13,49].

(ii) Macroeconomic data at the provincial level, which includes urban and rural residents' disposable income per capita and control variables such as social financing scale, urbanization, population, and degree of opening-up, is derived from widely recognized authoritative sources such as China's regional statistical yearbooks, the WIND database, the Guotaian database (CSMAR), and the Tong Hua Shun-iFind database.

**Table 1.** Variable description.

| Type | Variables | Description | Measured by |
|---|---|---|---|
| Independent variable | Indexaggr | Digital financial development | The Peking University Digital Financial Inclusion Index of China (PKU-DFIIC) |
| Dependent variables | Urbaninc | Urban residents' total income | Urban residents' disposable income per capita |
| | Ruralinc | Rural residents' total income | Rural residents' disposable income per capita |
| | Theil | Urban-rural income gap | Theil index |
| Regional control variables | Fdirt | Degree of opening-up | Ratio of foreign direct investment to GDP |
| | Govexpenrt | Government expenditure | Ratio of general budget expenditures to GDP |
| | Urbaniz | Level of urbanization | Rate of urbanization |
| | Lnenterpnum | Industrial foundation | Natural logarithm value of number of enterprises |
| | Studnum | Level of education | Number of students enrolled in general higher education institutions |
| | Lnavehousingprice | Housing conditions | Natural logarithm value of the average housing price |
| | Lnpopulation | Population | Natural logarithm value of the resident population |
| Residential control variables | Savings | Household savings | Saving balance of urban and rural residents at year-end |
| | Lnretailsale | Consumption | Natural logarithm value of retail sales for consumer goods |
| Financial control variables | Lnloan | Loan size | Natural logarithm value of loan balance of financial institutions at year-end |
| | Lnsocialfinance | Social financing scale | Natural logarithm value of social financing scale |

Sources: authors' elaboration.

It is important to note that this paper chooses the urban-rural income gap to represent residents' income distribution and adopts the Theil index to measure it, which will be discussed in detail in Section 3.3. As panel data are used in the study, a total of 279 observations covering a period of nine years are collected from 31 provinces for each variable.

Table 2 summarizes the descriptive statistics for this study. The analysis reveals that the standard deviations of several variables, such as urban and rural residents' disposable income per capita, digital financial development, government expenditure, and level of education, are all high across provinces. It is obvious that regional disparities still persist. Additionally, although the distribution of these variables among Chinese provinces shows some level of skewness, the differences between the mean and median values are quite small. This implies that the distributions are generally consistent with a normal distribution.

**Table 2.** Descriptive statistics.

| | Observations | Mean | Standard Deviation | Median | Min | Max |
|---|---|---|---|---|---|---|
| Indexaggr | 279 | 202.35 | 91.65 | 212.36 | 16.22 | 410.28 |
| Urbaninc (CNY) | 279 | 30,258.30 | 10,147.37 | 28,673.28 | 14,988.68 | 73,849.00 |
| Ruralinc (CNY) | 279 | 11,927.87 | 5113.20 | 10,992.50 | 3909.37 | 33,195.00 |
| Theil | 279 | 0.10 | 0.04 | 0.09 | 0.02 | 0.23 |
| Fdirt | 279 | 0.02 | 0.02 | 0.02 | 0.00 | 0.08 |
| Govexpenrt | 279 | 0.28 | 0.21 | 0.23 | 0.11 | 1.38 |
| Urbaniz (%) | 279 | 56.66 | 13.14 | 55.12 | 22.71 | 89.60 |
| Lnenterpnum | 279 | 8.69 | 1.40 | 8.69 | 4.04 | 10.92 |
| Studnum | 279 | 84.17 | 52.78 | 73.25 | 3.24 | 231.97 |
| Lnavehousingprice | 279 | 8.79 | 0.47 | 8.65 | 8.09 | 10.49 |
| Lnpopulation | 279 | 8.13 | 0.84 | 8.25 | 5.74 | 9.43 |

**Table 2.** *Cont.*

| | Observations | Mean | Standard Deviation | Median | Min | Max |
|---|---|---|---|---|---|---|
| Savings | 279 | 17,190.29 | 14,184.78 | 13,399.44 | 0.00 | 77,995.87 |
| Lnretailsale | 279 | 8.73 | 1.05 | 8.88 | 5.47 | 10.67 |
| Lnloan | 279 | 9.98 | 0.94 | 10.02 | 6.01 | 12.03 |
| Lnsocialfiance | 279 | 8.29 | 0.91 | 8.36 | 3.19 | 10.28 |

Sources: authors' elaboration.

### 3.3. Econometric Model

To test Hypothesis 1 (H1), the study draws on previous studies [50] to adopt a two-stage generalized method of moments (GMM) estimation approach with endogeneity treatment to construct an empirical model. This will enable us to learn the impact of digital financial development on residents' total income. The GMM model exhibits several robust properties that contribute to its widespread use and reliable estimation results in empirical analysis. First, the GMM model does not require the assumption of homoscedastic errors, allowing it to effectively handle the presence of heteroscedasticity. Second, the GMM model can utilize appropriate instrumental variables to address endogeneity issues, leading to consistent estimators. Third, the GMM estimators maintain their robustness even in small sample sizes, in contrast to traditional least squares methods. Fourth, the GMM model does not necessitate the assumption of normally distributed or any other specific error term distributions, as long as the first-moment conditions are satisfied. Given the robustness of the two-stage GMM model, this study employs the two-stage GMM approach to conduct the regression analysis.

In order to deal with endogeneity issues, endogeneity treatment is considered in the GMM model by using instrument variables. The models are presented as follows:

$$Urbaninc_{i,t} = \alpha_0 + \alpha_1 Indexaggr_{i,t} + \alpha_2 X_{,i,t} + \theta_i + \varepsilon_{i,t} \tag{1}$$

$$Ruralinc_{i,t} = \alpha_3 + \alpha_4 Indexaggr_{i,t} + \alpha_5 X_{,i,t} + \theta_i + \varepsilon_{i,t} \tag{2}$$

where $i$ represents province, $t$ represents year. The dependent variables $Urbaninc_{i,t}$ and $Ruralinc_{i,t}$ denote urban and rural residents' disposable income per capita, respectively, for province $i$ in year $t$; the independent variable $Indexaggr_{i,t}$ represents the value of the Peking University Digital Financial Inclusion Index for province $i$ in year $t$ as a measure of regional digital financial development. $X_{i,t}$ represents other control variables, as displayed in Table 1 above; $\theta_i$ represents the region fixed effect; $\varepsilon_{i,t}$ represents the random disturbance term. In addition, this study employs mobile phone ownership per capita as an instrumental variable to represent the digital financial development of a region. This variable is utilized in the regression analysis, maintaining consistency with the baseline model. The results of the exogeneity test, under-identification test, weak identification test, overidentification test, and endogeneity test for this instrumental variable can be found in Section 4.1.

### 3.4. Spatial Econometric Model

This study tests Hypothesis 2 (H2) based on the spatial econometric model, which has three parts: measuring residents' income distribution, spatial correlation, and spatial spillover effect. This will enable us to learn the impact of digital financial development on residents' income distribution.

As mentioned above, the research uses the urban-rural income gap to represent residents' income distribution. A large number of methods have been proposed to measure the urban-rural income gap, such as the Gini coefficient [51,52], the urban-rural income ratio [53], and the Theil index [54,55]. Among them, Theil Index is adopted in this paper because, compared with other measures, it takes into account the urban-rural population ratio in different areas additionally. This can reduce the income gap underestimation, which is commonly caused when rural populations are much larger than urban populations (as is the case in China) [54,56]. The model is presented as below:

$$Theil_{i,t} = \sum_{j=1}^{2} \left( \frac{I_{ij,t}}{I_{i,t}} \right) Ln \left[ \frac{\left( \frac{I_{ij,t}}{p_{ij,t}} \right)}{\left( \frac{I_{i,t}}{p_{i,t}} \right)} \right] \tag{3}$$

where $i$ represents province, $t$ represents year, and $j$ represents urban or rural area (1 for urban and 2 for rural). $I_{ij,t}$ represents the urban or rural residents' total income for province $i$ in year $t$; $I_{i,t}$ represents the sum of the urban and rural residents' total income for province $i$ in year $t$; $p_{ij,t}$ indicates population for urban or rural area in province $i$ in year $t$, and $p_{i,t}$ represents the sum of the urban and rural population for in year $t$. In general, a higher Theil index indicates a greater urban-rural income gap. The results of the Theil index for all Chinese provinces from 2011 to 2019 are presented in Appendix A.

Spatial clustering refers to a typical spatial distribution in which regions neighboring each other show a high degree of similarity but differ significantly from those of other regions. For the purpose of detecting the spatial clustering of the digital financial development together with the urban-rural income gap, respectively, for 31 Chinese provinces, Moran's $I$ index [57] is applied to compute the spatial correlation of these two variables. There are two types of spatial correlation calculated by Moran's $I$ index, i.e., global spatial correlation and local spatial correlation [58,59], whereas the former refers to the spatial correlation of all provinces as a whole and the latter refers to the spatial correlation of a specific province related to other neighboring provinces.

The global Moran's $I$ index ($Moran's\ I_g$) is computed as the following equations:

$$Moran's\ I_g = \frac{\sum_{i=1}^{n} \sum_{k=1}^{n} (x_i - \bar{x})(x_k - \bar{x})}{s^2 \sum_{i=1}^{n} \sum_{k=1}^{n} W_{ik}} \tag{4}$$

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{5}$$

$$s^2 = \frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n} \tag{6}$$

$$W_{ik} = \begin{cases} 1,\ if\ i\ is\ adjacent\ to\ k \\ 0,\ if\ i\ is\ not\ adjacent\ to\ k \end{cases};\ i,k = 1,2,\ldots,\ 31 \tag{7}$$

where $i$ and $k$ represent different provinces, $n$ = 31; $x_i$ represents the value of digital financial development or urban-rural income gap for province $i$ and $x_k$ represents the value of digital financial development or urban-rural income gap for province $k$; $\bar{x}$ represents the mean value of $x_i$; $s^2$ represents the variance of $x_i$; $W_{ik}$ denotes spatial weight matrix, and it is constructed to test whether the variables are spatially correlated. Based on the fact that the sample of this research met the spatial continuity sample requirements, the neighboring weight matrix model is selected among all spatial weight matrix models [60]. As a result, the provinces adjacent to each other are given a weight of 1, otherwise 0. In addition, although Hainan province is an island that is not adjacent to any other province, it is considered to be adjacent to Guangdong province in this paper. It is worth noting that global Moran's $I$ range $[-1, 1]$, and its absolute value reflects the degree of spatial correlation (spatial clustering). Thus, an index value of 0 means that the spatial distribution of $x_i$ and $x_k$ is random, while an index value of 1 (or $-1$) indicates the highly positive (or negative) clustered spatial distribution of $x_i$ and $x_k$.

The local Moran's $I$ index ($Moran's\ I_i$) is computed as the following equations:

$$Moran's\ I_i = \frac{Z_i \sum_{k \neq i}^{n} W_{ik} Z_k}{s^2} \tag{8}$$

$$Z_i = x_i - \bar{x};\ Z_k = x_k - \bar{x} \tag{9}$$

where the meanings of symbols are the same as those in Equations (4)–(7), while $Z_i$ denotes the relative value of variable $x$ for province $i$, and $\sum_{k \neq i}^{n} W_{ik} Z_k$ denotes the relative value of variable $x$ for the neighboring provinces of province $i$. It is worth noting that although the value of local Moran's $I$ indicates the degree of spatial correlation for province $i$, scholars [58,61] pay more attention to $Z_i$ and $\sum_{k \neq i}^{n} W_{ik} Z_k$, especially their signs. It is because $Z_i$ and $\sum_{k \neq i}^{n} W_{ik} Z_k$ can provide more detailed information than the single value of local Moran's $I$, and the combination of their signs can be used to observe four types of spatial correlation scenarios. This will be discussed in Section 4.2.1.

In this paper, spatial effect refers to the spatial impact of digital finance on residents' income distribution within the same or in different provinces. This is different from the spatial correlation illustrated above, which focuses on the spatial relationship of one variable itself. In that case, a spatial autoregression (SAR) model is constructed to calculate the spatial effect not only for the same province but also for its first-order and above adjacent provinces. The spatial autoregression (SAR) model excels at capturing spatial dependence, handling spatial heterogeneity, addressing endogeneity issues, quantifying spatial spillover effects, and accommodating different spatial scales, providing a robust framework for modeling spatial interactions, making it a powerful tool for spatial econometric analysis.

$$y_{i,t} = \delta W_{ik} y_{i,t} + X_{i,t} \beta + W_{ij} X_{i,t} \theta + v_i + \varphi_t + \varepsilon_{i,t} \tag{10}$$

$$\varepsilon_{i,t} \sim N\left(0,\ \sigma_\varepsilon^2 I_N\right) \tag{11}$$

where $\delta$ represents the coefficient of the dependent variable in the SAR model; $\beta$ represents the total spatial effect; $\theta$ represents the coefficient of the independent variable in the SAR model; $W_{ik}$ also represents the spatial weight matrix; $v_i$ represents the region fixed effect; $\varphi_t$ represents the time fixed effect; and $\varepsilon_{i,t}$ represents the random disturbance term.

According to Lesage and Pace [62], the total spatial effect in Equation (10) can be decomposed into two parts: spatial direct effect and spatial spillover effect. Spatial direct effect refers to the impact of one region's independent variable on the dependent variables for the same province, while spatial spillover effect refers to the impact of one region's independent variable on the dependent variables for its first-order and above adjacent regions. In Equation (10), the spatial direct effect is calculated by the mean value of all the elements on the main diagonal of the $\left(1 - \delta W_{ij}\right)^{-1} \beta$ matrix, while the spatial spillover effect is calculated by the mean value of all the elements on the non-main diagonal of the same matrix. Those are presented by the coefficients of the variables in the empirical results. The sum of the spatial direct effect and spatial spillover effect is equal to the total spatial effect.

## 4. Empirical Results

### *4.1. Impact of Digital Financial Development on Residents' Total Income*

In order to test Hypothesis 1 (H1), this study constructs the aforementioned two-stage GMM estimation model by using mobile phone ownership per capita as an instrumental variable in the GMM model to address endogeneity issues. This research first verifies the validity of this instrumental variable as specified below. In terms of exogeneity, mobile phone ownership per capita reflects the level of IT development within a region because it is primarily influenced by factors such as the level of local IT development and does not significantly correlate with local residents' total income. Thus, the exogeneity test is passed.

Table 3 presents additional validity test results for the instrumental variable. The control variables are introduced incrementally into the GMM model to examine their specific impact on the statistical significance of the findings: Column 1 presents the results that all the control variables are not included, with Column 2 showing control only for variables reflecting regional characteristics, Column 3 showing control for both regional and residential characteristics, and Column 4 showing control for all three types of control variables. For the under-identification test, all the $p$-values of the unidentifiable tests are zero, indicating that there is no evidence of under-identification with this instrumental variable. For the weak identification test, all the *F*-values exceed the Stock–Yogo value at the 10% significance level, indicating that this instrumental variable passes the weak identification test. For the overidentification test, all the *p*-values of the Sargan tests are greater than 0.1, indicating that this instrumental variable passes the overidentification test. For the endogeneity test, all the *p*-values are less than 0.1 except for the first test without control variables, which indicates that this instrumental variable is exogenous under the incorporation of control variables. Thus, the validity of this instrumental variable is justified, and the following baseline results have been confirmed to be robust.

**Table 3.** Instrumental variable validity test under two-stage GMM of digital financial development on urban residents' total income.

| | | **(1)** | **(2)** | **(3)** | **(4)** |
|---|---|---|---|---|---|
| | **Validity Test** | **2GMM** ***Urbaninc*** | **2GMM** ***Urbaninc*** | **2GMM** ***Urbaninc*** | **2GMM** ***Urbaninc*** |
| Under-identification test | Anderson test | 211.506 | 156.972 | 144.240 | 129.864 |
| | Chi-sq (2) *p*-value | 0.000 | 0.000 | 0.000 | 0.000 |
| Weak identification test | CDW F-value | 4138.503 | 271.955 | 204.186 | 152.017 |
| | Stock-Yogo 10% maximal IV size | 19.93 | 19.93 | 19.93 | 19.93 |
| Overidentification test | Sargan test | 0.758 | 1.157 | 2.482 | 2.518 |
| | Chi-sq (1) *p*-value | 0.384 | 0.282 | 0.115 | 0.113 |
| Endogeneity test | Endogeneity test | 0.001 | 3.399 | 4.150 | 4.408 |
| | Chi-sq (1) *p*-value | 0.980 | 0.065 | 0.042 | 0.036 |

Sources: authors' elaboration.

Table 4 presents the findings from the baseline model, with Columns 1 to 4 displaying results as control variables are introduced incrementally. The empirical analysis indicates that the coefficients for digital financial development are consistently positive across all models, achieving significance at the 1% level. This suggests a clear positive effect of digital financial development on the total income of urban residents. As additional control variables are included, the coefficient for digital finance stabilizes at 70.10, while the $R^2$ of the model increases first and then stabilizes. This means that the model fits well, and research Hypothesis 1a (H1a) has been verified. Additionally, the three types of control variables, i.e., variables representing regional, residential, and financial characteristics such as level of urbanization, industrial foundation, population, consumption, and household savings, tend to have a positive effect on urban residents' total income. In general, these findings are in accordance with economic theory.

**Table 4.** Two-stage GMM results of digital financial development on urban residents' total income.

| | **(1)** | **(2)** | **(3)** | **(4)** |
|---|---|---|---|---|
| **Variables** | **2GMM** ***Urbaninc*** | **2GMM** ***Urbaninc*** | **2GMM** ***Urbaninc*** | **2GMM** ***Urbaninc*** |
| Indexaggr | 80.221 *** | 84.483 *** | 68.995 *** | 70.104 *** |
| | (45.55) | (14.15) | (10.62) | (9.20) |
| Fdirt | | 44,282.388 *** | 28,107.847 * | 28,016.276 * |
| | | (2.81) | (1.90) | (1.88) |
| Govexpenrt | | −8171.122 | −945.279 | −894.955 |
| | | (−1.50) | (−0.18) | (−0.16) |
| Urbaniz | | 608.564 *** | 637.101 *** | 632.298 *** |
| | | (5.81) | (6.49) | (5.98) |

**Table 4.** *Cont.*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Variables** | **2GMM** ***Urbaninc*** | **2GMM** ***Urbaninc*** | **2GMM** ***Urbaninc*** | **2GMM** ***Urbaninc*** |
| Lnenterpnum | | 3727.802 *** | 3364.088 *** | 3317.492 *** |
| | | (3.88) | (3.69) | (3.43) |
| Studnum | | −3.971 | −49.065 ** | −49.273 ** |
| | | (−0.22) | (−2.57) | (−2.56) |
| Lnavehousingprice | | 6724.192 *** | 6312.414 *** | 6315.808 *** |
| | | (4.66) | (4.82) | (4.76) |
| Lnpopulation | | 34,456.784 *** | 21,467.097 *** | 21,741.782 *** |
| | | (6.11) | (3.74) | (3.73) |
| Savings | | | 0.186 *** | 0.182 *** |
| | | | (4.78) | (4.31) |
| Lnretailsale | | | 3909.155 *** | 3852.676 *** |
| | | | (4.03) | (3.90) |
| Lnloan | | | | −221.180 |
| | | | | (−0.16) |
| Lnsocialfinance | | | | 49.256 |
| | | | | (0.17) |
| Observations | 279 | 279 | 279 | 279 |
| $R^2$ | 0.908 | 0.943 | 0.953 | 0.953 |

Note: t-statistics are presented in parentheses, *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

It is worth noting that a limited sample bias correction method is adopted to avoid underestimating the standard errors of the coefficient estimates (Table 5). The instrumental variable also passes the validity test (see Table A2 for details), and the baseline results (see Table A3 for details) are the same as those generated without using the limited sample bias correction method.

**Table 5.** Instrumental variable validity test under two-stage GMM of digital financial development on rural residents' total income.

| | | (1) | (2) | (3) | (4) |
|---|---|---|---|---|---|
| | **Validity Test** | **2GMM** ***Ruralinc*** | **2GMM** ***Ruralinc*** | **2GMM** ***Ruralinc*** | **2GMM** ***Ruralinc*** |
| Under-identification test | Anderson test | 211.506 | 156.972 | 144.240 | 129.864 |
| | Chi-sq (2) $p$-value | 0.000 | 0.000 | 0.000 | 0.000 |
| Weak identification test | CDW F-value | 4138.503 | 271.955 | 204.186 | 152.017 |
| | Stock-Yogo 10% maximal IV size | 19.930 | 19.930 | 19.930 | 19.930 |
| Overidentification test | Sargan test | 1.663 | 1.700 | 4.119 | 1.961 |
| | Chi-sq (1) $p$-value | 0.197 | 0.192 | 0.142 | 0.161 |
| Endogeneity test | Endogeneity test | 0.269 | 5.859 | 8.809 | 11.445 |
| | Chi-sq (1) $p$-value | 0.604 | 0.016 | 0.003 | 0.001 |

Sources: authors' elaboration.

Therefore, Table 6 shows the results of the baseline model, and Columns 1 to 4 still report the results when the control variables are incorporated step by step. It could be noticed that the coefficients of digital financial development of each model are also significantly positive at the 1% significance level. When incorporating more control variables, the $R^2$ starts to rise and stabilizes at 0.954, suggesting that digital financial development also positively affects rural residents' total income. Therefore, Hypothesis 1b (H1b) has been verified. It is notable that the coefficients of digital financial development on rural residents' total income are relatively lower than those on urban residents' total income. This means digital financial development has a weaker impact on rural residents' income than it does on urban residents' income. It is most likely because residents in urban areas always have better digital infrastructures and macroeconomic conditions, while residents in rural areas may suffer from the "digital divide", which refers to the gap between demographics and regions that have differing access to modern information and digital technology. This will consequently affect digital financial development and promote residents' income in rural areas. These empirical results validate the findings of many other scholars [26].

**Table 6.** Two-stage GMM results of digital financial development on rural residents' total income.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Variables** | **2GMM** *Ruralinc* | **2GMM** *Ruralinc* | **2GMM** *Ruralinc* | **2GMM** *Ruralinc* |
| Indexaggr | 36.429 *** | 43.956 *** | 36.924 *** | 40.838 *** |
| | (45.94) | (15.95) | (12.67) | (11.95) |
| Fdirt | | 6184.255 | −836.293 | −2919.875 |
| | | (0.85) | (−0.13) | (−0.44) |
| Govexpenrt | | −3389.720 | −805.659 | 444.943 |
| | | (−1.35) | (−0.34) | (0.18) |
| Urbaniz | | −374.683 *** | −368.720 *** | −325.686 *** |
| | | (−7.75) | (−8.37) | (−6.86) |
| Lnenterpnum | | −1237.094 *** | −845.779 ** | −539.367 |
| | | (−2.79) | (−2.07) | (−1.24) |
| Studnum | | 13.954 * | −14.330 * | −15.100 * |
| | | (1.70) | (−1.67) | (−1.75) |
| Lnavehousingprice | | 1490.418 ** | 1164.424 ** | 1464.679 ** |
| | | (2.24) | (1.98) | (2.46) |
| Lnpopulation | | 12452.649 *** | 7222.850 *** | 8339.578 *** |
| | | (4.79) | (2.81) | (3.18) |
| Savings | | | 0.111 *** | 0.095 *** |
| | | | (6.34) | (5.03) |
| Lnretailsale | | | 1352.520 *** | 1249.286 *** |
| | | | (3.10) | (2.81) |
| Lnloan | | | | −1322.518 ** |
| | | | | (−2.15) |
| Lnsocialfinance | | | | 153.068 |
| | | | | (1.21) |
| Observations | 279 | 279 | 279 | 279 |
| R-squared | 0.909 | 0.941 | 0.954 | 0.954 |

Note: t-statistics are presented in parentheses, *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Moreover, when treated with the limited sample bias correction method, the instrumental variable also passes the validity test (see Table A4 for details), and the results of the baseline model are still robust (see Table A5 for details).

### *4.2. Impact of Digital Financial Development on Residents' Income Distribution*

#### 4.2.1. Spatial Correlation

As pre-tests for the exploration of Hypothesis 2 (H2), this study first performs a global and a local spatial correlation test to explore the spatial distribution of digital financial development and the urban-rural income gap. As for the global spatial correlation test, Table 7 presents the global Moran's $I$ values of digital financial development and the urban-rural income gap (measured by the Theil index) for 31 Chinese provinces from 2011 to 2019. It can be seen that at the 1% significance level, both the digital financial development and urban-rural income gap in China have significant positive spatial correlations, affirming that both of them have the characteristics of positive spatial correlation. To put it another way, regions with better digital financial development or a greater urban-rural income gap are close to one another, and vice versa. It is noteworthy that, as time goes by, the coefficient of global Moran's *I* in terms of digital financial development increases gradually from 0.563 to 0.625, and that of the urban-rural income gap increases from 0.621 to 0.631. In this regard, it becomes more evident that digital financial development as well as the urban-rural income gap are spatially clustered. It lends credence to the adage "birds of a feather flock together".

**Table 7.** The global Moran's *I* of the digital financial development and urban-rural income gap in China from 2011 to 2019.

| Year | Moran's *I* | | | |
|---|---|---|---|---|
| | Digital Financial Development | | Urban-Rural Income Gap | |
| | Coefficient | Z-Value | Coefficient | Z-Value |
| 2011 | 0.563 *** | 5.507 | 0.621 *** | 6.021 |
| 2012 | 0.573 *** | 5.654 | 0.621 *** | 6.036 |
| 2013 | 0.555 *** | 5.511 | 0.621 *** | 6.041 |
| 2014 | 0.556 *** | 5.524 | 0.633 *** | 6.166 |
| 2015 | 0.518 *** | 5.172 | 0.647 *** | 6.275 |
| 2016 | 0.551 *** | 5.498 | 0.645 *** | 6.262 |
| 2017 | 0.591 *** | 5.885 | 0.471 *** | 4.729 |
| 2018 | 0.619 *** | 6.103 | 0.641 *** | 6.236 |
| 2019 | 0.625 *** | 6.155 | 0.631 *** | 6.152 |

Note: t-statistics are presented in parentheses, *** indicates significance at 1% levels, respectively.

Figure 2 provides a visual illustration of the local spatial correlation test result, which is applied to analyze the spatial distribution of digital financial development and urban-rural income gap in each province. As can be seen, China's digital financial development and urban-rural income gap are spatially clustered at the provincial level. They are mainly distributed in the first and third quadrants, indicating "high-high" and "low-low" clustering, respectively. This means that a province tends to cluster with those provinces having similar levels of digital financial development (urban-rural income gap), and vice versa.

Specifically, Figure 2a shows the clustering distribution of digital financial development in 2011, in which most provinces are located in the "low-low" quadrant (quadrant 3) or "high-high" quadrant (quadrant 1). Furthermore, the number of provinces in the "low-high" and "high-low" quadrants significantly increased in China from 2011 to 2019. This is probably because of the "demonstration effect", that is, the development in one region will often act as a catalyst in another region, especially in geographically adjacent regions. Seeing the benefits of digital financial development in a region, neighboring regions are willing to emulate and adopt methods to develop digital finance, including policy supports and improvements in residents' financial literacy. In that case, the digital financial development in one region will benefit neighboring regions as well. We also notice that the trend in increasing number of provinces in the first and third quadrants also exists when it comes to the urban-rural income gap, as illustrated in Figure 2c,d. However, the trend is less obvious than that of digital financial development. It is most likely because the process of narrowing the urban-rural income gap is considerably more difficult and complex than that of digital financial development.


**Figure 2.** Scatterplot of local Moran's $I$ of digital financial development and urban-rural income gap for 31 provinces in China in 2011 and 2019. Note: (i) the $x$ axis represents $Z_i$ which is mentioned in Equation (9), the $y$ axis represents $\sum_{k\neq i}^{n} W_{ik}Z_k$; (ii) the first quadrant is the "high-high" quadrant, denoting that $Z_i > 0$ and $\sum_{k\neq i}^{n} W_{ik}Z_k > 0$; the second quadrant is the "low-high" quadrant, denoting that $Z_i < 0$ and $\sum_{k\neq i}^{n} W_{ik}Z_k > 0$; the third quadrant is the "low-low" quadrant, denoting that $Z_i < 0$ and $\sum_{k\neq i}^{n} W_{ik}Z_k < 0$; and the fourth quadrant is the "high-low" quadrant, denoting that $Z_i > 0$ and $\sum_{k\neq i}^{n} W_{ik}Z_k < 0$; (iii) Appendix D demonstrates the list of provinces corresponding to the serial numbers in the figure.

### 4.2.2. Spatial Effect

To test Hypothesis 2 (H2), this paper conducts the Lagrange multiplier (LM) test to select the most appropriate spatial model. As can be seen, all the $p$-values for the spatial lag model test are lower than 0.1; thus, the spatial autoregression (SAR) model is adopted in this research (see Appendix E for details).

First, in accordance with Equations (10) and (11), the results for the total spatial effect of digital financial development on the urban-rural income gap are reported in Column 1 of Table 8. The coefficient of digital financial development is significantly negative at the 1% significance level, suggesting that digital financial development in a region contributes to the decline of its urban-rural income gap. In other words, digital financial development can help to optimize residents' income distribution. Hence, Hypothesis 2a (H2a) is verified.

Second, this research further investigates the spatial direct and spillover effects of digital financial development on the urban-rural income gap. The results for the spatial direct effect are presented in Column 2 of Table 8, while Column 3 presents those for the spatial spillover effect. Clearly, digital finance does have a negative spatial direct effect and a spatial spillover effect on the rural–urban income gap, which confirms Hypothesis 2b (H2b) and Hypothesis 2c (H2c). This finding provides evidence that digital financial development can not only contribute to narrowing the income gap within the same region but also significantly optimize the income distribution in geographically adjacent areas. Meanwhile, the spatial spillover effect of digital financial development (−0.0004) accounts for 66.67% of the total spatial effect, which is significantly greater than the direct effect (−0.0002). Accordingly, a large portion of the impact of digital financial development on reducing the urban-rural income gap is due to the spatial spillover effect. The reasons for this are as follows: Digital finance can eliminate geographic constraints associated with financial services by facilitating instant cross-spatial information dissemination, allowing financial institutions in one province to serve residents in its neighboring provinces directly, which may contribute to narrowing income gaps within neighboring provinces. In addition to the aforementioned direct impact, the digital financial development in one province also has an indirect impact on the income gaps in the neighboring provinces. It is because the digital financial development in one province can first improve the digital financial development in its neighboring regions, and then the digital financial development in its neighboring regions will further narrow the income gaps within neighboring regions. Accordingly, the cross-regional penetration of financial inclusion is achieved, and its contribution to achieving the goal of financial inclusion should also be considered.

Furthermore, based on the preceding analysis, the spatial effect contributes significantly to the improvement of the urban-rural income distribution driven by digital financial development. To this end, spatial models can be used instead of traditional ordinary least squares estimation to better explore the relationship between digital financial development and residents' income gap.

**Table 8.** Spatial effect of digital financial development on urban-rural income gap.

| | **(1)** | **(2)** | **(3)** |
|---|---|---|---|
| **Variables** | **SAR**<br>**Total Spatial Effect** | **SAR**<br>**Spatial Direct Effect** | **SAR**<br>**Spatial Spillover Effect** |
| Indexaggr | −0.0006 *** | −0.0002 * | −0.0004 *** |
| | (−3.35) | (−1.66) | (−2.93) |
| Avegdp | −0.0000 | 0.0000 | −0.0000 |
| | (−0.43) | (1.09) | (−1.06) |
| Fdirt | −0.0215 | −0.2286 ** | 0.2071 |
| | (−0.12) | (−2.34) | (1.08) |
| Govexpenrt | −0.0394 | 0.0450 | −0.0844 |
| | (−0.47) | (1.07) | (−1.05) |
| Urbaniz | −0.0050 *** | −0.0035 *** | −0.0015 |
| | (−2.92) | (−3.50) | (−0.99) |
| Lnenterpnum | −0.0190 | 0.0190 *** | −0.0380 *** |
| | (−1.47) | (3.16) | (−3.12) |
| Studnum | −0.0001 | −0.0001 | −0.0000 |
| | (−0.34) | (−0.45) | (−0.17) |
| Lnavehousingprice | 0.0160 | −0.0072 | 0.0232 |
| | (0.75) | (−0.85) | (1.26) |
| Lnpopulation | −0.0449 | −0.0818 ** | 0.0368 |
| | (−0.58) | (−2.16) | (0.52) |
| Savings | −0.0000 | −0.0000 | −0.0000 |
| | (−0.95) | (−0.20) | (−0.98) |
| Lnretailsale | −0.0134 | −0.0141 ** | 0.0007 |
| | (−1.41) | (−2.07) | (0.07) |
| Lnloan | −0.0072 | −0.0073 | −0.0073 |
| | (−0.53) | (−0.62) | (−0.62) |
| Lnsocialfinance | 0.0086 ** | 0.0090 *** | 0.0090 *** |
| | (2.53) | (2.94) | (2.94) |
| Observations | 279 | 279 | 279 |
| R-squared | 0.800 | 0.793 | 0.808 |
| LR | 38.48 *** | - | - |

Note: t-statistics are presented in parentheses, *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

## 5. Conclusions

The purpose of this study is to investigate whether digital finance could contribute to sustainable wealth growth, that is, the increase in residents' total income as well as optimizing the income distribution. The paper first summarizes the theoretical mechanism of digital financial development to affect residents' total income and income distribution, and it puts forward two major hypotheses with several sub-hypotheses accordingly. It is found that when serving long-tail users, traditional financial institutions face three major pain points, that is, information asymmetry, geographical constraints, and diseconomies of scale, while those pain points undermine their capacity to raise residents' total income and optimize income distribution. Nevertheless, digital finance is characterized by three key attributes, namely a high capacity for acquiring and processing information, instant cross-spatial information dissemination, and a low marginal cost effect. These features can be effectively utilized to address three major pain points, ultimately enhancing residents' income and optimizing income distribution.

Second, based on panel data of 31 Chinese provinces between 2011 and 2019, a two-stage GMM estimation model with endogeneity treatment is constructed to investigate the impact of digital finance on residents' total income. The results confirm Hypothesis 1 (H1) with two sub-hypotheses. Specifically, the advancement of digital finance can significantly influence the enhancement of residents' total income in both urban and rural areas, with a weaker impact on rural residents' income than that on urban residents' income, most likely because residents in urban areas always have better digital infrastructures and macroeconomic conditions, while residents in rural areas may suffer from the digital divide. Consequently, these factors can hinder the development of digital finance and its effectiveness in boosting total income among rural areas.

Third, the study utilizes Moran's *I* and SAR models to explore the impact of digital finance on residents' income distribution. As a pre-test, the results of global and local spatial correlation tests show that both the digital financial development and the urban-rural income gap in China have significant positive spatial correlations at the 1% significance level, thus the spatial effect should be considered. The results of the SAR model confirm research Hypothesis 2 (H2) with three sub-hypotheses. More precisely, regarding the total spatial effect, digital financial development in a region contributes to the decline of its urban-rural income gaps with a coefficient at the 1% significance level. Furthermore, digital finance does have a negative spatial direct effect and a spatial spillover effect on the rural–urban income gap. The spatial spillover effect accounts for about 66.67% of the total spatial effect, accounting for most of the impact of digital financial development on narrowing the urban-rural income gap.

Our findings offer important insights for policymakers and financial institutions aiming to achieve sustainable growth and promote financial inclusion. On the one hand, considering that digital finance can increase residents' total income and optimize income distribution, policymakers could adopt targeted strategies, including tax incentives, dedicated industrial funds, and other initiatives, to promote the growth of digital finance. Besides, policymakers may take full advantage of the spatial effect of digital financial development (especially the spatial spillover effect) and invest in digital finance together with neighboring regions in order to benefit from the synergies associated with industrial clustering. During this process, it is important to focus on the construction of digital financial infrastructure and the prevention and control of financial risks to address potential barriers to the adoption of digital finance. On the other hand, financial institutions should increase their investments in digital finance, prioritize research and development of foundational digital financial technologies, and focus on recruiting and nurturing talent in this field. Concurrently, greater efforts are needed to expand the reach of digital finance and accelerate its integration into diverse application fields. To further bridge the "digital divide" between urban and rural areas, policymakers should focus on increasing investment in digital financial infrastructure and promoting digital financial literacy campaigns in rural communities, thereby facilitating the development of digital finance in the countryside. These can more effectively improve local digital financial development and thereby enhance its capacity to promote residents' income and improve income distribution.

The limitations of this paper are twofold. Due to data limitations, this study relies solely on a panel dataset at the provincial level in China. Future research could benefit from utilizing municipal or even county-level data, which would enhance the rigor of the arguments and the overall robustness of the findings. Furthermore, this study has demonstrated that digital financial development affects residents' total income and income distribution, but it has not examined other aspects of residents' income such as the income component or other aspects of residents' living standards such as consumption and financial literacy. This can be explored further.

**Author Contributions:** Conceptualization, D.L., Y.G., and J.L.; methodology, D.L. and F.W.; software, D.L.; validation, J.L. and F.W.; formal analysis, D.L.; investigation, D.L. and Y.G.; resources, D.L., F.W., and J.L.; data curation, D.L. and F.W.; writing—original draft preparation, D.L.; writing—review and editing, D.L. and J.L.; project administration, D.L. and J.L.; funding acquisition, D.L. and Y.G. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by "Zhejiang Provincial Philosophy and Social Sciences Planning Project—Leading Talent Cultivation Special Project (25YJRC004ZD-1)", "Hangzhou Normal University Alibaba Business School (4135C50222204130)", and "Open Topics of the Institute of Digital Finance, Hangzhou City College (grant number 11, 2022)".

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** Data available on request.

**Acknowledgments:** The authors would like to thank Yuchen Lu for her invaluable assistance with this paper. The authors thank the editors and anonymous reviewers for their kind reviews and helpful comments.

**Conflicts of Interest:** The authors declare no conflicts of interest.

## Appendix A

**Table A1.** Theil index by province in China, from 2011 to 2019.

| | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|---|
| Beijing | 0.026 | 0.025 | 0.025 | 0.032 | 0.032 | 0.032 | 0.032 | 0.032 | 0.031 |
| Tianjin | 0.034 | 0.030 | 0.027 | 0.021 | 0.020 | 0.020 | 0.020 | 0.020 | 0.020 |
| Hebei | 0.105 | 0.101 | 0.095 | 0.086 | 0.084 | 0.082 | 0.080 | 0.077 | 0.074 |
| Shanxi | 0.147 | 0.142 | 0.135 | 0.106 | 0.104 | 0.101 | 0.098 | 0.093 | 0.087 |
| Inner Mongolia | 0.122 | 0.118 | 0.111 | 0.103 | 0.101 | 0.099 | 0.097 | 0.092 | 0.085 |
| Liaoning | 0.073 | 0.071 | 0.067 | 0.075 | 0.073 | 0.072 | 0.071 | 0.070 | 0.066 |
| Jilin | 0.082 | 0.080 | 0.077 | 0.065 | 0.068 | 0.066 | 0.211 | 0.065 | 0.062 |
| Heilongjiang | 0.057 | 0.057 | 0.054 | 0.062 | 0.063 | 0.062 | 0.061 | 0.057 | 0.053 |
| Shanghai | 0.020 | 0.020 | 0.020 | 0.021 | 0.024 | 0.023 | 0.023 | 0.022 | 0.021 |
| Jiangsu | 0.075 | 0.073 | 0.069 | 0.062 | 0.060 | 0.057 | 0.056 | 0.054 | 0.052 |
| Zhejiang | 0.070 | 0.069 | 0.067 | 0.050 | 0.048 | 0.047 | 0.045 | 0.043 | 0.041 |
| Anhui | 0.138 | 0.132 | 0.124 | 0.096 | 0.094 | 0.092 | 0.089 | 0.086 | 0.083 |
| Fujian | 0.105 | 0.101 | 0.095 | 0.074 | 0.072 | 0.070 | 0.068 | 0.065 | 0.062 |
| Jiangxi | 0.102 | 0.100 | 0.095 | 0.087 | 0.084 | 0.081 | 0.079 | 0.077 | 0.073 |
| Shandong | 0.111 | 0.108 | 0.102 | 0.086 | 0.082 | 0.079 | 0.077 | 0.075 | 0.072 |
| Henan | 0.124 | 0.119 | 0.112 | 0.089 | 0.087 | 0.083 | 0.081 | 0.079 | 0.074 |
| Hubei | 0.104 | 0.101 | 0.095 | 0.074 | 0.072 | 0.072 | 0.071 | 0.069 | 0.067 |
| Hunan | 0.129 | 0.126 | 0.119 | 0.106 | 0.103 | 0.100 | 0.098 | 0.094 | 0.091 |
| Guangdong | 0.089 | 0.087 | 0.084 | 0.074 | 0.072 | 0.070 | 0.069 | 0.067 | 0.064 |
| Guangxi | 0.188 | 0.180 | 0.170 | 0.125 | 0.120 | 0.115 | 0.110 | 0.103 | 0.097 |
| Hainan | 0.120 | 0.116 | 0.109 | 0.088 | 0.084 | 0.080 | 0.077 | 0.076 | 0.075 |

**Table A1.** *Cont.*

| | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|---|
| Chongqing | 0.129 | 0.124 | 0.116 | 0.091 | 0.086 | 0.081 | 0.077 | 0.074 | 0.071 |
| Sichuan | 0.136 | 0.133 | 0.126 | 0.106 | 0.102 | 0.098 | 0.095 | 0.092 | 0.088 |
| Guizhou | 0.227 | 0.222 | 0.210 | 0.175 | 0.168 | 0.163 | 0.157 | 0.153 | 0.146 |
| Yunnan | 0.221 | 0.214 | 0.204 | 0.163 | 0.156 | 0.151 | 0.147 | 0.142 | 0.136 |
| Tibet | 0.168 | 0.154 | 0.146 | 0.144 | 0.155 | 0.153 | 0.145 | 0.144 | 0.138 |
| Shaanxi | 0.178 | 0.169 | 0.161 | 0.131 | 0.126 | 0.122 | 0.118 | 0.113 | 0.108 |
| Gansu | 0.213 | 0.209 | 0.199 | 0.179 | 0.173 | 0.172 | 0.168 | 0.163 | 0.158 |
| Qinghai | 0.164 | 0.154 | 0.144 | 0.136 | 0.137 | 0.134 | 0.130 | 0.124 | 0.117 |
| Ningxia | 0.148 | 0.143 | 0.137 | 0.109 | 0.106 | 0.104 | 0.100 | 0.097 | 0.092 |
| Xinjiang | 0.129 | 0.125 | 0.118 | 0.111 | 0.120 | 0.119 | 0.117 | 0.111 | 0.103 |

Note: the method of calculation is described in detail in Section 3.3.

## Appendix B

**Table A2.** Instrumental variable validity test under two-stage GMM of digital financial development on urban residents' total income with the limited sample bias correction method.

| | | (1) | (2) | (3) | (4) |
|---|---|---|---|---|---|
| **Validity Test** | **Program of the Test** | **2GMM *Urbaninc*** | **2GMM *Urbaninc*** | **2GMM *Urbaninc*** | **2GMM *Urbaninc*** |
| Under-identification test | KP LM value | 104.264 | 52.748 | 52.203 | 33.369 |
| | Chi-sq (2) $p$-value | 0.000 | 0.000 | 0.000 | 0.000 |
| Weak identification test | CDW $F$-value | 4138.503 | 271.955 | 204.186 | 152.017 |
| | KP Wald $F$ value | 0.000 | 339.999 | 251.329 | 150.429 |
| | Stock-Yogo 10% maximal IV size | 19.930 | 19.930 | 19.930 | 19.930 |
| Overidentification test | Hansen J test | 0.665 | 0.869 | 1.751 | 1.707 |
| | Chi-sq (1) $p$-value | 0.415 | 0.351 | 0.186 | 0.191 |
| Endogeneity test | Endogeneity test | 0.033 | 3.941 | 4.556 | 4.354 |
| | Chi-sq (1) $p$-value | 0.857 | 0.047 | 0.033 | 0.037 |

Note: (i) for the under-identification test, all the $p$-values of the unidentifiable tests are zero, indicating that there is no evidence of under-identification with this instrumental variable; (ii) for the weak identification test, all $F$-values with the exception of the first test without control variables exceed the Stock-Yogo value at the 10% significance level, thus indicating that this instrumental variable passes the weak identification test; (iii) for the overidentification test, the $p$-values of the Hansen J tests are all greater than 0.1, indicating that this instrumental variable passes the overidentification test; (iv) for the endogeneity test, all $p$-values are less than 0.1 with the exception of the first test without control variables, which indicates that the instrumental variables are stable exogenous and effective in incorporating the control variables gradually. The validity of the instrumental variables is justified.

**Table A3.** Two-stage GMM treated with the limited sample bias correction method results of digital financial development on urban residents' income.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Variables** | **2GMM *Urbaninc*** | **2GMM *Urbaninc*** | **2GMM *Urbaninc*** | **2GMM *Urbaninc*** |
| Indexaggr | 80.174 *** | 82.487 *** | 66.287 *** | 68.021 *** |
| | (31.87) | (10.35) | (8.37) | (6.99) |
| Fdirt | | 41,984.897 ** | 24,287.864 | 24,936.822 |
| | | (2.29) | (1.45) | (1.51) |
| Govexpenrt | | −7958.584 | −456.534 | −590.613 |
| | | (−1.25) | (−0.08) | (−0.10) |
| Urbaniz | | −545.962 *** | −542.284 *** | −546.354 *** |
| | | (−3.22) | (−3.47) | (−3.55) |

**Table A3.** *Cont.*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Variables** | **2GMM** ***Urbaninc*** | **2GMM** ***Urbaninc*** | **2GMM** ***Urbaninc*** | **2GMM** ***Urbaninc*** |
| Lnenterpnum | | −3785.911 *** | −3428.197 *** | −3383.592 *** |
| | | (−3.76) | (−3.38) | (−3.25) |
| Studnum | | −8.679 | −56.597 ** | −56.995 ** |
| | | (−0.40) | (−2.55) | (−2.56) |
| Lnavehousingprice | | 6665.854 *** | 6133.876 *** | 6163.113 *** |
| | | (5.01) | (5.13) | (5.08) |
| Lnpopulation | | 33,349.057 *** | 19,395.449 *** | 19,937.539 *** |
| | | (4.95) | (2.99) | (2.98) |
| Savings | | | 0.188 *** | 0.183 *** |
| | | | (4.19) | (3.83) |
| Lnretailsale | | | 3920.788 *** | 3851.246 *** |
| | | | (4.29) | (4.09) |
| Lnloan | | | | −272.644 |
| | | | | (−0.21) |
| Lnsocialfinance | | | | 41.369 |
| | | | | (0.16) |
| Observations | 279 | 279 | 279 | 279 |
| R-squared | 0.908 | 0.943 | 0.953 | 0.953 |

Note: t-statistics are presented in parentheses, ** and *** indicate significance at 5%, and 1% levels, respectively.

## Appendix C

**Table A4.** Instrumental variable validity test under two-stage GMM of digital financial development on rural residents' total income with the limited sample bias correction method.

| | | (1) | (2) | (3) | (4) |
|---|---|---|---|---|---|
| **Validity Test** | **Program of the Test** | **2GMM** ***Urbaninc*** | **2GMM** ***Urbaninc*** | **2GMM** ***Urbaninc*** | **2GMM** ***Urbaninc*** |
| Under-identification test | KP LM value | 104.264 | 52.748 | 52.203 | 33.369 |
| | Chi-sq (2) *p*-value | 0.000 | 0.000 | 0.000 | 0.000 |
| Weak identification test | CDW F-value | 4138.503 | 271.955 | 204.186 | 152.017 |
| | KP Wald *F* value | 0.000 | 339.999 | 251.329 | 150.429 |
| | Stock-Yogo 10% maximal IV size | 19.930 | 19.930 | 19.930 | 19.930 |
| Overidentification test | Hansen J test | 1.425 | 1.181 | 2.690 | 1.296 |
| | Chi-sq (1) *p*-value | 0.233 | 0.277 | 0.101 | 0.255 |
| Endogeneity test | Endogeneity test | 0.355 | 6.230 | 8.904 | 11.116 |
| | Chi-sq (1) *p*-value | 0.552 | 0.012 | 0.003 | 0.001 |

Note: (i) for the under-identification test, all the *p*-values of the unidentifiable tests are zero, indicating that there is no evidence of under-identification with this instrumental variable; (ii) for the weak identification test, all *F*-values with the exception of the first test without control variables exceed the Stock-Yogo value at the 10% significance level, thus indicating that this instrumental variable passes the weak identification test; (iii) for the overidentification test, the *p*-values of the Hansen J tests are all greater than 0.1, indicating that this instrumental variable passes the overidentification test; (iv) for the endogeneity test, all *p*-values are less than 0.1 with the exception of the first test without control variables, which indicates that the instrumental variables are stable exogenous and effective in incorporating the control variables gradually. The validity of the instrumental variables is justified.

**Table A5.** Two-stage GMM treated with the limited sample bias correction method results of digital financial development on rural residents' income.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Variables** | **2GMM *Urbaninc*** | **2GMM *Urbaninc*** | **2GMM *Urbaninc*** | **2GMM *Urbaninc*** |
| indexaggr | 36.348 *** | 42.442 *** | 34.918 *** | 39.234 *** |
| | (34.53) | (11.70) | (10.50) | (9.85) |
| fdirt | | 4352.487 | −3378.948 | −4478.410 |
| | | (0.48) | (−0.39) | (−0.55) |
| govexpenrt | | −3605.956 | −975.431 | 454.914 |
| | | (−1.28) | (−0.39) | (0.17) |
| urbaniz | | −332.063 *** | −306.466 *** | −281.486 *** |
| | | (−5.01) | (−4.67) | (−4.11) |
| lnenterpnum | | −1307.281 ** | −1057.372 ** | −678.034 |
| | | (−2.37) | (−1.96) | (−1.26) |
| studnum | | 11.737 | −15.147 | −16.339 |
| | | (1.32) | (−1.41) | (−1.53) |
| lnavehousingprice | | 1509.964 ** | 1214.415 * | 1420.677 ** |
| | | (2.00) | (1.78) | (2.25) |
| lnpopulation | | 11,559.098 *** | 5825.099 * | 7474.098 ** |
| | | (3.22) | (1.81) | (2.27) |
| savings | | | 0.101 *** | 0.091 *** |
| | | | (4.18) | (3.92) |
| lnretailsale | | | 1398.799 *** | 1269.267 *** |
| | | | (3.62) | (3.14) |
| lnloan | | | | −1255.524 ** |
| | | | | (−2.19) |
| lnsocialfinance | | | | 138.582 |
| | | | | (0.98) |
| Observations | 279 | 279 | 279 | 279 |
| R-squared | 0.909 | 0.941 | 0.954 | 0.954 |

Note: t-statistics are presented in parentheses, *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

## Appendix D

**Table A6.** The list of provinces corresponding to the serial numbers in Figure 2.

| Number | Province | Number | Province |
|---|---|---|---|
| 1 | Beijing | 17 | Hubei |
| 2 | Tianjin | 18 | Hunan |
| 3 | Hebei | 19 | Guangdong |
| 4 | Shanxi | 20 | Guangxi |
| 5 | Inner Mongolia | 21 | Hainan |
| 6 | Liaoning | 22 | Chongqing |
| 7 | Jilin | 23 | Sichuan |
| 8 | Heilongjiang | 24 | Guizhou |
| 9 | Shanghai | 25 | Yunnan |
| 10 | Jiangsu | 26 | Tibet |
| 11 | Zhejiang | 27 | Shaanxi |
| 12 | Anhui | 28 | Gansu |
| 13 | Fujian | 29 | Qinghai |
| 14 | Jiangxi | 30 | Ningxia |
| 15 | Shandong | 31 | Xinjiang |
| 16 | Henan | | |

## Appendix E

**Table A7.** LM test for the spatial model.

| LM Test | Coefficient | df | *p* Value |
|---|---|---|---|
| Spatial error model test | | | |
| Moran's *I* | 6.180 | 1 | 0.000 |
| Lagrange multiplier | 32.619 | 1 | 0.000 |
| Robust lagrange multiplier | 1.315 | 1 | 0.252 |
| Spatial lag model test | | | |
| Lagrange multiplier | 41.547 | 1 | 0.000 |
| Robust lagrange multiplier | 10.243 | 1 | 0.001 |

Note: (i) for the spatial error model test, the *p*-value of the robust Lagrange multiplier is higher than 0.1, indicating that there is no evidence to choose the spatial error model; (ii) for the spatial lag model test, all *p*-values are lower than 0.1, indicating that it is appropriate to choose the spatial lag model, i.e., the SAR model.

## References

1. United Nations. *The 2023 Global Multidimensional Poverty Index Report*; United Nations: New York, NY, USA, 2023.
2. Lakner, C.; Yonzan, N.; Mahler, D.; Aguilar, A.; Wu, H. *Updated Estimates of the Impact of COVID-19 on Global Poverty: Looking Back at 2020 and the Outlook for 2021*; World Bank: Washington, DC, USA, 2021.
3. Credit Suisse. *The Global Wealth Report 2021*; Credit Suisse: Zurich, Switzerland, 2021.
4. Demirguc-Kunt, A.; Klapper, L.; Singer, D.; Ansar, S.; Hess, J. *The Global Findex Database 2017: Measuring Financial Inclusion and the Fintech Revolution*; World Bank: Washington, DC, USA, 2018.
5. United Nations. *Inter-Agency Task Force on Financing for Development, Financing for Sustainable Development Report 2020*; United Nations: New York, NY, USA, 2020.
6. Subbarao, D.; Zhang, L.; Xu, M.; Zhang, H.; Li, M.; Esquivias, M. *Digital Finance Helps Reduce Global Poverty 2021*; Grandview Institution: Beijing, China, 2021.
7. Anderson, C. *The Long Tail: Why the Future of Business is Selling Less of More*; Hachette Livre: Paris, France, 2006.
8. Huang, Y.P.; Huang, Z. China's Digital Financial Development: Now and the Future. *Q. Econ.* **2018**, *17*, 1489–1502.
9. Jin, D. The inclusive finance has effects on alleviating poverty. *Open J. Soc. Sci.* **2017**, *5*, 233–242.
10. Park, C.Y.; Mercado, R.V. Fnancial inclusion, poverty and income inequality. *Singap. Econ. Rev.* **2018**, *63*, 185–206. [CrossRef]
11. Bachas, P.; Gertler, P.; Higgins, S. Digital financial services go a long way: Transaction costs and financial inclusion. *AEA Pap. Proc.* **2018**, *108*, 44–48. [CrossRef]
12. Ozili, P.K. Impact of digital finance on financial inclusion and stability. *Borsa Istanb. Rev.* **2018**, *18*, 329–340. [CrossRef]
13. Yi, X.J.; Zhou, L. Does the Development of Digital Inclusive Finance Significantly Affect Resident Consumption—Micro Evidence from Chinese Households. *J. Financ. Res.* **2018**, *11*, 47–67.
14. Bollaert, H.; Lopez, F.; Schwienbacher, A. Fintech and access to finance. *J. Corp. Financ.* **2021**, *68*, 101941. [CrossRef]
15. Chinoda, T.; Mashamba, T. Fintech, financial inclusion and income inequality nexus in Africa. *Cogent Econ. Financ.* **2021**, *9*, 1986926. [CrossRef]
16. Allen, F.; Gu, X.; Jagtiani, J. Fintech, cryptocurrencies, and CBDC: Financial structural transformation in China. *J. Int. Money Financ.* **2022**, *124*, 102625. [CrossRef]
17. Zou, F.; Li, T.; Zhou, F. Does the level of financial cognition affect the income of rural households? Based on the Moderating Effect of the Digital Financial Inclusion Index. *Agronomy* **2021**, *11*, 1813. [CrossRef]
18. Demir, A.; Pesqué, V.; Altunbas, Y. Fintech, financial inclusion and income inequality: A quantile regression approach. *Eur. J. Financ.* **2022**, *28*, 86–107. [CrossRef]
19. Bettinger, A. Fintech: A series of 40 Time shared models used at Manufacturers Hanover Trust Company. *Interfaces* **1972**, *2*, 62–63.
20. Arner, D.W.; Janos, B.; Ross, P.B. The evolution of Fintech: A new post-crisis paradigm. *Georget. J. Int. Law.* **2015**, *47*, 1271. [CrossRef]
21. Gomber, P.; Koch, J.A.; Siering, M. Digital Finance and FinTech: Current research and future research directions. *J. Bus. Econ.* **2017**, *87*, 537–580. [CrossRef]
22. Holly, S.; Pesaran, M.H.; Yamagata, T. A spatio-temporal model of house prices in the USA. *J. Econom.* **2010**, *158*, 160–173. [CrossRef]
23. Luo, C. Economic growth, income disparity and rural poverty. *Econ. Res.* **2012**, *47*, 15–27.
24. Sicular, T.; Ximing, Y.; Gustafsson, B. *The Urban-Rural Income Gap and Income Inequality in China: Understanding Inequality and Poverty in China*; Palgrave Macmillan: London, UK, 2008; pp. 30–71.
25. Easterlin, R.A.; Angelescu, L.; Zweig, J.S. The impact of modern economic growth on urban-rural differences in subjective well-being. *World Dev.* **2011**, *39*, 2187–2198. [CrossRef]
26. Wang, X.; Shao, S.; Li, L. Agricultural inputs, urbanization, and urban-rural income disparity: Evidence from China. *China Econ. Rev.* **2019**, *55*, 67–84. [CrossRef]
27. Lu, D. *Rural-Urban Income Disparity: Impact of Growth, Allocative Efficiency and Local Growth Welfare*; Routledge: London, UK, 2018; pp. 255–268.

28. Yao, Y.; Jiang, L. Urbanization forces driving rural urban income disparity: Evidence from metropolitan areas in China. *J. Clean. Prod.* **2021**, *312*, 127748. [CrossRef]
29. Xu, J.; Wang, J.; King, M. Rural–urban disparities in the utilization of mental health inpatient services in China: The role of health insurance. *Int. J. Health Econom. Manag.* **2018**, *18*, 377–393. [CrossRef]
30. Burgess, R.; Pande, R. Do rural banks matter? Evidence from the Indian social banking experiment. *Am. Econ. Rev.* **2005**, *95*, 780–795. [CrossRef]
31. Suri, T.; Jack, W. The long-run poverty and gender impacts of mobile money. *Science* **2016**, *354*, 1288–1292. [CrossRef]
32. Aghion, P.; Bolton, P. A theory of trickle-down growth and development. *Rev. Econ. Stud.* **1997**, *64*, 151–172. [CrossRef]
33. Greenwood, D.T.; Holt, R.P.F. Growth, inequality and negative trickle down. *J. Econ. Issues* **2010**, *44*, 403–410. [CrossRef]
34. Akinci, M. Inequality and economic growth: Trickle-down effect revisited. *Dev. Policy Rev.* **2018**, *36*, O1–O24. [CrossRef]
35. Xie, P.; Zou, C. Research on Internet Financial Model. *J. Financ. Res.* **2012**, *12*, 11–22.
36. FinTech Issues Group of Financial Stability Board. Financial stability implications from Fintech-supervisory and regulatory issues that merit authorities' attention. *Financ. Regul. Res.* **2017**. Available online: https://www.fsb.org/uploads/R270617.pdf (accessed on 1 July 2024).
37. Bauer, J.M. The Internet and Income Inequality: Socio-economic Challenges in a Hyperconnected Society. *Telecommun. Policy* **2018**, *42*, 333–343. [CrossRef]
38. Goldfarb, A.; Tucker, C. Digital economics. *J. Econ. Lit.* **2019**, *57*, 3–43. [CrossRef]
39. Appiah, O.I.; Song, N. The impact of fintech on poverty reduction: Evidence from China. *Sustainability* **2021**, *13*, 5225. [CrossRef]
40. Sarma, M. *Index of Financial Inclusion*; Working Paper No. 215; Palgrave MacMillan: London, UK, 2008.
41. Galor, O.; Zeira, J. Income Distribution and Macroeconomics. *Rev. Econ. Stud.* **1993**, *60*, 35–52. [CrossRef]
42. Luo, D.; Luo, M.; Lv, J. Can Digital Finance Contribute to the Promotion of Financial Sustainability? A Financial Efficiency Perspective. *Sustainability* **2022**, *14*, 3979. [CrossRef]
43. Yusuf, S.; Anthony, S. *China Urbanizes: Consequences, Strategies, and Policies*; World Bank: Washington, DC, USA, 2008.
44. Wen, T.; Zhu, J.; Wang, X.H. Elite Capture Mechanism of Agricultural Loans in China: A Stratified Comparison of Poor and Non-Poor Counties. *J. Econ. Res.* **2016**, *51*, 111–125.
45. Gomber, P.; Kauffman, R.J.; Parker, C. On the Fintech Revolution: Interpreting the Forces of Innovation, Disruption, and Transformation in Financial Services. *J. Manage. Inform. Syst.* **2018**, *35*, 220–265. [CrossRef]
46. Duarte, J.; Siegel, S.; Young, L. Trust and Credit: The Role of Appearance in Peer-to-Peer Lending. *Rev. Financ. Stud.* **2012**, *25*, 2455–2484. [CrossRef]
47. Li, W.Q. Research on Internet Finance to Crack the Financing Dilemma of Small and Medium-sized Enterprises. *Acad. J. Zhongzhou* **2014**, *8*, 51–54.
48. Liu, J.Y.; Liu, C.Y. The Rural Poverty Reduction Effect of Digital Inclusive Finance: Effects and Mechanisms. Collect. *Essays Financ. Econ.* **2020**, *1*, 43–53.
49. Xie, X.L.; Shen, Y.; Zhang, H.X.; Guo, F. Can Digital Finance Promote Entrepreneurship? Evidence from China. *Q. Econ.* **2018**, *17*, 1557–1580.
50. Zhou, J.; Wang, W.; Gong, M.; Huang, Z. Agricultural land transfer, occupational stratification and poverty reduction effects. *J. Econ. Res.* **2020**, *55*, 155–171.
51. Dixon, P.M.; Weiner, J.; Mitchell, T. Bootstrapping the Gini coefficient of inequality. *Ecology* **1987**, *68*, 1548–1551. [CrossRef]
52. Leydesdorff, L.; Wagner, C.S.; Bornmann, L. Interdisciplinarity as diversity in citation patterns among journals: Rao-Stirling diversity, relative variety, and the Gini coefficient. *J. Informetr.* **2019**, *13*, 255–269. [CrossRef]
53. Tang, J.; Gong, J.; Ma, W. Narrowing urban-rural income gap in China: The role of the targeted poverty alleviation program. *Econ. Anal. Policy* **2022**, *75*, 74–90. [CrossRef]
54. Theil, H. *Economics and Information Theory*; Rand McNally Co.: Chicago, IL, USA, 1967.
55. Yuan, Y.; Wang, M.; Zhu, Y. Urbanization's effects on the urban-rural income gap in China: A meta-regression analysis. *Land Use Pol.* **2020**, *99*, 104995. [CrossRef]
56. Justman, M.; Stiassnie, H. *Inequality in Annual Earnings, Volatility of Earnings, and Inequality in Lifetime Earnings in the United States, 1986–2018*; Ben-Gurion University: New York, NY, USA, 2022.
57. Fingleton, B. Equilibrium and economic growth: Spatial econometric models and simulations. *J. Reg. Sci.* **2001**, *41*, 117–147. [CrossRef]
58. Bivand, R.S.; Wong, D.W.S. Comparing implementations of global and local indicators of spatial association. *Test* **2018**, *27*, 716–748. [CrossRef]
59. Małkowska, A.; Telega, A.; Głuszak, M. Spatial interdependence in property taxation: The case of Polish municipalities. *Equilibrium* **2018**, *13*, 265–283. [CrossRef]
60. Ye, X. Spatial spillover effects of the diffusion of technological innovation in Internet finance. *China Circ. Econ.* **2016**, *9*, 76–84.
61. Tiefelsdorf, M.; Boots, B. A note on the extremities of local Moran's I is and their impact on global Moran's I. *Geogr. Anal.* **1997**, *29*, 248–257. [CrossRef]
62. Lesage, J.P.; Pace, R.K. *Introduction to Spatial Econometrics*; Chapman and Hall: London, UK, 2009.