Weathering the Storm: The Impact of Natural Disasters on Household Financial Decisions and the Role of Government Safety Nets[*]

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Abstract

We analyze how natural disasters influence household investment decisions and examine the role of government policies in mitigating these effects. Using a comprehensive household survey spanning 2011 to 2019, we find that experiencing natural disasters significantly reduces households' propensity to participate in the stock market and decreases the proportion of their stock investments. These effects are particularly pronounced among poor, uninsured households and those with limited financial literacy. However, the adverse effects are substantially mitigated with the implementation of government sponsored disaster and medical insurances, by 58% to 75%. The results are robust to falsification tests, instrumental variable analysis, subsample analysis, and matched sample analysis. These findings provide new insights into the role of government safety nets in mitigating the economic consequences of disaster shocks on household decision-making.

Keywords: Natural disasters, Household decisions, Government safety net, Insurance.

JEL Classifications: D1, D10, D81, G02, G11, G22, Q54, H12, O12

1. Introduction

The last several years have witnessed unprecedented growth in property damage from natural disasters worldwide. According to the Swiss Re Institute, total economic losses from natural catastrophes globally reached USD 302 billion in 2023, and are projected to rise to USD 320 billion in 2024, marking a striking annual growth of 6%.[1] Experts anticipate this trend will accelerate as climate change leads to more frequent and intense natural disasters (IPCC, 2023). While the financial and economic consequences of natural disasters have garnered growing attention, research on effective mitigation strategies remains limited.[2]

One promising yet underexplored mitigation solution is insurance. However, recent studies reveal that underinsurance is a significant issue, even in developed countries like the U.S. (Sastry, Sen, Tenekedjieva, and Scharlemann, 2024). Meanwhile, rising insurance premiums, the exit of high-quality insurance companies from high-risk areas, and unintended consequences of insurance regulations have imposed major challenges for regulators.[3] Given these complexities, it remains an open question what types of government policies are most effective in mitigating the adverse impacts of natural disasters on households.

In this paper, we address this critical question by investigating government-initiated policies that provide safety nets to households affected by natural disasters. Specifically, we analyze how natural disasters influence household investment decisions and examine the role of government policies in mitigating these effects. Using household-level data from the China Household Finance

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[1] Jérôme Jean Haegeli, Swiss Re's Group Chief Economist, warns "With rising natural catastrophe risks and higher price levels, the annual increase of 5–7% in insured losses will continue, leading to widening protection gaps." Source: Swiss Re Institute. "Hurricanes, Severe Thunderstorms and Floods Drive Insured Losses above USD 100 Billion for 5th Consecutive Year, Says Swiss Re Institute." Swiss Re, December 19, 2024.

[2] See Bernile et al. (2017), Bharath and Cho (2023), Cameron and Shah (2015), Dessaint and Matray (2017), and Gao et al. (2020).

[3] See Blickle and Santos (2022), Ge, Lam, and Lewis (2022), Sastry, Sen, and Tenekedjieva (2023), Ge, Johnson, and Tzur-llan (2024). See also news reports in the Los Angeles Times ("State Issues New Rule to Help Fix California's Troubled Home Insurance Market," December 30, 2024) and the Wall Street Journal ("Insurers Are in the Hot Seat on Climate Change," December 30, 2024).

Survey (CHFS) spanning 2011 to 2019, we find that experiencing natural disasters significantly reduces households' propensity to participate in the stock market and decreases the proportion of stocks in their total assets. However, these adverse effects are effectively alleviated following the implementation of two distinct public insurance policies introduced by the Chinese government.

We focus on household investment decisions because natural disasters not only cause immediate and direct damage to household wealth but also have profound and lasting effects on individual decision-making. One critical indirect consequence is the potential shift in households' risk preferences, leading them to become more risk-averse and subsequently reduce their investments in the stock market.[4] This behavioral response is particularly significant because it causes households to forgo valuable opportunities for wealth accumulation, thereby limiting their ability to build financial security over time. Over the long term, such diminished financial resilience can exacerbate economic vulnerabilities, especially for poorer, uninsured, and financially unsophisticated households, who are less equipped to recover from disaster shocks.

Based on these considerations, our study addresses two key questions: (1) how do natural disaster experiences influence household investment decisions, and (2) what roles can governmental policies play in providing safety nets to mitigate these effects? We approach these questions by utilizing one of the most comprehensive and widely used nationwide surveys of Chinese households, which offers rich and granular information on household financial decisions, including detailed portfolio allocations (e.g., deposits, stocks, and insurance coverage) and key household attributes such as risk aversion and financial literacy. This depth of information enables a thorough examination of household financial behavior.

[4] Psychological and financial research suggests that changes in the external environment, such as macroeconomic ups and downs (Malmendier and Nagel, 2011), significantly influence individual decision-making.

We leverage two key government-sponsored insurance policies: the medical insurance integration policy introduced in 2009 and the disaster recovery-related insurance initiatives launched in 2015. These policies serve as valuable exogenous shocks, allowing us to assess how government safety net policies moderate the impact of natural disasters on household decision making. By mitigating income volatility and facilitating post-disaster recovery, these policies act as critical safety nets, offering both financial security and risk-sharing benefits that shield households from the financial disruptions caused by natural disasters.

Building on this framework, our empirical analysis integrates household-level financial data from the CHFS with natural disaster records from the National Bureau of Statistics (NBS), China's most authoritative statistical agency. The NBS has recorded and compiled data on economic losses from natural disasters at the provincial level since 2010. We merge these two datasets at the province level and examine how households' financial decisions respond to the severity of local natural disasters, measured by the number of fatalities.[5]

We document the following main findings. First, we establish that natural disasters significantly reduce households' propensity to participate in the stock market and decrease the share of stock investments in their total assets. These results are consistent with prior literature (Bharath and Cho, 2023; Cameron and Shah, 2015). Specifically, a one standard deviation increase in the logarithm of natural disaster fatalities in a household's province reduces stock market participation likelihood by 8.3% and decreases the share of stock assets as a percentage of total assets by 14.8%, relative to the corresponding sample averages.

[5] The reason for merging at the province level is that the CHFS does not provide the exact addresses of households for privacy reasons. Therefore, the most granular locational information is at the province level. Nevertheless, we believe that these five waves of the national survey still provide a reasonably large sample of households for our research on the influence of natural disasters on households' risk attitudes.

Second, we show that the adverse impact of natural disasters on households' risk-taking behaviors is more pronounced among vulnerable subgroups, including poor, uninsured households and those lacking financial sophistication. This finding highlights the disproportionate burden borne by economically disadvantaged and financially unsophisticated households in the aftermath of natural disasters. These households, already struggling with limited resources, are less equipped to cope with the economic consequences of disasters and are more likely to withdraw from riskier but potentially higher-return financial opportunities.

Furthermore, we examine the moderating effects of government-sponsored insurance policies on these behaviors. Specifically, we exploit the introduction of two key policies: the Medical Insurance Integration Policy (MIIP) in 2009 and the China Residential Earthquake Insurance Pool (CREIP) established in 2015. As the first insurance initiative, MIIP eliminated the urban-rural divide and improved residents' access to medical services (Huang and Wu, 2020). Implemented in 2009 and rolled out in a staggered fashion, MIIP provides an exogenous shock to the provision of government safety nets, allowing us to study its effects.

The second insurance, CREIP, provides earthquake insurance services and facilitates disaster risk sharing to millions of households across the country (Fang and Yuan, 2024). The pool consists of 45 eligible property insurance companies and represents the largest catastrophe insurance pilot program in China (Li and Liu, 2023). Its establishment marks a critical step toward developing a formal and systematic catastrophe insurance system in the country.[6] By the end of 2023, CREIP had provided a cumulative 7.855 trillion RMB in earthquake risk coverage to 21.07 million households.[7]

[6] https://www.cpcr.com.cn/zhzcxeng/news%20center/Whats%20New%201/20220107035134550 94/index.html
[7] See report in http://www.cbimc.cn/content/2024-04/07/content_513369.html

Our analysis reveals that the implementation of the Medical Insurance Integration Policy in 2009 and the disaster recovery-related insurance initiative in 2015 significantly mitigates the negative effects of natural disasters on household investment decisions. Specifically, we find that households in provinces covered by these policies experience smaller declines in stock market participation and stock portfolio allocations following natural disasters. The mitigation effects are economically substantial: the negative impacts of natural disasters on stock market participation and portfolio allocations are reduced by 60% and 58%, respectively, following the 2009 medical insurance integration, and by 75% and 72%, respectively, following the 2015 CREIP, compared to the pre-policy period. This suggests that government safety net policies play a pivotal role in stabilizing household investments by reducing income volatility and providing robust post-disaster support.

We further investigate the comparative roles of public versus private insurance in shaping household investment decisions after natural disasters. Some studies have documented that the expansion of Medicaid eligibility in the U.S. has significantly crowded out private insurance coverage, suggesting a substitution effect between public and private health insurances (Cutler and Gruber, 1996; Shore-Sheppard et al., 2000). However, others argue that private insurance can complement existing public health insurance systems (Propper, 1989; Savedoff and Sekhri, 2005). Using detailed insurance-related varaibles from the CHFS, we find that after experiencing natural disasters, households are more likely to enroll in public medical insurance while showing a reduced inclination to purchase private insurance. One possible explanation is that Chinese households perceive government-sponsored insurance as a more reliable form of disaster protection, whereas they tend to view private insurance as relatively riskier.

Complementing the analysis of equity investments, we also investigate households' holdings

of other assets, such as cash and mutual funds. We measure households' cash holdings as their e-wallet cash balances and find that natural disasters prompt households to increase their holdings of safer assets, such as e-wallet cash deposits.[8] In contrast, households reduce their mutual fund holdings, although this reduction is smaller in magnitude compared to the decrease in stock holdings. These findings are consistent with our earlier results, which show that natural disaster experiences reduce households' risky investments and prompt them to park their funds in safer assets, foregoing opportunities for wealth accumulation.

We also investigate three potential mechanisms through which natural disasters influence households' risk-taking behavior. Our findings indicate that increased risk aversion and revised return expectation are the primary drivers of changes in households' risk-taking behaviors following natural disasters. This analysis extends the work of Cameron and Shah (2015) and Bharath and Cho (2023), providing external validation for the previous literature on the impact of risk attitude on household decision-making after disaster shocks.

Although natural disasters are exogenous in nature, alleviating some endogeneity concerns, our study may still be subject to potential omitted variable bias. For instance, regions prone to frequent natural disasters often suffer from systemic underdevelopment due to infrastructure challenges, which could independently influence local economic conditions and household investment decisions. To address this issue, we conduct an instrumental variable analysis, by instrumenting a household's disasters experience with the disaster experiences of their distant friends, based on the rationale that households' perceptions of local disaster risk are positively correlated with the disaster experiences of their distant friends that do not share common economic

[8] China has transitioned into a cashless economy, driven by the widespread adoption of e-wallet super-apps like Alipay and WeChat Pay. As e-wallets in China is the dominant payment method, accounting for 83% of e-commerce transactions in 2021.

fundamentals (Bailey et al., 2018b). Specifically, we construct *FriendDisaExp*, a weighted average of disaster-related fatalities in non-adjacent provinces, using weights derived from the Social Connectedness Index (SCI) based on train connections between provincial capitals. This approach satisfies the exclusion restriction, as disasters in non-adjacent provinces are exogenous to local economic conditions. By replacing our main disaster variable with *FriendDisaExp*, we obtain consistent estimates, confirming the robustness of our findings.

Lastly, we conduct additional robustness tests to further corroborate our main findings. First, to address the concern that our results may be mainly driven by areas with high occurrence of natural disasters, we exclude Sichuan, Yunnan, Gansu, Hunan, and Guizhou, the top five provinces most prone to natural disasters from our analysis. Second, we control for the household fixed effects in our baseline equations to include more potential unobservable factors across households. Third, we conduct falsification tests using pseudo-policy shocks for each of the two insurance policies. Finally, we apply the entropy matching method to alleviate concerns about sample selection bias. Across all these robustness tests, our main findings regarding the mitigating effects of government safety nets remain consistent.

This study contributes to the growing body of research documenting that government safety nets—such as unemployment benefits, disaster relief, and social insurance programs—help reduce households' exposure to income and asset risks (e.g., Gertler and Gruber, 2002) while enhancing welfare by smoothing consumption and preventing poverty traps during economic downturns or crises (e.g., Chetty and Looney, 2006). We extend this literature by demonstrating that, in the context of natural disasters, government insurance programs—such as medical and earthquake insurances—mitigate the adverse effects of natural disasters on households' risk aversion. This finding highlights the critical role of government safety nets in strengthening financial resilience

and facilitating economic recovery in the aftermath of natural disasters.

Our paper also contributes to the literature on the relationship between natural disasters and household risk-taking behaviors.[9] While prior studies have primarily examined this relationship in the context of the U.S. market, we provide novel evidence from China, a major developing nation high susceptibility to natural disasters and with a less mature private insurance market. In this setting, many households remain financially vulnerable to catastrophic events, underscoring the importance of government intervention. [10] By demonstrating how government safety nets mitigate the adverse effects of disasters on household risk-taking behaviors, our findings highlight their role in reducing households' economic vulnerability and promoting more efficient investment decisions in disaster-prone regions.

The insights from our analysis have broad relevance, extending to both developing and developed countries. For instance, even in advanced markets like the U.S., underinsurance remains a significant issue (Hu, 2022; Sastry et al., 2024). This challenge is exacerbated by rising insurance premiums and the withdrawal of private insurance companies from high-risk areas, creating significant financial burdens for households and regulatory challenges for policymakers (e.g., Blickle and Santos, 2022; Ge, Lam, and Lewis, 2022; Sastry, Sen, and Tenekedjieva, 2023). Our findings offer valuable insights into an alternative policy solution: government-led safety net

[9] See, for example, Cameron and Shah, 2015; Gao et al., 2020; Bharath and Cho, 2023). In particular for Chinese market (Yuan et al., 2024; Guo et al., 2023). Bourdeau-Brien and Kryzanowski (2020) show that major catastrophes increase the risk aversion of U.S. municipal bond investors. Dessaint and Matray (2017) study how managers respond to hurricane events when their firms are located in the neighborhood of the disaster area. They find that managers' perceived risks are increased by this sudden shock, and in response they increase their corporate cash holdings.

[10] China experiences some of the highest annual occurrences of natural disasters globally (Wang et al., 2011; Shi et al., 2016), with 8 of the 54 worst natural disasters in the world in the 20th century occurred in China, including earthquakes, floods, and typhoons, which caused losses of life and damages to property (Xu et al., 2018). Only about 18% of Chinese households taking up private insurance. Internet Appendix Table IA2 summarizes the insurance density (premium per capita) and insurance penetration (premium as a percentage of GDP) of China, the U.S., and the world. Between 2001 and 2021, the average commercial insurance density in China is about USD200, whereas the average commercial insurance density in the U.S. is about USD5,761. The insurance penetration in China (3.24%) is also below the global average (7.11%).

initiatives. Such policies can mitigate households' exposure to natural disasters, providing critical lessons for policymakers seeking to enhance financial resilience and disaster preparedness.

2. Institutional Backgrounds and Hypothesis Development

In this paper, we leverage the establishment of the CREIP in 2015 and the staggered province-level integration of urban and rural medical insurance as two exogenous shocks to examine how government safety nets mitigate the impact of natural disasters on household financial decisions. Below, we provide a detailed discussion of each policy.

2.1 China Residential Earthquake Insurance Pool

Earthquakes are among the most devastating natural hazards, causing significant casualties and substantial property losses (Fang and Yuan, 2024). Between 1996 and 2015, approximately 1.35 million people worldwide died from natural disasters, with over half of these fatalities resulting from earthquakes (CRED, 2016). In China, the 2008 Sichuan Earthquake stands out as a particularly catastrophic event, claiming over 69,000 lives, injuring 374,176 individuals, and causing economic losses estimated at 845.1 billion yuan (approximately US$130 billion). This makes it the deadliest earthquake in China since the 1976 Tangshan Earthquake.[11] In response to such disasters, the Chinese government has increasingly recognized the critical role of catastrophe insurance in ensuring rapid rehabilitation and recovery in their aftermath (World Bank, 2020).

The China Residential Earthquake Insurance Pool (CREIP), established in 2015, represents a significant milestone in China's efforts to develop a formal catastrophe insurance system (Li and Liu, 2023). It currently pilots the country's largest catastrophe insurance program, comprising 45

[11] See the statistics in https://en.wikipedia.org/wiki/2008_Sichuan_earthquake.

eligible property insurance companies that voluntarily participate.[12] According to the China Insurance Regulatory Commission (CIRC), the CREIP serves as a valuable initiative by the insurance industry to promote the implementation of a nationwide earthquake catastrophe insurance system. It marks a substantial step forward in building a comprehensive catastrophe insurance framework in China. A key function of the CREIP is providing earthquake insurance services and facilitating disaster loss sharing. By the end of 2023, the CREIP had provided a cumulative 7.855 trillion RMB in earthquake catastrophe risk coverage to 21.07 million households nationwide.[13]

2.2 Public Medical Insurance System in China

Unlike the U.S., which operates a market-driven healthcare system dominated by private insurance, China's healthcare insurance system is primarily financed and regulated by the government. Over the past few decades, China has undergone significant reforms to develop a multi-tiered system aimed at achieving universal coverage and improving healthcare accessibility. In 1998, China introduced a government-run, mandatory insurance program tied to employment. However, this program left many groups, including rural farmers and unemployed urban residents, without coverage. To address this gap and move toward universal coverage, the Chinese government introduced two voluntary insurance schemes for those not covered by the employer-based program. In 2003, the New Rural Cooperative Medical Scheme (NRCMS) was launched to provide basic health coverage for rural residents, and in 2007, the Urban Resident Basic Medical

[12] The earthquake insurance community is composed of property insurance companies that apply for membership based on the principles of voluntary participation and risk sharing. Property insurance companies in China can apply to join the earthquake insurance community as long as they have been established for more than three years, have a solvency ratio of more than 150% in the latest quarter, have a better branch network and stronger service capacity, and have experience in underwriting and handling claims for relevant types of insurances. See more details in http://finance.people.com.cn/insurance/n/2015/0427/c59941-26912839.html.

[13] See report in http://www.cbimc.cn/content/2024-04/07/content_513369.html

Insurance (URBMI) was established to cover urban residents who were excluded from the mandatory scheme. Both voluntary programs are heavily subsidized by the central and local governments to enhance healthcare access for the underserved (Yang, 2018).

A major milestone in China's healthcare reform occurred around 2016 when the government implemented a unified basic medical insurance system for both urban and rural residents. This reform merged the URBMI and NRCMS into a single Urban-Rural Resident Basic Medical Insurance (URRBMI) system. The goal was to address disparities in healthcare access, affordability, and fairness between urban and rural populations. Note that the integration of urban and rural medical insurance has been implemented by each province gradually over time. Table IA3 summarizes the integration timeline for each province.

Prior to this integration, out-of-pocket healthcare expenses remained high, placing an increasing financial burden on households, particularly in rural areas (Wang et al., 2014). For rural residents, out-of-pocket healthcare payments as a percentage of average annual household living consumption expenditure rose from 5.2% in 2000 to 8.4% in 2011, exacerbating their financial strain (Long et al., 2013). Furthermore, the URBMI and NRCMS were administered by separate institutions and had different financing pooling mechanisms, resulting in low risk protection and insufficient integration within the health insurance system. This fragmentation created significant low efficiency and inequities, particularly for migrants who moved from rural areas due to the fast urbanization during past years (Wang et al., 2014; Ma et al., 2021). As a result, the division between rural and urban health insurance schemes was identified as a key factor contributing to the disparities in social and economic development across China (Ma et al., 2021).

Based on this, provinces across China gradually began implementing the integration of urban and rural medical insurance around 2016. Research indicates that the integration reform has

expanded the risk pool, improving financial risk protection and reducing inequalities in healthcare access. For example, Tang et al. (2024) found that reimbursement rates for inpatient services increased in rural areas, helping to narrow the urban-rural healthcare gap. Li et al. (2023) showed that the integration led to higher hospital admission rates among rural residents, indicating better healthcare accessibility. Before the integration, rural residents covered by the NRCMS were less likely to seek care due to financial barriers, but after the reform, their utilization of medical services increased (Zhou et al., 2022). Additionally, Wang et al. (2014) highlighted that the unified healthcare insurance system improved coordination between urban and rural medical schemes, enhancing overall healthcare delivery efficiency.

2.3 Hypothesis Development

There is extensive literature that explores how risk preferences are changed by past personal experience. Fagereng et al. (2017) find that investors exposed to more macroeconomic uncertainty in their "impressionable years" (age cohort of 18–23 years old) invest less in stocks over their lifetime. Likewise, Malmendier and Nagel (2011) find that the Great Depression had a long-lasting effect on individuals' risk attitudes.

As extreme and random events, natural disaster experiences may shape people's financial decisions. A growing body of literature provides evidence of the impact of natural disasters on financial decisions. Cameron and Shah (2015) play standard risk games with randomly selected Indonesian individuals and find that people living in villages that have suffered a flood or earthquake in the prior three years exhibit more risk aversion than others. Rather than using experimental data, Bharath and Cho (2023) use survey data from the U.S. and suggest that after a disaster shock, households become more risk-averse and lower their expectations of future stock market returns. Based on U.S. municipal bond transactions, Bourdeau-Brien and Kryzanowski

(2020) document that natural disasters cause a statistically and economically significant increase in risk aversion at the local level.

As extremely adverse events, natural disasters exert a negative shock on households. We put forth our first two hypotheses as follows:

H1: Households exposed to more severe natural disasters exhibit a lower propensity to participate in the stock market and hold a smaller share of stock investments.

H2: Households exposed to more severe natural disasters would be more risk averse.

The impact of natural disasters on risk-taking may be heterogeneous with background risks. Guiso and Paiella (2008) find that individuals who are more likely to face income uncertainty or to become liquidity-constrained exhibit a higher degree of absolute risk aversion, indicating a positive relationship between background risks and risk aversion. Guiso and Sodini (2013) also document that background risks make investors more risk averse and less willing to invest in risky financial assets. Researchers identify sources of background risk in wealth components that cannot be fully diversified because of market incompleteness or illiquidity. Specifically, human capital (Bodie et al., 1992; Koo, 1995; Viceira, 2001), housing wealth (Flavin and Yamashita, 2002; Cocco, 2005; Yao and Zhang, 2005), and private business wealth (Heaton and Lucas, 2000a, 2000b) are used to explain the reluctance of households to invest in risky financial markets. Cai et al. (2013) extend the framework by identifying categories of background risks when investing: labor income, housing, wealth, health, and professional knowledge. Therefore, households that are poor, without insurance coverage, and with lower education level than other households face more background risks. Following this idea, we therefore propose the following hypothesis:

H3: The impact of natural disasters on household risk-taking is more pronounced among

households with lower wealth, lack of insurance coverage, or limited financial literacy.

Natural disasters can create significant financial uncertainty for households, leading to a shift in risk-taking behavior. In the absence of adequate safety nets, households may respond to heightened economic insecurity by adopting more conservative financial strategies, such as increasing precautionary savings and reducing investments in risky assets. This aligns with the precautionary savings hypothesis, which suggests that individuals facing greater uncertainty tend to hold safer, more liquid assets to buffer against future shocks (Carroll & Kimball, 1996).

However, government-provided insurance policies, such as public medical insurance and disaster relief programs, can mitigate these concerns by reducing income volatility and protecting against unexpected financial burdens. When households feel more financially secure due to these safety nets, they may be less inclined to alter their investment strategies in response to natural disasters.

Empirical evidence supports the role of insurance in shaping household financial behavior. For instance, research shows that access to health insurance reduces precautionary savings, allowing households to allocate more resources toward higher-yield investments (Zhou et al., 2015). Similarly, studies on disaster relief policies suggest that government compensation programs help stabilize consumption and wealth accumulation, preventing drastic shifts in financial decision-making (Fuchs & Wolff, 2011). Moreover, informal safety nets, such as remittances from family members, have been found to buffer the negative effects of natural disasters on household risk aversion (Cameron & Shah, 2015). These findings suggest that when formal government safety nets are in place, households may feel more financially resilient and, as a result, be less reactive to disaster-induced economic uncertainty.

Building on this literature, we hypothesize that the availability of public insurance and disaster relief policies in China weakens the adverse impact of natural disasters on household financial decisions. Specifically, we expect that insured households will exhibit a smaller decline in risky asset holdings following a disaster compared to uninsured households. By providing a financial cushion against unexpected shocks, government safety nets can encourage households to maintain or even increase their investment in riskier assets, thereby reducing the long-term economic consequences of natural disasters.

We leverage two exogenous safety nets insurance policies in China and propose our fourth hypothesis as follows:

H4: The adverse effect of natural disasters on household financial decisions is mitigated when the government provides safety nets, such as medical and natural disaster insurance policies.

3. Sample and Data

3.1 Household Investment Measures from China Household Finance Survey

In this paper, we collect detailed information on household stock market participation and risk attitude from the China Household Finance Survey (CHFS) in 2011, 2013, 2015, 2017, and 2019.[14] CHFS is one of the most comprehensive and widely used nationwide surveys of households in China, conducted every two years by the Survey and Research Center for China Household Finance (SRCCHF) of Southwestern University of Finance and Economics. The sampling procedure, data structure, questionnaire design, and data processing of the CHFS are analogous to their counterparts in the U.S. Survey of Consumer Finance (Pan and Wu, 2021). According to the

[14] The publicly available data from 2011 to 2019 are obtained from this website: https://chfs.swufe.edu.cn/sjzx/sjsq.htm. While the most recent wave in 2021 has been completed, the data is not available to the public. Moreover, the Covid-19 pandemic in 2019 may also affect households' decision, thus we choose not to use the CHFS survey in 2021.

SRCCHF, the recent SRCCHF survey conducted in 2019 consists of 34,643 unique households across 29 provinces,[15] 170 cities, 345 districts and counties, and 1,360 village (residence) committees. The survey collects household information on demographics, assets, liabilities, insurance, income, and expenses, which provides a comprehensive and detailed picture of household economic and financial management (Gan et al., 2016).

The CHFS data enables us to track the dynamics of households' risk attitude and financial behavior over time, thanks to its comprehensive follow-up survey strategy. Unlike other surveys that might encompass a broader range of decisions, such as job selection in NLSY79 survey (Bharath and Cho, 2023), the CHFS survey focuses specifically on respondents' risk preferences directly associated with finance and investment.[16] By directly eliciting information on households investment choices regarding projects with different scales of risks and returns (e.g., high-risk and high-return projects, or low-risk and low-return projects, etc), this CHFS survey enables us to construct measures on household risk attitude related to investment.

As each data from each survey wave contains three sub-databases: the individual database, household database, and region database, we merge these three sub-databases using the Household ID which uniquely identifies a household. We then construct measures on households' stock market participation and risk attitude, and other control variables (e.g., stock, total assets, income,

[15] The 29 provinces covered are Beijing, Shanghai, Tianjin, Yunnan, Inner Mongolia, Jilin, Sichuan, Ningxia, Anhui, Shandong, Shanxi, Guangdong, Guangxi, Jiangsu, Jiangxi, Hebei, Henan, Zhejiang, Hainan, Hubei, Hunan, Gansu, Fujian, Guizhou, Liaoning, Chongqing, Shanxi, Qinghai, and Heilongjiang.

[16] It is worth noting that Bharath and Cho (2023) constructed a job-related risk aversion measure from the National Longitudinal Survey of Youth (NLSY79) in U.S. to interpret their findings of salient reduction in propensity to invest in risky asset in respond to the natural disaster experience. We argue that this job-related risk aversion may not directly reflect people's risk preference in financial decisions. The risk aversion measures used in Bharath and Cho (2023) range from 1 (least risk averse) to 4 (most risk averse), which are obtained from the following sequence of three survey questions on the NLSY79 (1993, 2002, 2004, 2006): "Suppose that you are the only income earner in the family, and you have a good job guaranteed to give you your current (family) income every year for life. You are given the opportunity to take a new and equally good job, with a 50-50 chance that it will double your (family) income and a 50-50 chance that it will cut your (family) income (i) by a third, (ii) in half, and (iii) by 20 percent. Would you take the new job?"

financial literacy, age, gender, education level) at the household level.

After carefully cleansing the five waves of survey datasets, we apply the following data procedures. First, we exclude households that relocate across provinces during the sample period since families who prefer real estate investment may choose to move to other cities (Gao et al., 2023). Second, to address the influence of outliers, continuous variables are winsorized at the 1st and 99th percentiles. Third, we remove all observations with missing values for key variables such as stock participation, stock share, risk attitude, education level, and financial literacy. Our final sample consists of 111,505 household-year observations (56,865 unique households) across 29 provinces from 2011 to 2019. Refer to the Internet Appendix Table IA1 for more details on variable definitions.

3.2 Measures of Natural Disasters

We obtain the natural disaster data from the National Bureau of Statistic (NBS), the most authoritative statistical agency in China.[17] NBS records and aggregates natural disaster data each year at the province level, including fatalities and economic losses. Natural disasters include floods, droughts, typhoons, hail, freezing rain, blizzards, sandstorms, earthquakes, geological disasters (such as avalanches, landslides, mud and rockslides), tsunamis, and biological disasters. It is possible that a natural disaster may occur within a specific city and households in other cities within the same province may lack firsthand personal experience of the event. Nevertheless, we contend that such households can still undergo emotional impact from the disaster through the firsthand experiences of their friends and relatives, or by means of exposure to local news reports concerning the incident.

[17] Data on natural disasters is available at https://data.stats.gov.cn/easyquery.htm?cn=C01.

In this paper, we use the fatalities caused by natural disasters in a province to measure the disaster's severity at the province-year level. Table 1 provides descriptive statistics for natural disasters. As shown, the average number of deaths from natural disasters (*DeathNum*) is about 43.5. Figure 1 plots the average fatalities from disasters across 29 provinces from 2011 to 2019. For comparison, we also plot the direct economic losses from geological disasters (*GeoDisaEcoLoss*) in the figure. Fatalities and economic losses show similar trends, increasing from 2011 and peaking around 2013, when natural disasters, on average, caused about 74 deaths and resulted in economic losses of around 336.64 million yuan. Losses from natural disasters in general show a downward trend after 2013.

[--- Insert Figure 1 about here ---]

While natural disasters tend to occur randomly, they still exhibit salient geographic concentration. Figure 2 depicts the disaster distribution for the 29 provinces in our sample. Panels A and B present the distributions of fatalities and economic losses, respectively. A darker color indicates greater damage caused by natural disasters in the province. As shown, extreme natural disasters are concentrated in Sichuan, Yunan, Gansu, Hunan, and Guizhou where there are many mountain ranges with active tectonic movement. To eliminate the impact of these extreme samples on our results, we exclude these four provinces from our sample, then re-estimate the results in robustness tests.

[--- Insert Figure 2 about here ---]

3.3 Descriptive Statistics of Key Variables

After cleansing the two datasets, we proceed to match them at the province level.[18] Combining

[18] The reason for merging at the province level is that the CHFS does not provide the exact addresses of households for privacy reasons. Therefore, the most granular locational information is at the province level. Nevertheless, we believe that these five waves of the national survey still provide a reasonably large sample of households for our research on the influence of natural disasters

the five waves of survey data (2011, 2013, 2015, 2017, and 2019), our final sample contains 111,505 household-year observations (56,865 unique households) distributed across 29 provinces. We present summary statistics of key variables in Table 1, with detailed variable definitions reported in Internet Appendix Table IA1. The percentage of risk averse households (*RiskAverse*) in our sample is 72%, comparable to the risk aversion values for Chinese households in other studies (Li et al., 2021). The average ratio of stock investment to total assets is 0.40% for all households and 6.54% for those households that participate in stock market. The stock market participation rate (*StockParti*) for households is 6%, suggesting that Chinese households in general have a relatively low level of stock market participation. In comparison, Bharath and Cho (2023) document that U.S. households' average ratio of risky assets to total assets is about 38%.[19]

One potential reason for Chinse households' under-participation in stock market is insurance coverage. There is stark difference between Chinese and American insurance market development. Figure IA1 Panels A and B plots the average insurance density (premium per capita) and insurance penetration (premium as a percentage of GDP) of China, the U.S., and the world from 2001 to 2021. As Panel A reveals, over the past two decades, the insurance density in the U.S. (represented by the blue line) has risen drastically from approximately USD 4,000 to over USD 8,000. In contrast, the insurance density in China (represented by the red line) has remained consistently below the global average. Panel B reveals a similar trend: while insurance penetration in China has gradually increased over the past two decades, it still lags behind the global average.

[--- Insert Table 1 about here ---]

Figure 3 show the average stock share and natural disasters from 2011 to 2019; Panels (a) and

on households' risk attitude.

[19] Bharath and Cho (2023) identify those risky assets as common stocks, preferred stocks, stock options, government bonds, corporate bonds, and mutual funds. In this paper, we focus on stocks, the main type of risky assets of households.

(b) use fatalities and economic losses as a measure of disasters, respectively. To smooth the curve, we first linearly interpolate the missing values for the share of stock investment for each family in 2012, 2014, 2016, and 2018, then calculate the annual average stock share of the full sample. Generally, it appears that losses from natural disasters move in the opposite direction to the share of stock investments in total assets. For example, during the period from 2013 to 2015, as losses from natural disasters decreased, the average household's stock share experienced an increase.

[--- Insert Figure 3 about here ---]

Next, we conduct a univariate mean test to offer some preliminary evidence on whether households exposed to more severe natural disasters invest less in stock assets. As shown in Table 2, households residing in provinces with more natural disasters losses (above-average *DeathNum*) generally are associated with lower stock market participation rates and stock-to-assets ratios than those in provinces with fewer natural disasters losses (below-average *DeathNum*).

[--- Insert Table 2 about here ---]

4. Empirical Analysis

4.1 Natural Disasters and Household Risk Taking

We first examine the effect of natural disasters on the propensity of a household to invest in the stock market by estimating the following equation:

$$StockParti_{ijt} = \alpha + \beta_1 Log(1 + DeathNum_{j,t-1}) + \gamma X_{ijt} + \mu_r + \lambda_t + \varepsilon_{ijt}, \quad (1)$$

where $StockParti_{ijt}$ is an indicator that equals 1 if household *i* in province *j* participates in the stock market in year *t*, and 0 otherwise. $DeathNum_{j,t-1}$ is the number of deaths caused by natural disasters in province *j* in year *t*-1. X_{ijt} is a vector of control variables including risk attitude, financial literacy, gender, education level, age, age squared, married, total assets, total income, property holdings, past realized gain from stock investments, GDP, housing price, and whether the

households live in the rural areas of the province. To control for stock market condition and other unobserved time-invariant regional characteristics, we follow Zeng and Yu. (2023) to include year and region fixed effects (East, Central, and West), λ_t and μ_r, respectively.[20] As household financial decisions in different years may be correlated (Bu et al. 2022), we cluster the standard errors at household level. If fatalities resulting from past natural disasters reduce the probability of a household investing in the stock market, we expect $\beta_1 < 0$. It is possible that a natural disaster may occur within a specific city and households in other cities within the same province may lack firsthand personal experience of the event. Nevertheless, we contend that such households can still undergo emotional impact from the disaster through the firsthand experiences of their friends and relatives, or by means of exposure to local news reports concerning the incident.

We then explore the impacts of natural disasters on the share of stocks by estimating the following ordinary least squares (OLS) equation:

$$StockRatio_{ijt} = \alpha + \beta_2 Log(DeathNum_{j,t-1}) + \gamma X_{ijt} + \mu_r + \lambda_t + \varepsilon_{ijt}, \quad (2)$$

where $StockRatio_{ijt}$ denotes stock investment as a percentage of the total assets of household *i* in province *j* in year *t*. We also control for the same sets of variables and fixed effects as described in equation (1). We expect $\beta_2 < 0$ if fatalities caused by past natural disasters lead to a decrease in the proportion of stocks to total assets.

Table 3 presents the estimation results of equations (1) and (2). Columns (1) and (2) display the results with *StockParti* as the dependent variable, while Columns (3) and (4) show the results with *StockRatio* as the dependent variable. Based on Column (2), we find the coefficient on *Log(1+DeathNum)* is -0.003 and significant at 1% level, suggesting that a one standard deviation

[20] According to the CHFS, east region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. Central region includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. West region includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shannxi, Gansu, Qinghai, and Ningxia.

increase in logarithm of fatalities from natural disasters lowers the probability of households participating in the stock market by 0.005 (=0.003*1.55), a 8.3% (=0.005/0.06) decrease relative to the sample mean. Likewise, in Column (4), the coefficient on *Log(1+DeathNum)* is -0.038 and significant at 1% level, indicating that a one standard deviation increase in logarithm of fatalities from natural disasters leads to a 0.059 (=0.038*1.55) percentage reduction in households' stock share, a 14.8% (=0.059/0.4) decrease relative to the sample mean.

This effect is economically substantial in magnitude, especially when compared with the effects on U.S. families. Bharath and Cho (2023) focus on the influence of natural disasters on risk-taking behavior among U.S. families and find that a one standard deviation increase in the number of experienced disasters reduces the share of risky assets by 2.6%, relative to a sample average of 6.8%. We document that the impact of natural disasters on Chinese households' equity share, in contrast, is approximately two times greater.

In addition to our variable of interest, the characteristics of households exhibit the expected impacts on household risk-taking. Consistent with portfolio choice theory (Campbell and Viceira, 2002), we find a negative correlation between risk aversion and household risk-taking. Moreover, previous studies show that individuals with higher levels of financial literacy are more likely to participate in the stock market (see Kimball and Shumway, 2006; Van Rooij et al., 2011; Yoong, 2011). Similarly, education level, as an alternative measure of financial literacy, has also a positive impact on risk-taking behaviors (Vissing-Jorgensen, 2002). We provide similar evidence for these findings.

Table 3 shows that age has a positive impact on stock market participation and investments, while the term for age squared exerts a negative influence. This finding aligns with the notion that older household heads accumulate more wealth and investment experience, and more likely to

invest in risky assets, albeit with a marginal diminishing effect. This result is consistent with several studies, including Barsky et al. (1997), Dohmen et al. (2011), and Guiso and Paiella (2008), that provide evidence on this pattern that older people tend to allocate a larger proportion of their accumulated wealth to risky assets, although this effect is marginally diminishing. While some studies show that women are generally more risk-averse than men (Croson and Sundali, 2005; Croson and Gneezy, 2009), we find a negative and significant coefficient for *Male* in Panel A, indicating that males are less likely to participate in the stock market.[21]

Regarding the roles of marital status in risk-taking decisions, we find a significantly negative coefficient on *Married* in last column of Table 3, indicating that married household heads allocate less wealth into risky asset. One potential explanation is that having a family may raise the level of commitment consumption (or habit) and increases induced risk aversion. This result aligns with the findings of Roussanov and Savor (2014) which find that single CEOs invest more aggressively (in capital expenditures, R&D, advertising, and acquisitions) than married ones.

Consistent with Calvet et al. (2007) and Carroll (2002), we show a positive relationship between wealth and risk-taking behaviors. Moreover, the negative coefficient on *HouseRatio* suggests a substitution effect between property and stock investments. In addition, we find that the past realized stock gain serves as a proxy of market expectation, as we observe past gains are positively related to the stock market participation and stock share. We will elaborate on the relationship between natural disasters and stock return expectation in Section 5.3.

Table 3 also illustrates that rural households, compared with their urban counterparts, exhibit a lower propensity to participate in stock market and allocate a smaller share of their wealth to

[21] This finding aligns with Yuan et al. (2024) who also document a negative (albeit insignificant) coefficient on the effect of males on stock market participation, as shown in Table 3 Column (1) of their paper. We argue that this may be due to the fact that in all risk-averse household heads, male account for about 76% while female only account for about 24%.

stock assets. The lower rate of stock investment in rural can be attributed to two primary factors. First, rural families often face higher background risks arising from income uncertainty, particularly in relation to agricultural and labor income. Moreover, poor local economic conditions and limited infrastructure in rural areas, such as limited access to the Internet and inadequate financial services, may hinder rural families from engaging in financial activities.

[--- Insert Table 3 about here ---]

4.2 Heterogeneous Effects

Calvet et al. (2007) document that households with higher income, greater financial wealth, and higher levels of education are more inclined to participate in the stock market. Participation in risky investments, such as the stock market, involves fixed learning and setup costs, which are cognitively challenging for unsophisticated households with a low level of financial literacy. Gormley et al. (2010) document the role of insurance in shaping households' risk-taking behavior, finding that households with extensive insurance coverage against adverse health shocks are more likely to hold risky stocks.

Along this line, we expect the influence of natural disasters on households' risk-taking to vary by household wealth, insurance coverage, and financial sophistication. To test Hypothesis 3, we divide the full sample into subgroups based on several metrics. (1) ***Financial Wealth****:* household financial wealth is measured by final asset. *HighFinaAssets* = 1 if households' financial assets is above the mean value of the full sample, and 0 otherwise. (2) ***Insurance coverage***: *PrivateInsure (PublicInsure)* = 1 for households with private (public) insurance, and 0 for those without. (3) ***Financial sophistication***: is proxied by the household heads' education level and awareness level for economic and financial related news and information. Specifically, *EcoAttention* equals 1 if household heads usually pay attention to economic or financial related news and information, and

0 otherwise. *HighEdu* equals 1 if household heads have attained higher education, including the completion of a college or vocational degree, a bachelor's, master's, or doctoral degree, and 0 otherwise. For more detailed information on the construction of these variables and related survey questions, please refer to Appendix Table IA1.

[--- Insert Table 4 about here ---]

Table 4 presents the heterogeneous effects of natural disasters on households' risk-taking behaviors. In Columns (1), the significant and positive coefficient for the interaction terms of natural disasters and household wealth indicate that more affluent families are less affected by natural disasters. Columns (2) and (3) show that both public and private insurance coverage offset the negative influence of disasters on households' risk-taking behaviors. Furthermore, consistent with Calvet et al. (2007), we find that financially sophisticated households are less affected by losses from natural disasters, as shown in Columns (4) and (5). Taken together, these results support Hypothesis 3 that the effect of natural disasters on household risk-taking are stronger when households are poorer, uninsured, or less financially literate.

4.3 Baseline Results: Mitigating Role of Government Safety Nets

While prior research has examined the connection between natural disasters and financial decisions (e.g., Bharath and Cho, 2023), the potential of insurance in alleviating the adverse consequences of natural disasters has received limited attention. Notably, studies like Cameron and Shah (2015) that demonstrate that access to informal insurance mechanisms, such as remittances from individuals outside the home village, can reduce the impact of natural disasters on risk aversion. Similarly, Cai (2016) finds that agricultural insurance influences household behavior, with insured households more likely to borrow from rural banks for investment in tobacco production compared to uninsured households. In this paper, we investigate whether

formal insurance provision effectively mitigates the negative impacts of natural disasters on household risky investments, leveraging two distinct insurance policies in our analysis, including 1) the establishment of Earthquake Insurance Pool and 2) Medical Insurance Integration policy, elaborated respectively in two subsections below.

4.3.1 Earthquake Insurance Pool Establishment

First, we leverage the establishment of the CREIP in 2015 as an exogenous shock to examine its impact on mitigating the negative effects of natural disasters on household risk-taking. Table 5 Panel A presents the results. In Column (2), which adopts a three-year window around the shock, the coefficient on *Log(1+DeathNum)*EarthquakeInsure* is 0.006 and statistically significant at the 1% level. This suggests that, following the introduction of earthquake insurance, the negative impact of natural disaster-related fatalities on households' stock market participation is mitigated by 75% (=0.006/0.008).

Similarly, Column (4) shows consistent results when the dependent variable is the proportion of stock investments in total household assets. We find that the coefficient on *Log(1+DeathNum)*EarthquakeInsure* is 0.071 and statistically significant at the 1% level, implying that the negative impact of natural disaster-related fatalities on households' stock investment is mitigated by 72% (=0.071/0.098). Collectively, these findings indicate that natural disaster insurance effectively alleviates the adverse effects of natural disasters on household risk-taking.

4.3.2 Medical Insurance Integration

The second policy we exploit is the integration of urban and rural public health (or medical) insurance in China. In China, the health insurance is primarily operated by local governments, and

as of 2020, about 95% of the population has at least basic health insurance coverage.[22] Since 2003, China has implemented the New Rural Cooperative Medical Scheme (NRCMS), followed by the introduction of the Urban Resident Basic Medical Insurance (URBMI) system in 2007. Starting in 2009, to enhance and standardize healthcare coverage, provinces across China gradually integrated the NRCMS and URBMI into a unified Urban and Rural Resident Medical Insurance system, in accordance with national policy directives. Table IA3 summarizes the integration timeline for each province.

We leverage this staggered, province-level integration of urban and rural public health insurance as an exogenous shock to study its impact on the relationship between natural disasters and household risk-taking. It is documented that this policy integration eliminated the urban-rural divide, improved rural residents' access to medical services, and increased their reimbursement rates (Huang and Wu, 2020), thereby enhancing households' resilience to disaster-related risks. To investigate the mitigating effects of this public medical insurance integration, we assess whether households became less affected by natural disasters following the integration.

Table 5 Panel B presents the results, where *MedInsureInt* is a dummy variable denoting provinces having the integrated urban and rural medical insurance in a given year. Our main inferences are drawn from Columns (2) and (4), focusing on the three-years window around the integration event. In Column (2), the coefficient on *Log(1+DeathNum)*MedInsureInt* is 0.003 and statistically significant at the 1% level. This indicates that, following the integration of public medical insurance, the adverse effect of natural disaster related fatalities on households' stock market participation are reduced by 60% (=0.003/0.005). Likewise, the coefficient on the

[22] See introduction about the healthcare in China in https://en.wikipedia.org/wiki/Healthcare_in_China

interaction term of natural disasters and medical insurance integration is 0.034 in Column (4), indicating a 58% (=0.034/0.059) reduction in the adverse influence of natural disaster fatalities on the portion of household assets allocated to stocks.

Through the analysis of two distinct insurance policies, we show that while natural disasters reduce households' investment in risky assets, insurance provision can effectively counteract this negative effect, which supports our Hypothesis 4. Our findings align with those of Cameron and Shah (2015), highlighting that the availability of informal insurance options, such as remittances from individuals outside the home village, can effectively reduce the impact of natural disasters on risk aversion. This evidence offers novel insights and valuable policy implications for addressing the issue of limited participation of Chinese households in stock markets.

[--- Insert Table 5 about here ---]

5. Additional Analysis

5.1 Additional Measures of Government Intervention on Natural Disasters

To mitigate the losses caused by natural disasters, particularly geological disasters, the Chinese government has implemented prevention and control projects in local regions. In this section, we collect the annual number of geological disaster prevention and control projects for each province data from the National Bureau of Statistics (NBS) to examine whether these measures effectively reduce the adverse impacts of natural disasters.

As illustrated in Table 6, *HighPrevControlNum* is a dummy that equals one if the number of prevention and control projects in a province exceeds the annual average across the sample, and 0 otherwise. The results show that the coefficient on *Log(1+DeathNum)*HighPrevControlNum* is positive and statistically significant at the 1% level. This indicates that households in provinces with a higher number of prevention and control projects experience less severe impacts on their

stock investments compared to those in provinces with fewer projects.

These findings also align with our hypothesis that government safety nets, such as disaster prevention and control initiatives, play a crucial role in shielding households from the detrimental effects of natural disasters. This underscores the effectiveness of such interventions in reducing disaster-related losses.

[--- Insert Table 6 about here ---]

5.2 Public versus Private Insurance: Natural Disasters and Household Insurance Holdings

Unlike the U.S. market, which is primarily dominated by private insurance, Chinese insurance market is mainly government driven. In this section, we explore the natural disaster experience and insurance coverage decisions, especially comparing the holdings of private and public insurance. The CHFS collects detailed information on the private and public insurance coverage of each family member in a household. Specifically, household members were asked whether they held any commercial (private) insurance, including commercial life insurance, commercial health insurance, and so on. Additionally, they were also asked about their enrollment status in public medical insurance programs.

Based on this, we construct three dummies for private insurance coverage: (1) *PrivateInsure* = 1 if at least one household member is covered by commercial insurance, and 0 otherwise; (2) *PrivateLifeInsure* = 1 if at least one household member is covered by commercial life insurance, and 0 otherwise; (3) *PrivateHealthInsure* = 1 if at least one household member is covered by commercial health insurance, and 0 otherwise. For comparison, we also examine public insurance coverage by defining a dummy *PublicInsure*, which equals 1 if at least one household member is covered by government-sponsored social medical insurance, and 0 otherwise.

[--- Insert Table 7 about here ---]

As shown in Table 7 Panel A, 94% Chinese households are covered by public medical insurance, while only 18% households are covered by private insurance. Panel B Columns (1)-(3) report the impacts of natural disasters on private insurance, private life insurance, private health insurance coverages, respectively. Column (4) explores the impacts of disasters on public insurance holdings. For all columns, we include the lagged term of dependent variables to control for the persistency of insurance purchase decisions.

As shown in the first three columns, we find that the coefficients on fatalities from natural disasters remain significantly negative, suggesting that households are less likely to purchase private insurance to protect themselves from the impacts of disasters. Interestingly, the coefficients on *RiskAverse* in these columns are consistently negative and significant at the 1% level, indicating that risk-averse households are less likely to participate in the private insurance market.

In contrast, Column (4) shows that households are more likely to enroll in public medical insurance to mitigate losses. Unlike the first three columns, the coefficient on *RiskAverse* in Column (4) becomes significantly positive, implying that risk-averse households are more likely to participate in public insurance. Taken together, these results reveal a salient pattern: Chinese households may perceive private insurance as a risky financial product, and thus, are reluctant to choose it as a safeguard. Instead, they tend to rely on government safety nets in response to losses caused by natural disasters.

5.3 Natural Disaster and Other Asset Classes

In this section, we examine the impact of natural disasters on other asset classes in household portfolio, focusing on mutual funds—considered less risky than individual stocks—and cash

deposit in e-wallets like Alipay or WeChat Pay, which are considered as riskless safe assets. China possesses the most developed e-wallet market, with e-wallets being the most popular payment method and accounting for 83% of e-commerce transactions in 2021. The share of cash used in offline payment transactions at the point of sale (POS) in China has dropped to 10% in 2021, making China one of the most cashless countries.[23] Moreover, according to the annual reports on the operations of payment system by Chinese central bank, the number of ATMs had fallen below one million in 2021 and is continuing falling (Bian et al., 2024). Given this context, we expect that Chinese households may prefer to hold more e-cash in e-wallets as a form of precautionary savings in response to experiences with natural disasters.

[--- Insert Table 8 about here ---]

The results are reported in Table 8. Columns (1)–(2) present the estimates where the dependent variable is the percentage of e-cash held in e-wallets, such as Alipay or WeChat Pay, relative to total assets, while Columns (3)–(4) examine the percentage of mutual funds in total assets. Based on Column (2), the coefficient on number of deaths is 0.013 and significant at 1% level, indicating that a one standard deviation increase in *Log(1+DeathNum)* increases the e-cash ratio by 0.02 (=0.013*1.55) percentage, an approximately 9% (=0.02/0.22) rise relative to the sample mean. This result suggests that natural disasters experience prompt households to shift towards safer assets, such as e-cash, within their asset portfolio.

In Column (4), we find that the coefficient on number of deaths is -0.014, statistically significant at 5% level, implying a one standard deviation increase in *Log(1+DeathNum)* reduces the mutual funds ratio by 0.022 (=0.014*1.55) percentage, an approximately 12% (=0.022/0.18)

[23] Accessed from https://english.ckgsb.edu.cn/knowledges/will-china-first-cashless-society/ and https://www.statista.com/statistics/1277116/share-of-cash-at-pos-worldwide/.

decline relative to the sample mean. Notably, this reduction is smaller in magnitude compared to the decline in stock holdings observed in Table 3 Column (4). This result suggests that natural disasters prompt households to reduce their investments to risky financial assets. However, the extent of reduction varies by asset type—households decreases stock holdings more substantially (as shown in Table 3 Column (4)), while the decline in mutual fund holdings is of a smaller magnitude.

5.4 Mechanism Analysis

In this section, we investigate the main mechanisms underlying the impact of natural disasters on households' risk-taking behaviors, including the wealth and income reduction, the risk preference channel, as well as the expectation channel. These mechanisms are documented in the literature, yet which one is the dominant factor remains a subject of debate.[24]

5.4.1 Wealth and Income Reduction Channel

Natural disasters could exert a direct negative impact on household income and wealth. For instance, events like floods or earthquakes can cause damage to physical assets and lead to the loss of personal property. Individuals may also experience physical or emotional adversaries, which may result in higher medical expenses. Moreover, the opportunities for income generation are likely to be significantly diminished, leading to lower employment income. As a consequence, households are left with lower disposable income, reduced wealth, and fewer liquid assets in the

[24] Changes in risk preference are attributed to psychological effects linked to emotions and sentiments. Bharath and Cho (2023) show that while income and wealth shocks only explain a small portion of the variation in households' risk-taking, increased risk aversion due to disasters explains the majority of changes in risk-taking behavior. After decomposing the relative importance of the risk preferences and expectations channels on portfolio choices, only 25% of the changes in portfolios can be attributed to revised expectations, and 75% of the changes can be attributed to changes in risk aversion following disaster experiences. Guiso et al. (2018) argue that changes in the level of risk aversion in the wake of the global financial crisis is attributed to an emotional response based on fear rather than explanations based on variations in beliefs, wealth, or habits.

aftermath of a natural disaster, due to both the losses incurred during the disaster itself and the expenses associated with post-disaster recovery.

To explore the channel on wealth and income reduction, we examine whether the household wealth or income growth rate significantly decreases after experiencing natural disasters. Specifically, we estimate the following OLS equation:

$$\Delta Asset_{ijt} = \alpha + \beta_1 Log(1 + DeathNum_{j,t-1}) + \gamma X_{ijt} + \mu_r + \lambda_t + \varepsilon_{ijt}, \quad (3)$$

where $\Delta Asset_{ijt}$ denotes total assets growth rate of household i in province j in year t. $DeathNum_{j,t-1}$ is the number of deaths caused by natural disasters in province *j* in year *t*-1. We also modify this equation by replacing the dependent variable with household income growth rate, $\Delta Income_{ijt}$. We include the same set of control variables,[25] along with year and region fixed effects, as in baseline equations (1) and (2).

Table 8 Columns (1) and (2) presents the results for equation (4). As shown, the coefficients for *Log(1+DeathNum)* are insignificant, indicating that the number of deaths caused by natural disasters does not significantly affect total assets or income growth. These results imply that the wealth and income reduction may not be the primary channels driving households' risk-taking behaviors in respond to natural disasters. Our findings are consistent with Bharath and Cho (2023) which find that wealth and income shocks only explain a small part of the reduction in household risky asset investment following natural disasters.

5.4.2 Risk Preference Channel

Individuals exposed to natural disasters that cause substantial fatalities and severe economic losses could feel traumatized and their subsequent risk attitude may change. Loewenstein et al.

[25] When the dependent variable is Δ*Asset* (or Δ*Income*), we exclude the total assets (or income) of household from the control variables.

(2001) put forward the "risk-as-feeling" theory and argue that people's responses to risky situations result in part from the direct emotional influences. Having suffered so much from natural disasters, one would expect these individuals to be more risk averse, as they would try to reduce further losses from similar negative risk events and to minimize their emotional and economic suffering from such events in future. Van Den Berg et al. (2009) use survey and experimental data to demonstrate that individuals become more risk averse after experiencing natural shocks. Likewise, Guiso et al. (2018) show that investors' risk aversion increases following the 2008 global financial crisis and that fear, as an emotional response, is a potential mechanism underlying financial decisions. However, disaster experiences do not always result in more risk aversion. Said et al. (2015) find that flood experience in flooded villages leads to lower risk aversion. Ingwersen et al. (2023) document how individuals' risk attitude evolves over the five years after a tsunami and find that those who were directly exposed to the devastation of the tsunami were more willing to take financial risks than those not directly exposed. Nevertheless, these studies all emphasize the importance of the risk preference channel.[26]

To test the risk preference channel, we examine whether households' risk aversion level change significantly after experiencing natural disasters, based on the following probit equation:

$$Pr\ (MoreRiskAverse_{ijt}) = \alpha + \beta_2 Log(DeathNum_{j,t-1}) + \gamma X_{ijt} + \mu_j + \lambda_t + \varepsilon_{ijt}, \qquad (4)$$

where $MoreRiskAverse_{ijt}$ is a dummy that equals 1 if household head i in province j become more risk averse in year t (compared to the previous survey year), and 0 otherwise.

[26] A strand of the literature also focuses on the non-linear relationship between disaster experiences and risk-taking. Bernile et al. (2017) document a non-monotonic relationship between CEOs' early-life exposure to fatal disasters and corporate risk-taking. They find that CEOs who witness fatal disasters without extremely negative personal consequences lead firms that behave more aggressively, whereas CEOs who experience the extreme downside of disasters behave more conservatively. Gao et al. (2020) explore the "lucky disaster experience," referring to the experience of large-scale earthquakes that result in minor human losses. They show that households perceive less (more) risk when they experience disasters that have fewer (more) fatalities than expected.

$DeathNum_{j,t-1}$ denotes the number of fatalities from natural disasters in province *j* in year *t*-1. The control variables (excluding risk aversion) and fixed effects are the same as equations (1) and (2). If natural disaster experiences increase the likelihood of households being more risk averse, we expect $\beta_2 > 0$.

In Table 8 Column (3), we find that the coefficient on natural disasters is positive and significant at 1% significant level, suggesting that fatalities from natural disasters increases the probability of households being more risk averse. This result indicates that the households are inclined to become more risk averse after experiencing natural disasters, which supports the Hypothesis 2.

5.4.3. Expectation Channel

Negative experiences such as natural disasters may influence peoples' expectations about the stock market. This expectation channel posits that the belief that a natural disaster will strike again or the expectation of a future market downturn affects individuals' stock investment decisions. Based on field experiments with rural Indonesia households, Cameron and Shah (2015) show that households that have experienced a natural disaster more recently report significantly higher probabilities of a disasters occurring again in the next year and perceive the disaster to be more severe than those who have not experienced it. Using the UBS/Gallup survey data, Bharath and Cho (2023) find that natural disaster experiences are negatively related to expected future stock market returns, which explain the reduction in risky asset in households' portfolio choices.

Although we have included the household's past stock gain and year fixed effects in the baseline regression to account for stock market conditions and expectations, it is important to directly test the expectation channel, i.e., whether natural disasters experiences play any role in shaping household stock market expectations. Specifically, we take advantage of three specific

questions in CHFS that are most pertinent to household's expectations of future stock market. We describe the details in Table IA6 in the Appendix.[27] With household's expectation, we estimate the following ordinal probit regression:

$$Pr\ (StockMktExpect_{ijt}) = \alpha + \beta_2 Log(DeathNum_{j,t-1}) + \gamma X_{ijt} + \mu_j + \lambda_t + \varepsilon_{ijt}, \qquad (5)$$

where $StockMktExpect_{ijt}$ denotes the expectation for future stock market of household *i* of province *j* in year *t*, taking discrete value of 1, 2, and 3, which corresponds to "pessimism", "neutral", and "optimism" respectively. For robustness tests, we replace the dependent variable with $Optimism_{ijt}$ and estimate it with a probit regression. $Optimism_{ijt}$ is a dummy that equals 1 if household feel optimism about the future stock market (*StockMktExpect* = 3), and 0 if the household feel pessimistic or neutral (*StockMktExpect* = 1 or 2). In this section, we do not use the change in *StockMktExpect* because of the limited sample. $DeathNum_{j,t-1}$ is the number of deaths caused by natural disaster in province *j* in year *t*-1. We incorporate a consistent set of control variables along with year and region fixed effects, as in equations (1) and (2).

Table 8 Columns (4) present the result when the dependent variable is *StockMktExpect*, while Column (5) present the result when the dependent variable is *Optimism*. Both Columns (4) and (5) show that the coefficients for *Log(1+DeathNum)* are significantly negative, implying that natural disasters are negatively related with the probability of households feeling optimism about the future stock market conditions. Taken together, we also find evidence of expectation channels.

Based on the results of the three channel tests, we conclude that households' risk-taking behaviors in response to natural disasters are primarily driven by the risk preference and

[27] One may be concerned that for all survey years except 2019, the expectation variable (*StockMktExpect*) is based on "past" stock return experiences from personal investment to a greater extent than their expectation about future returns. To address this concern, we re-estimate the equation (7) using the CHFS 2019 subsample, and still find no significant result for the expectation channel.

expectation channels rather than the wealth or income reduction channel. Our finding aligns closely with the "risk-as-feeling" theory of Loewenstein et al. (2001) and is also in line with the findings of Cameron and Shah (2015) and Bharath and Cho (2023), which document the dominant role of the risk preference channel in the impact of natural disasters on households' risk-taking behaviors.

[--- Insert Table 9 about here ---]

6. Robustness Tests

6.1 Robustness Tests: Addressing Endogeneity Using an Instrumental Variable Approach

While we use lagged natural disasters as the independent variable and control for economic development in the baseline regression, there may still be some unobservable variables that affect households' risk asset allocation, which could be omitted in the error term and cause endogeneity issues. To address this concern, we employ an instrumental variable (IV) approach, using the disaster experiences of distant friends as an instrument for the focal household's disaster experience.

The rationale for this IV lies in the peer effects, wherein individuals' risk perceptions or financial decisions are influenced by their social circles (Bailey et al., 2018a, 2018b; Hu, 2022). For instance, Hu (2022) finds that households increase flood insurance purchase when their friends experience flooding events or are exposed to flood insurance campaigns. Importantly, the exclusion restriction is satisfied because natural disasters of "friend" in non-adjacent provinces are exogenous and unrelated to the economic circumstances in the local area of the household.

To quantify the natural disaster experience of the focal household's friend circle, we adopt the main idea of Bailey et al. (2018b) by calculating each province's *FriendDisaExp,* defined as the average disaster-related fatalities in non-adjacent provinces, weighted by the social connectedness

index (SCI). The SCI between provinces *j* and *k* is measured by the total number of direct train connections between their capital cities. Specifically, we construct this IV as follows:

$$FriendDisaExp_{jt} = \sum_k ShareTrains_{j,k,t} \times DeathNum_{k,t}, \quad (6)$$

where $ShareTrains_{j,k,t}$ denotes for the share of trains from a non-adjacent province *k* to province *j* to over trains from all non-adjacent provinces to province *j*. $DeathNum_{k,t}$ is the number of deaths caused by natural disasters in province *k* in year *t*. Based on this more exogeneous measure, we replace the dependent variable *Log(1+DeathNum)* with our *Log(1+FiendDisaExp)*, and re-estimate the baseline results in Table 5.

[--- Insert Table 10 about here ---]

Table 10 shows the estimation results. Panels A and B report the mitigating effects of Earthquake Insurance Pool Establishment and Medical Insurance Integration, respectively. Panels A and B show that the coefficients for *Log(1+FiendDisaExp)*EarthquakeInsure* and *Log(1+FiendDisaExp)*MedInsureInt* are consistently negative and significant across all specifications, suggesting that our baseline conclusion is robust even after addressing potential endogeneity.

6.2 Robustness Tests: Controlling for Household Fixed Effects

To further address the concern for potential omitted variable bias, we control for the household fixed effects in baseline results in Table 5. Table 11 displays the results. A shown, all coefficients on interaction terms of fatalities and two distinct insurance policies remain significantly positive , consistent with those in Table 5. These results lend further support to our baseline results, when controlling for the household fixed effects.

[--- Insert Table 11 about here ---]

6.3 Robustness Tests: Excluding Provinces Most Prone to Natural Disasters

As depicted in Figure 2, Sichuan, Gansu, Yunnan, Hunan, and Guizhou are the top five provinces most prone to natural disasters in our data. To eliminate the impact of these extreme samples, we remove these five provinces from the full sample and re-estimate the baseline regression in Table 5. As shown in Table 12, the two public insurance policies still exert significant mitigating effects on the negative impacts of natural disasters on households' risk-taking behaviors.

[--- Insert Table 12 about here ---]

6.4 Robustness Tests: Falsification Tests

To rule out the effects of potential confounders, we conduct a falsification test to evaluate whether randomly created pseudo-insurance policies alleviate the negative impacts of disasters on households' participation in risky asset markets. For the earthquake insurance policy, we construct a variable *PseudoEarthquakeInsure* by randomly assigning the post-dummy to provinces in our sample. We then run the baseline regressions from Columns (2) and (4) of Table 5 Panel A 500 times, saving the coefficients on *Log(1+DeathNum) * PseudoEarthquakeInsure*. Similarly, for the medical insurance integration policy, we construct a variable *PseudoMedInsureInt* by randomly assigning *MedInsureInt* to provinces in our sample and run the baseline regressions from Columns (2) and (4) of Table 5 Panel B 500 times, saving the coefficients on *Log(1+DeathNum) * PseudoMedInsureInt.*

Figure 4, Panels A and B, plot the distribution of coefficients on the interaction terms *Log(1+DeathNum) * PseudoEarthquakeInsure* and *Log(1+DeathNum) * PseudoMedInsureInt*, respectively. In both panels, Panel (a) plots the distribution with *StockParti* as the dependent variable, while Panel (b) plots the distribution with *StockRatio* as the dependent variable. Taking

Panel A-Panel (a) as an example, the blue line represents the estimated kernel density, and the red vertical line indicates the actual coefficient estimate of the interaction term (from Table 5 Panel A Column (2)). We find that the actual coefficient falls on the extreme left tail of the distribution. A similar pattern is observed in Panel A-Panel (b) when the dependent variable is *StockRatio*. Panel B shows a similar pattern when we examine the mitigating effects of *PseudoMedInsureInt*. A more detailed comparison between the actual and pseudo coefficients for the interaction terms of fatalities and insurance policies is provided in Internet Appendix Table IA4. Overall, these results imply that our main conclusion cannot be obtained by chance alone.

[--- Insert Figure 4 about here ---]

6.5 Robustness Tests: Matching Sample with the Entropy Matching Method

One potential endogeneity concern on the medical insurance integration policy is that treatment and control groups are intrinsically different in terms of economic conditions, which may also affect household stock market participations. To address this concern, we construct a balanced household sample with comparable characteristics. Each year, we conduct entropy matching where the treatment group is composed of households in provinces where urban and rural medical insurance have already been integrated, while the control group consists of households in provinces where the integration has not yet taken place. This matching process is repeated annually to ensure comparability of treatment and control groups in terms of the risk preference, financial literacy, total asset, properties, housing price and whether the households reside in rural areas.

Table IA5 presents the balance test result on the household characteristics after matching. The covariates are in general economically close in magnitude after matching. With this matched sample, we re-estimate baseline regressions in Table 5. As shown in Table 13, our main conclusion

is robust to using the matched sample.

[--- Insert Table 13 about here ---]

6. Conclusion

Using comprehensive panel of household survey from 2011 to 2019, we find that natural disaster experiences significantly reduce households' propensity to participate in the stock market and decrease the proportion of their stock investments. These effects are particularly pronounced among poorer, uninsured, and less financially sophisticated households.

Leveraging the implementation of two insurance policies—the establishment of the Earthquake Insurance Pool and the Rural-Urban Medical Insurance Integration policy—we provide robust evidence that government safety nets substantially alleviate the negative impact of natural disasters on households' risky investments. These findings underscore the critical role of government safety nets in enhancing financial resilience and promoting optimal risk-taking in the aftermath of natural disasters. Moreover, we find that households are more likely to participate in the public insurance markets initiated by the government, rather than private insurance markets, following natural disasters. Households also shift from risky assets such as stock and mutual funds, to safer assets, such as cash deposited in e-wallets.

We conduct a series of robustness tests, including instrumental variable analysis, exclusion of extreme subsamples, falsification tests using pseudo insurance policies, and matched sample analysis to address selection bias. Our results remain consistent across these tests, reinforcing the reliability of our findings.

Our study contributes to the growing literature on the relationship between natural disasters and household financial behavior, while addressing a key gap in understanding the role of government in mitigating the adverse effects of such events. Our findings offer important policy

implications, suggesting that expanding and strengthening insurance coverage can effectively alleviate the negative impact of natural disasters on household risk-taking.

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Figure 1: Natural Disaster: DeathNum and GeoDisaEcoLoss

This figure plots the average fatalities from natural disaster (*DeathNum*) and economic losses from geological disasters (*GeoDisaEcoLoss*) across 29 provinces from 2011 to 2019. Note that the data for *GeoDisaEcoLoss* is missing in 2014, we interpolate it by using the average of *GeoDisaEcoLoss* in 2013 and 2015.

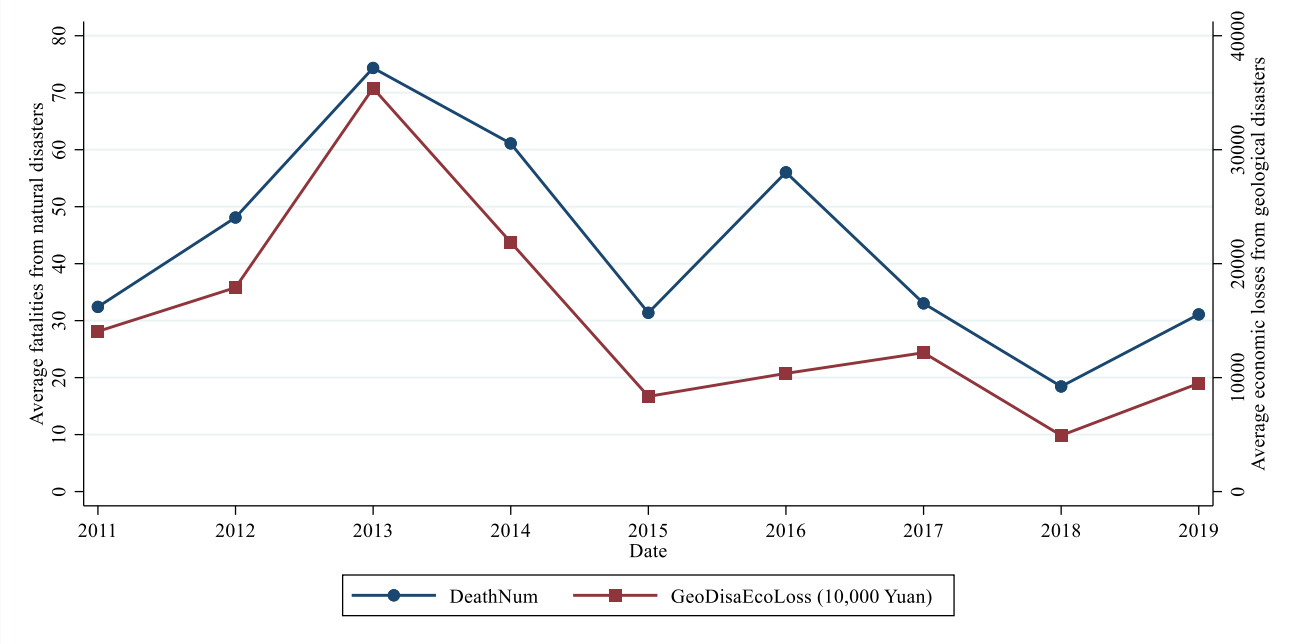
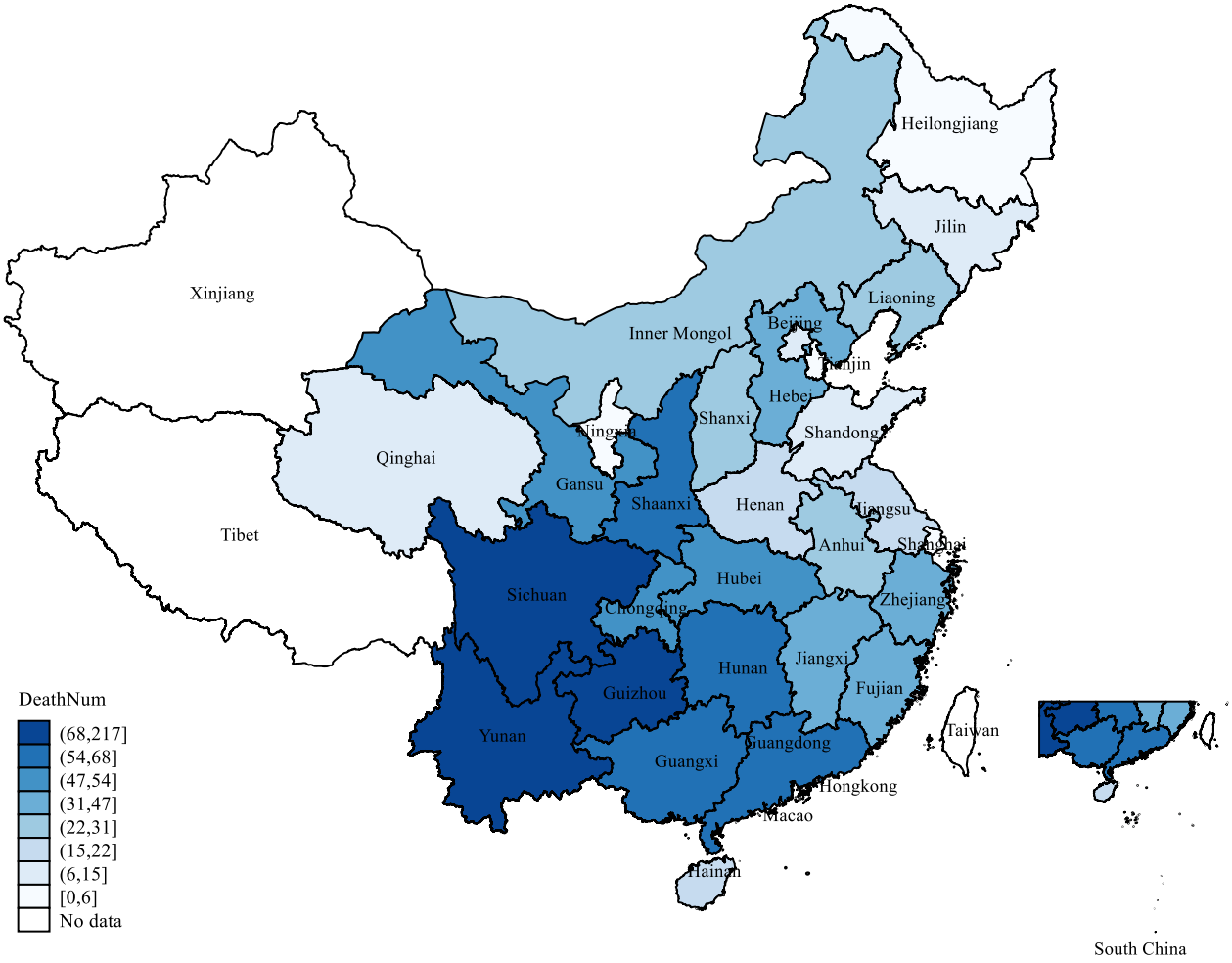


Figure 2: Natural Disaster Distribution

This heat map illustrates the geographic distribution of natural disasters from 2011 to 2019. Panels A and B plots the distribution of annual average of *DeathNum* and *GeoDisaEcoLoss* across 29 provinces, respectively. Note that our matched sample do not include Xinjiang, Tibet, Hongkong, Macao, and Taiwan.

Panel A. *DeathNum* Distribution



Panel B. *GeoDisaEcoLoss* Distribution

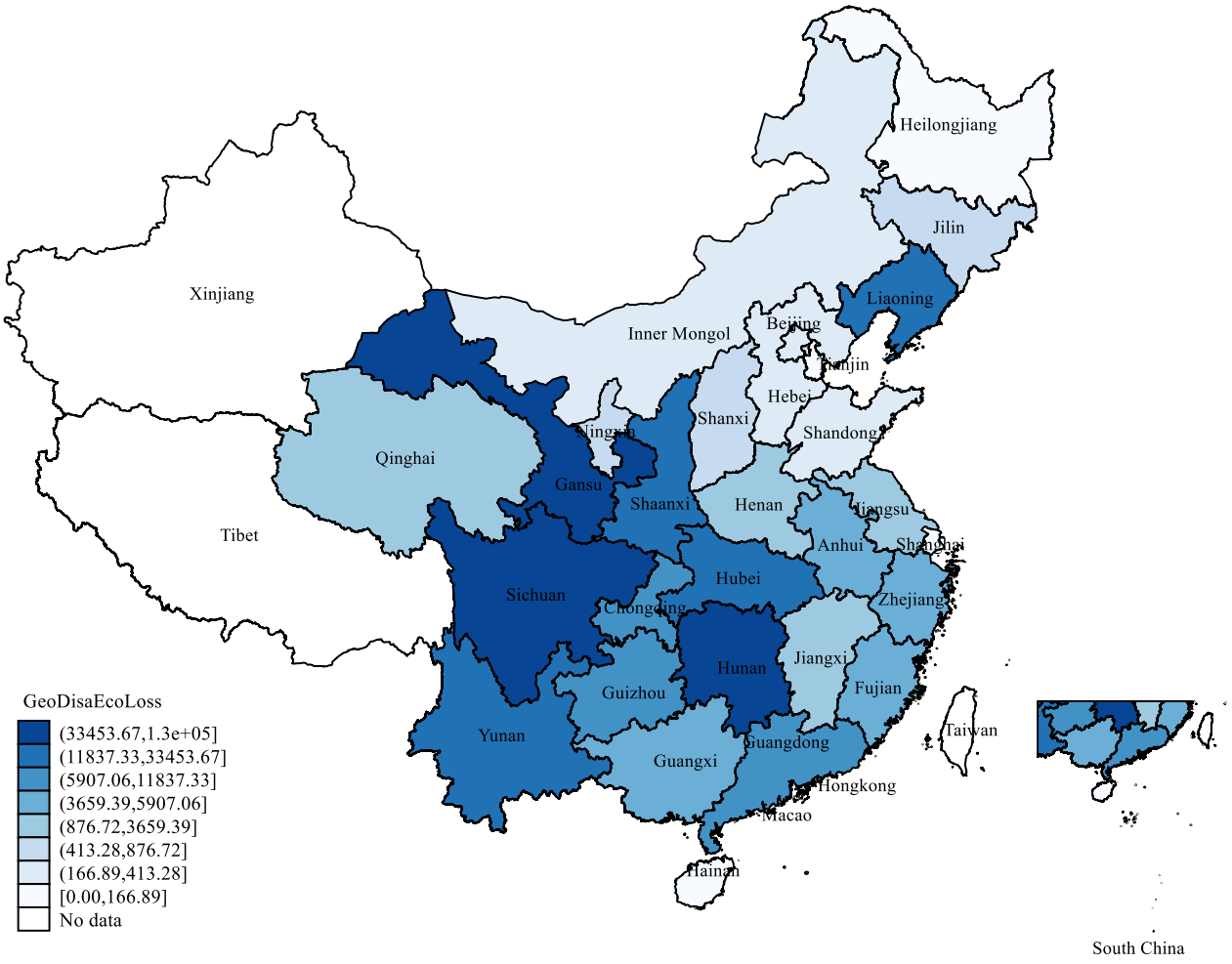
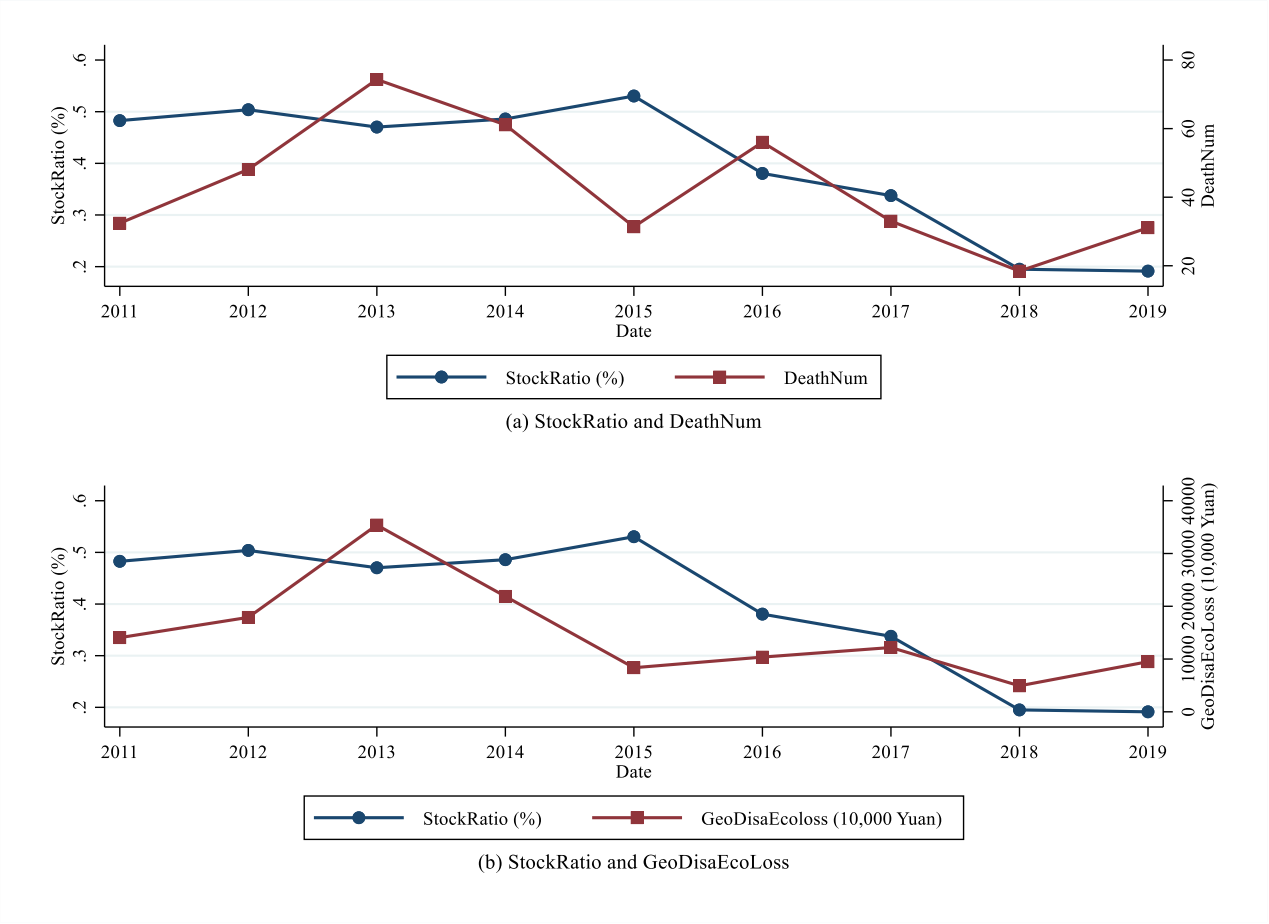


Figure 3: Natural Disaster and Stock Share

This figure shows the relationship between average natural disasters and stock share from 2011 to 2019. Panels (a) and (b) use average *DeathNum* and *GeoDisaEcoLoss* as disasters severity measures, respectively. We collect natural disasters from NBS, and stock share from CHFS that is conducted every two years. To smooth the curve, we performed linear interpolation on *StockRatio* for each household.



(a) StockRatio and DeathNum

(b) StockRatio and GeoDisaEcoLoss

Figure 4. Robustness Tests: Falsification Test

This figure reports the results of falsification test on baseline results in Table 5. In Panel A, for earthquake insurance, we first construct a variable *PseudoEarthquakeInsure* by randomly assigning the post dummy into provinces in our sample, and then run the following baseline regressions 500 times and save the coefficient $\hat{\beta}_2^{Pseudo}$:

$$StockParti_{ijt} = \alpha + \beta_1 Log(1 + DeathNum_{j,t-1}) + \beta_2^{Pseudo} Log(1 + DeathNum_{j,t-1}) \times PseudoEarthquakeInsure_t + \gamma X_{ijt} + \mu_r + \lambda_t + \varepsilon_{ijt},$$

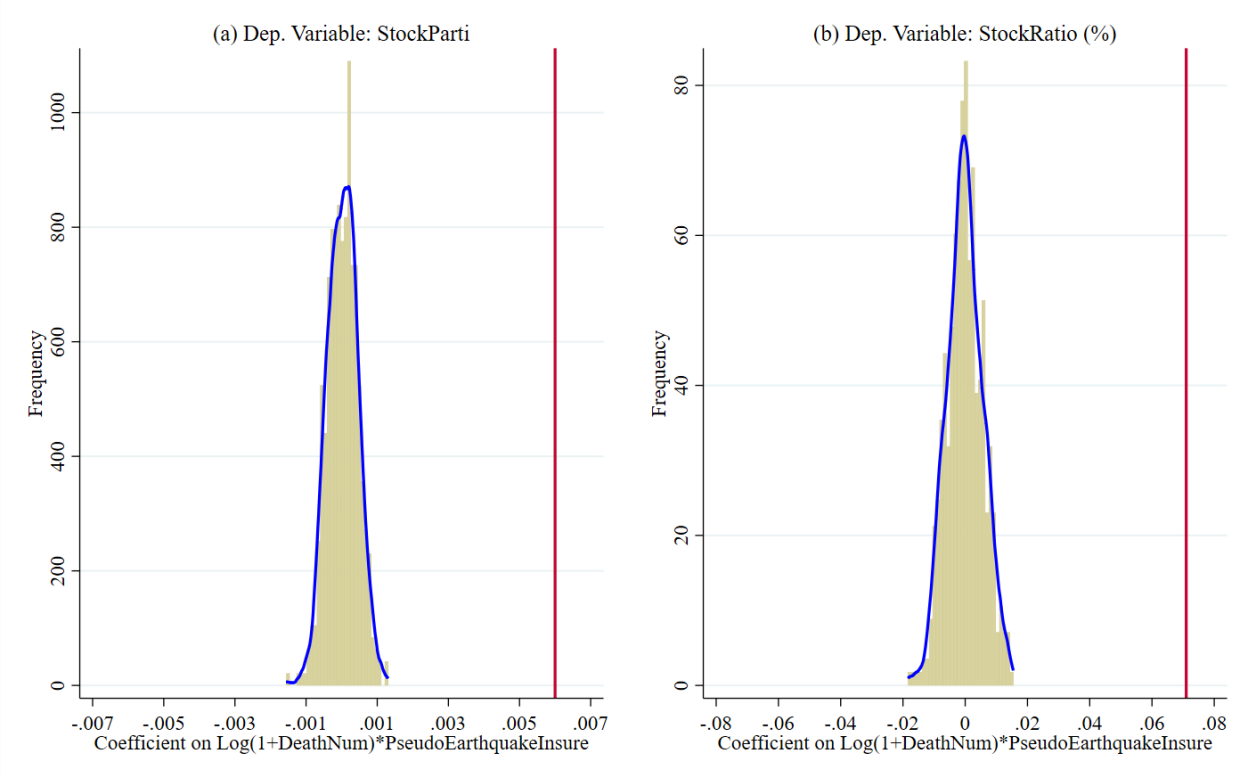
where $StockParti_{ijt}$ is an indicator that equals 1 if household i in province j participates in the stock market in year t, and 0 otherwise. $PseudoEarthquakeInsure_t$ is the pseudo earthquake insurance shock. X_{ijt} is a vector of control variables including risk aversion, financial literacy, education level, gender, age, age-square, married, total assets, total income, properties, past realized stock gain, housing price, GDP, and whether the household resides in a rural area of the province. μ_r and λ_t are region and year fixed effect, respectively. We also modify the equation by replacing the dependent variable with $StockRatio_{ijt}$ and estimate an OLS regression for Panel (b).

Second, in Panel B, for medical insurance integration policy, we construct a variable *PseudoMedInsureInt* by randomly assigning the *MedInsureInt* into provinces in our sample, then run the following baseline regressions 500 times and save the coefficient $\hat{\beta}_2^{Pseudo}$:

$$StockParti_{ijt} = \alpha + \beta_1 Log(1 + DeathNum_{j,t-1}) + \beta_2^{Pseudo} Log(1 + DeathNum_{j,t-1}) \times PseudoMedInsureInt_{jt} + \gamma X_{ijt} + \mu_r + \lambda_t + \varepsilon_{ijt}$$

where $StockParti_{ijt}$ is an indicator that equals 1 if household i in province j participates in the stock market in year t, and 0 otherwise. $PseudoMedInsureInt_{jt}$ denotes for the pseudo medical insurance integration policy. We control for the same sets of variables and fixed effects, as described in above equation. We also modify the equation by replacing the dependent variable with $StockRatio_{ijt}$ and estimate an OLS regression for Panel (b). For all subfigures, robust standard errors clustered at the household level. Panels A and B plot the density of $\hat{\beta}_2^{Pseudo}$ for earthquake insurance and medical integration policies, respectively. The vertical red line indicates the actual β_2 obtained from the baseline equations (1) and (2), respectively. We also summarize these 500 coefficients on pseudo number of deaths in Table IA4 in Internet Appendix.

Panel A. Earthquake Insurance Pool Establishment



Panel B. Medical Insurance Integration

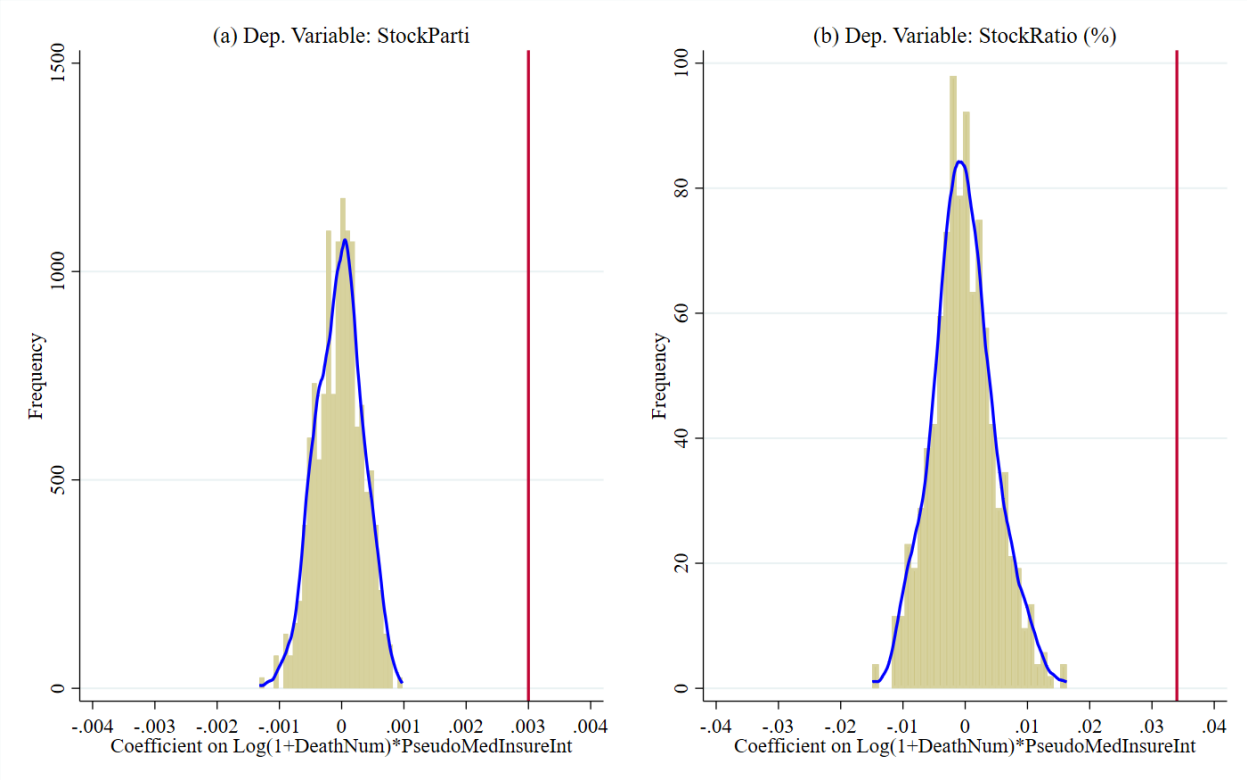


Table 1: Descriptive Statistics

This table presents the summary statistics for main variables used in this study. Natural disaster measures *DeathNum* and province level macroeconomic variables come from NBS. The household level and individual level (household head) variables come from CHFS. For variable type, C denotes continuous variable, I denotes indicator variable, and D denotes discrete variable.

Variables	(1) Type	(2) Mean	(3) Std	(4) Min	(5) Max
Household level					
StockParti	I	0.06	0.24	0.00	1.00
StockRatio (% of total assets)	C	0.40	3.03	0.00	95.99
StockRatio (% of total assets), participants	C	6.54	10.54	0.00	95.99
StockRatio (% of financial assets)	C	1.59	8.31	0.00	100.00
StockRatio (% of financial assets), participants	C	25.69	22.24	0.00	100.00
RealizedGain (1,000 Yuan)	C	3.85	51.88	-400.00	3,000.00
Income (1,000 Yuan)	C	82.96	184.58	0.00	12,122.42
FinaAssets (1,000 Yuan)	C	113.85	431.66	0.00	78,282.34
Assets (1,000 Yuan)	C	965.30	3,297.89	0.00	733,938.06
HouseRatio (%)	C	63.03	31.59	0.00	100.00
ECashRatio (%)	C	0.22	1.54	0.00	84.14
MutualFundRatio (%)	C	0.18	1.80	0.00	85.47
PrivateInsure	I	0.18	0.38	0.00	1.00
PrivateLifeInsure	I	0.09	0.29	0.00	1.00
PrivateHealthInsure	I	0.06	0.24	0.00	1.00
PublicInsure	I	0.94	0.24	0.00	1.00
Rural	I	0.33	0.47	0.00	1.00
StockMktExpect	D	1.75	0.78	1.00	3.00
Optimism	I	0.21	0.41	0.00	1.00
Individual level					
Male	I	0.77	0.42	0.00	1.00
Married	I	0.87	0.34	0.00	1.00
EcoAttention	I	0.33	0.47	0.00	1.00
FinLiteracy	D	0.46	0.65	0.00	2.00
Age	C	54.06	13.62	18.00	85.00
HighEdu	I	0.16	0.37	0.00	1.00
RiskAverse	I	0.72	0.45	0.00	1.00

AversionLevel	D	4.11	1.16	1.00	5.00
MoreRiskAverse	I	0.18	0.38	0.00	1.00
Province level					
DeathNum	C	43.50	73.23	0.00	575.00
Log(1+DeathNum)	C	2.91	1.55	0.00	7.91
FriendDisaExp	C	19.02	10.93	4.47	49.87
GDP (100 million Yuan)	C	30,427.26	22,453.17	1,370.40	107986.90
HP (Yuan per square meter)	C	8,124.78	5,737.14	3,090.01	38,433.00
EarthquakeInsure	I	0.70	0.46	0.00	1.00
MedInsureInt	I	0.53	0.50	0.00	1.00

Table 2: Univariate Tests: Does More Severe Natural Disasters Imply Lower Risk Taking?

This table presents univariate tests of stock market participation and stock shares for households located in provinces with above-average and below-average natural disaster losses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Risk Taking	Above-Average *DeathNum*		Below-Average *DeathNum*		Mean test	
	Mean	Std. dev.	Mean	Std. dev.	Diff.	t-value
StockParti	0.051	0.220	0.065	0.247	-0.014	9.819***
StockRatio (%)	0.320	2.579	0.433	3.217	-0.113	6.307***

Table 3: Natural Disaster and Household Risk-Taking

This table reports the impacts of natural disasters on household risk-taking behaviors. In first two columns, we examine the effect of natural disaster on the household's stock market participation by estimating the following regression:

$$Pr(StockParti_{ijt}) = \alpha + \beta_1 Log(1 + DeathNum_{j,t-1}) + \gamma X_{ijt} + \mu_r + \lambda_t + \varepsilon_{ijt},$$

where $StockParti_{ijt}$ is an indicator that equals 1 if household *i* in province *j* participates in the stock market in year *t*, and 0 otherwise. $DeathNum_{j,t-1}$ is the number of deaths caused by natural disaster in province *j* in year *t*-1. X_{ijt} is a vector of control variables including risk aversion, financial literacy, education level, gender, age, age-square, married, total assets, total income, properties, past realized stock gain, GDP, housing price, and whether the household is in a rural area of the province. To control for time trends and other unobserved time-invariant region characteristics, we also include year and region fixed effects (East, Central, and West) in λ_t and μ_r, respectively.

Second, in last two columns, we estimate the following regression to explore how households' stock share responds to the natural disasters:

$$StockRatio_{ijt} = \alpha + \beta_2 Log(1 + DeathNum_{j,t-1}) + \gamma X_{ijt} + \mu_r + \lambda_t + \varepsilon_{ijt},$$

where $StockRatio_{ijt}$ denotes the stock investment as a percentage of the total assets of household *i* living in province *j* in year *t*. We incorporate the consistent set of control variables along with year and region fixed effects, as in the above equation. For all columns, we estimate OLS regressions and robust standard errors clustered at the household level are in parentheses. The results in Columns (1) and (2) are also robust to Probit model. Finally, ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variables:	StockParti	StockParti	StockRatio (%)	StockRatio (%)
Log(1+DeathNum)	-0.006***	-0.003***	-0.052***	-0.038***
	(0.001)	(0.001)	(0.009)	(0.008)
RiskAverse		-0.043***		-0.390***
		(0.002)		(0.028)
FinLiteracy		0.007***		0.018
		(0.001)		(0.019)
HighEdu		0.070***		0.360***
		(0.003)		(0.046)
Male		-0.012***		-0.036
		(0.002)		(0.031)
Married		-0.001		-0.151***
		(0.002)		(0.042)
Age		0.005***		0.042***
		(0.000)		(0.005)
Age2		-0.004***		-0.030***
		(0.000)		(0.005)
Log(Income)		0.000		-0.015*
		(0.000)		(0.008)
Log(Asset)		0.009***		0.032***
		(0.000)		(0.008)
Log(FinaAsset)		0.010***		0.084***
		(0.000)		(0.003)
HouseRatio		-0.000***		-0.010***
		(0.000)		(0.001)
Log(RealizedGain)		0.067***		0.549***
		(0.001)		(0.024)
Log(GDP)		0.008***		0.063***
		(0.001)		(0.014)
Log(HP)		0.035***		0.235***
		(0.003)		(0.047)

Rural		-0.016***		-0.251***
		(0.001)		(0.018)
Region F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
R-squared	0.017	0.324	0.006	0.129
Observations	111,505	111,505	111,505	111,505

Table 4: Heterogeneous Effects

This table reports the heterogeneous impacts of natural disasters across various households. For variable definitions, *HighFinaAsset* is a dummy that equals 1 if the total financial asset of household in a year is higher than the average value of full sample in the same year, and 0 otherwise. *PublicInsure* is a dummy that equals 1 if the household hold public medical insurance (also called health insurance), and 0 otherwise. *PrivateInsure* is a dummy that equals 1 if the household hold any private insurance, and 0 otherwise. *EcoAttention* is a dummy that equals 1 if the household head usually pays attention to the information about economy, and 0 otherwise (if does not concern). *HighEdu* is a dummy that equals 1 if the household head graduated from college or vocational school, or has bachelor's degree, master's degree, or doctorate degree, and 0 otherwise. Panels A and B report the estimations results with dependent variable as *StockParti* and *StockRatio*, respectively. We incorporate the consistent set of control variables along with year and region fixed effects, as in baseline equations. For both panels, we estimate OLS regressions and robust standard errors clustered at the household level are in parentheses. Finally, ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Stock Market Participation

	(1)	(2)	(3)	(4)	(5)
Dependent Variables:	StockParti				
Log(1+DeathNum)	-0.009***	-0.005***	-0.005***	-0.007***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log(1+DeathNum)*HighFinaAsset	0.023***				
	(0.001)				
Log(1+DeathNum)*PublicInsure		0.002**			
		(0.001)			
Log(1+DeathNum)*PrivateInsure			0.009***		
			(0.001)		
Log(1+DeathNum)*EcoAttention				0.010***	
				(0.000)	
Log(1+DeathNum)*HighEdu					0.007***
					(0.002)
Controls	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
R-squared	0.325	0.324	0.326	0.335	0.325
Observations	111,505	111,505	111,505	104,879	111,505

Panel B. Stock Share

	(1)	(2)	(3)	(4)	(5)
Dependent Variables:	StockRatio (%)				
Log(1+DeathNum)	-0.076***	-0.055***	-0.044***	-0.060***	-0.049***
	(0.007)	(0.013)	(0.008)	(0.008)	(0.008)
Log(1+DeathNum)*HighFinaAsset	0.164***				
	(0.011)				
Log(1+DeathNum)*PublicInsure		0.018*			
		(0.010)			
Log(1+DeathNum)*PrivateInsure			0.040***		
			(0.009)		
Log(1+DeathNum)*EcoAttention				0.071***	
				(0.006)	
Log(1+DeathNum)*HighEdu					0.065***
					(0.025)
Controls	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
R-squared	0.132	0.129	0.129	0.130	0.129
Observations	111,505	111,505	111,505	104,879	111,505

Table 5. Baseline Results: The Mitigating Effect of Public Insurance Policies

This table reports the mitigating effects of public insurance on households risk-taking, with Panels A and B exploring two distinct policies, respectively. Specifically, In Panel A Columns (1)-(2), we estimate the following regression:

$$StockParti_{ijt} = \alpha + \beta_1 Log\left(1 + DeathNum_{j,t-1}\right) + \beta_2 Log\left(1 + DeathNum_{j,t-1}\right) \times EarthquakeInsure_t + \gamma X_{ijt} + \mu_r + \lambda_t + \varepsilon_{ijt},$$

where $StockParti_{ijt}$ is an indicator that equals 1 if household *i* in province *j* participates in the stock market in year *t*, and 0 otherwise. $EarthquakeInsure_t$ is a dummy that equals 1 for years equaling or later than 2015, when the earthquake insurance community was established. We modify the equation by replacing the dependent variable with $StockRatio_{ijt}$ and report the results in Panel A Columns (3) and (4). We incorporate the consistent set of control variables along with year and region fixed effects, as in Table 3.

In Panel B, we examine another public insurance policy—the integration of urban and rural medical insurance since 2009—by estimating the following regression across the full sample in Panel B Columns (1)-(2):

$$StockParti_{ijt} = \alpha + \beta_1 Log\left(1 + DeathNum_{j,t-1}\right) + \beta_2 Log\left(1 + DeathNum_{j,t-1}\right) \times MedInsureInt_{jt} + \gamma X_{ijt} + \mu_r + \lambda_t + \varepsilon_{ijt},$$

where $StockParti_{ijt}$ is an indicator that equals 1 if household *i* in province *j* participates in the stock market in year *t*, and 0 otherwise. $MedInsureInt_{jt}$ is a dummy that equals 1 if the urban and rural medical insurance has been integrated in province *j* in year *t*, and zero otherwise. See the integration timeline in the Internet Appendix Table IA3. We also modify the equation by replacing the dependent variable with $StockRatio_{ijt}$ and report the results in Panel B Columns (3) and (4). We incorporate the consistent set of control variables along with year and region fixed effects, as in as in Table 3. For both Panels A and B, we estimate OLS regressions and robust standard errors clustered at the household level are in parentheses. The results in Columns (1)-(2) of Panels A and B are also robust to Probit model. Finally, ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Earthquake Insurance Pool Establishment

	(1)	(2)	(3)	(4)
	Full Sample	[-3y, +3y]	Full Sample	[-3y, +3y]
Dependent Variables:	StockParti		StockRatio (%)	
Log(1+DeathNum)	-0.008***	-0.008***	-0.090***	-0.098***
	(0.001)	(0.001)	(0.016)	(0.019)
Log(1+DeathNum)*EarthquakeInsure	0.007***	0.006***	0.075***	0.071***
	(0.001)	(0.001)	(0.016)	(0.019)
Controls	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
R-squared	0.325	0.285	0.129	0.136
Observations	111,505	81,160	111,505	81,160

Panel B. Medical Insurance Integration

	(1)	(2)	(3)	(4)
	Full Sample	[-3y, +3y]	Full Sample	[-3y, +3y]
Dependent Variables:	StockParti		StockRatio (%)	
Log(1+DeathNum)	-0.005***	-0.005***	-0.056***	-0.059***
	(0.001)	(0.001)	(0.010)	(0.011)
Log(1+DeathNum)*MedInsureInt	0.003***	0.003***	0.032***	0.034***
	(0.001)	(0.001)	(0.008)	(0.009)
Controls	Yes	Yes	Yes	Yes

Region F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
R-squared	0.324	0.325	0.129	0.136
Observations	111,505	85,517	111,505	85,517

Table 6. Additional Measures of Government Intervention on Natural Disasters

This table reports the mitigating effects of government's prevents and control projects towards geological disasters on households risk-taking. Specifically, we estimate the following regression:

$$StockParti_{ijt} = \alpha + \beta_1 Log(1 + DeathNum_{j,t-1}) + \beta_2 Log(1 + DeathNum_{j,t-1}) \times HighPrevControlNum_{jt} + \gamma X_{ijt} + \mu_r + \lambda_t + \varepsilon_{ijt},$$

where $StockParti_{ijt}$ is an indicator that equals 1 if household *i* in province *j* participates in the stock market in year *t*, and 0 otherwise. $HighPrevControlNum_t$ is a dummy that equals 1 if the number of geological disaster prevention and control projects in province *j* in year *t* is higher than the average number of full samples in year *t*. We modify the equation by replacing the dependent variable with $StockRatio_{ijt}$ and estimate an OLS regression for Columns (3) and (4). We incorporate the consistent set of control variables along with year and region fixed effects, as in Table 3. For all columns, the robust standard errors clustered at the household level are in parentheses, and ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) StockParti	(2) StockParti	(3) StockRatio	(4) StockRatio
Log(1+DeathNum)	-0.009***	-0.004***	-0.072***	-0.045***
	(0.001)	(0.001)	(0.010)	(0.009)
Log(1+DeathNum)*HighPrevControlNum	0.005***	0.002***	0.038***	0.020***
	(0.001)	(0.001)	(0.007)	(0.007)
RiskAverse		-0.043***		-0.389***
		(0.002)		(0.028)
FinLiteracy		0.008***		0.018
		(0.001)		(0.019)
HighEdu		0.070***		0.360***
		(0.003)		(0.046)
Male		-0.012***		-0.035
		(0.002)		(0.031)
Married		-0.001		-0.151***
		(0.002)		(0.042)
Age		0.005***		0.042***
		(0.000)		(0.005)
Age2		-0.004***		-0.030***
		(0.000)		(0.005)
Log(Income)		0.000		-0.015*
		(0.000)		(0.008)
Log(Asset)		0.009***		0.033***
		(0.000)		(0.008)
Log(FinaAsset)		0.010***		0.084***
		(0.000)		(0.003)
HouseRatio		-0.000***		-0.010***
		(0.000)		(0.001)
Log(RealizedGain)		0.067***		0.549***
		(0.001)		(0.024)
Log(GDP)		0.007***		0.048***
		(0.001)		(0.015)
Log(HP)		0.034***		0.225***
		(0.003)		(0.048)
Rural		-0.016***		-0.252***
		(0.001)		(0.018)

Region F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
R-squared	0.018	0.324	0.006	0.129
Observations	111,505	111,505	111,505	111,505

Table 7. Natural Disasters and Insurance Holdings

This table reports the impacts of natural disasters on households' insurance coverage. Panel A reports the summary statistics of public and private insurance coverage, and Panel B exhibits the impacts of natural disasters on household insurance coverage. For variable definitions, *PrivateInsure* is a dummy that equals 1 if at least one member of the household has private insurance (including life, health, and other private insurances), and 0 otherwise. *PrivateLifeInsure* is a dummy that equals 1 if at least one member of the household has private life insurance, and 0 otherwise. *PrivateHealthInsure* is a dummy that equals 1 if at least one member of the household has private health insurance, and 0 otherwise. *PublicInsure* is a dummy that equals 1 if at least one member of the household has government-led public medical insurance, and 0 otherwise. We incorporate the consistent set of control variables along with year and region fixed effects, as in baseline equations. For all columns, to control for the persistency of insurance coverage, we also include the lagged term of dependent variables in equations. Finally, ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Summary of Insurance Holdings

	PrivateInsure = 0	PrivateInsure = 1	Total
PublicInsure = 0	5,672 (5%)	994 (1%)	6,666 (6%)
PublicInsure = 1	85,806 (77%)	19,033 (17%)	104,839 (94%)
Total	91,478 (82%)	20,027 (18%)	111,505 (100%)

Panel B. Public versus Private Insurance

	(1)	(2)	(3)	(4)
VARIABLES	PrivateInsure	PrivateLifeInsure	PrivateHealthInsure	PublicInsure
Log(1+DeathNum)	-0.005***	-0.004***	-0.002**	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
L.PrivateInsure	0.216***			
	(0.003)			
L.PrivateLifeInsure		0.140***		
		(0.003)		
L.PrivateHealthInsure			0.090***	
			(0.003)	
L.PublicInsure				0.052***
				(0.003)
RiskAverse	-0.018***	-0.010***	-0.014***	0.006***
	(0.003)	(0.003)	(0.002)	(0.002)
FinLiteracy	0.009***	0.009***	0.005***	0.001
	(0.002)	(0.002)	(0.001)	(0.001)
HighEdu	0.007	-0.002	0.009***	0.009***
	(0.004)	(0.003)	(0.002)	(0.003)
Male	-0.009**	-0.005*	-0.005**	0.001
	(0.004)	(0.003)	(0.002)	(0.002)
Married	0.002	0.001	-0.000	0.015***
	(0.005)	(0.004)	(0.003)	(0.002)
Age	0.004***	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.000)
Age2	-0.006***	-0.005***	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.000)
Log(Income)	0.014***	0.007***	0.007***	0.005***
	(0.001)	(0.001)	(0.001)	(0.000)
Log(Asset)	0.020***	0.012***	0.009***	0.003***
	(0.002)	(0.001)	(0.001)	(0.001)

Log(FinaAsset)	0.013***	0.010***	0.006***	0.005***
	(0.001)	(0.001)	(0.001)	(0.000)
HouseRatio	-0.000***	-0.000***	-0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Log(RealizedGain)	0.003***	0.001**	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.001)
Log(GDP)	0.011***	0.004**	0.004**	-0.006***
	(0.003)	(0.002)	(0.002)	(0.001)
Log(HP)	-0.025***	-0.014***	-0.012***	-0.004*
	(0.004)	(0.003)	(0.003)	(0.002)
Rural	-0.005	-0.012***	-0.010***	0.007***
	(0.004)	(0.003)	(0.003)	(0.002)
Region F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Pseudo R-squared	0.197	0.169	0.171	0.0970
Observations	54,640	54,640	54,640	54,640

Table 8. Natural Disasters and Other Financial Assets

This table reports the impacts of natural disasters on the ratio of other financial assets. For variable definitions, *ECashRatio* refers to the proportion of total assets held in electronic wallet balances, such as Alipay or WeChat balance. *MutualFundRatio* is the proportion of total assets allocated to mutual funds and other fund-based investment products. For all columns, we incorporate the consistent set of control variables along with year and region fixed effects, as in baseline equations. Finally, ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	ECashRatio (%)		MutualFundRatio (%)	
Log(1+DeathNum)	0.022***	0.013***	-0.027***	-0.014**
	(0.004)	(0.004)	(0.005)	(0.006)
Controls	No	Yes	No	Yes
Region F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Observations	77,893	77,893	87,734	87,734
R-squared	0.004	0.043	0.002	0.024

Table 9: Mechanisms: Wealth, Income, Risk Preference, and Expectation Channels

This table explores the impacts of natural disasters on the changes of household wealth, income, risk preference, and expectations. In Column (1), we first test the wealth channel by estimating the following OLS equation across the full sample:

$$\Delta Asset_{ijt} = \alpha + \beta Log(DeathNum_{j,t-1}) + \gamma X_{ijt} + \mu_r + \lambda_t + \varepsilon_{ijt},$$

where $\Delta Asset_{ijt}$ denotes the change rate of the total assets of household *i* of province *j* in year *t*. We also modify this equation by replacing the dependent variable with $\Delta Income_{ijt}$ to test the income channel, as shown in Column (2). $DeathNum_{j,t-1}$ is the number of deaths caused by natural disaster in province *j* in year *t-1*. We incorporate a consistent set of control variables along with year and region fixed effects, as in baseline equations.

Then, in Column (3), we test the risk preference channel by estimating the following Probit equation:

$$\Pr\left(MoreRiskAverse_{it}\right) = \alpha + \beta Log(DeathNum_{j,t-1}) + \gamma X_{ijt} + \mu_r + \lambda_t + \varepsilon_{ijt},$$

where $MoreRiskAverse_{it}$ is a dummy that equals 1 if the household *i* of province *j* become more risk averse in year *t*, and 0 otherwise (if the household head's risk attitude does not change or become less risk averse). We incorporate the consistent set of control variables (excluding risk averse) along with year and region fixed effects, as in the baseline equations. The margins of the Probit estimation at the mean are reported.

Finally, in Columns (4) and (5), we explore the impact of natural disasters on households' expectation for future stock market as following:

$$\Pr\left(StockMktExpect_{ijt}\right) = \alpha + \beta Log(DeathNum_{j,t-1}) + \gamma X_{ijt} + \mu_r + \lambda_t + \varepsilon_{ijt},$$

where $StockMktExpect_{ijt}$ denotes the expectation for future stock market of household *i* of province *j* in year *t*, taking discrete value of 1, 2, and 3, which corresponds to "pessimism", "neutral", and "optimism" respectively. See Internet Appendix Table IA6 for the variable construction process. For robustness check, we also replace the dependent variable as $Optimism_{ijt}$, a dummy that equals 1 if household feel optimism about the future stock market (*StockMktExpect* = 3) and 0 if the household feel pessimistic or neutral (*StockMktExpect* = 1 or 2). We incorporate a consistent set of control variables along with year and region fixed effects, as in baseline equations. For all columns, robust standard errors clustered at the household level are in parentheses. Finally, ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) ΔAsset	(2) ΔIncome	(3) Pr(MoreRiskAverse)	(4) Pr(StockMktExpect)	(5) Pr(Optimism)
Log(1+DeathNum)	-0.121	0.376	0.005***	-0.028**	-0.031*
	(1.348)	(0.354)	(0.001)	(0.014)	(0.017)
Controls	Yes	Yes	Yes	Yes	Yes
Regional F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared / R-squared	0.000	0.000	0.200	0.096	0.075
Observations	54,640	53,800	54,640	6,122	6,122

Table 10: Robustness Tests: Instrument Variable to Address Endogeneity

This table reports the mitigating effects of public insurance on households risk-taking, using friends' disaster experience as an instrument variable. Following Bailey et al. (2018b), we calculate each province's *FriendDisaExp*, representing the natural disaster exposure of its "friend provinces." This metric is defined as the average disaster-related fatalities in non-adjacent provinces, weighted by the social connectedness index (SCI). The SCI between provinces *j* and *k* is measured by the total number of direct train connections between their capital cities. More specifically, $FriendDisaExp_{jt} = \sum_k ShareTrains_{j,k,t} \times DeathNum_{k,t}$, where $ShareTrains_{j,k,t}$ denotes the share of trains from a non-adjacent "friend province" *k* to province *j* to over trains from all non-adjacent provinces to province *j*. Based on this, we re-estimate the baseline regressions in Table 5 by replacing the independent variable *Log(1+DeathNum)* with *Log(1+FriendDisaExp)* to explore the mitigating effects of public insurance policies. We incorporate the consistent set of control variables along with year and region fixed effects, as in Table 3. Panels A and B show the estimation results using earthquake insurance pool establishment and medical insurance integration as exogeneous shock, respectively. For both panels, the robust standard errors clustered at the household level are in parentheses, and ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Earthquake Insurance Pool Establishment

	(1)	(2)	(3)	(4)
	Full Sample	[-3y, +3y]	Full Sample	[-3y, +3y]
VARIABLES	StockParti		StockRatio (%)	
Log(1+FriendDisaExp)	-0.023***	-0.018***	-0.241***	-0.177***
	(0.005)	(0.005)	(0.068)	(0.069)
Log(1+FriendDisaExp)*EarthquakeInsure	0.024***	0.021***	0.177**	0.146**
	(0.005)	(0.005)	(0.070)	(0.071)
Controls	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
R-squared	0.331	0.284	0.129	0.135
Observations	104,944	81,160	104,944	81,160

Panel B. Medical Insurance Integration

	(1)	(2)	(3)	(4)
	Full Sample	[-3y, +3y]	Full Sample	[-3y, +3y]
VARIABLES	StockParti		StockRatio (%)	
Log(1+FriendDisaExp)	-0.006***	-0.005**	-0.109***	-0.086***
	(0.002)	(0.002)	(0.028)	(0.031)
Log(1+FriendDisaExp)*MedInsureInt	0.004***	0.004***	0.025**	0.022*
	(0.001)	(0.001)	(0.011)	(0.012)
Controls	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
R-squared	0.332	0.327	0.129	0.135
Observations	104,944	84,363	104,944	84,363

Table 11: Robustness Tests: Controlling for Household Fixed Effects

This table reports the mitigating effects of public insurance on households risk-taking controlling for the household fixed effects, with Panels A and B exploring two distinct policies, respectively. Specifically, In Panel A, we estimate the following regression:

$$\Pr\left(StockParti_{ijt}\right) = \alpha + \beta_1 Log\left(1 + DeathNum_{j,t-1}\right) + \beta_2 Log\left(1 + DeathNum_{j,t-1}\right) \times EarthquakeInsure_t + \gamma X_{ijt} + \nu_i + \lambda_t + \varepsilon_{ijt},$$

where $StockParti_{ijt}$ is an indicator that equals 1 if household *i* in province *j* participates in the stock market in year *t*, and 0 otherwise. $EarthquakeInsure_t$ is a dummy that equals 1 for years equaling or later than 2015, when the earthquake insurance community was established. X_{ijt} denotes for a set of control variables, and ν_i and λ_t denotes for the household fixed effects and year fixed effects, respectively. We modify the equation by replacing the dependent variable with $StockRatio_{ijt}$ and report the results in Panel A Columns (3) and (4).

In Panel B, we examine another public insurance policy, the integration of urban and rural medical insurance since 2009, by estimating the following regression across the full sample in Columns (1)-(2):

$$\Pr\left(StockParti_{ijt}\right) = \alpha + \beta_1 Log\left(1 + DeathNum_{j,t-1}\right) + \beta_2 Log\left(1 + DeathNum_{j,t-1}\right) \times MedInsureInt_{jt} + \gamma X_{ijt} + \nu_i + \lambda_t + \varepsilon_{ijt},$$

where $StockParti_{ijt}$ is an indicator that equals 1 if household *i* in province *j* participates in the stock market in year *t*, and 0 otherwise. $MedInsureInt_{jt}$ is a dummy that equals 1 if the urban and rural medical insurance has been integrated in province *j* in year *t*, and zero otherwise. See the integration timeline in the Internet Appendix Table IA3. X_{ijt} denotes for a set of control variables, and ν_i and λ_t represent the household fixed effects and year fixed effects, respectively. We modify the equation by replacing the dependent variable with $StockRatio_{ijt}$ and report the results in Panel B Columns (3) and (4). For both Panels A and B, the robust standard errors clustered at the household level are in parentheses, and ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Earthquake Insurance Pool Establishment

	(1)	(2)	(3)	(4)
	Full Sample	[-3y, +3y]	Full Sample	[-3y, +3y]
VARIABLES	StockParti		StockRatio (%)	
Log(1+DeathNum)	-0.005***	-0.005***	-0.053***	-0.082***
	(0.001)	(0.001)	(0.017)	(0.023)
Log(1+DeathNum)*EarthquakeInsure	0.003**	0.003**	0.045**	0.069***
	(0.001)	(0.001)	(0.018)	(0.022)
Controls	Yes	Yes	Yes	Yes
Household F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
R-squared	0.738	0.760	0.679	0.706
Observations	83,781	65,973	83,781	65,973

Panel B. Medical Insurance Integration

	(1)	(2)	(3)	(4)
	Full Sample	[-3y, +3y]	Full Sample	[-3y, +3y]
VARIABLES	StockParti		StockRatio (%)	
Log(1+DeathNum)	-0.004***	-0.004***	-0.040***	-0.049***
	(0.001)	(0.001)	(0.012)	(0.015)
Log(1+DeathNum)*MedInsureInt	0.002***	0.002*	0.030***	0.053***
	(0.001)	(0.001)	(0.010)	(0.016)
Controls	Yes	Yes	Yes	Yes

Household F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
R-squared	0.738	0.758	0.679	0.711
Observations	83,781	58,494	83,781	58,494

Table 12: Robustness Tests: Sub-sample Regression Excluding Provinces Most Prone to Natural Disasters

This table reports the mitigating effects of public insurance on households risk-taking with sample excluding Sichuan, Yunnan, Gansu, Hunan, and Guizhou, the top five provinces most prone to natural disasters in our data, as Figure 2 shown. Specifically, In Panel A, we estimate the following regression:

$$\Pr\left(StockParti_{ijt}\right) = \alpha + \beta_1 Log\left(1 + DeathNum_{j,t-1}\right) + \beta_2 Log\left(1 + DeathNum_{j,t-1}\right) \times EarthquakeInsure_t + \gamma X_{ijt} + \mu_j + \lambda_t + \varepsilon_{ijt},$$

where $StockParti_{ijt}$ is an indicator that equals 1 if household *i* in province *j* participates in the stock market in year *t*, and 0 otherwise. $EarthquakeInsure_t$ is a dummy that equals 1 for years equaling or later than 2015, when the earthquake insurance community was established. X_{ijt} denotes for a set of control variables, and μ_j and λ_t denotes for the region fixed effects and year fixed effects, respectively. We modify the equation by replacing the dependent variable with $StockRatio_{ijt}$ and report the results in Panel A Columns (3) and (4).

In Panel B, we focus on another public insurance policy, the integration of urban and rural medical insurance since 2009, by estimating the following regression across the full sample in Columns (1)-(2):

$$\Pr\left(StockParti_{ijt}\right) = \alpha + \beta_1 Log\left(1 + DeathNum_{j,t-1}\right) + \beta_2 Log\left(1 + DeathNum_{j,t-1}\right) \times MedInsureInt_{jt} + \gamma X_{ijt} + \mu_j + \lambda_t + \varepsilon_{ijt},$$

where $StockParti_{ijt}$ is an indicator that equals 1 if household *i* in province *j* participates in the stock market in year *t*, and 0 otherwise. $MedInsureInt_{jt}$ is a dummy that equals 1 if the urban and rural medical insurance has been integrated in province *j* in year *t*, and zero otherwise. See the integration timeline in the Internet Appendix Table IA3. X_{ijt} denotes for a set of control variables, and μ_j and λ_t represent the region fixed effects and year fixed effects, respectively. We modify the equation by replacing the dependent variable with $StockRatio_{ijt}$ and report the results in Panel B Columns (3) and (4). For both Panels A and B, the robust standard errors clustered at the household level are in parentheses, and ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Earthquake Insurance Pool Establishment

	(1)	(2)	(3)	(4)
	Full Sample	[-3y, +3y]	Full Sample	[-3y, +3y]
VARIABLES	StockParti		StockRatio (%)	
Log(1+DeathNum)	-0.009***	-0.009***	-0.102***	-0.115***
	(0.001)	(0.001)	(0.019)	(0.024)
Log(1+DeathNum)*EarthquakeInsure	0.008***	0.007***	0.086***	0.087***
	(0.001)	(0.001)	(0.020)	(0.024)
Controls	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
R-squared	0.330	0.291	0.127	0.134
Observations	93,877	68,540	93,877	68,540

Panel B. Medical Insurance Integration

	(1)	(2)	(3)	(4)
	Full Sample	[-3y, +3y]	Full Sample	[-3y, +3y]
VARIABLES	StockParti		StockRatio (%)	
Log(1+DeathNum)	-0.005***	-0.004***	-0.065***	-0.073***
	(0.001)	(0.001)	(0.012)	(0.014)
Log(1+DeathNum)*MedInsureInt	0.003***	0.003***	0.036***	0.042***
	(0.001)	(0.001)	(0.010)	(0.011)

Controls	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
R-squared	0.330	0.332	0.127	0.133
Observations	93,877	68,892	93,877	68,892

Table 13: Robustness Tests: Entropy Matching

This table reports the mitigating effects of public insurance on households risk-taking with matched sample controlling for risk preference, financial literacy, total asset, property asset ratio, local housing price, and whether the household resides in a rural area. The balanced test is reported in Internet Appendix Table IA5. Specifically, we estimate the following regression:

$$StockParti_{ijt} = \alpha + \beta_1 Log(1 + DeathNum_{j,t-1}) + \beta_2 Log(1 + DeathNum_{j,t-1}) \times MedInsureInt_{jt} + \gamma X_{ijt} + \mu_j + \lambda_t + \varepsilon_{ijt},$$

where $StockParti_{ijt}$ is an indicator that equals 1 if household *i* in province *j* participates in the stock market in year *t*, and 0 otherwise. $MedInsureInt_{jt}$ is a dummy that equals 1 if the urban and rural medical insurance has been integrated in province *j* in year *t*, and zero otherwise. See the integration timeline in the Internet Appendix Table IA3. X_{ijt} denotes for a set of control variables, and μ_j and λ_t represent the region fixed effects and year fixed effects, respectively. We also modify the equation by replacing the dependent variable with $StockRatio_{ijt}$ and estimate an OLS regression for Columns (3) and (4). For all columns, the robust standard errors clustered at the household level are in parentheses, and ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Full Sample	[-3y, +3y]	Full Sample	[-3y, +3y]
VARIABLES	StockParti		StockRatio (%)	
Log(1+DeathNum)	-0.001	-0.000	-0.063***	-0.068***
	(0.001)	(0.001)	(0.020)	(0.023)
Log(1+DeathNum)*MedInsureInt	0.003***	0.003***	0.027**	0.033**
	(0.001)	(0.001)	(0.014)	(0.016)
Controls	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
R-squared	0.348	0.363	0.172	0.181
Observations	63,950	48,376	63,950	48,376

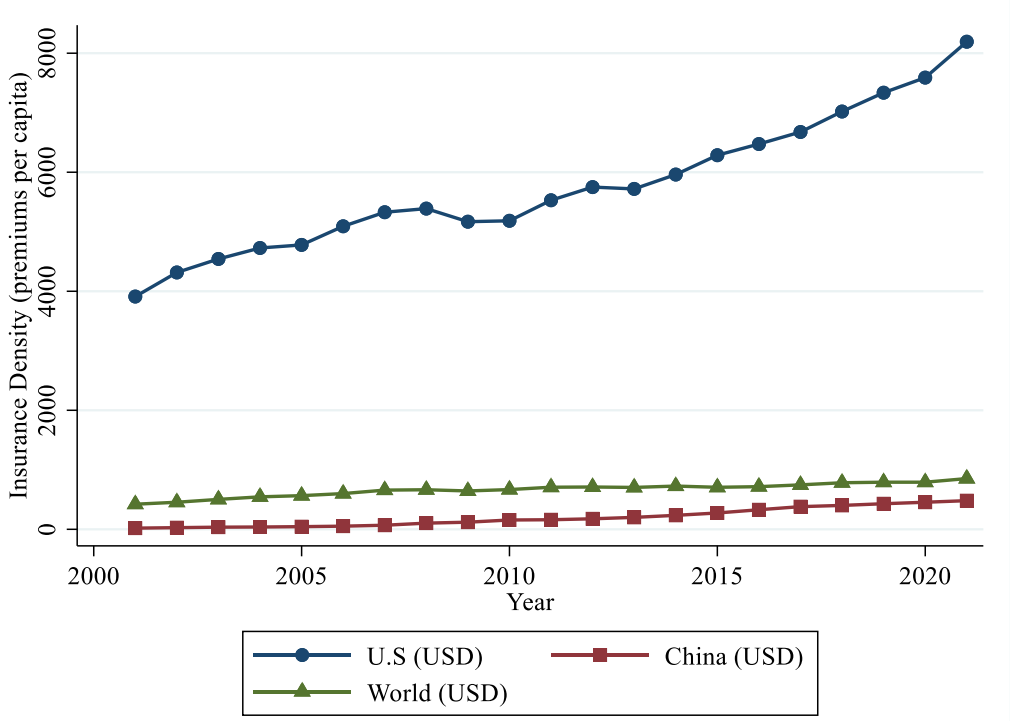
Internet Appendix for

Natural Disaster Experiences and Household Risk Taking

Figure IA1: Insurance Density and Penetration between U.S., China, and the World

This figure compares the insurance market development of U.S., China, and the world.[1] Panels A and B present the insurance density (premium per capita) and insurance penetration (premium as a percentage of GDP), respectively. The blue, red, and green line denotes U.S., China, and the world, respectively.

Panel A. Insurance Density



[1] The Data comes from https://www.sigma-explorer.com/.

Panel B. Insurance Penetration

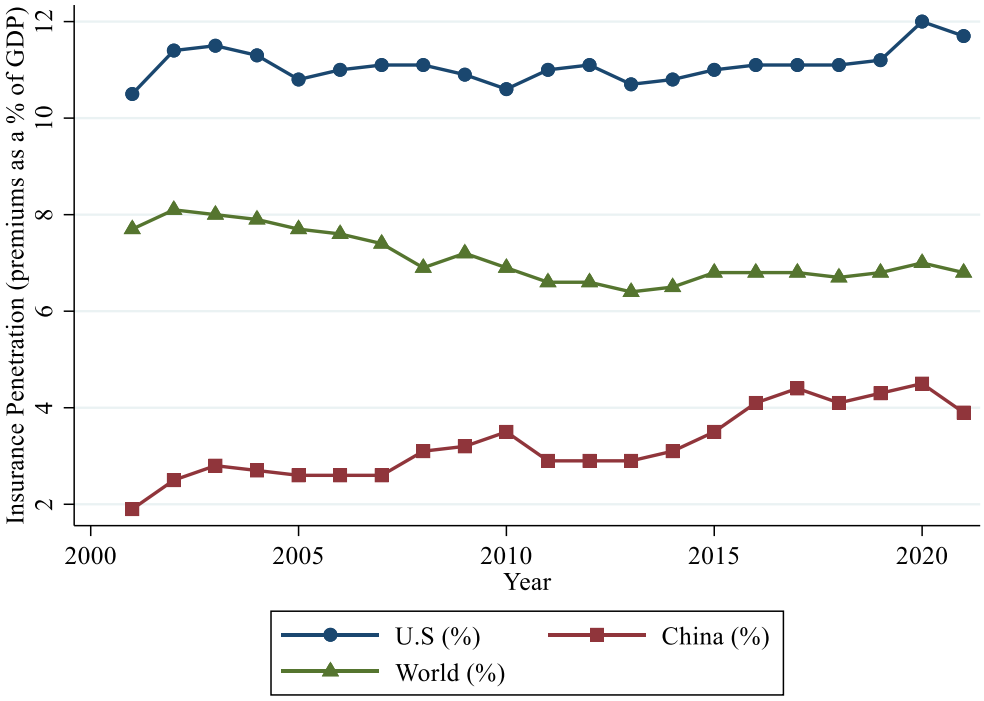


Table IA1: Variable Definitions

This table defines the main variables used in this study. For variable type, C denotes Continuous variable, and I denotes Indicator variable. D denotes discrete variables.

Variables	Type	Description
Household level		
StockParti	I	A dummy that equals 1 if a household owns stock, and 0 otherwise.
StockRatio (%)	C	Stock as a percentage of the total assets of a household.
RealizedGain	C	The realized gain from stock market of a household last year.[2]
Asset (1,000 Yuan)	C	The total assets of a household, including financial assets and non-financial assets.[3]
FinaAsset (1,000 Yuan)	C	The total financial assets of a household, including cash, deposits, financial products, stocks, funds, bonds, derivatives, non-RMB assets, gold, loaned money, social security account balances, and so on.
Income (1,000 Yuan)	C	The total annual income of a household, including wage, agricultural income, industrial and commercial income, property income and transfer income.
HouseRatio (%)	C	Properties as a percentage of the total assets of a household.
ECashRatio (%)	C	The proportion of total assets held in electronic wallet balances, such as Alipay or WeChat balance.
MutualFundRatio (%)	C	The proportion of total assets allocated to mutual funds and other fund-based investment products.
HighFinaAssets	I	A dummy that equals 1 if a household's financial assets in a year are higher than the average of full sample in the same year, and 0 otherwise.
PrivateInsure	I	A dummy that equals 1 if at least one member of a household owns private insurance (including life insurance, health insurance, and other private insurance), and 0 otherwise.
PrivateLifeInsure	I	A dummy that equals 1 if at least one member of a household owns private life insurance, and 0 otherwise.
PrivateHealthInsure	I	A dummy that equals 1 if at least one member of a household owns private health insurance, and 0 otherwise.
PublicInsure	I	A dummy that equals 1 if at least one member of a household owns government-led public health insurance, and 0 otherwise.
StockMktExpect	D	The expectation of a household about future stock market, which takes value of 1, 2, and 3, corresponding to "pessimism", "neutral", and "optimism" respectively. See Internet Appendix Table IA6 for the variable construction process.
Optimism	I	A dummy that equals 1 if household feel optimistic about future stock market (*StockMktExpect* = 3), and 0 if household feel pessimistic or neutral about future stock market (*StockMktExpect* = 1 or 2).

[2] The CHFS asks: "What was the total gain (or loss) your household received from stock purchases, sales, or dividends last year?" We calculate the logarithm of the gain as the *Log(RealizedGain)*. For households with stock investment losses, the *Log(RealizedGain)* is equal to the negative of the logarithm of absolute value of the losses. For households that do not participate in the stock market, we set *Log(RealizedGain)* to zero.

[3] Financial assets include cash, deposits, financial products, stocks, funds, bonds, derivatives, non-RMB assets, gold, loaned money, social security account balances, and so on. Non-financial assets include agricultural assets, industrial assets, housing, commercial assets, land, vehicle, garage, and so on.

ΔAsset	C	The change rate of a household's total assets compared to the previous survey year. Specifically, $\Delta Asset_{it} = \frac{Asset_{it} - Asset_{i,t-2}}{Asset_{i,t-2}}$.
ΔIncome	C	The change rate of a household's total income compared to the previous survey year. Specifically, $\Delta Income_{it} = \frac{Income_{it} - Income_{i,t-2}}{Income_{i,t-2}}$.
Individual (household head) level		
Age	C	Age of a household head. We exclude households where the head is outside the age range of 18 to 85 years.
HighEdu	I	A dummy that equals 1 if the head of a household graduated from college or vocational school, or has bachelor's, master's, or doctorate degree, and 0 otherwise.
RiskAverse	I	A dummy that equals 1 if the head of a household is risk averse, and 0 otherwise (if risk preferred or risk-neutral).
AversionLevel	D	The degree of risk aversion of household head, taking discrete value of 1 to 5. Higher value indicates higher risk aversion level.[4]
MoreRiskAverse	I	A dummy that equals 1 if the *AversionLevel* increased compared to the previous survey (i.e., household head becomes more risk averse), and 0 otherwise (if household head's risk attitude does not change or become less risk averse)
Male	I	A dummy that equals 1 if household head is male, and 0 otherwise.
Married	I	A dummy that equals 1 if household head is married, and 0 otherwise.
FinLiteracy	D	A household head's level of financial literacy, measured by the number of basic financial questions correctly answered.[5]
EcoAttention	I	A dummy that equals 1 if a household head concerns for the information of economy and finance, and 0 otherwise. [6]
Region/Province level		
Rural	I	A dummy that equals 1 if a household lives in rural area, and 0 if in urban area. The raw data is from CHFS.
GDP	C	The GDP of a province. The raw data is from NBS.

[4] A household head's risk attitude is measured by the following question in the CHFS: "Which of the choices below would you most want to invest if you had adequate money?" The response options are: (1) Project with high risk and high return, (2) Project with slightly high risk and slightly high return, (3) Project with average risk and return, (4) Project with slight risk and return, (5) Unwilling to carry any risk, and (6) No idea. After dropping household samples choosing "No idea", we code *RiskAverse* as 1 if respondents choose (4) or (5), and 0 if they choose (1), (2), or (3). To quantify the level of risk aversion, we assign a code of 1 to 5 to the variable *AversionLevel* based on the respondents' choices, where (1) corresponds to the lowest level of aversion and (5) represents the highest level of aversion.

[5] To test the respondents' mastery of basic financial knowledge, the CHFS asks respondents to answer two questions about finance: (1) "Given a 4% interest rate, how much will you have after five years if you have 100 RMB at first?" and (2) "With an interest rate of 5% and an inflation rate of 3%, after saving money in the bank for one year, can you buy more or less than in the previous year?" To obtain the level of financial literacy of each household, we calculate the number of questions that the household head can correctly answer and assign this number to *FinLiteracy*, whose values range from 0 to 2. A higher *FinLiteracy* indicates a higher degree of financial knowledge mastery. Note that these two financial literacy related questions were not included in the questionnaire in the first wave 2011 and there is also a significant proportion of missing values for the answers to these two questions in 2017. To maintain the integrity of the sample, for tracked households, we use the answers from the 2013 survey to fill in the missing values of *FinLiteracy* in 2011, and the answers in 2015 survey to fill in the missing values of *FinLiteracy* in 2017.

[6] In CHFS, household head is asked to answer "What is your degree of concern for economic and financial information?" and the here are available options: (1) Extremely concerned, (2) Very concerned, (3) Generally concerned, (4) A little concerned, and (5) Not concerned at all. If the respondent chooses the option (1), (2), or (3), then *EcoAttention* equals 1, and 0 if they choose (4) or (5).

(100 million Yuan)		
DeathNum	C	Fatalities caused by natural disaster of a province. The raw data is from NBS.
GeoDisaEcoLoss (10,000 Yuan)	C	Economic losses caused by geological disasters of a province. The raw data is from NBS.
FriendDisaExp	C	natural disaster exposure of "friend provinces" for each province. This metric is defined as the average disaster-related fatalities in non-adjacent provinces, weighted by the social connectedness index (SCI). The SCI between provinces *j* and *k* is measured by the total number of direct train connections between their capital cities. More specifically, $FriendDisaExp_{jt} = \sum_k ShareTrains_{j,k,t} \times DeathNum_{k,t}$, where $ShareTrains_{j,k,t}$ denotes the share of trains from a non-adjacent "friend province" *k* to province *j* to over trains from all non-adjacent provinces to province *j*.
HighPrevControlNum	I	A dummy that equals 1 if the number of geological disaster prevention and control projects in a province during a given year exceeds the average number of projects across all provinces for that year. The raw data is from NBS.
HP (Yuan/square meter)	C	Average sales price of residential housing in a province for a given a year. The raw data is from NBS.

Table IA2: Insurance Density and Penetration in U.S., China, and World From 2001 to 2021

This table reports the average insurance density and penetration in U.S., China, and world from 2001 to 2021. Insurance penetration = premium as a% of GDP; Insurance density = premium per capita; The data comes from https://www.sigma-explorer.com/.

VARIABLES	(1) Mean	(2) Sd	(3) Min	(4) Max
Insurance Penetration % (US)	11.095	0.353	10.500	12.000
Insurance Penetration % (China)	3.243	0.726	1.900	4.500
Insurance Penetration % (World)	7.105	0.528	6.400	8.100
Insurance Density (US)	5,760.619	1,129.751	3,911.000	8,193.000
Insurance Density (China)	199.952	156.783	20.000	482.000
Insurance Density (World)	665.238	113.987	422.000	853.000

Table IA3: Summary of Integration Date for Urban and Rural Health Insurance

No.	Province	Date of Integrating Urban and Rural Health Insurance
1	Beijing	2017 https://www.beijing.gov.cn/zhengce/zhengcefagui/201905/t20190522_60680.html
2	Tianjin	2009 https://www.tj.gov.cn/zwgk/szfwj/tjsrmzf/202005/t20200519_2365278.html
3	Hebei	2016 https://www.gov.cn/xinwen/2016-05/20/content_5074958.htm
4	Liaoning	2019 https://ybj.ln.gov.cn/ybj/ztzl/zsg/D44DF29587874F10B7A5DB96307ABBD0/index.shtml
5	Shanghai	2015 https://rsj.sh.gov.cn/tsj_17090/20200616/t0035_1365923.html
6	Jiangsu	2016 https://www.jiangsu.gov.cn/art/2017/1/22/art_46451_2557675.html
7	Zhejiang	2016 https://www.gov.cn/xinwen/2016-11/14/content_5132247.htm
8	Fujian	2015 https://www.fujian.gov.cn/zwgk/zfxxgk/szfwj/jgzz/kjwwzcwj/201502/t20150209_1183777.htm
9	Shandong	2013 http://www.shandong.gov.cn/art/2014/2/27/art_107868_63029.html
10	Guangdong	2012 https://hsa.gd.gov.cn/zwgk/content/post_2910299.html
11	Hainan	2016 https://www.mohrss.gov.cn/SYrlzyhshbzb/shehuibaozhang/gzdt/201704/t20170428_270182.html
12	Shanxi	2016 https://www.mohrss.gov.cn/SYrlzyhshbzb/shehuibaozhang/gzdt/201611/t20161121_259910.html
13	Jilin	2016 https://xxgk.jl.gov.cn/szf/gkml/201812/t20181205_5348071.html
14	Heilongjiang	2016 https://www.mohrss.gov.cn/SYrlzyhshbzb/shehuibaozhang/gzdt/201612/t20161227_263095.html
15	Anhui	2016 https://www.mohrss.gov.cn/SYrlzyhshbzb/shehuibaozhang/gzdt/201701/t20170111_264272.html
16	Jiangxi	2016 https://www.mohrss.gov.cn/SYrlzyhshbzb/shehuibaozhang/gzdt/201607/t20160727_244300.html
17	Henan	2017 https://www.henan.gov.cn/2017/08-01/377960.html
18	Hubei	2016 https://www.hubei.gov.cn/zfwj/ezf/201606/t20160614_1711953.shtml
19	Hunan	2016 https://fgw.hunan.gov.cn/fgw/xxgk_70899/zcfg/dfxfg/201612/t20161208_3533403.html
20	Inner Mongolia	2016 https://www.hlj.gov.cn/hlj/c108031/201702/c00_30644922.shtml
21	Guangxi	2016 https://www.mohrss.gov.cn/SYrlzyhshbzb/shehuibaozhang/gzdt/201608/t20160809_245137.html
22	Chongqing	2011 https://rlsbj.cq.gov.cn/zwgk_182/zfxxgkml/zcwj_145360/jfxzgfxwj/201210/W020230214613167374171.pdf
23	Sichuan	2016 https://www.sc.gov.cn/10462/c103044/2016/12/30/3cf15b217f2240ac81684de936647603.shtml
24	Guizhou	2016 https://www.mohrss.gov.cn/SYrlzyhshbzb/shehuibaozhang/gzdt/201701/t20170111_264273.html
25	Yunnan	2016 https://www.yn.gov.cn/zwgk/zcwj/yzf/201911/t20191101_183960.html
26	Shannxi	2019 http://ybj.shaanxi.gov.cn/zcwj/204.htm
27	Gansu	2016 https://www.mohrss.gov.cn/SYrlzyhshbzb/shehuibaozhang/gzdt/201611/t20161124_260269.html
28	Qinghai	2016 http://www.qinghai.gov.cn/xxgk/xxgk/fd/zfwj/201712/t20171222_20649.html
29	Ningxia	2010 https://www.mohrss.gov.cn/SYrlzyhshbzb/shehuibaozhang/gzdt/201012/t20101207_83688.html

Table IA4: Falsification Tests

This table reports the results of falsification tests. Panels A and B report the test for earthquake insurance policy and integration of urban and rural medical insurance, respectively. For each panel, the second column reports the actual coefficients on interaction term of fatalities and policy estimated in baseline equations (1) and (2), as also shown in the Columns (2) and (4) of Table 5 Panels A and B. For comparison, the last six columns exhibit the distribution of the 500 pseudo coefficients on *Log(DeathNum+1)*PseudoEarthquakeInsure (or PseudoMedInsureInt)*. We also plot this result in Figure 4.

Panel A. Earthquake Insurance Pool Establishment

Dep. Variable	Actual Coefficient on ***Log(1+DeathNum)*EarthquakeInsure***	Summary of Pseudo Coefficient on ***Log(1+DeathNum)*PseudoEarthquakeInsure***					
		Mean	Min	P25	Median	P75	Max
Pr(StockParti)	0.006	0.000	-0.002	-0.000	0.000	0.000	0.001
StockRatio (%)	0.071	-0.000	-0.018	-0.004	-0.000	0.004	0.015

Panel B. Medical Insurance Integration

Dep. Variable	Actual Coefficient on ***Log(1+DeathNum)*MedInsureInt***	Summary of Pseudo Coefficient on ***Log(1+DeathNum)* PseudoMedInsureInt***					
		Mean	Min	P25	Median	P75	Max
Pr(StockParti)	0.003	-0.000	-0.001	-0.000	-0.000	0.000	0.001
StockRatio (%)	0.034	-0.000	-0.015	-0.003	-0.000	0.003	0.016

Table IA5: Balance Test for Entropy Matching Method

This table reports the balance test for entropy matching method. Each year, we conduct entropy matching where the treatment group is composed of households in provinces where urban and rural medical insurance have already been integrated, while the control group consists of households in provinces where the integration has not yet taken place. This matching process is repeated annually to ensure comparability of treatment and control groups in terms of the risk preference, financial literacy, total asset, properties, housing price and whether the households reside in rural areas. Finally, ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Treated Group			Control Group			Mean Diff.
	N	Mean	Std	N	Mean	Std	
RiskAverse	13,816	0.67	0.47	50,134	0.67	0.47	0.00
FinLiteracy	13,816	0.45	0.64	50,134	0.45	0.64	0.00
Log(Asset)	13,816	0.86	0.35	50,134	0.86	0.35	0.00
HouseRatio	13,816	12.88	1.59	50,134	12.88	1.59	0.00
Log(HP)	13,816	65.59	32.61	50,134	65.58	32.61	0.01
Rural	13,816	8.93	0.43	50,134	8.93	0.43	0.00

Table IA6: Variable Construction Process of Stock Market Expectation from the CHFS

This table summarizes the questions in the CHFS we used to measure household's stock market expectation. In general, values 1, 2, and 3 of *StockMktExpect* represent households' pessimistic, neutral, and optimistic expectation toward the future stock market, respectively. Note that the *StockMktExpect* is missing in 2015 because there is no any related question that we can use to measure the expectation.

Related Questions in Five Waves from 2011 to 2019	Options	Construction
CHFS 2011: **[D3108]** In overall, does your family gain, loss, or break-even from the stock market since you participated in it?	(1) Profit (2) Break-even (3) Loss	*StockMktExpect* = 1 if chooses (3), = 2 if chooses (2), = 3 if chooses (1).
CHFS 2013: **[D3108]** In overall, does your family gain, loss, or break-even from the stock market since you participated in it?	(1) Profit (2) Break-even (3) Loss	*StockMktExpect* = 1 if chooses (3), = 2 if chooses (2), = 3 if chooses (1).
CHFS 2015: Do not asked question [D3108] anymore, and there is no related question to measure expectation	None	*StockMktExpect* = Missing
CHFS 2017: (Using new added question [D3118] to replace the old question [D3108] in waves 2011 and 2013) **[D3118]** What is the range of the overall gain or loss that your family has experienced from the stock market last year?	(1) Losses greater than 30% (2) 30% loss to 20% loss (3) 20% loss to 10% loss (4) 10% loss to zero (5) break-even (6) 0 to 10% profit (7) 10% to 20% profit (8) 20% to 30% profit (9) greater than 30% profit	*StockMktExpect* = 1 if chooses (1)-(4), = 2 if chooses (5), = 3 if chooses (6)-(9).
CHFS 2019: (Adding new question [H3602] to directly ask household's expectation about future stock market) **[H3602]** How do you think the stock market will change over the next three months?	(1) Up a lot (2) Up a little (3) Basically unchanged (4) Down a little (5) Down a lot	*StockMktExpect* = 1 if chooses (4)-(5), = 2 if chooses (3), = 3 if chooses (1)-(2).