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Digital financial inclusion and vulnerability to poverty: evidence from Chinese rural households

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Abstract

Purpose – Digital finance has the transformative power to realise financial inclusion. However, evidence on the relationship between digital finance and poverty reduction remains limited. This study examines the mitigating effects of digital financial inclusion (DFI) on vulnerability to poverty in rural China, explores potential mechanisms at the micro-level, and investigates the external conditions for DFI to validate these effects.

Design/methodology/approach – Rural household data from the China Labour Force Dynamics Survey and the regional DFI index compiled by Peking University are used. The probit and mediation effect models are employed to assess the impacts of the DFI on vulnerability to poverty and explore its mechanisms, with an appropriate instrumental variable to mitigate potential endogeneity.

Findings – DFI can mitigate vulnerability to poverty in Chinese rural households. Specifically, both sub-indices – coverage breadth and depth of use – have a significant effect. Further analyses based on the mediation model show that improving agricultural productivity, stimulating entrepreneurial activities and promoting non-agricultural employment are the core mechanisms for alleviating poverty vulnerability. Heterogeneity analysis shows that DFI is pro-poor and benefits those who lack economic opportunities. Moreover, adequate endowment in rural households, such as production and human capital, is an external condition for digital finance to mitigate vulnerability to poverty.

Originality/value – This study is among the first to examine the vulnerability-mitigation effects from the perspective of digital finance development, relying on data from a large-scale, nationwide household survey and the regional DFI index. It also checks for the mechanisms and heterogeneity of the effects, which prove the effects can help balance efficiency and equity.

Keywords Digital financial inclusion, Vulnerability to poverty, Rural households

Paper type Research paper

1. Introduction

Poverty reduction has been essential for developing countries, and as the largest developing country in the world, China's situation is especially arduous. Since 2013, the Chinese government has implemented targeted poverty alleviation policies, which have steadily lifted more than 60 million poor people out of poverty. Consequently, the national poverty rate dropped from 10.2% in 2013 to 0.47% in 2019, indicating that almost the entire impoverished population has been lifted out of poverty following the current income poverty line. However, eliminating income poverty does not mean eradicating poverty; vulnerable households still face the possibility of returning to poverty due to risk shocks. Therefore, mitigating vulnerability to poverty and establishing a mechanism to cope with it remains a challenge.

Inclusive finance aims to enable low-income groups excluded from formal finance to enjoy financial services. In the literature, the primary function of inclusive finance is alleviating poverty and promoting inclusive development, especially in rural areas (Sarma and Pais, 2011; Banerjee *et al.*, 2015; Li, 2018). For a long time, though, the lack of collateral, asymmetric information between farmers and financial institutions, and inadequate financial infrastructure have been the main obstacles to deepening financial inclusion (Gardeva and Rhyne, 2011). In recent years, the emergence of digital financial inclusion (DFI) has effectively

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overcome these shortcomings and become an important model for achieving inclusive finance. It has strengthened the effective distribution of financial services, and bridged the distance between financial institutions and customers (Demirguc-Kunt *et al.*, 2018). In terms of coverage area, the integration of information technology and finance has avoided the disadvantages of traditional finance models that have a low penetration rate in rural areas. Even though there are no physical facilities or hardware such as bank branches and ATMs in remote areas, farmers can still, via mobile terminal devices, obtain financial services, realise digital transactions and break through the geographic financial exclusion (Guo *et al.*, 2016). In terms of coverage groups, big data used in digital finance has become an alternative to collateral, effectively solving information asymmetry, while the affordability and convenience of digital finance resolve the price exclusion (Philippon, 2019; Guo *et al.*, 2020). DFI's low cost, wide-coverage and sustainability enable millions of users, especially low-income groups, to make mobile payments, apply for online loans, and purchase online insurance and investment products (Aisaiti *et al.*, 2019; Hua and Huang, 2020).

Since DFI has extended financial inclusion, it can provide social and economic values by improving equity and efficiency. First, it makes financial services more inclusive and efficient. Digital finance institutions, relative to traditional ones, have advantages in credit assessment. They can exploit their massive data generated by existing business lines such as e-commerce, reducing financial transaction costs and promote financial inclusion (Hau *et al.*, 2018; Frost *et al.*, 2019). Second, DFI creates economic opportunities and stimulates entrepreneurship (Xie, 2018). For rural households, highly dependent on the agriculture sector, it diversifies income sources (Wang, 2020). Finally, it plays a significant role in reducing inequity and promoting economic welfare, especially in remote rural areas. Hau *et al.* (2019) find that rural areas with fewer local bank branches benefit from digital finance services the most, indicating that digital finance can improve the penetrability and availability of rural residents' financial services. Couture *et al.* (2020) show that access to digital finance appears to offer economic gains for remote rural residents in China by reducing their living costs with online purchase facilities, especially for durable goods.

Although existing research finds a positive correlation between DFI and *social and economic benefits*, robust evidence of the relationship between DFI and poverty reduction remains limited, especially concerning vulnerability to poverty. This study used survey data from the China Labour Force Dynamics Survey (CLDS) in 2015 and the DFI index developed by Peking University (Guo *et al.*, 2016) to examine the impacts of DFI on rural households' vulnerability to poverty while further exploring its mechanisms. This study also takes appropriate instrumental variables, which refer to neighbouring cities' DFI index, to solve the endogeneity problem. The study results suggest that DFI can significantly mitigate Chinese rural households' vulnerability to poverty. Specifically, sub-indexes such as *coverage breadth* and *depth of use* have a significant effect. Further analysis results reveal the influencing mechanism, which implies that DFI has mitigated household vulnerability mainly through agricultural productivity growth, entrepreneurship promotion, and an increase in non-agricultural employment. The heterogeneity analysis shows that DFI is pro-poor and supports those who lack economic opportunities to reduce poverty. However, it is not conducive to households with low factor endowments.

Our analysis adds to the literature in three distinct ways. First, it is one of the first attempts to examine the vulnerability-mitigation effect from the perspective of digital finance development, relying on data from a nationwide and large-scale household survey and the regional DFI index. It has deepened the discussion about vulnerability to poverty in Chinese rural households and enriched the body of literature relating to digital finance. Second, this study examines the potential channels of how digital finance can mitigate rural households' vulnerability to poverty from the perspective of improving agricultural productivity, fostering entrepreneurship and encouraging non-agricultural *employment*. Third, it finds that the vulnerability-mitigation effect of DFI and its mechanism can help balance efficiency and equity. It has also been verified that the essential factor endowment is the external condition of this effect.

The remainder of this paper is organised as follows: Section 2 presents the mechanism and theoretical hypotheses, wherein we describe the link between DFI and vulnerability to poverty. Section 3 provides the data and variables used in this study. Section 3.2 details the definition of the variables. The econometric model and results are presented in Section 4, while Section 5 provides a discussion. Section 6 offers conclusions and policy implications.

2. Mechanism and theoretical hypotheses

The literature divides poverty vulnerability into risk- and poverty-induced vulnerability (Ligon and Schechter, 2003). Risk-induced vulnerability refers to the probability of poverty due to various adverse shocks that a family is likely to experience in the future. In contrast, poverty-induced vulnerability is usually caused by low income, which leads to persistent poverty. Fundamentally, the cause of poverty-induced vulnerability lies in the inefficiency of factor allocation among low-income groups, while credit constraint is a crucial factor leading to inefficiency. Low-income groups face financial exclusion from formal finance and thus must obtain credit via informal financial sources, which have disadvantages such as high transaction costs and high uncertainty. Furthermore, this type of financial exclusion will weaken agricultural productivity or deter farmers from participating in high-return non-agricultural activities in the long term, thus reducing household welfare and exacerbating vulnerability to poverty by weakening households' risk management capabilities (Ali *et al.*, 2014; Stiglitz, 2015).

Digital finance – including online loans and investments, mobile payments, Internet insurance, and many other kinds of innovative products – may reduce household vulnerability from various aspects. First, digital finance can reduce vulnerability by improving agricultural productivity. Modern agricultural advancements require considerable investment. Credit constraints often hinder farmers from renewing agricultural production factors or upgrading agricultural technology, restrict large-scale agricultural operations, and reduce the degree of conformity between agricultural products and market demand, thus diminishing productivity. The availability of online credit or loans can effectively alleviate farmers' financing constraints and effectively promote agricultural technology and machinery investment. Online transactions or payments can help farmers effectively connect to the market, reduce transaction costs, and achieve economies of scale. The improvement of agricultural productivity can increase the long-term income of the family while reducing their income risk. Both approaches can effectively reduce household vulnerability to poverty.

Second, digital finance can reduce vulnerability by promoting entrepreneurial activities. More favourable financing conditions and lower transaction costs effectively reduce the high uncertainty inherent in entrepreneurial activities (Klapper *et al.*, 2006; Kerr *et al.*, 2015). DFI is affordable and convenient in many aspects, including online credit or loans that do not require collateral assets and offer various forms of financial services at reasonable interest rates (Lorente and Schmukler, 2018). Online payments or transactions can help entrepreneurs connect with the market, promote information exchange and upgrade trust, and effectively reduce transaction costs (Zhou *et al.*, 2015; Beck *et al.*, 2018). Besides, online insurance can provide risk protection and mitigate the negative impact of economic activities.

Third, digital finance can reduce vulnerability to poverty through non-agricultural employment. Regional development of DFI can promote economic growth, especially in the small and medium enterprises (SMEs) that provide many employment opportunities. The literature has discussed that financial development has a substantial impact on the job opportunities created by enterprises, mainly through scale and quantity channels (Nykvist, 2008). The scale channel works under the assumption that the company's credit constraints are resolved, and its potential capacity expansion needs are met, thereby increasing labour demand (Benmelech *et al.*, 2011; Duygan *et al.*, 2015). The quantity channel refers to providing sufficient financial support for entrepreneurs with an innovative spirit to start new businesses and create new employment opportunities (Bianchi, 2010). Therefore, regional DFI development can effectively promote job creation to absorb surplus rural labour, thereby reducing vulnerability in the long term. Consequently, we derive the following hypotheses:

H1. The development of regional DFI has a mitigating effect on rural households' vulnerability to poverty.

H2. The mechanism for the vulnerability-mitigating effect is to improve the efficiency of household factor allocation, explicitly through an increase in agricultural productivity, entrepreneurial activities, and non-agricultural employment.

Employment opportunities are another critical factor affecting the activities and financial demands of rural households. Supposing the diminishing marginal returns for agricultural production, households with more employment opportunities can transfer surplus labour to non-agricultural sectors with higher returns to reduce the dependence on agriculture and avoid the transmission of agricultural risks to vulnerability and poverty. Seeking non-agricultural employment is the most convenient way and does not require much financial support. Nevertheless, farmers who lack such opportunities can only initiate entrepreneurial activities or upgrade agricultural productivity, both of which require additional financial support. Consequently, digital finance can offer low-cost financial services to support these activities.

Finally, digital finance impacts have been heterogeneous among different households, bringing digital dividends and digital divides (Banerjee *et al.*, 2019). The digital divide is induced most severely by usage, and the critical element causing usage differences is the factor endowment of rural households (Qiu *et al.*, 2016). Obtaining credit via digital finance, for example, can help farmers achieve more scaled production and upgrade agricultural technology. Usually, farmers with reliable information capture and absorption capability (high human capital) are good at securing economic opportunities and managing risk. They use digital finance to expand the market for their agricultural products, upgrade agricultural technology, or initiate entrepreneurial activities. Therefore, we derive the following hypothesis:

H3. The vulnerability-mitigating effect of DFI is more significant for rural households who lack employment opportunities but enjoy basic and essential factor endowment as an external condition.

3. Data and variables

3.1 Data source

A nationally representative data set on rural households was obtained from CLDS from 2012 by Sun Yat-Sen University. The survey adopts a multi-stage, multi-level, and probability sampling method, and designed questionnaires at the three levels of individuals, households, and communities, collecting demographic information on education, migration, health, and economic activities. This study uses three levels of the survey: first, individual factors, including gender, education, age, health, marital status and political status; second, household factors, including income, consumption, dependency ratio and size; and third, community factors, including the geographic distance, the proportion of minorities, numbers of enterprises and the pollution status. After deleting samples lacking information such as consumption, geographic distance, social capital, health condition, among others, we ultimately used 4,326 samples distributed across 27 provinces and 125 cities.

3.2 Measurement and definition of variable

3.2.1 Households' vulnerability to poverty. Vulnerability to poverty is distinguishable from poverty, as some households are currently non-poor but vulnerable to various shocks. Poverty can fluctuate, and residents who are exposed to risks are considered more vulnerable than ordinary ones. The literature consensus is that poverty cannot be conflated with vulnerability to poverty and that vulnerability analysis requires forward-looking information, including indicators of change in welfare over time. In the existing literature, there are many methods to measure poverty vulnerability, such as vulnerability as expected poverty (VEP), vulnerability as expected utility (VEU) and vulnerability as uninsured exposure to risk (VER) methods. Among these methods, the VEP approach is dominant since VER is suitable for measuring regional vulnerability, and VEU is based on a highly subjective expected utility assumption whereby the measured unexplainable risk is more significant (Chaudhuri *et al.*, 2002; Ligon and Schechter, 2003).

This study applies the VEP method, proposed by Chaudhuri *et al.* (2002), to measure rural households' vulnerability to poverty. We use consumption standards to measure household vulnerability because income data often have measurement errors in surveys; however, consumption data, widely used in the literature, can better reflect the household's actual welfare (Deaton, 1985). Under the assumption that per capita annual consumption's logarithm value follows a normal distribution (see Appendix), a three-stage generalised feasible least square approach (3SLS-FGLS) is used to estimate the vulnerability poverty of rural households. The specific form of the model is shown in Equation (1):

$$Vul_i = prob(\ln c_i < \ln z|X_i) = \phi\left[\frac{\left(\ln z - X_i\widehat{\beta}_{FGLS}\right)}{\sqrt{X_i\widehat{\theta}_{FGLS}}}\right] \tag{1}$$

whereby, Vul_i is a household's vulnerability to poverty, $\ln C_i$ is the logarithm value of the total consumption expenditure of households, $\ln Z$ is the logarithm value of the national poverty line [1], X_i represents the control covariates, $X_i\widehat{\beta_{FGLS}}$ is the consistent estimate of the expected value of consumption, and $X_i\widehat{\theta_{FGLS}}$ is the consistent estimate of the variance value of consumption. The standard setting of the vulnerability line is 0.5 as a cut-off, but the disadvantage is that it can only identify long-term poverty but will miss temporary poverty (Ward, 2016). To overcome this problem, some scholars have begun to use the probability value converted by time as the vulnerability line (Ward, 2016). By setting the condition that poverty may occur in the next two years, Gunther and Harttgen (2009) converted the 0.5 probability value to 0.29. If $Vul_i > 0.29$, we define the household as vulnerable to poverty; otherwise, the household is not vulnerable.

3.2.2 Digital financial inclusion. The regional DFI index, which was used in this research, was calculated based on consumer big-data. This data set was compiled by the joint research group of the Institute of Digital Finance of Peking University and Ant Financial Services Group and has been widely used to analyse the economic impacts of digital finance in China (Guo *et al.*, 2020; Zhang *et al.*, 2019). The DFI index includes three first-level indicators – *coverage breadth*, *depth of use* and the *degree of digital support*. Moreover, sub-indicators of the use depth include six secondary indicators – payment, monetary funds, lending, insurance, investments and credit investigations.

DFI is calculated based on three aspects: the *coverage breadth*, *depth of use* and *degree of digital support*, which express a considerable degree of representativeness and reliability. Coverage breadth is calculated by account coverage, while under the depth of use index, there are six second-level indicators: payment, monetary funds, loans, insurance, investment and credit investigation. Another indicator, degree of digital support, is calculated by two sub-indicators: financial convenience and financial service cost (see Appendix). The index has three levels: province, municipality and county. This manuscript mainly used the data at the municipal level for the regression analyses.

3.3 Mediator variables

Mediator variables, including *Entrepreneurship*, *Lnwage* and *Prod_loss*, are added into the regression to check the mechanism of how DFI reduces *vulnerability to poverty*. First, to measure the household's entrepreneurship, we check whether the household starts a business as a proxy variable for *entrepreneurship*; if the household starts a business, it is 1; otherwise, it is 0. Second, to check the non-agricultural employment increase mechanism, we choose the wage variable (*Lnwage*) rather than a dummy variable since a continuous variable can better depict employment benefits. Finally, a stochastic frontier (SFA) model is used to measure agricultural production productivity loss (*Prod_loss*). We assume the functional relationship between production input and output and set the agricultural production function of households as follows:

$$\begin{aligned} \ln Y_i = \alpha_0 + \beta_L \ln L_i + \beta_A \ln A_i + \beta_M \ln M_i \; + \beta_{LA} \ln L_i \ln A_i + \beta_{LM} \ln L_i \ln M_i \\ + \beta_{AM} \ln A_i \ln M_i + 0.5\beta_{LL}(\ln L_i)^2 + 0.5\beta_{AA}(\ln A_i)^2 + 0.5\beta_{MM}(\ln M_i)^2 + \nu_i - \mu_i \end{aligned} \tag{2}$$

In Equation (2), Y_i is the total agricultural output of household *i*. $L_i, A_i,$ and M_i represent the agricultural input of labour, land, and capital of household *i*, respectively. The vector β represents the estimated coefficient of the linear term, interactive term, and squared item of the input of labour, land, and capital, respectively. α_0 is a constant item, υ_i is the random error term and μ_i refers to the agricultural productivity loss of household *i*. It is assumed that μ_i is independent of υ_i and follows the normal distribution with mean Y_i^U and variance σ_μ^2. To avoid multicollinearity in the translog production function, we non-dimensionalise the input and output variables before the regression.

3.4 Control variables

The literature lists multiple factors that impact households' vulnerability to poverty (Chaudhuri *et al.*, 2002; Ligon and Schechter, 2003; Gunther and Harttgen, 2009); thus, the following control variables are used:

(1) household head characteristics comprising age, gender, marital status, political status, years of education and health condition of the household head;

(2) household characteristics comprising the family's wealth, family size, dependency ratio, and production and social capital;

(3) community characteristics consist of the distance from the village to the county, the pollution condition and the minority ratio.

We control these variables because the household demographic and community characteristics can, to a large extent, determine a families' future welfare status. For instance, the household head's health condition is a critical component of human capital; the assets of households reflect the production capital, and both could influence the family's capability to exploit economic opportunities. Moreover, the distance from the village to the county depicts the transaction costs, which causes an impact on the household economic welfare. Moreover, dummy variables of provinces are included to control the provincial fixed effect. The detailed variable descriptions and descriptive statistics are shown in Table 1.

As evident in Table 1, about 28.4% of households are vulnerable – indicating the probability of poverty. The mean value of the *DFI_index* is 171.1, with a maximum value of 231.1 and a minimum value of 141.0, indicating significant variations among regions that enable us to investigate its impact. For household head characteristics, the mean values of the variables gender, party, religion, and insurance are 0.907, 0.092, 0.099, and 0.577, respectively, indicating that 90.7% of household heads are male, 9.2% of household heads are Chinese Communist Party (CCP) members, 9.9% of household heads have religious beliefs and 57.7% of the household heads participated in the new rural cooperative insurance scheme. The mean value for *health* is 0.642, indicating that the household head's health level is generally healthy. The mean value for education is 7.654, indicating that most household heads have an education level beyond junior high school.

Household information shows that the mean value of Asset is 2.115, which indicates that most families have at least one living asset and one production asset. The mean value of Size and Ratio is 4.516 and 0.258, respectively, within a reasonable range. The values of Lnland and Lngift are within a reasonable range.

Variables	Description	Mean	SD
Vul	1 if the household is vulnerable to poverty, 0 otherwise	0.284	0.211
DFI_index	Regional index of DFI	171.1	19.50
Gender	1 if the household head is male, 0 otherwise	0.907	0.290
Education	The education year of the household head, no education: 0, primary school: 6, junior high school: 9, senior high school/professional high school/junior vocational school/senior vocational school: 12, university: 16, postgraduate: 19, doctor: 22	7.654	4.170
Age	Physical age of the household head	53.40	10.55
Marry	1 if the household head is married, 0 otherwise	0.976	0.153
Party	1 if the household head is CCP member, 0 otherwise	0.092	0.289
Religion	1 if the household head has religious faith, 0 otherwise	0.099	0.298
Insurance	1 if the household head participates in new rural cooperative medical insurance, 0 otherwise	0.577	0.494
Health	The health condition of the household head, 1 if the household head is healthy, 0 otherwise	0.642	0.427
Asset	The count value of the household asset[a]	2.115	0.857
Lnland	The logarithm value of arable land, including rented and cultivated land (mu)	1.506	0.887
Size	The number of family members	4.516	2.092
Ratio	The children's and elderly's dependency ratio of the household	0.258	0.244
Lngift	The logarithm value of gift expenditure of the household	5.682	3.514
Pollution_soil	Land pollution of the village	3.307	0.810
Lndist_county	The logarithm value of the distance from the village to the county	2.995	0.815
Minority	The proportion of ethnic minorities of the village (%)	9.706	26.31
Entrepreneurship	1 if the household has started a business, 0 otherwise	0.070	0.256
Lnwage	The logarithm value of employment income of household (yuan/year)	4.847	5.108
Prod_loss	Loss of agricultural production productivity	0.205	0.139

Note(s): [a]Referring to Booysen (2008) and Garbero (2014), we construct the asset index from household living and production demands which include productive assets and living assets. According to the CLDS family questionnaire section "Do you have cars, motorcycles, tractors, agricultural machinery, livestock, and durable consumer goods in your home", one of them is assigned a value of 1, otherwise 0

Table 1.
Variable descriptive statistics

Community information shows that the mean value of Pollution_soil is 3.307, which is close to 4, indicating that the surveyed village's environment is well maintained. The mean value of Lndist_county is 2.995, indicating that most villages surveyed are far from downtown. The mean value of variable *Minority* is 9.706, respectively, which is also realistic.

4. Econometric model and empirical analysis

4.1 Econometric model

Since vulnerability to poverty in our analysis is a dummy variable, we assess the relationship between DFI and vulnerability to poverty based on the binary probit regression model:

$$Prob(vul_{ic} = 1|DFI\_index_c, X_{ic}) = \alpha + \beta DFI\_index_c + \gamma X_{ic} + \varepsilon_{ic} \tag{3}$$

In Equation (3) Vul_{ic} takes a value of 1 if a household in city c is vulnerable to poverty and 0 if it is not. DFI_index_c is the index of the DFI for city c. Moreover, X_{ic} is a set of control variables, including individual, household, and community characteristics and provincial dummies. ε_{ic} is the error term. All regression errors were clustered at the city level.

4.2 Baseline results

We first investigate the impact of DFI on rural households' vulnerability to poverty. Table 2 presents the stepwise regression results of the probit model (Equation 3). Column (1) presents the results without other variables. In column (2), we gradually add relatively exogenous control variables, such as household head characteristics. In column (3) and (4), we control household and community characteristics, respectively. Column (5) shows the marginal effect coefficient of the model. The coefficients are significantly negative, both with and without control variables, suggesting rural households' use of digital finance has a positive mitigating effect on their vulnerability. The marginal effect of the DFI_index on vulnerability is −0.004 – a 1% increase in the *DFI_index* will significantly reduce the vulnerability to poverty of rural households by 0.4%.

The results of the control variables indicate that some advantage characteristics have a significant impact on vulnerability. Among them, the gender of male, younger age, higher education level, healthier condition and party membership can help mitigate poverty. Moreover, an increase in family assets and social networks can reduce vulnerability. However, religious beliefs and new rural insurance have no significant impact. The increase in family size and dependency ratio will exacerbate it, consistent with our expectations. The relationship between the proportion of ethnic minorities and vulnerability is not apparent, while the geographic distance significantly increases vulnerability, reflecting that the lack of convenience is still a critical factor leading to vulnerability.

Since the DFI index is multi-dimensional, this study not only examined the impacts of the total index of DFI on vulnerability but also used the second- and third-level indices. The second-level includes *DFI_breadth*, *DFI_depth* and *Digital_support,* while the third-level index includes *payment*, *credit*, *monetary fund*, *investment* and *insurance*. *DFI_breadth* represents the coverage of digital finance use; *DFI_depth* is measured based on the frequency of residents' use of services; *payment, credit, monetary fund, investment, and insurance* are secondary indicators of the depth of use; and *Digital_support* represents the degree of digital support. The results in Table 3 show that the second-level index, including *DFI_breadth* and *DFI_depth,* significantly affects vulnerability. The coefficients are −0.015 and −0.017, respectively, which indicates that digital finance can reduce vulnerability in both coverage and breadth. For the third-level index, *payment*, *credit*, *monetary funds* and *insurance* are significant. The coefficients are −0.014, −0.009, −0.015 and −0.006, respectively, which indicates digital finance can lower the threshold of financial services and improve financial

Table 2.
Impact of DFI on household vulnerability to poverty: total-index regression

	(1)	(2)	(3)	(4)	(5)
DFI_index	−0.016*** (0.005)	−0.019*** (0.006)	−0.019** (0.007)	−0.021*** (0.008)	−0.004*** (0.001)
Gender		−0.266*** (0.082)	−0.160* (0.089)	−0.169* (0.093)	−0.031* (0.017)
Education		−0.123*** (0.032)	−0.088*** (0.032)	−0.078*** (0.029)	−0.014*** (0.005)
Age		0.059*** (0.005)	0.054*** (0.005)	0.056*** (0.005)	0.010*** (0.001)
Marry		−1.200*** (0.204)	−1.071*** (0.226)	−1.066*** (0.246)	−0.197*** (0.044)
Party		−0.511*** (0.088)	−0.633*** (0.106)	−0.676*** (0.106)	−0.125*** (0.019)
Religion		−0.184 (0.175)	−0.273* (0.161)	−0.300* (0.158)	−0.055* (0.029)
Insurance		−0.094 (0.059)	−0.057 (0.070)	−0.064 (0.068)	−0.012 (0.013)
Health		−0.140*** (0.009)	−0.158*** (0.015)	−0.166*** (0.015)	−0.031*** (0.002)
Asset			−0.776*** (0.069)	−0.802*** (0.069)	−0.148*** (0.010)
Lnland			0.042 (0.069)	−0.027 (0.065)	−0.005 (0.012)
Size			0.083*** (0.030)	0.084*** (0.032)	0.016*** (0.006)
Ratio			1.411*** (0.146)	1.482*** (0.145)	0.274*** (0.025)
Lngift			−0.106*** (0.012)	−0.106*** (0.012)	−0.020*** (0.002)
Pollute_soil				0.223*** (0.064)	0.041*** (0.012)
Lndist_county				0.241** (0.110)	0.044** (0.020)
Minority				0.004 (0.004)	0.001 (0.001)
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.119	0.367	0.504	0.522	0.522
N	4,362	4,362	4,362	4,362	4,362

Note(s): *, **, and *** represent significance at the 10, 5, and 1% levels, respectively, and the corresponding standard errors in parentheses are clustered at the city level

Table 3. Impact of DFI on household vulnerability to poverty: sub-index regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DFI_breadth	−0.015*** (0.005)							
DFI_depth		−0.017** (0.008)						
Payment			−0.014*** (0.005)					
Credit				−0.009** (0.005)				
Monetary fund					−0.015*** (0.006)			
Investment						−0.008 (0.005)		
Insurance							−0.006* (0.003)	
Digital_support								0.003 (0.009)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.441	0.431	0.436	0.429	0.437	0.426	0.427	0.422
N	4,362	4,362	4,362	4,362	4,362	4,362	4,362	4,362

Note(s): *, **, and *** represent significance at the 10, 5, and 1% levels, respectively, and the corresponding clustering standard errors are in parentheses. In addition, the results of the control variables are no longer listed briefly. If necessary, the readers can request the author for details

service availability through diversified financial products, thus mitigating the household's vulnerability. Nevertheless, some indices are not significant, such as *investment* and *Digital_support*, which indicate that rural households rely slightly on investment to reduce vulnerability, and digital support of finance activities is insufficient in rural China.

5. Discussion

5.1 DFI mechanism on household vulnerability to poverty

The regression results show the positive impact of DFI in mitigating vulnerability to poverty. In this section, we investigated the possible mechanisms by which DFI reduces vulnerability to poverty. The main way for rural households to allocate their factors is by participating in agricultural and non-agricultural economic activities. Thus, we verify the mechanism using *agricultural productivity growth*, *entrepreneurship promotion* and *increase in non-agricultural employment*. Table 4 shows the results of the mechanism investigation.

5.1.1 Agriculture productivity growth. The literature has proved that farmers' agricultural productivity is closely related to poverty and vulnerability, and negatively related to credit

Panel A	(1) Full sample *Vul*	(2) Full sample *Prod_loss*	(3) Low-income *Prod_loss*	(4) High-income *Prod_loss*
DFI_index	−0.020*** (0.004)	−0.005*** (0.001)	−0.004*** (0.001)	−0.005*** (0.002)
Prod_loss	1.198*** (0.301)			
Controls	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
Empirical *p*-value				0.592
R^2	0.411	0.191	0.206	0.221
N	1,986	1,986	983	1,003
Panel B	**Full sample *Vul***	**Full sample *Entrepreneurship***	**Low-income *Entrepreneurship***	**High-income *Entrepreneurship***
DFI_index	−0.021*** (0.007)	0.007*** (0.002)	0.011*** (0.003)	0.005*** (0.002)
Entrepreneurship	−0.311*** (0.102)			
Controls	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
Empirical *p*-value				0.021
R^2	0.517	0.110	0.149	0.127
N	4,352	4,352	2,212	2,140
Panel C	**Full sample *Vul***	**Full sample *Lnwage***	**Low-income *Lnwage***	**High-income *Lnwage***
DFI_index	−0.020*** (0.003)	0.149*** (0.039)	0.097 (0.072)	0.155*** (0.021)
Lnwnge	−0.027*** (0.006)			
Controls	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
Empirical *p*-value				0.011
R^2	0.525	0.242	0.189	0.315
N	4,258	4,258	2,033	2,225

Note(s): *, **, and *** represent significance at the 10, 5, and 1% levels, respectively, and the corresponding clustering standard errors are in parentheses. In addition, the results of the control variables are no longer listed briefly. If necessary, the readers can request the author for details. Specially, results reported in Panel A also present bootstrapped standard errors

Table 4.
Mechanism of DFI on household vulnerability to poverty

constraints (Abro *et al.*, 2014). This section discusses the mechanisms of agriculture productivity. Panel A of Table 4 reports the effects of DFI for which agricultural productivity loss (*Prod_loss*) was selected as the mediating variable for household vulnerability since Prod_loss is a generated regressor, which is a variable calculated from the frontier regression. Thus, its sampling distribution is different from a variable that can vary freely and the default standard error does not account for this fact. To tackle this problem, we implement a two-step bootstrap: the first step resamples clusters with replacement and the second step resamples observations within a resampled cluster (Wooldridge, 2010). The results in column (2) show that the coefficient of the impact of DFI on agricultural productivity loss is negative, indicating that digital finance has promoted agricultural productivity (or reduced productivity loss). The results in column (1) show that DFI has a significant negative effect on household vulnerability. Moreover, after adding the variable *Prod_loss*, the coefficient of the impact of DFI on household vulnerability is still significantly negative, suggesting that agricultural productivity growth has a definite mediating effect.

The sub-sample regression results in columns (3) and (4) show that the mechanism of agricultural productivity growth is significant in low- and high-income households. Further, we employ Fisher's test to statistically identify the difference between these two coefficients. Specifically, we construct the empirical distribution of the coefficient difference by bootstrapping these samples 1,000 times before calculating the empirical p-value. As reported in Table 4, the empirical p-value is 0.592, indicating no difference between the coefficients. A possible explanation is that the scales and modes of agricultural production of Chinese rural households are similar, thus the economic outcomes of DFI on agricultural productivity can be approximated.

5.1.2 Entrepreneurship promotion. The mediator variable *Entrepreneurship* describes whether the household starts a business. Panel B of Table 4 indicates how entrepreneurship promoted by DFI mitigates vulnerability to poverty. Similar to Panel A of Table 4, columns (1) and (2) report the results of the mediating effect mechanism, indicating that the development of DFI can reduce vulnerability by promoting farmers' participation in entrepreneurial activities. DFI has a robust positive effect on promoting rural households' entrepreneurial activities, which can, to a certain extent, mitigate their vulnerability. The sub-sample regression results, which are reported in columns (3) and (4), show that the mechanism of entrepreneurship promotion exists in both high- and low-income groups. Moreover, the empirical p-value shows that the entrepreneurship promotion mechanism is more significant in low-than high-income families. Generally speaking, low-income groups are more affected by financial exclusion compared to high-income ones. Thus, the results of the sub-sample regression partially explain that the development of DFI promotes the equalisation of entrepreneurial opportunities – the mechanism of DFI is pro-poor rather than pro-rich.

5.1.3 Non-agricultural employment increase. Panel C of Table 4 shows the role of the *non-agricultural* employment mechanism of DFI in alleviating vulnerability to poverty. Column (1) shows the regression result of poverty vulnerability to the variables *DFI_ndex* and *Lnwage*. Column (2) represents the full-sample regression result of the variable *Lnwage* on the DFI index. Columns (3) and (4) represent the subsample regression results of the *Lnwage* variable on the DFI index of the low-income group and the high-income group, respectively. The empirical results show that DFI helps households resist poverty vulnerability by increasing non-agricultural income. The sub-sample regression results show that the non-agricultural employment mechanism is only significant in the high-income group. Possible explanations may be that the communities where low-income families settle have fewer non-agricultural employment opportunities; alternatively, compared with low-income rural households, the income of high-income households may rely more on non-agricultural incomes.

5.2 Heterogeneous effects of DFI on household vulnerability to poverty

5.2.1 Income and economic opportunity heterogeneity. Income per capita is an appropriate indicator to measure the economic gap between households. Following Zhang *et al.* (2019), we divide rural households into low-income (below the median) and high-income groups (above the median) and compare the coefficient differences. Columns (1)–(2) of Table 5 show that the vulnerability-mitigation effect is significant for both groups. Nevertheless, the coefficient of the *DFI_index* in the low-income group is significantly higher than that of the high-income group, indicating that the vulnerability-mitigation effect is pro-poor rather than pro-rich.

Meanwhile, local employment opportunities are one of the crucial factors leading to rural poverty and vulnerability. Rural households with local employment opportunities are more likely to achieve income growth through non-agricultural jobs, while those lacking opportunities usually rely heavily on agricultural income. Under the condition of low agricultural productivity, it is difficult for these households to achieve income growth; worse, agricultural risk exposure could easily lead to high vulnerability.

This study uses the number of enterprises in the village where the household settles as a proxy variable for local economic opportunities. For the regression analysis, rural households are further divided into two groups: those with abundant economic opportunities (the village has more than one enterprise) and those with scarce economic opportunities (the village has less than one enterprise). Villages with more enterprises tend to create more local employment, which will help households to be employed. The results in columns (3)–(4) of Table 5 show that *DFI* only significantly affects households lacking opportunities. This is consistent with the argument that DFI can create economic opportunities and promote employment activities as discussed earlier.

5.2.2 Factor endowment heterogeneity. Factor endowment is an essential factor affecting the poverty status of farmers. Factor endowment of rural households is reflected in both production and human capital. This study uses two proxies for production capital. The first is whether the household has production materials, including cars, machinery and livestock. If the household has at least one means of production, it is defined as a high production capital household; otherwise, it is a household with low production capital. The second proxy is the amount of arable land farmed by the household. As a production factor, land plays a vital role in the scale efficiency of agricultural production. We define households with landholdings above the median as high-production capital households and those below the median as low-production capital households. In addition to human capital, we select the education level of the household head as a proxy, divide the samples into low (elementary school and below) and high (junior high school and above) human capital groups and perform regressions.

Table 5. Impact of DFI on vulnerability to poverty: income and economic opportunity heterogeneity

	(1)	(2)	(3)	(4)
	Income		Economic opportunity	
	Low	High	Low	High
DFI_index	−0.027*** (0.007)	−0.019** (0.009)	−0.024*** (0.009)	−0.012 (0.015)
Controls	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
Empirical p-value		0.021		0.011
R^2	0.441	0.471	0.531	0.416
N	2,207	2,119	2,973	1,151

Note(s): *, **, and *** represent significance at the 10, 5, and 1% levels, respectively, and the corresponding clustering standard errors are in parentheses. In addition, the results of the control variables are no longer listed briefly. If necessary, the readers can request the author for details

The results in Table 6 indicate that an increase in *DFI* has a more significant effect on vulnerability reduction for households with high production capital and human capital. These results are consistent with expectations: Firstly, we propose that the core mechanism of DFI to reduce poverty vulnerability is to optimise the rural household's factor allocation. Therefore, if the rural household lacks fundamental production factors, the vulnerability-mitigation effect and its mechanism cannot function – improving the factor endowment of rural households is necessary for the exertion of DFI on poverty reduction. Secondly, DFI is based on digital technology, and it requires a certain level of knowledge; otherwise, the digital dividend may turn into a digital divide. The critical issue in poverty reduction is to assist deprived groups in obtaining and using production factors and skills. In this process, human capital plays a decisive role. In short, digital finance requires specific external conditions to fulfil vulnerability mitigation successfully, that is, households must have essential human and productive capital.

5.3 Robustness test

The selection of poverty and vulnerability lines is a critical factor affecting vulnerability to poverty (Gunther and Harttgen, 2009; Ward and Patrick, 2016). In the baseline regression, we chose China's poverty standard of RMB 2,800 as the baseline in 2015. In the robustness test, we choose the World Bank's standards per capita daily consumption of US$ 1.9 and US$ 3.1 for setting the poverty line, and we adopt the vulnerability line of 0.5 proposed by Ferreira *et al.* (2016). Moreover, we replace the explanatory variable with vulnerability, as measured by income data. The results in Table 7 indicate that the development of DFI is likely to reduce poverty vulnerability in rural China, regardless of which poverty line and which measurement method are considered.

5.4 Endogeneity discussion

Two major problems arise from the endogeneity problems in this study. The first is reverse causality. Although an increase in regional DFI could reduce venerability, the more affluent areas may also have higher DFI levels, leading to endogenous estimation errors due to the reverse causality problem. Second is the problem of omitted variables bias. Some unobservable factors may simultaneously affect the DFI index and households' vulnerability, which is inevitable in empirical research.

To mitigate this concern, following Chong *et al.* (2013), we instrument the DFI with the average value of DFI of the neighbouring cities in the same province. We chose this index as

	(1)	(2)	(3)	(4)	(5)	(6)
	Production materials		Arable land		Human capital	
	Low	High	Low	High	Low	High
DFI_index	−0.021**	−0.027***	−0.018**	−0.025**	−0.017**	−0.026***
	(0.008)	(0.010)	(0.009)	(0.010)	(0.008)	(0.009)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Empirical *p*-value		0.031		0.056		0.016
R^2	0.510	0.518	0.528	0.511	0.501	0.491
N	2,904	1,422	1,989	2,337	2,041	2,285

Note(s): *, **, and *** represent significance at the 10, 5, and 1% levels, respectively, and the corresponding clustering standard errors are in parentheses. In addition, the results of the control variables are no longer listed briefly. If necessary, the readers can request the author for details

Table 6. Impact of DFI on vulnerability to poverty: factor endowment heterogeneity

	(1) $1.9 a day per capital	(2) $3.1 a day per capital	(3) 0.5 vulnerability line	(4) Income-based VEP
DFI_index	−0.014*** (0.005)	−0.021*** (0.004)	−0.039*** (0.010)	−0.016** (0.006)
Controls	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
R^2	0.514	0.521	0.516	0.536
N	4,326	4,326	4,326	4,326

Note(s): *, **, and *** represent significance at the 10, 5, and 1% levels, respectively, and the corresponding clustering standard errors are in parentheses. In addition, the results of the control variables are no longer listed briefly. If necessary, the readers can request the author for details

Table 7.
Robustness test

an instrument for two reasons. First, it has a positive correlation with the local DFI. The same region tends to be consistent in promoting DFI development and inclusive financial policies, and thus DFI development in neighbouring areas is convergent. Second, with each city treated as a separate region, the DFI index of neighbouring cities is unlikely to affect local households' vulnerability to poverty due to regional disparities. However, a potential problem arises because unobserved factors that we do not consider in the regression may correlate with the instrumental variables (IV) and *DFI_index*. Therefore, using Acemoglu *et al.'s* (2003) methodology, we run the regressions to test the exclusion restriction. In the first regression, we add both the *DFI_index* and *IV*. In the second regression, we include only *IV*. Suppose the online DFI_index is significant and IV is insignificant in the first regression, while IV is significant in the second regression. In that case, the most likely interpretation is that the effect of *IV* is mainly through the online *DFI_index* channel and not through a range of other unobserved factors. Panel A of Table 8 is the result of an exclusion restriction test, indicating that IV is unlikely to be affected by the unobserved factors in the regression.

The results from the endogeneity test are presented in Panel B of Table 8. The first-stage regression indicates that the coefficient of *IV* is significantly positive, implying that the DFI of the neighbouring cities is positively associated with the DFI of the local city. The value of the F test is 19.56, exceeding the rule of thumb for strong instruments ($F > 10$), indicating that it is unlikely to be a weak instrumental variable. We find that after the introduction of *IV*, the impact of *the DFI_index* is still positive. The Hausman test and the Wald test both reject the endogeneity of variables at the 1% level, which indicates that the introduction of *IV* is necessary. Overall, after adding *IV*, the direction and significance of *the DFI* did not change significantly, which indicates that the estimation results are robust.

6. Conclusions and implications

Using survey data of rural households and the regional DFI index, this study discusses how DFI impacts vulnerability to poverty in rural China. The preliminary results show that an increase in regional DFI can help mitigate vulnerability to poverty. Among the sub-indicators, both the coverage breadth and use depth have significant impacts. Mechanism identification shows that DFI achieves vulnerability-mitigation effects by improving households' agricultural productivity, stimulating entrepreneurship and promoting non-agricultural employment. To a certain extent, DFI optimises rural households' factor allocation, thereby achieving a long-term poverty reduction mechanism. The heterogeneity analysis shows that DFI can help households with low incomes and a lack of economic opportunities to alleviate their vulnerability, indicating that it balances efficiency and equity. Meanwhile, we also find that external conditions exist for DFI to perform vulnerability-

Table 8. Exclusion restriction test and endogeneity test

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
	Exclusion restriction test					
	DFI_index		*DFI_breadth*		*DFI_depth*	
DFI_index	−0.018*** (0.004)		−0.016*** (0.004)		−0.012*** (0.003)	
IV	−0.001 (0.017)	−0.012*** (0.002)	−0.011 (0.018)	−0.011** (0.005)	−0.006 (0.019)	−0.011*** (0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B	First-stage	Second-stage	First-stage	Second-stage	First-stage	Second-stage
	Endogeneity test					
	DFI_index		*DFI_breadth*		*DFI_depth*	
DFI_index		−0.011*** (0.002)		−0.009*** (0.003)		−0.006*** (0.002)
IV	0.357*** (0.094)		0.517*** (0.087)		0.346*** (0.094)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Wald test		32.12***		31.11***		31.77***
Hausman test		24.22***		29.17***		21.48***
F-test		19.56***		28.15***		37.98***

Note(s): *, **, and *** represent significance at the 10, 5, and 1% levels, respectively, and the corresponding clustering standard errors are in parentheses. In addition, the results of the control variables are no longer listed briefly. If necessary, the readers can request the author for details

mitigation effects. In other words, improving the factor endowment of households will enhance these effects.

Our results have significant policy implications. First, the Chinese government should formulate a long-term digital financial development plan to increase financial support for vulnerable rural households. For instance, a more comprehensive credit investigation network should be established to reduce the information asymmetry between users and institutions. Second, financial institutions should use digital technology to identify better and serve the financial needs of rural residents and assist them in improving the efficiency of factor allocation, thereby reducing vulnerability. They can, for example, develop products to help farmers improve their agricultural technology or motivate them to start businesses to mitigate income risks. Finally, rural households must improve factor endowments, such as production and human capital, to enhance their ability to withstand financial shocks.

Note

1. In 2015, China's national poverty line was RMB 2,800, which is chosen for this analysis.

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Appendix

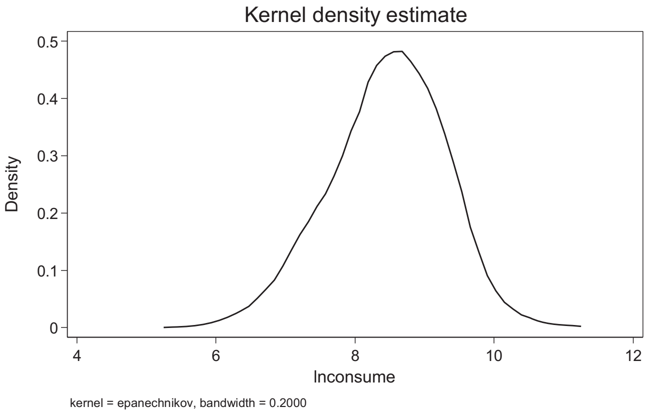

Figure A1.
Kdensity graph of lnconsume

First level indicators	Second level indicators		Measures
Coverage breadth	Account coverage		No. of accounts per 10,000 persons Ratio of accounts with credit card No. of debit and credit cards per Alipay account
Depth of use	Payment		Frequency of payment per capita Amount of payment per capita Ratio of high frequency user
	Monetary funds		Purchases frequency of Yu'ebao per capita Purchases amount of Yu'ebao per capita Number of Alipay users who purchased Yu'e Bao per 10,000 people
	Lendings	Individuals	No. of accounts with consumer credit per 10,000 accounts Frequency of loans per capita Amount of loans per capita
		Micro entrepreneurs	No. of accounts with micro enterprise credit per 10,000 accounts Frequency of loans per micro entrepreneurs Amount of loans per micro entrepreneurs
	Insurance		No. of accounts with insurance per 10,000 accounts Frequency of insurance per capita Amount of insurance per capita
	Investment		No. of accounts with investment per 10,000 accounts Frequency of investment per capita Amount of investment per capita
	Credit investigation		No. of accounts using credit investigation per 10,000 accounts Frequency of accounts using credit investigation
Degree of digital support	Financial convenience		Ratio of payment frequency with mobile Ratio of payment amount with mobile over total payment amount
	Cost of financial service		Average loan interest rate of micro enterprise Average loan interest rate of consumer credit

Note(s): Details from Guo *et al.* (2016)

Table A1. Constructions of index of DFI

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