The Impact of Natural Disasters on Risk Preferences, Subjective Expectations, and Related Behavior: Evidence from Typhoon Ketsana

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Abstract

We study how individuals' risk preferences, subjective expectations about future shocks and well-being, and related risk-taking behavior change following a natural disaster. We focus on the impact of Typhoon Ketsana in 2009—one of the most devastating storms to hit Southeast Asia in recent decades. Our analysis reveals that individuals affected by the typhoon became more risk averse one year after landfall, and that this effect persisted up to four years later. We base our findings on household-level panel data from Vietnam and a difference-in-differences strategy with a continuous treatment variable that exploits variation in typhoon intensity. We conclude that a standard deviation (SD) increase in excess rainfall during the typhoon led to a 0.11 SD increase in risk averseness one year after landfall and a 0.14 SD increase four years after landfall. Individuals exposed to higher excess rainfall also came to expect more frequent storms in the short term, but this effect dissipated over time. Because the change in risk preferences persisted after this belief response faded, belief updating about future storms is unlikely to be the primary mechanism driving the change in preferences. Instead, our mechanism analysis points more strongly to psychological responses, particularly increased pessimism about future well-being. Finally, we find that behavioral responses are concentrated in increased insurance purchasing in the long run, with weaker and less persistent evidence of other changes. Our paper contributes to the literature that empirically documents how negative shocks may alter risk preferences and helps illuminate the way climate-related hazards can induce lasting changes in individuals' attitudes and some aspects of their economic behavior.

Keywords: risk preferences; subjective expectations; natural disasters; Vietnam

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1 Introduction

Natural hazards are becoming more intense and frequent across the world (Hallegatte et al., 2016), and their impacts are projected to intensify in the future (IPCC, 2022). Between 1998 and 2017, the direct economic losses from disasters averaged $145.4 billion USD annually, an estimated 77% of which stemmed from climate-related disasters, a 9% increase in losses over the previous 20 years (EM-DAT, 2018). The increase in the frequency of natural disasters, number of persons affected, and economic losses are largely attributed to a rise in mean global surface temperatures and greater concentration of populations living in high-risk areas (IPCC, 2022; Mani et al., 2003). Climate change disproportionately affects those living in developing countries, with natural hazards often impacting poor households more severely than the general population (Hallegatte et al., 2020). While higher-income countries report 65% of climate-related disaster losses, this only accounts for 0.41% of their average GDP while losses reported by low-income countries account for an average of 1.8% of GDP (EM-DAT, 2018). Storms, in particular, account for the greatest economic losses, totaling $1.3 trillion USD from 1998 to 2017, and the second largest loss of life, accounting for 233,000 deaths (behind only earthquakes) (EM-DAT, 2018).

The impact of natural disasters can lead to systematic alterations in individuals' risk preferences, a key determinant in decision-making and behavior including labor market outcomes, investment, savings, health outcomes, and migration. Classic economic models assume individual risk preferences are stable over time (Stigler and Becker, 1977). However, if and in what direction risk preferences are altered is ultimately an empirical question. Researchers have begun to document how risk preferences are altered by negative shocks including violence or conflict, natural disasters, and financial crises suggesting that these preferences are malleable to life experiences. Both Chuang and Schechter (2015) and Schildberg-Hörisch (2018) provide comprehensive reviews on this growing body of literature.

Yet, there is no consensus on the direction in which negative events modify risk preferences even across the same domain. For instance, when assessing the impact of social conflict, Voors et al. (2012) report decreased risk aversion while others identify increased risk aversion (Callen et al., 2014; Kim and Lee, 2014; Moya, 2018; Brown et al., 2019; Jakiela and Ozier, 2019). Similarly, across natural disasters, several studies document decreased risk aversion (Eckel et al., 2009; Van Den Berg et al., 2009; Page et al., 2014; Hanaoka et al., 2018; Kahsay and Osberghaus, 2018; Reynaud and Aubert, 2020; Finger et al., 2023; Ingwersen et al., 2023) while others detect increased risk aversion (Cameron and Shah, 2015; Chantarat et al., 2015; Said et al., 2015; Cassar et al., 2017; Liebenehm et al., 2024). Interestingly, as documented by Liebenehm et al. (2024), with the exception of Ingwersen et al. (2023), the change in risk preference corresponds with the development status of the examined country, with individuals in developed countries displaying greater risk tolerance while those in developing countries exhibiting reduced risk tolerance (see Table 1 in their paper).[1] On the other hand, studies examining financial hardship have consistently found a decrease in risk tolerance (Malmendier and Nagel, 2011; Cohn et al., 2015; Necker and Ziegelmeyer, 2016; Guiso et al., 2018).

[1] Indeed, this observation holds for studies cited here but not in Table 1 of Liebenehm et al. (2024), again with the exception of Ingwersen et al. (2023).

Regarding natural disasters, limited evidence exists to determine the extent to which these effects persist in the long run. Some studies examine the long-term impact of climatic shocks, but do not isolate the impact of a single shock (Van Den Berg et al., 2009; Cameron and Shah, 2015; Reynaud and Aubert, 2020; Liebenehm et al., 2024). Others isolate the long-term impact of a single shock but lack longitudinal data (Chantarat et al., 2015; Said et al., 2015; Cassar et al., 2017). Hanaoka et al. (2018) and Ingwersen et al. (2023) are notable exceptions who use nationally representative panel data to examine short- and longer-term effects of natural disasters (the Great East Japan Earthquake and the 2004 Indian Ocean Tsunami) on risk preferences yet they come to different conclusions.

Not only can negative events alter risk preferences but they can also change the probability structure of subjective expectations of negative events occurring in the future. For instance, Cameron and Shah (2015) find that people in East Java who experienced a natural disaster in the previous three years anticipate these events to occur again with higher probabilities in the next year. Similarly, Kiely et al. (2023) find that households in Vietnam who had a member experience a disability anticipate an increase in health-related shocks in the future.

We study whether and in what direction risk preferences are altered in the wake of a natural disaster. In particular, we examine the impact of the intensity of exposure to Typhoon Ketsana, one of the most devastating storms in Vietnam in the last thirty years, on risk preferences in both the short and long term. We also examine whether these changes are accompanied by changes in subjective expectations about future storms and future well-being, whether these channels help explain the change in risk preferences, and whether exposure to the typhoon translates into changes in risk-related behavior.

We leverage a unique panel dataset that is representative of the rural population of Vietnam. The survey contains information on risk preferences of the same individuals before and after the storm. The use of panel data to study changes in risk preferences following a natural disaster is uncommon, as these events are unpredictable and data on preferences are rarely available before they occur. The majority of the literature on this topic is typically limited to cross-sectional data collected after the event and attempts to construct an appropriate counterfactual untreated group. Our panel data allow us to compare the same individuals over time and reduce concerns about selection effects, such as migration out of affected areas.

We find that individuals exposed to greater levels of excess rainfall from the typhoon become more risk averse in the year following landfall. A standard deviation (SD) increase in excess rainfall leads to a 0.11 SD increase in risk averseness one year later. This effect persists even four years after the event, where a SD increase in excess precipitation translates into a 0.14 SD increase in risk averseness, according to our preferred specification. These results remain robust across alternative specifications of the treatment variable that vary both the radius used to assign village-level exposure and the temporal window used to construct treatment intensity.

We then examine several mechanisms that could explain this change in risk preferences. Individuals exposed to higher excess rainfall come to expect more frequent storms in the short term, but this belief response dissipates in the long term. As the increase in risk averseness persists after the expectations about storm frequency return to their baseline levels, belief updating about future storms is unlikely to be the primary mechanism driving the long-term change in preferences. Consistent with this interpretation, a mediation analysis reveals that incorporating subjective expectations about future storms directly into our main specification does not attenuate the effect of excess rainfall on risk preferences.

Instead, our mechanism analysis points more strongly toward psychological responses after the typhoon. Exposure to higher excess rainfall increases individuals' pessimism about future well-being, and including this measure in the main specification substantially attenuates the estimated effect of typhoon exposure on risk preferences. This interpretation is consistent with the idea that severe shocks can affect risk preferences not only by changing expectations about future events, but also by inducing responses based on fear, stress, or vulnerability that alter how individuals evaluate risky prospects.

As a final potential mechanism, we examine pecuniary channels as well. Typhoon exposure increases some measures of material losses and extra expenditures, but these economic measures do not account for the main treatment effect as clearly as future pessimism. We therefore do not rule out the importance of economic channels in driving changes in risk preferences, but the empirical results lead us to place greater emphasis on psychological responses as a plausible mechanism behind the observed increase in risk averseness.

We further show that the effect of typhoon exposure on risk preferences differs by baseline wealth. In the short term, the increase in risk averseness is concentrated among households in the richest asset quartile. A plausible explanation is that wealthier households responded more immediately because they had more assets and investments exposed to the shock, making the consequences of the typhoon more salient in the short run. In the long term, however, the effects are negative across all asset quartiles, and the evidence of heterogeneity becomes weaker. Here, the effects are more broad-based, suggesting that the persistent change in risk preferences reflects a slower adjustment to the experience of a severe and unpredictable shock, rather than only the immediate salience of material losses. This interpretation is also consistent with the behavioral adjustments highlighted below, where some responses emerge only several years after landfall while others appear more short-lived.

In terms of behavioral change, we find that the clearest response is an increase in insurance purchasing in the long term. Individuals exposed to higher excess rainfall do not significantly increase insurance premiums in the year immediately following the typhoon, but they do so four years after landfall. This delayed response may reflect the fact that households take time to adjust insurance decisions, either because of liquidity constraints, recovery needs, contract timing, or other frictions present in insurance markets. Evidence of changes in other risk-related behaviors is weaker and less persistent. Exposure to the typhoon leads to short-term reductions in the drinking and smoking budget share and in the probability of gambling, but these effects do not persist in the long term.

The rest of the paper is organized as follows. Section 2 gives an overview of the destructive nature of Typhoon Ketsana. Section 3 describes both the satellite and household panel data, including the construction of the treatment variable and the risk measure. Section 4 introduces our identification strategy. Section 5 presents results, including the short- and long-term effects on risk preferences, evidence on subjective expectations about future storms and potential mechanisms, heterogeneous effects by baseline wealth, and changes in risk-related behavior.

Section 6 discusses the implications of our findings and concludes.

2 Background

Vietnam is beset by tropical storms each year during its typhoon season ranging from June to November. Areas along the central to south central coast between the provinces of Quang Binh and Bihn Dinh are particularly vulnerable during this season. Since 2000, the country has experienced an average of three tropical storms each year, with a representative district experiencing about one tropical storm per year. However, prior to Typhoon Ketsana, it was uncommon for storms to be intense enough to be categorized as a typhoon in Vietnam. Before Ketsana, only nine recorded storms were categorized as Category 1 typhoons or higher since 1980, only one of which was categorized as a Category 2 typhoon, making such an event uncommon and unanticipated (EM-DAT, 2024).

Typhoon Ketsana made landfall on September 29, 2009 in central Vietnam, approximately 30 km south of the city of Hoi An, and stretched across 400 km of coastline between the provinces of Thua Thien Hue and Quang Ngai.[2] Ketsana was classified as a Category 2 typhoon on the Saffir-Simpson scale with sustained windspeeds of 140 km/h, peaking at 170 km/h.[3] More notably, Ketsana brought torrential rainfall over a three-day period, leading to massive flooding. The Nam Dong station in Thua Thien Hue (one province in our household panel) recorded an accumulated rainfall of 884 mm (34.8 in.) over this period, approximately 2.5 times greater than the province's average monthly precipitation, resulting in unprecedented flood levels (Pham et al., 2018). Ketsana was the most devastating storm on record to strike Vietnam since at least 1989 affecting nearly 2.5 million Vietnamese people across fourteen provinces, including 109,000 homeless, 860 injured, and 182 killed. Typhoon Ketsana caused economic losses totaling $800 million USD in Vietnam, which, at the time, made it the most damaging storm in the country's history (EM-DAT, 2024).[4]

3 Data

3.1 Household Panel Data

Our household-level data comes from the Thailand Vietnam Socio Economic Panel (TVSEP). The TVSEP survey has been administered since 2007 and, to date, nine waves of data have been collected.[5] In this study, we use data from the 2007, 2008, 2010, and 2013 waves of the

[2]Typhoon Ketsana originally made landfall in the Philippines where it is there known as Tropical Storm Ondoy, causing widespread damage totaling over $200 million USD.

[3]The Saffir-Simpson scale classifies hurricanes and tropical cyclones into five distinct categories based on the intensity of their sustained windspeeds. A storm is classified as a hurricane or cyclone if it has sustained one-minute-average maximum windspeeds of at least 119 km/h. A storm is classified as Category 5, the highest category, with sustained winds of at least 252 km/h. To date, only five storms have made landfall in Vietnam of Category 2 or higher with Typhoon Mindulle achieving the highest sustained winds of 230 km/h.

[4]Typhoons Hato and Damrey, both in 2017, have since surpassed Ketsana as the most damaging storms in Vietnam.

[5]Nine waves have been collected in Thailand while seven waves have been collected in Vietnam.

Vietnamese sample. The TVSEP survey is administered to households in the provinces of Dak Lak, Ha Tinh, and Thua Thien Hue. Figure 1 provides a map of Vietnam highlighting the three provinces in the TVSEP dataset. Households were randomly selected through a stratification process taking into account the diverse agroecological conditions within each province and are representative of the rural population in Vietnam.[6] The surveys are conducted between June and August in each wave. As the typhoon made landfall on September 29, 2009 and intense rainfall and flooding occurred over two days, the data before and after the typhoon are from 2008 and 2010 in the short-term analysis. Therefore, the pre-typhoon data was collected 13 to 15 months before the typhoon and the post-typhoon data was collected 9 to 11 months after the typhoon.

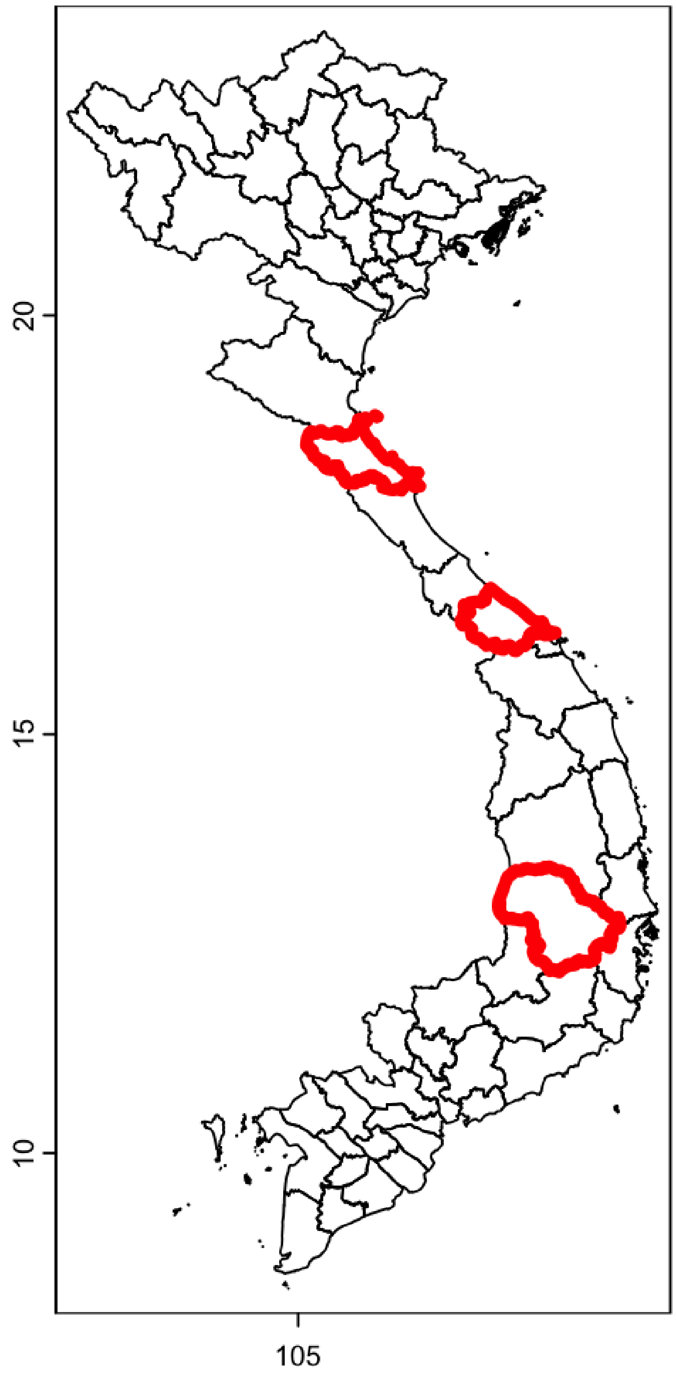
The TVSEP survey asks respondents about their willingness to take risks on an 11-point Likert scale ranging from 0 to 10, where 0 corresponds to "unwilling to take risks" and 10 means "fully prepared to take risks". This self-assessment of risk preferences has been shown to have predictive power across a range of risky behaviors (Dohmen et al., 2011). One concern with a self-reported risk measure, as opposed to an incentive-compatible measure, is that it may not accurately capture the true underlying risk preference. However, multiple studies have documented that survey-based self-assessments are reliable measures of real risk-taking behavior. This particular measure has also been shown to demonstrate greater external validity than incentive-compatible measures of risk preferences (Schildberg-Hörisch, 2018). A second concern is that this type of risk measure may be correlated with subjective expectations about the likelihood and frequency of risk occurring, making it difficult to assess changes in the risk preference parameter. The TVSEP survey asks respondents whether and how frequently numerous risks are likely to occur over the next five years. We use this information both as a robustness check to our main identification strategy to strip subjective expectations from risk preferences and as a test of whether these beliefs may mediate changes in risk preferences.

In addition to the risk preference measure, we use TVSEP data on individual characteristics, including household expenditure and assets, age, gender, household size, and changes in marital status, shocks experienced by the household, subjective expectations of future shocks well-being, and risk-related behaviors, including insurance premiums paid and expenditures on drinking, smoking, and gambling.

The sample selection is determined as follows. We begin with 2,197 households in the Vietnamese dataset. As we are interested in identifying changes in risk preferences at the individual level, we identify the households for which the respondent is the same in each wave from 2007 to 2013, leaving us with one-third of the sample, or 723 subjects. We do not have the risk measure in the 2007 TVSEP wave. Therefore, we use several risk-taking behaviors as a proxy for the risk measure to inspect the validity of pre-trends. Given that these risk behaviors are related to employment, financial, and expenditure decisions, we focus only on subjects who are the head of household and are likely to be making these decisions. We eliminate 6 respondents who are not the head of the household. We then remove respondents with missing values for the risk measure, demographic, and shock variables. Our final sample is 572 respondents across four waves and 216 villages. We merge the TVSEP data with the rainfall data at the village level, as this is the smallest geographic unit available in the TVSEP dataset.

[6]For details on the sampling strategy see Hardeweg et al. (2013).

Figure 1: Provinces of Vietnam



Notes: Map of the provinces of Vietnam. The highlighted provinces correspond to where the TVSEP dataset was collected. The northernmost highlighted province is Ha Tinh, the central province is Thua Tien Hue, and the southernmost province is Dak Lak.

Table 1: Summary Statistics

	Observations	Mean	SD	Min	Max
Risk Preference					
Risk Preference	572	3.44	3.04	0.00	10.00
Individual Characteristics					
Daily Expenditure (per capita, USD)	572	2.04	1.61	0.11	24.03
Assets (Log)	572	7.75	1.25	3.30	11.69
Age	572	51.67	13.68	22.00	91.00
Gender (1 = Male)	572	0.74	0.44	0.00	1.00
Household Size	572	4.77	2.12	1.00	14.00
Δ Marital Status	572	0.03	0.17	0.00	1.00
Shocks					
Death	572	0.03	0.18	0.00	2.00
Accident	572	0.02	0.15	0.00	1.00
Drought	572	0.10	0.35	0.00	3.00
Pest/Livestock Disease	572	0.30	0.51	0.00	2.00
Crime	572	0.02	0.15	0.00	1.00
Subjective Expectations about Occurrence of Shocks					
Storms	566	2.30	2.43	0.00	6.00
Behaviors					
Insurance Premium (Daily)	572	0.21	1.10	0.00	21.43
Drinking & Smoking Budget Share	572	0.03	0.05	0.00	0.26
Gambling Budget Share	572	0.00	0.00	0.00	0.02
$\mathbb{1}\{$Drinking & Smoking$\}$	572	0.56	0.50	0.00	1.00
$\mathbb{1}\{$Gambling$\}$	572	0.03	0.18	0.00	1.00
Weather Controls					
Flooding Propensity	572	0.15	0.11	0.02	0.60
Treatment Variable					
Excess Rainfall (mm)	572	31.23	29.76	-6.21	90.23

Notes: The data are from the TVSEP dataset in 2008 (one year prior to the typhoon), for all variables presented except for our treatment. The risk preference variable is a response to the question "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risk?", where 0 indicates "completely unwilling to take risks" and 10 indicates "fully prepared to take risks". The subjective beliefs section records the number of times the respondent anticipates facing a given shock in the next five years. The treatment variable of excess rainfall is calculated as daily average rainfall during landfall (September 28 and 29, 2009) minus daily average rainfall before landfall (September 26 and 27, 2009) and after landfall (September 30–October 10, 2009). The surveys prior to the 2013 wave limit the response to the subjective beliefs about future shocks to an upper bound of 6. In the 2013 wave, we similarly cap all values at this upper bound. The number of observations for the subjective probabilities for flooding, storms, and house damage is due to missing values.

Table 1 presents the summary statistics of the sample in the year 2008, one year before the typhoon.[7] The mean risk measure is 3.44, which takes on values between 0 and 10. The average age of subjects is 52—74% of which are male. The mean household size is about five members.

One possible concern with the sample is selection bias due to nonrandom attrition following typhoon exposure. We find that only thirty-three households with the same respondent prior to the typhoon attrite from the sample. Nonetheless, we estimate a linear probability model of attrition on treatment intensity and baseline covariates to test for this possibility and find no significant relationship between typhoon exposure and attrition (coefficient = -0.001, p = 0.892), alleviating concerns that selection bias drives our estimates (Appendix Table B2).[8][9] Our analysis also requires having the same respondent across survey waves, as risk preferences are individual-level characteristics and changes in respondent identity would confound our estimates. Appendix Table A6 compares baseline characteristics of households with a consistent respondent across all survey waves (2007–2013) to those of households with differing respondents. Households with consistent respondents tend to have more assets, are older, and these respondents are more likely to be male. While typhoon exposure does not differ significantly across these groups, our estimates should be interpreted as most representative of this type of household.

3.2 Precipitation

Our treatment variable T_v is a measure of precipitation, constructed using data from the National Oceanic and Atmospheric Administration's (NOAA) Rainfall Estimation Algorithm Version 2 (RFE 2.0).[10] The variable captures excess rainfall due to the typhoon by comparing precipitation during the days of the storm to the days immediately before and after. That is, we take the daily average rainfall during the storm (September 28 and 29, 2009) and subtract the daily average rainfall before (September 26 and 27, 2009) and after the storm (September 30– October 10, 2009).[11][12] In this way, the treatment variable captures the immediate impact of the storm during landfall at the village level.

Figure 2 shows the daily rainfall estimates from RFE 2.0 in South Asia for a period before, during, and after Typhoon Ketsana made landfall in Vietnam. Much of Central Vietnam experienced daily precipitation values exceeding 100 mm (3.94 in.) during the storm. By comparison, the average monthly precipitation in the country from 2001–2008 was 149 mm (5.87 in.)

[7] Please see Appendix Tables A2, A3, and A4 for summary statistics by province.

[8] Results are robust to using logit and probit specifications.

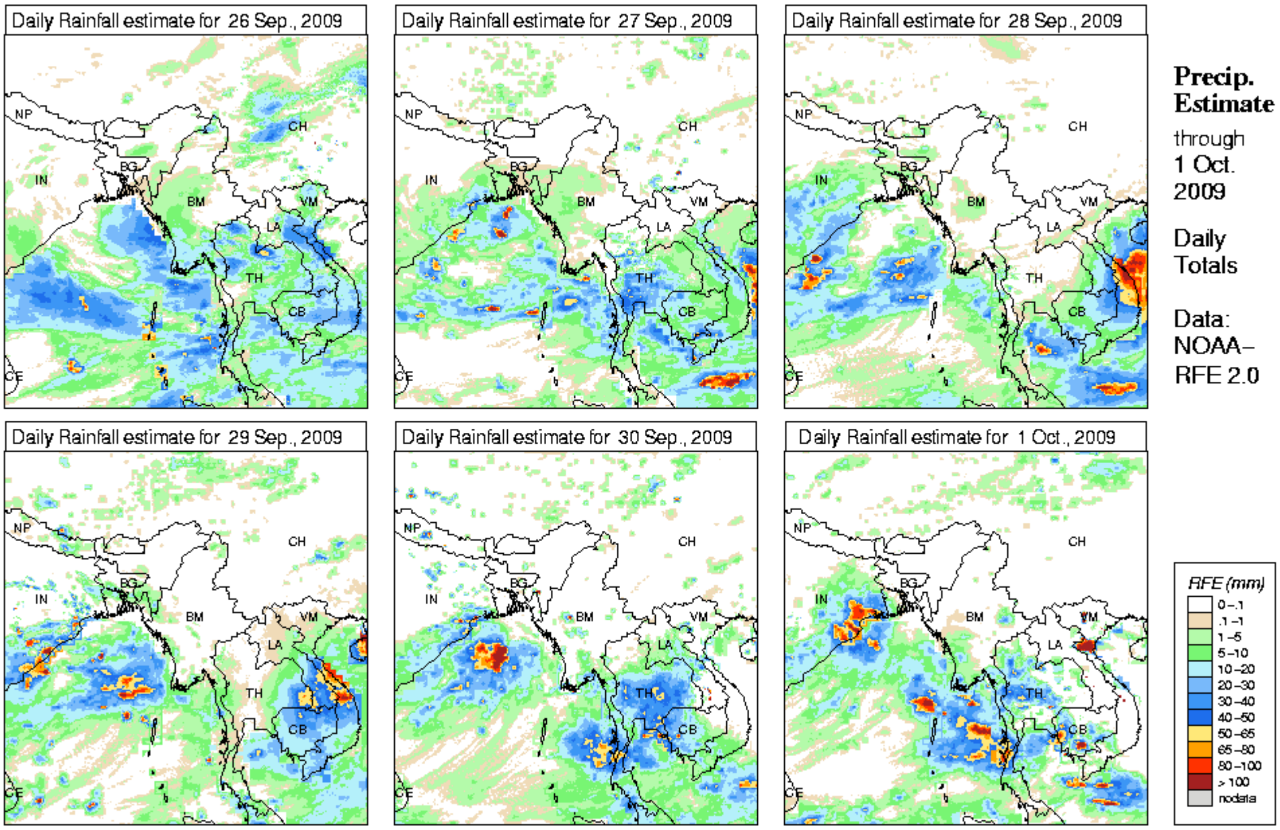
[9] Table A5 displays summary statistics between the two groups.

[10] The RFE 2.0 algorithm combines station rainfall measurements with data from different satellite sources and is implemented by NOAA's Climate Prediction Center. Version 2.0 of the algorithm, which has been operational since 2001, provides daily rainfall estimates at a resolution of 0.1 degrees. The data can be accessed publicly at https://ftp.cpc.ncep.noaa.gov/fews/S.Asia/data/.

[11] To verify whether our findings are sensitive to the days chosen for the construction of the treatment variable, we ran our same specifications using alternative treatment variables calculated using slightly different days. Our results are robust across these alternative constructions of the treatment variable and our preferred variable, which includes more days than the others.

[12] See Gröger and Zylberberg (2016) for similar treatment variable construction to estimate the impact of Typhoon Ketsana on labor migration and remittances.

Figure 2: Daily Rainfall Estimates from RFE 2.0, September 26 – October 1, 2009



Source: USGS Daily NOAA RFE and GFS Forecast. Available at https://earlywarning.usgs.gov/fews/product/83.

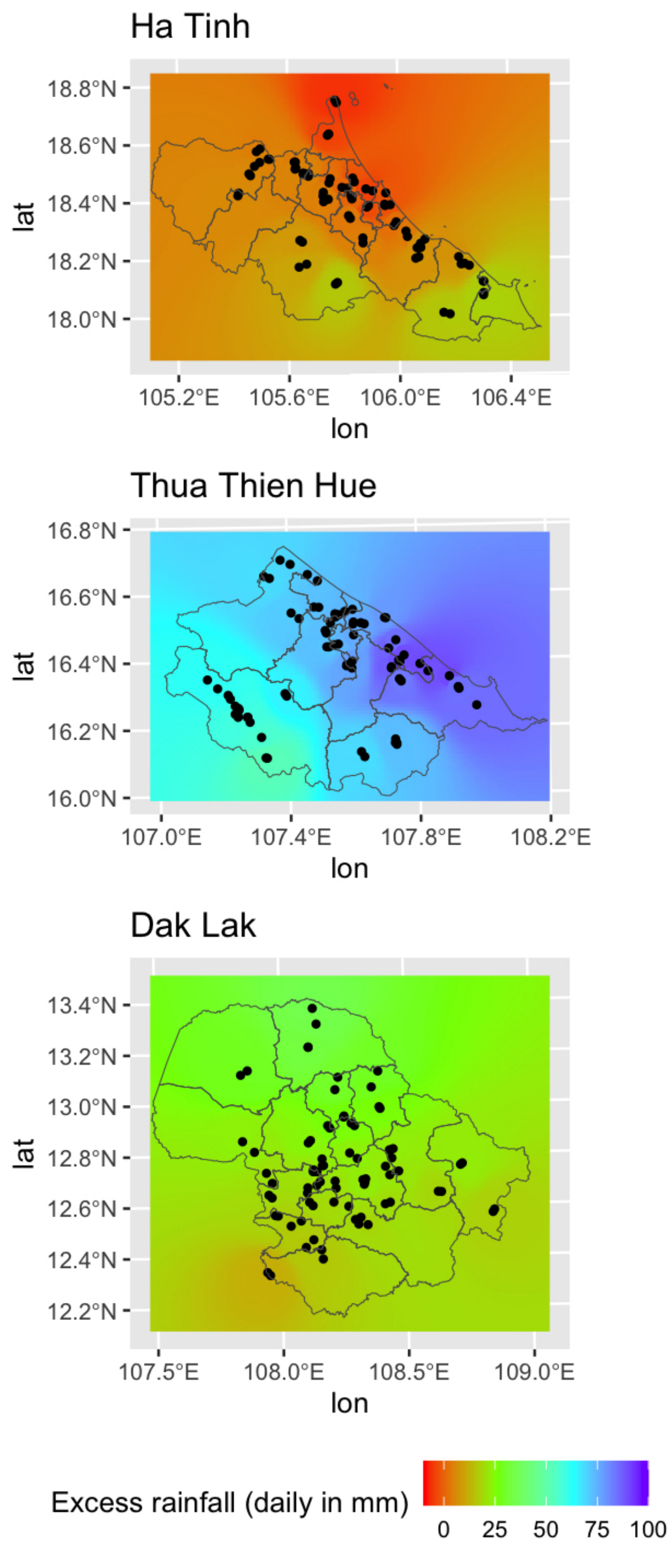
(World Bank, 2024). In our sample province of Thua Tien Hue, total rainfall from the typhoon reached 884 mm (34.80 in.) (ReliefWeb, 2009). At the same time, rainfall in some provinces was largely unaffected by the typhoon, which hints at the variation in treatment intensity we see in our data.

Figure 3 shows how the treatment variable varies across the different provinces covered by the survey. Villages in Thua Thien Hue, the most central province in the sample, were exposed to the heaviest excess rainfall during the passing of Typhoon Ketsana, with households receiving a mean value of 74.37 mm (2.93 in.) of additional rain per day compared to normal times. In contrast, Ha Tinh and Dak Lak were less exposed to excess rainfall during the typhoon. The average excess rainfall level in the entire sample is 31.23 mm (1.23 in.) per day.

4 Empirical Strategy

We explore the effect of the typhoon on risk preferences using the TVSEP panel data before (2008), after (2010), and long after (2013) the typhoon. Our identification strategy uses a difference-in-differences framework with a continuous treatment variable that exploits varia-

Figure 3: Rainfall intensity during the passing of Typhoon Ketsana in survey provinces



Notes: Excess rainfall estimates (measured in millimeters) on September 28–29 compared to September 26–27 and September 30–October 10, 2009.
Source: Authors' calculations based on NOAA RFE 2.0 data.

tion in the intensity of the typhoon. Using this panel data, we can isolate the impact of this exogenous exposure by comparing differences in risk preferences across individuals with differing levels of exposure to the typhoon.

The following equation describes our main specification to formally test whether the typhoon impacted risk preferences:

$$Y_{ivt} = Post_t + \beta T_v \times Post_t + \rho P_v \times Post_t + \gamma X_{ivt} + \delta Z_{ivt} + \pi_i + \varepsilon_{ivt}, \qquad (1)$$

where i indexes the individual, v the village, and t time ($t = 2008$, 2010, or 2013); Y_{ivt} is the self-reported risk measure; $Post_t$ is a dummy that turns on when $t = 2010$ when measuring short-term effects or $t = 2013$ when measuring long-term effects; T_v is excess rainfall within a 5 km radius of village v during typhoon days compared to days before and after; P_v is the water coverage within a 5 km radius of village v during normal times,[13] which we interact with $Post_t$ to account for potential heterogeneity in trends; X_{ivt} is a vector of time-varying socio-demographic characteristics; Z_{ivt} is a vector of controls for life changes and other shocks that may alter risk preferences (Kettlewell, 2019); and π_i is individual-level fixed effects. We cluster the standard errors at the subdistrict level.

To guard against the possibility that individual characteristics vary systematically with typhoon severity (e.g., asset holdings), we use entropy balancing weights to ensure covariate balance conditional on rainfall intensity, reporting results with and without reweighting (Hainmueller, 2012).[14]

The identifying assumption underlying any difference-in-differences framework is that trends in the outcome variable of interest are unchanged across both treatment and control groups if the treatment had never occurred. While a direct test of this assumption is not possible, we can test for similar pre-trends between the treatment and control groups. The TVSEP survey dates back to 2007, thus we can test pre-trends between 2007 and 2008, one and two years before the typhoon. However, the risk measure is not introduced into the TVSEP survey until the 2008 wave.

Therefore, to test for pre-trends we identify risk-taking behaviors that can serve as a proxy for the risk measure. Our preferred variable for risk-taking behavior is total yearly insurance premium payments (at the daily level).[15][16] By plotting the relationship between excess rainfall due to the 2009 typhoon and changes in insurance premiums between 2007 and 2008, Figure 4 suggests no relationship exists between typhoon intensity and pre-typhoon changes in insurance premiums. Table 2 confirms this relationship by showing the results from running equation (1) using the proxy risk measure as opposed to our main outcome variable, and comparing our two pre-typhoon periods.[17]

[13] Data obtained from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS).

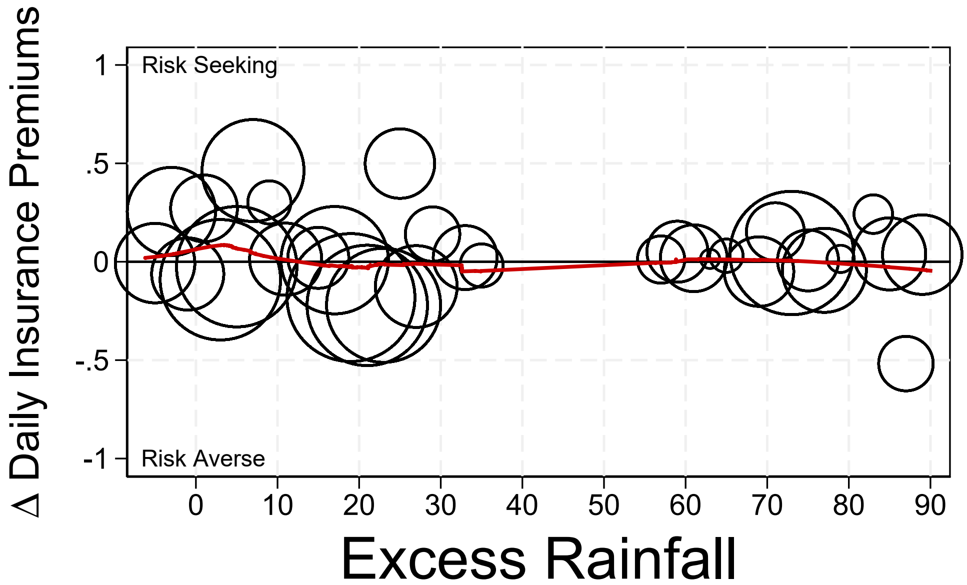
[14] Appendix Tables B6 and B7 display balance tests with and without entropy balancing weights.

[15] The TVSEP survey captures information on multiple types of insurance payments including life, property, health, disability health, livestock, crop, funeral, and accident insurance.

[16] We test additional risk-taking behaviors and report the results in Table B1, reaching the same conclusion.

[17] Pre-trends tests under alternative treatment specifications are reported in Table B3, with robust results across all specifications.

Figure 4: Change in Daily Insurance Premiums Before Typhoon and Exposure to Excess Rainfall During Typhoon



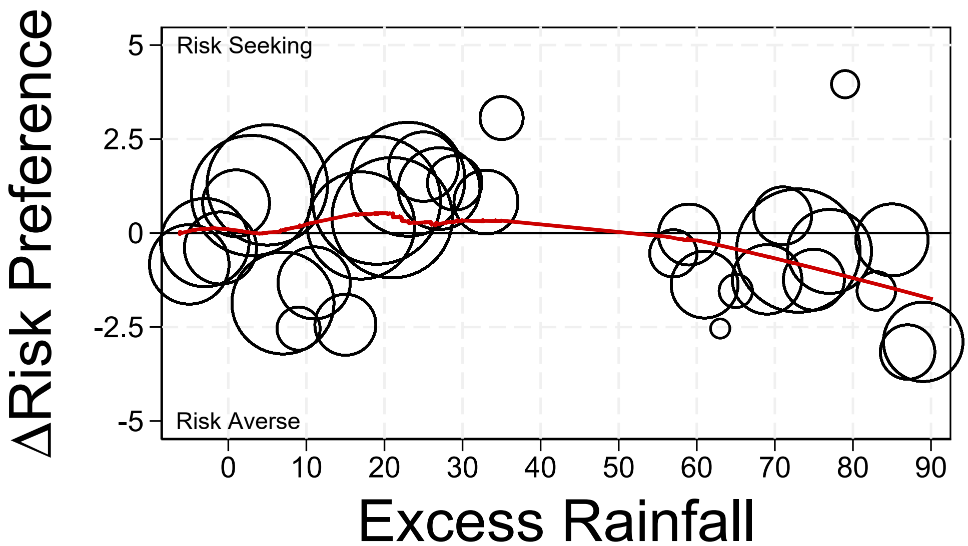
Notes: Change in the daily insurance premiums (USD) between 2007 and 2008 on the *y*-axis. Excess rainfall in millimeters on the *x*-axis is calculated as daily average rainfall during landfall minus daily average rainfall before and after landfall. Individuals are classified into 2-millimeter bins according to the exposure to excess rainfall during the typhoon. The size of each circle represents the number of individuals in the corresponding bin. We plot a *lowess* curve with a bandwidth of 0.8.

Table 2: Pre-treatment Trends: Changes in Daily Insurance Premium (2007-2008)

	(1)	(2)
Excess Rainfall	0.016	0.026
	(0.036)	(0.039)
Observations	1144	1144
Individual FE	✓	✓
Controls & Reweighting		✓

Notes: The dependent variable is the total amount of insurance premiums paid by the household, calculated at the daily level. We report the difference-in-differences coefficient, i.e., the coefficient before the treatment interacted with a dummy for the 2008 wave. Controls include expenditure, assets, age, change in respondent's marital status, household size, exogenous shocks to the household including accidents, drought, pest and livestock diseases, crime, and death of a household member, and historical flooding propensity. Flooding propensity refers to the historical average flooding for the same time window around the typhoon in 2001–2008. Entropy balancing weights are applied, ensuring covariate balance conditional on rainfall intensity. Standard errors are in parentheses and clustered at the subdistrict level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 5: Short-term Changes in Risk Preferences (2008–2010) and Exposure to Excess Rainfall During Typhoon



Notes: Change in self-reported risk preferences (measured on a 0-to-10 scale) between 2008 and 2010 on the *y*-axis. Excess rainfall in millimeters on the *x*-axis is calculated as daily average rainfall during landfall minus daily average rainfall before and after landfall. Individuals are classified into 2-millimeter bins according to the exposure to excess rainfall during the typhoon. The size of each circle represents the number of individuals in the corresponding bin. We plot a *lowess* curve with a bandwidth of 0.8.

5 Results

5.1 Short-term Effects on Risk Preferences

Figure 5 shows the relationship between the typhoon intensity measured by excess rainfall and the change in the risk preference measure one year after the storm. We refer to these as the short-term effects of the typhoon on risk preferences. The graph suggests a clear negative relationship, where those affected more severely by the typhoon become more risk averse by a greater degree.

Table 3 confirms our findings, where our preferred specification (column (2)) indicates that a one standard deviation increase in excess rainfall leads to a 0.11 standard deviation decrease in the risk measure. This result is robust to alternative specifications of the treatment variable that include varying the comparison window around landfall and the radii around villages.[18]

[18] In Appendix Table B4, we vary some of the elements used to construct the treatment variable. For the radius of the buffer around each village, we consider 1 km and 3 km as alternatives to our preferred choice of 5 km. For the time period against which we compare the typhoon days, we shorten our preferred window by three and five days. Across all combinations of these choices, the estimated short-term effect remains negative and similar

Table 3: Short-term Changes in Risk Preferences (2008–2010)

	(1)	(2)
Excess Rainfall	-0.160***	-0.112**
	(0.057)	(0.056)
Observations	1144	1144
Individual FE	✓	✓
Controls & Reweighting		✓

Notes: The dependent variable is the respondent's stated risk preference. The risk preference variable is a response to the question "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risk?", where 0 indicates "completely unwilling to take risks" and 10 indicates "fully prepared to take risks". We report the difference-in-differences coefficient, i.e., the coefficient before the treatment interacted with a dummy for the 2010 wave. Controls include expenditure, assets, age, change in respondent's marital status, household size, exogenous shocks to the household including accidents, drought, pest and livestock diseases, crime, and death of a household member, and historical flooding propensity. Flooding propensity refers to the historical average flooding for the same time window around the typhoon in 2001–2008. Entropy balancing weights are applied, ensuring covariate balance conditional on rainfall intensity. Standard errors are in parentheses and clustered at the subdistrict level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2 Long-term Effects on Risk Preferences

The short-term effect shown above could, in principle, be short-lived, and risk preferences soon revert to their pre-typhoon level. To investigate this possibility, we leverage the panel data structure by running equation (1) to test for the persistent effect of the typhoon on risk preferences four years later.

Figure 6 shows the relationship between typhoon intensity measured by excess rainfall and the change in the risk preference measure four years after the storm. We refer to these as the long-term effects of the typhoon on risk preferences. The graph suggests a clear negative relationship that appears even more pronounced than the short-term result.

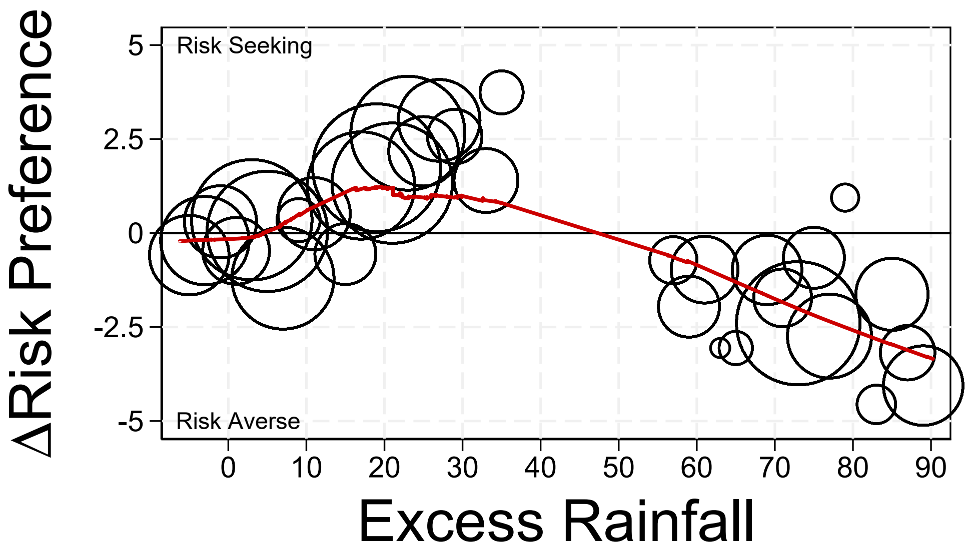
Table 4 confirms our findings, where our preferred specification (column (2)) indicates that a one standard deviation increase in excess rainfall leads to a 0.14 standard deviation decrease in the risk measure. This result is again robust to alternative specifications of the treatment variable that vary the comparison window around landfall and the radii around villages, as previously described (see Appendix Table B5).

5.3 Mechanisms

Next, we explore the mechanisms underlying the observed increase in risk aversion following typhoon exposure. We focus on three plausible explanations: changes in subjective expectations about future shocks, psychological responses related to future outlook and attitudes toward uncertainty, and pecuniary channels.

in magnitude to the estimate under our preferred specification. We use the 5 km radius and the longer temporal window as our preferred specification because, for gridded weather variables, this wider buffer is commonly used and reduces the influence of any single pixel on village-level exposure, while the longer comparison window provides a more stable measure of rainfall during normal times.

Figure 6: Long-term Changes in Risk Preferences (2008–2013) and Exposure to Excess Rainfall During Typhoon



Notes: Change in self-reported risk preferences (measured on a 0-to-10 scale) between 2008 and 2013 on the y-axis. Excess rainfall in millimeters on the x-axis is calculated as daily average rainfall during landfall minus daily average rainfall before and after landfall. Individuals are classified into 2-millimeter bins according to the exposure to excess rainfall during the typhoon. The size of each circle represents the number of individuals in the corresponding bin. We plot a *lowess* curve with a bandwidth of 0.8.

We first examine subjective expectations. Individuals' change in risk attitudes in response to a shock could relate to how the shock leads them to change their expectations about the frequency of future shocks. Our data allows us to test the hypothesis of whether the typhoon leads people to think that storms will be more frequent in the future compared to what they anticipated before the typhoon. We study this hypothesis by comparing the change in responses to the question "How often, do you think, will a storm occur in the next five years?" between 2008 and 2010 for short-term effects and between 2008 and 2013 for long-term effects, using our specification from equation (1).

Table 5 shows that, in the short term, individuals exposed to higher excess rainfall revise their expectations of future storms upward. In our preferred specification, a SD increase in excess rainfall increases the expected frequency of storms over the next five years by 0.27 SDs. However, this effect does not persist, and by the long run, the relationship between typhoon exposure and expected storm frequency is close to zero and statistically insignificant. This temporal pattern indicates that belief updating about the occurrence of future storms is short-lived. This conclusion stands in contrast to our main results, where the increase in risk aversion persists four years after landfall. If belief updating about future storms were the primary mechanism behind the change in risk preferences, we would expect the effect

Table 4: Long-term Changes in Risk Preferences (2008–2013)

	(1)	(2)
Excess Rainfall	-0.185***	-0.140***
	(0.033)	(0.032)
Observations	1144	1144
Individual FE	✓	✓
Controls & Reweighting		✓

Notes: The dependent variable is the respondent's stated risk preference. The risk preference variable is a response to the question "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risk?", where 0 indicates "completely unwilling to take risks" and 10 indicates "fully prepared to take risks". We report the difference-in-differences coefficient, i.e., the coefficient before the treatment interacted with a dummy for the 2013 wave. Controls include expenditure, assets, age, change in respondent's marital status, household size, exogenous shocks to the household including accidents, drought, pest and livestock diseases, crime, and death of a household member, and historical flooding propensity. Flooding propensity refers to the historical average flooding for the same time window around the typhoon in 2001–2008. Entropy balancing weights are applied, ensuring covariate balance conditional on rainfall intensity. Standard errors are in parentheses and clustered at the subdistrict level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

of typhoon exposure on subjective expectations to last over a similar horizon. Instead, the effect dissipates by 2013, while the risk preference effect remains. This mismatch suggests that changes in subjective expectations about future storms are unlikely to be the primary explanation for the long-term increase in risk aversion.

We then assess whether these changes in subjective expectations mediate the effect of the typhoon on risk preferences. Table 6 incorporates subjective expectations about future storm occurrence directly into our main specification. While subjective expectations are positively associated with risk preferences in the short term, their inclusion does not attenuate the magnitude of the excess rainfall coefficient. In the preferred short-term specification, the coefficient on excess rainfall changes only from -0.112 to -0.115 after controlling for expected storm frequency. This result indicates that, although subjective expectations respond to the typhoon in the short run, they account for little to no share of the main treatment effect.

As for psychological mechanisms, Table 7 examines the impact of typhoon exposure on individuals' outlook about the future. Respondents are asked whether they think they will be better off in five years, with higher values on a scale from 1–5 indicating a more pessimistic future outlook. Panel A shows that excess rainfall has a positive and statistically significant effect on future pessimism. Individuals more severely exposed to the typhoon are therefore more likely to report that they expect to be worse off in the future. Panel B then assesses whether this measure helps account for the effect of typhoon exposure on risk preferences. When future pessimism is added to the main specification, the coefficient on excess rainfall falls in magnitude from -0.112 to -0.090 and is no longer statistically significant. Future pessimism itself is negatively and significantly associated with the risk preference measure, indicating that individuals who are more pessimistic about the future report lower willingness to take risks. This pattern is consistent with the idea that the typhoon shock affected how individuals evaluated risky prospects partly through broader psychological responses, such as increased pessimism,

Table 5: Changes in Subjective Expectations about Storms in Next Five Years

	(1)	(2)
Panel A: Short-term Effects (2008–2010)		
Excess Rainfall	0.170**	0.269***
	(0.082)	(0.084)
Observations	1136	1136
Panel B: Long-term Effects (2008–2013)		
Excess Rainfall	-0.025	0.002
	(0.037)	(0.042)
Observations	1138	1138
Individual FE	✓	✓
Controls & Reweighting		✓

Notes: The dependent variable is the expected number of storms in the next five years. We report the difference-in-differences coefficient, i.e., the coefficient before the treatment interacted with a dummy for the 2010 wave for short-term effects and the 2013 wave for long-term effects. Controls include expenditure, assets, age, change in respondent's marital status, household size, exogenous shocks to the household including accidents, drought, pest and livestock diseases, crime, and death of a household member, and historical flooding propensity. Flooding propensity refers to the historical average flooding for the same time window around the typhoon in 2001–2008. Entropy balancing weights are applied, ensuring covariate balance conditional on rainfall intensity. Standard errors are in parentheses and clustered at the subdistrict level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Subjective Expectations About Storms as Risk Preference Mediator

	(1)	(2)	(3)	(4)
Excess Rainfall	-0.160***	-0.169***	-0.112**	-0.115**
	(0.057)	(0.054)	(0.056)	(0.056)
Storms		0.076**		0.042
		(0.037)		(0.037)
Observations	1144	1128	1144	1128
Individual FE	✓	✓	✓	✓
Controls & Reweighting			✓	✓

Notes: The dependent variable is the respondent's stated risk preference. The risk preference variable is a response to the question "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risk?", where 0 indicates "completely unwilling to take risks" and 10 indicates "fully prepared to take risks". We report the difference-in-differences coefficient, i.e., the coefficient before the treatment interacted with a dummy for the 2010 wave. The storms variable is the respondent's expected frequency of storms that will occur in the next five years. Controls include expenditure, assets, age, change in respondent's marital status, household size, exogenous shocks to the household including accidents, drought, pest and livestock diseases, crime, and death of a household member, and historical flooding propensity. Flooding propensity refers to the historical average flooding for the same time window around the typhoon in 2001–2008. Entropy balancing weights are applied, ensuring covariate balance conditional on rainfall intensity. Standard errors are in parentheses and clustered at the subdistrict level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

a heightened sense of vulnerability, or fear about the future—a channel previously alluded to in the literature on the effect of shocks on risk preferences.

Finally, we examine whether pecuniary channels help explain the effect of typhoon exposure on risk preferences. Table 8 first shows that exposure to increased excess rainfall led to tangible costs for affected households. In Panel A, we see that excess rainfall significantly increases asset losses and extra expenditures, while the effect on income losses is positive but noisily estimated. These results indicate that the typhoon did cause measurable economic harm to affected households, particularly through losses to assets and additional spending needs.

Panel B then incorporates these measures of economic cost directly into our main specification. If pecuniary losses were a key channel behind the increase in risk aversion, we would expect the coefficient on excess rainfall to fall substantially once these variables are included. Instead, the coefficient remains negative and similar in magnitude across specifications, with the inclusion of extra expenditure leading to the greatest decrease in the main coefficient. Moreover, we find that asset losses are not significantly associated with risk preferences, income losses are positively associated with the risk preference measure, and extra expenditures are negatively associated with the risk preference measure only at the 10% level.

Taken together, these results suggest that although the typhoon generated meaningful economic costs, these pecuniary channels do not appear to account for the main treatment effect as clearly as the psychological channel documented above. That is, while psychological responses are an important channel through which severe climate shocks may shape risk attitudes, there is still room for economic losses to matter as part of the broader experience of the shock.

Table 7: Future Subjective Well-being

	Future Pessimism (1)	
Panel A: Treatment Effect on Future Outlook		
Excess Rainfall	0.140***	
	(0.038)	
Observations	1048	
	Risk Preference (1)	**Risk Preference (2)**
Panel B: Mediation Analysis		
Excess Rainfall	-0.112**	-0.090
	(0.058)	(0.060)
Future Pessimism		-0.149***
		(0.055)
Observations	1144	1048

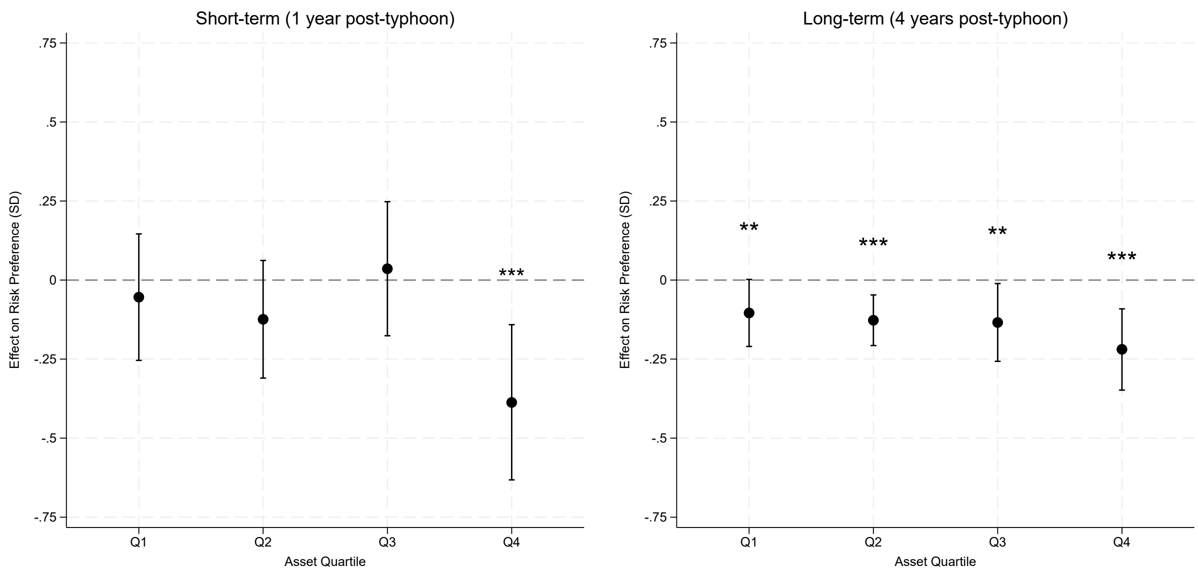
Notes: The dependent variable in Panel A is the respondent's subjective assessment of future well-being. The subjective well-being variable is a response to the question "Do you think you in person will be better off in 5 years?", where 1 corresponds to "much better off" and 5 corresponds to "much worse off". The dependent variable in Panel B is the respondent's stated risk preference. The risk preference variable is a response to the question "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risk?", where 0 indicates "completely unwilling to take risks" and 10 indicates "fully prepared to take risks". We report the difference-in-differences coefficient, i.e., the coefficient before the treatment interacted with a dummy for the 2010 wave. Controls include expenditure, assets, age, change in respondent's marital status, household size, exogenous shocks to the household including accidents, drought, pest and livestock diseases, crime, and death of a household member, and historical flooding propensity. Flooding propensity refers to the historical average flooding for the same time window around the typhoon in 2001–2008. Entropy balancing weights are applied, ensuring covariate balance conditional on rainfall intensity. Standard errors are in parentheses and clustered at the subdistrict level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Economic Mechanisms

	Asset Losses (1)	Income Losses (2)	Extra Expenditure (3)	
Panel A: Treatment Effect on Economic Costs				
Excess Rainfall	0.100**	0.116	0.238**	
	(0.045)	(0.074)	(0.092)	
Observations	1144	1144	1144	
	Risk Preference (1)	Risk Preference (2)	Risk Preference (3)	Risk Preference (4)
Panel B: Mediation Analysis				
Excess Rainfall	-0.112**	-0.109*	-0.118**	-0.104*
	(0.058)	(0.056)	(0.055)	(0.055)
Asset Losses		-0.029		
		(0.022)		
Income Losses			0.051***	
			(0.014)	
Extra Expenditure				-0.033*
				(0.020)
Observations	1144	1144	1144	1144

Notes: In Panel A, the dependent variables are standardized measures—coefficients therefore represent SD changes in each economic measure associated with a one SD increase in excess rainfall. The dependent variable in Panel B is the respondent's stated risk preference. The risk preference variable is a response to the question "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risk?", where 0 indicates "completely unwilling to take risks" and 10 indicates "fully prepared to take risks". We report the difference-in-differences coefficient, i.e., the coefficient before the treatment interacted with a dummy for the 2010 wave. Controls include expenditure, assets, age, change in respondent's marital status, household size, exogenous shocks to the household including accidents, drought, pest and livestock diseases, crime, and death of a household member, and historical flooding propensity. Flooding propensity refers to the historical average flooding for the same time window around the typhoon in 2001–2008. Entropy balancing weights are applied, ensuring covariate balance conditional on rainfall intensity. Standard errors are in parentheses and clustered at the subdistrict level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 7: Heterogeneous Treatment Effects by Wealth Quartile



Notes: Plot of risk preference coefficients across asset quartiles in one year (left panel) and four years post-typhoon (right-panel).

5.4 Heterogeneous Effects

We next examine whether the effect of typhoon exposure on risk preferences varies by households' baseline wealth. Heterogeneity by baseline wealth is economically important because the welfare and policy implications of climate shocks depend on who changes their attitudes and behavior in response to an event. Figure 7 plots the estimated treatment effects separately by asset quartile, while Table 9 reports the corresponding coefficients and pairwise and joint heterogeneity tests. We constructed asset quartiles using pre-typhoon asset holdings in 2008.

We find meaningful heterogeneity by baseline wealth in the short term. One year after landfall, the increase in risk averseness is concentrated among households in the richest quartile. For the top quartile, the coefficient is negative, large in magnitude (more than thrice the size of the average effect), and statistically significant at the 1% level. By contrast, the coefficients for the three lower wealth quartiles are smaller in magnitude and statistically indistinguishable from zero. The pairwise tests of equality featured in the table support this pattern, as we reject equality between the richest quartile and all lower quartiles at varying degrees of significance, and the joint test rejects equality across all four quartiles at the 5% level. These results indicate that the immediate response to the typhoon in terms of risk preferences was strongest among households with greater baseline asset holdings.

One plausible explanation is that wealthier households had more assets and investments vulnerable to the storm, making the consequences of the typhoon more salient in the short run. Based on this interpretation, the immediate increase in risk aversion may reflect not only

Table 9: Heterogeneous Treatment Effect on Risk Preference by Wealth Quartile

	Short-term (1)	Long-Term (2)
Asset Quartile		
Q1 (Poorest)	-0.054	-0.104*
	(0.101)	(0.053)
Q2	-0.124	-0.127***
	(0.094)	(0.040)
Q3	0.036	-0.134**
	(0.107)	(0.062)
Q4 (Richest)	-0.387***	-0.219***
	(0.124)	(0.065)
Tests of Heterogeneity		
Q1 = Q4	$F = 4.16$, $p = 0.044$	$F = 1.92$, $p = 0.169$
Q2 = Q4	$F = 3.07$, $p = 0.083$	$F = 1.79$, $p = 0.183$
Q3 = Q4	$F = 8.46$, $p = 0.004$	$F = 1.04$, $p = 0.310$
Joint Test (Q1 = Q2 = Q3 = Q4)	$F = 2.86$, $p = 0.041$	$F = 0.74$, $p = 0.528$
Observations	1144	1144

Notes: The dependent variable is the respondent's stated risk preference. The risk preference variable is a response to the question "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risk?", where 0 indicates "completely unwilling to take risks" and 10 indicates "fully prepared to take risks". We report the difference-in-differences coefficient, i.e., the coefficient before the treatment interacted with a dummy for the 2010 wave (short-term) or 2013 wave (long-term) and the asset quartile dummy. Asset quartiles are constructed from assets before the typhoon (2008). Estimation includes individual fixed effects. Controls include expenditure, age, change in respondent's marital status, household size, exogenous shocks to the household including accidents, drought, pest and livestock diseases, crime, and death of a household member, and historical flooding propensity. Flooding propensity refers to the historical average flooding for the same time window around the typhoon in 2001–2008. Entropy balancing weights are applied, ensuring covariate balance conditional on rainfall intensity. Standard errors are in parentheses and clustered at the subdistrict level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

asset exposure to the event itself, but also the perceived vulnerability of households with more to lose. While we cannot directly test this channel, the concentration of the short-term effect among wealthier households is consistent with this view.

The long-term pattern is different. Four years after landfall, the estimated effects are negative across all asset quartiles and statistically significant at conventional levels. While the effect coefficient remains largest in magnitude for the wealthiest quartile, the differences across quartiles become less pronounced, and the joint test no longer rejects equality of effects across the wealth distribution. This pattern indicates that the persistent effect of the typhoon was not confined to households with large baseline asset holdings. Rather, while material exposure and perceived vulnerability may have shaped the immediate response to the event, the long-run increase in risk aversion was more broad-based.

Taken together, Figure 7 and Table 9 suggest that wealth matters most for understanding the short-term adjustment in risk preferences after a climate shock. The richest households respond most strongly in the year following the typhoon, plausibly because the shock made their exposed assets and investments more salient. Over time, however, the effect extends across the wealth distribution, consistent with a broader and slower adjustment to the experience of a severe shock.

5.5 Risk-taking Behaviors

Finally, we investigate the relationship between exposure to the typhoon and changes in behavior related to risk. This exercise allows us to assess whether the persistent increase in risk aversion documented above is reflected in economically meaningful behavioral adjustments. We focus on examining insurance purchasing behavior as well as spending on temptation goods, namely drinking, smoking, and gambling. Table 10 reports the estimated effects of excess rainfall on these outcomes in the short and long term.

Table 10 shows that the clearest behavioral response is an increase in insurance purchasing four years after landfall. In the year immediately following the typhoon, the effect of excess rainfall on insurance premiums is positive but statistically insignificant. In the long term, however, the effect remains positive but becomes statistically significant. A one SD increase in excess rainfall corresponds to an increase of 0.028 SD in daily insurance premiums.

This delayed insurance response is consistent with the interpretation that households may take some time to adjust risk management behavior after a severe shock. Even if the typhoon increased the perceived value of insurance, immediate recovery needs, liquidity constraints, contract timing, limited access to suitable insurance products, or other frictions in insurance markets may have prevented households from modifying their insurance purchases right away. The emergence of a positive effect only in the long term thus suggests that behavioral adjustment may lag behind changes in risk attitudes. This timing pattern is also consistent with the heterogeneity results above, where the increase in risk aversion becomes more broad-based across asset quartiles only in the long term.

We find risk-related behaviors across temptation goods to be less persistent. In the short term, exposure to higher excess rainfall reduces drinking and smoking on the intensive margin

Table 10: Changes in Behavior

	Insurance Premiums (1)	Drinking & Smoking Budget Share (2)	Gambling Budget Share (3)	$\mathbb{1}$\{Drinking & Smoking\} (4)	$\mathbb{1}$\{Gambling\} (5)
Panel A: Short-term					
Excess Rainfall	0.014	-0.029*	-0.001	0.050	-0.261***
	(0.024)	(0.015)	(0.002)	(0.061)	(0.095)
Observations	1144	1144	1144	1144	1144
Panel B: Long-term					
Excess Rainfall	0.028*	-0.006	0.002	-0.003	-0.064
	(0.015)	(0.010)	(0.001)	(0.030)	(0.054)
Observations	1108	1102	1102	1144	1144

Notes: We report the difference-in-differences coefficient, i.e., the coefficient before the treatment interacted with a dummy for the 2010 wave (short-term) or 2013 wave (long-term). Estimation includes individual fixed effects. Controls include expenditure, assets, age, change in marital status of respondent, household size, exogenous shocks to the household including accidents, drought, pest and livestock diseases, crime, and death of a household member, and historical flooding propensity. Flooding propensity refers to the historical average flooding for the same time window around the typhoon in 2001–2008. Entropy balancing weights are applied, ensuring covariate balance conditional on rainfall intensity. Standard errors in parentheses and clustered at the subdistrict level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

and gambling on the extensive margin. These estimates indicate that affected individuals may reduce some risky or discretionary behaviors in the immediate aftermath of the shock. However, these effects do not persist in the long run. By the fourth year after landfall, the estimated effects on drinking and smoking, gambling budget shares, and the extensive-margin indicators are all small and statistically insignificant.

One interpretation of these results is that some behaviors only respond to the immediate disruption caused by the typhoon. Affected households may temporarily reduce spending on temptation goods while reallocating resources toward recovery needs. Over time, however, these short-term reductions dissipate, which is consistent with households returning to prior consumption habits once the most immediate effects of the shock fade. This pattern stands in contrast with the delayed increase in insurance purchasing, suggesting that some behavioral responses to the typhoon reflect temporary post-shock adjustment, while others involve slower changes in risk management decisions.

6 Discussion and Conclusion

We exploit variation in the intensity with which different villages were exposed to Typhoon Ketsana in Vietnam to show that a natural disaster can lead to a persistent increase in the risk aversion of individuals. Using panel data that follow the same respondents before and after the storm, we find that individuals exposed to higher levels of excess rainfall became more risk averse one year after landfall. These short-term effects are not transitory but rather last up to at least four years after the event. These findings contribute to the literature showing that natural disasters can make people more risk averse and provide evidence that such changes can linger well beyond the immediate aftermath of the shock, a fact that had previously not been well documented.

The persistence of the effect helps clarify what does and does not appear to explain the change in risk preferences. Exposure to higher excess rainfall increases expectations of future storms in the short term, but this response dissipates over time. By contrast, the effect on risk preferences remains. This difference in timing suggests that updated subjective expectations about the likelihood of future storms are unlikely to be the main reason exposed individuals remain more risk averse four years after landfall.

The evidence on plausible mechanisms points more strongly toward psychological responses. Individuals exposed to higher excess rainfall become more pessimistic about their future well-being, and including this measure in the main specification substantially reduces the estimated effect of typhoon exposure on risk preferences. This pattern suggests that the typhoon changed risk attitudes partly by altering how individuals viewed their own future prospects, perhaps motivated by fear, stress, or other emotional responses. We also find that typhoon exposure generated measurable economic costs, especially asset losses and extra expenditures, but these pecuniary channels do not appear to account for the main treatment effect as clearly as future pessimism.

We also show that the effect of typhoon exposure varies by baseline wealth. In the short term, the increase in risk aversion is concentrated among households in the richest asset quartile. This pattern is consistent with wealthier households having more assets and investments exposed to the storm, making the consequences of the event more salient in the immediate aftermath. In the long term, however, the effects are negative across all asset quartiles and the evidence of heterogeneity becomes weaker. It appears that while material exposure and perceived vulnerability may have shaped the immediate response, the persistent change in risk preferences was more broad-based.

Finally, we document changes in risk-related behavior. The clearest behavioral response is an increase in insurance purchasing in the long term. Individuals exposed to higher excess rainfall do not significantly increase insurance premiums in the year immediately following the typhoon, but they do so four years after landfall. This delayed response is consistent with households taking time to adjust insurance decisions. Evidence of changes in other risk-related behaviors is weaker and less persistent.

These findings show that the consequences of natural disasters unfold over time. In our setting, exposure to Typhoon Ketsana changed risk preferences in a persistent way, while other responses followed different timelines. Subjective expectations about future storms changed only temporarily, and insurance purchasing increased only in the long term. This timing matters because the immediate aftermath of a disaster may not reveal its full consequences, and assisting households properly with their recovery requires paying attention to the full impact pathways.

The results also suggest that recovery from severe shocks cannot be understood only through material losses. Asset losses, extra expenditures, and insurance responses matter, but so do psychological responses such as pessimism about future well-being. Supporting affected households therefore requires paying attention not only to asset and income recovery, but also to the behavioral and risk-management processes through which households adjust after severe shocks. As climate-related hazards become more frequent and severe, understanding these adjustment processes will be increasingly important for designing policies that support recovery, preparedness, and long-term resilience.

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Appendices

A Summary Statistics

Table A1: Summary Statistics

Variables	Observations	Mean	SD	Min	Max
Risk Preference					
Risk Preference	1716	4.30	3.04	0.00	10.00
Individual Characteristics					
Daily Expenditure (per capita, USD)	1716	6.02	7.99	0.00	62.27
Assets (Log)	1716	7.86	1.23	2.71	11.69
Age	1716	54.07	13.83	22.00	92.00
Gender (1 = Male)	1716	0.74	0.44	0.00	1.00
Household Size	1716	5.04	2.28	1.00	16.00
Δ Marital Status	1716	0.04	0.19	0.00	1.00
Shocks					
Death	1716	0.03	0.18	0.00	2.00
Accident	1716	0.07	0.26	0.00	3.00
Drought	1716	0.17	0.40	0.00	3.00
Pest/Livestock Disease	1716	0.32	0.53	0.00	3.00
Crime	1716	0.07	0.27	0.00	4.00
Subjective Beliefs about Occurrence of Shocks					
Storms	1708	1.87	2.25	0.00	6.00
Behaviors					
Insurance Premium (Daily)	1680	0.22	0.88	0.00	21.43
Drinking & Smoking Budget Share	1674	0.02	0.04	0.00	0.38
Gambling Budget Share	1674	0.00	0.00	0.00	0.04
$\mathbb{1}\{$Drinking & Smoking$\}$	1716	0.47	0.50	0.00	1.00
$\mathbb{1}\{$Gambling$\}$	1716	0.02	0.13	0.00	1.00
Weather Controls					
Flooding Propensity	1716	0.15	0.11	0.02	0.60
Treatment Variable					
Excess Rainfall (mm)	1716	31.23	29.74	-6.21	90.23

Notes: The data are from the TVSEP dataset in 2008 (one year prior to the typhoon), 2010 (one year after the typhoon), and 2013 (four years after the typhoon). The risk preference variable is a response to the question "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risk?", where 0 indicates "completely unwilling to take risks" and 10 indicates "fully prepared to take risks". The subjective beliefs section records the number of times the respondent anticipates facing a given shock in the next five years. The treatment variable of excess rainfall is calculated as daily average rainfall during landfall (September 28 and 29, 2009) minus daily average rainfall before landfall (September 26 and 27, 2009) and after landfall (September 30–October 10, 2009). The surveys prior to the 2013 wave limit the response to the subjective beliefs about future shocks to an upper bound of 6. In the 2013 wave, we similarly cap all values at this upper bound. The number of observations for the subjective probabilities for flooding, storms, and house damage is due to missing values. The number of observations for flooding propensity and rainfall refers to the number of villages in the dataset rather than the individuals.

Table A2: Ha Tinh Summary Statistics

Variables	Observations	Mean	SD	Min	Max
Risk Preference					
Risk Preference	202	3.99	2.76	0.00	10.00
Individual Characteristics					
Daily Expenditure (per capita, USD)	202	1.59	0.88	0.19	6.07
Assets (Log)	202	7.64	1.20	3.59	11.69
Age	202	54.00	13.37	23.00	86.00
Gender (1 = Male)	202	0.68	0.47	0.00	1.00
Household Size	202	4.27	1.79	1.00	11.00
Δ Marital Status	202	0.03	0.17	0.00	1.00
Shocks					
Death	202	0.04	0.23	0.00	2.00
Accident	202	0.04	0.21	0.00	1.00
Drought	202	0.07	0.28	0.00	2.00
Pest/Livestock Disease	202	0.39	0.58	0.00	2.00
Crime	202	0.04	0.20	0.00	1.00
Subjective Beliefs about Occurrence of Shocks					
Storms	199	3.60	2.49	0.00	6.00
Behaviors					
Insurance Premium (Daily)	202	0.11	0.46	0.00	3.81
Drinking & Smoking Budget Share	202	0.02	0.04	0.00	0.26
Gambling Budget Share	202	0.00	0.00	0.00	0.02
$\mathbb{1}\{$Drinking & Smoking$\}$	202	0.44	0.50	0.00	1.00
$\mathbb{1}\{$Gambling$\}$	202	0.01	0.12	0.00	1.00
Weather Controls					
Flooding Propensity	202	0.21	0.08	0.12	0.60
Treatment Variable					
Excess Rainfall (mm)	202	4.08	5.70	-6.21	18.13

Notes: The data are from the TVSEP dataset in 2008 (one year prior to the typhoon) for the province of Ha Tinh, for all variables presented except for our treatment. The risk preference variable is a response to the question "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risk?", where 0 indicates "completely unwilling to take risks" and 10 indicates "fully prepared to take risks". The subjective beliefs section records the number of times the respondent anticipates facing a given shock in the next five years. The treatment variable of excess rainfall is calculated as daily average rainfall during landfall (September 28 and 29, 2009) minus daily average rainfall before landfall (September 26 and 27, 2009) and after landfall (September 30–October 10, 2009). The surveys prior to the 2013 wave limit the response to the subjective beliefs about future shocks to an upper bound of 6. In the 2013 wave, we similarly cap all values at this upper bound. The number of observations for the subjective probabilities for flooding, storms, and house damage is due to missing values.

Table A3: Thua Tien Hue Summary Statistics

Variables	Observations	Mean	SD	Min	Max
Risk Preference					
Risk Preference	169	4.96	3.22	0.00	10.00
Individual Characteristics					
Daily Expenditure (per capita, USD)	169	1.99	1.41	0.11	10.56
Assets (Log)	169	7.50	1.17	4.00	9.63
Age	169	54.70	14.22	23.00	91.00
Gender (1 = Male)	169	0.73	0.45	0.00	1.00
Household Size	169	4.75	2.33	1.00	13.00
Δ Marital Status	169	0.03	0.17	0.00	1.00
Shocks					
Death	169	0.04	0.20	0.00	1.00
Accident	169	0.01	0.08	0.00	1.00
Drought	169	0.03	0.17	0.00	1.00
Pest/Livestock Disease	169	0.24	0.43	0.00	1.00
Crime	169	0.02	0.13	0.00	1.00
Subjective Beliefs about Occurrence of Shocks					
Storms	169	3.17	1.96	0.00	6.00
Behaviors					
Insurance Premium (Daily)	169	0.13	0.48	0.00	5.91
Drinking & Smoking Budget Share	169	0.04	0.05	0.00	0.24
Gambling Budget Share	169	0.00	0.00	0.00	0.02
$\mathbb{1}\{$Drinking & Smoking$\}$	169	0.57	0.50	0.00	1.00
$\mathbb{1}\{$Gambling$\}$	169	0.08	0.27	0.00	1.00
Weather Controls					
Flooding Propensity	169	0.23	0.09	0.12	0.58
Treatment Variable					
Excess Rainfall (mm)	169	74.37	9.36	56.32	90.23

Notes: The data are from the TVSEP dataset in 2008 (one year prior to the typhoon) for the province of Thua Tien Hue, for all variables presented except for our treatment. The risk preference variable is a response to the question "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risk?", where 0 indicates "completely unwilling to take risks" and 10 indicates "fully prepared to take risks". The subjective beliefs section records the number of times the respondent anticipates facing a given shock in the next five years. The treatment variable of excess rainfall is calculated as daily average rainfall during landfall (September 28 and 29, 2009) minus daily average rainfall before landfall (September 26 and 27, 2009) and after landfall (September 30–October 10, 2009). The surveys prior to the 2013 wave limit the response to the subjective beliefs about future shocks to an upper bound of 6. In the 2013 wave, we similarly cap all values at this upper bound. The number of observations for the subjective probabilities for flooding, storms, and house damage is due to missing values.

Table A4: Dak Lak Summary Statistics

Variables	Observations	Mean	SD	Min	Max
Risk Preference					
Risk Preference	201	1.61	2.09	0.00	9.00
Individual Characteristics					
Daily Expenditure (per capita, USD)	201	2.53	2.13	0.33	24.03
Assets (Log)	201	8.07	1.30	3.30	10.52
Age	201	46.77	12.15	22.00	78.00
Gender (1 = Male)	201	0.80	0.40	0.00	1.00
Household Size	201	5.28	2.13	1.00	14.00
Δ Marital Status	201	0.02	0.16	0.00	1.00
Shocks					
Death	201	0.01	0.10	0.00	1.00
Accident	201	0.01	0.12	0.00	1.00
Drought	201	0.20	0.49	0.00	3.00
Pest/Livestock Disease	201	0.26	0.48	0.00	2.00
Crime	201	0.01	0.10	0.00	1.00
Subjective Beliefs about Occurrence of Shocks					
Storms	198	0.24	0.91	0.00	6.00
Behaviors					
Insurance Premium (Daily)	201	0.38	1.74	0.00	21.43
Drinking & Smoking Budget Share	201	0.04	0.04	0.00	0.24
Gambling Budget Share	201	0.00	0.00	0.00	0.01
$\mathbb{1}\{$Drinking & Smoking$\}$	201	0.67	0.47	0.00	1.00
$\mathbb{1}\{$Gambling$\}$	201	0.02	0.14	0.00	1.00
Weather Controls					
Flooding Propensity	201	0.04	0.01	0.02	0.08
Treatment Variable					
Excess Rainfall (mm)	201	22.23	4.83	11.77	34.92

Notes: The data are from the TVSEP dataset in 2008 (one year prior to the typhoon) for the province of Dak Lak, for all variables presented except for our treatment. The risk preference variable is a response to the question "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risk?", where 0 indicates "completely unwilling to take risks" and 10 indicates "fully prepared to take risks". The subjective beliefs section records the number of times the respondent anticipates facing a given shock in the next five years. The treatment variable of excess rainfall is calculated as daily average rainfall during landfall (September 28 and 29, 2009) minus daily average rainfall before landfall (September 26 and 27, 2009) and after landfall (September 30–October 10, 2009). The surveys prior to the 2013 wave limit the response to the subjective beliefs about future shocks to an upper bound of 6. In the 2013 wave, we similarly cap all values at this upper bound. The number of observations for the subjective probabilities for flooding, storms, and house damage is due to missing values.

Table A5: Summary Statistics: Attrition

Variables	N	(1) No Attrition Mean/(SD)	N	(2) Attrition Mean/(SD)	(1)−(2) Pairwise t-test Mean Difference
Risk Preference					
Risk Preference	572	3.44	33	3.33	0.11
		(3.04)		(3.65)	
Individual Characteristics					
Daily Expenditure (per capita, USD)	572	2.04	33	2.66	-0.62**
		(1.61)		(2.34)	
Assets (Log)	572	7.75	33	7.40	0.35
		(1.25)		(1.43)	
Age	572	51.67	33	45.52	6.15**
		(13.68)		(15.38)	
Gender (1 = Male)	572	0.74	33	0.73	0.01
		(0.44)		(0.45)	
Household Size	572	4.77	33	4.24	0.53
		(2.12)		(1.80)	
Δ Marital Status	572	0.03	33	0.06	-0.03
		(0.17)		(0.24)	
Shocks					
Death	572	0.03	33	0.00	0.03
		(0.18)		(0.00)	
Accident	572	0.02	33	0.06	-0.04
		(0.15)		(0.24)	
Drought	572	0.10	33	0.15	-0.05
		(0.35)		(0.44)	
Pest/Livestock Disease	572	0.30	33	0.21	0.09
		(0.51)		(0.55)	
Crime	572	0.02	33	0.00	0.02
		(0.15)		(0.00)	
Subjective Beliefs about Occurrence of Shocks					
Storms	566	2.30	32	1.47	0.83*
		(2.43)		(2.29)	
Behaviors					
Insurance Premium (Daily)	572	0.21	33	0.22	-0.01
		(1.10)		(0.76)	
Drinking & Smoking Budget Share	572	0.03	33	0.05	0.02*
		(0.05)		(0.08)	
Gambling Budget Share	572	0.00	33	0.00	-0.00***
		(0.00)		(0.02)	
$\mathbb{1}${Drinking & Smoking}	572	0.56	33	0.52	0.04
		(0.50)		(0.51)	
$\mathbb{1}${Gambling}	572	0.03	33	0.06	-0.03
		(0.18)		(0.24)	
Weather Controls					
Flooding Propensity	572	0.15	33	0.13	0.02
		(0.11)		(0.11)	
Treatment Variable					
Excess Rainfall (mm)	572	31.23	33	31.56	-0.33
		(29.76)		(25.81)	

Notes: The data are from the TVSEP dataset in 2008 (one year prior to the typhoon), for all variables presented except for our treatment. The attrition group is all households who attrited from the sample in the survey wave immediately following the typhoon (2010). The risk preference variable is a response to the question "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risk?", where 0 indicates "completely unwilling to take risks" and 10 indicates "fully prepared to take risks". The subjective beliefs section records the number of times the respondent anticipates facing a given shock in the next five years. The treatment variable of excess rainfall is calculated as daily average rainfall during landfall (September 28 and 29, 2009) minus daily average rainfall before landfall (September 26 and 27, 2009) and after landfall (September 30–October 10, 2009). The surveys prior to the 2013 wave limit the response to the subjective beliefs about future shocks to an upper bound of 6. In the 2013 wave, we similarly cap all values at this upper bound. The number of observations for the subjective probabilities for flooding, storms, and house damage is due to missing values. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6: Summary Statistics: Household Respondents

Variables	N	(1) Sample Households Mean/(SD)	N	(2) Other Households Mean/(SD)	(1)−(2) Pairwise t-test Mean Difference
Risk Preference					
Risk Preference	572	3.44	157	3.96	-0.52*
		(3.04)		(3.34)	
Individual Characteristics					
Daily Expenditure (per capita, USD)	572	2.04	159	2.26	-0.22
		(1.61)		(2.18)	
Assets (Log)	572	7.75	160	7.32	0.43***
		(1.25)		(1.54)	
Age	572	51.67	160	48.67	3.00**
		(13.68)		(16.97)	
Gender (1 = Male)	572	0.74	160	0.52	0.22***
		(0.44)		(0.50)	
Household Size	572	4.77	160	4.49	0.28
		(2.12)		(2.19)	
Δ Marital Status	572	0.03	160	0.05	-0.02
		(0.17)		(0.22)	
Shocks					
Death	572	0.03	160	0.05	-0.02
		(0.18)		(0.22)	
Accident	572	0.02	160	0.03	-0.01
		(0.15)		(0.17)	
Drought	572	0.10	160	0.11	-0.00
		(0.35)		(0.37)	
Pest/Livestock Disease	572	0.30	160	0.23	0.07
		(0.51)		(0.52)	
Crime	572	0.02	160	0.04	-0.02
		(0.15)		(0.23)	
Subjective Beliefs about Occurrence of Shocks					
Storms	566	2.30	157	2.41	-0.11
		(2.43)		(2.39)	
Behaviors					
Insurance Premium (Daily)	572	0.21	160	0.21	0.00
		(1.10)		(0.75)	
Drinking & Smoking Budget Share	572	0.03	159	0.04	-0.01
		(0.05)		(0.07)	
Gambling Budget Share	572	0.00	159	0.00	-0.00
		(0.00)		(0.01)	
$\mathbb{1}${Drinking & Smoking}	572	0.56	160	0.48	0.08*
		(5.12)		(5.55)	
$\mathbb{1}${Gambling}	572	0.03	160	0.03	0.01
		(0.18)		(0.16)	
Weather Controls					
Flooding Propensity	572	0.15	160	0.17	-0.02
		(0.11)		(0.12)	
Treatment Variable					
Excess Rainfall (mm)	572	31.23	160	34.86	3.64
		(29.76)		(30.15)	

Notes: The data are from the TVSEP dataset in 2008 (one year prior to the typhoon), for all variables presented except for our treatment. The sample group is all households used in the analysis, i.e., households where the survey respondent was the same head of household in each wave between 2007 and 2013. The sample of other households refers to households where the respondent was not the same person at least once between 2007 and 2013. The risk preference variable is a response to the question "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risk?", where 0 indicates "completely unwilling to take risks" and 10 indicates "fully prepared to take risks". The subjective beliefs section records the number of times the respondent anticipates facing a given shock in the next five years. The treatment variable of excess rainfall is calculated as daily average rainfall during landfall (September 28 and 29, 2009) minus daily average rainfall before landfall (September 26 and 27, 2009) and after landfall (September 30–October 10, 2009). The surveys prior to the 2013 wave limit the response to the subjective beliefs about future shocks to an upper bound of 6. In the 2013 wave, we similarly cap all values at this upper bound. The number of observations for the subjective probabilities for flooding, storms, and house damage is due to missing values. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B Regressions

Table B1: Pre-treatment Trends

	Self-employment (1)	Loans : Assets (2)	Loans : Expenditure (3)	Drinking & Smoking Budget Share (4)	Gambling Budget Share (5)	$\mathbb{1}$\{Drinking & Smoking\} (6)	$\mathbb{1}$\{Gambling\} (7)
Excess Rainfall	-0.072	0.121	-0.471	0.003	0.013	-0.033	0.149
	(0.047)	(0.140)	(0.443)	(0.053)	(0.010)	(0.066)	(0.114)
Observations	1143	1144	783	783	783	1144	1144

Notes: We report the difference-in-differences coefficient, i.e., the coefficient before the treatment interacted with a dummy for the 2008 wave. Controls include expenditure, assets, age, change in marital status of respondent, household size, and exogenous shocks to the household including accidents, drought, pest and livestock diseases, crime, and death of a household member, and historical flooding propensity for the same time window around the typhoon in 2001–2008. Entropy balancing weights are applied, ensuring covariate balance conditional on rainfall intensity. Standard errors in parentheses and clustered at the subdistrict level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B2: Selective Attrition

	(1) Attrition
Excess Rainfall	-0.001
	(0.009)
Observations	605
Controls	✓

Notes: The table reports the results of a linear probability model of attrition on excess rainfall in the year before the typhoon (2008). The dependent variable is a binary variable taking the value of one if the household attrited between the 2008 and 2010 waves of the TVSEP dataset and had the same respondent in the 2007 and 2008 waves of the survey and zero otherwise. We include controls for expenditure, assets, age, change in respondent's marital status, household size, exogenous shocks to the household including accidents, drought, pest and livestock diseases, crime, and death of a household member, and historical flooding propensity. Flooding propensity refers to the historical average flooding for the same time window around the typhoon in 2001–2008. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B3: Robustness Check: Pretrends under Alternative Treatment Specifications

	(1) 1 km Radius	(2) 3 km Radius	(3) 5 km Radius
September 26 – October 5th	0.039	0.032	0.027
	(0.046)	(0.042)	(0.039)
September 26 – October 7th	0.038	0.032	0.027
	(0.044)	(0.042)	(0.040)
September 26 – October 10th	0.036	0.031	0.026
	(0.044)	(0.042)	(0.039)

Notes: The dependent variable is the total amount of insurance premiums paid by the household, calculated at the daily level. Each cell reports the coefficient from a separate pretrends regression testing whether outcomes trend differently prior to Typhoon Ketsana. Columns (1)–(3) vary the radius around a village while rows vary the temporal window around the typhoon to assign treatment intensity. The estimate using the 5 km treatment radius and the full window (column 3, row 3) corresponds to the preferred specification in Table 2. We include controls for expenditure, assets, age, change in respondent's marital status, household size, exogenous shocks to the household including accidents, drought, pest and livestock diseases, crime, and death of a household member, and historical flooding propensity. Flooding propensity refers to the historical average flooding for the same time window around the typhoon in 2001–2008. Entropy balancing weights are applied, ensuring covariate balance conditional on rainfall intensity. Standard errors are in parentheses and clustered at the subdistrict level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B4: Robustness Check: Short-term Changes in Risk Preferences under Alternative Treatment Specifications

	(1) 1 km Radius	(2) 3 km Radius	(3) 5 km Radius
September 26 – October 5th	-0.097*	-0.101*	-0.101*
	(0.057)	(0.057)	(0.056)
September 26 – October 7th	-0.107*	-0.110*	-0.109*
	(0.056)	(0.057)	(0.056)
September 26 – October 10th	-0.111*	-0.113*	-0.112**
	(0.057)	(0.057)	(0.056)

Notes: The dependent variable is the respondent's stated risk preference. The risk preference variable is a response to the question "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risk?", where 0 indicates "completely unwilling to take risks" and 10 indicates "fully prepared to take risks". Each cell reports the coefficient from a separate difference-in-differences regression estimating the effect of exposure to Typhoon Ketsana on risk preferences. Columns (1)–(3) vary the radius around a village while rows vary the the temporal window around the typhoon to assign treatment intensity. The estimate using the 5 km treatment radius and the full window (column 3, row 3) corresponds to the preferred specification in Table 3. We include controls for expenditure, assets, age, change in respondent's marital status, household size, exogenous shocks to the household including accidents, drought, pest and livestock diseases, crime, and death of a household member, and historical flooding propensity. Flooding propensity refers to the historical average flooding for the same time window around the typhoon in 2001–2008. Entropy balancing weights are applied, ensuring covariate balance conditional on rainfall intensity. Standard errors are in parentheses and clustered at the subdistrict level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B5: Robustness Check: Long-term Changes in Risk Preferences under Alternative Treatment Specifications

	(1) 1 km Radius	(2) 3 km Radius	(3) 5 km Radius
September 26 – October 5th	-0.122***	-0.129***	-0.132***
	(0.031)	(0.033)	(0.032)
September 26 – October 7th	-0.131***	-0.136***	-0.139***
	(0.030)	(0.032)	(0.032)
September 26 – October 10th	-0.132***	-0.138***	-0.140***
	(0.031)	(0.033)	(0.032)

Notes: The dependent variable is the respondent's stated risk preference. The risk preference variable is a response to the question "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risk?", where 0 indicates "completely unwilling to take risks" and 10 indicates "fully prepared to take risks". Each cell reports the coefficient from a separate difference-in-differences regression estimating the effect of exposure to Typhoon Ketsana on risk preferences. Columns (1)–(3) vary the radius around a village while rows vary the the temporal window around the typhoon to assign treatment intensity. The estimate using the 5 km treatment radius and the full window (column 3, row 3) corresponds to the preferred specification in Table 4. We include controls for expenditure, assets, age, change in respondent's marital status, household size, exogenous shocks to the household including accidents, drought, pest and livestock diseases, crime, and death of a household member, and historical flooding propensity. Flooding propensity refers to the historical average flooding for the same time window around the typhoon in 2001–2008. Entropy balancing weights are applied, ensuring covariate balance conditional on rainfall intensity. Standard errors are in parentheses and clustered at the subdistrict level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B6: Balance Test

Variables	Coefficient	Standard Error	Significance	Observations
Individual Characteristics				
Household Size	0.0051	0.0034		572
Daily Expenditure (per capita, USD)	0.006	0.0024	**	572
Assets (Log)	-0.0018	0.0019		572
Age	0.0203	0.0229		572
Δ Marital Status	0.0001	0.0002		572
Household Shocks since Last Wave				
Death	0.0000	0.0003		572
Accident	-0.0004	0.0002	*	572
Drought	-0.0007	0.0004		572
Pest/Livestock Disease	-0.0024	0.0008	***	572
Crime	-0.0003	0.0002		572

Notes: The data are from the TVSEP dataset in 2008 (one year prior to the typhoon), for all variables presented. The table shows a correlation between the treatment and observables. Each row is a separate regression where only the coefficient of the treatment variable is reported. This specification also controls for flooding propensity and the standard errors are clustered at the subdistrict level. The treatment variable of excess rainfall is calculated as daily average rainfall during landfall (September 28 and 29, 2009) minus daily average rainfall before landfall (September 26 and 27, 2009) and after landfall (September 30–October 10, 2009). The surveys prior to the 2013 wave limit the response to the household shocks question to an upper bound of 6. In the 2013 wave, we similarly cap all values at this upper bound. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B7: Balance Test w/ Entropy Balancing Weights

Variables	Coefficient	Standard Error	Significance	Observations
Individual Characteristics				
Household Size	0.0035	0.0031		572
Daily Expenditure (per capita, USD)	0.0031	0.0024		572
Assets (Log)	0.0016	0.0019		572
Age	-0.029	0.0252		572
Δ Marital Status	0.0000	0.0002		572
Household Shocks since Last Wave				
Death	-0.0001	0.0003		572
Accident	0.0000	0.0003		572
Drought	0.0005	0.0005		572
Pest/Livestock Disease	-0.0001	0.001		572
Crime	0.0000	0.0003		572

Notes: The data are from the TVSEP dataset in 2008 (one year prior to the typhoon), for all variables presented. The table shows a correlation between the treatment and observables. Each row is a separate regression where only the coefficient of the treatment variable is reported. This specification also controls for flooding propensity and the standard errors are clustered at the subdistrict level. The sample is reweighted using entropy balancing weights for a continuous treatment variable. The treatment variable of excess rainfall is calculated as daily average rainfall during landfall (September 28 and 29, 2009) minus daily average rainfall before landfall (September 26 and 27, 2009) and after landfall (September 30–October 10, 2009). The surveys prior to the 2013 wave limit the response to the household shocks question to an upper bound of 6. In the 2013 wave, we similarly cap all values at this upper bound. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.