

Article

Natural Risk Shocks and Rural Household Livelihood Resilience: Does Digital Transformation Make a Difference?

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Abstract

The natural disasters caused by climate change are increasingly threatening the livelihood sustainability of rural households. How to enhance the adaptability of farmers has become a major issue that urgently needs to be addressed in rural development. An increasing amount of research suggests that the digital transformation in rural areas may provide solutions to this problem. This study selected large sample data from the China Family Panel Studies (CFPS) from 2014 to 2020 to empirically test the role of digital economy in mitigating the adverse impact of natural disasters on livelihood resilience of rural households in China. The empirical results indicate that although natural disasters have a significant negative impact on the livelihood resilience of rural households, the embedding of digital technology can alleviate this negative impact to some extent by expanding non-agricultural employment opportunities for rural households, enhancing households' access to credit, and improving agricultural production strategies. During this process, the buffering capacity, self-organization ability, and learning ability of rural families have been significantly improved. Moreover, the mitigating effect of the digital economy exhibits heterogeneity. It is more pronounced in the central and western regions than in the eastern regions, and also more evident among high-income families relative to low-income families. The key to improving the benefits of digital technology may lie in tailored policy interventions and digital skills training for farmers. Finally, this study provides empirical evidence from rural China on the role of the digital economy in strengthening farmers' adaptive capacity against disaster risks. While these findings are context-specific, they may still provide valuable insights for other agriculture-dependent developing countries facing persistent climate risks.

Keywords: digital technology; natural risk; livelihood resilience of rural household; digital inclusion

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1. Introduction

In recent years, frequent natural disasters related to climate change have posed numerous challenges to agricultural production and rural livelihoods [1]. Extreme weather events (e.g., droughts, floods, frosts, etc.) have increased the vulnerability of agricultural systems, resulting in food yield declining, household income decrease, and population outflows [2–4]. The adverse effects of natural disasters are particularly severe

for smallholder farmers who are dependent on the use of farmland resources and have a single livelihood. Moreover, farmers have limited livelihood capital and weak capacity and may tend to return to poverty when exposed to risk shocks [5]. Existing research suggests that disaster relief instruments based on financial compensation can help to mitigate the negative impacts of disaster shocks by increasing the livelihood capital of farmer households in the short term [6]. However, this ‘blood transfusion’ approach cannot substantially address the long-term impacts of natural disasters on farm households. Based on the resilience perspective, the resilience of farmer household livelihoods highlights the ability of a household to resist risk and sustain development when faced with complex natural risk shocks [7,8]. Therefore, in the context of natural disaster shocks, enhancing the resilience of farm household livelihoods is an important strategy for farmers to withstand risks and achieve sustainable development.

On the one hand, livelihood resilience enhancement is predicated on the availability of livelihood capacity of farm households [9]. Because of their relatively disadvantaged position in the socio-economic system, farmers often find it difficult to compete with other actors in terms of resource allocation and market access. Farmers need to be provided with equal rights and opportunities through various policies or institutional means [10]. On the other hand, farmers have complex household assets, and the key to improving the resilience of their livelihoods lies not only in increasing the total amount of their assets, but also in achieving an efficient allocation of their asset portfolios and diversity of livelihood strategies [11].

China’s rapid development of the digital economy provides important momentum for the growth of the national economy [12]. In order to promote the process of agricultural and rural informatization, the state has introduced and implemented a series of policies, such as the “Information into Villages and Households Project”, the “Rural E-commerce Development Policy”, and the “Broadband Countryside Plan”. The implementation of these policies has protected the institutional equality of rural households in terms of their livelihood ability and facilitated the inclusive development of rural economy [13]. At the same time, a large number of scholars have proved that the development of the digital economy has achieved significant results in expanding the sale of agricultural products, promoting farmers’ income and accelerating the integration of rural industries, which effectively promotes the diversification of the livelihood capital of rural households [14,15]. The development of digital economy provides opportunities to alleviate the risk vulnerability faced by farming households [16]. However, current research has focused on the relationship between the digital economy and farm household income, but whether the digital economy has a significant role in mitigating risk vulnerability and empowering farm households to enhance their livelihood resilience, as well as the transmission mechanism between them, still needs to be further tested. Moreover, some past studies have shown that the information welfare brought by the digital economy cannot fully benefit all farmers [17,18]. In fact, the application of the digital economy has a threshold in different regions and individuals, and it is unclear whether the digital economy has a heterogeneous role in alleviating natural risk shocks.

Based on the above research background, the impact and transfer mechanism of digital economy between the natural risk and livelihood resilience of farmer households were empirically examined. The research contribution of this study includes the following three aspects. First, this study developed a comprehensive framework for measuring rural household livelihood resilience by integrating the three resilience capacities of buffering capacity, self-organization capacity, and learning capacity. It further extended existing frameworks by incorporating psychological capital into buffering capacity to capture households’ internal resources for coping with external shocks. Second, based on the constructed indicator of livelihood resilience, the moderating role of the digital economy

in the relationship between natural risks and livelihood resilience was examined. Third, three mechanistic paths of the digital economy, including non-farm employment, credit access, and agricultural production strategies, were further explored. Then, some theoretical and policy implications are provided for rural households to cope with disaster impacts and improve their livelihood resilience through the development of the digital economy.

2. Literature Review and Research Hypothesis

2.1. *The Concept of Livelihood Resilience*

Ecologist Holling [19] first introduced the term ‘resilience’ into ecosystem studies to analyze the dynamics of ecosystems and their ability to maintain stability in the face of external disturbances. Over time, the concept of livelihood resilience has been gradually applied to a variety of disciplines, such as ecology, engineering, and economics. The concept of livelihood resilience in this paper refers to the ability of rural households to avoid falling into poverty and maintain their livelihoods when faced with natural risk.

By sorting out the existing studies, three main approaches to livelihood resilience measurement are summarized: i. According to the sustainable livelihood framework, the livelihood resilience of farmer households can be divided into five types of capital: financial, physical, natural, human, and social capital [20]. ii. An analysis framework, namely “Capacity Framework”, based on buffering capacity, self-organizing capacity, and learning capacity, is constructed to measure livelihood resilience [21]. iii. The livelihood resilience of farmer households has been estimated through dynamic and non-linear modelling, which is measured based on conditional probabilities of specific welfare levels [22]. This paper followed the study of Speranza et al. [21] and measured the livelihood resilience of farmer households in terms of buffering capacity, self-organization capacity, and learning capacity. The buffering capacity referred to the ability of farmer households to cope with risky shocks and maintain their livelihoods at the same level; the self-organizing capacity was the ability to communicate with and receive assistance from external organizations when coping with risky shocks; and the learning capacity represented the ability of farmers to acquire knowledge and skills, as well as the ability of farmers to translate knowledge into action.

2.2. *Livelihood Resilience Needs in the Context of Disaster Vulnerability*

Rural households remain disproportionately exposed to natural hazards such as floods, droughts, and extreme storms, and these shocks affect rural livelihoods through multiple interdependent channels [23,24]. First, by causing physical damage to farmland and crops, natural disasters erode rural households’ natural and economic capital, thereby directly weakening their buffering capacity [25]. Second, natural disasters can severely undermine local social networks among villagers and organizations by triggering labor migration, destroying livelihood assets and infrastructure, disrupting information and communication channels, and intensifying resource competition, thus reducing households’ self-organizing capacity [26]. Third, the economic burden and psychological stress induced by disasters impair households’ learning capacity, diminishing both their motivation and their ability to acquire new knowledge for adaptive action [27]. In light of these multiple and interlinked pathways of influence, the vulnerability of rural households lies not only in their exposure to natural hazards, but also in the post-shock decline of the three core capacities (buffering capacity, self-organizing capacity, and learning capacity) that underpin livelihood resilience.

This recognition underscores an urgent need to shift the analytical focus from assessing disaster impacts to identifying the conditions that can sustain or restore

livelihood resilience when shocks occur. While existing research has examined post-disaster coping strategies, such as income diversification and asset adjustment, a critical question remains underexplored: which external interventions can durably mitigate the intensity of natural hazard impacts on rural household livelihoods, rather than merely compensating for losses *ex post*?

2.3. The Moderating Role of the Digital Economy

With the ongoing development of the digital economy in rural areas, digital technologies are increasingly supporting agricultural activities, offering practical channels for reducing farmers' disaster vulnerability [28]. First, digital platforms lower the barriers to non-farm employment and e-commerce entrepreneurship, enabling rural households to offset disaster-induced agricultural losses with off-farm income [29,30]. Mobile payment and digital credit services further allow households to rapidly mobilize financial resources for post-disaster recovery, thus alleviating the depletion of economic capital [31,32]. Digital technologies can broaden income sources and thereby strengthen households' buffering capacity.

Second, when physical social interactions are disrupted by disasters, the digital economy can restore and enhance self-organizing capacity. Online communication tools enable households to remotely maintain social networks, exchange recovery information, and access institutional support [33]. Such social connectivity becomes particularly valuable when geographical mobility is constrained in the aftermath of a disaster. Third, the digital economy can safeguard learning capacity by providing continuous access to knowledge and skill training, even during periods of livelihood stress. Through online platforms, household members can acquire agricultural techniques, disaster preparedness knowledge, and market information that are essential for adaptive action [34,35].

Notably, the existing literature on the rural digital economy has largely focused on its income-enhancing effects. Research on whether and how the digital economy alters the relationship between natural shocks and livelihood resilience remains limited. Moreover, the transmission mechanisms underlying such a moderating effect have yet to be empirically tested within a unified framework. This study aims to fill these gaps.

2.4. Transmission Mechanisms of the Digital Economy

Building on the preceding framework, three potential pathways through which the digital economy mitigates the impact of natural disaster shocks on rural household livelihood resilience are further explored: non-farm employment, credit access, and production strategy diversification.

2.4.1. The Non-Farm Employment Pathway

Natural disasters often compel rural households to seek non-farm income to compensate for agricultural losses; however, information asymmetries in the labor market tend to render this channel precarious. The digital economy reduces these frictions by providing timely labor market information, creating remote work opportunities, and facilitating e-commerce participation [36]. Through this pathway, the digital economy helps rural households enrich their income sources. As an alternative source of agricultural income, non-agricultural income reduces farmers' dependence on agricultural activities, allowing households to maintain basic consumption and production inputs when agricultural income decreases. Especially for households with limited land resources and a high proportion of agricultural income, this channel is particularly crucial. In the context of natural risk, the buffering capacity of rural households is consolidated through their participation in non-agricultural employment, and their livelihood resilience is further enhanced.

2.4.2. The Credit Access Pathway

Natural disasters often cause serious mobility restrictions on rural households, leaving them with insufficient funds for post-disaster recovery and consumption smoothing. However, for a long time, the problem of information asymmetry in traditional rural financial markets has led to farmers with good credit being excluded from formal loans. The development of the digital economy provides new technological possibilities to solve this dilemma. Digital finance utilizes big data and mobile technology to reduce information friction, enabling institutions to more accurately assess creditworthiness and provide credit to previously underserved households [35]. The core value of credit access lies in providing a liquidity support for farmers. When disasters occur, timely credit funds can alleviate the funding gap in household consumption and production recovery, prevent farmers from selling their productive assets due to short-term liquidity depletion, and thus avoid falling into a vicious cycle of poverty, asset shrinkage, and weak recovery. Therefore, the credit pathway not only enhances farmers' ability to allocate funds in response to current shocks, but also builds a financial defense line against future risks in their livelihood system, becoming a key support for enhancing farmers' livelihood resilience.

2.4.3. The Production Strategy Diversification Pathway

A key principle of risk management is that diversified production portfolios are better able to withstand idiosyncratic shocks [37]. Digital technologies, particularly including precision agriculture tools and big data analytics, can assist households in adjusting crop mixes, adopting integrated farming systems, and optimizing resource allocation based on real-time weather and market information [38]. The diversification of this production strategy not only enhances the flexibility of the agricultural system, but also establishes a dual resilience support for farmers. Firstly, diversification itself is an effective risk diversification mechanism. When a crop is reduced in yield due to disasters, the output of other crops or management projects can compensate for the loss of household income, avoiding livelihood difficulties caused by the collapse of a single link, and thus consolidating the buffering capacity of farmers. Secondly, diversified operations enable farmers to constantly come into contact with new crop varieties and production methods. Farmers accumulate knowledge through attempt and adaptation, thereby enhancing their learning capacity. The strengthening of buffering capacity and the improvement of learning ability complement each other, jointly building a more solid foundation for farmers' livelihood resilience.

Based on this, this article proposes hypotheses H1 to H3.

H1: *Natural risk shocks have a negative impact on the livelihood resilience of rural household.*

H2: *The digital economy alleviates the negative impact of natural disasters on the livelihood resilience of farmers.*

H3: *The digital economy alleviates the negative impact of natural disasters on farmers' livelihood resilience by promoting non-agricultural employment transfer, improving rural households' access to credit, and diversifying agricultural production strategies.*

After clarifying the dependent and independent variables and their relationships, we constructed the conceptual framework of this study (Figure 1), which linked the livelihood resilience of rural households, natural risk shocks, and the level of digital economic development. Livelihood resilience was the focus of this study and consisted of buffering capacity, self-organization capacity, and learning capacity. Natural shock

exposure and digital economy were considered as important influencing factors for livelihood resilience. As indicated by the arrows in Figure 1, the natural risk shocks had a negative impact of on livelihood resilience, while the direct impact of the digital economy on livelihood resilience was positive, and the digital economy played a moderating effect in the negative impact of natural risk shocks.

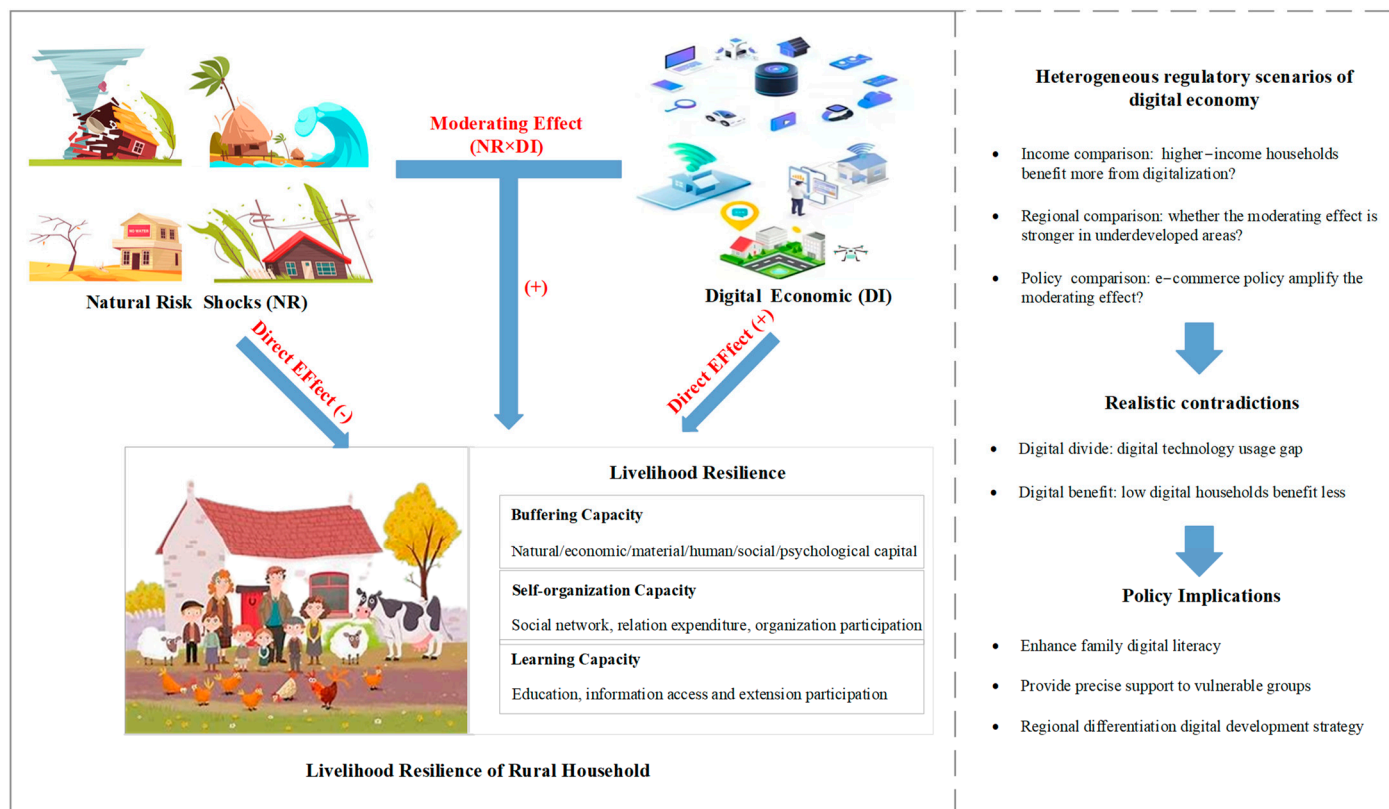


Figure 1. Conceptual framework linking natural risk shocks, resilience capacities, and digital economy. Solid boxes represent the relationships among the three core research variables; dashed boxes highlight the heterogeneous scenarios, realistic contradictions, and policy implications examined in this study.

3. Materials and Methods

3.1. Data Source

The empirical data used in this article comes from the China Family Panel Studies (CFPS) [39]. The CFPS databases are conducted by the Social Science Survey Center of Peking University in China. This survey has been operating since 2010, covering 25 provinces (cities, autonomous regions) across the country. It is designed from three levels: community, family, and individual. This hierarchical and multi-stage sampling survey can well represent the majority of households and individuals in China. Due to limitations in data integrity, this paper only selected survey data from four years: 2014, 2016, 2018, and 2020. This sample data had been processed as follows. Firstly, based on the rural research topic, households with a nature of village committee were retained. Secondly, the sample of underage farmers were deleted. Thirdly, all missing values of important explanatory variables were eliminated. Finally, the sample in this study consist of unbalanced panel data: 7319 household samples in 2014, 6983 in 2016, 6545 in 2018, and 4351 in 2020. After combining them, 25,198 samples were obtained as research data, and Figure 2 shows the regional distribution of the samples in China.

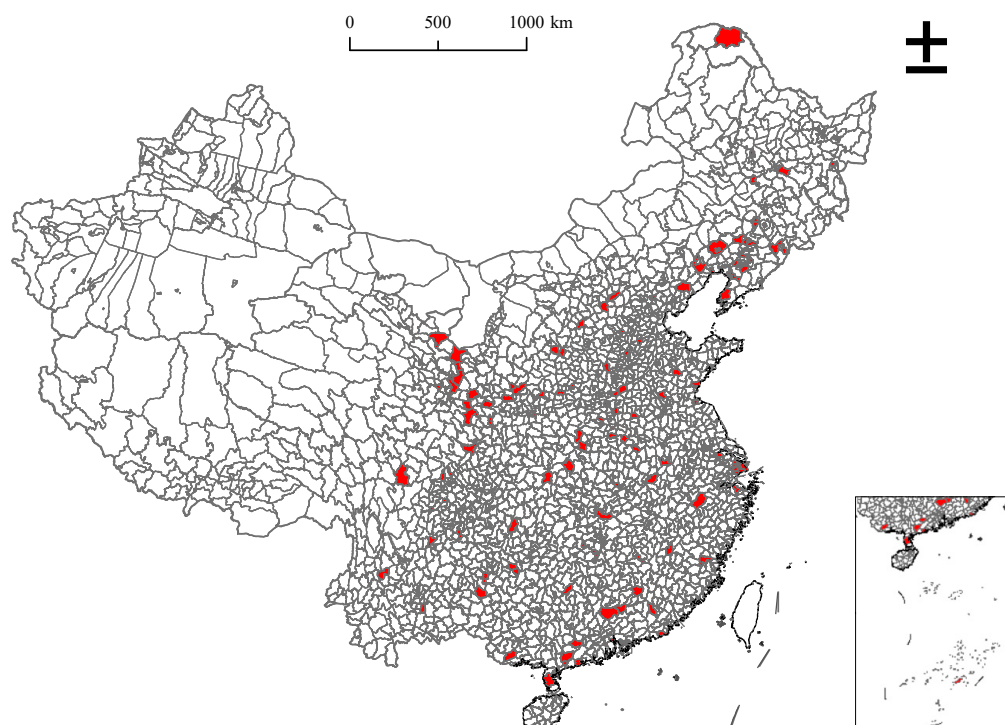


Figure 2. Regional distribution of sample data. The red color indicates the survey area.

3.2. Variable Selection

3.2.1. Dependent Variable

The dependent variable of this study was defined as the livelihood resilience of rural households. Following the framework proposed by the study of Speranza et al. [21], buffering capacity, self-organizing capacity, and learning capacity were selected to construct the livelihood resilience index. This framework provided a clear analytical structure for assessing the adaptive ability of rural households to natural shocks. However, the original framework solely emphasized tangible, social, and human capital and did not explicitly incorporate the psychological capital that shapes households' willingness and ability to mobilize resources in the face of shocks. This limitation was particularly important in the context of disaster recovery, as psychological factors such as self-efficacy, optimism, and perceived control have been shown to play critical roles in post-disaster coping [40,41]. To address this gap, psychological capital was incorporated into the livelihood resilience assessment framework, extending the existing capacity-based approach by capturing households' internal psychological resources and adaptive capabilities. Psychological capital was operationalized using indicators reflecting rural households' subjective beliefs and attitudes, including self-evaluated social status, life satisfaction, and confidence in the future. The complete indicator system of livelihood resilience is presented in Table 1.

Table 1. Livelihood resilience indicator system.

Livelihood Resilience	Secondary Indicator	Tertiary Indicator	Description
Buffering capacity	Human capital	Labor proportion	The proportion of people aged 18–60 in rural households
		Health status	Average health score of family members
	Natural capital	Land assets	Land of the village collective

Economic capital	Material capital	Water uses	Household cooking by using tap water and purified water
		Energy uses	Household cooking by using renewable energy sources
		Household assets	Total amount of family cash, deposits, and financial products
		House value	Total market value of house assets
		Durables value	Total market value of durable consumer goods
		Agri-machine	Total market value of agricultural machinery
	Psychological capital	Subjective social status	Average self-evaluation of local social status by family members, 5-point Likert scale ranging from 1 ("very low") to 5 ("very high")
		Life satisfaction	Average self-evaluation of life satisfaction among family members, 5-point Likert scale ranging from 1 ("very dissatisfied") to 5 ("very satisfied")
		Future confidence	Average self-evaluation of future confidence level, 5-point Likert scale from 1 ("not confident at all") to 5 ("very confident").
		Organizational participation	The situation of organizational participation, including membership of Communist Party or other organizations
Self-organization capacity	Social network	Social relation expenditure	Family favors and gifts expenses
		Village cadre relations	Average score of family members' trust in local officials
		Neighborhood relationship	Average score of family members' trust in neighbors
		Education level	Average education level of rural household
Learning capacity	Knowledge acquisition	Information access	The importance of newspapers and magazines as sources of information
		Extension participation	Family members attending agricultural extension

The livelihood resilience of farmers was a comprehensive indicator. In order to avoid bias caused by subjective setting of indicator weights, this article referred to the method used by Li et al. [9] and employed the entropy method to weight and sum up each indicator. In the robustness testing section, principal component analysis was used to test the livelihood resilience indicators. The detailed solution procedure was shown as below:

Before using the entropy method, all indicators were needed to be dimensionless, as shown in Equation (1):

$$nx_{ijt} = (x_{ijt} - \min\{x_j\}) / (\max\{x_j\} - \min\{x_j\}) \quad (1)$$

Among them, $i = 1, 2, \dots, n$; $j = 1, 2, \dots, m$; $t = 1, 2, \dots, s$; nx_{ijt} was the dimensionless result; x_{ijt} was the value of the j th indicator for family i in year t ; $\min\{x_j\}$ and $\max\{x_j\}$ respectively represented the minimum and maximum values of indicator j in all years and individuals.

Next, as shown in Equation (2), the proportion sx_{ijt} of the j th indicator of household i in the overall indicator for year t shall be calculated. Next, as shown in Equation (3), the information entropy e_j of indicator j could be obtained, where $K = \sum_{t=1}^T N_t$. Then, as shown in Equation (4), the information entropy redundancy d_j ($d_j \geq 0$) could be obtained.

$$sx_{ijt} = nx_{ijt} / \sum_{t=1}^T \sum_{i=1}^N nx_{ijt} \quad (2)$$

$$e_j = -1/\ln(K) \sum_{t=1}^s \sum_{i=1}^n (sx_{ijt} \times \ln(sx_{ijt})) \quad (3)$$

$$d_j = 1 - e_j \quad (4)$$

$$w_j = d_j / \sum_{j=1}^m d_j \quad (5)$$

The indicator weight w_j was calculated by information entropy and redundancy, which is expressed in Equation (5). Therefore, the resilience of farmers' livelihoods was obtained in Equation (6):

$$resilience_{it} = \sum_{j=1}^m (w_j \times nx_{ijt}) \quad (6)$$

where $resilience_{it}$ represented the livelihood resilience of rural households, with a value range of 0–1. The larger the value, the stronger the ability of farmers to recover their livelihoods in the face of natural risk shocks; on the contrary, the weaker the ability to restore livelihoods.

3.2.2. Independent Variable

The core independent variable of this article was the degree of natural disasters. Due to the incompleteness of the database, the data on natural disaster impacts in the questionnaire was only collected before 2014. Therefore, provincial disaster data from the China Rural Statistical Yearbook for the year preceding the survey were merged into the household sample according to the provincial codes and the survey year, and the intensity of regional natural disaster exposure faced by rural households was thereby measured. Natural disasters are defined as the ratio of the affected agricultural area at the provincial level to the total sowing area in the province. This measurement approach reflected the regional shock environment rather than individual household losses. Therefore, robustness tests were conducted using the data on natural disaster impacts from the 2014 questionnaire. In addition, this limitation is revisited in Section 5.5, and its implications for the results are discussed.

3.2.3. Moderator Variable

To further explore the moderating role of the digital economy under natural risk shocks, four dimensions of indicators were selected from the questionnaire, namely digital coverage, digital acquisition, digital usage, and digital dependence, to synthesize the digital development index of rural households, and the factor analysis method was employed to measure it. Firstly, the KMO test value of the digital development index was 0.851, and the p value of the Bartlett sphericity test was 0, which indicated that the research data meets the conditions of factor analysis. Then, the non-negative eigenvalues were solved. The results in Table 2 showed that the eigenvalues of the first four factor variables were all greater than 1, and after the maximum variance rotation, the cumulative variance contribution rate reached 74.76%. Therefore, four common factors were selected.

Table 2. Results of factor analytic approach.

Factors	Eigenvalue	Proportion	Cumulative
Factor1	7.64548	0.4778	0.4778
Factor2	2.05329	0.1283	0.6062
Factor3	1.15778	0.0724	0.6785
Factor4	1.10545	0.0691	0.7476

To construct the DI, the factor score coefficient matrix was first extracted from the principal component solution. This matrix was then weighted and aggregated according to the proportion of each factor's eigenvalue to the cumulative eigenvalues of the four factors, and the digital index score was thereby obtained. The weights for Factors 1 through 4 were 0.639, 0.172, 0.097, and 0.092, respectively. The results of the rotated factor loading matrix are reported in Table 3. The uniqueness of all variables is less than 0.6, indicating that the factor explanation is effective. Based on the variables with the highest loadings on each rotated factor, the correspondences between the rotated factors and the constituent variables of the digital index were derived. The composition of the digital economy indicator is shown in Table 4.

The composite factor score obtained by factor analysis was a relative value and represented the extent to which the digital family index of a single rural family deviates from the overall sample mean; a larger positive value indicated that the digital level of the family was relatively higher, and on the contrary, a smaller negative value indicated that the digital level of the family was lower than the average level. In addition, the entropy value method was employed in the robustness test section to measure the level of the regional digital economy.

Table 3. Rotating factor load matrix.

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Uniqueness
f1	0.7393	−0.2949	−0.1277	0.0892	0.3422
f2	0.6070	0.0187	0.0154	0.2373	0.5747
f3	−0.1032	0.7427	0.1277	0.1172	0.4144
f4	−0.1655	0.5656	−0.1571	0.2078	0.5848
f5	−0.0613	−0.0558	0.7831	0.1814	0.3452
f6	0.1295	−0.1802	0.7125	0.2387	0.3861
f7	0.0198	−0.0452	0.6205	0.2230	0.5628
f8	−0.1941	−0.1886	0.6759	0.1190	0.4558
f9	−0.1797	0.0443	−0.0940	0.7609	0.3779
f10	−0.0886	0.0546	−0.0711	0.6871	0.5120
f11	−0.1409	−0.1237	−0.1891	0.8618	0.1864
f12	−0.1401	−0.0006	−0.0032	0.8489	0.2597

Table 4. Digital economy indicator of rural households.

Digital Index	Explanation	CFPS Questionnaire Items	Weight
Digital coverage	Use of mobile phones or computers (f1); access to the Internet (f2), yes = 1; no = 0	“Does your family own a computer?”; “Does your family have Internet access?”	0.639
Digital accessibility	Information collection by internet (f3) or mobile phone (f4), survey value 0–7	“How often do you use the Internet/mobile phone to obtain information?” (0 = never, 7 = almost every day)	0.172
Digital usage	Frequency of study (f5), work (f6), socialization (f7), and commercial activities (f8), survey value 0–5	“How often do you use the Internet for study / work / socializing / commercial activities?” (0 = never, 1 = once every few months, 2 = once a	0.097

Digital dependence	Importance of digital technology in study (f9), work (f10), socialization (f11), and business online (f12), survey value 0–5	month, 3 = 2~3 times a week, 4 = almost every day, 5 = every day) “Generally, how important is the Internet to your study, work, socialization, and business?” 0.092 (0 = not important at all, 5 = very important)
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3.2.4. Control Variables

The control variables for rural household livelihoods focus on the household level and the individual level. From the aspect of the household, control variables consisted of member size and safeguards. For the individual, age, gender, and marriage were controlled.

3.3. Model Design

3.3.1. Main Regression Model

Based on the results of the Hausman test, the chi-square statistic was 52.71 ($p < 0.01$), which strongly rejected the null hypothesis of the random effects model at the 1% level. Accordingly, the household fixed effects model was used for the baseline regression to control for unobservable household-level differences. Multicollinearity was also examined using the variance inflation factor (VIF). As shown in Appendix A Table A1, the mean VIF was 2.34, and all individual VIF values were below 10, which confirmed that multicollinearity did not affect the precision of our estimates. The model was employed to empirically examine the impact of natural disaster risk shocks on the livelihood resilience of rural households and the moderating role of the level of the digital economy. The model was set up as follows:

$$LR_{it} = \beta_0 + \beta_1 NR_{pt} + \beta_2 NR_{pt} \times DI_{it} + \beta_3 DI_{it} + \gamma C_{it} + \varphi_i + \varphi_t + \varepsilon_{it} \quad (7)$$

where the i represented the rural household, p represented the province where the farmer is located, and t represented the study year. The dependent variable LR_{it} indicated the level of livelihood resilience of household i in year t ; NR_{pt} indicated the extent of agricultural disasters in the province p where the rural household is located in year t ; DI_{it} indicated the digital level of household i in year t ; $NR_{pt} \times DI_{it}$ was the interaction term between natural risk shocks and digital development level; C_{it} was a set of control variables that potentially affect household consumption; φ_i represented individual fixed effects, φ_t represented time fixed effects, and ε_{it} represented the random disturbance term.

3.3.2. Mechanism Model of Moderating Effects

$$M_{it} = \alpha_0 + \alpha_1 NR_{pt} + \alpha_2 NR_{pt} \times DI_{it} + \alpha_3 DI_{it} + \gamma C_{it} + \varphi_i + \varphi_t + \varepsilon_{it} \quad (8)$$

Based on the research conducted by [42], this paper determines the potential pathways through which the digital economy affects the livelihood resilience of farmers by analyzing the causal relationship between moderating variables and mechanism variables. In the above regression equation, M_{it} represented the mechanism variable. The question “Do you engage in non-agricultural employment?” was selected from the questionnaire as the mechanism variable for non-agricultural employment, “Has your family obtained loans from legitimate financial institutions?” as the mechanism variable for credit access, and “Types of agricultural, animal husbandry, forestry, and fishery engaged?” as the mechanism variable for agricultural production strategies.

4. Results

4.1. Descriptive Statistics

The variable settings and descriptions are provided in Table 5. The digital economy index had a mean of -0.003 , a standard deviation of 0.67 , and a range from -0.6 to 3.12 . These values suggested substantial variation in digitalization levels among rural households, with many households remaining below the average level of digital development. This observation was consistent with the widely documented digital divide among Chinese rural households in the existing literature and suggested that considerable room remained for further digital development in rural China. The mean value of the agricultural disaster ratio revealed that the sampled households were located in regions with substantial exposure to natural disasters. The livelihood resilience score had a mean of 0.22 and ranged from 0.01 to 0.77 . This relatively low average implied that the sampled rural households possessed limited capacity to withstand and recover from natural shocks, a finding that underscored the vulnerability of the study population and highlighted the practical significance of understanding how digitalization enhances household resilience. With respect to household-level control variables, family size averaged approximately four members. Among the household head characteristics, the mean age reflected the aging phenomenon in rural areas, and the gender ratio of household heads was roughly 11 to 9 in favor of males.

Table 5. Summary statistics of research variable.

Variable	Explanation	Min	Max	Mean	SD	Observations
LR	Livelihood resilience of rural households	0.01	0.77	0.22	0.09	25,198
NR	Ratio of farmland area affected by disasters to total cultivated area	0.00	0.62	0.15	0.11	25,198
DI	Digital score of rural households	-0.60	3.12	-0.003	0.67	25,198
Size	Number of household members	1.00	21.00	3.97	1.95	25,198
Age	Age of household head	18.00	95.00	50.00	15.54	25,198
Gender	Gender of household head, male = 1; female = 0	0.00	1.00	0.55	0.50	25,198
Marriage	Marital status of household head	0.00	1.00	0.88	0.32	25,198
Safeguards	Participation in at least one of pension insurance, health insurance and unemployment insurance = 1, or = 0	0.00	1.00	0.19	0.39	25,198

4.2. Benchmark Regression Results

The regression results of different variables on livelihood resilience are shown in Table 6. Only the impact of natural disaster shock variable on livelihood resilience is discussed in column (1). The digital economy index and the interaction term of digital economy index and natural disaster shock are further added in column (2). Control variables are then added in column (3). The results showed that the coefficient for natural disaster shock (*NR*) was significantly negative. This is consistent with Hypothesis 1. Livelihoods and production of rural households were negatively affected when families were exposed to regional natural disasters, leading to a decline in the livelihood resilience of households. The coefficient for the digital economy index (*DI*) and the coefficient of the interaction term between the digital economy index and natural disaster shock ($NR \times DI$) was also significantly positive, which were in contrast to the sign of the natural disaster shock coefficient. After control variables were added in modeling, the significance level of $NR \times DI$ increased from 5% to 1%. Hypothesis 2 was supported. With the development of digital economy, the negative impact of natural disaster shocks on household livelihoods had been alleviated. In addition, Figure A1 in Appendix A presents the

marginal effects of natural disaster shocks on livelihood resilience. The figure shows that the marginal effect of NR on LR was negative and statistically significant at low levels of DI and that as DI increased, this negative effect gradually weakened. The estimated marginal effect crossed the zero line at approximately $DI = 0.624$, suggesting that the adverse impact of natural disasters was substantially mitigated. This finding was consistent with the results reported in Table 6, demonstrating that the digital economy could significantly mitigate the adverse effects of natural disasters on rural household resilience.

Table 6. Benchmark regression results of livelihood resilience.

Variables	(1) Direct Regression	(2) Moderating Effect	(3) Control Variables
NR	−0.075 *** (0.020)	−0.079 ** (0.030)	−0.088 *** (0.022)
DI		0.091 *** (0.030)	0.093 ** (0.034)
NR × DI		0.106 ** (0.052)	0.141 *** (0.045)
Size			0.006 *** (0.001)
Age			−0.001 *** (0.000)
Gender			0.000 (0.001)
Marriage			0.008 *** (0.003)
Safeguards			0.014 *** (0.004)
Constant	0.226 *** (0.005)	0.205 *** (0.008)	0.231 *** (0.010)
Observations	25,198	25,198	25,198
R-squared	0.314	0.330	0.322
Yearfix	YES	YES	YES
Famfix	YES	YES	YES

Province-clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$. Famfix refers to household fixed effects, which absorb time-invariant household-level unobservables.

At the same time, the results of controlling variables showed that the household size was positively correlated with household livelihood resilience. This result aligned with the essence of household livelihood resilience, which suggested that the continuous accumulation of livelihood capital can help households to enhance their buffering capacity against disaster risk shocks. Household social security was also positively correlated with household livelihood resilience; the more social security support an agricultural household received, the stronger the social support for their post-disaster recovery.

4.3. Resilience Capacity Results

The entropy method was used to further decompose the sub-indicators of the three dimensions of rural household livelihood resilience, including buffering, self-organization, and learning capacity. The impact of the digital economy on them under natural disaster shocks is explored in Table 7.

Table 7. Extended analysis of resistance, self-organization, and learning capacity.

Variables	(1) LR	(2) Buffering	(3) Self-Organization	(4) Learning
NR	−0.088 *** (0.022)	−0.059 *** (0.020)	−0.043 *** (0.013)	−0.035 *** (0.010)
DI	0.093 ** (0.035)	0.080 * (0.047)	0.040 ** (0.015)	0.028 ** (0.012)
NR × DI	0.141 *** (0.045)	0.244 *** (0.081)	0.220 *** (0.016)	0.171 *** (0.059)
Constant	0.231 *** (0.010)	0.299 *** (0.020)	0.090 *** (0.005)	0.139 *** (0.013)
Observations	25,198	25,198	25,198	25,198
R-squared	0.322	0.341	0.295	0.417
Control Variable	YES	YES	YES	YES
Yearfix	YES	YES	YES	YES
Famfix	YES	YES	YES	YES

Province-clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results of the impact of digital economy on the livelihood resilience, resistance capacity, self-organization capacity, and learning capacity of rural households under natural disaster shocks are exhibited in columns (1)–(4). The impact coefficients of natural risk shocks on buffering capacity, self-organizing capacity, and learning capacity were significantly negative. The specific reasons for this may be threefold: first, natural risk shocks had a negative effect on buffering capacity by decreasing the capital of farmers' households. Second, natural risk shocks affected the self-organizing capacity of rural households by reducing the frequency of interactions among them. After suffering a risk shock, farmers' income decreased, and in order to spend more time on income generation, they would inevitably reduce the frequency of participation in village collective activities and social interactions. Moreover, natural risk shocks also had a negative impact on farmers' psychology. Due to the destruction of their livelihoods, farmers' enthusiasm for participating in agricultural production had declined, and their interactions with the outside world were gradually reduced. Third, natural risk shocks affected learning capacity by reducing farmers' ability to acquire knowledge. On the one hand, disaster-affected farmers' wealth accumulation was destroyed and they lacked sufficient funds to adopt new agricultural technologies. On the other hand, farmers who suffered from health risk shocks were pessimistic, which directly affected their endogenous development motivation, thus negatively affecting their learning ability.

The coefficients of the digital economy and the digital economy interaction term on buffering capacity, learning capacity, and self-organization capacity were significantly positive. The results indicated that the digital economy had effectively mitigated the negative effects of natural risk shocks and significantly improved the resistance capacity, self-organization capacity, and learning capacity of farm households. Firstly, the digital economy significantly enhanced the resistance capacity of farmers by improving their access to capital. With the help of microcredit and mobile payment services, farmers could resume agricultural production in a timely manner after a disaster. They could also expand their non-farm income sources through digital platforms, which greatly mitigated the economic fluctuations caused by natural disasters. Secondly, the digital economy had improved the self-organization capacity of farmers. Digital platforms provided farmers with more convenient online interaction and cooperation networks, and farmers could quickly acquire disaster recovery experience and agricultural production skills through exchanges with their neighbors and peers. Finally, the digital economy had significantly

enhanced the learning capacity of farmers. Farmers could learn the agricultural technology and market information by online educational resources, and then their technical efficiency and innovation capacity in agricultural production were greatly improved.

4.4. Mechanism Analysis

To explore the transmission channels through which digital economics mitigates the adverse effects of natural disasters, this study investigated whether the interaction term $NR \times DI$ significantly affected three mechanism variables: non-farm employment, credit access, and production strategy diversification. The results are presented in Table 8.

In column (1) of Table 8, the interaction term of non-farm employment was positive at the 10% level, indicating that digitalization has strengthened households' adjustment to non-agricultural work. The convenience and inclusiveness provided by digital platforms greatly reduced the barriers for rural households to engage in non-farm work. Through non-farm employment, rural households could expand the sources and stability of their agricultural income, which enhanced their economic resilience in the face of disaster impacts [36]. This finding provides suggestive evidence that labor reallocation is a potential channel through which digitalization boosts livelihood resilience.

The interaction term of credit access was positive and significant in column (2); under the impact of natural disasters, the development of the digital economy had expanded the credit sources for rural households. The improvement of credit channels provided timely funding for households in the post-disaster period to maintain basic consumption and restore agricultural production, strengthening their buffering capacity against future shocks [38]. This result shows that expanding credit channels is an important pathway by which digitalization empowers rural households in post-disaster recovery.

The results in column (3) showed a significant and positive impact of interaction terms on the diversification of farmers' production strategies. The widespread use of digital technologies in agricultural production had significantly improved the resource allocation efficiency of agricultural production and further enhanced farmers' risk resistance and output capabilities [43]. This further suggests that production diversification is a key mechanism through which digitalization enhances agricultural livelihood resilience.

Overall, the above analysis provided evidence that the development of the digital economy effectively promoted non-agricultural employment, credit access, and agricultural production strategy diversity for farmers, helping to enhance their ability to cope with risks and smooth consumption, thereby improving their livelihood resilience. To further validate Hypothesis 3, a robustness test was designed for mechanism analysis. Three alternative indicators for mechanism variables were selected for testing: the non-farm participation indicator was replaced with the proportion of non-farm income, the credit acquisition indicator was replaced with the logarithm of total borrowing amount, and the agricultural production diversity indicator was replaced with the types of crop types planted. As shown in Table A2, the interaction term $NR * DI$ was statistically significant in all three alternative regression results, consistent with the main results reported in Table 8. Hypothesis 3 was validated.

Table 8. Mechanism analysis of the digital economy.

Variables	(1) M ₁	(2) M ₂	(3) M ₃
NR	−0.083 *** (0.029)	−0.271 ** (0.125)	−0.027 ** (0.013)
DI	0.031 * (0.013)	0.213 ** (0.085)	0.036 * (0.018)

	(0.016)	(0.112)	(0.022)
NR × DI	0.280 *	0.133 **	0.205 **
	(0.159)	(0.062)	(0.098)
Constant	0.125 ***	0.207 ***	0.028 ***
	(0.030)	(0.023)	(0.006)
Observations	25,198	25,198	25,198
R-squared	0.316	0.344	0.372
Control	YES	YES	YES
Yearfix	YES	YES	YES
Famfix	YES	YES	YES

Province-clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.5. Robustness Test

4.5.1. Replacement of Main Variable

Due to potential errors in the measurement method, an attempt was made to use different methods for calculating the explanatory, moderator, and dependent variables to conduct robustness checks. The test results were shown in Table 9.

(1) The entropy method was used to calculate the digital economic index by matching panel data from 299 prefecture-level cities in China. The comprehensive development index of the digital economy was measured from four dimensions: digital usage, digital enterprises, digital industry, and digital transactions. Digital usage was composed of the number of mobile phone users and internet users per hundred people in rural areas; digital enterprises was the number of computers and websites owned by rural enterprises; digital industry was the total telecom business volume per capita in rural areas; and digital transactions consisted of the logarithm of e-commerce sales and the index of the development of digital inclusive finance in rural areas. (2) In total, 7279 samples were selected from 2014. The variable ‘whether the household has experienced disasters in the past three years’ was used as a substitute explanatory variable to conduct robustness checks on the natural risk shocks in this article. (3) Principal component analysis was employed to recalculate the resilience indicators of household livelihoods. The KMO value was 0.706 and the p value of the Bartlett’s test of sphericity was 0, which indicated that the data meets the conditions for factor analysis.

Table 9. Results of robustness test.

Variables	(1)	(2)	(3)
NR	−0.065 *** (0.017)	−0.020 *** (0.007)	−0.351 *** (0.091)
DI	0.021 *** (0.006)	0.051 *** (0.022)	0.261 *** (0.069)
NR × DI	0.021 * (0.012)	0.041 ** (0.020)	0.954 *** (0.421)
Constant	0.232 *** (0.005)	0.216 *** (0.014)	−0.139 *** (0.022)
Observations	25,198	7279	25,198
R-squared	0.329	0.412	0.423
Control	YES	YES	YES
Yearfix	YES	NO	YES
Famfix	YES	NO	YES

Province-clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The test results after substituting research variables are shown in Table 8. The coefficient of natural risk shocks was consistently significantly negative, while the coefficients of digital development and the interaction term of natural risk and digital development index were significantly positive. The results of the test are consistent with the results of the baseline regression. Therefore, the above robustness test results further support the core conclusions of H1 and H2 of this article.

4.5.2. Discussion of Endogeneity

Existing research demonstrated that there was a threshold for the application of digital technology in rural households, which might have a negative impact on the resilience-enhancing effects of the digital economy. Therefore, the effect of digital economy development on the livelihood resilience of rural households might be disturbed by reverse causality. The models in this paper might suffer from an endogeneity problem. Therefore, this study adopted the two-stage least squares (2SLS) method and constructed two instrumental variables to address endogeneity issues.

The first tool was the spherical distance between the provincial capital city where each household was located and Hangzhou city, which interacted with the natural disaster variable. Hangzhou was the headquarters of Alibaba and other large internet enterprises, which had a radiation effect on the development of China's digital economy. The physical distance was fixed and did not directly affect the livelihood resilience of the family, meeting exclusion restrictions. However, since distance itself was time invariant, it was included through interaction with natural disasters. The second tool followed a widely adopted method proposed by Nunn and Qian [44]: the historical fixed telephone penetration rate at the provincial level in 1984, interacting with the annual trend. This tool captured the long-term sustainability of regional telecommunications infrastructure, which shaped the subsequent dissemination of digital technology and had externalities on current rural livelihood conditions. This tool varied by province and year, allowing for identification within a panel fixed effects framework.

Table 10 reported the 2SLS estimation results. The first stage regression showed that both tools (reduced by 100 times) were closely related to their respective endogenous variables. The Cragg Donald Wald F statistic and Kleibergen Paap rk Wald F statistic both significantly exceed the Stock Yogo 10% maximum IV size critical value of 16.38, strongly rejecting the null hypothesis of weak tools. The results of the second stage indicated that the interaction term $NR \times DI$ remained significantly positive, consistent with the baseline findings. These results confirmed that the core conclusion was robust for addressing endogeneity issues through instrumental variable estimation.

Table 10. Regression results for instrumental variables.

Variables	(1) IV1: $(NR \times Distance)/100$	(2) IV2: $(Tel_{1984} \times Year)/100$
First stage (Dependent variable)	NR $\times$ DI	DI
	−0.037 *** (0.001)	−0.006 *** (0.000)
R-squared	0.702	0.815
Second stage (Dependent variable: LR)		
NR	−0.142 *** (0.055)	−0.593 *** (0.164)
DI	0.052 * (0.031)	0.251 *** (0.071)
NR $\times$ DI	0.477 ** (0.241)	0.303 *** (0.045)
Observations	25,198	25,198

Control	YES	YES
Yearfix	YES	YES
Famfix	YES	YES
Weak IV diagnostics		
Cragg-Donald Wald F	914.168	576.723
Kleibergen-Paap rk Wald F	639.476	424.676
Stock-Yogo weak ID test critical values:		
10% maximal IV size	16.38	16.38

Province-clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.6. Heterogeneity Discussion

Heterogeneity discussion of different sample group was conducted in this section. As shown in Table 11, the household samples were divided into families from the central–western regions (column 1) and families from the eastern regions (column 2); the low-income families (column 3) and high-income families (column 4) were classified based on the median total of the household income; non-e-commerce supported families (column 5) and e-commerce supported families (column 6) were categorized based on whether the county of households had benefited from e-commerce assistance policy.

Table 11. Heterogeneity regression.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
NR	−0.102 *** (0.022)	−0.093 * (0.043)	−0.085 *** (0.025)	−0.094 *** (0.032)	−0.081 *** (0.027)	−0.110 *** (0.034)
DI	0.082 * (0.046)	0.077 * (0.042)	0.061 (0.036)	0.074 * (0.037)	0.069 ** (0.032)	0.055 ** (0.021)
NR × DI	0.426 ** (0.163)	0.034 (0.245)	0.111 (0.157)	0.177 ** (0.088)	0.105 (0.126)	0.282 ** (0.134)
Constant	0.230 *** (0.006)	0.255 *** (0.003)	0.230 *** (0.009)	0.258 *** (0.013)	0.235 *** (0.012)	0.261 *** (0.011)
Observations	14,392	10,806	12,799	12,399	13,116	12,082
R-squared	0.413	0.401	0.305	0.357	0.397	0.385
Control	YES	YES	YES	YES	YES	YES
Yearfix	YES	YES	YES	YES	YES	YES
Famfix	YES	YES	YES	YES	YES	YES

Province-clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.6.1. Regional Comparison

Although the gap between the development levels of eastern and central–western regions in China were gradually narrowing, there was still a large gap in agricultural and rural development, especially the newly digital industry, which may show regional variability [45]. The regression results by different regions suggested that digital economy development in the central–western regions had a more significant influence in mitigating the negative impacts of natural disaster shocks than in the eastern regions, which confirmed the regional differences exhibited by the digital economy. This difference may stem from different regional development conditions: the overall economic level, infrastructure coverage, and digital utilization of rural households in the eastern region were better than those in the central–western regions. The marginal effect of the digital economy in enhancing the resilience of farmers’ livelihoods was relatively limited in the eastern region. Rural households in the eastern region were more likely to cope with natural risks through multiple means, such as financial support, social security systems, and original wealth accumulation. In contrast, in the central and western regions, there

were many development constraints such as resource scarcity and inadequate facilities, the introduction of the digital economy had not only played an important role in promoting farmers' income, but had also demonstrated significant advantages in strengthening industrial linkages and resource allocation efficiency. As a result, farmers in the central and western regions were more dependent on the digital economy, and their livelihood systems were more sensitive to the information access, market access, and risk management functions provided by digital technology when facing external disaster shocks. Thus, the promotion for digital transformation in the central and western regions of China was of great practical significance in enhancing their disaster response capacity and promoting coordinated regional development.

4.6.2. Income Group Comparison

The heterogeneity analysis by household income showed that the positive moderating effect of the digital economy under natural disaster shocks was stronger for higher-income households than for lower-income households. This difference revealed the real challenge of the current digital economy development in rural areas, which was the uneven distribution of digital dividends among different income groups [46]. Low-income rural households were usually faced with financial constraints and insufficient access to resources, which caused them had a high threshold in accessing, understanding, and using digital technologies. In contrast, households with higher income had sufficient financial support for hardware investment, technological learning, and information access and were more likely to participate in platforms and took full advantage of the opportunities presented by the digital economy to improve livelihood stability and risk resilience. The key to increasing the livelihood resilience of rural household lay in how to bridge the digital divide in the digital transformation of the countryside and achieve equality of opportunity for farmers' development.

4.6.3. Policy Implementation Comparison

The role of the digital economy in promoting the livelihood resilience of rural households under policy support was analyzed. The results showed that the digital economy had a more significant effect on the livelihood resilience of households in policy-supported counties. This result reflected the strong guiding and safeguarding role of policy support in the digital economy's development. Specifically, policy-supported districts had priority access to resources for e-commerce infrastructure construction, logistics network optimization, technical training, and market expansion, which were beneficial for local farmers to participate in digital economy activities. These policy measures not only enhance farmers' ability to access e-commerce platforms, but also increase their level of market adaptability and income diversification, thereby demonstrating greater livelihood resilience in the face of external risk shocks such as natural disasters. Therefore, the implementation of e-commerce policies had amplified the positive effects of the digital economy, and demonstrated the importance of precise policy support in enhancing the resilience of livelihoods in vulnerable areas.

5. Discussion

5.1. The Impact of Natural Disaster Shocks on Livelihood Resilience

Natural hazard shocks significantly weaken the livelihood resilience of rural households ($\beta = -0.088$, $p < 0.01$), consistent with the large body of empirical research on natural disasters. Furthermore, this paper decomposes livelihood resilience into three capabilities: buffering capacity, self-organization capacity, and learning capacity. Table 7 shows that natural disasters have the strongest direct negative impact on buffering

capacity, followed by self-organization ability and learning ability. This difference has not been systematically recorded in previous studies, as most research treats livelihood resilience as an integrated outcome. A reasonable explanation is that buffering capacity is rooted in tangible capital such as land, housing, and financial assets, which are immediately and noticeably affected by physical disasters, whereas the weakening of self-organization and learning abilities occurs through more gradual processes, such as network disruption and psychological stress [26]. The different degrees of capacity weakening observed here provide a more detailed perspective on how disasters undermine resilience.

5.2. *The Moderating Role of the Digital Economy*

While a growing amount of literature has examined the positive effects of digital technologies in rural areas, including on income, consumption, and agricultural productivity [17,18], this study departs from this tradition by testing a fundamentally different proposition: the digital economy will affect the intensity of the impact of natural disasters on the livelihood resilience of rural households. The significant positive interaction term between natural risk shocks and digital development ($\beta = 0.141$, $p < 0.01$, Table 6) provides robust evidence for such a moderating role. This finding resonates with a small but emerging strand of research. Digital technology is conceptualized as an institutional or infrastructural condition that reshapes the resilience of rural households [36]. The contribution of this study lies in providing large-sample, multi-year panel evidence for this moderation hypothesis and explicitly embedding it into the capability framework of Speranza et al. [21]. In the face of disasters, the digital economy exerts the strongest moderating effect on buffering capacity, followed by self-organization capacity and learning capacity (Table 7). This suggests that the digital economy may be particularly effective in restoring social connections and access to institutions [33]. The finding that learning capacity benefits least from the moderating effects of the digital economy is thought-provoking: it may indicate that the accumulation of skills and knowledge requires sustained investment and institutional support, which current digital platforms in rural China do not yet provide comprehensively.

5.3. *Heterogeneity: Digital Dividends and the Inclusivity Challenge*

Heterogeneity analysis indicates that the moderating effect of the digital economy on resilience is not uniformly distributed. This effect is more pronounced in central and western regions than in eastern regions, in high-income households than in low-income households, and in counties receiving e-commerce policy support (Table 11). These results are broadly consistent with findings documenting region-based and income-based digital divides in rural China [46].

Further, our analysis yields two novel observations. First, the mitigating effect of the digital economy is not statistically significant for low-income households, indicating that the resilience benefits of digitalization do not automatically reach vulnerable groups. This discovery reflects not only digital divides at the access level, but also resilience divides at the outcome level, which has received insufficient attention in the existing literature. Although low-income households may have gained access to digital tools, they appear to lack the complementary capabilities required to translate such access into effective disaster response. This finding implies that investment in digital infrastructure alone is unlikely to close the resilience gap; sustained efforts in digital skills training and community-based institutional support are equally critical. Moreover, the marked difference between counties with and without e-commerce policy support further confirms that the digital economy does not generate inclusive benefits automatically. This suggests that targeted policy support is crucial. Consistent with the policy-oriented

arguments put forward by Wei et al. [47], our findings further provide micro-level household evidence. Targeted policy interventions are essential to ensure that disadvantaged groups can benefit effectively from digitalization.

5.4. Policy Implications

The frequent occurrence of natural disasters in rural China has imposed persistent negative shocks on household livelihoods, undermining their buffering, self-organizing, and learning capacities. Strengthening the resilience of rural households to withstand and recover from such shocks is significant for developing agrarian economies. Our findings demonstrate that the digital economy significantly attenuates the adverse effects of natural disasters on livelihood resilience, and this moderating effect operates through non-farm employment, credit access, and production strategy diversification. Based on these empirical results, the following policy implications are proposed for leveraging digital transformation to enhance rural resilience.

First, for disaster-affected households, rural digital transformation is gradually becoming an important path to enhance farmers' resilience. Approaches include promoting the continuous extension of digital financial services, agricultural information services, and employment information services in rural areas, lowering the threshold for farmers to use digital technology, and truly transforming existing digital infrastructure into a normalized support tool for farmers to cope with risk shocks. At the same time, policy design should guide relevant resources to tilt towards rural areas with lower levels of digitalization, in order to avoid the formation of new differentiation of digital dividends between regions.

Second, digital access is not equivalent to digital empowerment. Even within areas of digital coverage, the digital divide persists, owing to differential resource endowments across households, and vulnerable groups may still struggle to translate digital technologies into practical risk resistance capacity. Hence, the evaluation criteria for digital rural development should take the digital welfare of disadvantaged populations as a core basis. Policy design needs to distinguish two levels of intervention. On the one hand, the barriers to digital use for low-income households should be lowered, so that they can acquire the economic means and skill base necessary for effective technology adoption. On the other hand, the depth of digital technology use must be enhanced to ensure that digitalization can be genuinely embedded in farmers' production decisions and risk management processes. To achieve these objectives, government and rural development agencies should integrate disaster risk management with digital rural construction. Digital literacy training ought to be embedded into the rural public-service system, and complementary pathways, such as expanding off-farm employment opportunities, improving credit access, and promoting innovation in production models, should be leveraged.

Finally, the development strategy of the digital economy should fully consider regional heterogeneity. The central and western regions not only have weaker information technology infrastructure, but also exhibit significantly lower average education levels and digital literacy among farmers than the eastern region. The construction of digital villages in the central and western regions should adopt a phased and targeted strategy. In areas where infrastructure is relatively underdeveloped, priority should be given to ensuring network coverage and access to digital devices. In areas where the basic conditions are already met, digital literacy training and localized application development should be promoted simultaneously. For the eastern region, although the digital moderating effect has reached a high level, its marginal benefits tend to decrease, and policy focus should shift from quantitative expansion to qualitative deepening.

5.5. Research Limitations and Future Directions

This study provides empirical evidence to understand the role of the digital economy in moderating natural risk shocks, yet there are still limitations that need to be improved in future research. The core independent variable of this study is the natural disasters exposure, measured by the proportion of agricultural areas affected by disasters at the provincial level. Measuring disaster exposure at the provincial level may obscure substantial spatial heterogeneity across counties and villages within the same province, as severe shocks in highly affected areas may be averaged out by less-affected areas. Moreover, this measure cannot fully capture household-level heterogeneity in disaster shock intensity, as households within the same province may differ in whether they are affected by natural disasters and in the intensity of the shocks they experience. Although this approach may sacrifice some micro-level variation, it allows us to examine the relationship between disaster exposure, digital economy development, and livelihood resilience within a comparable empirical framework. Moreover, our findings suggest that the digital economy helps rural households enhance their livelihood resilience against the adverse effects associated with regional disaster exposure.

Future research can attempt to match high-resolution satellite remote sensing data, such as crop damage index, with micro-level farmer survey data to construct more refined risk exposure indicators, thereby more accurately identifying the effects of disaster shocks on households. By incorporating household-level information on disaster types, such as floods, droughts, frosts, and storms, future research could further examine the heterogeneous moderating effects of the digital economy across different disaster scenarios and identify the underlying mechanisms through which digitalization strengthens household livelihood resilience.

6. Research Conclusions

This study utilized the large-scale panel dataset of CFPS from 2014 to 2020 to investigate whether and how the digital economy mitigates the adverse impact of natural disaster shocks on the livelihood resilience of rural households. A comprehensive livelihood resilience index of rural households has been constructed which integrates buffering capacity, self-organization capacity, and learning capacity. The empirical results of this article provide empirical evidence for the moderating effect of digitization in the context of disaster vulnerability.

Three main conclusions are drawn in this paper. Firstly, the digital economy significantly weakens the negative impact of natural disasters on the farmers' livelihood resilience. This mitigating effect also operates across three resilience capacities: buffering capacity, self-organizing capacity, and learning capacity. Secondly, the digital economy plays a moderating role by promoting non-agricultural employment, improving farmers' access to credit, and diversifying agricultural production strategies, revealing the diverse transmission mechanisms of digital empowerment in enhancing resilience in the context of disaster impacts. Finally, the moderating effect of digitalization exhibits heterogeneity, with stronger effects in the central and western regions, among higher-income households, and in counties with e-commerce policy support. This indicates that the dividends of the digital economy are not automatically inclusive, but are shaped by structural factors such as regional development level, household resource endowment, and institutional environment.

This study enhances the understanding of the digital economy's role in mitigating the adverse impacts of natural disaster shocks on rural households' livelihood resilience. Specifically, it clarifies the mechanisms through which it enhances resilience, including non-agricultural employment, credit access, and diversified agricultural production strategies. These findings offer practical insights and valuable references for other regions

seeking to enhance rural households' livelihood resilience in the face of increasing frequent natural disaster. First, policymakers should recognize the role of the digital economy in empowering farmers' livelihood resilience and promote digital transformation through inclusive digital development policies, with narrowing the household-level digital divide as the central concern. Second, in rural areas of developing countries, digital coverage does not necessarily translate into resilience empowerment. To tackle this challenge, embedding digital skills training into grassroots agricultural extension systems can help address the learning capacity constraints faced by low-income farming households and ensure that the benefits of the digital dividend are more inclusively distributed across rural households. Compared to post-disaster funding compensation, incorporating digital capacity building into the risk management system can help improve the sustainability of interventions. Finally, based on empirical evidence from rural China, this study highlights the importance of leveraging the digital economy to boost farmers' adaptive capacity against disaster risks, particularly for agriculture-dependent developing countries facing persistent climate risks.

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Appendix A

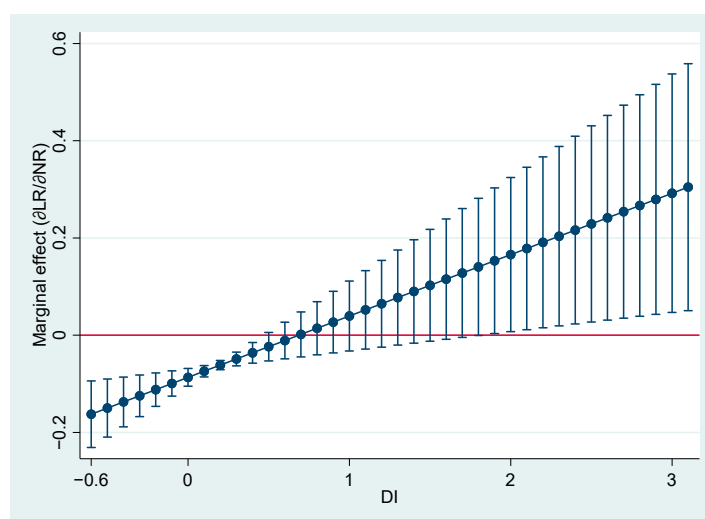


Figure A1. The marginal effect diagram of NR on LR. The horizontal red line at zero indicates the threshold where the marginal effect of NR on LR shifts from negative to positive.

Table A1. Results of multicollinearity test.

Variable	VIF	1/VIF
NR	4.39	0.23
DI	2.70	0.37

NR × DI	5.29	0.19
Size	1.11	0.90
Age	1.59	0.76
Gender	1.03	0.97
Marriage	1.31	0.76
Safeguards	1.28	0.90
Mean VIF	2.34	

Table A2. Robustness analysis of mechanism variables.

Variables	(1) M1	(2) M2	(3) M3
NR	−0.100 *** (0.029)	−0.353 *** (0.128)	−0.108 ** (0.046)
DI	0.153 *** (0.020)	0.295 *** (0.073)	0.234 *** (0.038)
NR × DI	0.257 ** (0.117)	0.194 ** (0.081)	0.238 ** (0.114)
Constant	0.332 *** (0.008)	0.210 *** (0.033)	0.188 *** (0.016)
Observation	25,198	25,198	25,198
R-squared	0.345	0.458	0.463
Control	YES	YES	YES
Yearfix	YES	YES	YES
Famfix	YES	YES	YES

Province-clustered robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$.

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