Rainfall Risk and Nonfarm Self-employment in Rural China: Does Digital Finance Have a Role to Play?

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Title

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Abstract

Although it is documented that digital finance can help insure households against covariate shocks, there is not much literature studying how this mitigating effect works out. Nonfarm business activities among households in rural China are viewed as one adaptation strategy against weather risks. Merging three-round household panel data with county-level precipitation data, we apply a lognormal double-hurdle model to study the role of digital finance use in enabling households to engage in nonfarm business activities against rainfall risks. The results show that households living in a risky production environment have a higher probability to engage in the nonfarm business activities, while access to digital finance is not the most important tool for households to cope with the long-term rainfall volatility and support implementation of nonfarm business. With respect to short-term rainfall shocks, which have a negative impact on farmers' engagement in nonfarm business and on the level of nonfarm income, digital finance can facilitate adaptation by helping households to overcome financial barriers of starting nonfarm business.

Keywords

Digital finance; Rainfall risks; Nonfarm activities; China

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Abstracts

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1. Introduction

Global climate change has increased the risk of weather shocks, such as droughts and floods, and posed a fundamental threat to agricultural production. Exposure to adverse weather events can lead to severe yield losses and threaten the rural households whose livelihoods rely largely on agriculture (Chavas et al., 2005; Dercon & Christiaensen, 2011). Therefore, adaptation to climate change is regarded as a priority for households especially in developing countries.

To better cope with the income variability associated with weather shocks, farmers could transfer the labor force from agriculture to non-agricultural sectors. The labor reallocation adjustments can diversify household income sources and improve resilience to negative income shocks (Barrett et al., 2001; De Janvry & Sadoulet, 2001). Starting self-employment in business activities is one of the strategies for rural labor adjustments response to income fluctuation. It allows households to obtain the additional income without abandoning agricultural activities (Branco & Féres, 2020). Zhi et al. (2013) find that rural households who work in self-employment sector have a lower probability of being unemployed, as compared to salaried workers during the economic crisis of 2008. This provides evidence that nonfarm business activities could serve as a safety net in regions where social safety nets provided by the government are insufficient.

Although weather shocks provide incentives for rural households to engage in nonfarm business activities, it is also dependent on other economic factors whether farmers are able to start nonfarm business activities, such as financial availability. The self-employment activity requires large amount of capital investment to start and the availability of financial services plays a significant role in supporting the rural households to implement the income-generating economic activities (Guiso et al., 2004; Jia et al., 2013; Mohapatra et al., 2007). However, traditional financial services are known for its narrow coverage, high labor service costs, and single supply of financial products. In the absence of perfect credit markets, rural households are encouraged to increase precautionary savings in response to the weather shocks, and this may reduce household willingness to invest in nonfarm businesses (Rijkers & Söderbom, 2013).

With the deepening of the application of information technology in the financial field, digital finance is expected to effectively solve these problems. Not only can digital finance serve a wide range of social classes and groups, but it also improves the availability of financial services for rural households in remote and poor areas. Digital finance includes various financial business products such as mobile payment, online credit, and Internet wealth management (Pazarbasioglu et al., 2020). By facilitating remittances and transfers, mobile money indirectly contributes to a more efficient allocation of labor within the family (Suri & Jack, 2016). Also mobile money can effectively reduce transaction costs and improve access to markets, encouraging rural households to start the business activities (Sekabira & Qaim, 2017). In addition, digital finance can effectively expand the risk-sharing network within the village, enabling households to smooth consumption in response to rainfall shocks (Jack & Suri, 2014; Riley, 2018). These analyses might suggest that digital finance could serve as a risk management tool and play a significant role in bridging the financial service access gap, thus helping the farmers to start nonfarm businesses as an adaptation to adverse weather risks.

However, it is still unclear whether and how the use of digital finance affects farm households' nonfarm business decisions to mitigate against the negative effects of adverse weather fluctuations. Little research examined the effects of weather-related risks while focusing on the potential role of digital finance in reducing the negative effects on the household livelihoods. An exception is a research by Fenton, Paavola and Tallontire (2017), which provides empirical evidence to examine the impact of microcredit on the household livelihood adaptation. They found that microcredit improved household adaptive capacity and instigated livelihood diversification by encouraging nonfarm business development. Their analysis indicates that access to finance resources is important to foster climate change adaptation. While their study does not look into a specific adaptation strategy adopted by farmers and mainly focuses on the role of microfinance in improvement of household adaptation capacity.

We add to the literature by investigating the relationship between digital finance as a risk management tool, weather shocks as covariate risk and self-employed business as household risk mitigation strategies. Firstly, we study the ex-ante impact of the general production environment risk and the ex-post impact of unanticipated rainfall shocks on the likelihood that farmers engage in nonfarm business activities and on their nonfarm business earnings. Secondly, we examine how the introduction of digital finance allows households to be involved in the nonfarm business activities to adapt to unfavorable production environments and rainfall shocks. To the best of our knowledge, we are among the first study to examine the potential role of digital finance in enabling the farm households to integrate nonfarm business into livelihood adaptation strategies in response to the income variability related to fluctuations in weather.

We choose Chinese rural households for the analysis based on the following three reasons. First, despite the fact that China's agricultural added value accounted for only 7.42 percent of GDP in 2019, agricultural employees made up 25.1 percent of employed population, a figure significantly higher than the 4% level in most of the developed countries. Rural households' livelihoods are vulnerable to income fluctuation resulting from climate change. Second, self-employed business activities have become a major channel for rural households to seek nonfarm employment in China. Between 2006 and 2019, the number of new self-employed people in rural areas has increased by about 40 million, and the self-employed labor accounted for 18% of the rural labor force in China. Third, China's digital finance development has been at the forefront of the world. Mobile and internet facilities are available to rural households.

To address the above research objectives, we use the three-round balance panel data set of 4554 households in rural China observed over five years, combining with monthly county-level precipitation data, to analyze how the adoption of digital finance affects nonfarm business activities of farm households to mitigate against the negative effects of rainfall variability. Our research results suggest that digital finance use can mitigate the negative impact of unexpected short-term rainfall shocks and significantly increase the likelihood of farmers shifting their labor supply toward nonfarm business activities. Moreover, farm households living in more risky production regions have a higher probability of engaging in the nonfarm business activities, while the financial benefits provided by digital finance is not the key to change the households' long-term livelihood strategy.

This paper is organized as follows. Section 2 introduces data sources and related descriptive statistics. Section 3 presents the empirical model. The regression results are presented in Section 4. Section 5 concludes.

2. Data and variables

2.1 Household panel

The data used in this study are obtained from the China Household Finance Survey (CHFS), a nationally representative dataset implemented the baseline survey in 2011 and four waves of full sample follow-up surveys in 2013, 2015, 2017 and 2019. The first four-round data have been made publicly available. The CHFS baseline sample interviews a total of 8438 households, covering 25 provinces/municipalities/autonomous regions and 320 communities/villages. In the follow-up surveys, it has increased the number of samples to 28143, 37340 and 40011 for the years of 2013, 2015 and 2017 respectively, covering 29 provinces/municipalities/autonomous regions across the country. The survey contains detailed information on household demographics, income sources, assets, and use of financial services. Since the survey in 2011 did not include information on the use of digital finance, we use data from the second, third and fourth round of the survey.

For the purposes of the research, we exclude the urban household samples, and focus on households who were less than 65 years old and engaged in agricultural production at least once over three rounds. Also, the head of the household must also be the household’s financial decision maker to ensure the individual's own characteristics can represent the household’s characteristics. As a result, balanced panel data with 4554 rural households are obtained (13662 household-year observations).

2.1.1 Nonfarm business activities

In this paper, we identify the nonfarm business activity as any income generation activity which is not involved with primary production of agricultural products. But any value addition to agricultural products, such as food processing, is also considered as the nonfarm business. The CHFS survey gathers information on the participation of households in nonfarm businesses, the type of business activities households operated, the share of the initial investment and the income from the business activities. With the information provided in the survey, we could identify whether households are self-employed in business activity. Table 1 gives an overview of the types of business activities operated by households. It can be seen from Table 1 that the wholesale and retail industry is the most popular type of business activities among rural households, with about 45% of self-employed households being engaged in it; next are the residential services, transportation and storage, and hospitality and catering services. This suggests that farmers prefer business activities that are easy to enter, as all these industries require low starting cost, low-skilled employees, and flexible business operations. In addition, the proportion of rural households whose business types are wholesale and retail, resident related services, and hospitality and catering services has shown an increasing trend.

Table 2 shows the organizational forms of farmers' entrepreneurship in the sample. We can note that more than 80% of enterprises are of sole proprietorship, suggesting that households are mainly self-employed and no additional non-household workers are involved. This is similar to the situation in other developing countries. Using data from African countries, Nagler and Naudé (2017) find that more than 80% of rural entrepreneurial families did not employ any non-household workers, and the proportion of households employing more than 5 labors is less than 3%.

Table 1. Type of business activity (%)

	2013	2015	2017
Transport, post and storage services	17.14	14.31	12.42
Wholesale and retail trades	41.55	45.16	45.01
Resident related services	7.98	8.67	10.20
Hospitality and catering services	15.73	13.71	16.41
Manufacturing	9.62	7.26	9.09
Construction	3.99	4.23	5.10
Others	3.99	6.65	1.77
Total	100	100	100

Notes: Resident related services include Social services, Health care, sports, and social welfare, Education, culture and arts, radio, film, and television.

Table 2. Legal form of the business (%)

	2013	2015	2017
Limited liability company	0.47	0.20	1.33
Partnership	4.46	1.61	1.77
Sole-proprietorship enterprises	77.47	85.29	83.37
Others	17.37	12.90	13.08
Total	100	100	100

2.1.2 Digital finance use

Regarding the use of digital finance, the survey asked the following questions to gather information on use of mobile payments, and online wealth management: (1) Which of the following payment methods are generally used in your household's shopping (related choices including mobile banking, *Alipay app, Wechat Pay, Apple Pay*, etc.)? (2) What banking services do you often use (related choices including mobile banking and online banking)? (3) What do you usually use mobile banking and online banking for? (related choices including inter-bank remittance service, payment platform transfers)? (4) Does your household currently have internet investment products, such as *Yu'Ebao, Wechat Finance, JD Finance* etc.? Based on above questions, we can identify whether households are digital finance users.

Figure 1 shows the trend of digital finance use for households engaged in business activities and those who do not. It can be seen that the proportion of digital finance users is increasing year by year. Notably, nearly 60 percent of rural households that are engaged in business activities use digital finance in the year of 2017, while the share is only half as much for those who do not operate business.

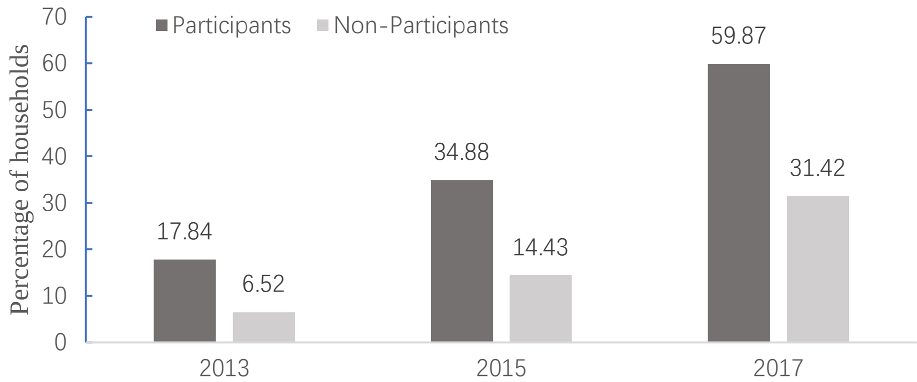

Figure 1. Digital finance adoption by business participants and non-participants

2.1.3 Other household characteristics

We also control variables on household economic and demographic characteristics. Household economic features mainly include three variables: the size of farmland, the total value of the family's assets, and whether the household is subject to credit constraints. The variable related to credit constraint is a dummy variable. If the household's loan application to the bank is rejected, the value is 1. The household demographic characteristics include six variables: the household size, the proportion of non-agricultural labor among family members, the number of children under 16, as well as the gender, age, and education level of the household head.

Table 3 presents descriptive statistics of household characteristics. Looking at the self-employment in business activities and digital finance use, we can see that about 10% of households are engaged in the nonfarm business activities and their average income from the business operation is around 111,000 CNY in levels. In 2013, 8% of households used a digital finance service, increasing to 34% in 2017. Looking at household economic characteristics, the average farm size owned by households is 10 mu, and the assets value has increased from 275,000 CNY to 321,000 CNY during the period of 2013 to 2017. The number of households subject to the credit constraint decreased slightly during the survey period. In terms of household demographics, the average household has 4 people, including one child under 16 years old, and around 26 percent of household members worked in off-farm sectors. 90 percent of household heads are male, and their average age is 50 years old; their average years of education is 7 years.

Table 3. Household summary statistics by waves

	2013		2015		2017	
	Mean	SD	Mean	SD	Mean	SD
Dependent variables						
Business activity participation	0.09	0.29	0.11	0.32	0.10	0.30
Business income (CNY, '000)	111.77	219.49	90.82	210.51	132.10	274.63
Explanatory variables						
Digital finance use (1 if used)	0.08	0.26	0.17	0.37	0.34	0.47
Land area (Mu)	8.85	14.96	11.76	19.44	10.96	19.13
Assets (CNY, '000)	275.17	371.36	300.65	399.72	321.83	449.54
Credit constrained (1 if	0.35	0.48	0.22	0.41	0.30	0.46
Household size	4.32	1.69	4.18	1.73	3.94	1.70
Nonfarm household member ratio	0.26	0.25	0.26	0.25	0.28	0.28
Number of children	0.86	1.00	0.87	1.02	0.75	0.96
Gender of head (1 if male)	0.91	0.28	0.91	0.29	0.92	0.27
Age of head	48.60	8.48	50.57	8.55	52.16	8.64
Education of head (years)	7.58	3.17	7.57	3.18	7.49	3.25

Note: 1000 CNY =146.664USD

2.2 *Rainfall risk measure*

Since the household panel data do not contain information on the climate conditions, we collect the local precipitation information from the Environment Cloud, a national environment data consisting of historical weather data obtained from weather stations. The dataset provides monthly precipitation for each county from 1996. As each rounds of the survey were conducted in July of the respective year and refer to the previous 12 months, we merge the household panel with precipitation data from the crop growing season (mainly concentrated in March to October) of the previous year.

We construct two different precipitation measures to characterize the unexpected rainfall shocks and the long-term rainfall environment. The rainfall shock is expected to reflect extreme weather events such as droughts and floods, and the long-term rainfall environment captures the riskiness of the general production environment. Following Jensen (2000) and Riley (2018), the rainfall shock is defined as a dummy variable if the precipitation deviation of a given year is higher or lower than its historical equivalent (15-year mean) by 1.5 standard deviation at the county level as follows:

$$Shock_{jt-1} = 1 \;\; if \;\; \frac{\left|R_{jt-1} - \bar{R_j}\right|}{{R_j}^{SD}} > 1.5 \tag{1}$$

where R_{jt} is the annual precipitation of county j in the crop growing season at year $t-1$, $\bar{R_J}$ is the average of historical annual precipitation (1996-2010) of county j in the crop growing season, ${R_j}^{SD}$ represents the standard deviation of the annual precipitation in county j in the crop growing season, which is a standardized index. In fact, any deviation from the long-term mean is not necessarily a shock. For instance, in arid regions, a mild increase in precipitation contributes to agricultural production; in areas with abundant precipitation, a slight decrease in precipitation can mitigate the effects of flooding. But the 1.5 standard deviation is a quite large difference from the historical mean. The average annual precipitation in our sample is 882 mm, and the 1.5 standard deviation is about 255 mm. The rainfall deviation is consistent with the measure of Riley (2018).

As for the measure of long-term rainfall environment, we use the 15-year seasonal rainfall standard deviation at the county level as the proxy variable, as used in Mathenge and Tschirley (2015) and Gao and Mills (2018). The standard deviations provide a relatively long-term inter-annual measure of rainfall variability, which can be perceived by the households and, thus, potentially influence household coping strategy adoption and business operation behavior.

In order to examine the effectiveness of the measure of rainfall variation, we empirically test the impact of the rainfall shock and long-term rainfall standard deviation on farm income. Table 4 shows that both rainfall shock and 15-year standard deviation have led to a significant reduction in farm income. The results provide evidence that rural households have stronger incentives to cope with the income variability associated with unfavorable weather conditions by adjusting their livelihood strategies.

Table 4. Effect of rainfall fluctuation on household farm income

	Log (farm income)	
	(1)	(2)
Rainfall shock	-0.058**	
	(0.029)	
15-year rainfall SD		-0.001**
		(0.000)
Constant	1.133***	1.184***
	(0.000)	(0.000)
Year dummy	Yes	Yes
District dummy	Yes	Yes
R^2	0.105	0.105
Observations	13662	13662

Note: Since the crop yield is not provided in the questionnaire, we use agricultural income as the proxy of yield.

3. Estimation strategy

3.1 Model specification

Our aim is to assess the impact of rainfall shock and long-term weather fluctuation on self-employed business activities for households with and without digital finance. However, a large percentage of households did not engage in nonfarm business activities and thus have no business income in any given year. A large number of zero observations in the dependent variable might produce inconsistent estimates if we use Ordinary Least Square (OLS) method. Zero observations in business income can be treated as actual outcomes due to households' actual choice not to participate in business. That is, the zero observation could be due to personal preference, fixed costs and other disability (Atamanov & Van den Berg, 2012). In such cases, the zero observation is the corner solution and can be seen as the household optimal choice.

The Tobit model is the common corner solution model. However, it imposes a fairly strong assumption that the factors have the same impact on the probability of being employed in nonfarm activities and on the size of nonfarm income. This model structure cannot handle the situation in which participation and income in nonfarm business activities might be separate decision mechanisms, possibly influenced by different variables or by the same variables but in different ways (Wooldridge, 2010). The double-hurdle (DH) model is a corner solution model as well, but it is more flexible and gives more room for these effects to differ compared with the Tobit model (Salmon & Tanguy, 2016). It allows two different mechanisms for the decision to start a nonfarm business and for the capacity to generate earnings. Therefore, the DH model is used in our study to estimate the impact of digital finance use on household participation in nonfarm business activity and on the size of nonfarm income in response to the negative weather conditions. Moreover, the lognormal double-hurdle (LDH) model and the truncated normal double-hurdle model (TDH) are common choices for DH model. But the LDH model is easy to explain from the economic perspective and is more robust than TDH (Hsu & Liu, 2008). In order to choose between LDH model, TDH model and the Tobit model, we also use Vuong tests to evaluate their estimators (Vuong, 1989). Based on the Vuong test results, the LDH model is preferred. The two-stage decision process of LDH model is specified as follows:

$$s_{it} = \begin{cases} 1, & if\ s_{it}^{*} = X'_{1it}\Gamma_1 + u_{it} > 0 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

$$y_{it} = \begin{cases} y_{it}^{*} = \exp(X'_{2it}\Gamma_2 + v_{it}) > 0 & if\ s_{it} = 1 \\ 0 & otherwise \end{cases} \tag{3}$$

Where

$$\begin{gathered} X'_{1it} = \beta_1 DF_{it} + \beta_2 Rainfall_{ct} + \lambda DF_{it} \times Rainfall_{ct} + Z'_{it}\Theta + \delta_t + \eta_c, \\ \text{and}\ \ u_{it} = c_{1i} + \varepsilon_{it}, \qquad u_{it} \sim N(0,1) \\ X'_{2it} = \gamma_1 DF_{it} + \gamma_2 Rainfall_{ct} + \mu DF_{it} \times Rainfall_{ct} + \mathrm{P}'_{it}\Lambda + \delta_t + \eta_c, \\ \text{and}\ \ v_{it} = c_{2i} + \epsilon_{it}, \qquad v_{it} \sim (0, \sigma^2) \end{gathered}$$

Where s_{it} is the participation decision variable which takes the value 1 if the household i at time t is observed to engage in nonfarm business activities. y_{it} represents the actual business income of household i at time t. s_{it}^{*} and y_{it}^{*} are latent variables for s_{it} and y_{it}, respectively. X'_{1it} and X'_{2it} represent vectors of variables for the hurdle 1 and hurdle 2, respectively, including the weather variable $Rainfall_{ct}$, digital finance use DF_{it} and their interaction term, other control variables, time fixed effect δ_t and county fixed effect η_c.

The error terms u_{it} and v_{it} in equations (2) and (3) both are functions of two components. The first component is unobserved time-constant heterogeneity, represented by c_{1i} and c_{2i}, which affect household involvement in nonfarm business and the size of business income. These factors include preference, risk attitude and management ability. The second part of the error term is the unobserved random variables ε_{it} and ϵ_{it}.

3.2 *Controlling for unobserved heterogeneity* c_i

In the nonlinear panel model, the assumption of independence between covariates and the unobserved heterogeneity c_i is difficult to be satisfied in practice. The violations of the assumption might lead to biased coefficient estimates. Mundlak (1978) and Chamberlain (1980) proposed a method called correlated random effect (CRE) to relax this assumption. The CRE framework allows dependence between vector covariates and the unobserved heterogeneity c_i by decomposing c_i as $c_i = \tau + \bar{X}_i \xi + a_i$, where τ and ξ are constants, $\bar{X}_i$ is the vector of time average for all time-varying variables in equation (2) and (3), the error term a_i follows a normal distribution. The CRE approach allows us to unify the fixed and random effects estimation approaches. It contains traditional random effects as a special case and can control for time-constant unobserved heterogeneity as with fixed effect while avoiding the incidental parameters problem.

3.3 *Controlling for endogeneity*

There is a possibility that the digital finance might be affected by some unobserved time-varying variables ε_{it} and ϵ_{it} even after controlling for the correlation between DF_{it} and c_i. In this case, digital finance use is likely to be endogenous and the coefficient estimates of DF_{it} and $DF_{it} \times Rainfall_{ct}$ are inconsistent. The control function (CF) approach is one of the solutions to correct for the self-selection bias of digital finance use. Compared with the two-stage least square (2SLS) method, the CF approach is more efficient when estimating nonlinear model with the endogenous variables, and it can be combined with the CRE model for nonlinear models with the unobserved heterogeneity and endogeneity (Wooldridge, 2015).

The CF approach involves two steps. First, using the Probit model to regress the endogenous variable digital finance use on the instrumental variable and other exogenous control variables. The residual term from the reduced-form model is expected to be the proxy for the unobserved time-varying factors. Second, the generated residual is added as an extra control variable in the LDH model. The significance of the residual term tests and corrects for the endogeneity (Papke & Wooldridge, 2008; Petrin & Train, 2010).

The instrumental variable used in the reduced form model should be correlated with the endogenous variable DF_{it} but not affect the unobserved variables ε_{it} and ϵ_{it} in the LDH model. In this study, we use the average distance between households and physical bank branches as an instrument. As banking sectors are significantly reshaped by digitalization process, we assume that households close to financial branches have an easy access to digital finance and thus, are more likely to use it. The existing studies have shown that households who use traditional financial services are more likely to be digital finance users (He et al, 2017). Moreover, the distance to bank branches is not expected to directly affect household decision on business activities. It is worth mentioning that the distance to bank branches was only investigated in the 2017 round of the survey. Considering that the setup of a physical bank branch is associated with population size, transportation, market environment and economic development, the number of branches was generally stable across time. Following Di Falco, Veronesi and Yesuf (2011), we also use a falsification test to check the validity of the instrument.

3.4 Estimating the marginal effects of the LDH model

From the LDH model, we can calculate the average partial effect (APE) by deriving partial effects of the explanatory variables of interest for every observation in the dataset. As the Probit estimation in the first hurdle is a non-linear model, the interaction marginal effect could be computed as follows (Frondel & Vance, 2013; Hangoma et al., 2018):

$$\frac{\Delta^2 P(s^* > 0|X_1)}{\Delta DF \Delta Rainfall} = [\Phi(Rainfall = 1, \mathrm{DF} = 1, \mathrm{X}_1) - \Phi(Rainfall = 1, \mathrm{DF} = 0, \mathrm{X}_1)] \\ -[\Phi(Rainfall = 0, \mathrm{DF} = 1, \mathrm{X}_1) - \Phi(Rainfall = 0, \mathrm{DF} = 0, \mathrm{X}_1)] \quad (4)$$

Where Φ is the normal cumulative distribution function (CDF), the DF and $Rainfall$ both are dummy variables. If the variable $Rainfall$ is measured as a continuous variable, the mixed interaction effect can be computed following Frondel and Vance (2013).

For the second hurdle, the interaction marginal effects can be similarly computed as in equation (4), The Φ is replaced by exponent. This is the conditional APE for the size of nonfarm business income given the first-stage participation decision.

The overall effect on nonfarm business income (unconditional APE) is estimated by combining the probability of engaging in the nonfarm business activity with the average size of nonfarm business income given that the business income is positive. The equation is as follows:

$$E(y_{it}) = P(s_{it}^* > 0|X_1) \times E(y_{it}|y_{it} > 0) \quad (5)$$

Standard errors for the APE and unconditional APE are obtained using delta method or bootstrapping with 150 replications.

4. Empirical results and discussion

4.1 Falsification test and endogeneity test

The upper part of Table 5 reports the results of the falsification test. If the distance to bank branches is a valid instrument, it will affect the digital finance use decision but not affect the income from business activities among digital finance non-users. The model 1 shows that the distance to bank branches affects digital finance use, confirming a strong correlation between the instrument variable and digital finance use. In model 2, the instrument has no significant effects on the business income of digital finance non-users.

The lower part of Table 5 reports the test results for the endogeneity of digital finance using the CF approach. The derived residuals from the reduced-form model is introduced as the control variable into both hurdles. It can be seen that the *P*-value of the residual coefficients for the hurdle 1 in both equations are not significant, while that of the hurdle 2 are highly significant. The results indicate that the digital finance use is endogenous in the model for nonfarm business income, but the test fails to reject the exogeneity of digital finance in a nonfarm business participation model. Therefore, we need to introduce the derived residual term into the second hurdle to address the endogeneity.

Table 5. Test for instrument validity and endogeneity of digital finance use

Falsification test		
	Model 1: Adoption of	Model 2: Earnings from
Log distances to financial branches	-0.166***	-0.257
	(0.000)	(0.180)
Wald test on the *log distances to*	χ^2=36.91***	*F*-test=1.80
Observations	13662	10996
Exogeneity test: *P*-value of the residuals		
	P-value	Conclusion
Short-term rainfall shock		
Hurdle 1: nonfarm business participation	0.342	Exogenous
Hurdle 2: income in nonfarm business	0.033	Endogenous
Long-term rainfall variation		
Hurdle 1: nonfarm business participation	0.873	Exogenous
Hurdle 2: income in nonfarm business	0.036	Endogenous

4.2 LDH model results for short-term rainfall shocks

Table 6 shows the results on the effect of short-term rainfall shocks on participation and earnings in nonfarm business activities for digital finance users and non-users. We include household characteristics specified in Table 3, as well as interaction terms between these household covariates and rainfall shock to control for these observable characteristics which might affect the digital finance use and households' ability to reduce shocks. To ensure that the LDH model can be identified, the number of children is included as a covariate in the first hurdle.

The coefficients and marginal effects in the first hurdle are shown in columns (1) and (2) of

Table 6. Our interest is to examine whether digital finance use is able to help farm households better cope with the rainfall shock by adjusting family labor allocation between farm and nonfarm business activities. The results show that digital finance use has a positive effect on the probability of nonfarm business participation. Compared with non-users, the digital finance use makes households about 2 percent more likely to choose employment in the nonfarm business activities. Turning to the interaction term between rainfall shock and the digital finance use, the coefficient is positive and statistically significant at a 5% level, which means that digital finance users are more able to engage in nonfarm business activities in the presence of short-term rainfall shocks than non-users. A possible reason is that digital finance use enables households to easily access financial services in response to risks, which helps alleviate financial constraints and redistribute resources between farm and nonfarm activities. Our results are in consistent with the findings of Riley (2018) who also showed that digital finance use can expand households' risk sharing network by obtaining financial support from relatives and friends outside the village.

The columns (3) and (4) present the coefficients and conditional APE in the second hurdle. The results show that, conditional on the decision to engage in the nonfarm business activities, households experience a large decline (roughly 5596 CNY) in business earnings after a rainfall shock. The result is in accordance with the findings of Grabrucker and Grimm (2020) who also found that rainfall shocks mostly have a negative impact on the performance of nonfarm enterprise due to the production and expenditure linkages between farms and nonfarms. The coefficient on digital finance use is positive and statistically significant, suggesting that the digital finance use results in an approximate 4807 CNY increase in nonfarm business income, holding other factors constant. The coefficient of the interaction term between rainfall shocks and digital finance is insignificant. Moreover, we calculate the unconditional APE for the key variables, which combines the impact on the propensity of starting nonfarm business activities and on the size of business income. As shown in column (1) of Table 8, digital finance use increases household income in nonfarm business by about 2603 CNY. The overall influence of the rainfall shock and its interaction with digital finance use on nonfarm business income are not statistically significant. This suggests that there are no mitigating effects of digital finance use on nonfarm business earnings for a household suffering a rainfall shock. There are many potential explanations for the results. For example, although digital finance can help households to overcome financial barriers for starting nonfarm business activities, farm households might be forced to decrease their investment in business activities and choose to insure consumption against the rainfall shock, thus limiting the mitigating effects on nonfarm business income.

Regarding other explanatory variables that affect the participation and income in nonfarm activities, the results show that the probability of participation in nonfarm business activities is mainly affected by assets, age and education of household head and household structures. Household heads at a young age and with higher education are more likely to start a business. This is in line with the study of Atamanov and Van den Berg (2012) who found that young individuals and better-educated people, especially with higher or vocational education, are more likely to choose pure nonfarm activities or a mixture of farming and nonfarming. Households with more children are more likely to start nonfarm business activities. A possible explanation for this is that self-employment in nonfarm business activities allows flexible working arrangements and helps achieve work-life balance. Similarly, conditional on the nonfarm business participation decision, gender, age and education are also identified as important determinants of nonfarm business income.

Table 6. Short-term rainfall shock—maximum likelihood estimates for LDH model

	Hurdle1 Nonfarm business participation decision (Probit estimator)		Hurdle 2 Income from nonfarm business upon participation (Lognormal estimator)	
	Coefficient (1)	Marginal effects (2)	Coefficient (3)	CAPE (4)
Rainfall shock	-0.040	-0.001	-2.157**	-5.596
	(0.392)	(0.007)	(0.915)	(6.329)
DF use	0.098**	0.020***	0.179*	4.807
	(0.046)	(0.006)	(0.102)	(4.486)
Rainfall shock*DF use	0.186**	0.034***	-0.304	-4.890
	(0.092)	(0.013)	(0.197)	(6.767)
Log(land area)	-0.037	-0.004	-0.074	-3.699
	(0.030)	(0.004)	(0.080)	(3.956)
Log(asset)	0.279***	0.037***	0.713***	25.226***
	(0.029)	(0.004)	(0.113)	(4.002)
Credit constrained	0.039	0.007	-0.103	-3.999
	(0.042)	(0.005)	(0.094)	(4.368)
Household size	0.024	0.003	0.105**	2.044*
	(0.015)	(0.002)	(0.042)	(1.118)
Nonfarm household member ratio	0.870***	0.118***	0.300	-2.853
	(0.102)	(0.013)	(0.293)	(10.343)
Gender	0.126*	0.017**	0.410**	17.629***
	(0.076)	(0.008)	(0.174)	(5.237)
Age	-0.009***	-0.001***	-0.038***	-0.805***
	(0.002)	(0.000)	(0.009)	(0.218)
Education	0.009	0.001*	0.039*	0.426
	(0.006)	(0.001)	(0.022)	(0.732)
Number of children	0.096***	0.014***		
	(0.026)	(0.003)		
Interactions with shock	Yes		Yes	
Constant	-5.407***		-3.712***	
	(0.306)		(1.310)	
Residual term			0.773**	
			(0.366)	
Year dummy	Yes		Yes	
District dummy	Yes		Yes	
Pseudo-R^2/ R^2	0.220		0.312	
Observations	13662		13662	

Notes: Coefficient estimates shown with robust standard errors in parentheses. ***, **, and * indicate the level of significance at $p < 0.01$, 0.05, and 0.1, respectively.

4.3 LDH model results for long-term rainfall variation

Table 7 shows the results for the impact of long-term rainfall variation on participation and income in nonfarm business activities for households with and without digital finance. We also control for household characteristics variables and their interactions with the 15-year rainfall standard deviation.

The first two columns of Table 7 reports coefficients and marginal effects for the first hurdle regression. The results show that the long-term rainfall standard deviation of a region positively affects households' decision to participate in nonfarm business activities. We may link the result to the fact that the unfavorable agricultural production environment leads to the instability of farm income. In order to reduce the negative effect of long-term weather conditions, households choose pure nonfarm activities or a mixture of farming and nonfarming. This suggests that engaging in the nonfarm business activities can work as a long-term adaptation strategy for household living in the risky farm production environment. The finding is in accordance with the results of Mathenge and Tschirley (2015) who also found that households living in regions prone to rainfall shortage are more likely to work in nonfarm sectors. The coefficient of the interaction between long-term rainfall variations and digital finance use is zero, indicating that the financial benefit provided by digital finance is not sufficient to cope with the systematic risk intrinsic to the region. Zhang et al. (2019) also showed that the credit supply for households in areas prone to natural disasters is limited by banking sectors in China due to the rise in non-performing loan rates and the decline in expected returns on a loan.

Columns (3) and (4) show the estimated coefficients and conditional APE in the second hurdle. After controlling for the long-term rainfall risks and their interaction with other household characteristics, it can be seen that conditional on the participation in nonfarm business activities, historical rainfall standard deviation has a positive impact on earnings from nonfarm business. This result reinforces the finding from the first hurdle that farm households adjust their labor allocation between farm and nonfarm activities in response to the risky production environment. Moving to the effects on overall earnings from nonfarm business activities (Column 2 of Table 8), although the coefficient of the interaction between long-term rainfall standard deviations and the digital finance use is statistically significant, but the economic effect is quite small. A possible explanation is that long-term rainfall fluctuations do not result in a decrease in nonfarm business income, and thus there is no greatly difference in impacts of digital finance use on the earnings from nonfarm business for households living in areas with different degree of rainfall variability.

Table 7. Long-term rainfall risk - maximum likelihood estimates for LDH model

	Hurdle1 Nonfarm business participation decision (Probit estimator)		Hurdle 2 Income from nonfarm business upon participation (Lognormal estimator)	
	Coefficient (1)	Marginal effects (2)	Coefficient (3)	CAPE (4)
15-year rainfall SD	0.004**	0.000	0.006	0.102*
	(0.002)	(0.000)	(0.005)	(0.054)
DF use	0.059	0.020***	0.147	3.246
	(0.091)	(0.006)	(0.198)	(4.447)
15-year rainfall SD * DF use	0.000	0.000	0.000	0.044
	(0.000)	(0.000)	(0.001)	(0.056)
Log(land area)	0.020	-0.005	-0.111	-4.283
	(0.042)	(0.004)	(0.110)	(3.890)
Log(asset)	0.288***	0.037***	0.674***	25.687***
	(0.048)	(0.004)	(0.135)	(4.057)
Credit constrained	0.077	0.007	0.198	-5.11
	(0.080)	(0.005)	(0.193)	(4.387)
Household size	0.012	0.003	0.129**	2.201**
	(0.029)	(0.002)	(0.064)	(1.119)
Nonfarm household member ratio	0.778***	0.118***	-0.196	-1.525
	(0.173)	(0.013)	(0.431)	(10.861)
Gender	0.159	0.016**	0.448	17.566***
	(0.154)	(0.008)	(0.310)	(5.108)
Age	0.007	-0.001***	-0.005	-0.919***
	(0.005)	(0.000)	(0.014)	(0.221)
Education	-0.004	0.001*	0.018	0.571
	(0.012)	(0.001)	(0.036)	(0.733)
Number of children	0.142***	0.014***		
	(0.053)	(0.003)		
Interactions with 15-year rainfall SD	Yes		Yes	
Constant	-6.198***		-5.192***	
	(0.463)		(1.486)	
Residual term			0.767**	
			(0.368)	
Year dummy	Yes		Yes	
District dummy	Yes		Yes	
Pseudo-R^2/ R^2	0.222		0.286	
Observations	13662		13662	

Notes: Coefficient estimates shown with robust standard errors in parentheses. ***, **, and * indicate the level of significance at $p < 0.01$, 0.05, and 0.1, respectively.

Table 8. Unconditional average partial effects (UAPE)

Dependent variable: earnings from nonfarm business activity (‘000	Short-term rainfall shock	15-year rainfall SD
	(1)	(2)
Rainfall fluctuations	-1.533	0.022*
	(1.369)	(0.012)
DF use	2.603**	2.345**
	(1.065)	(1.083)
Shock*DF use	0.820	0.055*
	(1.766)	(0.032)

5. Conclusion

Weather volatility is posing huge challenges to agricultural production, and thus strengthens the importance of nonfarm business activities, which are viewed as part of adaptation strategies for farm households in rural China. But participation in nonfarm business activities requires some level of investment, and thus whether farmers are able to start nonfarm business is also driven by the access to financial services. Digital finance is a new and fast-growing technology widely used in China, which might play a role in enabling households to use adaptation strategies against fluctuations in weather.

In this paper we study the relationship between digital finance as a risk management tool, weather shocks as covariate risk and self-employed business as household risk mitigation strategies. We use a comprehensive panel dataset of approximately 4554 rural households covering a period of five years from the China Household Finance Survey and link it with precipitation data at county level. A lognormal double hurdle model with correlated random effects is used to estimate the empirical model.

Our results show that households adjust their labor allocation between farm and nonfarm activities in response to the unexpected rainfall shocks and risky production environment. Digital finance plays a significant role in helping farm households start self-employed business in the presence of short-term rainfall risks. But the financial benefit provided by digital finance is not the key measure to cope with the systematic risk intrinsic to the region. Furthermore, we found that short-term rainfall shocks have a negative impact on nonfarm business income, while there are no mitigating effects of digital finance on nonfarm business earnings for a household suffering the rainfall shock.

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