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Digital Financial Inclusion and Income Inequality in China

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Digital Financial Inclusion and Income Inequality in China
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ABSTRACT: This paper uses both macro and household-level data to examine the relationship between digital financial inclusion, measured by the Peking University digital financial inclusion index, and income inequality in China. We find that a higher level of digital financial inclusion is associated with significantly lower income inequality *within* provinces, including through having larger positive effects on lower-income households' incomes from salaries and public and private transfers. However, we do not find a significant impact of digital financial inclusion on income inequality *across* provinces, as households in the relatively more developed southern region benefitted more from digital financial inclusion than those in the northern region. We also find that digital financial inclusion has larger effects on the incomes of rural, female-headed, and less educated households, which have likely contributed to the narrowing of the overall income inequality, but a smaller effect on the income of elderly households—pointing to the "digital divide" problem among the elderly in China.

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Contents

I. Introduction

A large body of literature has studied the relationship between financial inclusion and income inequality. From a theoretical perspective, financial inclusion, defined as access to and use of formal financial services by households, could reduce income inequality by increasing the opportunities for education and entrepreneurship among the poor (see, e.g., Aghion and Bolton, 1997; Banerjee and Newman, 1993; Dabla-Norris *et al*., 2021). Empirically, most studies have found a negative relationship between financial inclusion and income inequality, although the results differ across regions and countries (see, e.g., Čihák and Sahay, 2020; Mookerjee and Kalipioni, 2010; Neaime and Gaysset, 2018).

Amid the rapid development of digital financial services (including mobile payments and mobile banking) enabled by fintech in recent years, digital financial inclusion—defined as access to and use of formal financial services via digital financial services—has advanced in most emerging market and developing economies, even where traditional financial inclusion retreated (Khera *et al*., 2021; Sahay *et al*., 2020). That said, the literature has not reached a consensus on whether and how digital financial inclusion could affect income inequality. Some studies found that financial inclusion is a key channel through which fintech reduces income inequality (see, e.g., Demir *et al*., 2022), while some showed that financialization and digital technology could widen income inequality as high-income people have easier access to low-cost financial products and digital technologies (see, e.g., Daud *et al*., 2021). Others argued that digital financial inclusion reduces income inequality in more developed countries but increases it in countries that are in the early stage of development—as suggested by the Kuznets curve (Siregar, 2020).

China is a good candidate for exploring the relationship between digital financial inclusion and income inequality. On the one hand, income inequality has been a central challenge to be addressed in China in the context of economic transition. In fact, one of the major long-term targets in the Chinese authorities' *Vision 2035 of China* is to significantly reduce the disparities in the economic development and income distribution between urban and rural areas. On the other hand, after the rapid growth of digital finance (such as mobile payments and digital banking and insurance) for more than a decade, China has now been among the most advanced—sometimes the most advanced—of the major economies in adopting digital technologies in the financial system and leads the world in terms of digital financial inclusion (Dollar and Huang, 2022; Huang and Huang, 2018). Further developing digital technologies and a digital economy are also a key area in the authorities' 14th five-year plan until 2025. Moreover, the significant heterogeneity in the development of digital financial inclusion across the vast regions (see below) has made China an interesting case to investigate the effects of digital financial inclusion on income inequality.

The literature has broadly portrayed the dynamics in China's income inequality. On the one hand, according to the Gini coefficient estimated by China's National Bureau of Statistics (NBS) based on household survey samples, the overall income inequality was relatively high in China, exhibiting an upward trend until 2008 before starting to decline (Figure 1.1). This is somewhat consistent with findings based on micro-level data from the China Household Income Project Survey (CHIPS) (e.g., Li and Luo, 2011; Yang and Yang, 2015; Jain-Chandra *et al*., 2018; Li and Zhu, 2018; Li *et al*., 2019). That said, most of these studies found that the income inequality has likely only stabilized or declined modestly since 200Z8 rather than being on a declining trend.[1]

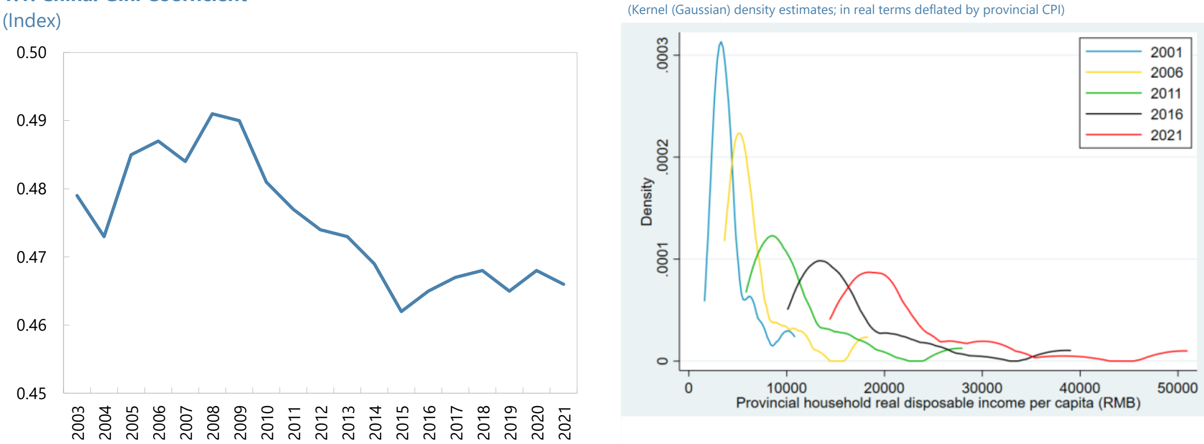
[1] Some studies (e.g., Yang and Yang, 2015; Yang and Zhao, 2018) also questioned the data accuracy of the Gini coefficient published by the NBS due to, for example, data sampling bias (of household survey data) or households' unstated income.

On the other hand, the distribution of household disposable income *per capita* across provinces has become more dispersed despite having higher average levels (Figure 1.2). This is consistent with earlier studies using GDP *per capita*, for example, Zhu *et al*. (2014) and Dai and Mao (2015) who found that the interprovincial economic convergence has not occurred in China despite some convergence within certain sectors such as the industrial sectors. These findings suggest that China's overall income inequality has stabilized or declined somewhat since 2008 while the interprovincial economic convergence remains lagging.

Figure 1. China: Gini Coefficient and Interprovincial Income Distribution

1.1. China: Gini Coefficient
(Index)

1.2. China: Distribution of Provincial Household Disposable Income *Per Capita*
(Kernel (Gaussian) density estimates; in real terms deflated by provincial CPI)



Sources: National Bureau of Statistics of China; CEIC; and authors' calculations.

However, the literature on the relationship between China's digital financial inclusion and income inequality is relatively limited, particularly with micro-level data. In China's context, digital finance can positively impact regional and household incomes in at least three ways. First, as digital financial inclusion evolves, new job opportunities (e.g., take-out and in-home services) based on mobile payments have emerged (Xie *et al*., 2018), enabling more people who otherwise do not have opportunities to access new jobs and earn wages and thus reducing income inequality. Second, digital financial inclusion can facilitate market integration with the help of the Internet and improve production efficiency. More specifically, in addition to transforming and upgrading business lines, lower-income people in the agriculture sector can sell their products across the country through e-commerce, live streaming, and other platforms, thereby boosting their income and narrowing the income gap with higher-income earners. Third, digital financial inclusion can also help the government in minimizing administrative costs and boosting the capacity to provide public services, thus enabling low-income groups to access welfare programs more easily and effectively. The recent distribution of consumption vouchers during the COVID-19 pandemic is a good example of leveraging the digital technology (Lin *et al*., 2020).

That said, different regions and groups of people could benefit differently from the digital financial inclusion in China. As found elsewhere in the literature, more developed regions, compared to less developed ones, tend to have better digital infrastructure and greater market capacity in utilizing digital technologies—in addition to more fiscal and financial resources and stronger governance. These factors could potentially widen the inter-regional income disparity. Moreover, different groups of people also vary in their abilities to use digital technologies, and some groups, particularly the elderly, may even face a "digital divide" for not being able to quickly learn and reap the benefits of such technologies.

This paper investigates the impact of digital financial inclusion on income inequality using both macro- and micro-level data of China and explores the micro mechanisms. The empirical analysis consists of two parts. In the first part, we use macro-level data to assess whether the development of digital financial inclusion has an impact on the convergence of regional GDP across provinces, within provinces, and between the northern and southern regions, respectively. We then merge the Peking University Digital Financial Inclusion Index with household-level data from the China Family Panel Studies (CFPS) led by Peking University and examine the impact of digital financial inclusion on household income inequality.[2] We also examine how such effects differ across groups of households (e.g., north/south, urban/rural, gender, income type, and age) and use quantile regressions to explore the transmission mechanisms at the micro level.

This paper makes several contributions to the literature. First, it provides empirical evidence for whether and how digital financial inclusion impacts income inequality in China using both macro data at the provincial and prefectural levels and micro data at the household level. More specifically, we first analyze whether digital financial inclusion promotes regional GDP convergence using macro-level data and then examine the impact for households in different quantiles and different household groups. To our knowledge, this is the first paper that provides both macro and micro-level evidence for the relationship between digital financial inclusion and income inequality. Second, the paper examines the interprovincial and intra-provincial differences using data of "Taobao villages" as a proxy for the degree of local digital financial inclusion. Third, we also explore the micro mechanisms through which digital financial inclusion impacts income inequality by considering different types of household income (i.e., wage, operating, and transfer incomes). Finally, this paper provides policy recommendations to reduce income inequality considering that digital financial inclusion can, on the one hand, facilitate income convergence within provinces and certain groups of households and, on the other hand, increase income disparity between provinces and widen the "digital divide" experienced by the elderly.

The paper is structured as follows. Section II reviews the literature on the impact of digital financial inclusion on income inequality. Section III presents the data and empirical models used in this study. Section IV presents the macro-level effects of digital financial inclusion on economic gaps *between* provinces and *within* provinces (using provincial data), as well as *between* prefectures in the same province and *within* prefectures (using prefecture level data). Section V examines the effects at the micro level using household survey data and explores the micro mechanisms for such effects. Section VI summarizes the paper and discusses policy options to reduce income inequality based on the empirical findings.

II. Literature Review

There is an extensive literature on income inequality. This section briefly reviews the literature on the measurement, current state, and influencing factors of income inequality, with a focus on studies of the impact of financial inclusion and digital technology on inequality. In terms of measurement, a large volume of literature discusses the measurement of income inequality from multiple perspectives. For example, Cowell (2011) provided an overview of various methods such as range, relative mean deviation, variance, Gini coefficient, and log variance, and analyzed income inequality in the U.K. based on household data from the country. In the context of China, Lin *et al*. (1998) calculated and studied the disparities in GDP and income *per capita* between

[2] The CFPS is a nationally representative, biennial longitudinal household survey launched in 2010 by the Institute of Social Science Survey of Peking University, China (see https://www.isss.pku.edu.cn/cfps/en/index.htm).

different regions in China using the Gini coefficient method and provincial panel data. Xu *et al*. (2019) measured regional and urban-rural gaps in China using the Gini coefficient and provincial panel data.

From a convergence perspective, earlier studies have observed convergence in the economic growth among developed countries, such as European countries and the U.S. (Maddison, 1991; Barro *et al*., 1991). However, when samples of developing countries are added, analyses have indicated no absolute convergence in economic growth among countries (Baumol, 1986; Barro and Sala-i-Martin, 1992). Rodrik (2013) found that while labor productivity in the manufacturing industries exhibits absolute convergence across countries, there is no absolute convergence in GDP *per capita* among countries in general. More recently, there is evidence suggesting that income inequality has declined across countries since 1990s amid the revived global economic cooperation in the in the middle twentieth century, but within-country inequality has risen (BIS, 2016; Bourguignon, 2015). Moreover, some gains in the reduction of global inequality are likely to be reversed as a result of the COVID-19 pandemic.

There is also a large body of literature aiming to uncover the drivers of income inequality among regions, including global factors, such as technological progress, globalization, and commodity price cycles, as well as country-specific factors, such as those related to economic developments and stability as well as to domestic policies—including financial integration, redistributive fiscal policies, and liberalization and deregulation of labor and product markets (see, e.g., BIS, 2016; Card and DiNardo, 2002; Goos and Manning, 2007). In the case of China, the existing literature has examined various factors impacting income inequality and interregional economic gaps, including sectoral factors (Chen *et al*., 2010), urban-rural (Chen and Xu, 2014), personal income tax (Xu *et al*., 2013), government subsidies for agricultural households (Cheng *et al*., 2016), and financial structure (Yang and Wang, 2012).

The literature on the impact of financial inclusion on income inequality includes both theoretical research and empirical findings. On the theoretical side, some studies have suggested that financial inclusion changes the way in which the initial wealth of individuals determines their ability to invest in human capital and physical capital in imperfect credit markets, and how it reduces income inequality by increasing access to education and entrepreneurship for the poor (Aghion and Bolton, 1997; Banerjee and Newman, 1993; Dabla-Norris *et al*., 2021; Galor and Moav, 2004; Galor and Zeira, 1993; Ghatak and Jiang, 2002). That said, theoretical predictions can be mixed. For example, looking at the education channel, Kling *et al*. (2022) found that the relationship depends on the type of financial inclusion, i.e., access to bank accounts or credit: access to bank accounts (and the associated saving and payment services) improves households' prospects in the future income distribution, but income inequality worsens if households rely on formal or informal loans to fund education. In addition, Dabla-Norris *et al*. (2021) examined the entrepreneurship channel and found that the specific type of financial constraints that are relaxed also matters: reducing the credit entry cost benefits every agent in the economy, while the welfare of some agents will fall when the collateral constraint is relaxed or when the intermediation cost is reduced due to general equilibrium effects.

On the empirical side, most studies have found a negative relationship between financial inclusion and income inequality, although the results differ across regions and countries (Čihák and Sahay, 2020; Fouejieu *et al*., 2020; Honohan, 2008; Kim, 2016; Le *et al*., 2019; Mookerjee and Kalipioni, 2010; Neaime and Gaysset, 2018; Omar and Inaba, 2020; Park and Mercado, 2018). For example, Mookerjee and Kalipioni (2010) and Neaime and Gaysset (2018) found that increased access to financial services (through bank branches) leads to a less unequal income distribution. However, Park and Mercado (2018) find that higher financial inclusion is significantly correlated with lower income inequality, except in developing Asia (including China). Moreover, Čihák and Sahay (2020) found that the relationship depends on the initial financial depth (defined as the size of the financial sector relative to the economy) in a cross-country context: greater financial inclusion in the form of higher access to and use of payment services is associated with lower income inequality; however, in the form of higher access to credit, the negative relationship only holds when the financial depth is low and eventually reverts, meaning that at high levels of depth, inequality increases with an expansion in the use of credit.

With respect to the impact of digital technology on income inequality, two main channels have been explored in the literature. The first channel is through affecting the complementarity or substitution of different types of labor; for example, the substitution effect of automation (David and Dorn, 2013; Goos and Manning, 2007; Michaels *et al*., 2014), the impact on jobs and wages (Acemoglu and Restrepo, 2018), and the impact on the remuneration of top earners, such as managers and other key employees (Aghion *et al*., 2019). The second channel is through changing market structures. For example, Guellec and Paunov (2017) argued that digital innovation gives rise to "winner-take-all" market structures, which affect income distribution by increasing market rents, benefiting disproportionately the top income groups. In terms of empirical evidence, Daud *et al*. (2020) have found that digital technology widens income inequality based on cross-country panel data. This is consistent with concerns expressed in the literature, i.e., technology may serve only some people and thus exacerbate inequality in production, income, distribution, and other areas (Acemoglu, 1998; Acemoglu, 2002; Jaumotte and Papageorgiou, 2013).

In the financial sector, amid the rapid development of fintech in recent years, particularly mobile payments and mobile banking, digital financial inclusion has advanced in most emerging market and developing economies, even where traditional financial inclusion retreated (Khera *et al*., 2021; Sahay *et al*., 2020). Some studies have provided direct or indirect evidence on the relationship between digital financial inclusion and income inequality. However, such relationship remains unclear, and research that combines macro- and micro-level data is still lacking. On the one hand, digital finance as an inclusive technology that promotes financial access for different regions and groups of households can narrow income inequality between countries, especially between advanced economies (Demir *et al*., 2022). On the other hand, however, the benefit of using fintech is particularly high for developed regions and affluent populations due to fixed costs, knowledge, and other factors, which may exacerbate inequality (Daud *et al*., 2021; Frost *et al*., 2020; Reher and Sokolinski, 2021). Moreover, using cross-country data, Siregar (2020) found that digital financial inclusion reduces income inequality in more developed countries, but increases it in countries that are in the early stage of development—as suggested by the Kuznets curve.

Similarly, empirical research with a focus on China has not yet reached a consensus on the relationship between digital financial inclusion and income inequality. Some studies have found that digital finance helps reduce the urban-rural income disparity (Song, 2017; Zhou *et al*., 2020), while others have shown that financial inclusion widens the economic gap between eastern provinces and those in the central and western regions (Li *et al*., 2020). Moreover, using prefectural-level data in China, Yao and Ma (2022) found that digital financial development has thresholds effects on the household income distribution because digital technologies that drive inclusive financial development have thresholds such as infrastructure, practical application, and institutional environment. In addition, empirical studies have also investigated the heterogeneous impact of digital finance on income inequality across different groups of households and regions. For example, they found that digital financial inclusion boosts the incomes of urban and rural households differently (Liu *et al*., 2020; Zhang *et al*., 2019), has a greater impact on encouraging entrepreneurship in provinces with lower urbanization rates and among micro- and small-sized businesses with less registered capital (Xie *et al*., 2018), and equalizes entrepreneurial opportunities (Zhang *et al*., 2019).

Existing literature has discussed three main channels through which digital financial inclusion may affect income inequality. First, the development of digital financial inclusion can raise residents' income from work by increasing jobs. More specifically, the rapid development of digital financial inclusion has given rise to flexible and diverse jobs. It has not only provided more traditional employment opportunities but also helped create new types of jobs, including self-employment, freelancing, and part-time jobs, offering opportunities for the jobless population and promoting entrepreneurship among rural residents, thereby equalizing entrepreneurial opportunities (Xie *et al*., 2018; Zhang *et al*., 2019). Data have revealed that jobs in the digital economy in China grew at a double-digit rate and reached 191 million in 2018 (CAICT, 2019). These new jobs can boost the income from work for low-income groups, thus reducing income inequality.

Second, digital financial inclusion narrows income inequality by changing the employment structure and promoting the transformation and upgrading of jobs, thereby increasing the income of low-income groups. For example, the spread of digital technology has enabled some farmers who originally work in the agricultural sector to give up part or all of their agricultural work to enter higher-income sectors. Suri and Jack (2016) have found that increased access to mobile payment lifted 2 percent of Kenyan households out of poverty and increased *per capita* consumption. For individuals who stay in their original job sector, digital financial inclusion can provide "industrial upgrading" opportunities and thus boost the income of farmers and other low-income groups. For example, sales of agricultural products produced by famers can be expanded through rapidly growing e-commerce platforms, and an increasing number of farmers are promoting their products on live streaming platforms to generate higher income.

Third, the development of digital financial inclusion can also help the government improve service efficiency, reduce administrative costs, and collect and use fiscal resources more rationally, thereby strengthening the government's ability in providing targeted transfers. For example, the replacement of cash transfers with mobile transfers in some developing countries has significantly reduced variable distribution costs for implementing agencies and cash transfer costs for program recipients (Aker and Mbiti, 2010; Aker *et al*., 2011). Aker *et al*. (2016) also found that transaction and waiting times were reduced by a quarter and the government's transfer management costs were cut by 20 percent in Niger after the government promoted mobile transfers in lieu of cash transfers. Another example is that during the COVID-19 pandemic, the Chinese government was able to distribute consumer vouchers nationwide through mobile payments, which helped boost consumption (Lin *et al*., 2020). The development of digital financial inclusion also significantly strengthens the "national capacity" of developing countries to implement welfare programs by increasing the security and transparency of funds, potentially curbing tax evasion by high-income groups, increasing the efficiency of transfers between the government and recipients, and promoting investment in infrastructure for secure payments.

Overall, the impact of digital financial inclusion on income inequality has not been adequately studied. The literature on China has mostly studied the impact of digital financial inclusion on interregional inequality has primarily focused on interprovincial or urban-rural differences, without considering the differences between inter- and intra-provincial inequality. The latter differences could be significant given the vast territory of China. Moreover, although some studies have combined the digital financial inclusion index and micro-level household survey data to explore the impact of digital financial inclusion, their analyses have primarily focused on the differences in urban-rural entrepreneurship, jobs, and gender—which are unlikely to fully explain how digital financial inclusion narrows household income inequality. A more comprehensive study considering all types of incomes (i.e., wage, operational, and transfer incomes) could enable the exploration of how digital financial inclusion impacts household income inequality and help investigate the transmission mechanisms at the micro level. This is the key purpose of this paper.

III. Empirical Strategy & Data

The empirical strategy of this paper includes a combination of macro and micro approaches to investigate the impact of digital financial inclusion on income inequality in China.[3] Specifically, we first apply an absolute convergence model to assess the convergence effect of digital financial inclusion on provincial and prefectural GDP. Next, we employ the Theil index regression decomposition method to explore why the impact of digital financial inclusion on the convergence is significantly different for provinces and prefectures. Building on the analysis above, we further examine the micro mechanisms through which digital financial inclusion impacts income inequality. This section introduces the data, variables, and model specifications.

Model specification

In the macro model used in the empirical analysis, we use an absolute β-convergence test to investigate the impact of digital financial inclusion on economic disparities across provinces and prefectures:

$$Growth_i = \lambda_0 + \lambda_1 \ln\left(pgdp_{i0}\right) + \lambda_2 index_i + \lambda_3 \ln\left(pgdp_{i0}\right) * index_i + u_{1i}, \tag{1}$$

where the dependent variable $Growth_i$ denotes the real GDP *per capita* growth rate in region i from 2011 to 2018, $pgdp_{i0}$ denotes the real GDP *per capita* in region i in 2011, $index$ denotes the level of digital financial inclusion, u is a random disturbance term, and $\ln(\cdot)$ denotes the natural logarithm. A negative and statistically significant λ_3 indicates that the development of digital financial inclusion can accelerate the narrowing or inhibit the widening of the economic disparity (i.e., economic gaps) among regions. A positive and statistically significant λ_3 suggests that the development of digital financial inclusion increases the economic disparity among regions.

In the micro model for empirical analysis, the micro mechanisms through which digital financial inclusion affects income inequality are examined by income type:[4]

$$\ln(income_{it}) = \beta_1 index_{it-1} + \beta_2' controls_{it} + u_{6it}, \tag{2}$$

where $income$ is the net household income and $controls$ are the control variables. The control variables at the household head level include: gender (male = 1), age, education level (4 categories: illiterate and semi-literate, elementary school, secondary school, and junior college and above), political affiliation (communist party member = 1), and marital status (married = 1). The control variables at the household level include: household size, ratio of elderly members to household size, ratio of young children to household size, and household attribute (urban household = 1). Meanwhile, in order to eliminate any effect of traditional financial development, this study controlled for the level of traditional financial development FD at the provincial level with a one-year lag. In model (2), we further control for county-level fixed effects instead of household fixed effects, considering that some of the control variables at the household-head level, such as gender and education level, hardly

[3] It is worth noting that the effects estimated in this paper are correlations and do not have a causal interpretation.

[4] In models (2) through (5) in the following sections, the dependent variable is specified as the natural logarithm of (income + 1) to avoid having negative values of the dependent variable. It is important to caution that the estimated coefficients may not be interpreted as percentage effects (see Chen and Roth, 2024); however, this should not affect the qualitative relationship between the dependent variable and the digital financial inclusion index.

change over time. The micro-level estimations of model (2) use household-level data for 2012, 2014, and 2016, and provincial-level digital financial inclusion indices for 2011, 2013, and 2015.

Data and variables

The data for the macro model include the GDP *per capita* and the digital financial inclusion index at the provincial and prefectural levels from 2011 to 2018, which are obtained from the Wind database and the Peking University Digital Financial Inclusion Index, respectively. Provincial- and prefecture-level panel data are used in the empirical study on the impact of digital financial inclusion development on the economic gaps within the provinces, between prefectures in the same province, and within the prefectures. The dependent variable $Growth$ is the real GDP *per capita* growth rate at the provincial- and prefecture-levels from 2011 to 2018. Intra-provincial Theil index and Gini coefficient are also used as dependent variables in the exploration of the mechanism behind the findings from the macro model. Table 1 presents the summary statistics for these key variables used in the macro model.

Table 1. Summary Statistics of Key Variables in the Macro Model[1]

	Obs.	Mean	Std. dev.	Min.	Max.
Digital financial inclusion index	248	187.17	85.08	16.22	377.73
Digital financial inclusion index (prefecture level)	2,692	152.34	62.20	11.30	302.98
Ln(real GDP *per capita*)	248	10.77	0.44	9.71	11.78
Ln(real GDP *per capita*) (prefecture level)	2,636	10.62	0.61	8.73	12.49
Intra-provincial Theil index (2013-19)[2]	217	21.12	8.56	1.59	40.33
Intra-provincial Gini coefficient (2013-19)[2]	217	33.84	7.67	9.39	47.08

Sources: National Bureau of Statistics of China; Institute of Digital Finance of Peking University; WIND; and authors' calculations.
[1] Provincial-level panel data during 2011-18 unless otherwise specified.
[2] Calculated using the estimated county-level GDP based on the nighttime light brightness data following Li and Shen (2022) (see below).

The key explanatory variable is the level of digital financial inclusion, measured by the digital financial inclusion index jointly developed by the Institute of Digital Finance (IDF) of Peking University and the Ant Group Research Institute using big data on digital financial inclusion from the Ant Group's transaction accounts, which are nationwide representative (Zhang *et al*., 2019). The aggregate index used in this paper measures digital financial inclusion from three aspects, i.e., breadth of the coverage of digital finance, depth of usage (e.g., payment, credit, etc.), and level of digitalization (mobility, affordability, credit, and convenience) (IDF, 2019).[5] Figures 2.1 and 2.2 show the provincial-level digital financial inclusion index over the sample period of 2011-18 and its distribution over the 31 provinces of Mainland China by year. Both figures indicate that the digital financial inclusion index has increased with a wider dispersion over the 31 provinces over time, suggesting that, although all provinces have experienced higher levels of digital financial inclusion during the sample period, the development might be uneven across provinces. For the empirical analysis below, we standardize the digital financial inclusion index by its mean and standard deviation for easier interpretation of the estimates. Other control variables in the macro model include the fiscal strength (ratio of fiscal expenditure to GDP), human capital (average years of education of working persons), traditional financial development (ratio of deposits in

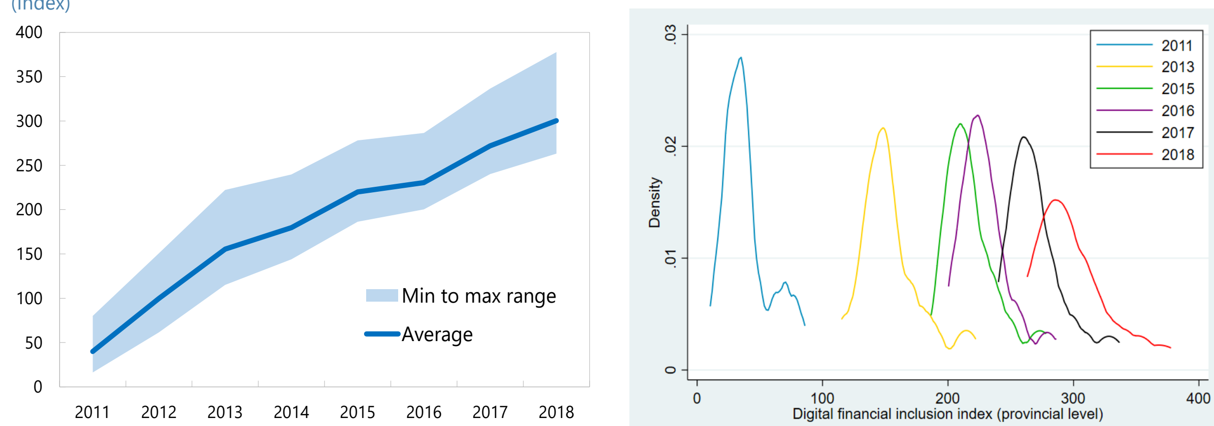
[5] The aggregate digital financial inclusion index is available at three geographical levels, i.e., province, prefecture, and county.

and loans from financial institutions to GDP), and transportation infrastructure (ratio of total road length to land area) of each province and prefecture.

Figure 2. China: Digital Financial Inclusion Index

2.1. China: Digital Financial Inclusion Index
(Index)

2.2. China: Distribution of Provincial Digital Financial Inclusion Index by Year
(Kernel (Gaussian) density estimates)



Sources: Institute of Digital Finance of Peking University; and authors' calculations.

In the micro model, the household-level data are obtained from the CFPS. The CFPS data are collected every other year since 2010 by tracking and gathering data at three levels: individual, household, and community. The data covers 162 counties in 25 provinces, with a target sample size of 16,000 households and a survey population that includes all members of the sample households. Detailed household-level variables include personal information (gender, age, political affiliation, marital status, years of education, etc.) from the adult questionnaire of the CFPS, as well as household information (household size, ratios of elderly members and young child members to household size, and net household income) from the household questionnaire and the household relationship questionnaire.

IV. Digital Financial Inclusion & Income Inequality: Macro Effects

The first subsection presents our estimation of the relationship between digital financial inclusion and economic convergence at the provincial level. The second subsection further analyzes the relationship at the prefecture level. The third subsection provides some interpretation and empirical tests for the significance of the different effects within and across provinces.

Digital financial inclusion and economic convergence at the provincial level

This subsection investigates whether digital financial inclusion has led to faster growth in less-developed provinces and thus demonstrated a convergence effect. We first estimate the impact of digital financial inclusion on provincial economic gaps using provincial GDP data. The results are reported in Table 2. Column (1) shows the estimates when no interaction term was introduced. Column (2) displays the estimates when an interaction term between the 2011 digital financial inclusion index ($index_{11}$) and the 2011 GDP *per capita*

($\ln pgdp_0$) is included. Column (3) shows the estimates when an interaction term between the average digital financial inclusion index during 2012-18 ($index_{12-18}$) and the 2011 GDP *per capita* ($\ln pgdp_0$) is included.

We have two key observations from this table. First, the estimated coefficient of the variable $\ln pgdp_0$ in column (1) is negative and statistically significant at the 1 percent level, indicating that the *per capita* GDP disparity across provinces in China has been converging since 2011.[6] Second, the cross-sectional regression using provincial data suggests, however, that increases in the digital financial inclusion index have not been associated with a narrowing in the economic disparity among provinces, as indicated by the estimated coefficients of the interaction terms between the digital financial inclusion variables and the 2011 GDP *per capita* variable in columns (2) and (3). We have also included other factors that could potentially explain growth in the regressions, e.g., general government spending, but the results do not change qualitatively.

Table 2. Impact of Digital Financial Inclusion on Economic Gaps Across Provinces[1]

	(1)	(2)	(3)
Dependent variable	$Growth$	$Growth$	$Growth$
$\ln pgdp_0$	-0.113***	-0.090	-0.168***
	(-4.30)	(-0.38)	(-3.73)
$index_{11}$		-0.281	
		(-0.20)	
$\ln pgdp_0 \times index_{11}$		0.035	
		(0.26)	
$index_{12-18}$			0.419
			(0.37)
$\ln pgdp_0 \times index_{12-18}$			-0.029
			(-0.28)
Constant	1.705***	1.601	2.285***
	(6.18)	(0.61)	(4.81)
Sample size	31	31	31
R^2	0.390	0.414	0.440

Sources: National Bureau of Statistics of China; Institute of Digital Finance of Peking University; WIND; and authors' estimates.
[1] The numbers in parentheses are *t*-values (using robust standard errors). *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively. The variable $pgdp_0$ denotes the 2011 GDP *per capita*, $index_{11}$ denotes the 2011 digital financial inclusion, and $index_{12-18}$ denotes the average digital financial inclusion index from 2012 to 2018.

Digital financial inclusion and economic convergence at the prefecture level

The above finding that digital financial inclusion has no convergence effect could be due to the small sample size of the provincial data or the fact that the regressions in Table 2 only focus on interprovincial variations without considering intra-provincial variations. To rule out these possibilities, we also use prefecture-level data to obtain estimates using model (1) again. The results are reported in Table 3. The explanatory variables remain the same as in Table 2, and columns (3) and (5) control for provincial fixed effects. First, similar to the previous observation with provincial data, column (1) shows that the *per capita* GDP disparity across prefectures in China exhibits a narrowing trend since 2011. The most notable information in Table 3 is that the interpretation of the marginal impact of digital financial inclusion depends on whether the provincial fixed effects

[6] Some studies have found that the *per capita* GDP across Chinese provinces is diverging (e.g., Dai and Mao, 2015), but the samples in these previous studies were older than the sample used in Table 2.

are controlled for or not. Specifically, when the provincial fixed effects are not controlled for, digital financial inclusion has no significant effects regardless of whether the initial GDP or the 2012-2018 GDP is used in the interaction term (see columns (2) and (4), respectively). However, when the provincial fixed effects are controlled for in columns (3) and (5), the estimated coefficients of the interaction terms are negative and statistically significant. This indicates that while a higher level of digital financial inclusion has not been associated with a significant narrowing of the economic disparity across prefectures nationwide, it is associated with a significantly lower disparity among prefectures in the same province. This suggests that higher digital financial inclusion is associated with a “digital dividend” rather than a “digital divide” among prefectures within the same province.

Table 3. Impact of Digital Financial Inclusion on Economic Gaps Across Prefectures[1]

Dependent variable	(1) $Growth$	(2) $Growth$	(3) $Growth$	(4) $Growth$	(5) $Growth$
$\ln pgdp_0$	-0.072***	-0.214**	-0.215***	-0.127***	-0.063***
	(-5.51)	(-2.58)	(-2.91)	(-6.02)	(-2.86)
$index_{11}$		0.740	1.025**		
		(1.48)	(2.31)		
$\ln pgdp_0 \times index_{11}$		-0.056	-0.088**		
		(-1.20)	(-2.09)		
$index_{12-18}$				0.699*	0.901**
				(1.79)	(2.41)
$\ln pgdp_0 \times index_{12-18}$				-0.051	-0.075**
				(-1.40)	(-2.15)
Provincial fixed effects	No	No	Yes	No	Yes
Sample size	325	325	325	325	325
R^2	0.086	0.116	0.493	0.135	0.494

Sources: National Bureau of Statistics of China; Institute of Digital Finance of Peking University; WIND; and authors’ estimates.
[1] The numbers in parentheses are *t*-values (using robust standard errors). *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively. The variable $pgdp_0$ denotes the 2011 GDP *per capita*, $index_{11}$ denotes the 2011 digital financial inclusion, and $index_{12-18}$ denotes the average digital financial inclusion index from 2012 to 2018.

Differences in the impact of digital financial inclusion on the economic convergence across and within provinces: exploration of the mechanism

The above results show that higher digital financial inclusion is associated with economic convergence within provinces but not across provinces. To investigate the mechanism behind this difference, this subsection primarily considers the difference between the less developed northern region and the more developed southern region, and examines the impact of digital financial inclusion on income inequality within and between the northern and southern regions by using the number of Taobao villages tbn in each province and prefecture as a proxy variable for the level of inclusion.[7] “Taobao villages” refer to administrative villages in rural China that meet the following criteria: each of such villages generates sales of at least RMB10 million from e-commerce annually, and the number of active online stores in each of these villages is at least 100 or 10 percent of the number of households in the village. The number of Taobao villages can represent—to some

[7] To be more precise, the natural logarithm of (tbn + 1) is used to avoid having negative values of the variable (source: www.AliResearch.com). As cautioned above, the estimated coefficients may not be interpreted as percentage effects, although this should not affect the qualitative relationship between the dependent variable and the digital financial inclusion index.

extent—the degree of local digital financial inclusion. According to AliResearch (2020), the Taobao villages continued to grow in 2020 despite a challenging environment during the pandemic and reached 5,425 in number. They were located in 28 provinces and constituted 1 percent of all administrative villages nationwide as of September 2020; in particular, 119 villages were located in 41 national poverty-stricken counties across 10 provinces. Transactions of online stores based in Taobao villages and Taobao towns reached over RMB1 trillion. In addition, there is significant regional disparity in the development of Taobao villages. For example, of the 4,310 Taobao villages nationwide in 2019, 1,573 were located in Zhejiang province, 798 in Guangdong province, and 615 in Jiangsu province, which in total accounted for nearly 70 percent of all Taobao villages in China. The rapid development of Taobao villages is likely associated with the digital financial inclusion across the country and could potentially reduce income inequality. However, the degree of inclusiveness within and across provinces (e.g., between the northern and southern provinces) may be different.

To verify the mechanism above, in the absence of county-level GDP, this study draws on the method of Li and Shen (2022) to estimate the county-level GDP using the estimated relationship between nighttime light brightness and GDP *per capita* with a fixed-effects model. First, the nighttime light data at the county level is used to estimate the GDP *per capita* at the county level.[8] We then calculate the Theil index or Gini coefficient as a measure of intra-provincial inequality using the county-level GDP *per capita* and examine the impact of digital financial inclusion on the intra-provincial inequality. This exercise uses a fixed-effects model and includes control variables of provincial-level fiscal strength, human capital, traditional financial development, transportation infrastructure, in addition to the provincial fixed effects. We also test for the differences between the northern and southern regions by introducing interaction terms between the north and south dummy variables ($north$ and $south$) and the two key variables, i.e., the digital financial inclusion index and the number of Taobao villages tbn. The panel data used in this exercise ranges from 2013 to 2019 for all 31 provinces, and all explanatory variables are included with a one-year lag. The estimation results are shown in Table 4.

In Table 4, the estimated coefficients in column (1) show that digital financial inclusion has a larger impact on the number of Taobao villages in the more developed southern provinces, suggesting that it could potentially contribute to a further widening in the economic gap between the northern and southern provinces. The estimation results in column (2) suggest that higher digital financial inclusion is associated with significantly lower intra-provincial income inequality measured by the Theil index within the southern provinces, but the effect is not statistically significant in the northern provinces. The results in column (3) with the same inequality measure indicate that the increase in the number of Taobao villages is associated with significantly lower income inequality within the southern provinces, but the effect is not statistically significant in the northern provinces. Finally, the estimates in columns (4) and (5) reveal similar findings to those from columns (2) and (3) when the dependent variable is replaced with the intra-provincial Gini coefficient. These findings suggest that the previous result that higher digital financial inclusion is associated with economic convergence within provinces is likely due to the more significant effect in the more developed regions with better digital infrastructure and greater market capacity in utilizing digital technologies. That said, other factors, e.g., frictions in the mobility of production factors across provinces, may also hinder the economic convergence across provinces—in addition to the lower effect of digital financial inclusion in less developed regions.

[8] See Li and Shen (2022) for a detailed analysis on the relationship between the nighttime light data and GDP *per capita*. One caveat is that the estimated county-level GDP could be subject to large uncertainties as the elasticities between nightlights and economic activities (e.g., consumption, employment) tend to vary widely across context and level of aggregation (Asher *et al*., 2021).

Table 4. Different Effects of Digital Financial Inclusion on Economic Convergence Across and Within Provinces: Exploration of the Mechanism[1]

Dependent variable	(1) Number of Taobao villages	(2) Intra-provincial Theil index	(3) Intra-provincial Theil index	(4) Intra-provincial Gini coefficient	(5) Intra-provincial Gini coefficient
$index \times north$	0.512***	-0.552	-1.649***	-0.334	-0.924**
	(3.78)	(-1.62)	(-3.44)	(-1.31)	(-2.61)
$index \times south$	0.895***	-0.961***	-0.714*	-0.664***	-0.553*
	(8.82)	(-3.76)	(-1.86)	(-3.48)	(-1.95)
$tbn \times north$			0.316		-0.010
			(0.82)		(-0.03)
$tbn \times south$			-0.572**		-0.408**
			(-2.51)		(-2.42)
Sample size	217	217	186	217	186
R^2	0.620	0.366	0.448	0.371	0.465

Sources: National Bureau of Statistics of China; Institute of Digital Finance of Peking University; WIND; and authors' estimates.
[1] The numbers in parentheses are *t*-values (using robust standard errors). *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively. The control variables include the fiscal strength, human capital, traditional financial development, transportation infrastructure, and fixed effects of each province.

V. Further Analysis: Micro Effects & Mechanisms

This section explores the micro mechanisms for the impact of digital financial inclusion on income inequality using micro-level data. Specifically, we examine the impact of digital financial inclusion on total income as well as different types of income using household survey data from the CFPS during 2012-16. Table 5 provides the descriptive statistics (means) of household incomes. As shown in this table, the average incomes of all households, urban households, and rural households increased significantly between 2012 and 2016. On average, urban households earn more than rural households and southern households earn more than northern households. The three types of household incomes, namely, wage income, operating income, and transfer income, account for nearly 95 percent of total income, with wage income being the largest part or approximately 68 percent of total income.[9]

Table 5. Descriptive Statistics of Household Income

	All households	Urban households	Rural households	Share of wage income	Share of operating income	Share of transfer income
2012	36578.84	45909.61	29176.12	66.26%	12.54%	14.58%
2014	44382.46	52786.89	37784.67	69.58%	10.59%	15.42%
2016	49151.83	62755.77	37875.60	68.23%	8.48%	17.54%
Total	43084.06	53595.96	34651.62	68.05%	10.41%	15.95%

Sources: CFPS and authors' calculations.

[9] Wage income refers to all labor remuneration and benefits, operating income refers to the income obtained by households engaged in production and business activities, and transfer income refers to transfer payments from public and private sources such as government transfers and remittances.

The rest of this section focuses on examining the impact of digital financial inclusion on wage, operating, and transfer incomes and uses the following regression models:

$$\ln(income\_wage_{it}) = \beta_3 index_{it-1} + \beta_4^{'} controls_{it} + u_{7it}; \quad (3)$$

$$\ln(income\_oper_{it}) = \beta_5 index_{it-1} + \beta_6^{'} controls_{it} + u_{8it}; \quad (4)$$

$$\ln(income\_tran_{it}) = \beta_7 index_{it-1} + \beta_8^{'} controls_{it} + u_{9it}; \quad (5)$$

where $income\_wage$, $income\_tran$, and $income\_oper$ denote household wage income, transfer income, and operating income, respectively. The control variables are the same as in model (2). To further test whether the effect of digital financial inclusion on income inequality is different across and within provinces at the micro level, we compare the different effects between the northern and southern regions using the (unconditional) quantile regression with fixed effects. Meanwhile, to empirically examine why digital financial inclusion is associated with lower intra-provincial income inequality, we also investigate the different effects of digital financial inclusion across different types of households, such as urban and rural households and male- and female-headed households.

Different effects of digital financial inclusion on economic convergence across and within provinces: micro evidence

We first examine the impact of digital financial inclusion on household total income inequality using model (2) and report the regression results in Table 6, where column (1) shows the OLS estimation results and columns (2)-(4) show the estimation results for different quartiles. Clearly, digital financial inclusion has the largest impact on households in the lower quartile among all the quartiles for any group of households. In addition, the estimates for different groups of households show that digital financial inclusion has larger effects on the incomes of female-headed and rural households, vis-à-vis male-headed and urban households, respectively. These findings suggest that higher-income households have already had access to financial services, and the development of digital financial inclusion has enabled more low-income households, especially those in rural areas and with female heads, to access more financial services. Overall, the development of digital financial inclusion has contributed to a "digital dividend" rather than a "digital divide".

When broken down by region, the estimated coefficients from the quantile regressions suggest that digital financial inclusion has a larger impact on the income of poorer households than that of richer households in both northern and southern regions, pointing to a convergence of income within both regions. However, the magnitude of these estimates also indicates that digital financial inclusion has a larger impact on the income of southern households than that of northern households for all income quartiles, suggesting that the convergence effect is only significant *within* two regions but not *between* them. Moreover, the difference between the estimated coefficients for the lower and higher quartiles is larger for the southern region, suggesting—to some extent—that digital financial inclusion has contributed more to the income convergence among households in the southern region. These findings echo the previous results from the macro model in Tables 2-4 that digital financial inclusion has contributed to income convergence *within* provinces but not *across* provinces and has shown greater inclusiveness in the southern region.

Table 6. Impact of Digital Financial Inclusion on Household Total Income[1]

	(1) OLS	(2) Lower income: 25%	(3) Median income	(4) Higher income: 75%
Full sample	0.290***	0.357***	0.265***	0.196***
	(18.16)	(15.10)	(17.77)	(11.82)
Southern households	0.291***	0.363***	0.265***	0.190***
	(12.64)	(11.45)	(13.22)	(8.51)
Northern households	0.250***	0.307***	0.228***	0.171***
	(9.57)	(8.09)	(9.68)	(6.58)
Urban households	0.238***	0.298***	0.214***	0.155***
	(10.62)	(9.05)	(10.46)	(6.90)
Rural households	0.339***	0.408***	0.315***	0.243***
	(15.11)	(12.38)	(14.82)	(10.16)
Male-headed	0.264***	0.313***	0.247***	0.197***
	(13.10)	(10.73)	(13.19)	(9.26)
Female-headed	0.339***	0.429***	0.304***	0.212***
	(12.41)	(10.22)	(11.68)	(7.44)

Sources: CFPS; Institute of Digital Finance of Peking University; and authors' estimates.
[1] The numbers in parentheses are *t*-values (using robust standard errors). *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively. The control variables include gender, age, education level, political affiliation, marital status, household size, ratio of elderly members to household size, ratio of young children to household size, household attribute, traditional financial development level, a time trend, and county fixed effects.

Micro mechanisms for the impact of digital financial inclusion on income inequality

To understand the channels through which digital financial inclusion has a significantly negative impact on the total income inequality among households, we explore the micro mechanisms by considering different types of household incomes, including wage, operating, and transfer incomes. Based on the channels through which digital financial inclusion could affect income inequality in the literature, we consider the following key micro mechanisms: "innovation", "transformation and upgrading", "income boosting", and "efficiency of government welfare programs".

Micro mechanisms for the impact of digital financial inclusion on income inequality: "innovation" effect

The "innovation" effect of digital financial inclusion refers to the hypothesis that digital financial inclusion enables more rural or low-income households to enter the workforce and boosts their wage income, thereby reducing the wage income inequality among households. To test this hypothesis, we estimate model (3) and the results are reported in Table 7. Clearly, digital financial inclusion is associated with significantly higher household wage income. In addition, similar to the total income inequality in Table 6, digital financial inclusion is associated with lower wage income inequality for all groups of households and has larger effects for female-headed and rural households. The latter suggests that digital financial inclusion plays a greater role in supporting female-headed and rural households to earn higher wage income.

Moreover, the quantile regression results indicate that digital financial inclusion has a larger effect on the wage income of lower-income households than that of higher-income households, thereby contributing to a narrowing of the wage income inequality. This converging effect also holds within each of the two regions (southern and northern). However, digital financial inclusion has a slightly larger effect on the wage income of southern households than that of northern households, thereby contributing to a widening of the wage income disparity between the two regions. Moreover, the difference between the estimated coefficients for the lower and higher quartiles is slightly larger for the southern region, which is largely consistent with the finding above with the total income inequality. Given that wage income is the main type of household income accounting for about 68 percent of total income, the impact of digital financial inclusion on total income inequality is likely to be driven by its impact on wage income inequality.

These results suggest that digital financial inclusion is associated with lower wage income inequality in general, although it is also likely associated with a widening of the wage income disparity between northern and southern households. However, the estimates above do not necessarily mean that the effect is through creating more jobs. Digital finance can create jobs, but some households already have jobs. For these households, the development of digital finance inclusion may still raise their income by increasing their work efficiency, and for households who did not have jobs, they could earn higher income by starting new jobs. To further verify the "innovation" effect of digital financial inclusion, we break down the sample into two groups of households who have always had wage income (i.e., the wage income in each sample period was greater than 0) and the remaining households, and run separate regressions for each of these two groups. The estimation results show that the marginal effect of digital financial inclusion on wage income is 0.162 and 1.673 for the two groups, respectively, and both coefficients are statistically significant at the 1-percent level. This suggests that, while digital financial inclusion significantly contributes to households who was already earning wage income, its marginal effect of 0.162 on the wage income for this group through increased work efficiency is much lower than the marginal effect of 1.099 for the full sample. This therefore implies that creating new jobs is likely a major channel through which digital financial inclusion affects household wage income.

Table 7. Impact of Digital Financial Inclusion on Wage Income[1]

	(1) OLS	(2) Lower income: 25%	(3) Median income	(4) Higher income: 75%
Full sample	1.099***	1.468***	0.921***	0.708***
	(20.02)	(14.50)	(17.71)	(12.48)
Southern households	1.251***	1.669***	1.031***	0.760***
	(16.31)	(11.53)	(14.05)	(9.73)
Northern households	1.150***	1.561***	0.969***	0.756***
	(12.24)	(9.13)	(10.87)	(7.60)
Urban households	0.917***	1.182***	0.754***	0.546***
	(11.95)	(8.80)	(9.00)	(5.88)
Rural households	1.276***	1.659***	1.117***	0.917***
	(16.38)	(11.79)	(14.76)	(10.70)
Male-headed	0.966***	1.247***	0.846***	0.696***
	(13.61)	(10.06)	(12.83)	(9.42)
Female-headed	1.337***	1.761***	1.074***	0.765***
	(14.81)	(2.98)	(5.80)	(7.95)

Sources: CFPS; Institute of Digital Finance of Peking University; and authors' estimates.
[1] The numbers in parentheses are *t*-values (using robust standard errors). *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively. The control variables include gender, age, education level, political affiliation, marital status, household size, ratio of elderly members to household size, ratio of young children to household size, household attribute, traditional financial development level, and county fixed effects.

Micro mechanisms for the impact of digital financial inclusion on income inequality: "transformation and upgrading" effect

The "transformation and upgrading" effect refers to the impact of digital financial inclusion on income inequality through providing households with opportunities for job upgrading, e.g., from agricultural to non-agricultural sectors. In reality, the development of digital technology should help agricultural households sell their agricultural products through digital platforms such as *Pinduoduo* and thus could lead to an increase in their operating income. However, if we directly apply the OLS to estimate model (4), we would obtain negative coefficients, suggesting that digital financial inclusion has a negative, rather than positive, impact on household operating income. One reason for this could be that the better job opportunities resulting from digital financial inclusion can incentivize some residents to leave their former low-income jobs or businesses. For example, some farmers who previously engaged in agricultural operation and production are now able to spend more time on their new work with the digital technology. As a result, these farmers would give up part or all of their previous agricultural work to earn higher wages from their new jobs or businesses, giving rise to the "transformation and upgrading" effect. In this regard, we need to first analyze whether digital financial inclusion impacts production. Specifically, a logit model is used estimate the impact: the dependent variable is a dummy variable that indicates whether a household engaged in production (0 if it has no operating income or 1 if it has operating income), the key explanatory variable is the digital financial inclusion index, and the same control variables are included as in model (2). The results are shown in Table 8.

Table 8. Impact of Digital Financial Inclusion on Production: Logit Regressions[1]

	(1) Full sample	(2) Southern	(3) Northern	(4) Male-headed	(5) Female-headed	(6) Urban	(7) Rural
index	-0.247***	-0.357***	-0.240***	-0.273***	-0.251***	-0.386***	-0.280***
	(-7.12)	(-6.04)	(-3.99)	(-6.32)	(-4.00)	(-6.07)	(-6.31)
Sample size	22091	12897	9194	13539	8125	8181	13128

Sources: CFPS; Institute of Digital Finance of Peking University; and authors' estimates.
[1] The numbers in parentheses are *t*-values (using robust standard errors). *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively. The control variables include gender, age, education level, political affiliation, marital status, household size, ratio of elderly members to household size, ratio of young children to household size, household attribute, traditional financial development level, and county fixed effects.

As shown in Table 8, the estimated coefficients of the digital financial inclusion index are negative and statistically significant for all types of households. This means that households in areas with higher digital financial inclusion are more likely to exit production.[10] This finding suggests that digital financial inclusion could also lead to disruptive effects on traditional production businesses through a reallocation of labor and business owners from the traditional businesses to those that benefit more from digital financial inclusion.

We then estimate model (3) for the households who left production and the results are shown in Table 9. Clearly, the estimated coefficients of the digital financial inclusion index in all the columns of Table 9 are positive and statistically significant at the 1-percent level, suggesting that for households who exited production, digital financial inclusion has a significantly positive effect on their wage income. Moreover, all the estimated coefficients are greater than the corresponding estimates in column (1) of Table 7, indicating larger effects for

[10] The estimates also imply that digital financial inclusion has facilitated the exit of urban households from agricultural and other production. This is likely due to the fact that approximately 45 percent of urban households are headed by rural *hukou* holders (migrant workers), although the percentage of rural households headed by rural *hukou* holders is higher at about 93 percent.

these households. Overall, these findings suggest that digital financial inclusion has helped increase wage income for households who exited production, providing evidence for the "transformation and upgrading" effect.

Table 9. Impact of Digital Financial Inclusion on Wage Income[1]
(Households who have exited production)

	(1) Full sample	(2) Southern	(3) Northern	(4) Male	(5) Female	(6) Urban	(7) Rural
index	1.365***	1.923***	1.278***	1.296***	1.366***	1.166***	1.486***
	(11.53)	(9.03)	(6.09)	(8.68)	(6.48)	(4.98)	(10.36)
Sample size	5572	3260	2312	3608	1964	1614	3958
R^2	0.308	0.314	0.303	0.318	0.334	0.358	0.307

Sources: CFPS; Institute of Digital Finance of Peking University; and authors' estimates.
[1] The numbers in parentheses are *t*-values (using robust standard errors). *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively. The control variables include gender, age, education level, political affiliation, marital status, household size, ratio of elderly members to household size, ratio of young children to household size, household attribute, traditional financial development level, and county fixed effects.

Micro mechanisms for the impact of digital financial inclusion on income inequality: "income boosting" effect

The "income boosting" effect is similar to the "transformation and upgrading" effect but focuses more on the additional opportunities for households to grow their income without changing jobs. With the rapid development of digital platforms such as *Pinduoduo*, farmers can expand the sales of their agricultural products through these platforms and earn higher income. To analyze this effect, we estimate model (4) for households who have been engaged in production during the entire sample period. The estimation results are shown in Table 10.

Table 10 shows that even for the full sample of households who have always been engaged in production, digital financial inclusion still has a significantly positive effect on operating income. Moreover, the estimated coefficient of the digital financial inclusion index increases from 0.043 (insignificant) at the lower quartile to 0.124 at the higher quartile, suggesting that the higher the operating income is, the greater the effect of digital financial inclusion on the operating income. One possible explanation why households with higher operating incomes have benefited more from digital financial inclusion is that households with lower operating incomes may have been engaged in production for self-sufficiency only and hence had less incentives to adopt digital financial technologies while those with higher operating incomes are more likely engaged in business operations and more incentivized to adopt such technologies. In addition, the estimates also suggest that rural households benefited more from digital financial inclusion through the "income boosting" effect than urban households, despite that the former has typically lower operating incomes. For male- vs. female-headed households, the estimated coefficients do not differ significantly, indicating that the "income boosting" effect is similar with respect to gender. From a regional perspective, the effect is greater in the northern region, despite that households there have lower incomes on average than those in the south. In summary, among households who have been engaged in production, digital financial inclusion still has a significantly positive effect on their operating incomes, especially for households in the rural and northern regions. However, this effect may not help narrow income inequality as it is greater for higher-income households than lower-income ones.

Table 10. Impact of Digital Financial Inclusion on Operating Income[1]
(Households who have been engaged in production)

	(1) OLS	(2) Lower income: 25%	(3) Median income	(4) Higher income: 75%
Full sample	0.079***	0.043	0.084***	0.124***
	(2.82)	(1.12)	(3.01)	(3.64)
Southern households	0.112*	0.113	0.112*	0.111
	(1.92)	(1.35)	(1.86)	(1.48)
Northern households	0.136***	0.124**	0.138***	0.151***
	(2.98)	(2.08)	(3.15)	(2.87)
Urban households	-0.012	-0.070	-0.002	0.053
	(-0.17)	(-0.75)	(-0.03)	(0.69)
Rural households	0.083***	0.056	0.087***	0.115***
	(2.68)	(1.31)	(2.79)	(3.06)
Male-headed	0.088***	0.043	0.093***	0.140***
	(2.65)	(0.94)	(2.82)	(3.48)
Female-headed	0.089	0.062	0.092*	0.118*
	(1.56)	(0.82)	(1.70)	(1.78)

Sources: CFPS; Institute of Digital Finance of Peking University; and authors' estimates.
[1] The numbers in parentheses are *t*-values (using robust standard errors). *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively. The control variables include gender, age, education level, political affiliation, marital status, household size, ratio of elderly members to household size, ratio of young children to household size, household attribute, traditional financial development level, and county fixed effects.

It is worth noting that there may be alternative explanations, apart from digital financial inclusion, for the results presented in Table 10. For example, as the traditional businesses were hit by digital financial inclusion, some labor and business owners have migrated to sectors that benefit more from digital financial inclusion. As a result, the surviving owners of the traditional businesses have gained more market powers and hence could charge higher markups. In this case, the reallocation of labor and business owners has also contributed to the higher operating income of those that remained in the traditional businesses.

Micro mechanisms for the impact of digital financial inclusion on income inequality: increasing the "efficiency of government welfare programs"

Digital financial inclusion could help reduce the government's administrative costs and strengthen the efficiency of fiscal transfers from government welfare programs to target recipients, thus having a positive effect on the income of lower-income households and helping with the narrowing of income inequality. To analyze this effect, we estimate model (5) with household transfer income and report the estimation results in Table 11. Clearly, the estimated coefficients of the digital financial inclusion index are greater at the lower quartiles, suggesting that higher digital financial inclusion is associated with lower income inequality in the full sample. This also broadly holds for the various groups of households, i.e., southern, northern, urban, rural, male-headed, and female-headed households. This suggests that this effect helps reduce transfer income inequality within each of these household groups. Moreover, similar to the "innovation" effect on wage income in Table 7, digital financial inclusion also has greater effects on transfer incomes of southern households (implying a diverging effect between the north and south) and rural households (implying a converging effect between urban and rural).

Table 11. Impact of Digital Financial Inclusion on Transfer Income[1]

	(1) OLS	(2) Lower income: 25%	(3) Median income	(4) Higher income: 75%
Full sample	0.433***	0.487***	0.414***	0.377***
	(9.95)	(6.16)	(9.56)	(7.75)
Southern households	0.410***	0.418***	0.407***	0.401***
	(6.61)	(3.67)	(6.11)	(5.23)
Northern households	0.294***	0.402***	0.251***	0.183**
	(4.06)	(2.82)	(3.34)	(2.18)
Urban households	0.385***	0.400***	0.384***	0.370**
	(5.42)	(3.37)	(3.76)	(2.49)
Rural households	0.468***	0.484***	0.459***	0.447***
	(9.12)	(5.66)	(9.51)	(8.66)
Male-headed	0.529***	0.566***	0.517***	0.490***
	(10.01)	(6.08)	(9.88)	(8.39)
Female-headed	0.258***	0.300	0.244***	0.215**
	(3.30)	(1.60)	(2.76)	(2.39)

Sources: CFPS; Institute of Digital Finance of Peking University; and authors' estimates.
[1] The numbers in parentheses are *t*-values (using robust standard errors). *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively. The control variables include gender, age, education level, political affiliation, marital status, household size, ratio of elderly members to household size, ratio of young children to household size, household attribute, traditional financial development level, and county fixed effects.

In summary, we have found evidence that "innovation", "income boosting", "transformation and upgrading", and "efficiency of government welfare programs" are important micro mechanisms through which digital financial inclusion affects income inequality. Overall, although higher digital financial inclusion is associated with lower income inequality among households in general, it tends to be associated with a widening of the income inequality between the northern and southern regions while the converging effect is only found *within* each of the two regions. At the same time, the greater contribution of digital financial inclusion to the wage incomes of rural and female-headed households is a key reason why higher digital financial inclusion is associated with lower income inequality among all households.

Robustness

We use the following methods to test the robustness of the estimation results above. First, the main method for examining the impact of digital financial inclusion on income inequality so far is the quantile regression. Another method, which breaks down the sample into high- and low-income groups, could also be used to test whether lower-income households have benefitted more from digital financial inclusion. Therefore, we split the households in the sample equally into high- and low-income households (based on the minimum income over the sample period) and conduct the estimation for each group. The results are presented in Table 12.

Table 12. Robustness Check: Estimation by Group[1]

	(1) Full sample	(2) Southern	(3) Northern	(4) Male	(5) Female	(6) Urban	(7) Rural
Low-income group	0.434***	0.450***	0.361***	0.393***	0.498***	0.368***	0.448***
	(17.00)	(10.23)	(8.48)	(12.34)	(11.02)	(9.34)	(12.87)
High-income group	0.132***	0.116***	0.137***	0.140***	0.129***	0.109***	0.158***
	(12.86)	(8.31)	(8.32)	(10.62)	(7.46)	(8.08)	(9.89)

Sources: CFPS; Institute of Digital Finance of Peking University; and authors' estimates.
[1] The numbers in parentheses are *t*-values (using robust standard errors). *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively. The control variables include gender, age, education level, political affiliation, marital status, household size, ratio of elderly members to household size, ratio of young children to household size, household attribute, traditional financial development level, and county fixed effects.

The estimation results in Table 12 indicate that digital financial inclusion has a greater effect on the income of the low-income group in the full sample as well as in each of the categories of southern, northern, male-headed, female-headed, urban, and rural households. This is broadly consistent with the previous finding that digital financial inclusion is associated with lower income inequality among households in general and within certain groups of households. Meanwhile, the estimated coefficients are 0.450 and 0.116 for low- and high-income households in the southern region, respectively, and 0.361 and 0.137 for those in the northern region, respectively. These estimates indicate that digital financial inclusion has greater effects on household incomes in the southern low-income group (compared to the northern region) and in the northern high-income group, implying—to some extent—that digital finance is more inclusive in the southern region, which is consistent with previous findings. We also perform estimation for subgroups, such as wage and transfer incomes, and reach similar conclusions to those obtained using quantile regressions previously.

Since the models used so far could be subject to the endogeneity problem, we also perform estimations using the internet penetration rate in each province as an instrumental variable for the digital financial inclusion index, which is likely to be more exogenous than the digital financial inclusion index. The alternative estimation results with the instrumental variable remain consistent with previous findings.[11]

Finally, as mentioned earlier, the data only cover three years and some of the control variables are relatively stable during the sample period. Therefore, controlling for the household fixed effects could lead to inaccurate estimates for some of the household-level control variables, such as gender of the household head and other factors that do not vary significantly over time. Nevertheless, we still re-run the regressions above with the household-level fixed effects (in lieu of the county-level fixed effects) for robustness check. We find that the estimated coefficients become less significant, but the main qualitative findings still hold: higher digital financial inclusion is associated with lower income inequality *within* the southern or northern region but a widening of the income inequality *between* the two regions, and has greater effects on the incomes of female-headed and rural households. We also find evidence for the micro mechanisms discussed above with the household-level fixed effects.[12]

[11] It should be cautioned that, although the internet penetration rate passes the overidentifying restrictions test for instrumental variables, it could also affect the income or income inequality measures through other channels beyond just digital financial inclusion, which could lead to a violation of the exclusion restriction for instrumental variables.
[12] Detailed results are omitted here but available upon request.

Heterogeneous impact of digital financial inclusion on household income: educational and age differences

Previous sections have explored the micro mechanisms through which digital financial inclusion could affect income inequality based on different types of incomes. It may be worthwhile to dive further into some of the findings. For example, the "innovation" effect of digital financial inclusion works through creating more jobs for households, which could help narrow not only the wage income inequality within urban or rural households but also that between them. Meanwhile, some other characteristics of households, e.g., educational level and age, may also affect the benefits from digital financial inclusion, which would also affect the impact of digital financial inclusion on income inequality. We explore the potentially heterogeneous effects of digital financial inclusion for each of these household characteristics in the following subsections.

Education and the impact of digital financial inclusion on household income

The level of education of a household is an important factor that affects the household's income (Heckman, 2011). Less educated households are more frequently excluded from financial services due to their relative lack of knowledge and lower financial literacy. The development of digital financial inclusion has enabled these households to quickly access financial services because digital financial tools, such as WeChat Pay and Alipay, typically have lower barriers of learning and are less costly to use than traditional financial services such as bank accounts and borrowing. As a result, the income disparity between less educated and more educated households could be reduced. In fact, most previous studies have found that human capital is a major factor in driving economic growth and inequality (Erosa *et al*., 2010; Fleisher *et al*., 2010; Gennaioli *et al*., 2013). To examine whether education matters for the impact of digital financial inclusion on income inequality for both urban and rural households, we split the sample into more educated and less educated households based on their educational levels and estimate the models (3)-(5) for the full sample as well as urban and rural households separately. The results are reported in Table 13.

The estimation results indicate that digital financial inclusion has a larger effect on the total income of less educated households than that of more educated ones, which is also true for wage and transfer incomes, implying that the effect is greater for less educated households than more educated ones. In addition, this result also holds for both urban and rural households. In other words, higher digital financial inclusion is associated with lower income inequality between less educated and more educated households in urban areas and that in rural areas. This could reflect that digital financial inclusion has enabled less educated households to quickly gain access to financial services and hence contributed more to their income growth. Moreover, the estimated coefficients are larger for rural households than urban households in the regressions with total and wage incomes, suggesting that digital financial inclusion may also be associated with a narrowing of the income disparity between urban and rural households. Finally, for operating income, the estimates suggest that, although digital financial inclusion has contributed to operating income, the impact is only significant for the less educated rural households but not the other groups. Overall, these findings imply that the higher digital financial inclusion is associated with lower income inequality between more educated and less educated households, and has also contributed to the narrowing of the income gap within urban or rural households as well as that between them.

Table 13. Education and Impact of Digital Financial Inclusion on Household Incomes[1]

	More educated			Less educated		
	Full sample	Urban	Rural	Full sample	Urban	Rural
Income type	(1)	(2)	(3)	(4)	(5)	(6)
Total income	0.224***	0.213***	0.244***	0.356***	0.284***	0.398***
	(10.52)	(8.22)	(6.85)	(14.89)	(6.66)	(13.61)
Wage income	0.951***	0.805***	1.138***	1.269***	1.071***	1.376***
	(12.61)	(8.67)	(9.12)	(15.79)	(7.83)	(13.61)
Transfer income	0.202***	0.233***	0.173**	0.664***	0.675***	0.664***
	(3.21)	(2.58)	(2.13)	(11.41)	(6.01)	(9.95)
Operating income[2]	0.061	0.017	0.070	0.104***	0.019	0.095**
	(1.47)	(0.17)	(1.52)	(2.72)	(0.19)	(2.24)
Sample size	12088	6744	5344	11726	3856	7870
Sample size[2]	3180	669	2511	4370	792	3578

Sources: CFPS; Institute of Digital Finance of Peking University; and authors' estimates.
[1] The numbers in parentheses are *t*-values (using robust standard errors). *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively. The control variables include gender, age, education level, political affiliation, marital status, household size, ratio of elderly members to household size, ratio of young children to household size, household attribute, traditional financial development level, and county fixed effects.
[2] The operating income denotes the estimated results for households who have been engaged in production, and the sample size is the corresponding sample size for such households.

Age and the impact of digital financial inclusion on household income

The so-called "digital divide" problem faced by the elderly has long been an important social issue in China (see, e.g., Lu and Wei, 2021). The rapid development of digital technologies (e.g., out-of-home code scanning and reservations) has put a significant part of the elderly at risk of falling behind in the digital age. Moreover, the "digital divide" problem among the elderly is becoming more significant as the population aging problem worsens in China. To examine the role of age, we split the sample into elderly households (defined as those with all family members being 65 years or older) and young households, and report the results in Table 14. The results suggest that, broadly speaking, digital financial inclusion has a larger impact on total household income for young households than for elderly households, indicating that higher digital financial inclusion is likely associated with higher rather than lower income inequality between elderly and young households. In other words, the "digital divide" problem among the elderly may still exist.

More specifically, for wage income, the estimates show that higher digital financial inclusion has contributed less to elderly households and more to young households in each of the categories of urban, rural, southern, and northern households, suggesting that digital financial inclusion is associated with a widening of the wage income disparity between elderly and young households. Meanwhile, with respect to transfer income, the estimation results indicate that digital financial inclusion contributes more to the transfer income of elderly households and hence may help reduce the income disparity between elderly and young households. However, the greater impact of digital financial inclusion on the transfer income of elderly households does not result in a greater impact on their total income because wage income accounts for a dominant share in total income. In terms of operating income, the results suggest that for households who have been engaged in production, digital financial inclusion tends to have a greater impact on the operating income of young households than that of elderly households, thereby likely contributing to the income disparity between elderly and young households.

Table 14. Age and Impact of Digital Financial Inclusion on Household Income[1]

	Elderly households					Young households				
	Full	Urban	Rural	Southern	Northern	Full	Urban	Rural	Southern	Northern
Income type	(1)	(2)	(3)	(4)	(5)	(4)	(5)	(6)	(9)	(10)
Total	0.241***	0.219***	0.288***	0.330***	0.068	0.296***	0.241***	0.343***	0.285***	0.274***
income	(5.59)	(4.15)	(4.16)	(6.10)	(0.93)	(17.33)	(9.87)	(14.38)	(11.26)	(9.78)
Wage	0.667***	0.650***	0.533***	0.741***	0.557***	1.174***	0.949***	1.395***	1.303***	1.271***
income	(5.28)	(3.78)	(2.77)	(4.52)	(2.76)	(19.65)	(11.26)	(16.53)	(15.29)	(12.33)
Transfer	0.987***	0.680***	1.415***	1.284***	0.384**	0.328***	0.307***	0.330***	0.274***	0.250***
income	(9.84)	(5.37)	(9.02)	(10.24)	(2.28)	(7.03)	(3.90)	(6.11)	(4.04)	(3.19)
Operating	-0.071	-0.108	-0.080	-0.032	-0.477**	0.086***	-0.001	0.085***	0.112*	0.159***
income[2]	(-0.59)	(-0.39)	(-0.59)	(-0.17)	(-2.15)	(2.97)	(-0.01)	(2.65)	(1.82)	(3.40)
Sample size	3031	1523	1508	1804	1227	20783	9077	11706	12048	8735
Sample size[2]	564	137	427	367	197	6986	1324	5662	3851	3135

Sources: CFPS; Institute of Digital Finance of Peking University; and authors' estimates.
[1] The numbers in parentheses are *t*-values (using robust standard errors). *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively. The control variables include gender, age, education level, political affiliation, marital status, household size, ratio of elderly members to household size, ratio of young children to household size, household attribute, traditional financial development level, and county fixed effects.
[2] The operating income denotes the estimated results for households who have been engaged in production, and the sample size is the corresponding sample size for such households.

In summary, the estimation results suggest that higher digital financial inclusion is associated with a narrowing of the income inequalities between more educated and less educated households, as well as between urban and rural households. That said, higher digital financial inclusion also tends to have a smaller effect on the income of elderly households than that of young households, and hence may have contributed to the income inequality between elderly and young households, suggesting the existence of the "digital divide" problem between the elderly and the young.

VI. Conclusions and Policy Implications

This paper examines the impact of digital financial inclusion on the economic gap between and within provinces and on the income inequality among households in China. We provide both macro- and micro-level evidence using the provincial and prefecture-level data as well as micro-level household survey data from the CFPS in conjunction with the digital financial inclusion index developed by the IDF of Peking University and the Ant Group. We further investigate the micro mechanisms through which digital financial inclusion affects income inequality, including "innovation" effect, "income boosting" effect, "transformation and upgrading" effect, and the "efficiency of government welfare programs". The main findings are as follows:

- First, higher digital financial inclusion does not seem to be associated with lower economic gap *across* provinces, but there is evidence that it is associated with significantly lower economic gap *within* provinces (i.e., among prefectures in the same province). This suggests that digital financial inclusion is only associated with a "digital dividend" rather than a "digital divide" within provinces. The analysis of the mechanisms also finds that digital financial inclusion has played a more inclusive role in the more developed southern provinces. These findings suggest that digital financial inclusion has likely contributed to intra-provincial but not inter-provincial economic convergence.

- Second, higher digital financial inclusion is associated with significantly higher household income growth and lower income inequality for each category of household income, particularly total, wage, and transfer incomes. This provides evidence that digital financial inclusion has likely contributed to the narrowing of income inequality by facilitating the "innovation" effect and increasing the "efficiency of government welfare programs". In addition, digital financial inclusion has facilitated more households, especially rural households, to exit from agricultural or other production and switch to higher-paying jobs, pointing to the "transformation and upgrading" effect. Finally, for households who have always been engaged in production, digital financial inclusion has also contributed significantly to their operating income, reflecting the "income boosting" effect. However, digital financial inclusion has a greater effect on household income in the southern region than the northern region, suggesting that higher digital financial inclusion is likely associated with a widening of the income gap between the two regions.

- Third, digital financial inclusion also has a notable convergence effect on the income distribution, mainly by having larger effects on the incomes of rural households (than urban households), female-headed households (than male-headed households), and less educated households (than more educated households). That said, digital financial inclusion has a smaller effect on the income of elderly households (than young households), which implies that higher digital financial inclusion is likely associated with a widening of the income gap between elderly and young households—pointing to the "digital divide" problem between the elderly and the young.

These findings have important policy implications for how to leverage digital financial inclusion to alleviate income inequality and promote sustainable growth in China:

- First, our findings confirm the inclusive role of digital financial development, meaning that digital financial inclusion tends to have large effects on the incomes of low-income, female-headed, and rural households. Therefore, further expanding digital infrastructure and increasing households' access to digital financial services, particularly in the poorer and rural areas, could help achieve higher inclusiveness, lower income inequality, and hence more sustainable growth.

- Second, the finding that digital financial inclusion is associated with a widening of the economic gap *across* provinces or the income gap between the northern and southern regions should not be overlooked. One of the reasons why the less developed regions seem to have benefitted less from digital financial inclusion could be the threshold effect or Kuznets effect (Daud *et al*., 2021; Siregar, 2020): the more developed regions also have more advanced digital infrastructure and hence can provide easier and less costly access to digital financial services for their residents. In this context, leveraging public and private resources to enhance the digital infrastructure and promote the use of digital financial services could help the less developed regions benefit more from digital financial inclusion.

- Third, the large number of e-commerce stores, most of which are micro- and small-sized enterprises (MSEs), in the (more developed) southern region is associated with a narrowing of the intra-provincial inequality in the region. This suggests that the less developed regions could consider adopting policies to support these MSEs, for example, by removing entry barriers or lowering entry costs, which could help them better leverage the digital financial inclusion and contribute to a narrowing of the economic and income gaps within the regions.

- Last but not least, the "digital divide" problem for the elderly in China may have also contributed to the overall income inequality. Local governments could provide targeted training programs on digital finance to the elderly to improve their ability to cope with the rapid development in digital technologies and increase the benefits that they could gain from digital financial inclusion, which could help reduce the income gap between the elderly and young households and address the "digital divide" problem.

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