Does Digital Financial Inclusion Reduce China’s Rural Household Vulnerability to Poverty: An Empirical Analysis From the Perspective of Household Entrepreneurship

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Abstract
This paper evaluates the impact of digital financial inclusion (DFI) powered by digital technologies on rural household vulnerability to poverty based on data from the China Family Panel Studies (CFPS) and DFI data from the Institute of Digital Finance Peking University. The results show that both DFI and its secondary indicators reduce rural household vulnerability to poverty. Household entrepreneurship is an intermediary factor of DFI influencing vulnerability to poverty; that is, DFI stimulates rural households’ entrepreneurial behavior, thereby reducing their vulnerability to poverty. Through the analysis of income heterogeneity, financial development level, and human capital in the region, it is found that DFI is more helpful in reducing the vulnerability to poverty for rural households with low income, a low level of financial development and low human capital. Therefore, the Chinese government should map out the DFI development path, build a DFI control system with internet technologies, and actively play the mutually supporting role of DFI and other influencing factors to boost DFI development, minimize the risk of returning to poverty and thereby reduce rural household vulnerability in China.

Keywords
digital financial inclusion, vulnerability to poverty, household entrepreneurship

Introduction
Eradicating poverty and achieving common prosperity are the common ideals of people all over the world. As the largest developing country in the world, China is both an advocate and a promoter of poverty control and poverty reduction endeavors in the world, and it has played a great positive role in promoting poverty alleviation. For more than 40 years of reform and opening up, the Chinese government has vigorously carried out poverty alleviation actions in rural areas and promoted the rapid development of the national economy to alleviate rural poverty and to promote poverty reduction and elimination in rural areas. After more than 40 years of efforts, the per capita income and consumption levels of rural households in China have been greatly improved, and remarkable achievements have been made in poverty control. By the end of 2020, all poor counties were removed from the poverty list, and all rural underprivileged populations were lifted out of poverty. The fight against poverty has achieved a complete victory. According to the international poverty standard of the World Bank, China has set an example for reducing world poverty by moving more than 70% of the global poor out of poverty over the same period.

Most Chinese rural households increase their income and lift themselves out of poverty in two ways: one is to work away from their hometown to increase nonagricultural income; the other is to engage in self-employed business and other entrepreneurial activities. Entrepreneurship, as the primary way of effectively increasing permanent income in rural areas, however, is largely hindered by financial constraints (Nykvist, 2008). Traditional financing means, primarily Rural Credit Cooperatives loans and usurious loans, are costly, difficult, and slow to access for farmers, which severely dampens the enthusiasm of rural household entrepreneurship.

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The booming development of digital technologies such as the internet, big data and cloud computing has provided a broad space for the development of digital inclusive finance. With the help of advanced digital technology, digital inclusive finance has entered the public horizon with low cost and high convenience. The concept of digital financial inclusion (DFI) was defined for the first time at the 2016 Hangzhou G20 Summit (Global Partnership for Financial Inclusion [GPFI], 2016): All actions to promote financial inclusion through the use of digital financial services, including the use of digital technologies to meet the needs of those who have no access to or lack access to financial services by providing formal and sustainable financial services in a responsible and affordable manner. The development of digital inclusive finance can promote economic growth (Shen et al., 2021).

The Chinese government actively advocates mass entrepreneurship and innovation, bringing unprecedented opportunities for rural households to engage in entrepreneurial activities. Household entrepreneurship has become an effective means for rural households to increase their permanent income in China and has played an important role in alleviating poverty.

In the traditional definition, poverty, as a static concept, is an ex-post measure of a household’s well-being. It can be measured only by current income or consumption which reflects the current poverty status instead of future poverty dynamics (Ligon & Schechter, 2003). However, in reality, poverty is dynamic and changes all the time. Even if a household enjoys a high level of income and consumption in the current period, the expected future income is extremely volatile, and the fluctuation of consumption may increase due to various immeasurable external shocks at all times. At some indeterminate future point, households that are currently not in poverty may fall into poverty due to a shock of some sort.

Therefore, to study poverty issues, we should not only focus on the status quo of a household poverty but also consider the possibility of a household falling into poverty in the future even when it is currently above the poverty line and we should carry out long-term research on poverty alleviation. The main contributions of this paper are as follows: First, from the innovative perspective of DFI, this paper analyzes its impact on rural household vulnerability to poverty, enriching, and expanding the related research on vulnerability to poverty. Second, this paper focuses on the mediation effect of household entrepreneurship and expands the indirect theoretical research on the DFI influencing rural household vulnerability to poverty. By constructing an empirical model, it scientifically identifies the indirect mechanism of action of household entrepreneurship in DFI influencing vulnerability to poverty. Finally, this paper explores in detail whether DFI is inclusive when there are differences in income, regional financial development level and human capital. Exploring the impact of DFI from a more detailed perspective can help provide ideas for solving poverty issues. This study shows that digital inclusive finance can stimulate the entrepreneurial motivation of rural families, increase employment opportunities for surplus labor, improve household income, and reduce poverty vulnerability.

### Literature Review

Vulnerability comes up in the natural science fields such as disaster science, which is used to describe the exposure of a system to external shocks or disasters. Subsequently, this concept increasingly found its way into the fields of social sciences (such as social system vulnerability) and welfare economics. The approaches to assess vulnerability to poverty can be summarized in the following three types in and out of China. The first approach is the vulnerability as the expected poverty (VEP). The VEP approach, an ex-ante vulnerability measure, was first proposed by Chaudhuri in 2002. It goes beyond the “ex post” measure of poverty and captures the dynamic aspects of poverty; that is, it predicts the future consumption of a household based on the characteristics economic and social capital conditions at the individual or household level to provide a basis for future poverty prediction and prevention. The second approach is the vulnerability as the low expected utility (VEU). In this measure of VEU, under the conditions of risks, vulnerability is defined as the difference between the expected utility of an individual or household and the utility derived from certainty-equivalent consumption. Ligon and Schechter (2003) proposed this approach and based on it used the utility function to quantitatively analyze vulnerability; the third approach is the vulnerability as an uninsured exposure to risk (VER). The consumption level of a household will decline due to a lack of consumption smoothing ability (Calvo & Dercon, 2013) in the face of shocks.

From the perspective of empirical research, it mainly involves the selection of the poverty line, the prediction method of future permanent income (Günther & Harttgen, 2009) and the setting of the vulnerability line (Zhang & Wan, 2009). Zhang and Wan (2008) show that when other influencing factors remain unchanged, the higher the poverty line is, the more accurate the prediction of vulnerability to poverty. When permanent income follows the log-normal distribution, it is more appropriate to set the poverty vulnerability line at 50%. From the perspective of research samples, the existing vulnerability research literature mainly focuses on the rural areas of developing countries. Due to the lack of panel data in developing countries, the existing literature mainly studies cross-sectional data (Imai et al., 2009) and uses measurement methods such as ordinary least squares, generalized least squares, and three-stage generalized least squares (Günther & Harttgen, 2009). From the perspective of vulnerability influencing factors, existing studies mainly focus on the impact of nonfinancial factors on vulnerability as expected poverty (VEP), such as employment and education, market accessibility, nonagricultural activities,
agricultural tax abolition, and social security (Sun et al., 2020; Wang & He, 2020; Xiang et al., 2021; Zhang & Wan, 2006).

The core function of finance is to promote the optimal allocation of resources, achieve economic growth and reduce poverty through the rational and effective allocation of resources. Based on data from Southeast European countries, the empirical analysis of Milcher (2010) shows that households using banking services are less vulnerable to poverty than those that do not. Mina and Imai (2017) also considered the penetration of banking institutions at the provincial level when decomposing vulnerability to poverty. Urrea and Maldonado (2011) believed that the more households use credit and savings, the lower their vulnerability to poverty by analyzing Colombian data. The empirical analysis of Bali Swain and Floro (2014) shows that households participating in microfinance projects have a lower level of vulnerability to poverty than those that do not.

Previous literature has studied the relationship between traditional financial inclusion and household vulnerability to poverty. Choudhury (2014) established a theoretical relationship between financial inclusion and household vulnerability to poverty and believed that financial inclusion improves the availability and usage of financial services and their capabilities in responding to risks and helps reduce vulnerability to poverty. Park and Mercado (2015) constructed the Financial Inclusion Index in 2015. By using data from developing countries in Asia, their study found that the development of financial inclusion is negatively correlated with the incidence of poverty. In-depth research (Park and Mercado, 2018) concluded that financial inclusion will not only significantly reduce poverty but also reduce income inequality.

In contrast to inclusive finance, digital inclusive finance, as a typical form of financial technology, can effectively solve the information asymmetry in technology, improve the service breadth and depth, reduce the service cost and have better penetrability. It is able to solve the problem of the uneven distribution of financial resources to help farmers, low-income, and other disadvantaged groups eliminate obstacles to obtaining financial resources and alleviating capital shortages. This means that the previously unrealized or difficult goals of inclusive finance can be realized through the application of digital technology. The application of digital technology makes digital inclusive finance play a more prominent and crucial role in promoting rural family entrepreneurship and reducing poverty vulnerability.

In summary, domestic and foreign scholars are currently conducting modeling and empirical analyses of vulnerability to poverty and the financial inclusion index. However, few studies have examined the vulnerability of rural families to poverty from the perspective of digital inclusive finance. Theoretical analysis, model construction, and empirical analysis of the impact of digital inclusive finance on the vulnerability of rural families to poverty are not sufficient, and a systematic research framework has not been formed. Moreover, the existing literature lacks theoretical analysis and lacks empirical research on the internal transmission mechanism of digital financial inclusion affecting poverty vulnerability from the perspective of family entrepreneurship. Entrepreneurship is an effective way to greatly increase the income of rural families and improve their ability to cope with risks. In particular, with the help of digital inclusive finance, rural families in China are showing unprecedented entrepreneurial opportunities and promoting entrepreneurship (Liu et al., 2021). Nguyen et al. (2021) also conclude that economic policy uncertainty is conducive to promoting entrepreneurial actions. As an economic policy, the contribution of digital inclusive finance to entrepreneurial behavior can also be seen. In addition, digital inclusive finance uses digital technology to collect information, realizes cross-platform supervision, optimizes credit approval technology, carries out risk management and decision-making in a multi-dimensional manner, reduces risk misjudgment caused by information asymmetry, improves risk control ability, and thus reduces entrepreneurial risks. Normally, self-starters are more proactive, and are able to maximize their creativity and activate endogenous motivation. Digital financial inclusion not only solves employment problems for self-starters but also generates a large number of jobs, absorbs idle labor, invigorates the rural economy, improves farmers’ sustainable income, improves their living standards, is conducive to the long-term development of the rural economy, helps poor people escape the “poverty trap,” and reduces the vulnerability of poverty. See Figure 1 for a graphical illustration of how digital financial inclusion affects the vulnerability of rural households to poverty.

**Model Construction**

**Constructing a Household Vulnerability Model**

To measure household vulnerability to poverty, it is necessary to estimate the household’s future consumption or income level. This paper adopts consumption standards to measure vulnerability to poverty, mainly because:

1. If the income standard is used to measure vulnerability to poverty, it is impossible to add the income variable as an explanatory variable in the regression model, as it will cause a serious variable omission problem.
2. Consumption data are smoother than income data and can more accurately reflect the level of household vulnerability.
welfare (Deaton, 1981). Based on the research of Chaudhuri et al. (2002), this paper assumes that household consumption follows a log-normal distribution and uses the three-stage feasible generalized least squares (FGLS) method proposed by Amemiya (1977) to estimate rural household vulnerability to poverty.

The first step is to estimate the per capita consumption logarithm and residual:

\[ \ln c_h = X_h \beta + e_h, \]
\[ \sigma^2 e_h = X_h \rho + \eta_h, \]

where \( X_h \) are related variables that affect the per capita consumption of the household, including individual characteristic variables such as the age of the household head (Age), the square of age (\( \text{Age}^2 \)), gender (Gen), marital status (Mar), education status (Edu), health status (Health), household characteristic variables such as the size of household population (Size), the household dependency ratio (Ratio), and the logarithm of household income per capita (Ln income), and the region dummy variables (eastern, central, and western regions). Note that the main function of taking logarithm is to reduce the absolute difference between data and avoid the influence of individual extreme values. Taking logarithm will not change the relative relationship of data (Fan & Xie, 2014; Yi & Zhou, 2018). The data of age, age square, and family population size are small and the gap between the data is also small, so that we think there is no need to take logarithm and it will not have a great impact on the results of this paper.

The second step is to use the fitted value obtained in the first step to construct the weight of the heteroscedasticity structure and re-estimate the logarithmic consumption and the squared residuals with FGLS to obtain the estimators \( \hat{\beta}_{FGLS} \) and \( \hat{\rho}_{FGLS} \). Then these estimators are substituted back into Formulas (1) and (2) to predict the expected value and variance of future logarithmic consumption: \( \hat{E}(\ln c_h | X_h) \) and \( \hat{V}(\ln c_h | X_h) \).

\[ \hat{E}(\ln c_h | X_h) = X_h \hat{\beta}_{FGLS}, \]
\[ \hat{V}(\ln c_h | X_h) = X_h \hat{\rho}_{FGLS} \]

The third step is to select the poverty line and calculate the vulnerability to poverty of household \( h \):

\[ \hat{V}_{h,t} = \phi \left( \frac{\ln Z - X_h \hat{\beta}_{FGLS} \cdot S}{X_h \hat{\rho}_{FGLS}} \right). \]

Existing studies generally believe that the poverty line set by China is much lower than the international poverty line, so this paper chooses the latter. The World Bank released the extreme poverty line of “US$1.9/person/day” in 2015. The poverty line determined by the median per capita consumption of developing countries is “US$3.1/person/day.” This paper uses two poverty line standards of US$1.9 and US$3.1 (converted into RMB units by the base period PPP from the World Bank) to calculate vulnerability to poverty (Ferreira et al., 2016).

In addition to choosing a poverty line, it is also necessary to set a specific vulnerability line to determine whether a household is vulnerable. There are generally two standards
for setting the vulnerability line: (1) Consider a 50% probability value as the vulnerability line (Zhang & Wan, 2008). However, the disadvantage of using a 50% probability value as the vulnerability line is that it can only identify long-term poor rural households but will omit temporarily poor rural households (Ward, 2016). To solve this problem, Günther and Harttgen (2009) converted the 50% probability value to 29% over a time period and used it as the vulnerability line. (2) Take the incidence of poverty as the vulnerability line. The incidence of poverty is the ratio of the number of poor households to the total number of households (Foster et al., 1984), among which households with income below the poverty line are poor households. This paper uses the 29% probability value and the incidence of poverty as the vulnerability line.

**DFI and Household Vulnerability**

After building the Vulnerability as Expected Poverty (VEP) model, this paper builds a regression model taking rural household vulnerability as a dependent variable and the DFI index as an independent variable. This paper constructs the model, which is expressed as follows:

\[
V_{h,p,t} = \alpha_0 + \alpha_1 DFI_{p,t} + \lambda X_{h,p,t} + \phi_h + \epsilon_{h,p,t},
\]

where \(V_{h,p,t}\) denotes the vulnerability of the \(h\)-th household in region \(p\) in period \(t\), \(DFI_{p,t}\) is the Digital Financial Inclusion index in \(p\) region in period \(t\), \(X_{h,p,t}\) is a series of control variables, which contain the age of the head of household (Age), marital status (Mar), gender (Gen), education status (Edu), health status (Health), household dependency rate (Rate), household size (Size), per capita net income (Income), per capita health care expenditure (Med), per capita government subsidy (Gover), etc. \(\phi_h\) is a time fixed effect. \(\epsilon_{h,p,t}\) is a random disturbance term. The construction of the explained variables has been analyzed previously and will not be discussed here. The DFI, however, is standardized to avoid an excessively small estimated coefficient value and the incidence of poverty as the vulnerability line.

**Conduction Mechanism: DFI and Household Entrepreneurship**

In the context of China’s slowing economic growth and booming internet economy, sustainable development can be achieved only through entrepreneurship and innovation. Sufficient capital is a vital condition for both. DFI enables more groups to access financial support and ease financing constraints, which greatly facilitates the establishment of MSMEs (Karaivanov, 2012; Nykvist, 2008), creates more jobs, boosts employment rates, brings higher income to households, and addresses household vulnerability to poverty. This paper constructs the following household entrepreneurship intermediary model to verify the intermediary role of household entrepreneurship in the impact of DFI on vulnerability to poverty.

\[
Vul_{h,p,t} = \alpha_0 + \alpha_1 DFI_{p,t} + \lambda_1 X_{h,p,t} + \phi_h + \epsilon_{h,p,t}, \quad \text{(10)}
\]

\[
Ent_{h,p,t} = \alpha_0 + \alpha_2 DFI_{p,t} + \lambda_2 X_{h,p,t} + \phi_h + \epsilon_{h,p,t}, \quad \text{(11)}
\]

\[
Vul_{h,p,t} = \alpha_0 + \alpha_3 DFI_{p,t} + \eta_1 Ent_{h,p,t} + \lambda_3 X_{h,p,t} + \phi_h + \epsilon_{h,p,t}, \quad \text{(12)}
\]

where household entrepreneurship (Ent) is a mediator variable, and the control variables are the same as those in Model (6). Model (10) is a benchmark model (i.e., Model (6)). The mediator variable in this paper, household entrepreneurship, is a binary categorical variable, and we should use logistic regression instead of linear regression when the mediator variable is categorical in nature. Therefore, this paper uses logistic regression to estimate Model (11) and performs linear regression on Models (10) and (12). The mediating effect value is the product of the regression coefficient \(\alpha^2\) in equation (11) and \(\eta^2\) in equation (12) to test the significance of the mediating effect, that is, the significance of \(\alpha^2 \times \eta^2\), but the regression coefficients of the three models are not measured on the same scale and therefore are not comparable. To unify the scales and determine the existence of a mediating effect, this paper draws on the findings of Iacobucci (2012) and uses Wald’s \(\chi^2\) test to determine the significance of the coefficients in the logistic model with a statistic of \(\chi^2 = \frac{\alpha^2}{SE(\alpha^2)}\) and a square root of \(\frac{\alpha^2}{SE(\alpha^2)}\), which is the t-test statistic. When the degree of freedom of the sample size is greater than 30, it can be regarded as a Z-test: \(Z_{\alpha} = \frac{\alpha^2}{SE(\alpha^2)}\); in linear regression analysis, the significance test of the coefficients is a t-test with the statistic of \(t = \frac{\eta^2}{SE(\eta^2)}\), when the degree of freedom of the sample size
The mean value of the Digital Financial Inclusion (DFI) index is 136.9179, the maximum value is 285.4300, and the minimum value is 17.9400, with a very large standard deviation, indicating great differences between the extent of poverty, and vulnerability was calculated using two poverty poverty lines in each year. By observing the mean value (Table 3) and the percentage of vulnerable households (Table 4), we find that the level of vulnerability to poverty of the selected rural sample households generally trends downward over time and at a significant rate, which indicates the decreasing likelihood of rural households falling into poverty in the future.

From the perspective of the poverty line, the poverty threshold increases from US$1.9 a day to US$3.1 a day, the mean household vulnerability tends to increase with the increase in the poverty line, and so does the percentage of vulnerable households, indicating that whether a rural household is classified as poor hinges on the selection of the poverty line.

In addition, if we take 29% as the vulnerability line and US$3.1 as the day poverty line, the number of vulnerable households in the sample decreases from 1,777 (0.4212 × 4219) in 2012 to 1,600 (0.3792 × 4219) in 2018. The above data on rural household vulnerability show that the number of poor people has decreased, great progress has been made in rural poverty reduction, and remarkable achievements have been attained in poverty alleviation.

DFI and Household Vulnerability

A Hausman test was performed on Model (6), and according to the test results, a fixed-effect model was selected, and a two-way fixed effects regression of time and household was added. Model (6) was estimated, and the estimated results of the model are listed in Table 5.

Columns (1) and (2) consider only the relationship between the development of digital financial inclusion (DFI)
and rural household vulnerability to poverty (Vul). In Columns (3) and (4), the head of household and household variables are added. This series of regression results all show that the DFI coefficient is negative and statistically significant, that is, DFI is beneficial in reducing vulnerability to poverty. In Column (3), that is, for every one standard deviation increase in the DFI index when the US$1.9 poverty line is used as the benchmark, vulnerability to poverty will decrease by 1.98%; in Column (4), when the US$3.1 poverty line is used as the benchmark, vulnerability to poverty will decrease by 2.71%. As a result, Hypothesis H1 is verified.

From the regression results of the model, the regression results of US$1.9 are consistent with those of US$3.1 in Table 1.
terms of significance and direction of the regression coefficient. To reduce redundancy, the paper mainly uses the regression result of US$3.1 as the analysis object.

Among the characteristics of the household head, gender (Gen), marriage (Mar), education (Edu), age (Age), and health status (Health) all significantly impact household vulnerability to poverty (Table 5). Specifically, the gender (Gen) of a household head plays a significant role in reducing vulnerability to poverty, probably because men are relatively more capable of creating wealth and play a greater role in increasing income and reducing poverty vulnerability if they are the household heads. The marital status (Mar) of a household head is significant at the 1% confidence level, indicating that a married household head tends to reduce household vulnerability, probably because a married household head has a stronger sense of family responsibility, is more capable of earning money, earns higher income, and is less likely to fall into poverty. The education status (Edu) of a household head is negative and statistically significant at the 1% confidence level, indicating that the higher the education level of a household head is, the less likely he or she will fall into poverty in the future, which is consistent with expectations. The coefficient of the age (Age) of a household head is significantly positive, indicating that the impact of the age of a household head on household vulnerability to poverty shows a positive correlation. This is possibly because middle age is the prime of life when a household head is at the apex of physical strength and is capable of engaging in more agricultural activities or manual labor to obtain income. As the household head gets older, his or her family income decreases as he or she has less opportunity to engage in agriculture or become a worker. Therefore, the older a household head is, the higher the vulnerability to poverty. The health status (Health) coefficient is also negative and statistically significant, indicating that the healthier a household head is, the more likely vulnerability to poverty will be reduced. It may be that the better the health of a household head is, the more productive he or she, the more future income he or she will earn, and the less the probability for him or her to fall into poverty.

In terms of household characteristics, the coefficients of household size (Size) and household dependency ratio (Rate) are significantly positive, indicating that the higher the household size and household dependency ratio are, the heavier the burden of the household and the higher the risk of falling into poverty. The coefficients of health care expenditure (Med) are negative at the 1% significance level, indicating that households that pay attention to health care are risk-conscious, and are investing money in health care and can avoid the risk of falling into poverty in the future. The increase in net income per capita (Income) significantly reduces the probability of falling into poverty, reflecting a highly negatively correlated relationship between household economic status and household vulnerability to poverty, and the higher the income of a household is, the lower the probability of it falling into poverty in the future. The coefficient of government subsidy (Gover) is negative and statistically significant at a 1% confidence level, indicating

### Table 5. Benchmark Regression Results.

|   | (1)            | (2)                      | (3)            | (4)                      |
|---|----------------|--------------------------|----------------|--------------------------|
|   | Vul1          | Vul2                     | Vul1          | Vul2                     |
| Dfi | -0.0159*** (0.0010) | -0.0224*** (0.0013) | -0.0198*** (0.0010) | -0.0271*** (0.0013) |
| Gen | -0.0100*** (0.0028) | -0.0115*** (0.0034) |               |                          |
| Mar | -0.0528*** (0.0058) | -0.0607*** (0.0070) |               |                          |
| Edu | -0.0133*** (0.0011) | -0.0165*** (0.0013) |               |                          |
| Age | 0.0050*** (0.0002)  | 0.0064*** (0.0002)    |               |                          |
| Health | -0.0064*** (0.0010) | -0.0090*** (0.0013) |               |                          |
| Rate | 0.0271*** (0.0057)  | 0.0423*** (0.0069)    |               |                          |
| Size | 0.0301*** (0.0011)  | 0.0392*** (0.0013)    |               |                          |
| Med | -0.0385*** (0.0023) | -0.0595*** (0.0028) |               |                          |
| Income | -0.0021*** (0.0006) | -0.0027*** (0.0007) |               |                          |
| Gover | -0.0065*** (0.0008) | -0.0060*** (0.0010) |               |                          |
| Constant term | 0.1247*** (0.0010) | 0.1925*** (0.0012) | -0.1487*** (0.0118) | -0.1717*** (0.0142) |
| Year effect | Yes            | Yes                     | Yes           | Yes                      |
| Household effect | No                | No                       | Yes           | Yes                      |
| N  | 16876          | 16876                    | 16876         | 16876                    |
| R² | .0179           | .0235                    | .1827         | .2122                    |

Note. The data in brackets are standard errors. A negative coefficient indicates that the variable and vulnerability to poverty are negatively correlated and vice versa. Vul1 represents the vulnerability to poverty estimated below the poverty line of US$1.9, and Vul2 represents the vulnerability to poverty estimated below the poverty line of US$3.1.

***Indicates that the coefficient is statistically significant at the level of 1%.
that government subsidies play a great role in alleviating household poverty, reflecting the key role of government at the current stage of targeted poverty alleviation.

All three DFI dimensions significantly reduce household vulnerability (Table 6). The largest effect was observed for the breadth of coverage (Cov), which reduced rural household vulnerability by 2.95% for each standard deviation increase; depth of use (Dep) was the next largest, which reduced rural household vulnerability by 2.55% for each standard deviation increase; and extent of digitization (Dig) reduced rural household vulnerability by 2.4% for each standard deviation increase.

The reasons are as follows: At present, increasing the breadth of DFI coverage in rural areas allows farmers and low-income groups in remote areas to access financial services, expands the availability and accessibility of financial resources to households, enables disadvantaged groups to fairly enjoy the benefits from DFI development and helps lower the vulnerability to poverty of rural households. Financial institutions, including banks, have seen the withdrawal of branches from rural areas in recent years, resulting in an insufficient breadth of financial coverage in rural areas. Even if farmers put their funds into financial institutions, most of them will still flow to the industrial sectors and cities, which further exacerbates the lack of financial resources in rural areas. Therefore, enhancing the breadth of DFI coverage in rural areas can significantly reduce rural household vulnerability to poverty. The depth of use measures the frequency of using internet financial services. Increased depth of use indicates that rural households can make greater use of service features such as credit and insurance of DFI to fund them and reduce their possibility of falling into poverty. The extent of digitalization measures the convenience and efficiency of regional financial services. The application of digital technologies makes payments more convenient, transaction operations simpler and costs cheaper, which can effectively solve the problem of information asymmetry, increase the willingness of banks and financial institutions to lend, effectively address the issue of difficult, expensive, and slow financing for rural households, and reduce household vulnerability to poverty.

### Table 6. Dimensions of DFI and Rural Household Vulnerability.

| Dependent variable: household vulnerability | Breadth of coverage | Depth of use | Extent of digitization |
|---------------------------------------------|---------------------|--------------|------------------------|
| Estimated coefficient                      | -0.0295***          | -0.0255***   | -0.0240***             |
| Control head of household characteristics  | Yes                 | Yes          | Yes                    |
| Control household characteristics          | Yes                 | Yes          | Yes                    |
| Household fixed effects                    | Yes                 | Yes          | Yes                    |
| Year fixed effects                         | Yes                 | Yes          | Yes                    |
| R²                                          | .2157               | .2096        | .2091                  |

Note. The data in brackets are standard errors. A negative coefficient indicates that the variable and vulnerability to poverty are negatively correlated and vice versa.

### Mediation Effect: Household Entrepreneurship

In this part, Household Entrepreneurship is used as a mediator variable to explore the impact pathway of DFI on vulnerability to poverty. Table 7 lists the test results of the pathway “Digital Financial Inclusion (DFI)—Household Entrepreneurship (Ent)—Vulnerability to Poverty (Vul).”

First, the DFI regression coefficient in equation (1) is negative and statistically significant, meaning that DFI has an overall impact on vulnerability to poverty. Hence, \( \alpha_1 = -0.0271 \), \( SE(\alpha_1) = 0.0013 \), and \( Z_{\alpha_1} = 20.8462 \). Second, after the logistic regression for Model (11), the regression coefficient of Dfi in equation (2) is positive and statistically significant, meaning DFI and Household Entrepreneurship are significantly positively correlated, where a higher DFI level implies a higher entrepreneurial possibility of rural households. Hence, \( \alpha_2 = 0.0963 \), \( SE(\alpha_2) = 0.0461 \), and \( Z_{\alpha_2} = 2.09 \). Finally, linear regression is conducted on Model (12) in equation (3). Hence, \( \eta_2 = -0.0425 \), \( SE(\eta_2) = 0.0065 \), and \( Z_{\eta_2} = -6.54 \). According to Formula (13), \( Z = 1.99 \) (1.99 > 1.96) and the null hypothesis where the mediating effect is not statistically significant is rejected. Therefore, household entrepreneurship plays a vital and statistically significant mediating role in the relationship between DFI and vulnerability to poverty. According to the above formulas, the relative size of the mediating effect is \( Z_{\alpha_1} \times Z_{\eta_2} / Z_{\alpha_2} = 65.6\% \).

### Heterogeneity Test

The essence of DFI is to provide equitable and reasonable financial access to lower-income and poverty-stricken groups previously excluded by the traditional financial industry. To gain deeper insight into the relationship between DFI and vulnerability to poverty, this paper further analyzes which group benefits most from DFI development (more reduction in vulnerability to poverty), that is, whether there is a difference in the impact of DFI on the vulnerability to poverty of different groups. This paper then analyzes the DFI distribution effect and elaborates on how DFI achieves inclusiveness. This paper conducts a heterogeneity analysis on the
samples with grouped regression by referring to the method employed by Gomez (2019).

**Income heterogeneity.** To measure the difference in the DFI impact on vulnerability to poverty from the perspective of income disparities, the paper groups per capita household net income by median into high-income and low-income groups. To test the intergroup coefficient difference after the grouped regression, this paper preliminarily removes individual effects and conducts an OLS regression on transformed data to apply seemingly unrelated tests. The results indicate a statistically significant difference in the DFI coefficients between the two groups, and it is reasonable to carry out a comparative analysis of the regression coefficients between the two groups. DFI has a stronger effect on lowering the vulnerability to poverty of low-income households than on lowering that of high-income households. This indicates that DFI expands the range of financial services and lowers the household vulnerability to poverty by providing low-income households with necessary funds and creating their wealth and increasing their income either directly or indirectly. High-income households, however, have weaker financial constraints, which is manifested in a way that DFI plays a relatively weak role in facilitating financial services for them and reducing their vulnerability to poverty (Table 8).

**Area heterogeneity.** To measure the difference in the DFI impact on vulnerability to poverty from the perspective of area disparities, this paper employs the standard of the Institute of Digital Finance Peking University to divide the provinces in question into the mid-western and eastern regions and conducts regressions on them. A seemingly unrelated test is also conducted in this grouped regression. The results show a statistically significant difference in the DFI coefficients between the two groups. By observing the regression of the DFI coefficients of the two groups from the sample in Table 9, we find that the DFI coefficients in the eastern region are smaller than those in the midwestern region, indicating the stronger effect of DFI on reducing vulnerability to poverty in the midwestern region than in the eastern region. The results further prove the inclusiveness of DFI. This is possibly because DFI development can reach a more poverty-stricken group in the mid-western region, which is remote and lacks formal financial institutions. DFI development can significantly improve financial services and give residents in the midwestern region access to a great deal of financial information and services, which is conducive to reducing their probability of falling into poverty. The eastern region, however, enjoys faster financial development, so DFI has a relatively small effect on reducing rural household vulnerability.

**Human capital heterogeneity.** To explore the difference in human capital and the difference in DFI impact on vulnerability to poverty, this paper divides the samples according to the education level of the household heads into low-education-level (primary school and below) and high-education-level (above primary school) groups. The reason to set the dividing line at primary school is that the years of education farmers receive are generally low, with samples below primary school accounting for 1/2 of the sampled population. A higher dividing line would lead to insufficient data in the high-education-level group.

A seemingly unrelated test is also conducted in this grouped regression. The results show a statistically significant difference in the DFI coefficients between the two groups. Table 10 reveals that under different education levels, the DFI impact on household vulnerability to poverty differs. DFI displays a stronger inhibiting effect on the vulnerability to poverty of the low-education-level group than on that of the high-education-level group, which further demonstrates the inclusiveness of DFI toward disadvantaged groups. By introducing digital technologies and facilitating more effective information transfer, DFI reduces the impact of the education gap, which alleviates the problem of low-quality workforce and helps reduce the vulnerability to poverty of the low-education-level group.

### Table 7. DFI and Household Entrepreneurship.

|       | (1)   | (2)   | (3)   |
|-------|-------|-------|-------|
|       | Vul2  | Ent   | Vul2  |
| Ent   |       |       |       |
| DFI   | −0.0271*** (0.0013) | 0.0963** (0.0461) | −0.0425*** (0.0065) |
| Constant term | −0.1717*** (0.0142) | — | −0.1673*** (0.0142) |
| Year effect | Yes | Yes | Yes |
| Household effect | Yes | Yes | Yes |
| N     | 16,876 | 4,376 | 16,876 |
| $R^2$ | 0.2136 | — | 0.2163 |

Note. The data in brackets are standard errors. A negative coefficient indicates that the variable and vulnerability to poverty are negatively correlated and vice versa. (4) Vul2 represents the vulnerability to poverty estimated below the poverty line of US$3.1.

***Indicates that the coefficient is statistically significant at the level of 1%.

indicating the stronger effect of DFI on reducing vulnerability to poverty in the midwestern region than in the eastern region.
Using the heterogeneity test, this paper proves the inclusiveness of DFI that targets low-income, low-human-capital groups in areas with low financial development. By offering them financial services and resources to ease their financial constraints, we help lift them out of poverty and prevent them from falling back into poverty.

### Robustness Test

Considering the possible endogeneity issues in this study and to make the benchmark regression analysis more reliable, this paper also conducts a robustness test. The endogeneity issues mainly stem from omitted variable bias, simultaneous equation bias (impact of two-way causality), and measurement error bias. Endogeneity issues are addressed by replacing explanatory variables, alternative models, and instrumental variables in this study (Gormley & Matsa, 2014).

**Replacing explanatory variable.** Measurement error bias is addressed by matching the county-level DFI index from Peking University with CFPS data. As the county-level index includes only data from 2014 to 2020, data from 2014, 2016, and 2018 are selected to match the CFPS data in these years. The regression results are listed in Table 11. The regression coefficients of the county-level index (Dfi_county) in equations (1) and (2) are negative and statistically significant, which demonstrates that the DFI impact on vulnerability to poverty is still present and that the results of the benchmark regression are robust.

| Explained variable | (1) | (2) | (3) | (4) |
|--------------------|-----|-----|-----|-----|
| DFI                | -0.0038*** (0.0009) | -0.0075*** (0.0012) | -0.0278*** (0.0020) | -0.0353*** (0.0024) |
| Constant term      | -0.0881*** (0.0102) | -0.1295*** (0.0141) | -0.1769*** (0.0221) | -0.1672*** (0.0255) |
| Year effect        | Yes | Yes | Yes | Yes |
| Household effect   | Yes | Yes | Yes | Yes |
| N                  | 8,438 | 8,438 | 8,438 | 8,438 |
| R²                 | .1831 | .2241 | .2216 | .2396 |

*Note. The data in brackets are standard errors. A negative coefficient indicates that the variable and vulnerability to poverty are negatively correlated and vice versa. Vul1 represents the vulnerability to poverty estimated below the poverty line of US$1.9, and Vul2 represents the vulnerability to poverty estimated below the poverty line of US$3.1.***Indicates that the coefficient is statistically significant at the level of 1%.

### Table 9. Regression Results of Different Areas.

| Explained variable | (1) | (2) | (3) | (4) |
|--------------------|-----|-----|-----|-----|
| DFI                | -0.0176*** (0.0015) | -0.0257*** (0.0020) | -0.0246*** (0.0016) | -0.0312*** (0.0019) |
| Constant term      | -0.0844*** (0.0213) | -0.1081*** (0.0271) | -0.2673*** (0.0225) | -0.2739*** (0.0266) |
| Year effect        | Yes | Yes | Yes | Yes |
| Household effect   | Yes | Yes | Yes | Yes |
| N                  | 6,641 | 6,641 | 10,235 | 10,235 |
| R²                 | .1171 | .1491 | .1783 | .2006 |

*Note. The data in brackets are standard errors. A negative coefficient indicates that the variable and vulnerability to poverty are negatively correlated and vice versa. Vul1 represents the vulnerability to poverty estimated below the poverty line of US$1.9, and Vul2 represents the vulnerability to poverty estimated below the poverty line of US$3.1.***Indicates that the coefficient is statistically significant at the level of 1%.

**Alternative model.** Drawing from the conclusions of Günther and Harttgen (2009), this paper sets the vulnerability threshold at 29% to divide rural households into vulnerable-to-poverty households and nonvulnerable-to-poverty households. By setting households with vulnerability to poverty higher than 29% to 1 and those lower than 29% to 0, we transform the vulnerability to poverty index into a binary variable. On such a basis, this paper applies a panel logit model to explore the relationship between DFI and the household vulnerability to poverty. The regression results are listed in Table 12, which further proves that DFI can reduce vulnerability to poverty.
To best mitigate the impact of endogeneity, this paper employs two-stage least-squares (2SLS) analysis. Learning from Bartik’s (2009) practice, we construct a “Bartik instrument” in a way as shown in the model:

$$Df_{i,t}^iv_{jt,t} = Df_{i,t-1}^iv_{jt,t-1} \times \Delta Df_{i,t-1}$$

Table 10. Regression Results of Different Human Capital.

| Explained variable | Vul1              | Vul2              | (1)       | (2)       |
|--------------------|-------------------|-------------------|-----------|-----------|
| DFI                | −0.0176*** (0.0015) | −0.0257*** (0.0020) |           |           |
| Constant term      | −0.0844*** (0.0213) | −0.1081*** (0.0271) |           |           |
| Year effect        | Yes               | Yes               |           |           |
| Household effect   | Yes               | Yes               |           |           |
| N                  | 9,145             | 9,145             | 7,731     | 7,731     |
| $R^2$              | .1401             | .1741             | .2030     | .2240     |

Note. The data in brackets are standard errors. A negative coefficient indicates that the variable and vulnerability to poverty are negatively correlated and vice versa. Vul1 represents the vulnerability to poverty estimated below the poverty line of US$1.9, and Vul2 represents the vulnerability to poverty estimated below the poverty line of US$3.1.

***Indicates that the coefficient is statistically significant at the level of 1%.

Table 11. Regression Results of the County-Level DFI Index.

|                | Vul1              | Vul2              |
|----------------|-------------------|-------------------|
| $Df_{i,\text{county}}$ | −0.0063*** (0.0014) | −0.0138*** (0.0026) |
| Constant term  | −0.0986*** (0.0094) | −0.1560*** (0.0179) |
| Year effect    | Yes               | Yes               |
| Household effect | Yes               | Yes               |
| N              | 11,619            | 11,619            |
| $R^2$          | .1236             | .1973             |

Note. The data in brackets are standard errors. A negative coefficient indicates that the variable and vulnerability to poverty are negatively correlated and vice versa. Vul1 represents the vulnerability to poverty estimated below the poverty line of US$1.9, and Vul2 represents the vulnerability to poverty estimated below the poverty line of US$3.1.

***Indicates that the coefficient is statistically significant at the level of 1%.

Table 12. Logit Regression Results.

|                | Vep1              | Vep2              |
|----------------|-------------------|-------------------|
| $Df$           | −0.3440*** (0.0437) | −0.3059*** (0.0361) |
| N              | 5,560             | 8,152             |

The data in brackets are standard errors. A negative coefficient indicates that the variable and vulnerability to poverty are negatively correlated and vice versa. Vep1 represents poor households below the poverty line of US$1.9, and Vep2 represents poor households below the poverty line of US$3.1.

***Indicates that the coefficient is statistically significant at the level of 1%.

**Instrumental variable method.** To best mitigate the impact of endogeneity, this paper employs two-stage least-squares (2SLS) analysis. Learning from Bartik’s (2009) practice, we construct a “Bartik instrument” in a way as shown in the model:

$$Df^\text{iv}_{i,t} = Df^\text{iv}_{i,t-1} \times \Delta Df_{i,t-1}$$

Observations of regression results: DFI still significantly impacts vulnerability to poverty. When the coefficient is negative, DFI can reduce vulnerability to poverty. The empirical result remains the same when the endogeneity issue is considered, thereby proving the robustness of the empirical analysis in this paper.

**Conclusions**

Since the reform and opening-up, China has taken huge strides in alleviating poverty and achieved extraordinary success and shall continue its efforts to secure this long-lasting achievement. By leveraging technologies such as the
internet, DFI substantially improves the convenience and accessibility of financial services, especially for rural residents who used to be excluded from traditional finance, which contributes greatly to rural poverty reduction. This paper empirically tests the impact of DFI on households’ vulnerability to poverty in China and finds that DFI development has reduced vulnerability to poverty and had a greater impact on rural groups. This paper also deep-dives into the conduction mechanism from DFI to vulnerability to poverty and finds that DFI development is more conducive to rural entrepreneurship. Finally, the analysis of the heterogeneity of income, regional financial development level, and human capital reveals that DFI is more effective in helping reduce the vulnerability to poverty of low-income, low human capital rural households in financially underdeveloped areas.

This paper confirms the significance of policies in addressing rural poverty issues. First, financial institutions should develop an overall DFI development strategy and plan and actively explore new markets. They should target farmers, self-employed entrepreneurs, and small- and micro-enterprises and other disadvantaged groups as major customers, provide them with suitable DFI products and improve DFI accessibility in rural areas. Financial institutions also need to launch diverse DFI services and products to offer more choices for customers and step up the information and financial support from DFI to rural entrepreneurship, thereby reducing vulnerability to poverty. Second, the government should promote assistance to rural areas and foster a positive environment for entrepreneurship. Farmers need resources and funds to start their business. Government support and the availability of entrepreneurial resources play an almost decisive role in farmers’ decisions on whether to start a business and how the business will end. Therefore, the government should offer favorable policies to encourage farmers to carry out entrepreneurial activities, optimize the entrepreneurial support system, and make efforts in advocacy of the positive effects of entrepreneurship. In addition, the government can attract foreign investors to rural areas with more incentives and favorable terms and help rural residents to better position themselves and embrace the outside world by taking advantage of the local natural environment and resources.

Declaration of Conflicting Interests
The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding
The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This paper is funded by the General Program “A Study on the Impact of Digital Inclusive Finance on Household’s Vulnerability of Rural China: Theoretical Mechanism and Empirical Analysis” (No. GD20CYJ41) of Philosophy and Social Sciences of Guangdong Province.

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**Table 13.** Instrumental Variable Regression Results.

|                  | Stage 1 regression | Stage 2 regression |
|------------------|--------------------|--------------------|
|                  | Dfi                | Vul1               | Vul2               |
|                  |                    |                    |
| Dfi _iv          | 1.0113*** (0.0030) |                    |                    |
| DFI              |                    | −0.0202*** (0.0011) | −0.0278*** (0.0013) |
| Constant term    | 0.2333*** (0.0313) | −0.1490*** (0.0118) | −0.1722*** (0.0142) |
| Year effect      | Yes                |                    |                    |
| Household effect | Yes                | Yes                | Yes                |
| N                | 16,876             | 16,876             | 16,876             |
| $R^2$            | 0.9191             | 0.1827             | 0.2121             |

*Note.* The data in brackets are standard errors. A negative coefficient indicates that the variable and vulnerability to poverty are negatively correlated and vice versa. Vul1 represents the vulnerability to poverty estimated below the poverty line of US$1.9, and Vul2 represents the vulnerability to poverty estimated below the poverty line of US$3.1.

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