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EVIDENCE FROM HOUSEHOLDS

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ABSTRACT

By capturing the adoption of digital services and applications as well as digital industry development, this paper constructs a comprehensive index to measure digitalization at the city level in the People's Republic of China (PRC) and investigates the impact of digitalization on income inequality using household-level data in the PRC. The findings reveal that a one-unit advancement in the digitalization index significantly reduces the income gap by 1.83% for an average household. This mitigating effect remains statistically and economically significant after addressing endogeneity and robustness concerns. The impact is more pronounced in less-developed areas and among households with lower education levels. Further analysis shows that digitalization narrows the income gap by increasing earnings more for lower-income households, primarily through enhanced employment and investment opportunities. Additionally, digitalization boosts business income for entrepreneurial households. These findings provide valuable policy insights, suggesting that developing economies can reduce income inequality by promoting digitalization, supporting digital-related job creation, and enhancing financial literacy.

Keywords: digitalization, inclusiveness, income inequality

JEL codes: D30, O10, O30

1. Introduction

Income inequality, which is prevalent in both developing and developed countries, is a persistent phenomenon and a fundamental issue of concern. According to the 2022 *World Inequality Report* released by the World Inequality Lab, the richest 10% of the global population currently accounts for 52.0% of global income, whereas the poorest half of the population earns only 8.5% (Chancel et al. 2023). Rising income inequality is also seen in Asia and the Pacific, though income levels have increased along with rapid economic growth and poverty reduction (Zhuang 2023).

With the increasing penetration of digital technology in the lives of residents, digitalization has been embraced by governments because of its potential for promoting economic growth and reducing inequality. Digitalization can transcend geographical limits; offers opportunities to new businesses and easy access to finance; and enhances accessibility to information, goods, and services to reach less-developed regions and vulnerable groups with limited connectivity. However, the lack of digital connectivity and digital literacy can limit people from enjoying the benefits of the digital dividend, which can also widen the income gap between groups. Thus, the influence of digitalization on income distribution is still controversial. On the bright side—digital technologies such as big data, cloud computing, fintech, and online platforms—can promote economic growth and offer opportunities to vulnerable groups, thus increasing household income and narrowing income gaps (Ahmed and Al-Roubaie 2013; Asongu and Odhiambo 2019; Faizah, Yamada, and Pratamo 2021; Demir et al. 2022). Meanwhile, on the negative side, opportunities brought by digital technologies may not be equally accessible to all groups, leading to a significant digital divide that deteriorates income equality (Guellec and Paunov 2017; Daud, Ahmad, and Ngah 2021).

However, most of the existing studies are based on macro data at the country level, and it is difficult to deeply discuss heterogeneity and the impact mechanism of digitalization on income inequality. Using household micro survey data, this paper empirically examines the impact of digitalization on income inequality at the household level in the People's Republic of China (PRC). The evidence from the PRC offers useful policy implications to other developing Asian economies in several ways. First, the PRC has experienced rapid but unequal progress in digitalization.[1] The PRC has a variety of digitalization development levels across cities and regions, which offers a good sample to assess how the development of digitalization can affect income gaps. Second, despite an increase in income levels in recent decades, there remains significant inequality in income distribution across the PRC. According to data released by the National Bureau

[1] CAICT. 2022. White Papers Research. caict.ac.cn.com/white-papers-research/202220.

of Statistics of China, the PRC's Gini coefficient rose from 0.28 in 1981 to 0.47 in 2022, crossing the international warning line of 0.40 and exceeding the global average. Thus, the PRC offers a good sample to test how digitalization can influence income gaps.

Utilizing micro household-level survey data from the China Household Finance Survey (CHFS) covering about 10,000 randomly selected households across approximately 544 cities from 2013 to 2019, this study measures income inequality using the Kakwani index at the household level, following Bossert and D'Ambrosio (2006) and Beck, Demirgüç-Kunt, and R. Levine (2007). Following Bukht and Heeks (2018), this study constructs a digitalization index at the city level to capture various aspects of digital technology development, including digital industry development, and adoption of digital devices and applications. The analysis results show that a city's digitalization development can significantly reduce income gaps at household level. In particular, a one unit increase in the digitalization index measure is associated with a 0.0183 reduction in Kakwani index of an average household, which is 1.94% of the sample mean. This means, for example, when the average digitalization development during the sample period increases from 1.06 in Hohhot to 1.68 in Chengdu, the household-level income inequality narrows by 0.011, or 2.04% of an average household in the sample. Moreover, this impact is more pronounced in less-developed regions in the country and households with relatively lower education levels.

To address the possible endogeneity issues, we employed the instrument variable approach. This instrument variable is derived by grouping cities with similar economic profiles and calculating the average digitalization index of other cities within the same group. Such an instrument is related to digitalization development as it captures economic development of a typical city in the groups but does not necessarily link to the income inequality of local households of the city that is not part of the instrument. This variable is a strong instrument, and the instrumented digitalization of a city is still significantly and negatively related to income gaps in local households. We also conducted various robustness checks and found robust results on the negative impact of digitalization of a city on its households' income inequality.

To better understand the underlying driver of this effect, this study explores potential mechanisms. There is evidence to show that digitalization is able to increase income levels, especially in less-developed regions and for lower-educated populations. The increase in income is related to employment, investment, and business income. We find evidence that digitalization is related to more job opportunities, especially for less-educated populations and in less-developed regions, but we did not find significant increases in wages associated with digitalization. Meanwhile, digitalization also fosters participation in financial markets, which offers more investment opportunities to

households. And the investment opportunities via access to financial markets apply to all populations, regardless of local development status or education levels.

This study contributes to the existing literature in the following way. First, this paper adds to extant literature with a measure that captures more comprehensive information on the level of digitalization development. Existing studies tend to measure digitalization focusing on certain digital technologies, such as digital finance (Daud, Ahmad, and Ngah 2021; Yang and Zhang 2022) and artificial intelligence (Stevenson 2019), or accessibility to digital infrastructure and devices, such as mobile phone and internet penetration rates (Asongu and Nwachukwu 2018, Wang and Xu 2023). Such measures may not have comprehensively gauged the digital transformation in recent years. The measure adopted in this study adds to existing measures with information on development of the digital industry, which presents a more comprehensive picture of digitalization in economic activities.

Second, current literature tends to show evidence at the country level, while this paper provides consistent and robust empirical evidence at the household level. Moreover, the empirical estimates obtained from the fixed-effects model are convincing by controlling for heterogeneity across the panels.

Lastly, this study lends support to the inclusiveness of digitalization from the perspective of income inequality in less-developed regions and for less-educated populations, and it unveils the possible working channels of this effect. Such evidence has policy implications for peer developing economies in Asia and the Pacific by demonstrating that digitalization may work well as a tool to boost income levels and close income gaps in less-developed areas by fostering job creation.

This paper is structured as follows. Section 2 reviews the current literature and outlines the testable hypothesis. Sample construction and research methods are outlined in section 3. Section 4 discusses the empirical results, and section 5 discusses the findings and policy implications.

2. Literature Review

The literature on the impact of technological advances on income distribution, as well as income inequality, is inconclusive and offers many different explanations and conclusions.

One stream of literature argues that digitalization helps narrow income inequality via the following three channels. First, digitalization enhances connectivity by breaking geographical constraints and making virtual markets and remote workplaces possible

(Shaikh and Karjaluoto 2015). Enhanced connectivity opens new business opportunities and enables new jobs for populations facing constraints such as physical location and education levels, and it helps to optimize resource allocation across different regions. For example, emerging digital business models—such as e-commerce, short videos, and online live streaming—provide new job and income opportunities for people from remote areas and low-income groups (Atasoy 2013, Dauth et al. 2017). Second, digitalization enables greater access to services such as finance for vulnerable groups and populations who are domiciling in areas with limited financial resources and services (Jack and Suri 2011; Tchamyou, Erreygers, and D. Cassimon 2019; Demir et al. 2022). By enhancing access to financial services, digitalization enables more investment opportunities and also lowers financing costs, thus narrowing the income gap (Hong, Lu, and Pan 2020; Asongu and Odhiambo 2019). Third, digitalization reduces information barriers for vulnerable groups and facilitates information acquisition and analysis for investment, business, and job opportunities, which could increase their income and narrow the income gap. For example, Hong, Lu, and Pan (2020) find that digitalization allows residents to be exposed to various digital application scenarios, which can effectively alleviate information asymmetry and reduce risk aversion among residents, thereby promoting their participation in financial market investment; this effect is more visible among vulnerable groups in alleviating income inequality through income gains.

Meanwhile, other scholars argue that digitalization can widen income inequality (Yeo, Hwang, and Lee 2023). This is because the Schumpeterian type of creative destruction brought by technological advances does not bring the same opportunities to different groups. For example, high-income and better-educated people have better chances to apply the latest digital technology and enjoy digital dividends, thus widening the gap with low-income and less-educated groups (Acemoglu and Restrepo 2020; Daud, Ahmad, and Ngah 2021). Moreover, skilled workers may adapt to new technology and learn new knowledge more quickly compared to unskilled workers, leading to a widening of the income gap (Guellec and Paunov 2017; Acemoglu and Restrepo 2018; Tica, Globan, and Arčabić 2022). In addition, algorithmic mechanisms, based on digital technologies such as big data and machine learning, may strengthen the supply discrimination in credit (Philippon 2016)— that is, higher-income and better-educated people have greater access to low-cost financial products and digital technologies, thereby contributing to a widening of the income gap.

There is also evidence that a nonlinear relationship may exist between income inequality and technological progress. On the one hand, according to the technological Kuznets curve hypothesis proposed by Kim (2012), income inequality first rises and then declines with technological progress (i.e., an inverse U-shaped relationship). In the initial stage of technological innovation, the cost of adopting a new technology is relatively large and

only the capitalists of a few enterprises that adopt new technology get surplus value because of the improvement of labor productivity, thereby increasing the income gap. However, with the widespread distribution of new technologies into society, labor productivity is generally improved, which in turn promotes production and income growth and eventually reduces the income gap. On the other hand, given the nature of Schumpeterian innovation, income inequality falls first and then rises with technological progress. Acemoglu and Restrepo (2018) theoretically prove the U-shaped relationship between income inequality and technological progress. Gravina and Lanzafame (2019) provide empirical evidence supporting a U-shaped relationship between income inequality and technological progress by using a panel of 90 advanced and emerging economies from 1970 to 2015.

3. Empirical Design

3.1 Data Source

The household data used in this paper is from the CHFS in 2013, 2015, 2017, and 2019. The CHFS is a nationwide survey conducted by the Southwestern University of Finance and Economics since 2011. It is one of the three most authoritative surveys in the PRC, with the other two being the Chinese Family Panel Studies and the Chinese General Social Survey. The CHFS collected 28,141 samples in 2013; 37,289 samples in 2015; 40,011 samples in 2017; and 34,643 samples in 2019. The method of probability proportionate to size sampling is adopted, which ensures the representativeness of samples. The survey collects detailed information on household demographic features, assets and liabilities, income and consumption, insurance, and security.

There is no unified and authoritative measurement for digitalization development in the literature. Bukht and Heeks (2018, p.13) define digitalization as “a segment of economic output primarily or entirely generated from digital technologies, where the underlying business models revolve around digital goods or services.” This encompasses core digital sectors, such as telecommunication and information services, as well as digital and platform services, and broadly extends to concepts such as Industry 4.0 and other related industrial digitalization concepts. To gauge digitalization, we follow the definition of digitalization in Bukht and Heeks (2018) and propose a comprehensive digitalization measurement by extending Lu et al. (2023) and incorporating more information on the development of digital industry at the city level. Empirically, we collect six digitalization-related indicators that capture digital services and adoption as well as digital industry development, including: (i) digital payment coverage, (ii) mobile telephone subscribers, (iii) telecommunication service revenue, (iv) patent licenses in the 5G industry, (v) number of digital enterprises, and (vi) digital industry employment. **Table 1** lists the definition of

digitalization indicators as well as related data sources. These indicators are standardized then used to create a comprehensive digitalization index at the city level.

Table 1: Definition of Digitalization Indicators

Digitalization Indicator	Definition	Data Source
Digital payment coverage	An index based on digital-inclusive finance data from Alipay. The index consists of three variables: (i) number of Alipay accounts per 10,000 people, (ii) proportion of Alipay users who have linked bank cards, and (iii) average number of bank cards linked to each Alipay account.	Peking University
Mobile telephone subscribers	The number of mobile telephone subscribers divided by the population of the city where the household resides in. (in percentage points).	CEIC database
Telecommunication service revenue	The gross revenue of telecommunication services divided by the population of the city the household resides in.	China City Statistical Yearbook
Patent licenses in the 5G industry	The number of patents authorized for 5G industries such as smart phone applications and smart home appliances.	*Qiyan Data*
Number of digital enterprises	The number of enterprises in the digital industries in a city.	*Qiyan Data*
Digital industry employment	The number of employees in information transmission, computer services, and software industries divided by the number of employees in the city.	China City Statistical Yearbook

5G = fifth generation, CEIC = China Entrepreneur Investment Club.

Note: The above indicators all consist of standardized data.

Source: Authors' compilation.

3.2 Variables Definition

Income Inequality

We use the Kakwani index to measure income inequality. Kakwani (1984, p. 386) derived a relative income deprivation curve and associated income inequality measure to show that "the relative deprivation suffered by an individual with average income is equal to the relative mean deviation." When using the Kakwani index to measure an individual's income deprivation, it is necessary to provide a reference group for comparison. Bossert and D'Ambrosio (2006) formed a reference group that includes all members in the sample with whom the individual is compared, and a comparison group as a subset of members with higher income. Following Bossert and D'Ambrosio (2006)'s approach, we group the sample households by communities where the households reside and compare each household to other households in the same community with higher incomes. Suppose X

is a group (i.e., a community with n households). Its corresponding income vector is $\mathrm{x} = (\mathrm{x}_1, \mathrm{x}_2, \ldots, \mathrm{x}_\mathrm{n})$, in ascending order of income per capita. The income deprivation of a household is denoted as *KKWN*(x, x_k). The measure formula for household income deprivation given by Kakwani is set as follows:

$$\mathrm{KKWN}(\mathrm{x}, x_k) = \frac{1}{n\mu_X}\sum_{i=k+1}^{n}(x_i - x_k) = \gamma_{x_k}^{+}\left[(\mu_{x_k}^{+} - x_k)/\mu_X\right], \quad (1)$$

where $\mu_{x_k}^{+}$ refers to the average income of the group X whose income exceed x_k, and $\gamma_{x_k}^{+}$ is the share of the group of X whose income exceed x_k as a percentage of the total sample of X. μ_X is the average value of X. According to equation (1), we can calculate the income deprivation suffered by each household in each community.

Digitalization Index

In this paper, we construct a digitalization index to measure the digital development level of a city. We conduct factor analysis to consolidate the six digitalization indicators into one comprehensive index at the city level. The Kaiser–Meyer–Olkin test statistics is 0.85, which means the factor analysis is proper as shown in **Table 2**.

Table 2: Factor Loadings and the Kaiser–Meyer–Olkin Test Statistics of Factor Analysis

Panel A: Factor Analysis

Factor	Eigenvalue	Variance Contribution Rate	Cumulative Variance Contribution Rate
Factor1	3.499	0.583	0.583
Factor2	0.826	0.138	0.721
Factor3	0.623	0.104	0.825
Factor4	0.443	0.074	0.899
Factor5	0.410	0.068	0.967
Factor6	0.199	0.033	1.000

Panel B: KMO and Factor Loading

Variable	KMO	Factor Loading
Mobile telephone subscribers	0.801	0.869
Telecommunication service revenue	0.893	0.761
Digital payment coverage	0.809	0.877
Digitalization-related enterprises	0.874	0.694
Digital industry employment	0.860	0.567
Patent licenses in the 5G industry	0.899	0.771
Total	**0.847**	

5G = fifth generation, KMO = Kaiser–Meyer–Olkin.

Source: Authors' calculations.

Control Variables

To examine how city-level digitalization affects household-level income inequality, we also control household and city level variables that are related to income distribution. At the household level, we control household size, children ratio, elderly ratio, unhealthy ratio, household total assets as well as the age, schooling years, and marital status of the household head. We also control per capita gross domestic product (GDP) of the city where a household is located. In the empirical analysis, we include household-level fixed effects as well as year fixed effects to account for possible time-invariant and household-invariant information.

After matching household level variables to city level variables, the final sample consists of 107,671 observations, covering 107,671 households from 544 cities from the sample years of 2013, 2015, 2017, and 2019. Detailed definitions and summary statistics of variables are presented in **Table 3**.[2]

[2] After trimming and winsorizing the ICT Development Index, the results of this study remain unaffected.

Table 3: Variables Definition and Summary Statistics

Variable	Definition	Obs.	Mean	Median	Min	25th Percentile	75th Percentile	Max	SD
Digitalization index	A comprehensive index that measures the level of digitalization based on six indicators	544	0.031	–0.294	–1.68	–0.703	0.478	6.02	1.061
KKWN index	An index that measures household relative income deprivation, which is calculated based on per capita household income.	107,671	0.540	0.532	0	0.283	0.807	1	0.304
Age	Age of the head of a household.	107,671	54.448	54	24	44	65	85	14.173
Household size	The number of household members	107,671	3.495	3	1	2	4	23	1.728
Children ratio	Ratio of the number of children (under age 16) to the size of the household	107,671	0.107	0	0	0	0.25	0.857	0.158
Elderly ratio	Ratio of the number of older people (above age 60) to the size of the household	107,671	0.267	0	0	0	0.4	1	0.368
Unhealthy ratio	Ratio of the number of household members that are unhealthy to the size of the household	107,671	0.109	0	0	0	0.111	1	0.229
Ln (household total asset)	Logarithm of total assets of the household	107,671	5.687	5.91	0	4.78	6.82	13.8	1.681
Ln(GDP per capita)	Logarithm of gross domestic product per capita of the city	544	3.861	3.82	2.61	3.44	4.25	5.25	0.541

Max = maximum, Min = minimum, SD = standard deviation, Obs. = observation.

Source: Authors' calculations.

3.3 Model Specification

In the baseline regression, we use the following panel fixed-effect model specification to estimate the association between digitalization and income inequality:

$$KKWN\_index_{i,t} = \alpha_0 + \alpha_1 Digitaization_{i,t-1} + \beta X_{i,t} + \varphi_t + \theta_i + \varepsilon_{i,t}, \qquad (2)$$

where $KKWN\_index_{i,t}$ denotes the Kakwani index of a household *i* at year *t*. $Digitalization_{i,t-1}$ is the digitalization index of the city where household *i* is located at year *t-1*. Vector X is a series of control variables that may affect income inequality at the household level. φ_t represents the year fixed effect, θ_i represents the household fixed effect, and $\varepsilon_{i,t}$ is a random term that follows the normal distribution.

4. Empirical Results

4.1 Digitalization and Income Inequality

We first examine the relationship between digitalization and income inequality at household level using the baseline model specification in equation (2). Regression results are shown in **Table 4**. Column (1) reports the estimated association between digitalization and income inequality. Results suggest that digitalization is significantly negatively related to household income inequality with a coefficient of –0.0183 after control variables are included. This means that a one-unit increase in the digitalization of a city where a household lives in is associated with an average 0.0183 reduction in the Kakwani index for households located in the city. This effect is both statistically significant at the 1% level and economically significant at 1.94% of sample mean. Given that the literature has documented mixed impacts of digitalization on income equality, we also consider the possible nonlinear influence of digitalization on income inequality. To do so, we add a squared term of the digitalization index into the baseline estimations and report the estimated results in column (2) of Table 4. As shown, the coefficient of the quadratic term for digitalization is not significant, which suggests that there is no nonlinear influence of digitalization on income inequality. In sum, Table 4 thus shows that when a city has more advanced digitalization levels, the household income inequality levels are lower.

To address potential endogeneity issues, we instrument digitalization with instrument variables that are exogenous to the income distribution of households in a city but are related to digitalization of the city. Digitalization level of a city is closely related to its economic development and industrial structures. (Brynjolfsson and McAfee 2014) To capture these attributes, we group sample cities along these two attributes: (i) the proportion of tertiary industry output in GDP in 2012, and (ii) GDP in 2012. Specifically, cities are first divided into three groups based on the levels of their tertiary industry output

as a percentage of GDP. Within each group, we further divide cities into three groups by ranking their GDP. This exercise results in nine groups of cities. Within each group, we exclude the city where a household is located and compute the mean value of the digitalization index of other cities in the group to be the instrument variable. To ensure the robustness of the results, we also repeat this exercise using a 5 by 5 grouping and obtain an instrument variable based on the 25 groups (5 x 5) of cities. To further exclude possible similarity of cities from the same province, we reconstructed the instrumental variable by excluding cities from the same province in sorted city groups as an extra robustness test. The instrument that captures digitalization of similar cities may be related to the digitalization level of a city but may not affect the household income distribution of this city directly.

Table 4: Digitalization and Income Inequality

	(1) KKWN Index	(2) KKWN Index
Digitalization index	–0.0183***	–0.0220***
	(0.0056)	(0.0067)
Digitalization index sq.		0.0029
		(0.0022)
Age	–0.0075***	–0.0075***
	(0.0013)	(0.0013)
Age sq.	0.0078***	0.0077***
	(0.0012)	(0.0012)
Household size	0.0087***	0.0087***
	(0.0018)	(0.0018)
Children ratio	–0.0437***	–0.0432***
	(0.0148)	(0.0148)
Old ratio	–0.0195**	–0.0196**
	(0.0096)	(0.0096)
Unhealthy ratio	0.0416***	0.0414***
	(0.0100)	(0.0100)
Ln (household total asset)	–0.0251***	–0.0251***
	(0.0010)	(0.0010)
Ln (per capita GDP)	0.0333*	0.0364*
	(0.0196)	(0.0198)
Year FE	Y	Y
Household FE	Y	Y
N	107671	107671
R^2	0.014	0.014
Adj. R^2	0.014	0.014

Continued on the next page

FE = fixed effects, GDP = gross domestic product, N = number of observed values.
Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The standard errors are clustered at the city-year level to ensure heteroscedasticity robustness.
Source: Authors' calculations.

The results using the instrumental variable are reported in Table 5. The results of the first-stage regression in columns (1) and (3) suggest that the instrumental variable is significantly associated with digitalization of the city. And the second-stage results shown in columns (2) and (8) demonstrate that the instrumented digitalization is still significantly and negatively associated with household income inequalities, confirming the findings from the baseline regression in Table 4. To mitigate the influence of linear trend factors, we also use first-order differences of variables. The results from column (9) of Table 5 indicate that, even after first-order differencing, the digitalization index remains significant and negatively correlated with income inequality.

To ensure robustness of the above results, we conduct various additional tests. Column (1) of **Table 6** reports the first set of robustness check where we replace the digitalization index from previous period in the baseline with the digitalization in the current period. As shown, the coefficient remains significant and negative for the Kakwani index, which is consistent with the finding stated earlier. Other robustness checks include: 1) computing the Kakwani index using total household income rather than per capita income of the households in Column (2); 2) removing the top and bottom 5% of households by per capita income, then recalculated the Kakwani index for the remaining households in column (3); 3) excluding households that suffered from major events in the recent 5 years from our sample in column (4); and 4) excluding rural samples that may have a large gap with urban households to avoid the results being driven by rural households in column (5). Overall, these robustness checks generate consistent findings that confirm that digitalization is significantly and negatively correlated with income inequality.

To further understand the source of the impact of digitalization on income inequality, we run separate regression of individual digitalization indicators on income inequality and report the results in **Table 7**. As shown, the results are largely driven by development in digital industry, such as the patent licenses in the 5G industry, the number of digital enterprises, and the number of digital enterprises.

The literature shows that digitalization may have a heterogeneous impact on households in different economic development regions and with different educations levels. (Knight 2014, Zhang 2021, and Li, Wu, and Xiao 2020) In empirical tests, we divide the sample into different subsamples and explore how digitalization can affect income inequality differently. Columns (1) and (2) of **Table 8** report the impacts of digitalization on income inequality in the more advanced regions of the eastern provinces and the relatively less-

developed central and western areas provinces. As shown, while the coefficients of digitalization are significantly and negatively associated with the Kakwani index in both subsamples, the impact is more pronounced for less developed central–western area. In columns (3) and (4) of Table 8, we examine how digitalization may affect household income inequality with different education levels. In doing this, we divide the sample into two groups based on the median of average schooling years of the household labor force in 2017. The results show that the effect of digitalization on the Kakwani index is more pronounced in households with less education than in households with more education. Overall, Table 8 shows that the impact of digitalization on income inequality is more pronounced in less-developed areas and for households with lower education levels, further shedding light on the inclusiveness benefit of digitalization.

4.2 How Does Digitalization Narrow Income Inequality?

The previous session shows that digitalization can narrow income inequality, especially in less-developed areas and among less-educated households. It is natural to ask how digitalization can reduce income inequality. This section answers the question by looking at how digitalization affects income levels of households. **Table 9** reports the estimated results of digitalization on household income, by replacing income inequality with household income in the baseline model of equation (2). It shows that city-level digitalization is significantly and positively associated with household income across different quantile household income levels. The effect is both statistically and economically significant. Moreover, the magnitude of coefficients increases as income level decreases. Overall, Table 9 shows that digitalization positively affects household income, and the impact is more pronounced for lower income households, thus narrowing income inequality.

To check further whether the finding is consistent with the previous session, we repeat the test in Table 9 by examining the results in less-developed areas and less-educated households. The results are reported in **Table 10**. Consistently, we find that a stronger positive impact of digitalization on household income in less developed central–western regions in columns (1) and (2), and for less-educated households in columns (3) and (4). These additional results confirm that the impact of digitalization on household income is more pronounced for disadvantaged groups, thus reducing income inequality.

4.3 Working Mechanisms

In this section, we further explore the possible working mechanism in which digitalization may affect income distribution. First, we breakdown household income into three major sources: (i) wage income from employment, (ii) business income from commercial activities, and (iii) investment income from investing in financial markets. **Table 11** presents the results on how digitalization is related to different types of household income,

showing that digitalization is significantly and positively related to all three types of household incomes.

To further investigate how digitalization could boost household wage income, we examine the impact of digitalization on employment opportunities. **Table 12** reports the estimated relationship between the digitalization level of a city and household labor force participation using a Probit model. Results show that digitalization is positively and significantly associated with household-level employment status, and the impact is more pronounced for households in the less-developed regions and with lower-education levels. Besides employment status, it is also interesting to know what types of jobs are related to digitalization. We analyze the relationship between digitalization and employment types and report the results in **Table 13**. As shown, digitalization is significantly related to jobs in private companies and MSME business. This implies that the role of digitalization enables flexible and new jobs in the private sector as well as MSMEs.

To understand how digitalization boosts household investment income, we examine the association between digitalization and new financial market participation of households. A household is considered a participant in the financial markets if that household holds any financial assets in the form of stocks, funds, bonds, derivatives, or gold. If a household did not participate in the financial market in the previous year but participated in the current year, it is defined as a new participant of the financial market. As shown in **Table 14**, digitalization is not significantly positively correlated with overall financial market participation in the full sample. However, among households in the less developed central–western regions and those with lower education levels, digitalization is significantly and positively correlated with new financial market participation. This indicates that digitalization offers new income opportunities by enabling accessibility to financial markets and investment opportunities for less-privileged households. This provides additional evidence of the inclusive characteristics of digitalization.

5. Conclusion

This study examined how digitalization is associated with household income inequality. By constructing a comprehensive index to capture digitalization and utilizing household level data from the CHFS in 2013, 2015, 2017, and 2019, this paper documents a positive role of digitalization in reducing income inequality at the household level. This income inequality reduction impact is more pronounced in the less-developed central–western regions and among less-educated households. This impact on income inequality remains statistically and economically significant after addressing endogeneity concerns and a few robustness checks.

We further demonstrate how digitalization reduces income inequality. Evidence shows that digitalization has a significant and positive impact on household income. The income promotion impact is larger for lower-income households and households in less developed areas and with lower education levels, thereby reducing income inequality. This further confirms the inclusiveness benefit of digitalization. Furthermore, evidence shows that digitalization boosts household incomes by boosting wage income, business income, and investment income.

This study provides micro-level evidence for policymakers to speed up digitalization and promote income opportunities for disadvantaged groups, narrowing income inequality. Our findings imply that digitalization can promote inclusive development, with a larger marginal effect for less-developed areas and households with lower levels of education. Promoting digitalization in less-developed areas will help boost inclusiveness. Policymakers may strengthen digitalization, particularly in remote and underdeveloped areas, to deliver inclusive benefits.

Table 5: Addressing Endogeneity in the Estimation

	(1) First stage	(2) Second stage	(3) First stage	(4) Second stage	(5) First stage	(6) Second stage	(7) First stage	(8) Second stage	(9) First-order difference estimation
	Digitalization index	KKWN index	Digitalization index	KKWN index	Digitalization index	KKWN index	Digitalization index	KKWN index	Difference of KKWN index
Digitalization index in 9 subgroups	0.6213***								
	(0.0040)								
Digitalization index in 25 subgroups			0.7932***						
			(0.0028)						
Digitalization in 9 subgroups excluding cities from the same province					0.5433***				
					(0.0039)				
Digitalization index in 25 subgroups excluding cities from the same province							0.6787***		
							(0.0029)		
Instrumented Digitalization index		–0.0190***		–0.0191***		–0.0202**		–0.0323***	
		(0.0038)		(0.0039)		(0.0088)		(0.0088)	
Difference of Digitalization index									–0.0155*
									(0.0081)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Household FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	107,671	107,671	107,671	107,671	107,671	107,671	107,671	107,671	48,957
R^2	0.703		0.792		0.692		0.757		0.011
Adj. R^2	0.703		0.792		0.692		0.757		0.010

FE = fixed effects, N = number of observed values.

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The standard errors are clustered at the city-year level to ensure heteroscedasticity robustness.

Source: Authors' calculations.

Table 6: Robustness Check—Digitalization and Income Inequality

	(1)	(2)	(3)	(4)	(5)
KKWN Index	**Based on Income per Capita**	**Based on Total Income**	**Removed 5% Top and Bottom Income of Households**	**Excluded Households that Suffer from Major Events**	**Exclude Rural Sample**
Digitalization index		–0.0119**	–0.0189***	–0.0091***	–0.0234***
		(0.0052)	(0.0056)	(0.0033)	(0.0062)
Digitalization in contemporary period	–0.0165**				
	(0.0088)				
Year FE	Y	Y	Y	Y	Y
Household FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
N	82,034	107,541	97,894	98,995	72,417
R^2	0.008	0.015	0.004	0.005	0.015
Adj. R^2	0.008	0.015	0.004	0.004	0.015

FE = fixed effects, N = number of observed values.

Notes: ** and *** denote significance at the 5% and 1% levels, respectively. The standard errors are clustered at the city-year level to ensure heteroscedasticity robustness.

Source: Authors' calculations.

Table 7: Digitalization indicators and Household Income Inequality

	(1)	(2)	(3)	(4)	(5)	(6)
KKWN Index	**Mobile Telephone Subscribers**	**Telecommunication service revenue**	**Digital Payment Coverage**	**Number of digital enterprises**	**Digital industry employment**	**Patent licenses in the 5G industry**
Subindex of Digitalization index	–0.0156	0.0106	–0.0494	–0.0802***	–0.0742***	–0.1427**
	(0.0297)	(0.0276)	(0.0696)	(0.0239)	(0.0230)	(0.0615)
Year FE	Y	Y	Y	Y	Y	Y
Household FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
N	107,671	107,671	107,671	107,671	107,671	107,671
R^2	0.013	0.013	0.013	0.014	0.014	0.013
Adj. R^2	0.013	0.013	0.013	0.014	0.014	0.013

FE = fixed effects, N = number of observed values.

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The standard errors are clustered at the city-year level to ensure heteroscedasticity robustness.

Source: Authors' calculations.

Table 8: Digitalization and Income Inequality—Heterogeneity Tests

	(1)	(2)	(3)	(4)
KKWN Index	**Eastern Region**	**Central and Western Regions**	**High Education Households**	**Low Education Households**
Digitalization index	–0.0108*	–0.0335***	–0.0178***	–0.0221***
	(0.0064)	(0.0116)	(0.0062)	(0.0077)
Year FE	Y	Y	Y	Y
Household FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
N	53,562	54,109	43,961	33,411
R^2	0.015	0.014	0.003	0.002
Adj. R^2	0.015	0.013	0.003	0.002

FE = fixed effects, N = number of observed values.

Notes: * and *** denote significance at the 10% and 1% levels, respectively. The standard errors are clustered at the city-year level to ensure heteroscedasticity robustness.

Source: Authors' calculations.

Table 9: Digitalization and Household Income

	(1)	(2)	(2)	(3)	(4)	(5)
Ln (household income per capita)	**Full sample**	**Q10**	**Q25**	**Q50**	**Q75**	**Q90**
Digitalization index	0.0622***	0.2550***	0.1304***	0.0621***	0.0623***	0.0567***
	(0.0142)	(0.0268)	(0.0154)	(0.0107)	(0.0100)	(0.0140)
Year FE	Y	Y	Y	Y	Y	Y
Household FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
N	106,226	106,098	106,098	106,098	106,098	106,098
R^2	0.032					
Adj. R^2	0.032					

FE = fixed effects, N = number of observed values.

Notes: *** denotes the significance at the 1% level. The standard errors are clustered at the city-year level to ensure heteroscedasticity robustness.

Source: Authors' calculations.

Table 10: Digitalization and Household Income—Heterogeneity Tests

	(1)	(2)	(3)	(4)
Ln (household income per capita)	**Eastern Region**	**Central and Western Regions**	**High Education Households**	**Low Education Households**
Digitalization index	0.0399**	0.0994***	0.0371***	0.0899***
	(0.0161)	(0.0333)	(0.0128)	(0.0201)
Year FE	Y	Y	Y	Y
Household FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
N	52,888	53,338	43,577	32,764
R^2	0.064	0.060	0.064	0.065
Adj. R^2	0.064	0.060	0.064	0.064

FE = fixed effects, N = number of observed values.

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The standard errors are clustered at the city-year level to ensure heteroscedasticity robustness.

Source: Authors' calculations.

Table 11: Digitalization and the Categories of Household Income

	(1) Ln (wage income per capita)	(2) Ln (business income per capita)	(3) Ln (investment income per capita)
Digitalization index	0.0698***	0.1052**	0.3197***
	(0.0179)	(0.0484)	(0.0727)
Year FE	Y	Y	Y
Household FE	Y	Y	Y
Controls	Y	Y	Y
N	106,098	15,662	106,098
R^2	0.041	0.059	0.296
Adj. R^2	0.041	0.058	0.296

FE = fixed effects, N = number of observed values.

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The standard errors are clustered at the city-year level to ensure heteroscedasticity robustness.

Source: Authors' calculations.

Table 12: Digitalization Development and Employment Status

	(1)	(2)	(3)	(4)	(5)
Employment Status	**Whole Sample**	**Eastern Region**	**Central and Western Regions**	**High Education Group**	**Low Education Group**
Digitalization index	0.0184***	0.0142*	0.0357**	–0.0023	0.0277***
	(0.0066)	(0.0074)	(0.0144)	(0.0070)	(0.0092)
Year FE	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
N	149,231	75,917	73,314	74,586	75,848
R^2	0.008	0.008	0.008	0.016	0.005
Adj. R^2	0.008	0.008	0.008	0.016	0.005

FE = fixed effects, N = number of observed values.

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The standard errors are clustered at the city-year level to ensure heteroscedasticity robustness.

Source: Authors' calculations.

Table 13: Digitalization Development and Employment Type

	(1)	(2)	(3)	(4)	(5)
	Government Employment	**State-Owned Employment**	**Private and MSME Employment**	**MSME Employment**	**Foreign Business Employment**
Digitalization index	–0.0035	–0.0004	0.0205***	0.0098**	0.0009
	(0.0029)	(0.0025)	(0.0073)	(0.0046)	(0.0016)
Year FE	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
N	149,231	149,231	149,231	149,231	149,231
R^2	0.004	0.002	0.001	0.009	0.005
Adj. R^2	0.004	0.002	0.001	0.009	0.005

FE = fixed effects; MSME = micro, small, and medium-sized enterprises; N = number of observed values.

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The standard errors are clustered at the city-year level to ensure heteroscedasticity robustness.

Source: Authors' calculations.

Table 14: Digitalization and New Financial Market Participation

	(1)	(2)	(3)	(4)	(5)
	Whole Sample	**Eastern Region**	**Central and Western Region**	**High Education Group**	**Low Education Group**
Digitalization index	0.0041	0.0021	0.0096***	–0.0026	0.0079***
	(0.0026)	(0.0035)	(0.0036)	(0.0044)	(0.0027)
Year FE	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
N	56,342	26,519	29,823	17,124	39,218
R^2	0.038	0.034	0.040	0.028	0.021
Adj. R^2	0.037	0.033	0.039	0.026	0.020

FE = fixed effects, N = number of observed values.

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The standard errors are clustered at the city-year level to ensure heteroscedasticity robustness.

Source: Authors' calculations.

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Digitalization and Income Inequality

Evidence from Households

This paper examines how digitalization affects income inequality, using household data from the People's Republic of China. The findings indicate that digitalization significantly reduces income inequality, particularly in less-developed areas and among lower-educated households. The effect remains significant after addressing robustness and endogeneity concerns. Digitalization narrows the income gap by increasing earnings more for lower-income households through improved employment and investment opportunities. It also boosts business income for entrepreneurial households. These results suggest that promoting digitalization can help reduce income inequality in developing economies.

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