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Climate Physical Risk and Rural Household Income: Evidence from Chinese Household Panel Data

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Article

Keywords: Climate Risk, Rural Households, Permanent Income, Income Structure

Posted Date: November 10th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11259137/v1

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Additional Declarations:
No competing interests reported.

Figures 2 is not available with this version.

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Abstract

Climate change poses a growing threat to the livelihoods of rural households, yet its relationship with household income in an era of increasingly diversified rural income portfolios remains insufficiently understood. Drawing on four waves of the China Family Panel Studies (2016–2022) matched with a prefecture-level physical climate risk index, this paper examines the association between physical climate risk and the income of Chinese rural households. The results show that higher climate risk is associated with significantly lower current and permanent income, with operating and property income most affected. Mechanism analysis indicates that the negative association is partly cushioned by increased social assistance, whereas agricultural participation, labour mobility, and credit constraints show no statistically significant mediating role. Access to commercial insurance and stronger social networks significantly attenuate the negative association, while the moderating role of medical insurance is not statistically supported. Heterogeneity analysis reveals that the adverse association is more pronounced among better-educated and higher-asset households, whose income portfolios are concentrated in climate-sensitive, marketised income sources, as well as among households in plains, mountainous and major grain-producing areas; the point estimate is also larger for female-headed households. By livelihood type, non-farm and part-time households are negatively affected, whereas farm-dominant households are not. Placebo tests, subsample restrictions, alternative climate measures and a lead-and-lag specification corroborate the pattern, and parallel trends are not rejected. The association does not survive the introduction of city fixed effects, so we read it as a regional gradient rather than a local treatment effect: within a locality, income is redistributed away from households whose portfolios are priced in local markets and towards those whose income is administratively determined or self-provisioned. The results remain associational rather than strictly causal. These findings inform targeted policies for strengthening rural household resilience to climate risk.

Keywords: Climate Risk; Rural Households; Permanent Income; Income Structure

JEL classification: Q54; Q15; R11; D13

1 Introduction

The escalating impact of climate change has emerged as a major global challenge. Extreme weather events induced by climate change—such as heatwaves, droughts, and floods—exert heterogeneous effects on the assets, human capital, and physical resources of different regions and populations (Rao et al. 2017). Rural residents, particularly those in less-developed regions who depend primarily on agriculture, are more susceptible because their livelihoods are both highly climate-sensitive and inherently vulnerable to external shocks. On

one hand, rural populations are often more exposed to climate risks because of their relatively disadvantaged living conditions and occupational environments. Frequent natural disasters not only disrupt agricultural production but also expose farmers to health risks, leading to reduced labour productivity and, in severe cases, prolonged incapacity to work.. On the other hand, the limited access of rural households to diversified assets, social networks, and credit support undermines their adaptive and recovery capacities, thereby exacerbating income vulnerability.

China, with one of the world's largest rural populations, faces the dual challenge of low rural household income and severe climate change impacts. According to the China Statistical Yearbook (2025), rural per capita disposable income reached 23,119 yuan in 2024—less than half the urban level. A 2024 report from the China Meteorological Administration warns that China is warming faster than the global average, making it both highly sensitive to and significantly affected by climate change. Since 2024, the country has experienced frequent extreme rainfall, severe flooding in southern provinces, prolonged drought in the southwest, and record-low temperatures in the central and eastern regions, alongside recurrent typhoons disrupting southeastern coastal areas. These escalating climate events have drawn substantial government attention and prompted calls for enhanced monitoring and proactive response. At the same time, boosting rural incomes and advancing rural revitalization remain policy priorities. However, climate risk may substantially constrain rural income growth. Investigating how climate risk affects rural household income is therefore critical for informing policies aimed at promoting rural revitalization in China.

Existing studies have primarily explored the factors influencing rural household income from macroeconomic and household capital perspectives, spanning areas such as the digital economy, industrial structure, financial markets, human capital, and social capital. These studies suggest that such factors influence rural income by increasing employment opportunities, enhancing skills, improving access to financial resources,and optimizing entrepreneurial environments. In the context of climate risk research, macro-level analyses suggest that climate risk leads to casualties and material losses (Mirza 2003; Ferreira 2024; Cappelli et al. 2021; Frame et al. 2020). These impacts reduce the productivity of labor and deplete the physical assets essential for economic growth, thereby inhibiting long-term economic development. At the micro level, scholars have focused on the effects of climate risk on migration, labor mobility, intra-household labor allocation, and the distribution of educational resources among households (Jessoe et al. 2018; Kayaga et al. 2021; Ahmad et

al. 2024). These studies indicate that households typically adjust their livelihood strategies in response to the immediate challenges posed by climate events. For instance, households may reallocate labor resources to ensure survival and maintain economic stability.

However, few studies have systematically examined the full impact of climate risk on total rural household income, particularly when income portfolios are increasingly diversified beyond agriculture. Some scholars have approached this issue from the perspective of income structure. For instance, Song et al. (2018) and Chidakwa et al. (2020) point out that the direct effects of climate risk on farm households primarily manifest as crop and asset losses, thereby mainly reducing operating income and affecting property income. In contrast, scholars such as Deschenes (2014) and Bloom et al. (2020), taking a long-term indirect perspective, suggest that climate risk not only affects farmers' current health status but also shapes their long-term health outcomes, thereby influencing subsequent employment and production efficiency and reducing wage income. Naturally, government compensation for disaster-affected farmers may lead to an increase in corresponding transfer income (Radel et al. 2018). However, a small but significant body of literature challenges this view, arguing that adaptive behaviors introduce uncertainty into the net impact of climate risk on income components. For example, farmers may diversify crops (Cui 2020), adjust agricultural production methods (Osberghaus and Abeling 2022), migrate, or enhance human capital as protective measures, and these adaptation preferences may partially offset the heterogeneous effects of climate risk on different income sources.

Studies mentioned above explore the effects of climate risk on rural household income, yet their findings remain inconclusive (Gao and Mills 2018; Aggarwal 2021; Li et al. 2024). Most of them focus on how climate risk affects rural households' operating income and the role of protective measures in mitigating such shocks. However, with the growing prevalence of non-farm employment, rural income portfolios have become more diversified, rendering the impact of climate risk on household income distinct from that on traditional farm households dominated by operating income. Moreover, the expansion of non-farm employment has broadened coping strategies beyond crop substitution or new machinery to include migration and temporary local employment. At the same time, rural households, constrained by limited financial access and weak social security, often rely on loans and social assistance to cope with risks, further shaping household income dynamics. This study thus provides a detailed investigation into the impact of climate risk on both total rural household income and its components.

Using four waves of data from the China Family Panel Studies (CFPS) spanning 2016–2022, matched with a prefecture-level physical climate risk index, this study examines the association between physical climate risk and rural household income. The results show that higher climate risk is associated with significantly lower current and permanent income, with operating and property income bearing the brunt of the adjustment. Mechanism analysis indicates that climate risk is accompanied by significantly greater social assistance, which partially cushions household income, whereas the hypothesised mediating roles of agricultural participation, labour mobility, and credit constraints are not statistically supported in the data. Access to commercial insurance and stronger social networks significantly attenuate the negative association, while the moderating role of medical insurance is not supported. Heterogeneity analyses further reveal that the association varies systematically with household head education and gender, household risk-bearing capacity, topographic location, agricultural production zone, and livelihood type.

This paper offers four main contributions. First, by matching meteorological records with nationally representative household panel data, it provides systematic evidence on the association between physical climate risk and rural household income in China, a relationship on which existing findings remain inconclusive. Second, it employs a panel MIMIC model to estimate permanent income, so that the association can be examined from both a current and a long-term perspective. Third, it identifies social assistance as a statistically supported compensatory channel and documents the attenuating roles of commercial insurance and social networks, offering actionable insights for policy intervention. Fourth, the heterogeneity analyses yield a counterintuitive but economically coherent pattern: households with better-educated heads and greater asset holdings—whose income portfolios are concentrated in climate-sensitive, marketised income sources—experience larger proportional income losses, as do non-farm and part-time households relative to farm-dominant ones. These findings underscore the importance of designing climate adaptation policies that account for the marketisation exposure of rural livelihoods, rather than targeting socio-economic disadvantage alone.

2 Literature review and theoretical analysis

Climate risk affects rural household income through a dual mechanism: acute shocks (e.g., floods, extreme heat, typhoons) and chronic, gradually evolving risks (e.g., rising temperatures, shifting precipitation patterns). Extreme events rapidly erode livelihood capital

by damaging productive and living assets—such as farmland and housing—leading to abrupt income declines (Cui and Tang 2024; Ahmad et al. 2024). Chronic risks, in contrast, undermine agricultural productivity cumulatively; persistent heat and drought disrupt crop cycles and reduce yields, destabilizing income for agriculture-dependent households (Li and Li 2025). Over time, these effects degrade livelihood capital, lower productivity, reduce employment stability, and depress asset values, imposing systemic constraints on income growth. A 2024 FAO study reports that in low- and middle-income countries, rural households lose an average of $83 per capita from heat stress and $35 from flooding, with losses accelerating as temperatures rise (OECD and FAO 2024). We therefore propose Hypothesis 1.

Hypothesis 1: Climate risk reduces rural household income.

As the sector most sensitive to climate change, agriculture is directly affected by climate risk (Abebaw 2025), which influences rural household income by altering farmers' production decisions and reducing agricultural participation. Cumulative climate shocks increase production uncertainty, prompting risk-averse farmers to reduce input, scale back planting, or exit agriculture altogether—directly undermining operating income (Wang et al. 2025; Yan et al. 2025). From a factor allocation perspective, long-term climatic anomalies reduce land-use efficiency by shifting crop suitability boundaries and altering cropping systems, thereby lowering the multiple cropping index and sown area in some regions. This decline in agricultural output weakens expected returns from farming (China Meteorological Administration (CMA) 2023, 2024). Under extreme shocks, damage to farmland and facilities raises fixed costs, while heightened uncertainty dampens investment intentions (Li and Li 2025), leading some farmers to transfer land out and pursue non-agric livelihoods. Extreme events also increase production vulnerability and erode farmers' confidence, affected farmers exhibit lower marginal propensity to invest in agriculture, and risk aversion further constrains operating income (Cameron and Shah 2015; Cui and Tang 2024). Moreover, climate risk impairs the health of agricultural labor, reduces labor supply efficiency, and may force labor withdrawal, exacerbating factor shortages and indirectly constraining agricultural income growth (Ghadge et al. 2020). Therefore, we propose Hypothesis 2.

Hypothesis 2: Climate risk reduces rural household income by decreasing households' participation in agricultural activities.

The impact of climate risk on agricultural production constrains rural employment, creating a “push effect", while the stability of urban non-agricultural sectors exerts a “pull effect". This dual force drives significant labor mobility (Jin et al. 2025; Song and Zhang 2024), breaking geographic and sectoral lock-in and reshaping rural household income through resource reallocation (Liu et al. 2023). As labor moves to non-agric sectors, occupational transitions optimize income structure: skill accumulation and promotion mechanisms sustain wage growth, and newly formed social networks improve access to employment information and opportunities (Yang et al. 2024), further boosting income potential. Out-migration also increases demand for transferring homesteads and contracted land, enabling property income through leasing or shareholding (Dayrit et al. 2022). Additionally, migrant workers gain financial knowledge and investment access in urban areas, with some households investing non-agricultural earnings in low-risk financial products (Cattaneo et al. 2019), creating new income streams. Therefore, we propose Hypothesis 3.

Hypothesis 3: Climate-induced labour mobility serves as an adaptive livelihood strategy that partially offsets the negative impact of climate risk on rural household income.

Rural households commonly face credit exclusion, a condition intensified by climate risk (Thein et al. 2025) and relaxed by digital financial inclusion (Cheng et al. 2024). Extreme events depreciate or destroy collateral such as farmhouses and farmland, prompting financial institutions to tighten credit supply to affected farmers (Haile et al. 2017). Concurrently, climate-induced income uncertainty raises default risk, leading lenders to raise access thresholds and reduce loan amounts, leaving farmers unable to meet production and operation needs. Tightened credit constraints then undermine income through insufficient inputs and weakened coping capacity (Niraula et al. 2026; Brown and Taylor 2008). In agriculture, they prevent timely acquisition of adaptive inputs—such as stress-resistant crops and irrigation—limiting households' ability to hedge against climate shocks, reducing yields and quality, and ultimately lowering operating income. In non-agric sectors, credit constraints curtail investment in entrepreneurial activities, limiting income diversification (Shankara et al. 2024). Moreover, post-shock production recovery is delayed, prolonging income losses and amplifying volatility. Therefore, we propose Hypothesis 4.

Hypothesis 4: Climate risk reduces rural household income by tightening households' credit constraints.

The significant negative shocks of climate risk substantially increase rural households' demand for social assistance, with relief becoming a key income supplement for affected families. In extreme scenarios, governments compensate for lost livelihood capital through disaster subsidies and temporary resettlement funds, providing rapid short-term income support. Social assistance ensures basic needs through direct financial and material aid, preventing income from falling below subsistence—a “safety net" function (Oza et al. 2025). Additionally, assistance directed toward restoring production facilities and enhancing disaster resilience helps rebuild income-generating capacity, reflecting a “capacity restoration" function (Preña and Labayo 2026). Thus, as a policy tool, social assistance directly supplements income via transfers while indirectly stabilizing it by mitigating shock impacts (Kehinde et al. 2025). Therefore, we propose Hypothesis 5.

Hypothesis 5: Climate-induced social assistance serves as a compensatory transfer mechanism that partially offsets the negative impact of climate risk on rural household income.

Due to differences in income source characteristics and risk sensitivity, the impact of climate risk on rural household income components is heterogeneous (Jin et al. 2025). Climate risk deteriorates the operating environment for rural enterprises (e.g., agricultural processing and tourism), forcing production cuts or closures that reduce demand for labour, depress wages, and eliminate job opportunities. Concurrently, climate-induced health impairments and increased care demands reduce labour mobility and employment stability, further limiting wage income (Zhang et al. 2024; Wang et al. 2025). Operating income faces persistent shocks from yield and quality declines, farmland damage, crop failure, and disrupted production cycles due to agriculture's inherent vulnerability (Pettigrew and McCauley 2026). Property income suffers from both the physical destruction of assets during acute events and the erosion of asset values under chronic climate risks—for example, through reduced land productivity and inhibited property transfers. Conversely, transfer income may increase through activated social assistance and subsidies for innovative agricultural products (Sitko et al. 2026). Thus, we propose Hypothesis 6.

Hypothesis 6: Climate risk reduces rural households' wage income, operating income, and property income, while increasing transfer income.

2.1 Relative exposure across market-exposed and sheltered income sources

The literature reviewed above treats climate risk predominantly as a level shock to agricultural or local production. A rural household's income, however, is a portfolio whose components are priced in different ways. Wage income and non-farm operating income are transacted in local labour and product markets: their returns are set by local demand and therefore fall when a climate shock contracts local activity. Property income is tied to asset values that climate risk erodes directly. Transfer income, by contrast, is administratively determined—pensions, subsidies and disaster relief do not clear in a local market—while agricultural output retained for household consumption is valued at the household's own reservation price rather than at a market-clearing one. In the language of the trade literature, the first group behaves like a market-priced margin and the second like a sheltered margin whose return is largely insulated from local climate conditions.

The distinction changes what a climate shock does. If the shock shifts the *relative* returns of a market-exposed and a sheltered margin, it redistributes income across household types: within a locality, households whose portfolios are weighted towards wage and non-farm business income lose relative to households weighted towards transfers and subsistence production, and the aggregate effect is the composition-weighted average of the two. Two implications follow. First, the average effect *within* a locality may be small or indistinguishable from zero, because the two margins offset; the association will then appear mainly as a regional gradient across places with different portfolio compositions rather than as a sharply identified local effect. Second, the sharpest test is not the average coefficient but the difference between households with different portfolio weights, together with the decomposition of the association into income components, which should carry opposite signs.

Hypothesis 7: Because climate risk reprices market-exposed income sources more than sheltered ones, its association with rural household income is relative rather than uniform. The association is more negative for households whose income portfolios are weighted towards wage and non-farm operating income, and less negative or positive for households weighted towards transfers and subsistence production.

3 Research design

3.1 Data and sample selection

This study utilizes microeconomic data from the China Family Panel Survey(CFPS)[1] conducted by the Center for Social Survey of Peking University (2016-2022) and

meteorological data from the National Oceanic and Atmospheric Administration(NOAA)[2] and the Daily Data of China Surface Climate (V3.0) from the National Meteorological Science Data Center, along with macroeconomic data from the National Bureau of Statistics and Regional Statistical Yearbook.

Based on the research theme “Climate Change and household income”, the raw data are processed and filtered as follows: (1) The adult and household questionnaires are matched each year and the unmatched samples are removed. After screening for farming household samples, the four waves of data are longitudinally merged based on household and individual codes. (2) Key variables are checked and cleaned by removing outliers, missing values, and samples with responses such as “uncertain”, “not clear”, or “not applicable”. Continuous variables like household income are winsorized at the 1st and 99th percentiles. (3) Microeconomic data are merged with meteorological and macroeconomic data by region and year, and only matching samples are retained. Through these data cleaning and processing steps, 7852 valid household-year observations are obtained, covering 4 waves of data from 25 provinces. Because the physical climate risk index is constructed at the prefecture-city level, households that cannot be matched to a city-level climate value are excluded from the estimation sample.

3.2 Variables

(1)Explained variable: Rural household income includes current household income, permanent income, and disaggregated income (wage income, operating income, property income, and transfer income). Permanent income is estimated using the MIMIC model. The other income measures are derived from the CFPS questionnaire items: “total household income in the past 12 months", “total household wage income from all members in the past 12 months", “total household net operating profit in the past 12 months", “total household income from rent, land rent, housing demolition compensation, land acquisition compensation, and financial investments in the past 12 months", and “total household income from government subsidies, social donations, pensions, and assistance from children and relatives in the past 12 months." All income variables are logarithmically transformed. (2)Explanatory variable: Following Guo et al. (2024) and Li and Li (2025), this study employs the $CPRI$ (Climate Physical Risk Index) to measure climate risk. (3)Control variables: Following Li and Li (2025) and Yan et al. (2025), control variables are selected at the individual, household, and city levels, including age, gender, household size, agricultural

land transfer, industrial structure, and educational development. Definitions of all variables are shown in Table 1.

Table 1. Variable definitions and descriptive statistical analysis

Variable	Definitions and Unit	Observations	Mean	S.D.	Min	Max
		Explained Variable				
Total Income *(lnincome)*	Annual total household income (log)	7852	10.913	1.144	0	16.248
Wage Income *(lnw)*	Annual household wage income (log)	7852	7.793	4.809	0	15.607
Operating Income *(lnb)*	Annual household net operating profit (log)	7806	3.659	4.502	0	13.815
Property Income *(lnp)*	Annual household income from rent (land/housing), relocation compensation, and financial investments (log)	7847	1.559	3.324	0	13.815
Transfer Income *(lnt)*	Total annual household transfers, including government subsidies, social donations, pensions, and support from children/relatives (log)	7760	6.188	4.066	0	16.131
		Independent Variable				
Climate Risk *(cpri1)*	NOAA's physical climate risk index	7852	28.248	5.594	14.029	52.579
		Mediating Variables				
Agricultural Engagement *(agriengage)*	Input in agricultural productive fixed assets (yuan, log)	7810	3.264	4.450	0	16.118
Labor Mobility*(labormob)*	Whether any household laborer has migrated for work (Yes=1, No=0)	3477	0.357	0.479	0	1
Credit Constraint*(credit)*	Whether the household faces credit constraints (Yes=1, No=0)	5042	0.318	0.466	0	1
Social Assistance*(assitance)*	Transfers/subsidies from government, society, and relatives/friends (yuan, log)	3528	6.857	1.343	0	11.513
		Moderating Variables				
Commercial Insurance *(comins)*	Whether purchased commercial insurance (Yes=1, No=0)	7852	0.533	0.499	0	1
Medical	Whether	7852	0.934	0.248	0	1

Insurance*(medins)*	purchased medical insurance (Yes=1, No=0)					
Social Networks*(socialnet)*	Expenditure on gifts and social rituals (yuan, log)	7785	7.128	2.622	0	12.206
		Control Variable				
Age*(age)*	Age of household head (years)	7852	52.518	13.231	17	88
Gender*(gender)*	0 = Female, 1 = Male	7852	0.565	0.496	0	1
Marital Status*(spouse)*	1 = Married, 0 = Other	7852	0.879	0.326	0	1
Education Level*(edu)*	0 = Illiterate/Semi-literate, 1 = Primary school, 2 = Junior high school, 3 = Senior high school/Technical secondary school/Technical school/Vocational high school, 4 = Associate's Degree, 5 = Bachelor's Degree, 6 = Master's Degree, 7 = Doctoral Degree	7852	2.035	1.377	0	7
Health Status*(health)*	Health status of the household head: 1 = Unhealthy, 2 = Average, 3 = Moderately healthy, 4 = Very healthy, 5 = Extremely healthy	7852	2.852	1.212	1	5
Social Status*(social)*	Self-assessed social status (Ordinal 1-5: Low to High)	7852	3.099	1.060	1	5
Household Registration Type*(hukou)*	1 = Agricultural, 0 = Non-agricultural	7852	0.771	0.420	0	1
Computer Usage*(computer)*	Whether the household uses a computer 1 = Yes, 0 = No	7852	0.152	0.359	0	1
Household Size*(size)*	Number of permanent residents in the household (persons)	7852	3.902	1.853	1	14
Government Trust*(govtrust)*	Trust in county/city government (Ordinal 1-5: Low to High)	7852	2.548	0.932	1	5
Elderly Dependency*(elderly)*	Number of elderly dependents in household	7852	0.574	0.780	0	4
Land Transfer*(land-trans)*	Whether engaged in land transfer (in	7852	0.046	0.210	0	1

	or out) (Yes=1, No=0))					
Household Assets*(household)*	Household net assets (yuan, log)	7852	11.555	3.354	0	18.198
Land Assets*(land)*	Value of land assets (yuan, log)	7852	5.658	5.038	0	14.985
Industrial Structure*(industrial)*	Industrial output value / GDP	7852	0.314	0.053	0.118	0.499
Consumption Level*(c-level)*	Total retail sales of consumer goods / GDP	7852	0.398	0.044	0.221	0.498
Education Development*(edudevelop)*	Number of college/university students / Total population	7852	0.023	0.004	0.014	0.044

3.3 Empirical model

3.3.1 Panel Tobit model

Based on the theoretical analysis of the impact of climate change on rural household income, as well as the distributional characteristics of the dependent variable (household income), we adopt a panel Tobit model for estimation:

$$\ln income_{it}^{*} = \beta_0 + \beta_1 cpri_{it} + \boldsymbol{BX}_{it} + \mu_i + \varepsilon_{it}$$
$$\ln income_{it} = \max(0, \ln income_{it}^{*})$$

where $\ln income_{it}$ represents the total and sub-item income of household i in year t, $cpri_{it}$ is the climate risk in year t, $\boldsymbol{X}_{it}$ is a matrix of control variables, μ_i denotes individual random effects, and ε_{it} is the idiosyncratic error term.

Since the coefficient β_1 captures the marginal effect of $cpri_{it}$ on the latent variable $\ln income_{it}^{*}$ rather than on the observed dependent variable $\ln income_{it}$, we further compute the average marginal effect using Equation (3) and report it in the tables.

$$\frac{\partial E[\ln income_{it} \mid cpri_{it}]}{\partial cpri_{it}} = \beta_1 \Phi\left(\frac{\beta_1 cpri_{it} + \boldsymbol{BX}_{it}}{\sqrt{\sigma_\mu^2 + \sigma_\varepsilon^2}}\right)$$

where $\sqrt{\sigma_\mu^2 + \sigma_\varepsilon^2}$ is the standard deviation of the composite error term, and $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution.

3.3.2 Multiple indicators and multiple causes (MIMIC) model

Beyond its immediate impact on current income, climate risk may also erode long-term earning potential. From a life-cycle perspective, climate shocks can impair health, disrupt human capital accumulation, and hinder skill formation. We therefore examine the impact of climate risk on permanent income, which captures this long-term dimension (Pomeranz and

Kast 2024). Following Blundell et al. (2008) and Naga and Burgess (1997), we employ a panel MIMIC model to estimate household permanent income.

$$\ln pincome_{it} = \gamma_0 + \sum_{k=1}^{7} \gamma_{1} \boldsymbol{Z}_{k,it} + \mu_i + \varepsilon_{it}$$

$$X_{j,it} = \lambda_j \ln pincome_{it} + \delta_{j,it}$$

Equation (4) represents the structural equation, and Equation (5) represents the measurement equation, where $\ln pincome_{it}$ is the latent variable denoting the permanent income of household i in period t. $\boldsymbol{Z}_{k,it}$ are the k-th cause variables, including demographic characteristics such as age, years of education, household size, and marital status, as well as household variables such as financial assets, physical assets, and the asset-liability ratio. $\boldsymbol{X}_{j,it}$ are the indicator variables, including current household income, consumption, and savings. λ_j is the factor loading of permanent income on the indicator variables, and $\delta_{j,it}$ is the random error term. After estimation of the model, the permanent income factor score is generated as the predicted value of permanent income for the household i in period t.

4 Empirical results

4.1 Descriptive statistics

Fig. 1 illustrates the distribution of the logarithm of total rural household income in 2016 and 2022. Over the sample period, the average rural household income increased from 82,030 yuan in 2016 to 125,660 yuan in 2022, indicating an overall improvement in rural household income levels. Households reporting zero total income accounted for no more than 0.3% of the sample in any of the four waves.[3]

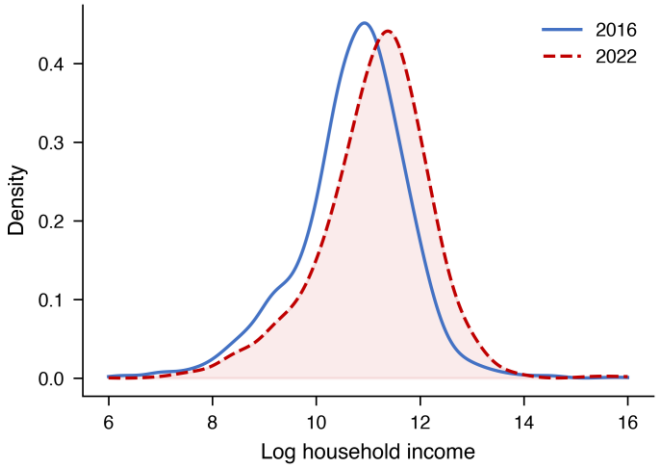


Figure 1. Distribution of rural household income in 2016 and 2022

To further explore income heterogeneity, we classify rural households into five income tiers: low, lower-middle, middle, upper-middle, and high. Supplementary Table S20 presents the composition of each group's income, disaggregated into wage income, operating income, property income, and transfer income. The income gap between the low- and lower-middle-income groups, as well as between the upper-middle- and high-income groups, is relatively pronounced. In contrast, income differences among the lower-middle, middle, and upper-middle groups are comparatively modest, suggesting that upward mobility from low to middle income and from middle to high income may face greater barriers.

Regarding income structure, several patterns emerge. First, wage income constitutes the largest share across all groups except the low-income category, accounting for over 60% of total income in the middle-income group. Second, as income rises, the shares of wage income and property income generally increase, while those of operating income and transfer income tend to decline. Third, the income composition of the low-income group differs markedly from that of the middle- and high-income groups. In the low-income group, wage and operating income contribute almost equally, consistent with the contemporary reality that Chinese rural households often engage in both agricultural operations and off-farm employment. The middle- and high-income groups, by contrast, rely predominantly on wage income. Notably, the high-income group exhibits a relatively high share of transfer income—exceeding even that of the low-income group—potentially attributable to the inclusion of one-time government transfers—such as land acquisition and housing demolition compensation—in the transfer income measure, which may be more frequently received by wealthier households with greater asset holdings.

Moreover, we aggregate variables at the provincial level and conduct a fitted analysis (Fig. 2). The results suggest a negative correlation between rural household income and physical climate risk.

Figure 2. Scatter plot of climate risk and rural household income

4.2 Benchmark regression results

Using a Tobit model, the regression results presented in Table 2 indicate that climate risk significantly reduces both total household income and permanent income in rural areas, thereby validating Hypothesis 1. Specifically, a one-unit increase in climate risk is associated with decreases of approximately 1.1% in current income and 0.3% in permanent income for rural households. Given that the mean value of climate risk is approximately 28.248, this

implies that during the period from 2016 to 2022, climate risk led to an average reduction of 26.7% in current household income and 8.1% in permanent income across Chinese households. Moreover, the impact of climate risk on current income is substantially larger than that on permanent income, highlighting the immediate and direct nature of climate risk shocks (Cui and Tang 2024; Li and Li 2025).

Table 2. Impact of climate risk on rural household total income and income structure

Dependent Variable:	Total	Total	Wage	Operating	Property	Transfer	Permanent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CPRI	-0.008***	-0.011***	0.010	-0.032*	-0.108***	0.013	-0.003***
	(0.0023)	(0.0019)	(0.0114)	(0.0175)	(0.0351)	(0.0097)	(0.0004)
age		-0.002	-0.084***	-0.045***	0.047**	0.121***	-0.002***
		(0.0011)	(0.0063)	(0.0100)	(0.0191)	(0.0055)	(0.0002)
gender		-0.034	-0.391***	0.608***	-1.335***	0.111	-0.083***
		(0.0223)	(0.1309)	(0.2075)	(0.3945)	(0.1122)	(0.0050)
edu		0.195***	0.451***	0.073	0.738***	0.149***	0.198***
		(0.0097)	(0.0575)	(0.0919)	(0.1722)	(0.0492)	(0.0022)
spouse		0.311***	0.664***	0.658*	-1.396**	-0.719***	0.288***
		(0.0346)	(0.2073)	(0.3430)	(0.6069)	(0.1740)	(0.0078)
health		0.071***	0.079	0.367***	0.078	-0.124***	0.062***
		(0.0093)	(0.0546)	(0.0849)	(0.1668)	(0.0467)	(0.0021)
social		0.011	0.087	-0.052	0.006	0.021	0.014***
		(0.0107)	(0.0631)	(0.0992)	(0.1937)	(0.0537)	(0.0024)
internet		0.351***	0.235	0.659*	3.504***	-0.090	0.378***
		(0.0358)	(0.2073)	(0.3440)	(0.6016)	(0.1825)	(0.0081)
govtrust		0.006	-0.069	-0.082	-0.028	-0.132**	-0.001
		(0.0118)	(0.0694)	(0.1085)	(0.2097)	(0.0593)	(0.0027)
size		0.182***	1.052***	0.221***	0.074	0.282***	0.160***
		(0.0065)	(0.0386)	(0.0586)	(0.1165)	(0.0329)	(0.0015)
elderly		-0.075***	-1.639***	-0.188	0.584**	1.513***	-0.067***
		(0.0158)	(0.0934)	(0.1433)	(0.2748)	(0.0780)	(0.0035)
land-trans		0.345***	0.672**	0.311	-0.508	3.474***	0.238***
		(0.0517)	(0.2999)	(0.4518)	(0.9317)	(0.2540)	(0.0116)
land		-0.020***	-0.112***	1.243***	0.460***	0.091***	0.003***
		(0.0026)	(0.0150)	(0.0284)	(0.0489)	(0.0129)	(0.0006)
household		0.052***	0.162***	0.102***	0.668***	0.048***	0.023***
		(0.0088)	(0.0203)	(0.0356)	(0.0701)	(0.0172)	(0.0008)
industrial		-2.170***	2.180*	11.899***	-23.640***	-12.262***	-1.009***
		(0.2086)	(1.2248)	(1.9812)	(3.7250)	(1.0498)	(0.0469)
c-level		-0.772***	-1.230	5.571**	-11.386**	1.195	-0.523***
		(0.2959)	(1.7424)	(2.7677)	(5.2713)	(1.4906)	(0.0665)
edudevelop		12.385***	4.211	11.850	90.708*	-20.499	-4.183***

		(2.9375)	(17.1748)	(27.1249)	(51.5407)	(14.8629)	(0.6596)
Constant	11.135***	10.413***	4.668***	-15.148***	-11.793***	0.006	9.850***
	(0.0665)	(0.2115)	(1.2544)	(2.0080)	(3.8302)	(1.0763)	(0.0480)
N	7852	7852	7852	7806	7847	7760	7852
LR test	11.60	2873.94	2439.68	3412.68	384.91	2076.99	17427.31
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log likelihood	-12212.46	-10781.296	-19932.16	-13062.56	-8001.87	-18857.80	960.37

Note: ***, ** and * represent significance at the 1%, 5%, and 10% level, respectively. The value in parentheses is the corresponding standard error (hereinafter the same).

Furthermore, climate risk significantly reduces both operating income and property income for rural households. A one-unit increase in climate risk is associated with reductions of 3.2% in operating income and 10.8% in property income, providing partial support for Hypothesis 6. These findings align with theoretical expectations. Given that most rural households rely primarily on agricultural operations, climate risks such as droughts and floods not only damage farmland and reduce crop yields, but also diminish operating and property income by reducing employment opportunities, impairing health and labour productivity, and damaging assets including housing, land and agricultural machinery (Wang et al. 2025; Yan et al. 2025).

4.3 Placebo test and policy evaluation

To assess whether the baseline association could be an artefact of model specification, we conduct a placebo test based on random permutation; in addition, following Yan et al. (2025), we evaluate the Climate Resilient Cities Construction (CRCC) pilot as a policy intervention aimed at improving local climate resilience. The results are reported in Fig. 3 and Column (1) of Table 3.

Table 3. Subsample estimates, conservative inference, and policy evaluation

Dependent Variable:	***lnincome***	***lnincome***	***lnincome***	***lnincome***	***lnincome***	***lnincome***
	DID: CRCC pilot	**2020 wave**	**2020 and 2022**	**balanced panel (all waves)**	**5% trimmed dependent variable**	**OLS, year FE**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
CPRI		-0.013***	-0.006**	−0.012***	−0.007***	-0.006
		(0.0037)	(0.0029)	(0.0032)	(0.0014)	(0.0051)
Treat × *Post*	-0.014					
	(0.1343)					
Estimator	DID	Tobit	Tobit	Tobit	Tobit	OLS
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	Yes	Yes
City FE	Yes	No	No	Yes	Yes	No

City-clustered SE	Yes	No	No	Yes	Yes	Yes
N	7852	1917	3740	2692	7066	7852
LR test		1108.46	1857.45	1390.32	2983.18	
		(0.000)	(0.000)	(0.000)	(0.000)	
R-squared	0.457					0.381
Log likelihood		-2472.67	-5043.92	-3544.61	-6864.50	

Note: Constant terms and control-variable coefficients are omitted for brevity. Column (1) reports difference-in-differences estimates with city and year fixed effects and city-clustered standard errors, where the treated group consists of the Climate Resilient Cities Construction pilot cities and the post-treatment period begins in 2017.Columns (2)–(5) report Tobit estimates on the indicated subsamples. Column (6) reports OLS estimates with year fixed effects and city-clustered standard errors.

For the placebo test, we randomly permute the assignment of city-level climate risk values across household observations and re-estimate the baseline Tobit specification. Repeating this procedure 500 times yields an empirical distribution of placebo coefficients centred tightly around zero (Fig. 3). The actual baseline estimate lies in the left tail of this distribution, and the randomisation-inference p-value—the share of placebo coefficients at least as extreme as the actual estimate—is 0.092. The baseline association is therefore unlikely to be spurious, although the evidence should be read with caution given the marginal significance level.

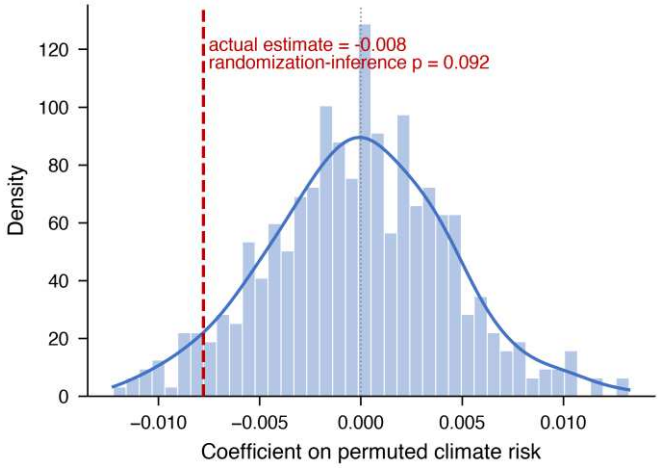


Figure 3. Placebo test: distribution of coefficients from 500 random permutations of climate risk

The Chinese government launched the Climate Resilient Cities Construction (CRCC) pilot in 2017, a major initiative within the framework of China's climate governance (Yan et al. 2025). If the pilot effectively enhances local climate resilience, its introduction should raise rural household income in the treated cities relative to the untreated ones. Column (1) of Table 3 reports difference-in-differences estimates with city and year fixed effects, the full set of control variables, and city-clustered standard errors. The coefficient on the interaction term is small and statistically insignificant, indicating that within our sample window the CRCC pilot did not generate a detectable income effect for rural households. This null result should not be read as evidence against the policy itself: the pilot covered a limited set of

predominantly urban districts, and any rural spillovers may require a longer horizon to materialise. We therefore report the estimate for completeness and refrain from a causal interpretation.

4.4 Robustness test

To assess the robustness of the empirical findings, three approaches are employed, with the corresponding results reported in Table 3 and Table 4.

Table 4. Robustness tests: alternative measures of climate risk

Dependent Variable:	***lnincome***	***lnincome***	***lnincome***	***lnincome***	***lnincome***	***lnincome***
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
HTD	0.005***					
	(0.0009)					
LTD		-0.011***				
		(0.0017)				
ERD			-0.004***			
			(0.0005)			
EED				0.004***		
				(0.0009)		
Mean temperature					0.039***	
					(0.0024)	
Precipitation (log)						0.368***
						(0.0249)
Estimator	Tobit	Tobit	Tobit	Tobit	Tobit	Tobit
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	7852	7852	7852	7852	7852	7852
LR test	3668.03	3680.38	3698.08	3651.28	3896.20	3852.79
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log likelihood	-10384.26	-10378.08	-10369.23	-10392.63	-10270.17	-10291.88

Note: All columns are estimated by Tobit with the full set of control variables; constant terms and control-variable coefficients are omitted for brevity. HTD, LTD, ERD and EED denote the annual numbers of extreme high-temperature, extreme low-temperature, extreme rainfall and extreme drought days, respectively. Mean temperature is the annual mean temperature, and precipitation enters in logarithms.

First, the sample is restricted. Given the notable intensification of extreme climate events in China since 2020, the baseline specification is re-estimated on the 2020 wave, on the pooled 2020 and 2022 waves, on balanced panel comprises households observed in all four waves and on the trimmed specification drops observations below the 5th and above the 95th percentile of log income (Columns (2) and (5) of Table 3). Climate risk retains a significant negative coefficient in both subsamples, and the point estimate for the 2020 wave is larger in magnitude than the full-sample estimate.

Second, alternative measures of climate risk are employed. The composite CPRI is replaced by six underlying meteorological measures: the annual numbers of extreme high-temperature days, extreme low-temperature days, extreme rainfall days (Kirschbaum et al. 2020), and extreme drought days, as well as annual mean temperature and annual precipitation (Table 4). The disaggregated results are informative. More extreme low-temperature days and more extreme rainfall days are significantly associated with lower household income, in line with the baseline finding; related evidence similarly shows that extreme heat reduces household consumption in China (Guo and Yu 2026). By contrast, the coefficients on extreme high-temperature days, extreme drought days, annual mean temperature, and annual precipitation are positive. These positive coefficients most likely reflect the persistent north–south gradient of China's climate—warmer and wetter prefectures are concentrated in the more prosperous south—rather than any beneficial effect of warming or drought per se. The contrast underscores that the composite index captures dimensions of physical risk that no single meteorological variable can represent on its own.

Third, the sensitivity of statistical inference is examined. Because the climate risk index varies only at the prefecture-city-by-year level, the association is re-estimated with year fixed effects and city-clustered standard errors (Column (6) of Table 3). The point estimate is essentially unchanged, but the coefficient becomes statistically insignificant under this more conservative inference, which suggests that the baseline precision partly reflects within-city correlation of the regressor. We therefore complement the asymptotic standard errors with two resampling-based procedures appropriate when the regressor varies at a coarser level than the outcome (Efron 1979; Cameron et al. 2008): a non-parametric bootstrap that resamples cities with replacement, and a wild cluster bootstrap-t test. Re-estimating the baseline in 500 city-level bootstrap samples leaves the centre of the coefficient distribution essentially unchanged and produces a negative coefficient in about nine of ten replications, but the 95% percentile interval contains zero, and the wild cluster bootstrap-t test yields $p = 0.28$ for the conservative specification. The coefficient-stability bounds of Oster (2019) indicate that unobserved factors would have to be almost six times as important as the observed control set to drive the estimated coefficient to zero. Taken together, these diagnostics indicate that the sign and magnitude of the association are stable, whereas its statistical precision depends materially on the level at which inference is conducted. Once city fixed effects are introduced, the within-city coefficient is close to zero (Section 4.5); the negative association documented above is therefore better understood not as a uniform local

shock but as a regional gradient, arising from the uneven spatial distribution of market-exposed and sheltered income portfolios. We develop that reading in Sections 4.5–4.6 and test it directly in Section 5.1. Additional checks—bootstrap inference, sample composition, forward-looking and provincial climate terms, and a non-parametric dose–response specification—are reported in the Supplementary Information (Supplementary Tables S1–S8).

4.5 Timing and event-study evidence

The composite index varies at the prefecture-city-by-year level but retains substantial within-city variation: its within-city standard deviation across the four waves is 3.88 against a between-city standard deviation of 3.77, so a city fixed effect does not exhaust the identifying variation. Only nine observations (0.11 per cent) are left-censored at zero, so the Tobit and least-squares estimates of the baseline coefficient coincide to five decimal places; the models below are therefore directly comparable with the Tobit baseline, and all standard errors are clustered at the city level.

Supplementary Table S16 reports the baseline coefficient under progressively stricter fixed effects. Pooled with controls it is -0.0078 (s.e. 0.0054) and with year fixed effects alone -0.0063 (s.e. 0.0051); adding city fixed effects moves the point estimate to $+0.0024$ (s.e. 0.0018) and allowing provinces their own year effects to $+0.0053$ (s.e. 0.0027). The negative association documented in Table 2 therefore does not survive the introduction of a city fixed effect. Because the panel has only four waves, a lead or a lag corresponds to one wave, that is, two years, and the specification that includes both is a short-panel lead-and-lag test rather than a full multi-period event study. The estimated one-wave lead in the specification of Supplementary Table S17 is -0.0045 (s.e. 0.0054), and the joint test that it is zero is not rejected ($F(1,3758) = 0.64$, $p = 0.42$); the contemporaneous and lagged coefficients are equally imprecise. Anticipation is therefore not detectable, but neither is a within-city dynamic response.

Fig. 4 presents both exercises. The left panel plots the coefficients on the one-wave lead, the contemporaneous value and the one-wave lag of the composite index, estimated with city and year fixed effects; the right panel traces the coefficient on the composite index as progressively stricter fixed effects are added, with city-clustered confidence intervals. The sign reversal that occurs once a city fixed effect is introduced is the central evidence for reading the association as a regional gradient rather than a local treatment effect: within a

locality the coefficient is close to zero and statistically insignificant, so the negative association in the pooled sample reflects cross-sectional differences across localities rather than a within-city response.

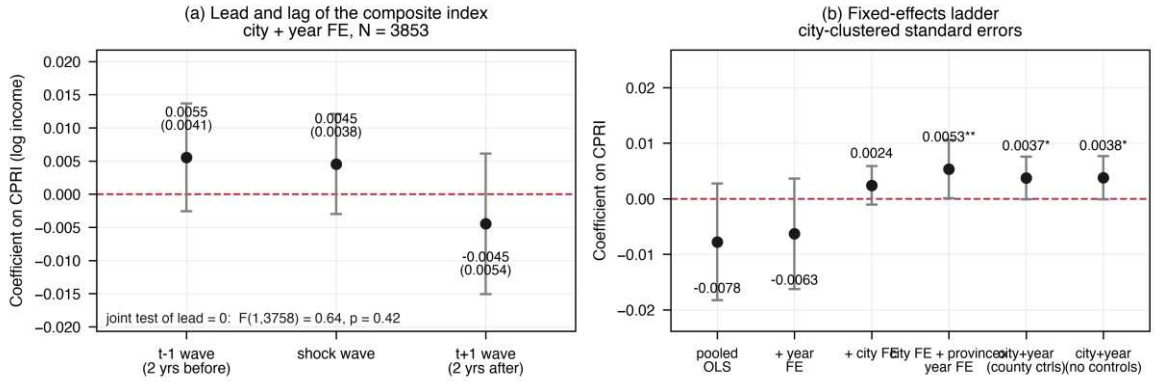


Figure 4. Lead and lag of the composite climate index, and the fixed-effects ladder

Note: Left panel: coefficients on the one-wave lead, the contemporaneous value and the one-wave lag of the composite index, with 95 per cent confidence intervals, estimated with city and year fixed effects on the subsample for which a lead and a lag are both defined. Right panel: the coefficient on the composite index as fixed effects are added, with city-clustered 95 per cent confidence intervals. The association is negative and insignificant with year fixed effects alone and changes sign once a city fixed effect is introduced, which is the central evidence for reading the association as a regional gradient rather than a local treatment effect.

An alternative exposure measure that does not use the composite index gives the same picture. Replacing it with a direction-aligned composite of the four meteorological day counts—standardised within city and estimated with city and year fixed effects—the joint test of the lead term is again not rejected ($F = 0.21, p = 0.65$), and the lead terms of all four components are individually indistinguishable from zero (p between 0.30 and 0.59). The one component with a within-city dynamic signal is extreme drought days, whose contemporaneous and lagged coefficients are both negative and marginally significant (-0.061 and -0.120). The parallel-trends test is therefore passed, but the within-city estimates are small and imprecise, so these data contain no sharply identified local treatment effect (Supplementary Figs. S11–S12).

4.6 Extended graphical and distributional analyses

Because both climate risk and household income display wide cross-sectional dispersion and a pronounced geographic structure, we additionally explored the graphical and semi-parametric specifications common in this literature. All of them are reported in the Supplementary Information (Supplementary Note 3, Supplementary Tables S9–S15 and Supplementary Figs. S1–S9), including the exercises that turned out to be uninformative. Four of them add information beyond the main results. First, replacing the linear climate term

with indicators for CPRI deciles produces negative coefficients in every decile above the lowest, and seven of the nine are individually significant (Supplementary Fig. S2, left panel); the linear specification therefore does not conceal a sign reversal at either end of the distribution. Second, the lead-and-lag specification discussed in the preceding subsection shows that the one-wave lead is statistically indistinguishable from zero, consistent with an association that materialises without anticipation (Supplementary Fig. S3). Third, decomposing total income into wages, operating income, property income and transfers shows that the two largest contributions, from wages and transfers, carry opposite signs and roughly offset each other (Supplementary Fig. S4); we return to this decomposition in Section 5.1. Fourth, the descriptive trajectories in Supplementary Fig. S5 show that mean log income rises monotonically across the four waves while the composite risk index does not, so the headline association is not an artefact of a common time trend.

The same exercises also delimit what these data cannot support. A piecewise specification identifies a candidate break in the interior of the climate distribution, but a wild bootstrap test cannot reject the null of no threshold, and the slopes on either side are almost identical. Estimating the model separately by income quintile yields coefficients that are individually insignificant and non-monotonic, and their interaction with climate risk is likewise insignificant. Kernel densities of log income by CPRI quartile are visually indistinguishable, and the unconditional correlation between the index and log income is only -0.04. The correlation matrix of Supplementary Fig. S8 shows why: the composite index is strongly collinear with the interior drought measure, and mean temperature with precipitation, so the meteorological coefficients in Table 4 cannot be read as independent effects. Taken together, these diagnostics do more than delimit a boundary. The cross-section identifies a regional gradient rather than a sharply identified local treatment effect, and that gradient is what one would expect if climate risk operated not as a uniform shock to local production but by repricing the market-exposed margin of rural income portfolios against the sheltered margin. The event-study evidence above and the composition evidence in Section 5.1 support that reading directly. We therefore treat the regional structure of the association as a finding about the transmission channel rather than as a limitation.

5 Further analysis

5.1 Mechanisms

To further examine the channels through which climate risk relates to household income, this study investigates four candidate mechanisms—agricultural participation, labour mobility, credit constraints, and social assistance—with the results presented in Table 5. Only the social-assistance channel receives clear statistical support: higher climate risk is associated with a significant increase in the social assistance received by rural households (Column (4)), consistent with the compensatory-transfer role of disaster relief and government subsidies (Oza et al. 2025; Kehinde et al. 2025). By contrast, the coefficients on agricultural participation (Column (1)), labour mobility (Column (2)), and credit constraints (Column (3)) are small and statistically insignificant. Hypotheses 2, 3, and 4 are therefore not supported by the data, whereas Hypothesis 5 is supported. One plausible interpretation is that measurement constraints attenuate the estimated channels: labour mobility and credit constraints are observed only for subsamples of the data, and agricultural fixed-asset investment is a coarse proxy for the intensity of farming activity. The significant social-assistance response nonetheless indicates that public transfers react to climate shocks in a timely manner, providing an automatic stabiliser for rural household income.

Table 5. Mechanism tests

Dependent Variable:	***agriengage***	***labormob***	***credit***	***assistance***
	(1)	**(2)**	**(3)**	**(4)**
CPRI	-0.003	0.002	-0.002	0.010**
	(0.0219)	(0.0029)	(0.0017)	(0.0038)
Estimator	Tobit	LPM	LPM	Tobit
Controls	Yes	Yes	Yes	Yes
N	7810	3477	5042	3528
LR test	1353.46			207.45
	(0.000)			(0.000)
R-squared		0.141	0.042	
Log likelihood	-13000.86			-5946.82

Note: Constant terms and control-variable coefficients are omitted for brevity. Columns (1) and (4) are estimated by Tobit; Columns (2) and (3) are linear probability models. Labour mobility and credit constraints are observed only for subsamples of the data.

To explore potential strategies for mitigating the adverse association between climate risk and rural household income, this study incorporates interaction terms between climate risk and commercial insurance, medical insurance, and social networks into the model, drawing on the mechanism analysis. This approach is motivated by prior studies documenting positive associations between these factors and rural household income (Gruber and Yelowitz 1999; Li and Li 2025). Purchasing commercial insurance may alleviate liquidity constraints and provide compensatory income, while social networks are conducive to accessing informal

support and social assistance. The estimation results are reported in Table 6. The interaction between climate risk and commercial insurance is positive and statistically significant (Column (1)), and the interaction with social networks is positive and marginally significant (Column (3)), while the coefficient on climate risk itself remains negative and significant in both specifications. These findings suggest that commercial insurance coverage and stronger social networks can attenuate the negative association between climate risk and household income. By contrast, the interaction with medical insurance is statistically insignificant (Column (2)); given the near-universal coverage of basic medical insurance in rural China—over 93% of households in the sample—variation is too limited for credible identification, and this null result should not be read as evidence that health protection is irrelevant.

Table 6. Moderation effect tests

Dependent Variable:	***lnincome***	***lnincome***	***lnincome***
	(1)	**(2)**	**(3)**
CPRI	-0.013***	-0.006	-0.017***
	(0.0029)	(0.0070)	(0.0054)
comins	-0.683***		
	(0.1081)		
CPRI × *comins*	0.011***		
	(0.0037)		
medins		0.116	
		(0.2067)	
CPRI × *medins*		-0.002	
		(0.0073)	
socialnet			0.009
			(0.0201)
CPRI × *socialnet*			0.001*
			(0.0007)
Estimator	Tobit	Tobit	Tobit
Controls	Yes	Yes	Yes
N	7852	7852	7785
LR test	3890.03	3657.57	3770.54
	(0.000)	(0.000)	(0.000)
Log likelihood	-10273.25	-10389.48	-10186.81

Note: Constant terms and control-variable coefficients are omitted for brevity. All columns are estimated by Tobit.

The pattern in Table 5 is better read as a test of a mechanism than as a list of channels, , and the decomposition in Fig. 5 helps explain it. The left panel reports the coefficient on the climate index in a regression of the logarithm of each income component on the full control set; the right panel reports the contribution of each component to the overall effect, computed as the level coefficient multiplied by the component's mean income share. The offsetting

pattern of the two largest components is directly visible in the right panel. If climate risk simply reduced local production, every income component that depends on local production would move in the same direction. Instead the decomposition shows reallocation across components of opposite sign. In level regressions, a one-unit increase in the composite index is associated with a fall of 6.1 per cent in property income (s.e. 0.034) and a rise of 2.0 per cent in transfer income (s.e. 0.010), while the coefficients on wage income ($+1.1$ per cent) and operating income (-1.3 per cent) are small and insignificant. Weighted by their sample shares, wage income ($+0.0062$) and transfer income ($+0.0050$) enter with opposite signs and almost exactly offset, which is why the aggregate coefficient is modest and its precision so sensitive to the level of inference.

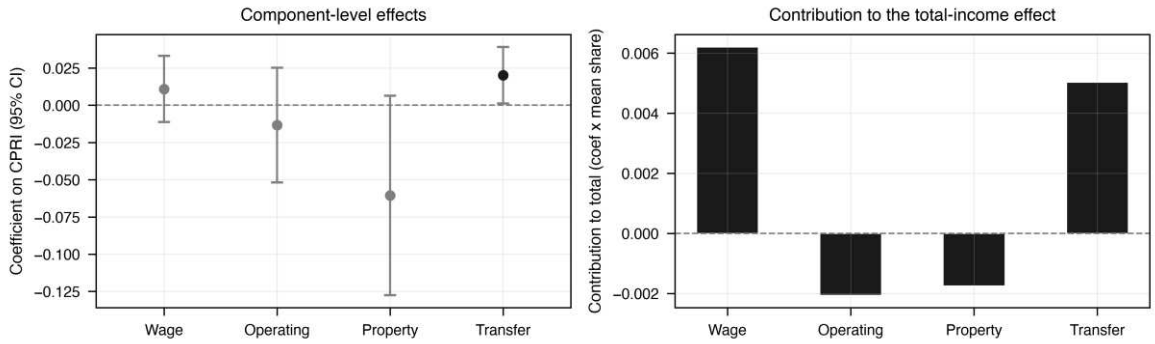


Figure 5. Decomposition of total income into components

Note: Left panel: coefficient on the climate index in a regression of the logarithm of each income component on the full control set. Right panel: contribution of each component to the overall effect on total income, computed as the level coefficient multiplied by the mean income share of that component. Filled bars and markers denote coefficients significant at the 10% level or better. Corresponding estimates are reported in Supplementary Table S13.

This is the relative-exposure mechanism of Hypothesis 7, and it can be tested directly on income composition. We split households by the wage share of their classified income, above or below the sample median, and interact the split with climate risk under city and year fixed effects. Because a contemporaneous share may itself respond to the shock, the split uses the share observed in the household's first sample wave, which is fixed within the household. Supplementary Tables S18–S19 and Supplementary Fig. S11 present the results. Allowing the control coefficients and the city fixed effects to differ across groups, a one-unit increase in climate risk is associated with a rise of 0.90 per cent (s.e. 0.28) for households below the median wage share and a fall of 0.56 per cent for those above it, a difference of -1.46 percentage points (s.e. 0.38). Restricting the sample to households first observed in 2016, so that the split is fully predetermined, leaves the difference at -1.30 percentage points (s.e. 0.41). In separate-sample event studies the lead term is insignificant in both groups (-0.0059, s.e. 0.0064, and -0.0048, s.e. 0.0074), whereas the contemporaneous coefficients

are $+0.0191$ (s.e. 0.0048) and -0.0089 (s.e. 0.0053); parallel trends are therefore not rejected within either group. Two caveats apply: the contrast is not detected by a parsimonious single-interaction model (-0.0033, s.e. 0.0045), and the shares are computed on the four classified income components rather than on reported total income, which is larger for about 54 per cent of households.

Taken together, this evidence describes a transmission channel rather than a level effect. Within a locality, climate risk is associated with a redistribution of income away from households whose portfolios are priced in local markets and towards households whose income is administratively determined or self-provisioned. That redistribution is invisible in the average within-city coefficient and appears in the cross-section as a regional gradient, because market-exposed and sheltered portfolios are unevenly distributed in space. It also rationalises the asymmetry reported below: better-educated, higher-asset and non-farm households are more exposed not because they adapt less but because more of their income clears in the markets that a climate shock disrupts.

5.2 Heterogeneity analysis

The association may vary with household head education, risk-bearing capacity, gender, topography, agricultural production zone and livelihood type. Households with different education levels and asset holdings differ not only in adaptive capacity but also in the climate sensitivity of their income portfolios, and grain-producing regions may be more vulnerable than other areas. Accordingly, a heterogeneity analysis is conducted from six dimensions—household head education level, household risk-bearing capacity, gender of the household head, local topography, whether the region is a major grain-producing area, and household livelihood type—with the results presented in Supplementary Table S21 and Supplementary Table S22.

The empirical results reveal significant and partly counterintuitive heterogeneity. Contrary to the conventional expectation that disadvantaged households are always the most exposed, the negative association between climate risk and household income is stronger among households with better-educated heads and greater risk-bearing capacity (Columns (1)–(4) of Supplementary Table S21), and interaction tests confirm that the differences across the education and asset groups are statistically significant. This pattern can be interpreted as a marketisation-exposure effect: better-educated and wealthier rural households derive a larger share of their income from climate-sensitive, market-based sources—wage employment in

local industries, non-farm businesses, and asset returns—so that climate shocks propagate to their income through local labour and product markets. Households with lower educational attainment, by contrast, rely more heavily on transfer income such as pensions, subsidies, and remittances, which is comparatively insulated from local climate conditions and even expands through social assistance after shocks (Table 5). Vulnerability to climate risk is therefore not synonymous with socio-economic disadvantage; it also depends on the climate sensitivity of the income portfolio itself. This reading complements Ahmad et al. (2024) and Luo and Chen (2025), who emphasise adaptive capacity, by highlighting the exposure side of the income distribution.

With respect to gender, the negative association is statistically significant for both male- and female-headed households, with a larger point estimate for female-headed households (Columns (5) and (6) of Supplementary Table S21); the corresponding interaction term is positive but not statistically significant at conventional levels, so the difference should be interpreted with caution. This pattern is consistent with evidence that climate shocks reshape household labour allocation along gendered lines (Huang et al. 2020), and it suggests that female-headed households—often facing tighter labour-market and credit constraints—merit particular attention in the design of climate adaptation programmes.

With regard to topography, climate risk exerts a significant negative effect on households situated in plain and mountainous areas, with the strongest impact observed in mountainous regions, whereas no significant effect is detected in hilly areas. These results align with those reported by Schröder et al. (2024). In plain areas, climate shocks tend to propagate more readily across plots under large-scale cultivation patterns, and the sensitivity of grain yield to climatic conditions further accelerates the transmission of shocks. In mountainous areas, underdeveloped infrastructure, a high degree of agricultural dependence, and weak disaster resilience collectively amplify the compounding effects of climate shocks. In contrast, hilly areas benefit from diversified livelihood strategies that permit flexible adjustments, thereby mitigating the impact of such shocks.

Regarding production zones, climate risk exerts a significant negative effect on household income in major grain-producing areas, while a marginally positive coefficient is observed in non-major grain-producing areas. This finding is consistent with studies conducted by Feng et al. (2025). In major grain-producing areas, household income is predominantly derived from large-scale grain cultivation, characterized by a simplified cropping structure and pronounced climate dependence, rendering yields and revenues directly susceptible to

climatic fluctuations. In non-major grain-producing areas, where agriculture accounts for a relatively modest share of income, households may leverage non-agricultural industrial transformation or climate-adapted speciality economies, and may even benefit from spillover gains arising from supply gaps in major grain-producing areas.

With respect to livelihood type, households are classified by the share of operating income in total income into non-farm households (essentially no operating income), part-time households (operating income below one-half of total income), and farm-dominant households (operating income above one-half). The negative association between climate risk and household income is strongest for non-farm households, weaker and only marginally significant for part-time households, and statistically indistinguishable from zero for farm-dominant households (Columns (6)–(8) of Supplementary Table S22); an interaction test confirms that the farm-dominant group differs significantly from the rest of the sample. This finding reinforces the marketisation-exposure interpretation above and is consistent with evidence that climate shocks induce labour reallocation across sectors rather than uniform income losses (Liu et al. 2023). For farm-dominant households, the direct damage to agricultural output appears to be substantially cushioned by compensatory transfers and within-household adjustments, whereas non-farm households—whose earnings depend on local non-agricultural labour markets that contract under climate stress—lack such automatic buffers. Livelihood diversification alone thus does not guarantee climate resilience; what matters is the climate sensitivity of the sectors into which households diversify (Li et al. 2024).

Fig.6 summarises the heterogeneity pattern on a common scale, pooling the subsample estimates reported in Supplementary Tables S21 and S22 together with the regional and income-quintile splits. The negative association is largest in absolute value for better-educated heads, higher-asset households, households in mountainous areas and major grain-producing regions, and for non-farm households; it is statistically indistinguishable from zero for farm-dominant households, for hilly areas and for non-major grain-producing regions. The figure makes the marketisation-exposure reading visible at a glance: the groups that lose most are precisely those whose income portfolios are concentrated in climate-sensitive, marketised sources.

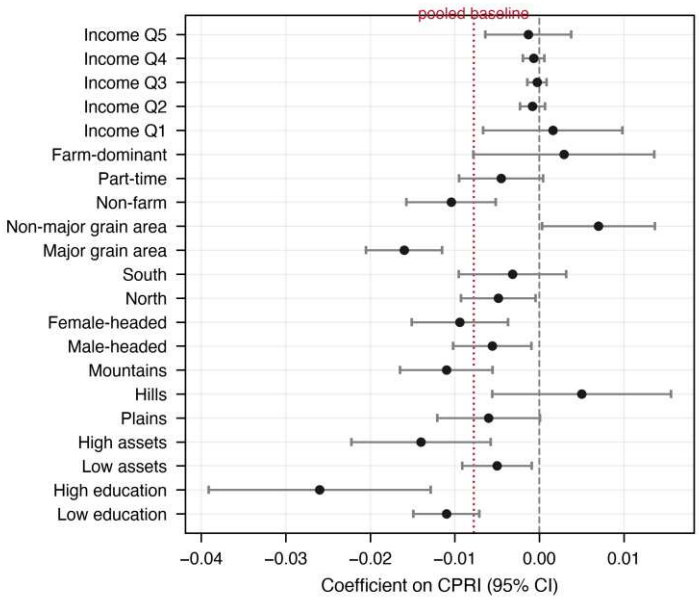


Figure 6. Heterogeneity forest plot

Note: Compilation of estimates already reported in Supplementary Tables S21 and S22, Supplementary Table S1 and Supplementary Table S14, plotted on a common scale. The vertical dotted line marks the pooled baseline estimate and the dashed line marks zero. Estimates are conventional Tobit coefficients with 95% confidence intervals; the confidence intervals do not adjust for city-level clustering.

6 Conclusion and policy implications

Based on data from the China Family Panel Studies (CFPS) spanning 2016 to 2022, this study theoretically analyses and empirically examines the association between physical climate risk and rural household income and its underlying transmission mechanisms. The findings indicate that: First, there is a robust negative association between climate risk and rural household income. Climate risk is associated with lower current income and lower permanent income, with operating and property income most affected. Placebo tests based on random permutations, subsample restrictions, and alternative climate measures corroborate this pattern; at the same time, inference based on city-clustered standard errors and a difference-in-differences evaluation of the Climate Resilient Cities Construction pilot yield statistically insignificant estimates, so the results are interpreted as associational rather than strictly causal. Second, among the candidate transmission channels, only social assistance responds significantly to climate risk, operating as a compensatory transfer that partially cushions household income; the hypothesised mediating roles of agricultural participation, labour mobility, and credit constraints are not statistically supported. Commercial insurance and, more tentatively, social networks significantly attenuate the negative association, whereas the moderating role of medical insurance is not supported. Third, the association is relative rather than uniform. Within a locality, climate risk is associated with a redistribution

of income away from market-exposed, wage- and business-dependent households and towards households whose income is administratively determined or self-provisioned, so that the average within-city effect is close to zero and the aggregate association appears mainly as a regional gradient; the decomposition of the association into income components, whose leading terms carry opposite signs, and the difference between households with high and low wage shares of classified income both support this reading (Hypothesis 7). Fourth, the association exhibits systematic heterogeneity. Contrary to the conventional vulnerability narrative, better-educated and higher-asset households—whose income portfolios are concentrated in climate-sensitive, marketised income sources—experience larger proportional losses, as do non-farm and part-time households relative to farm-dominant ones. Households in plains and mountainous areas and in major grain-producing regions remain more exposed, and the point estimate is larger for female-headed households.

Based on these findings, this study offers the following four policy implications: First, policies should target the climate sensitivity of income portfolios rather than socio-economic status alone. Because better-educated, higher-asset, and non-farm households face larger proportional losses through local labour and product markets, climate adaptation programmes should extend beyond the traditionally disadvantaged to encompass market-exposed rural households—for example, through business-continuity support for rural enterprises and the stabilisation of local non-farm employment during climate shocks. Second, the compensatory-transfer channel should be consolidated. Social assistance responds significantly to climate risk and cushions household income; disaster relief and subsidy disbursement should therefore be made faster, more rules-based, and better targeted at affected households. The continued expansion of inclusive commercial insurance should be prioritised, while the scope for further gains from near-saturated basic medical insurance schemes appears limited. Third, infrastructure and livelihood policies should be tailored to exposed locations and groups. Investment in irrigation, drainage, and disaster-resilient infrastructure should prioritise households in plains, mountainous areas, and major grain-producing regions, and female-headed households should receive explicit attention in the design of adaptation programmes. Fourth, climate risk monitoring and early warning should be strengthened. The null finding for the Climate Resilient Cities Construction pilot suggests that urban-centred resilience policies have yet to generate measurable rural income benefits within the sample window; extending resilience investment to rural areas should be a policy priority.

Data availability

The data that support the findings of this study are available from multiple sources. The household-level microdata are drawn from the China Family Panel Studies (CFPS), administered by the Institute of Social Science Survey, Peking University, and are available to researchers on application to the CFPS programme at https://www.isss.pku.edu.cn/cfps/. The authors are not permitted to redistribute the raw CFPS data. The meteorological data are publicly available from the National Oceanic and Atmospheric Administration (https://www.noaa.gov/) and the National Meteorological Science Data Center (https://data.cma.cn/), and the macroeconomic data from the National Bureau of Statistics of China (https://www.stats.gov.cn/). The de-identified analysis dataset derived for this study and the complete statistical code used for data processing and analysis are provided as supplementary files accompanying this submission and are available in a public repository at https://osf.io/zdw4e/.

Competing interests

The authors declare no competing interests.

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Notes

1. The China Family Panel Studies(CFPS) aim to track and collect data at the individual, family, and community levels to reflect changes in Chinese society, economy, population, education, and health. It provides a data foundation for academic research and public policy analysis. The CFPS sample covers 25 provinces, municipalities, and autonomous regions, with a target sample size of 16,000 households. The survey subjects include all family members in the sample households.

2. The National Oceanic and Atmospheric Administration (NOAA) is part of the Science Agency within the United States Department of Commerce. It focuses primarily on changes in Earth's atmosphere and oceans, providing warnings for severe weather, charting the seas and skies, managing the use and protection of ocean and coastal resources, and researching ways to improve understanding and protection of the environment

3. A small proportion of households report zero total income in certain waves. This may arise from genuine reporting of nil income across all sources. These observations are retained in the sample and naturally accommodated by the Tobit estimator.

Supplementary Files

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