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Digital Financial Inclusion and Farmers' Vulnerability to Poverty: Evidence from Rural China

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Abstract: Access to finance is often cited as a key factor for sustainable poverty alleviation, but expanding access to the poor remains an important challenge for financial institutions. Much hope has, therefore, been placed in the transformative power of digital financial inclusion. However, evidence on the relationship between digital financial inclusion and poverty is limited. This paper is one of the first attempts to study the effects of digital financial inclusion on farmers' vulnerability to poverty in China, using survey data on 1900 rural households. Vulnerability to poverty, here defined as the likelihood of poverty in the future, is measured by the Asset-Based Vulnerability model. In our survey, the proportion of farmers using digital financial services is 35.63%. Our estimations show that farmers' use of digital financial services have positive effects on reduction in their vulnerability. We also find that such effects rely mainly on improvement in farmers' ability to cope with risk, that is, alleviating their vulnerability induced by risk. Further investigation reveals that digital financial services provided by ICT companies have a larger impact on farmers' vulnerability than that provided by traditional banks. The lessons learned from China's digital financial inclusion is valuable for other developing countries where financial exclusion looms large.

Keywords: digital financial inclusion; risk-coping ability; vulnerability to poverty; instrumental variable estimation

1. Introduction

Expanding access to finance is often cited as one of the most important poverty alleviation policies [1]. However, it is well recognized that financial institutions face challenges in expanding access to the poor [2]. The government in China, as in many other developing counties, has actively employed numerous policies to improve financial services in rural areas [3], often with disappointing results [4]. Despite the variety of financial institutions—such as Rural Commercial Banks, Agricultural Banks, Postal Savings Banks, Village and Township Banks, and Credit-Only Companies—in Chinese rural areas [5], as pointed out by He et al. [6], farmers remain underserved or excluded by the traditional banking sector because of the fundamental questions of high transaction cost, information asymmetry, and the shortage of collateral.

Much hope has, therefore, been placed in the growth of financial digital innovations. The term "digital financial inclusion", defined as digital access to and use of formal financial services by underserved and excluded populations [7], has attracted attention from many researchers and policy makers. In particular, in 2016, when China was the leader of the G20, the G20 Global Partnership for Financial Inclusion (GPFI) developed a set of High-Level Principles (HLPs) for digital financial inclusion that encourage governments to use digital technologies to foster inclusive finance. In this decade, successful business models for digital financial inclusion have emerged worldwide, following the introduction in Kenya in 2007 of M-Pesa, a key innovation initially developed for peer-to-peer

(P2P) payment—mobile money. Using SMS, it is used mainly for money transfer and cash storage, primarily through mobile network operators [8]. The service was first expanded to Tanzania, and then to Afghanistan, South Africa, India, Romania, and most recently to Albania.

In China, digital financial inclusion differs in important ways, using a completely different model [9]. Unlike M-Pesa, mobile financial services in China are offered mainly by third-party payment platforms based on smartphone apps, such as those offered by Alipay or WeChat. In addition, digital financial inclusion is more than a payment innovation in China, which has a broad range of digital financial products and services, such as online banks, peer-to-peer (P2P) online lending, online fund sales, online crowdfunding, and online insurance [10].

Digital finance, also known as internet finance or FinTech, has experienced explosive development in China since 2013, when Yu'ebao (Yu'ebao is an online sales platform for money market funds, which was launched by Alibaba's Ant Financial Services in June 2013), an online fund sales platform was launched, and in 2016 the term "digital financial inclusion" began to draw attention when it was formally proposed in G20 HLPs. The providers of digital financial services in China can be divided into two groups—information and communication technologies (ICT) companies providing financial services, such as Alibaba or JD.com, and financial institutions applying ICT to their traditional services, such as the E-Housekeeper services of the Agricultural Bank [11], which are both crucial to financial inclusion goals [12]. In fact, providers of such financial services have actively expanded their business in rural China, including e-commerce platforms, P2P lending platforms and traditional financial institutions (see Appendix A Table A1). The Peking University Digital Finance Development Index (IFDI) shows the rapid development of digital finance at the county level across 30 provinces of China (see Appendix A Figure A1). The IFDI measures the growth in China's digital finance with rich data from Ant Financial Services. Several recent papers find a positive correlation between digital financial inclusion and rural economic activities, such as self-employment, income growth, and improvement in income distribution [13,14].

However, evidence on the relationship between digital financial inclusion and poverty reduction remains limited, especially at the micro level. This paper is one of the first attempts to provide evidence from rural China regarding the impact of digital financial inclusion on farmers' vulnerability to poverty. Vulnerability to poverty, defined here as the possibility that a household will fall below the poverty line in the future, is an ex-ante poverty indicator, while poverty represents an ex-post welfare outcome. Vulnerability to poverty is a better indicator in China, given that its government has pledged to lift all people out of poverty by 2020, when what really matters is vulnerability of a household, that is, poverty prevention is more important than alleviation. Using survey data on 1900 rural households, this paper first applies the Asset-Based Vulnerability model to measure farmers' vulnerability to poverty, then rely on an instrumental variable (IV) and two-stage least squares (2SLS) regression to study the effects of farmers' use of digital financial services on their vulnerability to poverty. We also examine the potential channels through which digital financial services may affect farmers' vulnerability to poverty.

The remainder of the paper is organized as follows. Section 2 first reviews the existing literature and then develops our hypothesis. Section 3 presents the research design. Section 4 reports the estimate results including the endogeneity tests. Section 5 presents additional robustness checks, and Section 6 concludes with a brief discussion of policy implications.

2. Literature Review and Hypothesis Development

2.1. Literature Review for Vulnerability to Poverty

The concept "vulnerability to poverty" was initially coined by the World Bank [15], which defined it as the possibility that a household will fall below the poverty line in the future. Poverty is an ex-post welfare condition, whereas vulnerability is an ex-ante poverty indicator of a household's ability to cope with risks [16,17]. In fact, the expanding literature on vulnerability has produced a multitude of definitions and corresponding approaches [18], including vulnerability as expected poverty (VEP), vulnerability as low expected utility (VEU), and vulnerability as uninsured exposure to risk (VER), among which the VEP approach is dominant [17–19]. However, as noted by Carter and Barrett [20], the VEP approach, as well as many other approaches, fails to unpack the nature and sources of vulnerability.

This paper thus adopts the Asset-Based Vulnerability approach developed by Chiwaula et al. [18], who combined the VEP approach and measured farmers' vulnerability based on their asset endowments. This approach allows us to decompose vulnerability into structural vulnerability and risk-induced vulnerability and thereby identify the sources of vulnerability. Structural vulnerability refers to a situation in which a household moves in and out of poverty in the future mainly because of changes in the level of assets (e.g., land endowment), while risk-induced vulnerability is when a household moves in and out of poverty because of positive or negative risk events [19], such as excessive rainfall or drought. It is important to distinguish structural from risk-induced vulnerability, which allows us to establish whether the farmers' vulnerability is driven by structural factors or risk events.

2.2. Literature Review on Digital Financial Inclusion

After the important stages of microcredit, microfinance and financial inclusion, the development of financial inclusion has arrived at a fourth stage: digital financial inclusion, which stresses the importance of ICT in expanding the scale and deepening the reach of financial services [7]. As the first stage, microcredit was coined initially to refer to institutions, such as the Grameen Bank of Bangladesh, that were founded to provide small loans to the poor [4]. By the early 1990s, the term "microcredit" was pushed to a much broader concept "microfinance," meaning the supply of a range of financial services, such as savings, mutual funds, insurance, loans, and so on [21]. Another important departure has involved the shift from "microfinance" to "financial inclusion," which was put forward by United Nations and CGAP in 2006. Historically, traditional financial institutions like Grameen Bank developed microcredit, microfinance and financial inclusion based on manual and field-based operation, a structure that weakened their efficiency in serving the poor [22]. Relying on ICT, the development of financial inclusion comes to a fourth stage: digital financial inclusion, a radical innovation that can be a changer for the population at the bottom of the pyramid [7,11]. As noted by Hart and Prahalad [22], doing business with population at the bottom of the pyramid requires radical innovations in technology and business models.

Digital financial inclusion refers broadly as digital access to and use of formal financial services by underserved and excluded populations [7]. This term began to attract attention mainly due to the success of M-PESA, a payment technology innovation introduced in Kenya in 2007 [8]. In Kenya, mobile money is used mainly for digital payments [23]. Several recent papers also provide some evidence on positive [8,24] or negative [23] correlations between this payment tool and economic activity. Digital financial inclusion in China, however, represents more than a payment instrument. It has been recognized as a new financial format, which includes three basic business: digital payments, digital investments, and digital financing.

The existing literature pointes out several important differences between traditional and digital financial inclusion. First, digital financial services greatly reduce transaction costs in rural areas because of their lower marginal cost [10,12,25]. Relying on ICT, such financial services need not establish physical outlets. Although new digital technologies often face higher initial costs to establish digital system, their marginal cost then tends toward zero with the increase of business volume [25,26]. Second, digital finance may overcome information asymmetry by developing ICT [27,28]. Online products and services, such as online shopping platforms and online social networks, produce a large amount of information on individuals [27], which will alleviate information asymmetry between individuals and financial institutions [13]. Finally, digital technology may improve access to credit for farmers who lack collateral [29]. Based on big data analysis, cloud computing, and other technologies, digital finance, such as P2P lending, uses new credit score mechanisms to create collateral-free loan products [25]. In summary, digital financial inclusion is considered a great method for alleviating financial constraints faced by farmers, especially those who are vulnerable [26]. In fact, the digital financial inclusion movement has made inroads around the world in the past decade. For instance, Grameen Bank, as the best-known microfinance institution, has broadly developed online business model to automate its operation [22].

2.3. Hypotheses Development

Based on the nature and sources of vulnerability to poverty, as mentioned above, the literature notes that farmers' vulnerability can be directly decomposed into two parts: structural vulnerability, in which households remain at a low level of consumption in the future because they have low asset endowments, and risk-induced vulnerability, in which households face consumption fluctuations in the future because of stochastic events. Figure 1 motivates our research by revealing these two channels through which digital financial inclusion affects farmers' vulnerability.

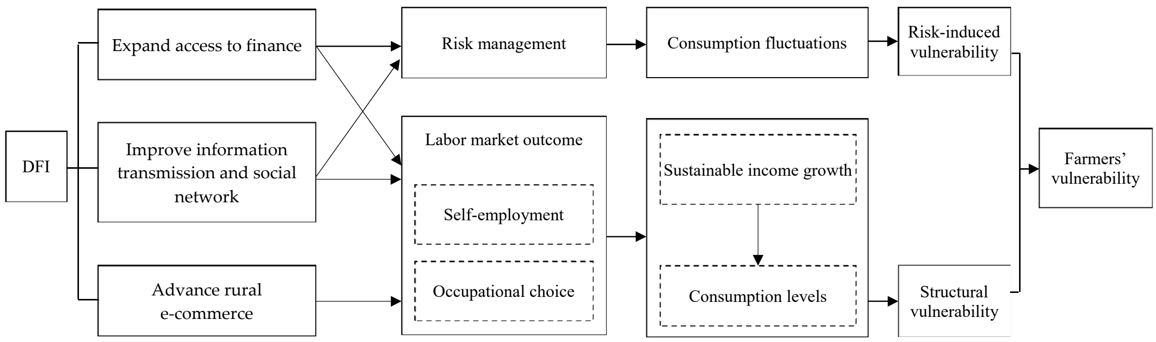

Figure 1. Logit Relationship between Digital Financial Inclusion (DFI) and Farmers' Vulnerability.

Access to digital financial services provides farmers with a more proactive way to cope with risks and thereby reduces fluctuations in their consumption and vulnerability. The intuition for this "primary impact channel" is first related to digital financing, through which farmers who lack collateral can expand access to formal loans based on big data analysis. Internet technology enables a rich information database to be established rapidly. The database in rural China includes three categories: direct credit data collected by traditional banks, information on individuals collected from online platforms, such as e-commerce platform and online social networks, and public information collected by governments, such as tax and social security records. Second, digital technology, as a way of lowering participation costs, makes it easier for farmers to manage their cash flows and savings and thereby improve their ability to cope with risk [30]. In addition, through associated internet-based financial services, farmers can draw on a wider network of social support in response to negative shocks, because they can receive more remittances more quickly from more people [31].

Farmers with higher use of digital finance are more likely to achieve sustainable income growth and consumption improvement through labor market outcomes, a "secondary impact channel". First, having a smaller asset endowment is often cited as the key reason the poor remain poor, especially small farmers. Thus, access to finance plays a fairly important role in both initial investment in production activities and their subsequent expansion [32]. Digital financing, as He and Li [14] noted, enables Chinese farmers to transform and expand their production activities. In addition, the use of digital financial services may improve information transmission and expand social networks, both of which are key factors for small farmers. Second, as the Klapper and Singer [31] reported, digital finance is a critical factor in advancing the expansion of e-commerce, which creates more opportunities and changes occupational choices. It allows farmers to move out of agriculture and into business and thereby obtain sustainable income growth [33].

Based on the theoretical analysis, our hypotheses can therefore be stated as follows:

H1: *Farmers' use of digital financial services has positive effects on alleviating their vulnerability to poverty.*

H2a: *Risk management is a potential channel through which digital financial services affect fluctuations in consumption and thereby alleviate farmers' vulnerability induced by risk events, that is, risk-induced vulnerability.*

H2b: *The labor market outcome is a potential channel through which digital financial services affect consumption levels and thereby alleviate farmers' vulnerability induced by structural factors, that is, structural vulnerability.*

3. Research Design

3.1. Sample and Data

In this paper, we rely on the China Rural Financial Inclusion Survey Data 2018, conducted by the China Agricultural University, which includes a set of questions on the use of digital financial services. The data were collected through a stratified random sample survey of 1979 rural households through face-to-face interviews in July 2018. The survey was designed and conducted as follows: first, we selected Shandong, Henan and Guizhou provinces in the eastern, central, and western regions of China, respectively; second, in each province, we chose three counties based on their level of gross domestic product per capita; third, in each county, we chose three townships based on their level of economic development; and, fourth, in every township, we randomly chose two villages, in which the number of farm households is between 30 and 50. After deleting questionnaires with missing data, we ended up with 1900 valid samples for analysis (see Table 1).

Table 1. Districts studied and sample size.

Province	Shandong	Henan	Guizhou	Total
Counties	3	3	3	9
Townships (three per county)	9	9	9	27
Villages (two per township)	18	18	18	54
Farmers in all villages	666	691	543	1900

3.2. Variable Definition and Measurement

3.2.1. Measuring Farmers' Use of Digital Financial Services

Payment, investment, and financing are key aspects of digital financial inclusion. Therefore, following Guo et al. [10] and He and Li [14], we measure farmers' use of digital financial services in terms of digital payments, digital investments, and digital financing. The corresponding survey questions are shown in Table 2.

Table 2. Questions and possible responses about the use of digital financial services.

Type	Questions and Possible Responses
Payment	Question 1: Which digital payment methods have you used? a. online banking transfer; b. mobile banking transfer; c. Alipay; d. Wechat pay; e. other digital payment methods; f. none
Investment	Question 2: Have you invested in the following financial products? a. bonds; b. funds; c. bank wealth management products; d. foreign assets; e. gold; f. derivatives; g. stocks; h. online investment; i. online crowdfunding; j. none
financing	Question 3: Have you ever used the internet to borrow money or to raise money? a. yes; b. no

In Question 1, digital payment takes a value of 1 for any response other than f, and 0, otherwise. In Question 2, digital investment takes a value of 1 for any response other than i or j, and 0, otherwise. In Question 3, digital financing takes a value of 1 if the response is a, and 0, otherwise. Digital financial services use here is a dummy variable that equals 1 if the value of digital payment, digital investment, or digital financing is 1, which means that the respondent has used digital financial services, and 0, otherwise.

In our sample, the proportion of farmers using digital financial services is 35.63%. The proportion of farmers using digital payment instruments is 35.58%. The proportion of farmers using digital investment and digital financing is 0.3% and 0.6%, respectively, both of which are relatively low compared with digital payment. These results are similarly to those of a study on the Global Findex Database 2017 [9], which shows that in China 40% of adults in rural and urban areas use digital payment.

3.2.2. Measuring Farmers' Vulnerability to Poverty

This paper applies the Asset-Based Vulnerability Approach, proposed by Chiwaula et al. [18], to measure farmers' vulnerability to poverty. Carter and Barrett [20] developed an Asset-Based Poverty Approach that established a functional relationship between assets and welfare indicators, such as consumption. The Asset-Based Vulnerability Approach introduces risk to the Asset-Based Poverty Approach by incorporating the variance of income or consumption [18]. Defined as the likelihood that a household will move into or out of poverty in the future, farmers' vulnerability can be calculated as

$$V_h = \Pr(V_h \leq Z) = \begin{cases} 0 & if \left[\hat{E}(C_h) - \sqrt{\hat{V}(C_h)}\right] \geq Z \\ \frac{Z - \left[\hat{E}(C_h) - \sqrt{\hat{V}(C_h)}\right]}{2\sqrt{\hat{V}(C_h)}} & if \left[\hat{E}(C_h) - \sqrt{\hat{V}(C_h)}\right] < Z \leq \left[\hat{E}(C_h) + \sqrt{\hat{V}(C_h)}\right] \\ 1 & if \left[\hat{E}(C_h) + \sqrt{\hat{V}(C_h)}\right] \leq Z \end{cases} \quad (1)$$

where V_h is a household's vulnerability to poverty. $\Pr(\cdot)$ is the likelihood that household consumption will fall below the poverty line in the future. Z is the poverty line, and C_h is per capita consumption expenditure. $\hat{E}(C_h)$ of a given household is structural (or expected) consumption, and the approach assumes that this structural consumption is defined by the household stock of assets. $\sqrt{\hat{V}(C_h)}$ is the standard deviation of structural consumption. $\hat{E}(C_h) - \sqrt{\hat{V}(C_h)}$ is the lower consumption bound, and $\hat{E}(C_h) + \sqrt{\hat{V}(C_h)}$ is the upper consumption bound. In the presence of risk, household consumption has stochastic variations between the upper and lower bounds.

The approach applies model (1) to measure a specific household's vulnerability and uses a 50% cut-off to identify the structural and risk-induced vulnerability to poverty. The different categories are defined as:

a. Structural vulnerability ($StruV_h$), if $V_h \geq 0.5$
b. Risk-induced vulnerability ($RiskV_h$), if $0 < V_h \leq 0.5$
c. Never poor, if $V_h = 0$

Furthermore, the approach specifies an asset-based consumption Equation (2), which allows us to estimate expected consumption $\hat{E}(C_h)$ and variance in consumption $\hat{V}(C_h)$ using a three-step feasible generalized least squares (FGLS) procedure. (Following Chiwaula et al. [18], the first step of FGLS applies ordinary least squares (OLS) to estimate Equation (2). In the second step, the log of the squared residuals is regressed on the same variables as in the first step. The last step corrects for inefficiency of the OLS model by weighting it with the square root of the predicted values of the second step.) The equation is specified as follows:

$$\ln(C_h) = \beta_0 + \beta_1 Asset_h + \beta_2 X_h + e_h \quad (2)$$

where C_h is per capita consumption expenditure. Here, $Asset_h$ is understood to broadly include productive capital, human capital, financial capital, and social capital. X_h represents a number of control variables.

Using the FGLS estimation, this approach predicts $\hat{E}(C_h)$ and $\hat{V}(C_h)$, which we apply to estimate a household's vulnerability level.

We then calculate V_h, a household's vulnerability, using the Chinese poverty line of RMB 2300 and the international poverty line of $1.90 USD, respectively. In our sample, based on the international poverty line, the average vulnerability is 0.03, which is lower than 0.08, the result derived by Wan et al. [33], who used the same approach to calculate Chinese farmers' vulnerability in 2004. The decomposition of the vulnerability in our study, as in theirs, shows that the proportion of farmers with structural vulnerability and risk-induced vulnerability is 0.79% and 12.37%, respectively. The results-based poverty line of RMB 2300 remain unchanged.

3.2.3. Control Variables

This study includes three categories of control variables: household characteristics, household-head characteristics, and the ability to manage risk. Household characteristics include household size, labors, and land area. Household-head characteristics include age, education level, and financial literacy. The ability to manage risk includes job security, access to formal bank loans, and informal insurance networks. The definitions of these variables and descriptive statistics are in Table 3. To reduce noise in the data, we drop the top and bottom 0.05% outliers on the continuous variables.

Table 3. Definition and description of variables.

Variable Labels	Definition of Variables	Mean	S.D.	Min	Max
size	Household size	4.319	1.767	1	10
labor	Proportion of labor in a household	0.416	0.293	0	1
land	Land area (measured in mu [a])	5.436	4.496	0	24.25
h_age	Age of household head	51.330	12.360	21	77
h_age^2	Age of household head, squared	2787	1240	441	5929
h_edu	Education of household head (1 = 0–8 years of education; 2 = 9–15 years of education; 3 = >15 years of education)	1.614	0.535	1	3
h_finknow	Level of financial knowledge by household head (1 = lowest; 2 = low; 3 = high; 4 = highest)	0.550	0870	0	4
worksecur	Number of migrant workers	0.941	1.014	0	4
fincap	Having access to bank loans or not (1 = yes; 0 = no)	0.800	0.400	0	1
socialcap	Number of relatives proving assistance	7.771	8.118	0	40

[a] One mu equals to 666.666 m^2.

3.3. Econometric Model

To test H1, we construct the following Ordinary Least Squares (OLS) regression model:

$$V_h = \alpha_0 + \alpha_1 DFI_h + \alpha_2 X_h + \varepsilon_h \quad (3)$$

where h is a household. V_h is farmers' vulnerability calculated on basis of the Chinese poverty line of RMB 2300 and the international poverty line of $1.90, respectively; the range is [0, 1]. DFI_h equals 1 if a household uses digital financial services, and 0, otherwise. X_h represents additional control variables, and ε_h is the error term.

The OLS estimate may be biased for various reasons, such as omitted-variable bias or reverse causality. In order to address these potential problems, we instrument the digital financial services use index with the average value of the digital financial services use index of the same age group in the same county. Following Bucher and Lusardi [34] and He and Li [14], we assume that famers are more likely to use digital financial services when they are exposed to an environment in which many other people use them (this is beyond the control of the respondent). The age groups are divided as follows: 18–30, 40–50, 50–60, and over 60.

To test H2, we construct the following Logit regression model:

$$\mathrm{Prob}(Vtype_h = k|DFI_h, X_h) = \frac{exp(\alpha_0 + \alpha_1 DFI_h + \alpha_2 X_h + \varepsilon_h)}{1 + \sum_{k=1}^{K} exp(\alpha_0 + \alpha_1 DFI_h + \alpha_2 X_h + \varepsilon_h)} \quad (4)$$

where k takes a value of 0 if a household will never be poor, a value of 1 if a household has risk-induced vulnerability, and a value of 2 if a household has structural vulnerability. Other variables are the same as in model (3).

4. Empirical Results

4.1. Does Digital Financial Inclusion Have an Effect on Farmers' Vulnerability?

We first investigate the impact of farmers' use of digital financial services on their vulnerability to poverty. Table 4 presents the regression results of OLS. Columns (1) to (3) in Table 4 use farmers' vulnerability calculated on basis of the Chinese poverty line of RMB 2300 as dependent variables. All estimations control for county dummy variables. Column (1) shows the relationship without other control variables. In column (2), we gradually add the relatively exogenous control variables, such as household size, dependency ratio, land area, and age of household head. In column (3), we control for all variables. Similarly, columns (4) to (6) in Table 4 use vulnerability calculated according to the international poverty line of $1.90 as dependent variables, which are also results of OLS regressions.

Table 4. Impacts of farmers' use of digital financial services on their vulnerability to poverty: OLS results.

Poverty line	**RMB 2300 a Year Per Capita**			**$1.90 a Day Per Capita**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
DFI	−0.032 ***	−0.009 ***	−0.006 **	−0.032 ***	−0.009 ***	−0.006 *
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
size		0.018 ***	0.019 ***		0.017 ***	0.019 ***
		(0.002)	(0.002)		(0.002)	(0.002)
labor		0.028 ***	0.018 ***		0.027 ***	0.018 ***
		(0.006)	(0.006)		(0.006)	(0.005)
land		−0.001 ***	−0.001 ***		−0.001 ***	−0.001 ***
		(0.000)	(0.000)		(0.000)	(0.000)
h_age		−0.006 ***	−0.006 ***		−0.006 ***	−0.006 ***
		(0.001)	(0.001)		(0.001)	(0.001)
h_age^2		0.000 ***	0.000 ***		0.000 ***	0.000 ***
		(0.000)	(0.000)		(0.000)	(0.000)
h_edu			−0.015 ***			−0.015 ***
			(0.003)			(0.003)
h_finknow			0.002			0.002
			(0.001)			(0.001)
worksecur			−0.006 ***			−0.006 ***
			(0.002)			(0.002)
fincap			−0.014 ***			−0.014 ***
			(0.005)			(0.005)
socialcap			−0.000			−0.000
			(0.000)			(0.000)
County	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1900	1900	1900	1900	1900	1900
R-squared	0.084	0.304	0.320	0.084	0.303	0.319

Note: The poverty lines are adjusted according to purchasing power parity (PPP) according to the World Bank in 2015 and the Chinese consumer price index (CPI) of rural residents in 2017. Robust standard errors are in parentheses. ***, **, * denote the significance at 1%, 5% and 10% level, respectively.

The results in Table 4 indicate that the use of digital financial services is likely to reduce farmers' vulnerability to poverty regardless of which poverty line is considered. In columns (1) to (3) in Table 4, the coefficients of *DFI* are significantly negative whether with or without control variables, suggesting that farmers' use of digital financial services have positive effects on reducing their vulnerability to poverty. Results in columns (4) to (6) in Table 4 show that the relationship between digital financial services use and farmers' vulnerability remains negative and statistically significant. Suri and Jack [24] obtain similar results, finding that using mobile money in Kenya has a significant impact on poverty reduction. Their analysis focuses mainly on digital payments, whereas ours considers digital payment as well as digital investment and digital financing.

Considering that the OLS regression may be biased, we further rely on an instrumental variable (IV) mentioned in Section 3 and two-stage least squares (2SLS) regression to deal with potential endogeneity. Table 5 presents both first- and second-stage 2SLS regression results. The 2SLS models here use vulnerability based on the poverty lines of RMB 2300 and $1.90 USD, as in the OLS models in Table 4. At the same time, we also gradually added the controls variables in the 2SLS models. The first-stage regressions in columns (1) to (6) in Table 5 show that the Cragg–Donald F-statistics and Hansen *J*-statistics are significant, suggesting that our IV is valid. The second-stage regressions in columns (1) to (6) show that the coefficients of *DFI* are significantly negative, which confirms the relationship between digital finance and vulnerability while mitigating endogeneity concerns.

Table 5. Impacts of farmers' use of digital financial services on their vulnerability to poverty: 2SLS results.

Poverty Line	**RMB 2300 a Year Per Capita**			**$1.90 a Day Per Capita**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
				2SLS_Second Stage		
DFI	−0.075 ***	−0.035 **	−0.032 *	−0.074 ***	−0.035 **	−0.032 *
	(0.007)	(0.015)	(0.018)	(0.007)	(0.015)	(0.018)
Exogenous control variables		Yes	Yes		Yes	Yes
Potential endogenous control variables			Yes			Yes
County	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1900	1900	1900	1900	1900	1900
R-squared	0.031	0.291	0.308	0.031	0.290	0.307
				2SLS_First Stage		
Average *DFI* of same age group in the same township	1.000 ***	0.694 ***	0.543 ***	1.000 ***	0.694 ***	0.543 ***
	(0.025)	(0.068)	(0.067)	(0.025)	(0.068)	(0.067)
Cragg–Donald *F*-statistic	929.735	115.223	73.174	929.735	115.223	73.174
Hansen *J*-statistic	0.000	0.000	0.000	0.000	0.000	0.000

Note: The poverty lines are adjusted according to purchasing power parity (PPP) according to the World Bank in 2015 and the Chinese consumer price index (CPI) of rural residents in 2017. Exogenous control variables and Potential endogenous control variables are the same as in Table 4. For more details on the impact of control variables on vulnerability, see Appendix A Table A2. Robust standard errors are in parentheses. ***, **, * denote the significance at 1%, 5% and 10% level, respectively.

4.2. How Does Digital Financial Inclusion Affect Vulnerability: Structural or Risk-Induced?

The regression results above show the positive impact of farmers' use of digital financial services on reduction in their vulnerability. In this section, we go one step further by investigating the channels through which digital financial services play a role in reducing farmers' vulnerability. We decompose vulnerability into structural vulnerability induced by the low asset endowments and risk-induced vulnerability due to stochastic events. Table 6 presents the Logit regression results for vulnerability with the poverty line of RMB 2300 in Panel A and $1.90 USD in Panel B, respectively.

Table 6. Impact Channels of Digital Financial Services on Farmers' Vulnerability.

Panel A	**RMB 2300 a Year Per Capita**					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	$RiskV_h$	$StruV_h$	$RiskV_h$	$StruV_h$	$RiskV_h$	$StruV_h$
DFI	−2.314 ***	−15.447	−1.586 ***	−14.916	−1.329 ***	−15.038
	(−8.150)	(−0.020)	(−3.960)	(−0.030)	(−3.110)	(−0.020)
Exogenous controls			Yes	Yes	Yes	Yes
Possible endogenous controls					Yes	Yes
County	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1900		1900		1900	1900
Panel B	**$1.90 USD a Day Per Capita**					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	$RiskV_h$	$StruV_h$	$RiskV_h$	$StruV_h$	$RiskV_h$	$StruV_h$
DFI	−2.297 ***	−15.682	−1.564 ***	−16.509	−1.299 ***	−14.998
	(−8.100)	(−0.020)	(−3.910)	(−0.020)	(−3.050)	(−0.020)
Exogenous controls			Yes	Yes	Yes	Yes
Possible endogenous controls					Yes	Yes
County	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1900	1900	1900	1900	1900	1900

Note: For more details on the impact of control variables on vulnerability, see Appendix A Table A3. Robust standard errors are in parentheses. *** denotes the significance at 1% level.

The results in Table 6 indicate a significant and positive impact of digital financial services use on reducing risk-induced vulnerability, suggesting that digital financial inclusion may alleviate poverty vulnerability primarily through the channel of coping with risk. Panel A in Table 6 shows that the coefficients of *DFI* are negative and significant at the 1% level in columns (1), (3), and (5), while the coefficients of *DFI* are not significant in columns (2), (4), and (6). These results indicate that the use of digital financial services has a significant impact only on risk-induced vulnerability. The results in Panel B in Table 6 show that the coefficients of *DFI* are negative and significant at the 1% level only in columns (1), (3), and (5), which is consistent with the results in Panel A. Zhang and Yin [35] obtain similar results, finding that financially inclusive services provided by commercial banks have a greater impact on farmers' risk-induced vulnerability than on structural vulnerability.

4.3. Further Analysis: Different Providers of Digital Financial Services

The providers of digital financial services in China can be divided into two groups—ICT companies providing financial services, and financial institutions applying ICT to their traditional services [11,36]. Compared with traditional banks, the ICT companies have a comparative advantage in information technology and collection mechanisms. Having established that farmers' use of digital financial services has a positive effect on reducing their vulnerability to poverty, we further investigate whether digital financial services provided by ICT (*DFI_ICT*) have a larger impact than that provided by traditional banks (*DFI_Bank*). We measure *DFI_ICT* and *DFI_Bank* based on Question 1 in Table 3. In Question 1, *DFI_ICT* takes a value of 1 if the response is c or d, and 0, otherwise; *DFI_Bank* takes a value of 1 if the response is a or d, and 0, otherwise. At the same time, we also separately instrument the *DFI_ICT* and *DFI_Bank* index with the average value of the *DFI_ICT* and *DFI_Bank* index of the same age group in the same township.

We separately investigate the impact of *DFI_ICT* and *DFI_Bank* on farmers' vulnerability to poverty. Table 7 presents both OLS and second-stage 2SLS regression results. The Cragg–Donald *F*-statistics and Hansen *J*-statistics are significant, suggesting that our IV is valid. The results in Table 7 shows that the coefficients of *DFI_ICT* are significantly negative in Columns (2), (4), (6), and (8), while the coefficients of *DFI_Bank* are not significant in Columns (1), (3), (5), and (7). These results indicate that different providers of digital financial services result in a heterogeneous effect, and only *DFI_ICT* has a positive effect on reducing farmers' vulnerability to poverty.

Table 7. Impacts of different providers of digital financial services on farmers' vulnerability.

Poverty Line	RMB 2300 a Year Per Capita				$1.90 a Day Per Capita			
	OLS		2SLS_Second Stage		OLS		2SLS_Second Stage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DFI_Bank	0.003		0.014		0.003		0.014	
	(0.003)		(0.014)		(0.003)		(0.014)	
DFI_ICT		−0.005 *		−0.037 *		−0.005 *		−0.037 *
		(0.003)		(0.019)		(0.003)		(0.019)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1900	1900	1900	1900	1900	1900	1900	1900
R-squared	0.320	0.320	0.318	0.301	0.318	0.319	0.317	0.300
Cragg–Donald *F*-statistic			132.328	70.253			132.328	70.253
Hansen *J*-statistic			0.000	0.000			0.000	0.000

Note: Robust standard errors are in parentheses. * denotes the significance at 10% level.

5. Additional Robustness Checks

Our main results above show that farmers with higher use of digital finance are associated with lower vulnerability, a finding that is robust to the different choices of poverty line and to instrumental variable estimation. In this section, we present further robustness checks and these results further confirm the positive effect of digital financial inclusion on reduction in farmers' vulnerability to poverty.

First, we use an alternative variable to measure farmers' use of digital financial services in order to reduce the possibility of measurement error. Specially, we construct the frequency of farmers' use of digital payments (*DP_Num*) based on the following survey question.

Question 4: How often do you use the digital payment?

a. Never; b. Only once or twice; c. Sometimes; d. Often

In Question 4, *DP_Num* takes a value of 0 if the response is a, 1 if the response is b, 2 if the response is c, and 3 if the response is d. We instrument the *DP_Num* index with the average value of the *DP_Num* index of the same age group in the same township. Results of OLS and 2SLS regressions in Table 8 show that *DP_Num* has a significant impact on farmers' vulnerability regardless of which poverty line is considered.

Table 8. Impacts of frequency of farmers' use of digital payments on their vulnerability.

Poverty Line	RMB 2300 a Year Per Capita			$1.90 USD a Day Per Capita		
	OLS	2SLS_First	2SLS_Second	OLS	2SLS_First	2SLS_Second
	(1)	(2)	(3)	(4)	(5)	(6)
DP_Num	−0.004 ***		−0.036 ***	−0.004 ***		−0.035 ***
	(0.001)		(0.012)	(0.001)		(0.012)
Average *DP_Num* in same age group in the same township		0.647 ***			0.647 ***	
		(0.084)			(0.084)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1900	1900	1900	1900	1900	1900
R-squared	0.321	0.269	0.261	0.319	0.269	0.260
Cragg–Donald *F*-statistic		67.401			67.401	
Hansen *J*-statistic		0.000			0.000	

Note: Robust standard errors are in parentheses. *** denotes the significance at 1% level.

Second, we further calculate farmers' vulnerability according to a higher international poverty lines of $3.20 USD, which is more typical of national poverty lines found in lower income economies. Results of OLS and 2SLS regressions in Table 9 show that the coefficients of *DFI* remain significantly negative while using the higher international poverty lines.

Table 9. Impacts of farmers' use of digital financial services on their vulnerability to poverty (poverty line: $3.20 USD a day per capita).

	OLS	2SLS_First	2SLS_Second
	(1)	(2)	(3)
DFI	−0.033 ***		−0.107 **
	(0.008)		(0.045)
Average *DFI* of same age group in the same township		0.543 ***	
		(0.067)	
Controls	Yes	Yes	Yes
Counties	Yes	Yes	Yes
Observations	1900	1900	1900
R-squared	0.575	0.417	0.561
Cragg–Donald *F*-statistic		73.174	
Hansen *J*-statistic		0.000	

Note: Robust standard errors are in parentheses. ***, ** denote the significance at 1% and 5% level, respectively.

6. Conclusions and Policy Implication

After the important stages of microcredit, microfinance, and financial inclusion, the development of financial inclusion has arrived at a fourth stage: digital financial inclusion, which has experienced explosive growth in China. However, evidence on the relationship between digital financial inclusion and poverty reduction remains limited, especially at the micro level. Using survey data on 1900 farmers in rural China, this paper sheds light on this relationship and its potential impact channels. The main conclusions are as follows.

First, farmers' broader participation in digital financial inclusion has a sizable positive effect on reduction in their vulnerability. Our empirical results show that farmers' vulnerability tends to be alleviated as a result of the use of digital financial services. Digital financial services are different from traditional financial services and have a great potential to expand farmers' access to finance. It also has a potential impact on information transmission, social networks and e-commerce.

Furthermore, the effect of digital financial services provided by ICT companies is more pronounced than that provided by traditional banks. We split the sample based on the provider types and the results show that digital financial services provided only by ICT companies have a statistically significant effect. Compared with traditional banks, the ICT companies have a comparative advantage in information technology and collection mechanisms, which further strengthens the potential impact of digital financial services on information transmission, social networks and e-commerce.

Second, our results shed a light on a channel through which digital financial inclusion reduces farmers' vulnerability. To investigate the potential impact channels, we decompose farmers' vulnerability into structural vulnerability induced by asset endowments and risk-induced vulnerability due to risk events. Our empirical results show that the use of digital financial services has a significant impact on risk-induced vulnerability but not on structural vulnerability. These results, as a theoretical prediction, highlight the channel of ability to cope with risk through which digital financial inclusion can reduce fluctuations in consumption and thereby alleviate farmers' vulnerability.

Our results have important policy implications. One direct policy implication is that farmers' access to and use of digital financial services, especially digital financing, should be expanded. First, more targeted efforts and programs may be needed to improve farmers' understanding of digital financing. According to our survey data, 80.76% of the respondents seemed unwilling to borrow money through the P2P platforms or online banks because they were unfamiliar with the tools or worried about security. Therefore, financial knowledge is as important as infrastructure, such as the internet penetration rate or smartphone, for expanding farmers' participation in digital financial inclusion. Second, a rich information database is one of the most important parts of the development of digital financial models. To improve information transmission and collection, policy makers should stimulate the development of rural e-commerce, which provides invaluable data about farmers' buying habits, as well as selling conditions. For instance, based on the rich data on buyers and sellers collected from the e-commerce platform, Ant Financial of the Alibaba Group established three digital financial products targeting farmers in rural areas. At the same time, local governments can support the availability of information by establishing a public information sharing system, including direct credit information, such as credit default records, and indirect information, such as tax and social security records.

In addition, paying attention to the effect of digital financial services on sustainable income growth is crucial if policy makers wish to reduce farmers' vulnerability through digital financial inclusion. Our results show that digital financial services have little impact on labor market outcomes which has a direct effect on structural vulnerability induced by lower asset endowments. This is consistent with the evidence showing that digital finance reduces the level of farmers' demand for credit for production but that increases their demand for credit for consumption [37]. Therefore, more targeted products and services for credit for production should be encouraged to expand in China's rural areas.

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Appendix A

Table A1. Key providers of digital financial services in rural areas in China.

Types of Providers	Examples of Providers	Main Online Services
e-commerce platforms	Ant Financial Services [a]	Payment, Insurance, Lending
	JD.com [b]	Investment, Crowdfunding, Lending
P2P lending platforms	CreditEase [c]	Lending
	Yi Longdai [d]	Lending
Financial institutions	Agricultural Bank of China [e]	E-Housekeeper app including payment, investment, lending, and other services

[a] Ant Financial Services of Alibaba group has produced three products for rural areas: Wangnong payment, Wangnong insurance, and Wangnong Lending, which have reached RMB 180 million, RMB 1.5 billion, and RMB 213 billion, respectively, at the end of June 2017. [b] JD.com proposed "Finance to Country" strategy in 2015, since which its digital financial services have involved 1700 counties and 300,000 villages. [c] CreditEase, as the largest P2P firm in the world, has a lending product targeting at farmers' financial demand for their production and entrepreneurship. [d] Yi Longdai is a P2P platform proving online lending primarily for rural areas. [e] To develop digital finance in rural areas, this bank designed a smartphone app—E-Housekeeper—through which farmers can expand access to payment, investment, lending and other services without physical outlets.

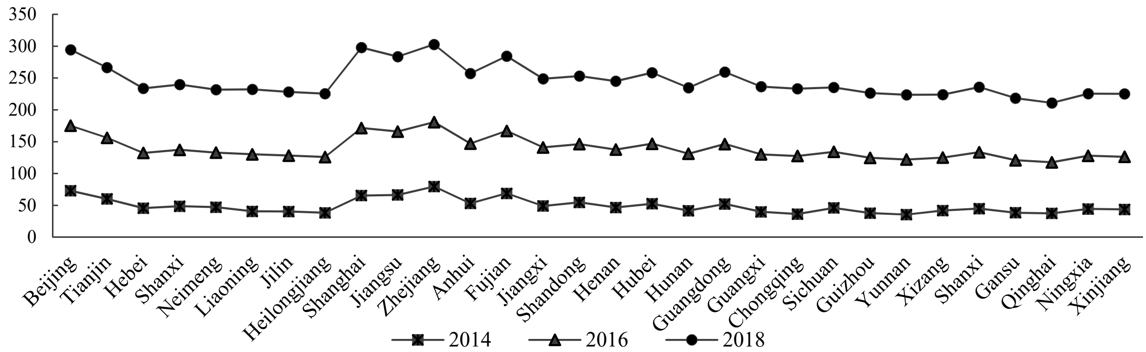

Figure A1. County-level digital finance development index across 30 provinces, 2014 to 2018. Source: authors' calculations based on the Peking University IFDI.

Table A2. Impacts of digital inclusive finance on vulnerability to poverty: 2SLS results.

Poverty Line	RMB 2300 a Year Per Capita			$1.90 USD a Day Per Capita		
	(1)	(2)	(3)	(4)	(5)	(6)
			2SLS_second stage			
DFI	−0.075 ***	−0.035 **	−0.032 *	−0.074 ***	−0.035 **	−0.032 *
	(0.007)	(0.015)	(0.018)	(0.007)	(0.015)	(0.018)
size		0.018 ***	0.020 ***		0.018 ***	0.019 ***
		(0.002)	(0.002)		(0.002)	(0.002)
labor		0.027 ***	0.018 ***		0.027 ***	0.018 ***
		(0.006)	(0.005)		(0.006)	(0.005)
land		−0.001 ***	−0.001 ***		−0.001 ***	−0.001 ***
		(0.000)	(0.000)		(0.000)	(0.000)
h_age		−0.007 ***	−0.007 ***		−0.007 ***	−0.007 ***
		(0.001)	(0.001)		(0.001)	(0.001)
h_age^2		0.000 ***	0.000 ***		0.000 ***	0.000 ***
		(0.000)	(0.000)		(0.000)	(0.000)
h_edu			−0.012 ***			−0.012 ***
			(0.004)			(0.004)
h_finknow			0.005 *			0.005 *
			(0.002)			(0.002)
worksecur			−0.007 ***			−0.007 ***
			(0.002)			(0.002)
fincap			−0.013 ***			−0.013 ***
			(0.005)			(0.005)
socialcap			−0.000			−0.000
			(0.000)			(0.000)
County	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1900	1900	1900	1900	1900	1900
R-squared	0.031	0.291	0.308	0.031	0.291	0.307
			2SLS_first stage			
instrument	1.000 ***	0.694 ***	0.543 ***	1.000 ***	0.694 ***	0.543 ***
	(0.025)	(0.068)	(0.067)	(0.025)	(0.068)	(0.067)
size		0.004	0.008		0.004	0.008
		(0.005)	(0.005)		(0.005)	(0.005)
labor		−0.048	−0.026		−0.048	−0.026
		(0.030)	(0.030)		(0.030)	(0.030)
land		0.001	−0.001		0.001	−0.001
		(0.002)	(0.002)		(0.002)	(0.002)
h_age		−0.016 ***	−0.015 ***		−0.016 ***	−0.015 ***
		(0.005)	(0.005)		(0.005)	(0.005)
h_age^2		0.000 *	0.000 *		0.000 *	0.000 *
		(0.000)	(0.000)		(0.000)	(0.000)

Table A2. *Cont.*

Poverty Line	RMB 2300 a Year Per Capita			$1.90 USD a Day Per Capita		
	(1)	(2)	(3)	(4)	(5)	(6)
h_edu			0.079 ***			0.079 ***
			(0.018)			(0.018)
h_finknow			0.097 ***			0.097 ***
			(0.011)			(0.011)
worksecur			−0.014			−0.014
			(0.010)			(0.010)
fincap			0.040 *			0.040 *
			(0.021)			(0.021)
socialcap			0.003 ***			0.003 ***
			(0.001)			(0.001)
County	Yes	Yes	Yes	Yes	Yes	Yes
Cragg–Donald *F*-statistic	929.735	115.223	73.174	929.735	115.223	73.174
Hansen *J*−statistic	0.000	0.000	0.000	0.000	0.000	0.000

Note: Robust standard errors in parentheses: ***, **, * denote the significance at 1%, 5% and 10% level, respectively.

Table A3. Impact mechanism of digital finance on vulnerability to poverty.

Panel A	RMB 2300 a Year Per Capita					
	(1)	(2)	(3)	(4)	(5)	(6)
	$RiskV_h$	$StruV_h$	$RiskV_h$	$StruV_h$	$RiskV_h$	$StruV_h$
DFI	−2.314 ***	−15.447	−1.586 ***	−14.916	−1.329 ***	−15.038
	(−8.150)	(−0.020)	(−3.960)	(−0.030)	(−3.110)	(−0.020)
size			1.083 ***	2.276 ***	1.272 ***	2.516 ***
			(0.080)	(0.286)	(0.096)	(0.342)
labor			4.084 ***	17.734 ***	3.874 ***	16.557 ***
			(0.521)	(3.633)	(0.567)	(3.950)
land			−0.123 ***	−0.289 **	−0.136 ***	−0.313 **
			(0.029)	(0.135)	(0.031)	(0.146)
h_age			0.202 *	0.371	0.220 *	0.173
			(0.114)	(0.761)	(0.122)	(0.825)
h_age^2			−0.000	−0.000	−0.001	0.001
			(0.001)	(0.006)	(0.001)	(0.006)
h_edu					−1.162 ***	−1.851 *
					(0.240)	(1.026)
h_finknow					−0.331 *	−1.141
					(0.196)	(1.263)
worksecur					−0.316 **	−0.338
					(0.127)	(0.468)
finca					−0.351	−2.429 **
					(0.258)	(1.057)
socialcap					−0.037 **	0.089
					(0.018)	(0.102)
County	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1900	1900	1900	1900	1900	1900

Table A3. *Cont.*

Panel B	$1.90 USD a Day Per Capita					
	(1)	(2)	(3)	(4)	(5)	(6)
	$RiskV_h$	$StruV_h$	$RiskV_h$	$StruV_h$	$RiskV_h$	$StruV_h$
DFI	−2.297 ***	−15.682	−1.564 ***	−16.509	−1.299 ***	−14.998
	(−8.100)	(−0.020)	(−3.910)	(−0.020)	(−3.050)	(−0.020)
size			1.083 ***	2.273 ***	1.264 ***	2.504 ***
			(0.080)	(0.286)	(0.095)	(0.342)
labor			4.125 ***	17.775 ***	3.917 ***	16.596 ***
			(0.523)	(3.636)	(0.568)	(3.954)
land			−0.120 ***	−0.286 **	−0.132 ***	−0.309 **
			(0.029)	(0.134)	(0.031)	(0.146)
h_age			0.193 *	0.362	0.211 *	0.161
			(0.113)	(0.760)	(0.121)	(0.825)
h_age^2			−0.000	−0.000	−0.000	0.002
			(0.001)	(0.006)	(0.001)	(0.006)
h_edu					−1.108 ***	−1.794 *
					(0.238)	(1.024)
h_finknow					−0.355 *	−1.160
					(0.196)	(1.262)
worksecur					−0.311 **	−0.332
					(0.127)	(0.469)
fincap					−0.320	−2.398 **
					(0.258)	(1.056)
socialcap					−0.035 *	0.091
					(0.018)	(0.102)
County	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1900	1900	1900	1900	1900	1900

Note: Robust standard errors in parentheses: ***, **, * denote the significance at 1%, 5% and 10% level, respectively.

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