Journal of Global Economics, Public Policy and Development

jglobed.com

Research Article

Climate Risks and Household Economic Resilience: Effects and Moderating Effects

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Cite This: https://doi.org/10.65638/0000-0000.2026.1.04

ABSTRACT: This paper constructs a panel dataset by using data from the China Household Finance Survey (CHFS) and the Climate Physical Risk Index (CPRI) for the period 2011-2017 to examine the impact of climate risks on household economic resilience and the moderating roles of digital inclusive finance and social security. The findings reveal that: (1) climate risks negatively affect household economic resilience, a finding that holds up following a series of robustness tests; (2) heterogeneity analysis indicating that the negative effect of climate risks on household economic resilience is more distinctive in female-headed households and unmarried households. (3) Higher levels of digital inclusive finance and social security are associated with a weaker negative climate-risk-resilience relationship, although the economic magnitudes are modest. Consequently, based on the above findings, this paper presents a series of policy recommendations to assist households in coping with climate risks and enhancing their economic resilience.

Keywords: Climate risks, Household economic resilience, Digital inclusive finance, Social security.

1. INTRODUCTION

Against the backdrop of global climate change, climate risks are affecting every aspect of human society at an unprecedented rate and with unprecedented intensity (IPCC, 2021). For the fourth consecutive year, the Global Risks Report 2024 has identified extreme weather events as the single risk most likely to occur and have the greatest impact over the next decade. The IPCC AR6 further notes that even if global warming is limited to 1.5 °C, the intensity of extreme events will still increase by 70%, with agricultural belts in the mid-to-low latitudes bearing the brunt of the impact. In recent years, China has seen a trend towards an increase in extreme weather and climate events. Heavy rainfall and flooding, heatwaves and droughts, cold damage, tropical cyclones, severe convective storms and sandstorms have exhibited characteristics such as extreme intensity, distinct regional and seasonal patterns, and frequent occurrences of abnormal conditions (Zhang Cunjie *et al*., 2024). These climate risks not only impact the macroeconomy—affecting national GDP growth and industrial restructuring (Sun Yongping and Liu Lingna, 2023)—but also profoundly affect household economic conditions at the micro level. Research into climate change and its impacts on society, households and the economy has become a central theme in recent years. Existing research has extensively demonstrated the impact of climate change on the economy (Jung *et al*., 2022) and people's livelihoods (Yu *et al*., 2025), affecting all aspects of social production and daily life, with far-reaching implications for contemporary human society. In particular, the relationship between climate-related risks and their economic and livelihood impacts is emerging as a hot topic in academic circles.

As the basic unit of socio-economic activity, the economic resilience of households is crucial to maintaining their

Received: July 13, 2026
Accepted: August 16, 2026
Published: August 19, 2026

standard of living, safeguarding the prosperity of family members, and promoting social stability (Adger, 2006). Economic resilience refers to a household's ability to maintain or rapidly recover its original economic status when faced with external shocks (Cutter *et al*., 2008). In recent years, climate change has intensified around the globe, with frequent occurrences of extreme weather events (such as floods, droughts and hurricanes) posing a severe challenge to household economic stability (IPCC, 2022). Climate risks may adversely affect household finances through various channels, such as reducing household income, damaging assets and increasing expenditure, thereby undermining household economic resilience. In China, the impact of climate risks on household finances is particularly pronounced. China is one of those countries that is most severely affected by climate change, the frequency and intensity of extreme weather incidents are on the rise (China Meteorological Administration Bulletin)[1].

At the same time, given China's vast population, a large number of households are directly or indirectly affected by climate risks. According to statistics from the National Bureau of Statistics, the annual economic losses contributed by climate-related disasters in China amount to hundreds of billions of yuan, a significant proportion of which is borne by households. Currently, there is a scarcity of research on impacts of climate risks on household finances. Consequently, conducting in-depth research into the effects of climate risks on the economic resilience of Chinese households holds significant practical importance. What, then, are the micro-level mechanisms through which climate risks affect household economic resilience? How do these risks exert heterogeneous effects on the economic resilience of households with different characteristics? And what are the underlying transmission mechanisms? Answers to these questions are crucial for vulnerable groups in China to cope with future external shocks and enhance household economic resilience. This paper utilises panel data from the China Household Finance Survey (CHFS) for 2011-2017 and the Climate Physical Risk Index (CPRI) dataset to construct indices of climate risk and household economic resilience, and empirically examines the impact of climate risk on household economic resilience and its underlying mechanisms.

Compared with existing literature, this paper makes the following potential marginal contributions: First, it explores the relationship between climate risk and household economic resilience, providing a new perspective for research on the determinants of household economic resilience; Second, it delves into the mechanisms through which climate risks affect household economic resilience, broadens the channels of influence, and provides theoretical support and policy recommendations for households to cope with climate risks and enhance their economic resilience; Third, by examining heterogeneous effects of climate risks on household economic resilience from the perspectives of gender and marital status, it contributes to a deeper understanding of the impact of climate risks on household economic resilience.

2. LITERATURE REVIEW

2.1. Relevant Research on Climate Risk

Climate risk refers to the potential threats impending to human society and economic systems by changes in the natural environment resulting from climate change (IPCC, 2021). As global warming intensifies, research into climate risks has gradually become a focal point of academic attention. Early studies primarily focused on the physical aspects of climate change, such as rising temperatures, altering precipitation patterns and rising sea level (Mendelsohn *et al*., 1994). In recent years, research has gradually expanded to examine the impact of climate risks on socio-economic systems, including their effects on various sectors such as agriculture, industry and the service sector (Feng, X *et al*., 2025).

Regarding the impact of climate risks on agriculture, numerous studies indicate that climate change has a remarkable negative impact on agricultural production. Factors such as rise of temperatures and abnormal precipitation can lead to reduced crop yield and increased pest and disease incidences, thereby affecting farmers' incomes (Schlenker *et al*., 2005). Xie *et al*. (2020), after accounting for factors such as temperature, precipitation and standard deviation, utilized the China Agricultural Policy Simulation and Projection Model (CAPSIM) to find that climate change has a downside impact on China's agricultural output. Ding Yugang and Sun Qixiang (2022) found that climate risks directly affect agricultural economic output, reducing it, and exert an adverse impact on agricultural economic development by increasing the severity of natural disasters, thereby further amplifying the negative effects on the agricultural economy. Furthermore, Zheng Wolin and Hu Xinyan (2021) constructed a 'climate change-risk generation-farmer risk-hedging strategies' framework, pointing out

[1] https://www.mee.gov.cn/zcwj/zcjd/202206/t20220614_985479.html

that climate risks affect the agricultural economy through a chain reaction of ‘yield fluctuations → income decline → investment contraction’.

Relatively few studies have examined the impact of climate risks on the industrial and service sectors. Some studies have pointed out that climate change may lead to issues such as increased energy demand, supply chain disruptions and reduced investment in research and development, thereby affecting industrial production efficiency (Liu Yuanzhe *et al*., 2020; Liu Bo *et al*., 2023). For example, Yang Lu *et al*. (2020), using microdata on Chinese industrial enterprises from 1998 to 2007, found that high temperatures have a negative impact on industrial output. In the service sector, Jin Gang *et al*. (2020), using county-level data from 2000 to 2015, found that high temperatures and drought reduced profits in labor-intensive service sectors such as wholesale and retail, accommodation and catering by 3%-6%, and that micro and small enterprises were unable to pass on costs through price increases.

2.2. Related Research on Household Economic Resilience

Research on household economic resilience originated in the fields of sociology and economics, with the aim of exploring households’ capacity to cope with and recover from external shocks (Adger, 2006; Cutter *et al*., 2008). In recent years, as research has deepened, the concept of household economic resilience has been continually expanded to encompass multiple dimensions, including household asset accumulation, income diversification and access to social services (Yuan Nianxing, 2023).

Regarding the determinants of household economic resilience, existing research indicates that factors such as household asset status, income levels, educational attainment, internet usage, digital finance and social networks exert a significant influence on household economic resilience (Si Chuanning and Zhang Xiaofan, 2024; Hu Zihao and Xiong Xueping, 2025).

For instance, Si Chuanning and Zhang Xiaofan found that high-income households typically possess greater financial strength and more resources to cope with shocks, whereas low-income households are more vulnerable to the effects of such shocks (Si Chuanning and Zhang Xiaofan, 2024); furthermore, research has shown (Li Chanjuan and Wang Jun, 2025) that households with higher levels of education are often better able to understand and manage risks, adopting more effective coping strategies; in addition, strong social networks can provide households with information, resources and emotional support, thereby enhancing their economic resilience (Hu Zihao and Xiong Xueping, 2025).

There is currently no standardized method for measuring household economic resilience. Some studies employ econometric models to assess this, which is the prevailing approach at present. The methodology employed by Cissé and Barrett (2018) primarily defines resilience as the probability that a household can maintain its standard of living above the poverty line even when faced with external shocks. Using household consumption levels as an indicator of welfare, they estimate the conditional expectation and conditional variance of the welfare function to measure household economic resilience as the possibility that household welfare exceeds a certain threshold. Other studies construct indicator systems from multiple dimensions, including household assets, income, social services and public services, to measure household economic resilience (Yuan Nianxing, 2023).

2.3. Relevant Research on the Impact of Climate Risks on Household Economic Resilience

As climate risks intensify, their impact on household economic resilience has gradually become a key area of research. Existing studies have primarily examined the impact of climate risks on household economic resilience from the following perspectives.

Household income: The impact of climate risks on household income is primarily manifested in two areas: agricultural production and employment. For households relying on agriculture as their main source of income, climate risks such as extreme heat, torrential rain and drought can lead to reduced crop yields and livestock deaths, thereby diminishing household income (China Meteorological Administration Bulletin). For example, in Bangladesh, due to the lack of arrangements on risk-sharing or formally insurance mechanisms, the livelihoods of rural households are highly vulnerable to climate shocks; those shocks increase the risk of households falling into poverty and reduce their opportunities to escape it (Alam, 2017). In terms of employment, climate risks may lead to a reduction in job opportunities in certain sectors; for instance, outdoor workers may be unable to work normally due to extreme weather, thereby affecting household income (U.S. Department of the Treasury, 2023). Furthermore, some studies have found that climate risks may cause changes in the supply and demand structure of the labor market, which in turn affects households' employment and income situations (Burke *et al*., 2015).

With regard to household assets: the impact of climate risks on household assets is primarily manifested in direct losses and depreciation in value. Extreme weather events such as floods, hurricanes and earthquakes can directly damage household assets such as homes, vehicles and tools of production, inflicting significant financial losses on households (U.S. Department of the Treasury, 2023). Furthermore, in the United States, frequent disasters such as wildfires and hurricanes have resulted in many households' homes being burnt down or damaged, causing a significant reduction in household wealth. In addition, climate risks may lead to a depreciation in asset values; for instance, properties in coastal areas face the risk of depreciation due to rising sea levels (Hallegatte *et al*., 2013).

In terms of household expenditure: climate risks lead to increased household expenditure, primarily manifested in two aspects: rising living costs and increased expenditure on disaster response. On the one hand, climate risks may result in reduced agricultural yields, which in turn leads to rising food prices and increases household living costs; on the other hand, following a climate-related disaster, households face costs associated with home repairs, property replacement and medical treatment, further exacerbating their financial burden (U.S. Department of the Treasury, 2023). Such additional costs can compress households' disposable resources and weaken their capacity to absorb subsequent shocks (U.S. Department of the Treasury, 2023).

In terms of household finance: Research by Liu Zhonglu *et al*. (2023) indicates that climate disasters affect household financial risk through three channels: by tightening credit constraints, increasing household debt leverage, and reducing the diversification of financial asse*t al*location. Climate disasters tighten credit constraints on households, increasing their difficulties to obtain sufficient credit support; at the same time, they may lead to an increase in household debt leverage, thereby increasing the household debt burden. Furthermore, in response to climate risks, households may adjust their financial asse*t al*location by reducing holdings of risky assets and increasing precautionary savings. Dercon (2002) found that in Africa, climate risks lead some rural households to reduce investment in agricultural production and instead increase savings to cope with future uncertainty (Dercon, 2002).

2.4. Review

Although existing research has achieved some results regarding the impact of climate risks on household economic resilience, certain shortcomings remain. Firstly, most existing studies examine the effect of climate risks on economic systems at the macro or meso level, whilst research conducted at the micro household level is relatively scarce. As the basic unit of economic activity, a household's economic resilience influenced by a variety of factors, and there is significant heterogeneity between households. Consequently, conducting in-depth research at the micro-household level on the impact of climate risks on household economic resilience is of great significance. Secondly, existing research has not yet explored mechanisms through climate risks affecting household economic resilience in sufficient depth. Although previous studies have indicated that climate risks may influence household economic resilience via household income, assets, expenditure and financial aspects, further research and validation are required regarding the specific pathways and mechanisms of action. Furthermore, the behavioral differences among households in coping with climate risks and the factors influencing these differences also warrant further investigation.

In summary, building upon existing research, this study will adopt a micro-level household perspective and comprehensively consider multiple climate factors to thoroughly examine the mechanisms and extent impact of climate risks on household economic resilience. The aim is to provide more targeted policy recommendations to assist households in coping with climate risks and enhancing their economic resilience.

3. THEORETICAL ANALYSIS

3.1. The Relationship between Climate Risks and Household Economic Resilience

Research into the relationship between climatic conditions and household dynamics has long been extensive. The impact of climate risks caused by climate disasters on household economic resilience manifests in three ways, subject to constraints such as socio-economic conditions and household circumstances: direct or indirect property loss; the deterioration of physical and mental health; and a direct impact on the allocation of household financial resources. Specific mechanisms are shown as follows:

Climate risks, through direct or indirect economic and property losses, directly affect the strength of household economic resilience. This situation most frequently occurs in specific production sectors where household economic livelihoods are heavily dependent on climatic conditions, such as agriculture (Wang Guoping *et al*., 2022) and light industry with weak infrastructure (Yang Lu *et al*., 2020); geographically, these are predominantly found in economically underdeveloped regions in central and western China. Due to inherent regional constraints, these areas lack the physical and social infrastructure necessary to directly withstand extreme weather conditions. Furthermore, they suffer from inadequate social security and disaster response mechanisms, coupled with highly fragile ecosystems; consequently, they exhibit systemic vulnerability when confronted with sudden meteorological disasters (Cao Zhijie and Chen Shaojun, 2016). For some households in these regions, household income and economic livelihoods depend on a single source of employment, such as agricultural or light industrial labor. Furthermore, due to the impact of fragile infrastructure and social response mechanisms, households often lack effective emergency response and recovery capabilities when faced with meteorological disasters. Consequently, when disasters strike, these households are particularly susceptible to the direct impact of climate risks, resulting in significant economic and property losses. Furthermore, the fragility of local social security systems and both hard and soft infrastructure means that households that have lost their primary sources of income are unable to access the necessary financial and resource support, thereby further undermining the economic resilience and strength of the household unit.

Furthermore, extreme weather conditions, such as extreme heat and frequent rainfall, have a significant impact on the breadwinners within a household. This is primarily due to the detrimental effects on the physical and mental health of household members, which in turn weakens the household's economic resilience. Firstly, the household's main source of income depends on the working capacity of its members. Under the onslaught of extreme weather, particularly the two typical types of disasters—heatwaves and heavy rainfall—it is inevitable that the health of household members will affected by climate change under current conditions. The loss of property and damage to personal health and safety caused by meteorological disasters will further affect the psychological well-being of household members. Their sense of happiness and fulfilment is eroded, causing some members to lose the motivation and psychological resilience to cope with disasters, which in turn further impairs the ability of household members and the household unit as a whole to withstand the onslaught of disasters.

Household asse*t al*location is one of the key indicators of a household's financial resilience. It primarily refers to the allocation of a household's assets and liquid funds, and constitutes a vital component of a household's financial structure and sources of income. A sound household asse*t al*location can help a household cope with the vast majority of financial risks and minimize the direct impact of such risks on the household's finances. For households with a certain level of financial foundation, asse*t al*location will include a component of risk-taking investments. Such investments, alongside savings-oriented financial activities, can provide a secondary source of income for the household beyond its primary sources, and this income does not require any additional effort beyond the capital itself. However, high-risk financial activities often carry inherent risks and require a certain level of capital, meaning that households with lower incomes are unable to generate a secondary income stream through such investments (Pan Min and Li Jingjing, 2024). As a key factor that can severely impact investment risks in financial markets, climate risk will drive the reallocation of household asse*t al*location through direct or indirect economic losses, increasing the likelihood of households purchasing insurance and engaging in borrowing and saving activities. However, by reducing the likelihood of households being able to repay their debts, it consequently reduces the intensity and volume of risk investments. For households with better economic conditions, a reduction in the intensity of risky investments has a severe long-term impact on the distribution of household asse*t al*location and exerts a negative influence on household economic resilience.

H1: Climate risk has a negative effect on household economic resilience.

3.2. The Moderating Effect of Digital Inclusive Finance

Digital inclusive finance is characterized by 'low barriers to entry', 'high efficiency' and 'low interest rates'. Beyond its role as a vehicle for ordinary household savings, it exerts a positive influence on household financial allocation. Most previous studies have demonstrated and, to a certain extent, substantiated this effect. The mechanism through which digital inclusive finance influences relationship between climate risk and household economic resilience is as follows:

Furthermore, digital inclusive financial products are characterized by low risk and high returns. Households can secure substantial long-term income by purchasing these products in advance, thereby facilitating their ass*et al*location during normal times and mitigating the negative impact of future climate risks on their economic resilience. As one of the direct indicators of household economic resilience, efficient ass*et al*location can help individuals or households generate additional income. To a certain extent, risk-taking investments can provide households with excess returns, enabling the accumulation of household assets in the shortest time and with the greatest efficiency, and preparing for potential future household economic risks.

Finally, as an emerging sector and an indispensable component of the social system, digital inclusive finance possesses long-term development potential. Vigorously developing digital inclusive finance and adapting its application scenarios to meet demand can facilitate the rapid growth of the industry of digital finance, provide new job opportunities for workers with relevant professional skills, and increase sources of income, thereby mitigating the downside impact of climate risks on household economic resilience.

H2: Digital inclusive finance mitigates the negative impact of climate risks on household economic resilience.

3.3. The Moderating Effect of Social Security

As a ‘stabilizer’ for society, a ‘safety net’ for households, and an effective pathway to achieving common prosperity, the positive impact of social security on household finances has been partially validated in previous research. The mechanism through which it interacts with climate risks is primarily reflected in how the safety net and additional income provided to households mitigate the impact of climate risks; the specific mechanisms are outlined below:

Social security mitigates the impact of climate risks on household economic resilience by providing a safety net for households. As part of the government’s safety-net system and social welfare initiatives for households, social security can, by design, directly provide households with a basic income and material living allowances. Through mechanisms such as income redistribution (Yang Fengshou and Shen Mo, 2016) and horizontal income transfers (He Min and Zhu Minglai, 2024), social security funds are distributed equitably to individuals or households according to need. Furthermore, for households with low-income levels and members with disabilities, the safety-net function of social security is particularly pronounced. For low-income urban households, social security benefits may also constitute one of the primary sources of household income. This compensatory income can partially offset household property losses whilst ensuring the supply of basic necessities during times of hardship; consequently, social security can mitigate the impact of climate risks on household economic resilience.

Furthermore, social security can directly increase household income levels, boost basic household consumption and provide opportunities for households to undertake moderate risk-taking, thereby strengthening household economic resilience and mitigating the impact of climate risks on such resilience. Previous research has found that social security exerts a certain influence on the risk-taking behavior of households (Zong Qingqing *et al*., 2015). Specifically, in households with a certain income base, social security support for households and individuals is primarily reflected in the coverage and supplementation of basic living costs. Social security enables those with a certain income level to have surplus funds to undertake limited risk-taking and future-oriented investments at the household level. In such circumstances, the profits from these investments lay a more solid economic foundation for the household, enhancing its consumption and income capacity. At the same time, certain financial products associated with risk investments offer stable returns, meaning that even in the event of natural disasters, earning capacity remains unaffected. Consequently, this further enhances the economic resilience of the household unit and mitigates the negative effects of climate risks.

Social security can also ensure household economic resilience by reducing the sense of deprivation experienced by family members during climate disasters, for example by preventing a decline in well-being and mitigating health risks. The impact of social security on health risks and well-being is primarily reflected in its safety-net mechanism; when household income falls, social security can assist family members at risk of health issues in covering medical expenses at a lower cost through financial assistance and the social security safety-net mechanism. At the same time, social security mechanisms play a role in promoting household well-being (Ma Hongge and Xi Heng, 2020), helping families to better overcome the sense of deprivation caused by property and health losses resulting from meteorological disasters, and enabling family members to emerge from difficult periods, thereby ensuring the strength of household economic resilience.

H3: Social security moderates the relationship between climate risk and household economic resilience, such that higher social security provision is associated with a weaker negative relationship.

4. RESEARCH DESIGN

4.1. Sample and Data Sources

The data sources comprise three components: (1) Household data: The data is drawn from the CHFS (China Household Finance Survey), a survey led by Southwestern University of Finance and Economics. Conducted biennially since 2011, the survey covers approximately 29 provinces, 355 counties (districts and county-level cities) and 1,428 communities across China. It provides a comprehensive and detailed portrait of household economic and financial behavior and is nationally representative. We selected data from the 2011, 2013, 2015 and 2017 waves and processed the aggregated sample as follows: first, we matched household information with head-of-household information; second, we excluded samples with missing values for key variables. (2) Climate data: The Climate Physical Risk Index (CPRI) dataset is sourced from Guo *et al*. (2024). This dataset comprises climate physical risk assessment data for 170 countries worldwide, 31 provinces and autonomous regions in China, and 229 cities from 1993 to 2023. We selected the 2011, 2013, 2015 and 2017 CPRI data for Chinese cities as our study sample; (3) Urban data: The data are sourced from the China Urban Statistical Yearbook and the National Bureau of Statistics. Finally, we matched the household data, climate data and urban data, ultimately obtaining 9,824 observations.

4.2. Selection of Variables

4.2.1. Household Economic Resilience

Household economic resilience refers to a household's ability to withstand external shocks and mitigate fluctuations in risk when faced with external risks and uncertainty. Drawing on existing literature (Cissé & Barrett, 2018; Phadera *et al*., 2019), this paper measures household economic resilience.

The first step involves estimating a first-order Markov process, with the specific model specification as follows:

$$W_{it} = \sum_{j=1}^{k} \beta_{Mj} W_{i,\ t-1}^{j} + \gamma_M X_{it} + \varepsilon_{Mit} \tag{1}$$

Equation (1) models the welfare indicator W_{it} at time t as a polynomial function of the welfare $W_{t,\ t-1}$ at the previous time step $t-1$. Additionally, other explanatory variables X_{it} and a random disturbance term ε_{Mit} are included. The subscript M denotes the expectation equation, and j denotes the order of the higher-order moment. Furthermore, given the typical S-shaped dynamic characteristics of the multiple equilibrium poverty trap theory, this report sets k to 3 (Barrett *et al*., 2006).

$$\hat{\mu}_{1it} = E\left[W_{it} | W_{t,t-1}, X_{it}\right] = \sum_{j=1}^{k} \hat{\beta}_{Mj} W_{t,t-1}^{j} + \hat{\gamma}_M X_{it} \tag{2}$$

Once again, denoting the variance equation by V, and following Justand and Pope (1979) and Antle (1983), we use the first-order centrality residuals to estimate the second-order centrality equation:

$$\hat{\varepsilon}^2{}_{Mit} = \sum_{j=1}^{k} \hat{\beta}_{Vj} W_{i,\ t-1}^{j} + \hat{\gamma}_V X_{it} \tag{3}$$

Similarly, under the assumption of a zero mean $E[\varepsilon_{Vit}] = 0$, the estimate of the conditional variance for household i at time t can be expressed as:

$$\hat{\mu}_{2it} = \sum_{j=1}^{k} \hat{\beta}_{Vj} W_{i,\ t-1}^{j} + \hat{\gamma}_V X_{it} \tag{4}$$

If the distribution of $W_{j,\ t-1}$ is assumed, the distribution of household i's welfare W_{it} at time t can be described using the above estimates of the conditional expectation and conditional variance. Assuming that the form of the distribution function and point estimates allows for the estimation of the conditional probability density function and the associated complementary cumulative distribution function for household welfare at a specific time, this report uses them to estimate the probability that household i will meet a standardized minimum welfare threshold at time t. Following the framework of Barrett and Constas (2014), resilience $(\hat{\rho}_{it})$ is defined as the probability that household i's welfare at time t exceed a certain threshold $(\overline{W})$. The specific equation is set as follows:

$$\hat{\rho}_{it} \equiv P(W_{it} \geq \overline{W}) = \bar{F}_{Wit}\left(\overline{W}\ ;\ \hat{\mu}_{1it}(W_{it},\ X_{it}),\ \hat{\mu}_{2it}(W_{it},\ X_{it})\right) \tag{5}$$

Drawing on experience in measuring poverty vulnerability, this report uses per capita household consumption (log-transformed) as a measure of welfare. Since household consumption must remain non-negative, this report assumes that the household welfare variable W_{it} follows a Poisson distribution. The 2015 World Bank standard of US$1.90 per capita daily consumption is adopted as the threshold $\overline{W}$, and this is converted into comparable 2011 data using the exchange rates and consumer price indices for the corresponding year. Generalised linear models (GLMs) are employed to perform maximum likelihood estimation of the aforementioned conditional expectation and conditional variance equations, thereby deriving data on household economic resilience.

To assess whether the estimates depend on the US$1.90 threshold, the analysis also reconstructs resilience using three sample-period-compatible benchmarks: 50% of each survey wave's median per capita daily consumption; the World Bank societal poverty line, max[US$1.90, US$1.00 + 0.5 × median per capita daily consumption], expressed in 2011 PPP and converted with the private-consumption PPP factor; and China's corresponding annual rural poverty standard published by the National Bureau of Statistics. The China standard is treated as a rural policy benchmark rather than a universal urban poverty line.

4.2.2. Climate Risk (CPRI)

Drawing on the research by Guo *et al*. (2024), we have developed a Climate Physical Risk Index to measure the climatic impacts caused by extreme weather events and natural disasters. This process primarily comprises three steps. Step 1: Calculate the four sub-indicators: LTD (number of days with extreme low temperatures), HTD (number of days with extreme high temperatures), ERD (number of days with extreme rainfall), and EDD (number of days with extreme drought); Step 2: Standardize the four sub-indicators; Step 3: Calculate the Climate Physical Risk Index using a simple average (for the detailed procedure, see Guo *et al*., 2024). As an alternative to equal weighting, the four standardized climate-risk dimensions are also aggregated using the CRITIC method (Diakoulaki *et al*., 1995), which combines each indicator's contrast intensity with its conflict relative to the remaining indicators. The resulting weights are 0.1941 for extreme low temperature, 0.2776 for extreme high temperature, 0.2822 for extreme rainfall and 0.2461 for extreme drought.

4.2.3. Other Control Variables

We selected control variables as follow: (1) Household characteristics: total household income (total income) and household size (pop); (2) Household head characteristics: gender of the household head (sex, 1 for male, 0 for female), age (lnage, logarithm of age), marital status (marriage, 1 for married, 0 for unmarried) and educational attainment (edu, 1. No schooling; 2. Primary school; 3. Lower secondary school; 4. Upper secondary school; 5. Technical secondary school/vocational high school; 6. College/vocational college; 7. Undergraduate; 8. Master's degree; 9. Doctorate); (3) Urban characteristics: Urbanization rate (Urbanrate, proportion of urban population in total population), industrial structure (Urbanrat, ratio of secondary industry output to tertiary industry output) and foreign trade (Foreign, ratio of import and export value to GDP).

4.3. Baseline Model

To examine the impact of climate risk on household economic resilience, the following econometric model is constructed:

$$resilience_{ijt} = \alpha_0 + \alpha_1 CPRI_{ijt} + X_{ijt}\beta + \delta_t + \varphi_i + \varepsilon_{ijt} \quad (6)$$

Where i denotes the household; j denotes the city; t denotes the year; the dependent variable $resilience_{ijt}$ represents household economic resilience; the independent variable $CPRI_{ijt}$ represents climate risk; X_{it} represents all control variables; δ_t represents the time fixed effect; φ_i represents the household fixed effect; and ε_{ijt} is the random error term.

Table 1: Descriptive Statistics

Variable	Mean	p50	SD	Min	Max	N
resilience	0.5000	0.4987	0.0117	0.3444	0.7995	9,824
CPRI	0.2576	0.2515	0.0661	0.1069	0.4309	9,824
totalincome	20.6325	20.3700	1.2378	6.0326	51.0337	9,824
sex	0.5357	1.0000	0.4987	0.0000	1.0000	9,824
lnage	3.7829	3.8501	0.3889	2.8904	4.6540	9,824
marriage	0.8617	1.0000	0.3453	0.0000	1.0000	9,824
edu	3.2336	3.0000	1.6695	1.0000	9.0000	9,824
pop	3.0564	3.0000	1.8973	1.0000	18.0000	9,824
Urbanrate	54.5263	52.4600	15.2002	25.9617	100.0000	9,824
Indstructure	1.0020	0.8674	0.6271	0.3755	4.2378	9,824
Foreign	0.0169	0.0125	0.0138	0.0004	0.0591	9,824

Because the panel covers four survey waves from 2011 to 2017, the household and year fixed effects identify within-household associations over this period but do not permit a reliable assessment of long-term adaptation responses. The results are therefore interpreted within the observed short- to medium-term window.

4.4. Descriptive Statistics

Table **1** presents the descriptive statistics for the main variables. The mean value of household economic resilience (resilience) is 0.5, with a minimum of 0.3444 and a maximum of 0.7995, indicating significant disparities in economic resilience across households; the mean value of climate risk (CPRI) is 0.2576, the minimum value is 0.1069 and the maximum value is 0.4309, indicating that there are certain differences in the climate risks faced by different cities, but overall climate risks are relatively low.

5. EMPIRICAL ANALYSIS

5.1, Baseline Regression

Table **2** presents the estimation results of the baseline regression for Model (1). Column (1) reports the initial regression results omitting all covariates and fixed effects, where the climate risk coefficient remains statistically

Table 2: **Baseline Regression Results**

Variables	(1)	(2)	(3)	(4)
	resilience	*resilience*	*resilience*	*resilience*
CPRI	0.0000	-0.0112***	-0.0028**	-0.0101***
	(0.0018)	(0.0013)	(0.0012)	(0.0015)
totalincome		0.0085***	0.0089***	0.0089***
		(0.0000)	(0.0003)	(0.0003)
sex		0.0003***	0.0003*	0.0003*
		(0.0001)	(0.0002)	(0.0002)
lnage		0.0007***	0.0002	0.0002
		(0.0002)	(0.0002)	(0.0002)
marriage		-0.0008***	-0.0006**	-0.0006*
		(0.0002)	(0.0003)	(0.0003)
edu		-0.0003***	-0.0002**	-0.0001*
		(0.0000)	(0.0001)	(0.0001)
pop		-0.0002***	-0.0002***	-0.0002***
		(0.0000)	(0.0000)	(0.0001)
Urbanrate		-0.0000***	-0.0002***	0.0001
		(0.0000)	(0.0000)	(0.0001)
Indstructure		-0.0005***	-0.0067***	-0.0024***
		(0.0001)	(0.0006)	(0.0007)
Foreign		-0.0084*	-0.0116	-0.0188**
		(0.0051)	(0.0078)	(0.0078)
_cons	0.5000***	0.3325***	0.3345***	0.3190***
	(0.0005)	(0.0013)	(0.0074)	(0.0089)
Controls	NO	YES	YES	YES
Household effect	NO	YES	NO	YES
Year effect	NO	NO	YES	YES
N	9824	9824	9824	9824
adj. R2	-0.000	0.756	0.743	0.748

Notes: Household-clustered standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels. The same applies below.

insignificant. After conditioning on control variables and incorporating household fixed effects in Column (2) and time fixed effects in Column (3), the estimated coefficients for climate risk become -0.0112 and -0.0028, respectively. Both of these estimates are highly significant at the 1% level. Column (4) presents the results of a regression with two-way fixed effects, where the estimated coefficient for climate risk is -0.0101, significant at the 1% level. The above findings indicate that climate risk leads to a decline in household economic resilience.

5.2. Robustness Tests

To ensure the robustness of the baseline regression results, we have conducted a series of robustness tests.

5.2.1. Substitution of Independent Variables - Dimension-Specific Tests

We categorised climate risks into four dimensions for a dimensional analysis: LTD (number of days with extreme low temperatures), HTD (number of days with extreme high temperatures), ERD (number of days with extreme rainfall), and EDD (number of days with extreme drought). The results are shown in Table **3**. The estimated coefficient for LTD is not significant, indicating that extreme low-temperature events have a negligible impact on household economic resilience; the estimated coefficients for HTD, ERD and EDD are all significantly negative, indicating that extreme high-temperature events, extreme rainfall events and extreme drought events have an adverse effect on household economic resilience. These findings demonstrate that, following the dimensional analysis, the baseline model remains robust.

5.2.2. Oster Test

Following the robustness tests for omitted variables, we further employed the Oster test to examine the potential impact of omitted variables. The results are as shown in Table **4**. To evaluate potential selection on unobservable, we first re-estimated the baseline specification by restricting the maximum R^2 to 1.3 times that of the baseline regression; the results revealed that the confidence interval (-0.0324, -0.0314) strictly excludes zero. Furthermore, the calculated Delta statistic is -2.5734, indicating that the relative importance of unobserved covariates would need to be 2.5734 times greater than that of the observed controls to fully nullify the baseline regression. These results indicate that the issue of omitted variables is not severe, and the regression results are robust.

5.2.3. Heckman Test and Post-Trimming Test

To address potential endogeneity stemming from sample selection bias, we employ a Heckman two-stage framework. In the first stage, we construct a binary variable, Climate, based on a mean-split of the climate

Table 3: Dimension Specific Tests

Variables	(1)	(2)	(3)	(4)
	resilience	*resilience*	*resilience*	*resilience*
Ltd	0.0017			
	(0.0014)			
Htd		-0.0023***		
		(0.0005)		
Erd			-0.0017***	
			(0.0006)	
Eed				-0.0026***
				(0.0006)
_cons	0.3125***	0.3162***	0.3127***	0.3155***
	(0.0090)	(0.0091)	(0.0090)	(0.0091)
Controls	YES	YES	YES	YES
Household effect	YES	YES	YES	YES
Year effect	YES	YES	YES	YES
N	9824	9824	9824	9824
adj. R2	0.746	0.747	0.747	0.747

Table 4: Oster Test

Variables	(1) Controlled effect	(2) Oster bound	(3) Rmax value	(4) Delta
CPRI	-0.0319**	(-0.0324, -0.0314)	0.970	-2.5734
Controls	YES	YES	YES	YES
Household	YES	YES	YES	YES
Year	YES	YES	YES	YES

risk data: it takes a value of 1 if the climate risk exceeds the sample mean, and 0 otherwise. This dummy variable serves as the dependent variable in the first-stage estimation to calculate the Inverse Mills Ratio (IMR). In the second stage, the IMR is integrated into the structural regression model to control for potential selection-induced estimation bias. The estimation results are presented in Table **5**. As shown in Columns (1) and (2), the estimated coefficient for climate risk remains robustly negative and statistically significant even after adjusting for selection bias. This confirms that escalating climate risks deteriorate household economic resilience, thereby validating our core hypothesis. Furthermore, we re-estimated the model under a stricter specification where all variables satisfy a 1% significance threshold; as reported in Column (3), the climate risk coefficient remains significantly negative, further reinforcing the stability of our primary findings.

5.2.4. Alternative Poverty Lines and Objective Weighting

Table **6** shows that the climate-risk coefficient remains significantly negative when resilience is reconstructed using the 50% median line, the World Bank societal poverty line and China's rural poverty policy benchmark.The three alternative thresholds (RMB per person per day) are, respectively, 6.0066, 9.7041 and 7.0444 in 2011; 8.6062, 12.3866 and 7.6000 in 2013; 19.0104, 22.9182 and 7.9306 in 2015; and 20.4762, 24.4399 and 8.2000 in 2017. The China line is a rural poverty policy benchmark rather than a universal urban poverty line. The coefficient is also significantly negative when the equally weighted climate index is replaced by the CRITIC-weighted index. The baseline conclusion therefore does not depend on a single poverty threshold or on equal weighting of the four climate-risk dimensions.

5.2.5. Continuous-Treatment Adjustment

To avoid the arbitrary mean split used in the original Heckman first stage, a generalized propensity score (GPS) adjustment is implemented for continuous climate-risk exposure following Hirano and Imbens (2004). The first-stage GPS model uses 140 city-year observations and has an R^2 of 0.4970. The adjusted average marginal effect remains negative and significant. Because GPS

Table 5: Heckman Test

Variables	(1)	(2)	(3)
	Climate	***resilience***	***resilience***
CPRI		-0.0095***	-0.0112***
		(0.0015)	(0.0010)
imr		0.0207**	
		(0.0096)	
_cons	1.2099***	0.3182***	0.3407***
	(0.2814)	(0.0088)	(0.0040)
Controls	YES	YES	YES
Household effect	YES	YES	YES
Year effect	YES	YES	YES
N	9824	9824	9627
adj. R2	0.054	0.748	0.612

Table 6: Alternative Poverty Lines and Weighted Climate Risk Index

Variables	(1)	(2)	(3)	(4)	(5)
	Baseline	50% Median	WB Societal	China Rural	Weighted CPRI
CPRI	-0.0101***	-0.0752**	-0.0991***	-0.1338***	
	(0.0015)	(0.0307)	(0.0357)	(0.0321)	
Weighted CPRI					-0.0096***
					(0.0014)
Controls	YES	YES	YES	YES	YES
Household effect	YES	YES	YES	YES	YES
Year effect	YES	YES	YES	YES	YES
N	9,824	7,368	7,368	7,368	9,824
adj. R2	0.748	0.218	0.392	0.622	0.748

adjustment addresses selection on observed covariates rather than unobserved confounding, this estimate is treated as a robustness check.

Table 7: Continuous-Treatment Generalized Propensity Score Adjustment

Variables	(1)
	GPS-adjusted resilience
Average marginal effect of CPRI	-0.0096***
	(0.0022)
Controls	YES
Household effect	YES
Year effect	YES
N	9,824
adj. R2	0.748

5.3. Heterogeneity Analysis

We analyzed the heterogeneous effects of climate risk on household economic resilience using gender, marital status and educational attainment respectively; the results are shown in Table **8**.

Columns (1), (2) present the heterogeneity analysis by head of household gender. Observed statistics shows that the estimated coefficient for climate risk in households lead by male respondent is -0.009, whilst that for households lead by female is -0.0109; both are significant at 1% level. This indicates that climate risk exerting a negative impact on the economic resilience of both male- and female-headed households, while the negative effect being more pronounced for those households lead by female. This is because traditional gender roles result in women bearing a greater share of household care responsibilities, whilst men shoulder

Table 8: Heterogeneity analysis by Gender and Marital Status

Variables	(1)	(2)	(3)	(4)
	Male	Female	Married	Unmarried
CPRI	-0.0090***	-0.0109***	-0.0100***	-0.0142***
	(0.0025)	(0.0025)	(0.0017)	(0.0029)
_cons	0.3291***	0.3099***	0.3214***	0.3052***
	(0.0172)	(0.0065)	(0.0101)	(0.0068)
Controls	YES	YES	YES	YES
Household effect	YES	YES	YES	YES
Year effect	YES	YES	YES	YES
N	5263	4561	8465	1359
adj. R2	0.725	0.716	0.726	0.882

more economic responsibilities. Consequently, female-headed households possess less human, physical and social capital compared to male-headed households, rendering them less resilient to external shocks and leaving their economic resilience more severely compromised.

Columns (3) and (4) present a heterogeneity analysis of the household head's marital status. Observed data shows that the estimated coefficient for climate risk in married households is -0.01, whilst that for unmarried households is -0.014; both are significant at 1% level. This indicates that climate risk exerting a negative impact on the economic resilience of both married and unmarried households, though the adverse effect is more pronounced for unmarried households. This is because marriage enables the effective integration of household resources. Compared to married households, unmarried households are smaller in size and have fewer members, resulting in limited household income and social capital. When faced with climate risks, this disadvantage in resource endowment makes unmarried households more vulnerable to shocks, thereby subjecting their economic resilience to a more pronounced negative impact.

The usable household registration indicator is invariant in the analytical sample and therefore cannot support a household-level urban-rural split. Instead, Table **10** distinguishes cities by their average urbanization rate (median 52.4271%) and average GDP per capita (median RMB 39,116.97). Groups are defined using city-level sample medians. The difference rows report the higher-group slope minus the lower-group slope. The climate-risk slopes are significantly negative in every subsample and are numerically larger in more urbanized and higher-income cities. However, the formal high-low differences have p-values of 0.106 and 0.107, so the apparent subgroup gaps are not statistically distinguishable.

6. MODERATING EFFECTS

The preceding estimates show a negative relationship between climate risk and household economic resilience. This section examines whether city-level digital inclusive finance and social security are associated with differences in the strength of that relationship. Because these policy environments may respond to common local shocks, the interaction coefficients are interpreted as moderating associations rather than as formal causal mediation effects.

Building upon Model (1), we introduce interaction terms to test the moderating effects of digital inclusive finance (Model 2), and social security (Model 3). To prevent multicollinearity issues arising from the interaction terms and to ensure comparability of the coefficients of the independent variables before and after the interaction terms, we apply centring to both the independent and moderating variables. The specific models are as follows:

$$resilience_{ijt} = \alpha_0 + \alpha_1 CPRI_{ijt} + \alpha_3 DF_{ijt} + \alpha_4 CPRI_{ijt} \times DF_{ijt} + X_{ijt}\beta + \delta_t + \varphi_i + \varepsilon_{ijt} \tag{7}$$

$$resilience_{ijt} = \alpha_0 + \alpha_1 CPRI_{ijt} + \alpha_3 Social_{ijt} + \alpha_4 CPRI_{ijt} \times Social_{ijt} + X_{ijt}\beta + \delta_t + \varphi_i + \varepsilon_{ijt} \tag{8}$$

6.1. Digital Inclusive Finance

The online financial products offered by digital inclusive finance can enhance households' access to and integration of financial resources (Peng & Liu, 2024), enabling them to easily obtain the financial services they

Table 9: Heterogeneity by Urbanization Context and Regional Development

Variables	(1)	(2)	(3)	(4)
	Lessurbanized	Moreurbanized	Lower GDPper capita	Higher GDPper capita
CPRI	-0.0076***	-0.0124***	-0.0076***	-0.0125***
	(0.0022)	(0.0021)	(0.0021)	(0.0021)
High-low difference		-0.0048		-0.0049
Difference p-value		0.106		0.107
Controls	YES	YES	YES	YES
Household effect	YES	YES	YES	YES
Year effect	YES	YES	YES	YES
N	4,704	5,120	4,548	5,276
adj. R2	0.499	0.813	0.490	0.815

require and manage diversified investments in line with their financial circumstances and risk preferences. At the same time, it helps alleviate the financial constraints faced by households, thereby facilitating more stable household consumption (Li *et al*., 2020). We therefore hypothesized that, when faced with the impact of climate risks, digital financial inclusion can effectively prevent households from falling into financial distress and enhance their resilience to such risks. To test the above hypothesis, we selected the Peking University Digital Financial Inclusion Index of China (PKU_DFIIC) to measure digital financial inclusion. The PKU_DFIIC comprises three dimensions—the breadth of digital financial coverage, the depth of digital financial usage, and the degree of digitalization of financial inclusion—and 33 indicators. The PKU_DFIIC is scientifically constructed, and its data coverage is extensive, enabling a comprehensive assessment of digital financial inclusion. The empirical results are presented in Table **10**, Column (1). The positive interaction coefficient indicates that higher digital financial inclusion is associated with a weaker negative climate-risk-resilience relationship.

6.2. Social Security

The inherent attributes of social security—mutual aid and risk-sharing—can effectively stabilize consumer expectations and alleviate consumption budget constraints. In the process of pursuing utility maximization, households are constrained by budget limitations and thus plan their savings and consumption based on expected income (Bird, 2001; Laitner & Silverman, 2012). We therefore hypothesize that, when faced with climate risk shocks, social security can effectively act as a stabilizer, mitigating the impact of income volatility and enhancing households' ability to withstand risks. To test this hypothesis, we use per capita social security expenditure as a measure of social security provision; the results are presented in Table **10**, Column 2. The positive interaction coefficient in Table **10**, Column (2) indicates that higher city-level social security expenditure is associated with a weaker negative climate-risk-resilience relationship.

6.3. Economic Magnitudes of the Moderating Effects

Table **11** translates the interaction coefficients in Table **10** into changes associated with simultaneous one-standard-deviation increases in climate risk and the corresponding moderator. The joint one-standard-deviation calculation multiplies each interaction coefficient by the standard deviation of CPRI and that of the corresponding moderator. The implied resilience

Table 10: Modulating Effects

Variables	(1)	(2)
	Digital Inclusive Finance	***Social Security***
CPRI×DF	0.0053***	
	(0.0012)	
CPRI	-0.0125***	0.0023***
	(0.0019)	(0.0008)
DF	-0.0029***	
	(0.0004)	
CPRI×Social		0.0323***
		(0.0070)
Social		0.0383**
		(0.0170)
_cons	0.3452***	0.3508***
	(0.0042)	(0.0013)
Controls	YES	YES
Household effect	YES	YES
Year effect	YES	YES
N	9824	9824
adj. R2	0.604	0.711

Table 11: Economic Magnitudes of the Moderating Effects

	(1)	(2)
	Digital Inclusive Finance	Social Security
Interaction coefficient	0.0053***	0.0323***
	(0.0012)	(0.0070)
Joint one-SD change in resilience	0.000236	0.000024
Share of resilience SD	2.02%	0.21%

change is 0.000236 for digital inclusive finance, or 2.02% of the standard deviation of resilience, and 0.000024 for social security, or 0.21%. Thus, although both interaction terms are statistically significant, their practical magnitudes are modest.

7. CONCLUSIONS AND IMPLICATIONS

This paper examines the relationship between climate risk and household economic resilience using a panel that combines the 2011-2017 China Household Finance Survey, the Climate Physical Risk Index and city-level statistical data. The household and year fixed-effects estimates show a significant negative association, and this result remains stable under alternative poverty lines, CRITIC weighting and a continuous-treatment generalized propensity score adjustment. The negative slopes are also present in both less- and more-urbanized cities and in lower- and higher-income cities, although the formal high-low differences are not statistically significant at conventional levels. Digital inclusive finance and social security are associated with weaker negative climate-risk-resilience relationships, but their estimated joint one-standard-deviation magnitudes are modest and should be interpreted as moderating associations rather than causal mediation effects. These findings motivate the following prioritized policy recommendations:

Firstly, in the short term (0-1 year), municipal emergency-management and meteorological agencies should link high-frequency weather warnings to household-level risk maps, while civil-affairs and finance departments pre-authorize targeted temporary cash relief for vulnerable households. Operational protocols should specify warning thresholds, beneficiary lists, disbursement channels and post-event verification so that support can be released immediately after a qualifying shock.

Secondly, over the medium term (1-3 years), local financial regulators and financial institutions should establish emergency credit lines and payment-continuity arrangements, while human-resources, social-security, civil-affairs and finance departments develop shock-responsive assistance triggers. These instruments should prioritize households in high-risk cities and be evaluated against take-up, disbursement speed, repayment stress and coverage gaps; the modest interaction magnitudes imply that digital finance and social security should complement, rather than replace, direct relief.

Thirdly, over the long term (more than 3 years), local development-and-reform, housing, transport and water authorities should incorporate climate-risk screening into capital budgeting and prioritize resilient drainage, transport, housing and public-service infrastructure in repeatedly exposed areas. Project appraisal should disclose the target risk reduction, responsible agency, construction timetable and maintenance funding.

Finally, implementation should be differentiated by local exposure and economic capacity. Municipal governments should publish annual monitoring results, coordinate data across meteorological, civil-affairs, social-security and financial agencies, and adjust beneficiary targeting without treating the nonsignificant between-group coefficient differences as evidence of sharply different structural effects.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Kun Xie: Writing -original draft, Investigation, Data curation, Conceptualization, Formal analysis.

DECLARATION OF COMPETING INTEREST

The author declares that she has no conflicts of interest related to this work.

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