The Heterogeneous Impacts of Natural Disasters on Risk Preferences in Indonesia*

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ABSTRACT:

Risk preferences influence many economic decisions, and new evidence suggests that shocks may impact individual risk aversion. Increases in risk aversion from shocks, such as natural disasters, may lead to under-investment and over-saving by households, especially in developing countries where levels of risk aversion are high and social safety nets may not be available. Using data from Indonesia, a large developing country highly exposed to disasters, I evaluate the impact of disasters on individual risk attitudes. Using an individual fixed effects model to account for unobserved, time-invariant heterogeneity, I find that risk aversion increases following disasters for a sustained period of time, but the effect eventually fades. Additionally, more severe disasters with high mortality rates, namely earthquakes, are most salient to individuals than higher frequency, lower-mortality disasters. The results are robust to attrition and migration-related selection concerns. These outcomes shed light on how disaster survivors in a developing country respond to and internalize these shocks, and can be informative to policymakers in addressing the increasing threat of severe disasters due climate change and growing population density.

JEL Classification: D12, D81, O12, Q54
Keywords: Risk Preference, Natural Disasters, Indonesia

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1 Introduction

It is well documented that risk and uncertainty play a significant role in determining economic choices such as savings (Dohmen et al., 2011; Rosenzweig and Stark, 1989; Lawrance, 1991), investment in education and health (Dasgupta et al., 2015; Shaw, 1996; Strauss and Thomas, 1998), as well as technology adoption (Liu, 2013; Feder, 1980; Kebede, 1992). However, it is unclear if risk preferences are immutable throughout an individual's life. While there is a substantial literature documenting the effects of negative life shocks on particular economic outcomes, such as educational attainment and earnings, there is no conclusive evidence on the impact of shocks, including natural disasters, financial crises, and conflict, on individual risk preferences. This could have differential consequences for individuals in developing countries as poorer households display already higher levels of risk aversion, compounding the consequences of credit constraints and uninsurable risks that these individuals face (Haushofer and Fehr, 2014).

Given the traumatic nature and devastating human costs of natural disasters, it is plausible that these events would impact an individual's view of risk and uncertainty. However, it is not immediately clear whether natural disasters would make individuals more risk averse or more risk tolerant. Indonesia is located on the Pacific Ring of Fire, and is frequently plagued by a variety of major disaster events including earthquakes, tsunamis, volcanic eruptions, wildfires, floods, landslides, tornadoes, etc. Additionally, there is substantial regional heterogeneity of economic and social development, which makes Indonesia an ideal research setting for exploring the varied ways in which natural disasters may influence risk attitudes. Using data from Indonesia, I investigate whether the intensity and severity of natural disasters over time impact individual risk attitudes. I combine data on risk attitudes from two waves of the Indonesian Family Life Survey (IFLS), a longitudinal household survey, with national natural disaster statistics reported by Indonesia's National Disaster Management Authority (BNPB) at the district level to assess whether increased mortality and destruction from disasters changes attitudes toward risk measured by a hypothetical lottery.

Currently, the literature on risk and disasters is not only conflicted on whether natural disaster shocks change individual risk attitudes, but also the direction of the changes. It is unclear whether these extreme weather shocks would result in higher or lower levels of risk aversion. The main challenge in this literature is the lack of available longitudinal data on individual risk preferences, especially in developing countries, leading to the reliance on cross-sectional data where individuals can only be viewed at one point in time. Additionally, the majority of the studies look at single disaster events rather than the perpetuation of disasters or analyzing different types of disasters. While Hanaoka et al. (2018) are able to use panel data to evaluate the before and after changes in risk attitudes, they focus on a single event, the largest earthquake in Japan's history, in a developed country context. While their results may be valid for the developed country context, they may not hold true in a developing country such as Indonesia or for other types of disaster.

In the developing context, previous literature has found that poor households and individuals in developing countries tend to be more risk averse (Haushofer and Fehr, 2014) than those in wealthier countries as a result of ineffective institutions, lack of educational opportunities, poor health, exposure to violence and crime, and other economic challenges (Guiso and Paiella, 2008; Haushofer and Fehr, 2014; Rosenzweig and Binswanger, 1993). This higher level of risk aversion may lead to under-investment in risky but potentially rewarding behavior and activites, and therefore have negative economic consequences.[1] Because the poor face considerable credit constraints and uninsurable risks, they are also particularly vulnerable to income and health shocks (Haushofer and Fehr, 2014).

Cameron and Shah (2015), Cassar et al. (2017), P. Brown et al. (2018), and Beine et al. (2020) find that natural disaster shocks increase risk aversion in developing countries. Cameron and Shah (2015) specifically explore whether floods and earthquakes affect risk preferences in Indonesia and find that individuals living in villages that had experienced a

[1] For example, because of the environments they live in, the poor may be less willing to adopt new technologies (Liu, 2013), be less entrepreneurial (Kihlstrom and Laffont, 1979; Guiso and Paiella, 2008), have short-sighted views on savings and financial investment (Guiso and Paiella, 2008), and may underinvest in health and education, thus making it difficult to escape poverty traps.

flood or earthquake in the last 3 years are more risk averse than those who did not.[2] Cassar et al. (2017), P. Brown et al. (2018), and Beine et al. (2020) similarly show that risk aversion increases after the 2004 Indian Ocean Tsunami, Cyclone Evan in Fiji, and an earthquake in Albania, respectively. However, all of these studies rely on cross-sectional experiments post-disaster and assume that the disasters are not correlated with time-invariant and time-varying unobservables, such as residential sorting. These results are in line with Eeckhoudt et al. (1996), Guiso and Paiella (2008), Gollier and Pratt (1996) who find that increased risk environments and background risk make individuals more risk averse.

In contrast to these findings, studies by Hanaoka et al. (2018), Eckel et al. (2009), Bchir and Willinger (2013), and Page et al. (2014) find the opposite result: natural disasters cause individuals to become more risk tolerant or have no impact on risk preferences. These results more closely corroborate the literature by Kahneman and Tversky (1979) on prospect theory, the idea that an individuals' reference point of gains and losses will inform their risk preferences – an individual will be more risk-loving following losses and more risk averse following gains - or the literature that finds negative shocks can result in risk preference changes driven by emotion (see, e.g., Loewenstein et al. (2001); Lerner and Keltner (2001)). Studies showing little or no effect of shocks on risks could suggest that disasters don't in fact have an effect on risk preferences or that the methods used by economists to elicit risk preferences may be lacking.

Cross-sectional and single event studies are unable to capture variation over time and the heterogeneous impact of different disasters by severity and type. It is unlikely that all disasters impact individuals in the same way. This paper shows that the results are more nuanced than a "yes" or "no" answer to whether an individual has experienced a natural disaster. In fact, both time and severity matter greatly in determining changes in risk

[2]While Cameron and Shah (2015) have studied the impact of floods and earthquakes on risk preferences in Indonesia, their research solely explores cross-sectional differences in risk preferences, and their sample is restricted to interviewing the head of household in households with children in the rural areas of East Java, which limits their sample to a small geographical area of the country. Risk attitudes may differ from individuals in other provinces, as well as from non-heads of household and from people residing in different types of households (i.e., without children).

attitudes following disasters. Because the IFLS follows the same individuals over time, I am able to address concerns about unobserved heterogeneity using individual fixed effects. I find that individuals become more risk averse as the cumulative district mortality rate and district destruction from disaster increases. Results indicate that individuals are most affected from three to nine years following disasters. Individuals are not significantly impacted in the short term (one to two years), where despite the higher magnitude on the coefficient, the results are statistically insignificant. Additionally, while the impact is long-lived, the effect of disasters on risk fades to zero after about a decade and is no longer significant, with some evidence of long run increases in risk tolerance.

I also find that the severity of the disaster matters, and there is evidence of threshold effects. Below certain thresholds, disasters do not significantly impact risk aversion, while disasters significantly increase risk aversion above the threshold. I additionally find evidence that the changes in risk attitude may be driven by specific types of disaster, namely earthquakes (which often result in a high number of deaths and are often more unpredictable that other types of disaster such as floods). Mortality appears to be the most salient of severity measures in its impact on risk attitudes among respondents, and may indicate that the death toll matters more than destruction or other measures such as evacuations. This is consistent with the psychology literature linking major natural disasters to psychological impacts such as Post-Traumatic Stress Disorder and depression, typically caused or exacerbated by the traumatic experience of injury and death, specifically the fear of death or death of a loved one, as well as personal property loss (Briere and Scott, 2015).

This paper adds to the growing literature that attempts to measure the economic and psychological impacts of natural disasters and how individuals recover from the experience of a large shock. Governments are constantly confronted with the challenges that climate change presents, especially for our most vulnerable populations, which have serious implications for development. Individual changes in risk aversion may inform policy and disaster recovery programs in a variety of ways, including insurance take-up, the importance of early warning systems, the willingness of individuals to change jobs or start their own businesses, as well as other important household decisions such as fertility and marriage. The mix in outcomes from a developed versus developing standpoint may be indicative of the importance of social safety nets and access to credit as mitigation mechanisms in low-income countries.

This paper contributes to the literature on shocks and risk attitudes in the following important ways. First, it is the first to use panel data from a developing country to examine the impact of disasters on risk attitudes, accounting for time-invariant unobservables in order to address an important source of selection bias. I am therefore able to make stronger causal claims between disasters and risk relying on weaker stochastic assumptions compared to the current literature. Second, the unique aspects of my disaster data allow me to explore the heterogeneous impacts of disasters on risk. Specifically, the measure of disaster severity and the type of disaster (earthquake, flood, etc.) matter for explaining risk attitudes. The data I use measures the human impact from disaster and includes the number of deaths, evacuations, houses/facilities destroyed, injuries, number of people affected, and economic damages. Third, my paper is the first to look at the longer term consequences of disasters on risk attitudes, and shows that while the impacts are long-lived, they are not permanent and individuals do show resilience after 10 years. The results from this paper can help inform policy surrounding disaster risk reduction as changes in risk attitudes will likely affect savings, consumption, farming and livestock, as well as other important economic decisions made at the individual level.

The rest of this chapter is organized as follows. Section 2 describes the data and methodology, including a background of disasters in Indonesia. Section 3 describes the empirical specification. Results are discussed in Section 4, including the heterogeneous impacts of disaster on risk attitudes. I investigate pathways in Section 6 and conduct Robustness checks in Section 7. Section 8 concludes the paper.

2 Data & Methodology

2.1 IFLS Data

The Indonesian Family Life Survey is a household survey conducted in Indonesia that started in 1993 and at that time covered individuals in 13 out of the country's 26 provinces. The survey was representative of 83% of Indonesia's population in 1993, and because of the extensive effort to find and survey individuals that had moved or migrated, the IFLS was able to re-interview close to 90% of the original households, including split-off households. Since the initial survey wave in 1993, there have been 5 waves of surveys, the most recent of which was completed in 2015. The IFLS initially surveyed 33,081 individuals from 7,224 households and to the best of their ability attempted to track these individuals over all five waves. The survey includes data on a variety of socioeconomic and demographic indicators on the individual, household and community levels. This includes variables such as age, ethnicity, religion, migration history, household expenditures, availability of facilities in the community, etc. This paper primarily uses the individual data from waves four (2006/07) and five (2014/15) as risk questions were only introduced in wave four.

In wave 4, 13,535 households were contacted and 44,103 individuals were surveyed. In wave 5, 16,931 households were contacted and 52,568 individuals were surveyed. Additional interviewees are added as households split off as children of original households grow up and have their own families.

Beginning in fourth wave of the IFLS, a section on risk and time preferences was added to the questionnaire. In the risk section, hypothetical lottery choices are presented to all household members above the age of 15. The respondent is told, "Suppose you are offered two ways to earn some money." The respondent is then presented a scenario that provides two options, one where the payoff is certain, and one where the payoffs are uncertain. The uncertain option includes two possible payoffs with equal probability.[3] There were two

[3]While in other experiments and surveys this question is typically phrased as a gamble between two choices, due to the substantial Muslim population in Indonesia among whom gambling is prohibited, it is

different sets of questions, one where the return was always positive (Game A) and one where there were possible zero outcomes or losses (Game B). See Table I.1 for the specific scenarios that were presented to the individuals.[4] From the respondent's decision between the safe choice (certain payment) versus the risky choice (the gamble between a higher and lower amount than the certain choice with equal probability), I can estimate the risk attitude of the individual. This analysis will focus on the risk preferences elicited from Game A, as the majority of respondents fall into the most risk averse category with Game B.

Table 1: IFLS Lottery Choices

Scenario	Option 1 ***certain choice***	Option 2 ***risky choice*** *(equal chance of either outcome)*
Game A		
Q1	800,000 Rps	800,000 or 1.6 million Rps.
Q2	800,000 Rps	400,000 or 1.6 million Rps.
Q3	800,000 Rps	600,000 or 1.6 million Rps.
Q4	800,000 Rps	200,000 or 1.6 million Rps.
Game B		
Q1	4 million Rps	4 million or 2 million Rps.
Q2	4 million Rps	12 million or 0 Rps.
Q3	4 million Rps	8 million or 2 million Rps.
Q4	4 million Rps	16 million or -2 million Rps.

The responses to these questions put individuals on a risk scale from 1 to 4, where 1 is always choosing the certain option, and 4 is always choosing the gamble (excluding the Q1 response which is a logic check). An illustration on how the 1 to 4 scale is composed is shown below in Figure I.1.

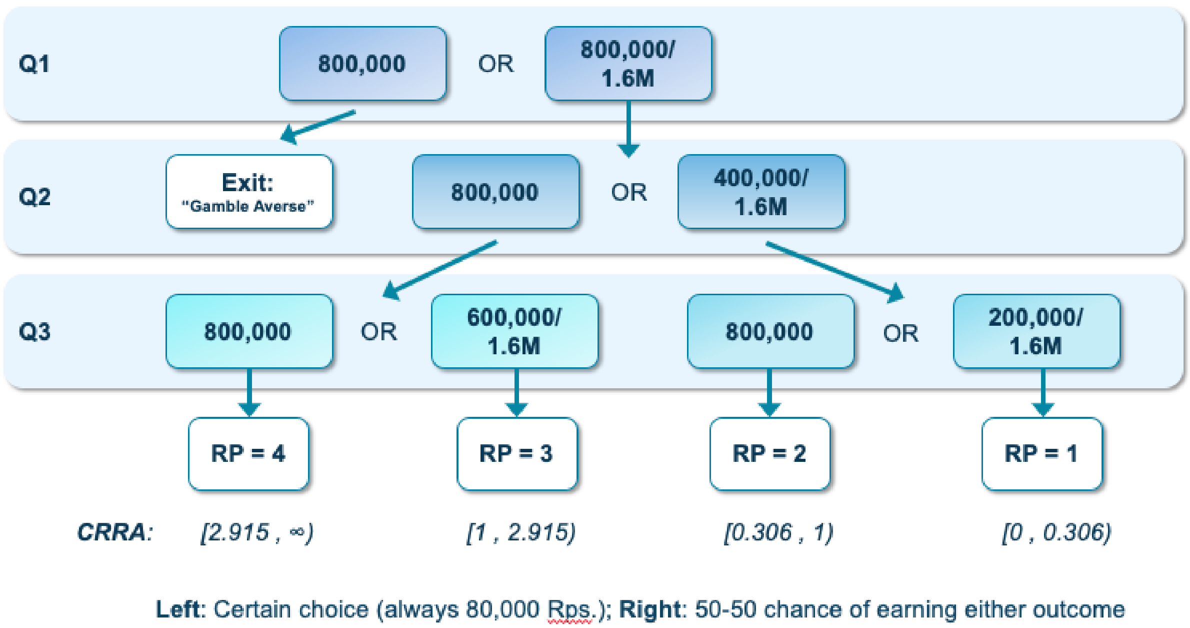
A total of 17,980 individuals have risk data for both wave 4 and wave 5 of the IFLS.

phrased in a way that the respondent would earn money with the option of becoming "lucky" and earning extra if the uncertain option is chosen.

[4]If individuals choose the certain choice in Q1 they are asked again if they would choose the certain choice (there is only an upside for choosing the gamble in this scenario). If they continue to choose the certain choice, despite logic, the respondents are not asked any more questions. It is plausible that these respondents are so averse to uncertainty that they would choose the certain choice even when it does not make sense. Following R. Brown et al. (2019), I consider alternative specifications where these individuals are included as "gamble averse," with similar results to the main analysis which exclude these respondents.

These individuals form the basis of my analysis as I am able to measure the change in risk over the two waves.[5]

Figure 1: Risk aversion scale based on non-incentivized lottery choices



2.1.1 Defining Risk Attitudes and Socioeconomic factors

I use three measures of risk aversion as dependent variables: (1) risk attitude measured on a scale of 1-4 (least to most risk averse), (2) a dummy variable for being "most risk averse," and (3) a constant relative risk aversion (CRRA) parameter. For the primary measure of risk attitude I use the categories displayed in Figure I.1. This includes the 4 categories of risk and a dummy variable for being the "most risk averse" which includes the individuals that always choose the certain choice. This variable will take a value of 1 if the individual falls into the category of risk where he/she always chooses the gamble. I evaluate the CRRA measure (following much of the experimental economics literature including Cameron and

[5]There are a variety of reasons that individuals do not have data in both waves of the survey, such as dying between waves, refusing to respond, not being home during the interview, being added to the survey in wave 5, etc. There are also additional individuals who qualify as "gamble averse" in at least one wave and are not included in the 17,980.

Shah (2015)) by estimating risk aversion parameters for each individual in the data assuming CES utility: $U(c) = \frac{c^{1-\theta}}{1-\theta}$, By defining utility over winnings from the risk experiment, I am able to calculate CRRA intervals for the four categories of risk aversion (shown in the last line in Figure I.1 below).

Table I.2 shows summary statistics of the overall sample. On average, individuals fall between Category 2 and 3 on the four-point scale, and half of the sample falls in the most risk averse category. About half of the sample is male, the average age is 34 (recall the minimum age to respond to the risk questions is 15), 71% are married and live in households with an average of 4 people. Urban residents make up 55% of the sample and the majority (89%) are Muslim. The two largest ethnicities are Javanese (43%) and Sundanese (12%) and the average years of schooling is nine years. Average annual household income is $7,678 and the per capita average annual household income is a little over $2,000 (which adjusts for household size). A little more than a third of the sample that works is self-employed and close to 75% of the sample are currently working. Migration for work is fairly low at 6%. Additionally, a third of the sample is currently a smoker. Summary statistics by risk category can be found in Table A.1 in the online appendix, which most importantly shows that males tend to make riskier lottery choices, consistent with the current literature (Eckel et al. (2009)).[6]

2.1.2 Validation of Risk Measure

If the risk measures from the IFLS lottery choices are a true representation of risk attitudes, they should be able to predict risky behavior of individuals. Before I examine the impacts of disasters on risk attitudes, I first validate the measures of risk obtained from the hypothetical lottery. I use IFLS data on risky behavior and analyze whether this behavior is correlated with the individual's risk attitude from the lottery choices. Following Jakiela and Ozier (2019), Hanaoka et al. (2018) and R. Brown et al. (2019), I use a probit model to evaluate

[6]For a full review of the literature on gender and risk see Croson and Gneezy (2009).

Table 2: Individual Summary Statistics

	Observations	Mean	SD	Min	Max
Risk Category	8,990	2.84	1.28	1	4
Risk Category (alternative)	8,023	3.55	0.91	1	4
CRRA (lower bound)	8,990	1.60	1.34	0.00	2.91
Risk Averse Dummy	8,990	0.50	0.50	0	1
Male (=1)	8,990	0.51	0.50	0	1
Age	8,990	33.88	12.81	15	94
Household Size	8,990	4.34	1.92	1	22
Married (=1)	8,990	0.71	0.45	0	1
Urban (=1)	8,990	0.55	0.50	0	1
Javanese (=1)	8,990	0.43	0.49	0	1
Sundanese (=1)	8,990	0.12	0.32	0	1
Years of Schooling	7,947	9.25	4.39	0	16
Muslim (=1)	8,989	0.89	0.31	0	10
HH Income (2007 USD)	8,990	7,678.37	8,076.22	0.00	83,426.32
Per Capita HH Income (2007 USD)	8,990	2,006.77	2,459.81	0.00	46,165.63
Self-Employed (=1)	6,526	0.36	0.48	0	1
Working (=1)	8,990	0.73	0.45	0	1
Migrated for Work	8,990	0.06	0.23	0	1
Smoker	8,985	0.33	0.47	0	1

Notes: All summary statistics measured in 2007, Wave 4 of the IFLS. Observations less than 8,990 indicate missing values. Income is converted from IDN Rps. to USD at the average 2007 exchange rate.

whether risk choices influence the likelihood of migrating for work, being self-employed, or smoking.[7] Owning your own business and seeking out job opportunities away from home are both behaviors that may result in higher returns in the long run but are risky in the short run, and smoking is generally considered a health risk and as such we would expect individuals with a higher risk tolerance to be more likely to smoke. The results of this analysis are shown in Online Appendix Table A.2 and indicate that risk category based on lottery choices predicts observed risky behaviors.

[7] Only males are included in the probit for migrating for work.

2.2 Disaster Data

2.2.1 Background on Indonesian Disasters

Sitting on the Pacific Ring of Fire, Indonesia is exposed on many fronts to many types of disasters. There are earthquake faults throughout the country, and 129 volcanoes lie along its southern coast. In 2018, the Sulawesi Earthquake was the deadliest disaster globally, and the 2004 Indian Ocean Tsunami was one of the deadliest disasters in recorded history. The BNPB, National Indonesian Statistics Agency (BPS) and the UN Population Fund (UNFPA) estimate that 97% of Indonesian's population lives in areas exposed to disasters (*Population Exposed to Natural Hazards*, 2015).

Earthquakes (and often the tsunamis that follow) have caused the most deaths overall in Indonesia, as evidenced by the recent 2018 Sulawesi Earthquake as well as the 2004 Indian Ocean Tsunami. Close to 150 million people (62% of the population) live in earthquake prone areas and this is the highest disaster risk the country faces (*Population Exposed to Natural Hazards*, 2015). The most frequent and pervasive type of disaster that the country experiences are floods, which accounted for 43% of all disasters in Indonesia between 1995 and 2015. Flooding is primarily driven by rains during the monsoon season, but other factors such as deforestation and development have resulted in excess runoff that has caused river basins to overflow. While total deaths from flooding remains relatively low, floods affect the second highest number of people after earthquakes and cause extensive economic damage. Of the 129 active volcanoes in Indonesia, 70 are currently considered dangerous and 23 have erupted in the last 20 years, 2 of which are currently erupting as of early 2020. In 2010, Mt. Merapi erupted multiple times and resulted in casualties of 353 people and left much of the surrounding area (Yogyakarta and Central Java) in ruin. Landslides are also common in Indonesia, and typically follow other disasters like earthquakes, floods and volcanic eruptions. Just as Indonesia experiences flooding because of seasonal changes in rainfall during the wet season, the same is true of droughts during the dry season. Drought is less pervasive than flooding in Indonesia, but the effects of drought can be severe. The last major drought occurred in 1997, when lower than expected rainfall was exacerbated by El Niño, killing over 600 people and affecting close to a million people. One of the less discussed but severe disasters are wildfires, particularly in the provinces of East Sumatra and South Kalimantan, where the burning of peat forests becomes uncontrollable and causes extensive damage and economic costs. Wildfires accounted for the most out of any other type of disaster in economic damages due to the massive amounts of smoke they create and the threat these fires have to communities when they are uncontainable(*CFE-DMHA Report*, 2015).

Figure 2: District Population in IFLS communities from 2010 Census

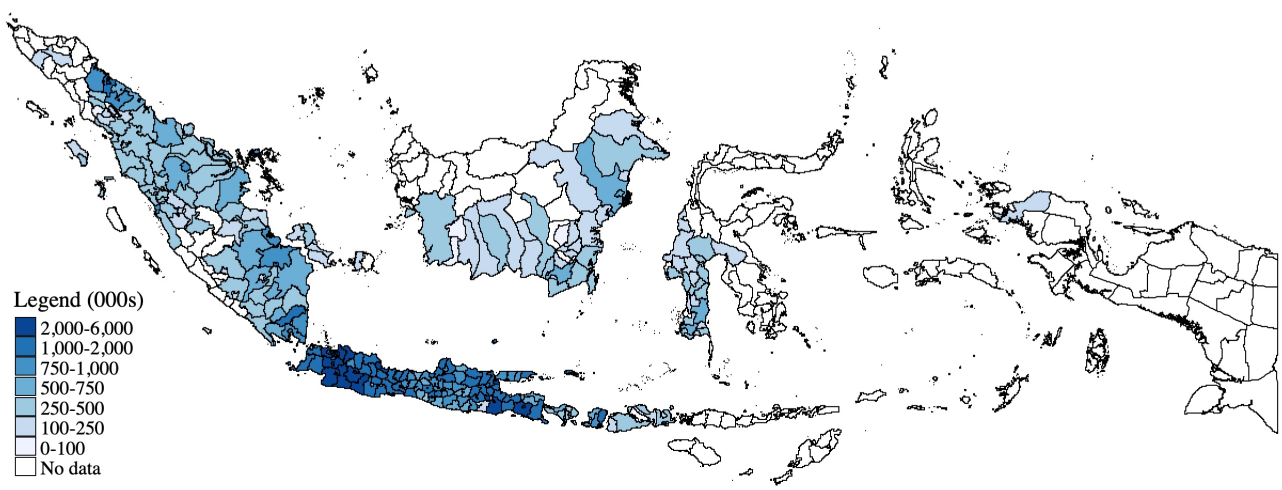


Figure I.2 shows the population for IFLS districts as of the 2010 census. The population is heavily concentrated on the island of Java, where over half of the total population of the country resides. The island of Java is considered one of the most densely populated regions on the planet. Otherwise, population density varies across the country, and the least populated IFLS districts primarily lie in the northern islands of Sulawesi and Kalimantan as well as certain parts of Sumatra.

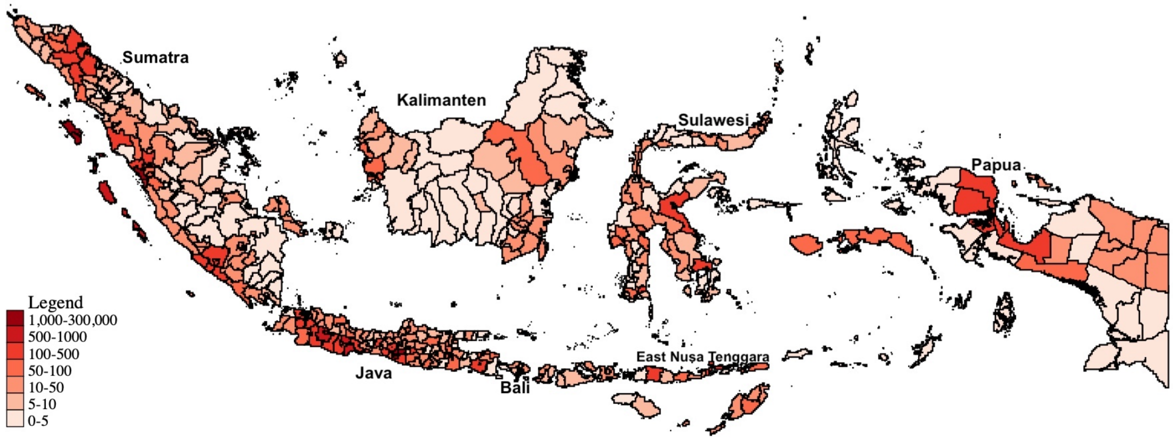
2.2.2 Historical Disaster Data

In 2007, following the historic 2004 Indian Ocean Tsunami, the Indonesian Government passed legislation to strengthen disaster management and disaster relief in the country, including Law 24/2007 which established the National Agency for Disaster Management (BNPB) and called for new disaster risk reduction (DRR) plans for Indonesia. In 2008, the BNPB created a national natural disaster database called DIBI (Indonesian Disaster Data and Information) which took over from the National Disaster Management Coordinating Board (previously established in 1979).

Disaster statistics are reported regionally to the Agency, which verifies the data and has published it publicly online. The database is organized by each individual disaster and includes basic information about the disaster including type (earthquake, flood, terrorism), the date of the disaster, the districts that were affected as well as several measures of the severity of the disaster. These severity measures include the number of people who died, affected, evacuated, and wounded by the disaster, as well as the number of houses that were lightly, moderately and severely damaged by the disaster and the number of worship, health and education facilities that were damaged by the disaster. I focus specifically on natural disasters as they are plausibly more exogenous than other disasters such as conflict and epidemics, as the exposure to these types of shocks often depend on human behavior that might be correlated with risk preference. The dataset starts in 1815, but measurements and tracking of these numbers have likely gotten more intensive and accurate in recent years, especially as there has been a heightened focus on DRR by the Indonesian government since 2007.

The figure above shows the cumulative number of people killed by disasters between 1998 and 2015 by district (including non-IFLS districts). The figure shows the distribution of disaster deaths is quite varied across the country, with a concentration in the densely populated districts of West Java and fewer disasters occurring in South Kalimanten. The data is heavily skewed. There are frequent disasters that occur on a small scale, killing

Figure 3: Cumulative Number of People Killed by Natural Disasters By District
By District, 1998-2015



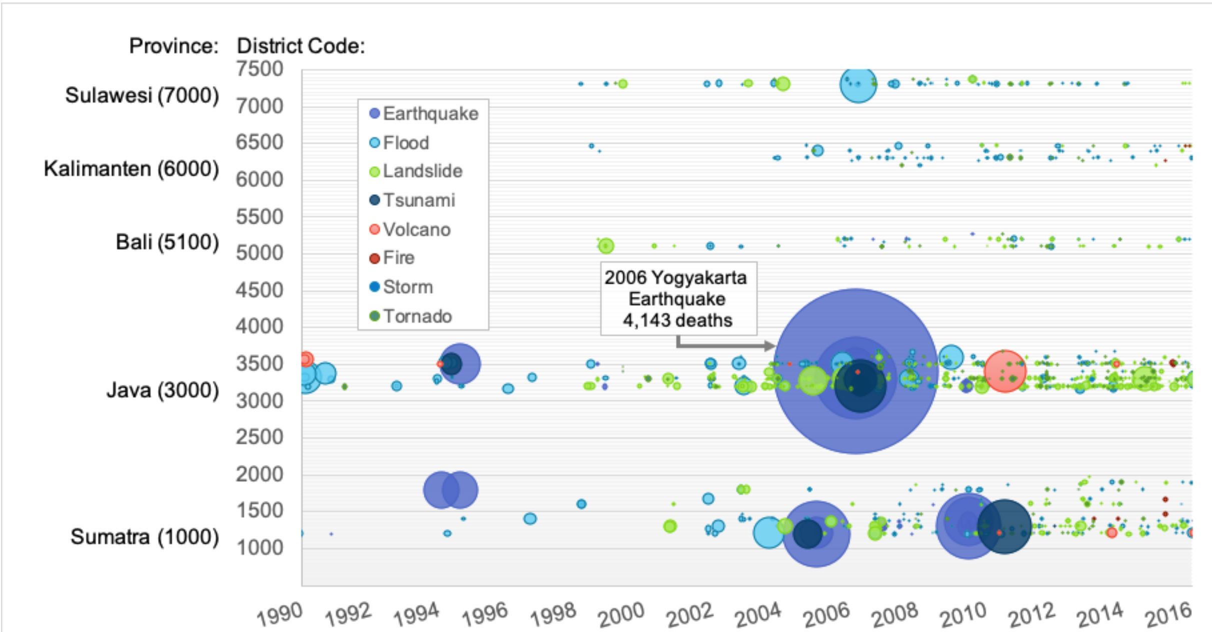
anywhere from 0 to 10 people and are relatively minor events, the most frequent of which are floods and landslides. On the other extreme, there are high-impact events, such as earthquakes and tsunamis, that are less frequent but can kill thousands of people per event. The below figure displays a timeline of disaster events (that apply specifically to the districts that appear in the sample) where the size and frequency of different types of disasters can be observed. The y-axis plots the four digit district code and is meant to display the geographic variation of the disasters. The largest of these events was the 2006 Yogyakarta Earthquake that killed thousands of individuals.[8]

The summary statistics on the disaster variables are shown below in Table I.3. Disaster Deaths in the past 1 year are low, with an average of less than 2 deaths in the year preceding the wave 4 and wave 5 interviews. In wave 4, the average deaths in the last 5 years is driven up by a few larger disasters, the most significant of which was the 2006 Yogyakarta Earthquake. In wave 5 the deaths in the past 5 years is 9, but again once the Earthquake and other big disasters are captured at the 10 year time frame, the average is driven up to over 160 deaths. These numbers also reflect the large number of individuals that did not experience any fatal disasters during these time periods. The other categories follow a similar

[8]The 2004 Indian Ocean Tsunami was the country's deadliest disaster to date, but the tsunami hit the Banda Aceh district, which is not included in the IFLS sample.

Figure 4: Indonesian Natural Disaster Events

Number of people killed by disaster (1990-2015)



Note: The y-axis plots the geographic location of districts by district code. The first two digits indicate the province, the second two digits represent the district. District codes are numerically ordered from West to East for the Southern Isands (Sumatra to Nusa Tenggara) and then again West to East for the Northern Islands (Kalimanten to Papua). Only IFLS districts are shown in the figure.

pattern. Average houses destroyed by disasters in wave 4 is 136 in the past year and jumps to over 3 thousand for the past 5, 10 and 15 years. In wave 5, average houses destroyed in the past year is only 47, then increases to 280 when the past 5 years are considered, and then to over 4,500 at the 10 year time frame and beyond. Average evacuations are close to 7,000 and over 3,000 in the past 1 year at wave 4 and wave 5, respectively. This jumps to over 50,000 in the 5 year time frame for wave 4 and for wave 5, average evacuations increase to 12,000 in the past 5 years, 68,000 in the past 10 years, and 73,000 in the past 15 years. Damages are only measured up to 10 years, and average damages in the past year are 3 million USD in wave 4 and 7 million USD in wave 5. The jump in the past 5 years at wave 4 is again driven by the 2006 Earthquake and increases slightly in the 10 year time frame to 62 million USD. In wave 5, average damages are driven by a Sumatra earthquake, the 2015 wildfires, and a few severe floods and average 58 million USD. The disaster statistics are very skewed, and driven by a handful of large disasters that killed many people and caused significant damage. While there are some districts that did not see any disasters, others dealt with deaths in the thousands and damages in the billions of dollars.

Table 3: Disaster Summary Statistics

Wave 4:	Mean	SD	Min	Max
Disasters: Deaths				
Past 1 Year	1.77	5.18	0	63
Past 5 Years	150.69	712.61	0	4,148
Past 10 Years	153.33	712.16	0	4,149
Past 15 Years	155.46	711.95	0	4,149
Disasters: Houses Destroyed				
Past 1 Year	136.33	487.19	0	3,590
Past 5 Years	3,432.34	13,598.25	0	78,622
Past 10 Years	3,810.09	13,622.36	0	78,683
Past 15 Years	3,778.04	13,604.19	0	78,683
Disasters: Evacuations				
Past 1 Year	6,970.60	27,707.96	0	222,180
Past 5 Years	53,114.09	149,160.65	0	802,804
Past 10 Years	55,698.28	150,038.55	0	802,804
Past 15 Years	55,159.56	149,948.37	0	802,804
Disasters: Damages, '000 USD				
Past 1 Year	3,217.66	26,359.49	0.00	333,333.34
Past 5 Years	59,889.27	155,170.50	0.00	630,000.00
Past 10 Years	62,700.35	155,090.90	0.00	641,500.00
Wave 5:	Mean	SD	Min	Max
Disasters: Deaths				
Past 1 Year	1.46	3.43	0	101
Past 5 Years	9.02	17.19	0	285
Past 10 Years	167.04	709.60	0	4,437
Past 15 Years	173.19	709.35	0	4,437
Disasters: Houses Destroyed				
Past 1 Year	47.38	337.86	0	3,801
Past 5 Years	280.11	739.32	0	8,657
Past 10 Years	4,561.46	14,428.37	0	97,927
Past 15 Years	5,266.12	14,493.87	0	97,933
Disasters: Evacuations				
Past 1 Year	3,201.63	15,404.44	0	182,912
Past 5 Years	12,003.63	34,806.74	0	305,991
Past 10 Years	68,284.62	162,568.07	0	982,859
Past 15 Years	73,327.49	164,586.46	0	982,859
Disasters: Damages, '000 USD				
Past 1 Year	6,967.65	53,671.21	0.00	600,000.00
Past 5 Years	58,588.39	194,312.47	0.00	801,637.50
Past 10 Years	124,006.63	256,869.13	0.00	1,427,000.00

Notes: Disaster statistics are measured as of interview month for each individual at the district level. Wave 4 interviews were conducted in 2007-2008 and Wave 5 interviews were conducted in 2014-2015. Disaster deaths, houses destroyed and evacuations are from the Indonesian database (BNPB) while damages are from the international database (EMDAT).

3 Empirical Specification

As mentioned above, most existing studies show the impact of exposure to disaster on risk from a cross-sectional perspective. Even when controlling for some demographic characteristics, there may be individual unobservables as well as time effects that are formative to an individual's risk preference. For instance, it's possible that individuals with different risk preferences are choosing to live in areas that are more or less exposed to natural disasters. A cross-sectional approach will not capture the fact that more risk averse individuals self-select into areas that experience less disasters. If individuals who are more risk averse choose to live in low-disaster regions, they are less likely to be exposed to disasters. In this case, the unobserved residential sorting is correlated with both disaster exposure and risk preference, and comparing risk preferences of those in disaster exposed areas to non-exposed areas may simply be evaluating preexisting differences between the two groups. Additionally, if risk-tolerant individuals move to unaffected areas following the disaster, researchers may falsely conclude that disasters induced an increase in risk aversion, when in fact the disaster simply induced less risk-averse people to move away and be excluded from the sample. Additionally, if the comparison group then includes these less risk-averse individuals that moved into the non-affected area, the average level of risk aversion would be lower, confounding the results.

Due to the panel nature of the IFLS and disaster data, I can follow the same individuals over time and I can therefore employ an individual fixed effects framework to evaluate the impact of natural disasters on risk attitudes accounting for the time-invariant unobserved individual heterogeneity. This strengthens the case for drawing causal claims between disasters and risk, relying on weaker stochastic assumptions compared to the current literature.[9]

Natural disasters are a plausibly exogenous shock. While there have been substantial advances in early warning systems and evacuation procedures, experts are still not able to tell exactly when or where a disaster will hit. Early warning systems in Indonesia were completed in 2008, so they are fairly new to the country, and are not perfect. For instance, the system failed in the 2018 Sulawesi earthquake due to destruction of cell phone towers (people were unable to receive evacuation text alerts), a nonoperational buoy network from

[9]For additional evidence that a fixed effects model is preferred to a random effects model, I use a cluster-robust Hausman test (Woolridge, 2002) to provide support for using a fixed effects model. The null hypothesis of the Wald test is rejected, implying that the fixed effects model is preferred (p-value < 0.01).

lack of maintenance and vandalism, and lack of observation equipment in the area. Because of this, residents were not prepared for the earthquake and subsequent tsunami that hit the shores of Palu. While there are certain areas that are more prone to certain types of disasters (e.g., close proximity to fault lines and volcanoes, peat forests prone to wildfires, and flood-prone areas during monsoon), the timing and severity of disasters can't be known by the individuals living in these areas. As such, disasters can be treated as a random shock, given I control for selection caused by decisions made to live in a particular location.

For comparison purposes, it is useful to look first at the results from the cross-sectional results from both waves of the IFLS, which is the focus of the current literature in the developing country context. I run separate regressions for waves 4 and 5 of the IFLS using equation [I.1] below, controlling for individual demographic characteristics.[10] Equation [I.1] assumes that there is zero correlation between experiencing a disaster and the time-invariant as well as time-varying unobservables, as the two are indistinguishable in a cross-sectional model. I then remove individual-specific time-invariant unobservables and IFLS wave characteristics using a fixed effects specification, shown in equation [I.2]. This specification relies on weaker stochastic assumptions than equation [I.1] as it only assumes zero correlation between the time-varying unobservables and the disaster term.

$$Risk_{ij} = \alpha_0 + \beta_1 D_j + \beta_2 X_i + \sum_{k \epsilon K} \beta_k X_{ki} + \epsilon_{ij} \tag{1}$$

$$Risk_{ijt} = \alpha_0 + \beta_1 D_{jt} + \sum_{k \epsilon K} \beta_k X_{kit} + \delta_i + \sigma_t + u_{ijt} \tag{2}$$

In the specifications above, $Risk_{ijt}$ refers to the risk category of individual i, in district j, at survey wave t. This ranges from 1 (most risk tolerant) to 4 (most risk averse). I also run additional specifications using a risk averse dummy and the coefficient of relative risk aversion as the risk preference parameter. D_{jt} is a continuous variable that measures the number of district deaths (adjusted for district population) in the past one to fifteen years.

[10] Individual controls include age, gender, ethnicity, religion, marital status, and a dummy for living in an urban area.

I additionally include other measures to capture disaster severity, including house destroyed and economic damages. δ_i and σ_t represent individual and wave fixed effects, respectively. All standard errors are clustered at the district level. The main specification in equation [I.2] shows the individual impact of an increase in district deaths from disaster on risk attitudes, where β_3 represent the increase (or decrease if negative) the risk aversion category given additional exposure of 1 death per 1,000 people in the district.

4 Results

4.1 Intent to Treat Effects of Disasters on Risk Aversion

Results show that individuals who are exposed to increasing district mortality from disasters become significantly more risk averse for a sustained period of time before the effect fades. There are multiple ways to measure whether an individual has been exposed to a natural disaster. Recall that the measure of disaster used in the main results is cumulative mortality. When individual disasters or years are evaluated, there is no significant change in risk preferences, likely because individual years are correlated with each other, or that separately they do not have a large enough impact, and it is the cumulative effect that matters. In fact, Beine et al. (2020) find that a second earthquake has a cumulative effect on risk aversion in Albania, equal in magnitude to the impact of the first earthquake, showing that experiencing multiple disasters can compound changes in risk preference. For the main measure of severity I use the district mortality rate, similar to Gennaro et al. (2017), who use the county mortality rate of a variety of disasters to evaluate their impact on CEO risk behavior.[11]

[11]While the IFLS has a simple question posed to households about whether they experienced a natural disaster in the last five years, to which the respondent can answer yes or no, there is virtually no information on severity and only captures the last 5 years. Additionally, a disaster could mean different things to different people. In order to avoid possible bias of the self-reported measure of disaster in the IFLS and gain more detail on disaster severity and exposure, I use national disaster statistics reported at the district level in Indonesia as my main measure for disaster.

Table I.4 shows the impact of an additional district death per 1,000 people in the district from disaster on an individual's risk category (1-4) over multiple time periods.[12] At first glance, there does not seem to be a consistent pattern in how disaster deaths impact risk attitudes. The table shows that the disaster mortality rate in the past year does not have a significant impact on risk aversion, the five-year mortality has a positive impact and is significant at the 1% level, at 10 years is slightly negative and is no longer statistically significant, and increases in cumulative mortality rates over the past 15 years appear to make individuals more risk tolerant and is statistically significant.[13]

Table 4: Risk Category on Total District Deaths from All Disasters
adjusted for district population (per 1,000)

	Risk Category			
Disaster Mortality:	(1)	(2)	(3)	(4)
Past 1 Year	3.532			
	(3.827)			
Past 5 Years		0.085***		
		(0.012)		
Past 10 Years			-0.066	
			(0.070)	
Past 15 Years				-0.136**
				(0.062)
Avg Mortality Rate	0.002	0.092	0.186	0.190
Observations	15,894	15,894	15,894	15,894
Number of respondents	7,947	7,947	7,947	7,947
Adjusted R-squared	0.0197	0.0210	0.0195	0.0198

Notes: Standard errors in parentheses, clustered at the district level. All regressions include individual fixed effects, round fixed effects, and demographic controls. Mortality rate is per 1,000 people in district. *** p<0.01, ** p<0.05, * p<0.1

The pattern appears more clearly when each coefficient is plotted from three to 15 years,

[12]See Table A.3 in the appendix for the cross sectional comparison using Equation I.1

[13]As the main measure of risk preference is a categorical measure, it may be argued that a linear estimation is not appropriate. I alternatively estimate equation [I.2] using an ordered logit with individual fixed effects. The results are similar in direction and significance to the main results, however there is more evidence in the long-term (10+ years) of the effect fading to zero instead of an increase in risk-tolerance. Marginal effects can only be measured at the average, and results show that an increase in 1 death per 1,000 people in the district leads to a 3% increased likelihood of falling into the most risk averse category, and a 3% decreased probability of falling into the least risk averse category. It should be noted that this estimation excludes those individuals who do not have a change in risk category between rounds.

as seen in Figure I.5. The results from one and two years are removed because of their out-sized and statistically insignificant coefficient sizes. There is a clear pattern that arises when looking over the fifteen-year time frame of disasters. An increase in district deaths measured over a three- to nine-year time frame causes a statistically significant increase in risk aversion measured by risk category. As time goes on, the effect fades and eventually reverses direction. The coefficients on the 10+ year measurements for cumulative deaths are negative. This suggests a strong medium-run impact that fades over the long term back to an individuals' baseline risk preference.

Figure 5: Coefficient Estimates for Risk on Disaster Deaths, all disasters and severe disasters

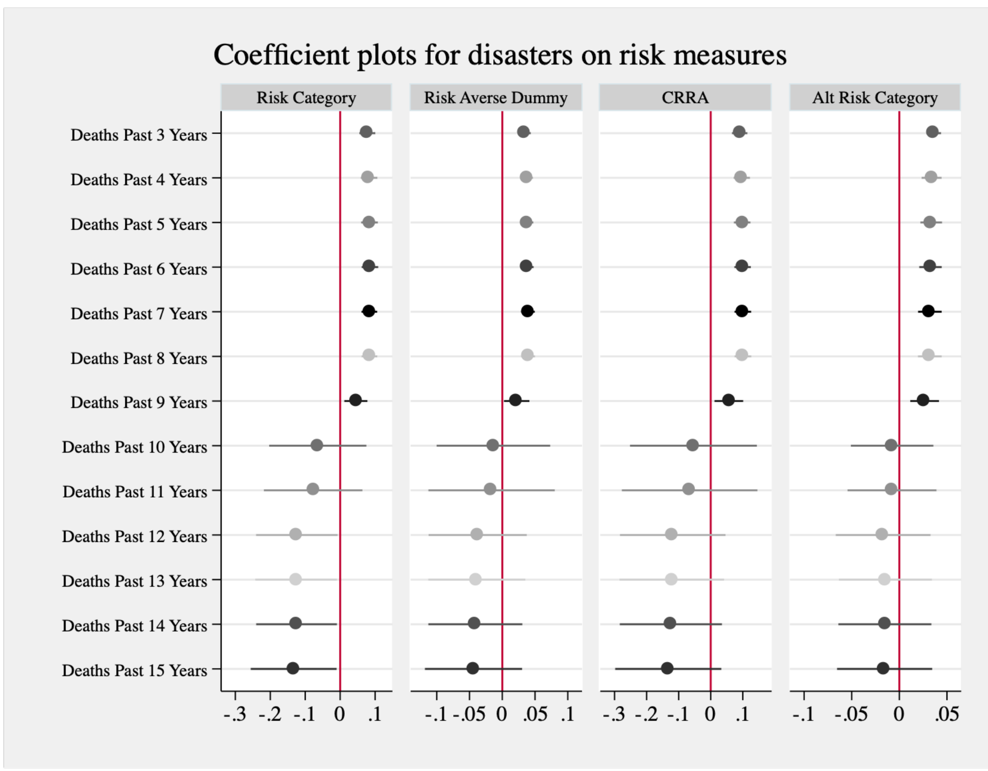


Figure Notes: Coefficient estimates for separate regressions using district deaths from disaster as primary independent variable and confidence intervals. Standard errors are clustered at the district level. All regressions use individual and individual fixed effects and control for demographic characteristics.

To put the coefficient size into context, the average deaths in the last five years in the sample was 0.092. When multiplied by the coefficient of 0.085, this impact is quite small. However, the impact is large when individuals are exposed to high fatality disasters. The highest level of district deaths from disaster is 7.45 deaths per 1,000 residents in the district, largely driven by the 2006 Yogyakarta Earthquake. This would imply an increase in risk aversion of 0.63 (0.085*7.45), which equates to half of a standard deviation increase in risk. Extending this to a more recent example (admittedly not included in the sample) the 2018 Sulawesi Earthquake resulted in a mortality rate of 6.36, which equates to a 0.54 increase in risk category. This is more than double the difference in risk aversion between men and women (0.25).

Another way to conceptualize the results is by using alternative measures to risk than the categorical measure. Results from linear probability models with fixed effects show that an increase by 1 in the five-year mortality rate makes individuals 3.7% more likely to fall into the most risk averse category, and 1.8% less likely to be in the least risk averse category. At the high end of disaster mortality, this results in a 27% increase in the likelihood of being in the most risk averse category and 15% decrease in the likelihood of being in the least risk averse category.

Whether I look at the main categorical measure of risk, a dummy for being in the most risk averse group, a lower bound for the CRRA translation of the risk category, or an alternative risk measurement using responses from a second lottery game that includes possible zero or negative payouts, the pattern remains the same. Only the primary measure of risk preference shows a significant increase in risk tolerance in the long term, while the other measures are negative but statistically insignificant.

While it may be hard to measure the direct impacts of an increase in risk aversion in Indonesia, previous literature suggests that higher risk aversion impacts risk taking behavior. Dohmen et al. (2011) finds that a one standard deviation in an individual's willingness to take risks[14] results in 3% increased participation in the stock market, and 2.4% increase in self-employment. Jaegar (2010) find that a one standard deviation increase in the willingness to take risks increases the likelihood of migration by 1.7%, and by 3.1% for individuals who

[14]It should be noted that their measure of risk preference differs from a hypothetical lottery question and directly asks respondents about their willingness to take risks.

are relatively more willing to take risks (using an indicator dummy for those who are more risk tolerant). Additionally, and more appropriate to the developing country context, Liu (2013) finds that a one standard deviation increase in loss aversion lowers the probability of adopting new technology by 12%. These results show that even a half a standard deviation increase risk aversion can have large impacts for those exposed to high-fatality disasters.

Table 5: Impact of Severe Disasters

	Risk Category			
	(1)	(2)	(3)	(4)
1-Year Mortality	8.806***			
	(1.528)			
5-Year Mortality		0.085***		
		(0.012)		
10-Year Mortality			-0.088	
			(0.062)	
15-Year Mortality				-0.159***
				(0.058)
Avg Mortality Rate	0.001	0.085	0.175	0.179
Number of pidlink	7,947	7,947	7,947	7,947
Observations	15,894	15,894	15,894	15,894
Adjusted R-squared	0.020	0.021	0.020	0.020

Notes: Standard errors in parentheses, clustered at the district level. All regressions include individual fixed effects, wave fixed effects, and demographic controls. Severe Disasters defined as 10 or more people dying or affecting 100 people or more. Mortality rate is per 1,000 people in district. *** p<0.01, ** p<0.05, * p<0.1

There are two potential explanations for the lack of a significant effect in the shorter term: that there is a threshold of severity that needs to be met in order to have a change in risk attitude (and the sum of deaths over one year (measured in 2007 and 2015) is not sufficient for this threshold) or that there is an immediate emotional response to the disaster which conflicts with the change in risk in the longer term. Eckel et al. (2009) find that Katrina evacuees are more risk-loving in the short term than the longer term and compared to a comparable control sample and that this is explained by negative-emotion variables. Additionally, most of the studies done in this literature focus on large scale natural disasters (e.g., the Great Japanese Earthquake, Cyclone Evan, the 2004 Indian Ocean Tsunami), results of which may be reflective of the severity of these events. It is possible that immediately following disasters, individuals are either in shock or expect aid to come, distorting the risk measure. To investigate this, I first re-estimate equation [I.2] to only include disaster deaths for significant disasters.[15] Table I.5 shows that increases in deaths from significant deaths have a positive and significant impact on risk even in the short run.[16] The results for disasters measured over longer time frame mirror the direction and significance displayed in the main specification using all disasters. Figure I.6 shows that for severe disasters, the initial increase in risk aversion is higher, and the subsequent decrease in risk aversion over the longer term is more negative. This would indicate that individuals who experienced severe disasters 15 years ago are then more risk tolerant than if they had not experienced the disaster. There is very little evidence on the long-term impacts of natural disasters, and it is somewhat confounding why individuals would be less risk averse many years after the disaster occurred. However, Frankenberg et al. (2020) do find that mortality risks increase 10 years after the 2004 Indian Ocean Tsunami and Gennaro et al. (2017) find that moderately disaster fatality experience in childhood leads to riskier decisions by CEOs later in life. It is possible that individuals experience higher mortality rates in the long term following disasters which impact their perception of risk and uncertainty, or that making it through the disaster experience desensitizes individuals to risk in the long-term. This may also point to additional resilience among the most affected people, where surviving such a serious life shock means that you are able to bounce back to the point of becoming even more risk tolerant than before experiencing the disaster.

[15] EM-DAT and the Red Cross only consider disasters severe enough to include in their data if at least 10 deaths or more than 100 people are affected by the disaster. (https://www.emdat.be/frequently-asked-questions)

[16] The coefficient on disaster deaths from in the last one year seems impossibly large, but this simply reflects the steep slope of the regression. Given the number of deaths in the past year (per 1,000 residents) is below 1, and increase in 1 death per 1,000 residents would not be possible. The coefficient is better interpreted if you consider an increase of 1 death per 10,000, which would lead to 0.8 increase in risk category

Figure 6: Coefficient Estimates for Risk on Disaster Deaths, all disasters and severe disasters

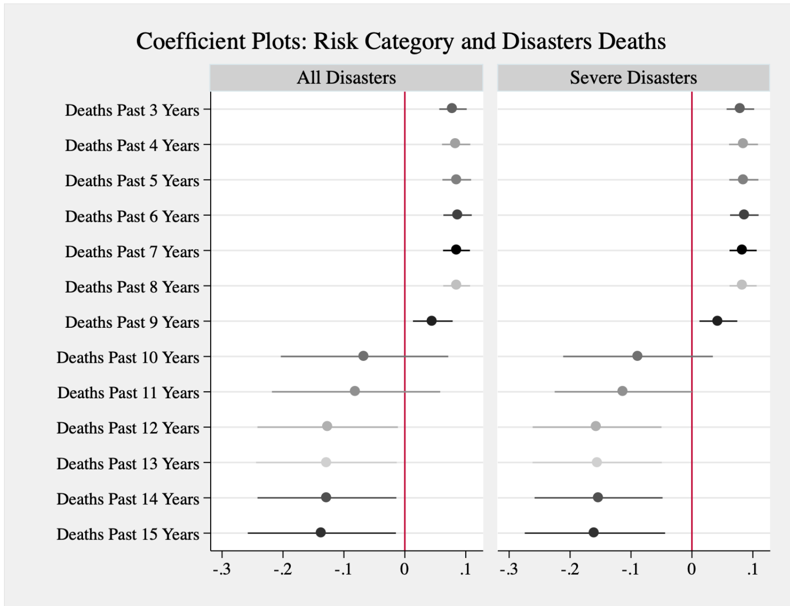


Figure Notes: Coefficient estimates for separate regressions using district deaths from disaster as primary independent variable and confidence intervals. Standard errors are clustered at the district level. All regressions use individual and individual fixed effects and control for demographic characteristics. Severe disasters are classified as those that have killed 10 or more people or affected more than 100 people.

4.2 Threshold Effects

To further test the theory that more fatal and destructive disasters are more salient to individuals and therefore more likely to change risk attitudes, I also run a spline regression. By using a spline regression, I investigate whether the data is kinked, specifically whether a threshold exists, where for individuals who experience lower levels of district deaths (i.e., less severe disasters) there is a different risk response than those who experience disaster deaths above a certain threshold. Equation [I.3] shows the spline regression, where T is the threshold tested depending on the disaster measure (deaths, damages, houses destroyed). I use the following thresholds: 1 death per 100,000 people in the district, $100,000 in damages, and 20 houses per 1,000 people in the district. *I* represents an indicator for whether the disaster measure is below or above the threshold.[17] Most districts have a population between

[17]Because the district deaths are measured per 1,000 people, the indicator equals 0.01 in the equation.

500,000 and 1 million people so this would equate to about 5-10 people dying in disasters over the last 5 years.

$$Risk_{ijt} = \alpha_0 + \alpha_1 I_b[D_{jt} < T]D_{jt} + \alpha_2 I_a[D_{jt} \geq T]D_{jt} + \sum_{k \epsilon K} \alpha_k X_{kit} + \delta_i + \sigma_t + u_{ijt} \quad (3)$$

I find that below the threshold of 1 per 100,000 individuals in the district there is no significant change in risk preference, and above the threshold, district disaster mortality has a positive and statistically significant effect on risk aversion, see Table I.6. I also do alternative measures of the spline where economic damages and houses destroyed are used in place of deaths and a similar threshold effect exists above $100,000 in damages and above 20 houses destroyed (both population adjusted) and the results are similar. This indicates that individuals must be hit by a significant enough shock for it to impact their risk preference, small shocks below a certain threshold are not salient enough to cause a shift. To distinguish between a frequency and severity effect, I also run regressions with disaster counts, which have a negative and statistically insignificant impact on risk preference (individuals become more risk tolerant). This further indicates that it is large, infrequent disasters that are driving the results. It makes sense that larger, more deadly and destructive disasters would be more salient to individuals than smaller more frequent disasters as it is likely the shock and devastation that causes a shift in preferences, rather than those that live in areas that are constantly exposed to small threats that become part of daily life.

4.3 Alternative Disaster Measurements

So far the main measurement used to evaluate the impact on risk attitudes is deaths from disaster. There are, however, other measurements of disaster severity that can be used to explore whether the results are consistent across measurements. EM-DAT, the international database for disasters, reports deaths as well as economic damages from disasters. Accuracy of economic damages from natural disasters relies on the reporting capabilities of the gov-

Table 6: Spline Regressions

	Risk Category		
	Deaths	Damages	Houses
	(1)	(2)	(3)
Spline Cutoff:	=0.01	=0.1	=20
Below Cutoff	-2.901	-0.847	-0.017
	(8.645)	(0.622)	(0.012)
Above Cutoff	0.090***	0.032**	0.009***
	(0.021)	(0.013)	(0.003)
Average	1.33	0.457	2.45
Observations	15,894	13,457	15,894
Number of Respondents	7,947	6,816	7,947
Adjusted R-squared	0.021	0.019	0.022

Notes: Deaths measured as deaths per 1,000 residents in district from disasters in last 5 years. Damages measured in millions of US Dollars from disasters in last 5 years per district. Houses Destroyed is measured as the number of severely damaged houses per 1,000 residents in district in the last 5 years. Robust standard errors in parentheses, clustered at the district level. Spline regressions include both individual and round fixed effects. Averages are calculated for individuals who experienced disasters above the threshold. *** p<0.01, ** p<0.05, * p<0.1

ernment and is inconsistent across different countries. As Indonesia has focused efforts on disaster management since the 2004 Tsunami, damages are likely more accurate than other developing countries. However, EM-DAT data reports the damages from each disaster event and lists affected districts, not damages per district (therefore is less geographically accurate) and may be less reliable than the Indonesian database.[18] I assume that each district listed is affected equally, and divide the damages among the affected districts.

When I run equation [I.2] using the deaths from EM-DAT instead of the BNPB, the results hold in sign and significance, although the coefficients are smaller. Also, the 10 year mortality is statistically significant. The results of the EM-DAT regressions can be found in Table I.7. When I use economic damages as the D_{jt} measure, damages (population adjusted) have no significant impact and the coefficient is relatively small. Results are statistically significant at the five year time frame, and then fades at the 10 year time frame. Therefore

[18]Additionally, some disasters only have province information. In these instances, I use secondary sources to corroborate specific districts that were affected.

Table 7: *EMDAT Data*: Deaths and Damages Effect on Risk Category

	Risk Category					
	(1)	(2)	(3)	(4)	(5)	(6)
Deaths Past 1 Year	-1.396					
	(0.962)					
Deaths Past 5 Years		0.042***				
		(0.015)				
Deaths Past 10 Years			0.029***			
			(0.004)			
Damages Past 1 Year				0.081		
				(0.088)		
Damages Past 5 Years					0.024**	
					(0.012)	
Damages Past 10 Years						0.004
						(0.005)
Mean # Deaths	0.001	0.090	0.172			
Mean # Damages				0.036	0.457	1.224
Number of respondents	7,947	7,947	7,947	7,947	7,947	7,947
Observations	15,894	15,894	15,894	15,894	15,894	15,894
Adjusted R-squared	0.020	0.021	0.020	0.020	0.021	0.020

Note: Standard errors in parentheses, clustered at the district level. Deaths measured as deaths per 1,000 residents in district from disasters, damages measured in USD millions. All regressions include individual fixed effects, wave fixed effects. *** p<0.01, ** p<0.05, * p<0.1

the results are largely consistent with the impact of mortality from BNPB, and I find that damages for larger events are correlated with higher mortality rates. This emphasizes the importance of death and destruction from disasters that cause a shift in risk attitudes.

Additionally, the BNPB also reports other measures of disaster, including houses destroyed and evacuations, and I use these as alternative disaster severity measurements, see Tables I.8 and I.9. For houses destroyed, results for the 5 year time frame are similar in sign and significance, and while the coefficients are smaller in magnitude, this is because the number of houses destroyed in a disaster is typically higher than the mortality rate. When this is taken into account, the results closely mirror the main results. Houses destroyed in the district in the past year, however, has a negative impact on risk attitudes. This could

Table 8: Risk Category on Total Houses Destroyed in District from All Disasters
adjusted for district population (per 1,000)

	Risk Category		
	(1)	(2)	(3)
Houses Destroyed Past 1 Year	-0.118***		
	(0.031)		
Houses Destroyed Past 5 Years		0.003***	
		(0.001)	
Houses Destroyed Past 9 Years			0.001
			(0.001)
Mean # Houses	0.13	2.37	4.45
Number of respondents	7,947	7,947	7,947
Observations	15,894	15,894	15,894
Adjusted R-squared	0.023	0.020	0.020

Notes: Standard errors in parentheses, clustered at the district level. All regressions include individual fixed effects, wave fixed effects. Mean number of houses destroyed are per 1,000 people in district. *** p<0.01, ** p<0.05, * p<0.1

be because there is a different psychological response in the short run causing people to become more risk loving when there is physical damage rather than human costs, or that in the short term the community support, temporary housing, or aid received counteracts the impact on risk aversion. Because the BNBP only started tracking houses destroyed in 1999, I am only able to show results for houses destroyed up to 9 years, but a similar pattern to mortality appears over the 7-9 year time period, suggesting the effect fades faster than when measuring mortality, similar to the EMDAT damages result.

Evacuations also negatively impact risk attitudes after 1 year but have a smaller impact than destroyed houses and is only significant at the 10% level. Generally, when looking over time frames longer than one year, evacuations do not influence risk attitudes significantly. When evacuations are higher, or early warning systems work to evacuate people earlier, death may be avoided. Therefore, results indicate that being displaced to avoid disaster means that the disaster does not significantly impact risk attitudes. This may have implications for policy as it may be worth investing in technology that will allow governments to evacuate residents earlier and more efficiently to avoid disaster mortality.

Table 9: Risk Category on Total Evacuations in District from All Disasters
adjusted for district population (per 1,000)

	Risk Category			
	(1)	(2)	(3)	(4)
Evacuation Past 1 Year	-0.003*			
	(0.002)			
Evacuation Past 5 Years		0.0002		
		(0.0002)		
Evacuation Past 10 Years			-0.0003	
			(0.0004)	
Evacuation Past 15 Years				-0.0001
				(0.0003)
Mean # Evacuations	4.0	35.1	67.8	70.7
Number of respondents	7,947	7,947	7,947	7,947
Observations	15,894	15,894	15,894	15,894
Adjusted R-squared	0.02	0.02	0.02	0.02

Notes: Standard errors in parentheses, clustered at the district level. All regressions include individual fixed effects, wave fixed effects. Mean Evacuations are per 1,000 people in district. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

4.4 Disaster Type

Another source of differential impact of disaster on risk attitudes is the type of disaster. The type of damage and death toll often depends on whether the disaster is intensive or extensive. Extensive disasters are higher frequency, low-severity disasters such as floods, landslides, wildfire, etc. Intensive disasters are lower frequency and high-severity disasters including earthquakes, tsunamis, volcanic eruptions, etc. Floods are the most common extensive disaster in Indonesia, while earthquakes are the most common and deadly intensive disaster. When equation [I.2] uses floods and earthquake deaths as the D_{jt} measure, the results contrast each other. Table I.10 shows that individuals become more risk averse following additional exposure to deaths from flooding, but these results disappear when looking at longer time frames. Conversely, results from the earthquake regression are consistent with the main results. There are no significant impacts at 1 and 10 years, but a statistically significant increase in risk aversion from increased earthquake deaths over the last 5 years.[19]

Table 10: Risk Category on Total District Deaths from Floods vs. Earthquakes
adjusted for district population (per 1,000)

	Risk Category							
	Floods				**Earthquakes**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-Year Mortality	6.141**				-26.970			
	(3.059)				(23.010)			
5-Year Mortality		3.526				0.084***		
		(2.363)				(0.012)		
10-Year Mortality			0.365				-0.095*	
			(1.217)				(0.056)	
15-Year Mortality				0.276				-0.142**
				(1.261)				(0.058)
Avg Mortality Rate	0.001	0.004	0.007	0.009	0.0002	0.079	0.162	0.162
# respondents	7,947	7,947	7,947	7,947	7,947	7,947	7,947	7,947
Observations	15,894	15,894	15,894	15,894	15,894	15,894	15,894	15,894
Adjusted R-squared	0.021	0.021	0.020	0.020	0.021	0.021	0.020	0.020

Notes: Standard errors in parentheses, clustered at the district level. All regressions include individual fixed effects, wave fixed effects. Mortality rate is per 1,000 people in district. *** p<0.01, ** p<0.05, * p<0.1

4.5 Heterogeneous Effects

From the variety of measurements for disaster and the different subsets of the sample that are tested, it is clear that the impact of disasters is not homogeneous. Larger, more intensive disasters affect risk attitudes more than extensive disasters with lower mortality. Death also has a more significant influence on risk than other measures, such as evacuations. This may indicate that while risk attitudes change following the trauma of the natural disaster, there is evidence of resilience or a return to the status quo, after a certain amount of time has passed. There is evidence in the psychological literature that suggests that those who have longer lasting psychological effects from natural disasters stem from the traumatic experience of injury and death, specifically the fear of death or death of a loved one, as well as personal property loss (Briere and Scott, 2015).

[19] When I extend this more generally to all intensive versus all extensive disasters the results are similar to the floods versus earthquakes regression results.

I next examine heterogeneity of the impact on risk preferences by gender and age within the sample. While many studies document the fact that females are typically more risk averse than men, the literature is varied on whether risk responses to shocks would differ by gender. As mentioned above in Section 2.2, Hanaoka et al. (2018) find that men become more risk tolerant following the Earthquake and women are unaffected, while Eckel et al. (2009) finds that women are more risk tolerant compared to men immediately after Hurricane Katrina. Table I.11 shows that when equation [I.2] is estimated separately for women and men, the results generally hold for both. The results at the one- and 10-year time frame are insignificant. The coefficient on deaths from disasters in the district over the last five years is positive and statistically significant for both genders, but the coefficient is larger for women than men (0.092 for women vs. 0.067 for men).[20] This differs from Hanaoka et al. (2018) who find significant gender differences in their results. I also find that women, especially those in households with children, have a higher positive risk response than males. Additionally, the inclusion of "gamble averse" individuals does not impact my overall results.

Table 11: By Gender: Risk Category on Total District Deaths from Disasters
adjusted for district population (per 1,000)

	Risk Category							
	Males				**Females**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-Year Mortality	5.475				0.995			
	(3.658)				(5.671)			
5-Year Mortality		0.079***				0.092***		
		(0.011)				(0.016)		
10-Year Mortality			-0.115				0.083	
			(0.091)				(0.097)	
15-Year Mortality				-0.129				-0.124
				(0.094)				(0.165)
Avg Mortality Rate	0.002	0.094	0.192	0.197	0.002	0.089	0.180	0.184
Number of respondents	4,559	4,559	4,559	4,079	3,868	3,868	3,868	3,868
Observations	8,158	8,158	8,158	8,158	7,736	7,736	7,736	7,736
Adjusted R-squared	0.026	0.027	0.026	0.026	0.016	0.018	0.016	0.016

Notes: Standard errors in parentheses, clustered at the district level. All regressions include individual fixed effects, wave fixed effects. Mortality rate is per 1,000 people in district. *** p<0.01, ** p<0.05, * p<0.1

[20] Additionally, when I test the sample for just severe disasters, total deaths in the past year is positive and becomes statistically significant for both genders, in line with the results from the full sample.

More interesting than the slight overall differences between men and women is the difference among age groups by gender, as shown in Table I.12. Frankenberg et al. (2020) examine the impact of the 2004 Tsunami on mortality risk in the long run. They look at how community mortality rates from the tsunami influence the community mortality rate 5 and 10 years after the tsunami struck. They find that mortality risk varies among genders and different age groups and while overall there is evidence of positive mortality selection, after 10 years they find that older men have higher mortality risk due to scarring. Following the age groupings in Frankenberg et al. (2020), I look at men and women who are under 35, between 35 and 50, and over 50 years old.

Table 12: Heterogeneous Effects - Coefficient Estimates By Age & Gender

	Risk Category					
	<35		**35-50**		**50+**	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
1-Year Mortality	-0.576	12.710***	0.571	-0.704	4.270	1.711
	(6.215)	(4.814)	(8.460)	(4.328)	(8.542)	(8.697)
5-Year Mortality	0.095***	0.087***	0.126***	0.034**	0.003	0.169***
	(0.014)	(0.015)	(0.035)	(0.015)	(0.026)	(0.035)
10-Year Mortality	-0.042	-0.109	0.343**	-0.139	-0.653	-0.449
	(0.118)	(0.079)	(0.168)	(0.194)	(0.745)	(0.576)
15-Year Mortality	-0.185	-0.123	0.028	-0.126	-0.842	-0.564
	(0.133)	(0.092)	(0.270)	(0.167)	(0.672)	(0.479)
Observations	4,494	4,446	2,212	2,600	1,030	1,112
Number of respondents	2,247	2,223	1,106	1,300	515	556

Notes: Table shows coefficient estimates for separate regressions of disasters deaths on risk category. Standard errors in parentheses, clustered at the district level. All regressions include individual fixed effects, wave dummy, and demographic controls. *** p<0.01, ** p<0.05, * p<0.1

Results are presented in Table I.12. While increased mortality causes increased risk aversion in the five-year time frame for both genders and most age groups, surprising patterns appear. Younger men are affected earlier, becoming more risk averse one to five years after experiencing a disaster and the effect fades after five years, while women aged 35-50 have a later onset affect, becoming more risk averse five to ten years after the disaster, but not in the short term nor at the fifteen-year time frame. Additionally, the largest impact appears for men over 50 years old at the five-year time frame, with coefficient sizes double that of the overall results. This could be indicative of the income channel, where men above 50 are less able to smooth consumption over their lifetimes.

5 Pathways

There are three plausible pathways through which disasters can impact risk preference: emotional response, income loss, and probability updating.

As explored by Hanaoka et al. (2018) and Eckel et al. (2009), individuals may have an emotional response to disasters, which impact how they answer the lottery questions. It is likely that severe disasters cause fear, as lives are threatened and there is worry about recovery. This fear may result in individuals displaying higher risk aversion. Additionally, depression and PTSD have been closely linked to the experience of disaster and these conditions may also impact emotions and perceptions of risk. The IFLS includes information on mental health. There is a module that asks the respondents a series of questions about their current emotional state, including if they are fearful, hopeful, have trouble sleeping, etc. The IFLS instructs that the 10 questions on mental health and emotions can be indexed into a depression score, where individuals are considered depressed if they are above a score of 10, which I have standardized for the sample. Table 13 shows that there is a relationship between natural disaster mortality and an individual's mental health and propensity for depression at the 1- and 5-year time frame, which bolsters the argument that it is through emotions that individual's display different risk preferences. While not displayed in the table, the results of the same analysis at the 10- and 15-year time frames are insignificant, indicating that these feelings are not lasting over the long term.

The second pathway through which disasters are inducing a change in risk aversion is through income, where disasters cause a loss in wealth and that loss in wealth drives

Table 13: Impact of Disasters on Mental Health

	Standardized Score for Depression					
	Full Sample	Females	Males	Full Sample	Females	Males
	(1)	(2)	(3)	(4)	(5)	(6)
1-Year Mortality	33.05*	47.91*	22.31*			
	(17.07)	(27.41)	(13.28)			
5-Year Mortality				0.17***	0.28***	0.08**
				(0.04)	(0.06)	(0.04)
Observations	15,894	7,736	8,158	15,894	7,736	8,158
Mean Mortality	0.002	0.002	0.002	0.092	0.089	0.094
Max Mortality	0.116	0.077	0.116	7.50	7.50	7.50
# Respondents	7,947	3,868	4,079	7,947	3,868	4,079
Adjusted R-squared	0.164	0.163	0.166	0.163	0.162	0.166

Depressed is a standardized score based on 10 mental health questions asked in the IFLS. Standard errors in parentheses, clustered at the district level. All regressions include individual fixed effects, wave dummy, and demographic controls. *** p<0.01, ** p<0.05, * p<0.1

individuals' risk preferences. The IFLS also has information on individual and household income. I run a similar regression as the mental health analysis to investigate whether risk attitudes are being impacted through the income channel. In this case, individuals appear more risk averse because their risk is evaluated at a lower income level. In fact, Table 14 shows that district disaster mortality is negatively correlated with income, and is significant when measured as five-year mortality. The higher the disaster mortality in a district, the less income (measured as the natural log of per capita household income) an individual has.

The third possibility, as cited by Cassar et al. (2017) and Cameron and Shah (2015), is that individuals update their expectations of future events occurring once they are hit by a disaster they did not expect. The likelihood of being struck by an earthquake or tsunami are low, but once an individual has already experienced this, they may be more inclined to believe it will happen again, thereby adding to the background risk an individual perceives. This change in expectations may make individuals perceive that the world is a riskier place because of their experience. Cameron and Shah (2015) do show some evidence of probability updating, but unfortunately none of the IFLS questions ask about future probabilities of

Table 14: Impact of Disasters on Income

	Natural Log of Per Capita Household Income					
	Full Sample	Females	Males	Full Sample	Females	Males
	(1)	(2)	(3)	(4)	(5)	(6)
1-Year Mortality	-1.195	-0.192	-2.006*			
	(1.027)	(1.406)	(1.137)			
5-Year Mortality				-0.019***	-0.020***	-0.016***
				(0.004)	(0.004)	(0.006)
Mean Mortality	0.002	0.002	0.002	0.092	0.089	0.094
Max Mortality	0.116	0.077	0.116	7.50	7.50	7.50
Observations	15,807	7,676	8,131	15,807	7,676	8,131
# Respondents	7,928	3,856	4,072	7,928	3,856	4,072
Adjusted R-squared	0.019	0.018	0.020	0.019	0.019	0.020

Standard errors in parentheses, clustered at the district level. All regressions include individual fixed effects, wave dummy, and demographic controls. *** p<0.01, ** p<0.05, * p<0.1

events or expectations so it would be difficult to test for my sample. This result is also found by Gibson and Mullins (2020), who find that the decrease in property values resulting from Hurricane Sandy and updated FEMA maps are driven by belief-updating regarding flood risk in the area. They emphasize the importance of belief-updating, especially as climate change is increasing the risk of disaster events.

Belief-updating could have important implications for policy-makers, as the demand for insurance may increase following disasters and there is evidence that the distribution of disaster losses may be fat-tailed in nature. Conte and Kelly (submitted) explore the implications of fat-tailed events, where disaster events measured by damages and mortality may not follow a normal distribution, and tail events may occur with higher frequency than expected. One property of these events is that the largest observations in the data are poor predictors for subsequent tail events. The fact that disasters are fat-tailed may be driving the change in risk perceptions which requires belief updating, since this would be unexpected if these losses were normally distributed. While Conte and Kelly (submitted) focuses on climate change specifically, they do also speculate on the implications for disaster management. They point out that large disaster events decrease property values in affected communities, cause an uptick in insurance policy purchases after major flooding, and can have important bankruptcy risk consequences as there may be an underestimation of damage from catastrophic events. Under such circumstances, tail event occurrences may increase the reserve requirements and could in turn increase insurance rates to cover the increase. This is exacerbated by some findings that these events likely have non-stationary distributions due to climate change (Coronese et al., 2019). Additionally, these events are unlikely to impact the population uniformly, and maybe affect low-income property owners who are less likely to be insured more than wealthier individuals. Policy makers must think about the welfare cost associated with tail events that cause large damages and high mortality, and are likely to impact those residents with lower wealth. For some suggestive evidence that disaster mortality and damages are likely fat-tailed events that require particular policy attention, see Figure I.7 which shows Quantile-Quantile Plots.[21] This is especially important during a time when Indonesia is engaging the World Bank on disaster risk financing and insurance programs, as well as implementing Rice Farming Insurance programs to protect rice farmers in the face of increased flooding, typhoons, and other disasters. As can be seen in the figure, for both damages and deaths caused by disasters, the right tail lies above the normal distribution and log-normal distributions (the modeling used by the World Bank to determine estimates for future losses and the requirements for future public spending), indicating that disaster are fat-tailed events. While outside the scope of this paper, it would be beneficial to understand how alternative policies would be affected by fat-tailed events, especially as it pertains to belief updating and insurance pricing.

[21] Das and Resnick (2008) recommend using quantile-quantile plots to detect fat tails.

Figure 7: Quantile-Quantile Plots for Disaster Mortality and Damages

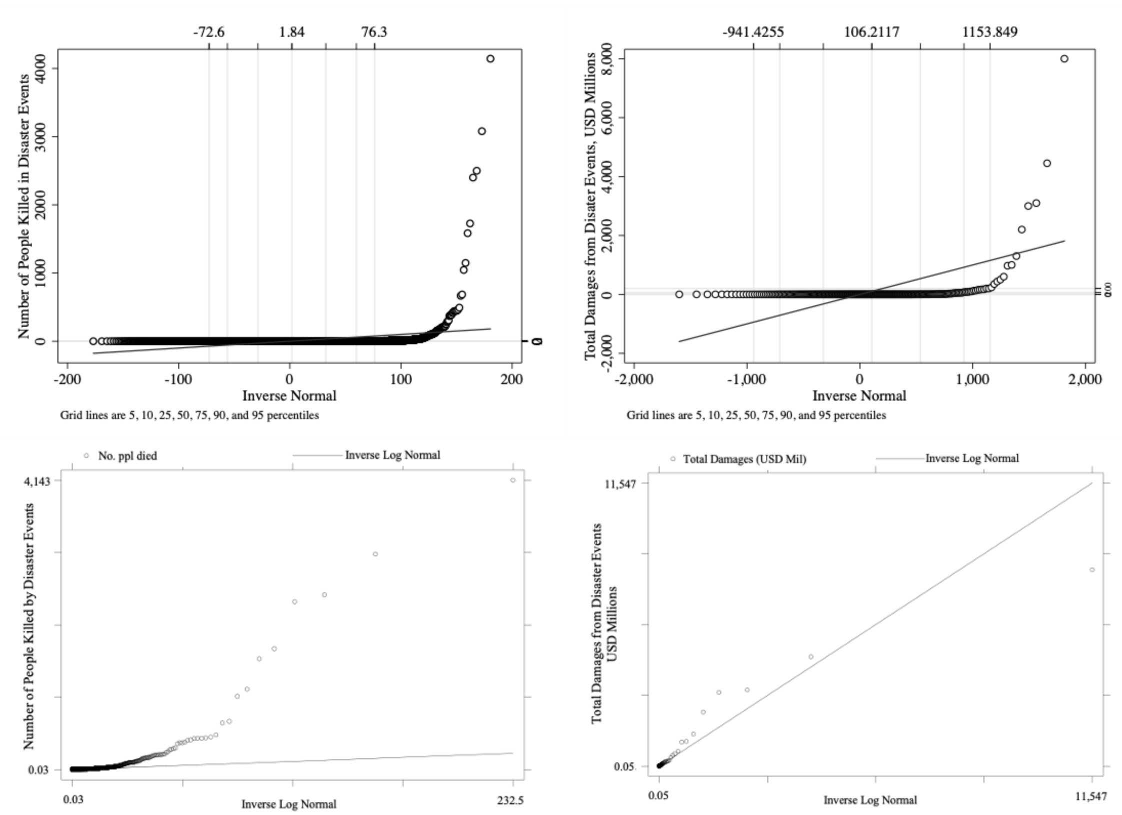


Figure Notes: The first row shows the Q-Q normal distribution plots for Deaths (left) and Damages (right) for all disaster events in Indonesia (excluding the 2004 Tsunami as this is an extreme outlier). The second row shows the same as row one, except now comparing to a log-normal distribtion (used in loss modeling by the World Bank for the Indonesian Goverment). This shows the possible underestimation of losses and mortality for extreme disaster events.

6 Robustness

I examine the robustness of my results to a number of concerns. I test for selective attrition, analyze possible bias from endogenous migration, compare results to regressions that include individuals who are "gamble averse," and discuss the relationship between risk and time preference.

6.1 Selective Attrition

There were 28,859 individuals that answered the lottery questions in 2007.[22] When interviewers followed up with IFLS households in 2014, there were 7,577 individuals out of the original 28,859 respondents that did not play the game in wave 5.[23] This is due to a variety of reasons, which I have partial information on. Out of those who were not re-interviewed, 1,561 refused to answer the questions, 1,381 died between waves, 1,089 individuals had a proxy answering questions for the person (risk and time preference questions were not asked on behalf of the individual), and the rest were not interviewed for a variety of other reasons.[24] This may indicate selective attrition and may confound the main results if individuals who drop out of the sample have inherently different risk preference or have differential experiences with natural disasters. First, I analyze whether individuals who drop out of the sample in wave 5 are inherently different from panel individuals in terms of demographics. The two groups do differ significantly in terms of demographics, and attritors are more likely to be older (logical as a substantial portion died), female, less educated, unmarried, living in rural areas, Javanese, and muslim. While this may be some cause for concern, my main preoccupation is whether these individuals are different in terms of their risk attitudes and exposure to disasters.

[22] This includes 12,059 individuals who are "gamble averse" but does not include approximately 140 individuals who answered "I don't know" during the lottery questions in wave 4.

[23] An additional 145 are excluded from my final dataset because they answered "I don't know" when presented with lottery choices.

[24] These include illness and not being home during the time of interview. There are over 2,000 individuals for whom there is not a clear answer for why they were not re-interviewed in 2014.

Table 15: Selective Attrition

	Attrition Dummy								
	Round 4					**Round 5**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Risk Category (Rd 4 only)	-0.001								
	(0.003)								
1-Year Mortality		2.435				-2.078*			
		(1.828)				(1.165)			
5-Year Mortality			-0.022				0.002		
			(0.055)				(0.446)		
10-Year Mortality				-0.008				-0.006	
				(0.041)				(0.015)	
15-Year Mortality					-0.025				-0.005
					(0.017)				(0.014)
Observations	16,800	28,859	28,859	28,859	28,859	27,552	27,552	27,552	27,552
Adjusted R-squared	0.038	0.031	0.031	0.031	0.031	0.018	0.018	0.018	0.018

Notes: Standard errors in parentheses, clustered at the district level. Includes district fixed effects. Attrite is equal to 1 if someone who had risk data in IFLS 4 is not re-interviewed in IFLS 5. Mortality rate is per 1,000 people in the district and only pertain to disasters for IFLS 5. *** p<0.01, ** p<0.05, * p<0.1

In order to determine whether individuals who attrite are inherently different in terms of risk preference, I test the null hypothesis that risk attitudes of panel respondents and attritors are the same at the baseline wave (wave 4, conducted in 2007). I cannot reject the null hypothesis (p-value=0.51), suggesting that respondents who are not re-interviewed do not have significantly different risk preferences than those appear in both waves of data. Additionally, I regress an attrition dummy on risk category in wave 4 and the resulting coefficient (see Table 15) is not statistically significant, further confirming that differences in risk preference are not driving the probability of attrition.[25] It may also be that individuals that experience natural disasters are more likely to drop out of the sample (due to displacement, death, etc.). To determine whether disasters are correlated with attrition, I regress an attrition dummy on deaths from disasters in both waves. Table 15 shows that at baseline, individuals who live in districts with higher disaster deaths (measured in 2007) are not more likely to drop out of the sample. This is true for disasters measured by deaths over the last 1, 5, 10 and 15 years. Additionally, those who live in districts that had higher levels of disaster deaths measured in 2014 are not more likely to drop out of the sample, suggesting

[25] All attrition regressions include district fixed effects.

that disasters are not driving attrition (see columns 6-9 in Table 15). The exception is 1-year mortality measured at wave 5 which is significant at the 10% level, but the relationship is negative, so those hit by a shock are less likely to attrite and should not bias the main results.

6.2 Endogenous Migration

Selectivity from endogenous migration could be a concern if individuals moved from a district after being interviewed in 2007 and were not able to be traced in 2014 due to differences in disaster exposure and/or risk preference. Given the extensive efforts RAND undertakes to recontact all family members, the portion of individuals not interviewed because they have moved is low. Further, the small number of individuals that are excluded from the sample because they moved and were unable to be located are included in the attrition analysis as attritors. As described in the previous section, attritors do not affect the main results of the paper. Additionally, the IFLS has data on reasons for migrating, and only 4 respondents out of the near 2,000 who migrated out of the district answered that they moved due to a natural disaster, adding evidence that disasters are not driving migration.

Endogenous migration is a greater concern for cross sectional studies where migration cannot be disentangled from selectivity on risk. For instance, if generally more risk tolerant people move away from the district after a disaster and only the residents that remained in the district were interviewed, there would be selection bias in the sample. These concerns are largely addressed by following the same people over time and further bolsters the importance of a longitudinal analysis.

It is possible that the change in risk preferences would induce migration following disasters, where individuals become more risk averse and want to move away from the area after the disaster hits. If a disaster experience forced an individual to migrate and this in turn influenced the individual's risk preference, the impact of disasters on risk could be upward biased by not properly accounting for migration in the identification strategy. However, Table 16 shows that higher disaster mortality has no significant effect or results in less migration

Table 16: Effects of Disaster Deaths on Migration

	Migration Dummy						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1-Year Mortality	-0.423						
	(0.560)						
2-Year Mortality		-0.021					
		(0.135)					
3-Year Mortality			-0.004**				
			(0.002)				
4-Year Mortality				-0.003*			
				(0.002)			
5-Year Mortality					-0.003		
					(0.002)		
6-Year Mortality						-0.004**	
						(0.002)	
7-Year Mortality							-0.008*
							(0.004)
Observations	15,894	15,894	15,894	15,894	15,894	15,894	15,894
# Respondents	7,947	7,947	7,947	7,947	7,947	7,947	7,947
Adjusted R-squared	0.006	0.008	0.009	0.009	0.011	0.013	0.016

Note: Standard errors in parentheses, clustered at the district level. Mortality rate is per 1,000 people in the district. All regressions include individual fixed effects, wave dummy. *** p<0.01, ** p<0.05, * p<0.1

away from the district, addressing the concern that it is migration driving the increase in risk aversion, not the shock itself. Additionally, I test whether the results differ for those who have never moved from the district. While coefficient estimates are higher at the five-year mortality and insignificant for 15 year mortality, the results are largely similar.

6.3 Gamble Averse Respondents

There is a group of individuals that has been only briefly mentioned thus far and I address them more directly here. There is a substantial portion of the IFLS sample who can be labeled “gamble averse” based on their answer to the first lottery questions they are asked, meant as a comprehension check. They are asked to choose between 800,000 rupiahs and a 50-50 chance of receiving 800,000 rupiahs or 1,600,000 rupiahs. If they choose the 800,000 for certain the interviewer asks, "Are you sure? In option 2 you will get at least Rp 800 thousand per month and you may get Rp 1.6 million per month. In option 1 you will always get Rp 800 thousand per month." If the respondent sticks with the certain choice, they are not asked any further questions. This could be indicative of a lack of comprehension, but it could also indicate an extreme aversion to uncertainty. It may be that individuals would rather know with certainty the amount they will receive rather than any uncertain outcome, regardless of the possible amounts. R. Brown et al. (2019) encounters a similar issue in the Mexican Family Life Survey and includes these individuals in his "most risk averse" category, showing that his results are robust when these individuals are excluded. I remain unconvinced it would be appropriate to include all of these individuals as a separate risk category (say risk category = 5) as it would be hard to tease out those who did not understand the question versus those who truly are "gamble averse." I have, however, included an analysis where I estimate equation [2] using a dummy for "most risk averse," including and excluding "gamble averse" individuals. Results from this analysis appear in Table 17.

The results are consistent across the two groups and are in line with the main specification where risk category is used as the dependent variable. While results are insignificant in the short and long run (one and ten years, respectively), additional deaths from disaster in the district over the last 5 years positively and significantly predicts the likelihood of being in the "most risk averse" category. The effect is smaller when "gamble averse" individuals are included, likely because of the dampening effect of those that did not understand the game or the possibility that "gamble averse" individuals are more likely to remain gamble averse compared to individuals that fall into other categories and thus provide less variation in outcomes.

6.4 Time Preference

Risk preferences are closely tied to time preferences, or the amount of patience an individual displays. Several studies have found that there is a negative relationship between time and

Table 17: Most Risk Averse on Total District Deaths from All Disasters, with and without Gamble Averse Individuals
adjusted for district population (per 1,000)

	Most Risk Averse Dummy							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-Year Mortality	0.789	0.655						
	(1.433)	(1.373)						
5-Year Mortality			0.038***	0.021***				
			(0.005)	(0.004)				
10-Year Mortality					-0.014	0.026		
					(0.044)	(0.028)		
15-Year Mortality							-0.044	-0.006
							(0.038)	(0.026)
Includes Gamble Averse	NO	YES	NO	YES	NO	YES	NO	YES
Avg Mortality Rate	0.002	0.002	0.092	0.084	0.186	0.170	0.190	0.175
Number of respondents	7,947	18,636	7,947	18,636	7,947	18,636	7,947	18,636
Observations	15,894	37,272	15,894	37,272	15,894	37,272	15,894	37,272
Adjusted R-squared	0.035	0.048	0.037	0.048	0.035	0.048	0.035	0.048

Note: Standard errors in parentheses, clustered at the district level. Most Risk Averse = 1 if risk category = 4. For columns that include "gamble averse" individuals Most Risk Averse = 1 if the individual is "gamble averse". All regressions include individual fixed effects, wave fixed effects. "Gamble averse" individuals answered the certain choice even when choosing the gamble would provide equal or higher payouts. Mortality rate is per 1,000 people in the district. *** p<0.01, ** p<0.05, * p<0.1

risk preferences. One way to corroborate the main results on risk preferences is examining the impact of disasters on time preferences. In additions to the risk preference questions, the IFLS also includes questions on time preference. The questions follow a similar structure to the games in the risk preference section, except individuals are given the option between an amount today or another amount one or five years from now. The specific questions can be found below in Table 18.

The results show a similar pattern to risk preference, but in the opposite direction. One might expect that if disasters are making people more risk averse, they would also make individuals more impatient due to the increase in uncertainty and weighing the present more heavily. However, I find that individuals are much more patient in the short run (deaths measured over the past year), are mildly more patient when analyzing disasters over three to nine years and in the longer term (10+ years) are more impatient, again suggesting a reversion back to the original time preference (although the long term results are insignificant). These

Table 18: IFLS Time Preferences

Scenario	Option 1 ***Money Today***	Option 2 ***Money Later***
Game A		
Q1	1 million Rps Today	or 500,000 Rps. in 5 years
Q2	1 million Rps Today	or 4 million Rps. in 5 years
Q3	1 million Rps Today	or 10 million Rps. in 5 years
Q4	1 million Rps Today	or 2 million Rps. in 5 years
Game B		
Q1	1 million Rps Today	or 1 million Rps. in 1 year
Q2	1 million Rps Today	or 3 million Rps. in 1 year
Q3	1 million Rps Today	or 6 million Rps. in 1 year
Q4	1 million Rps Today	or 2 million Rps. in 1 year

results are summarized in Table 22 and Figure I.8. The table shows the numerical results looking at snapshots for disasters measured over 1, 5, 10, and 15 years, while the figure shows coefficient estimates for each year. Individuals may become more patient because after experiencing a disaster they understand the importance of saving for future negative shocks, or they may be receiving aid in the short term, making the choice to receive a higher amount of money later more attractive (when aid runs out).

Figure 8: Coefficient Estimates for Time on Disaster Deaths, all disasters and severe disasters

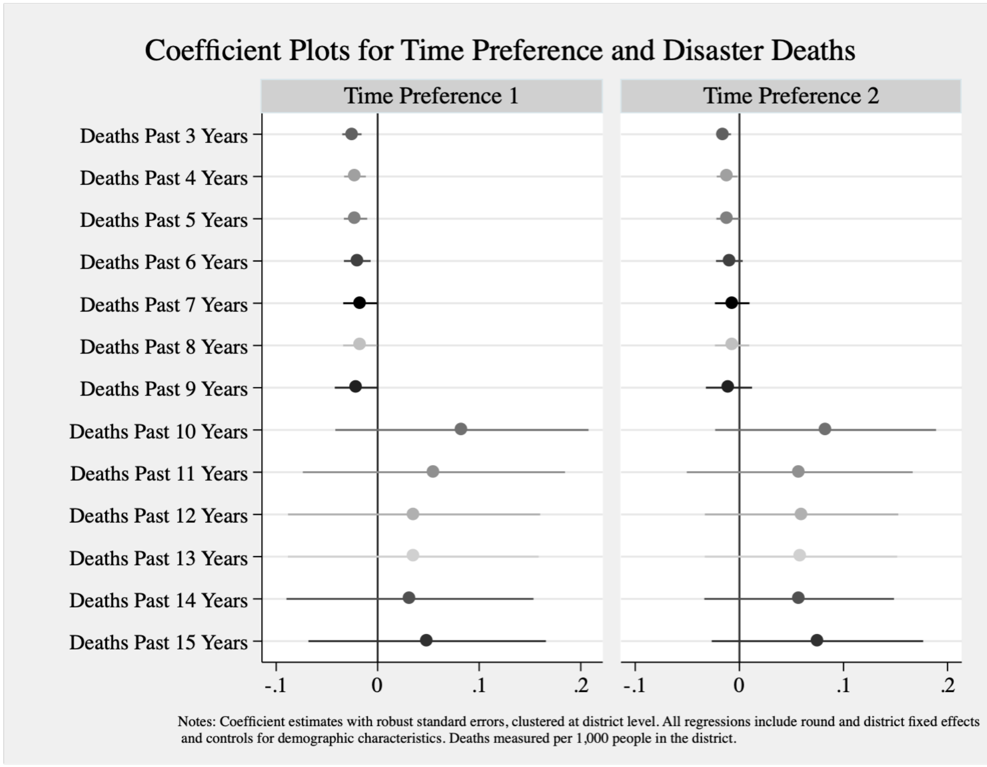


Table 19: Time Preference Category on Total District Deaths from All Disasters
adjusted for district population (per 1,000)

	Time Category			
	(1)	(2)	(3)	(4)
1-Year Mortality	-5.521**			
	(2.493)			
5-Year Mortality		-0.0218***		
		(0.006)		
10-Year Mortality			0.083	
			(0.063)	
15-Year Mortality				0.0487
				(0.059)
Avg Mortality Rate	0.002	0.084	0.171	0.175
Number of pidlink	17,825	17,825	17,825	17,825
Observations	35,650	35,650	35,650	35,650
Adjusted R-squared	0.00583	0.00493	0.00493	0.00482

Notes: Standard errors in parentheses, clustered at the district level. All regressions include individual fixed effects, wave fixed effects, and demographic controls. Mortality rate is per 1,000 people in the district.
*** p<0.01, ** p<0.05, * p<0.1

7 Conclusion

Economists have long sought to understand the factors that influence our economic decision-making and lifetime earnings. There has been substantial debate over whether risk preferences are immutable throughout one's life or if experiences can shape these preferences.

As nations build programs and policies around disaster preparedness and risk reduction, it is important to understand the factors that affect our decision-making following disasters and how we recover from these shocks. While the frequency and intensity of disasters across the world can be variable, the burden of these events is not equally shared. In recent years, developed countries have made significant strides in reducing the death toll and economic loss from disaster, while developing countries continue to bear the highest human costs due to exposure, poor infrastructure and building construction, low household savings, and the tendency of the poorest populations to live in remote areas where it is hard to receive aid.[26] While the costs of these disasters can be substantial for all countries, extreme weather events can affect those in developing nations more acutely.[27] Natural disasters leave the most vulnerable populations even more impoverished by increasing food insecurity, water insecurity, and health risks, as well as causing physical damage, agriculture loss, and income loss (*CRED & USAID*, 2016). While physical damage and health impacts are explicit and have been widely estimated in both a developing and developed context,[28] there is much to be explored in the indirect impacts of natural disasters for those in developing countries, such as psychological and behavioral effects.

Because disasters can be severe and traumatic events causing death and property loss, it is plausible that they impact our individual risk preferences. Using longitudinal data from a household survey and national disaster statistics in Indonesia, I evaluate how disasters impact risk attitudes, removing time-invariant individual heterogeneity by including individual

[26]In 2018, Asia accounted for 80% of the disasters globally, and Indonesia itself accounted for close to half of the deaths caused by disaster (*CRED, USAID, UCLouvain*, 2018).

[27]see *CRED & UNISDR*, 2018, as well as *UNSD*, 2016.

[28]See, for example, Stern, 2008; Frankenberg et al., 2014; Maccini and Yang, 2009; **brando˙nina˙2015**; Datar et al., 2013; Desbureaux and Rodella, 2019.

fixed effects. The literature has produced mixed results on the impact of disasters on risk preferences due to primarily ex post disaster analysis and differences between developing and developed countries.

Because the disaster data I have is extensive, covering multiple disaster severity measurements and disaster types, I can evaluate several aspects of disaster that may be more salient to individuals than a simple "yes" or "no" question about whether they've experienced a natural disaster. In fact, from the variety of measurements for disaster and the different subsets of the sample that are tested, it is clear that the impact of disasters is not homogeneous. Larger, more severe disasters affect risk attitudes more than extensive disasters with lower mortality. Death and destruction also have a more significant influence on risk than other measures, such as evacuations or the number of people affected by a disaster. This may indicate that while risk attitudes change following the trauma of the natural disaster, there is evidence of resilience or a return to the status quo, after a certain amount of time has passed. There is evidence in the psychological literature that suggests that those who have longer lasting psychological effects from natural disasters stem from the traumatic experience of injury and death, specifically the fear of death or death of a loved one, as well as personal property loss. Intensive disasters which are less frequent and more destructive, such as earthquakes and tsunamis, drive the results, while extensive disasters, such as floods and landslides, that are more frequent and less severe have a short term impact but fades quickly.

I find that women have a higher positive risk response than males, and that younger males are impacted more heavily in the shorter term while women aged 35-50 are impacted later and for a longer period of time. Selective attrition, endogenous migration, the inclusion of "gamble averse" individuals and time preference does not impact my overall results. Overall, high death toll disasters increase risk aversion in the medium term (three to nine years) before the impact fades and the risk parameter sees a reversion after 10 years. This indicates that while disasters are impacting risk preferences, it is not for life, and that after a sufficient amount of time has passed, individuals are resilient and return to life as it was before the disaster experience, and some evidence that they are even more risk tolerant than if they hadn't experienced a disaster.

There are three possible pathways through which risk attitudes may be changing: emotional responses, income loss, or updating of future probabilities. I find evidence that both income loss and emotional responses may be the mechanism through which risk preferences are changing, but do not have sufficient data to test whether expectations of future events are changing. These results have important implications for policymakers, as increases in risk aversion can cause sub-optimal levels of household investment and savings, and may make individuals less likely to open businesses or adopt new technologies. As climate change and population density continue to impact the human cost from disasters, governments should think about investing in early warning systems (as evacuations do not seem to cause any change in risk attitude) and other mitigation strategies which can reduce disaster mortality. Another important consideration for policymakers is the implications for disasters resulting in extreme levels damages and losses that occur with higher frequency than expected under a normal distribution, and would have consequences for insurance pricing and how individuals update their beliefs.

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A Appendix

A.1 Summary statistics by risk category

Table 20: Summary Statistics by risk category

	Full Sample	Risk = 1 *Most Risky*	Risk = 2 $\rightarrow$	Risk = 3	Risk = 4 *Least Risky* $\rightarrow$	Risk = GA *Gamble Averse*
Male	0.46	0.57	0.51	0.53	0.47	0.40
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)
Age	35.36	34.73	33.52	32.33	33.87	36.31
	(13.54)	(12.53)	(12.92)	(12.67)	(12.91)	(13.99)
Married	0.73	0.74	0.69	0.65	0.72	0.75
	(0.44)	(0.44)	(0.46)	(0.48)	(0.45)	(0.43)
Urban	0.51	0.52	0.56	0.55	0.57	0.48
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Javanese	0.43	0.36	0.41	0.44	0.47	0.45
	(0.49)	(0.48)	(0.49)	(0.50)	(0.50)	(0.50)
Sundanese	0.12	0.11	0.12	0.08	0.13	0.11
	(0.32)	(0.32)	(0.33)	(0.27)	(0.33)	(0.31)
Years of Schooling	8.28	9.15	9.32	9.84	9.16	7.59
	(4.48)	(4.51)	(4.46)	(4.14)	(4.34)	(4.40)
Muslim	0.90	0.90	0.89	0.88	0.89	0.89
	(0.30)	(0.30)	(0.31)	(0.32)	(0.31)	(0.31)
5 Yr Disaster Mortality Rate	0.16	0.14	0.14	0.09	0.21	0.15
	(0.77)	(0.71)	(0.71)	(0.50)	(0.90)	(0.77)
Observations	21,137	2,330	1,259	922	4,479	8,786

Note: Standard Deviation in parentheses. Summary statistics measured in wave 4, and only include those who have risk data in wave 4 and wave 5. Disaster mortality rate is adjusted for district population per 1,000 residents.

A.2 Risk Behavior

Recall that higher risk categories equate to higher risk aversion, so one would expect the relationship between risk category and risky behavior to be negative. Risk category is in fact negatively associated with all behaviors, and is most significantly associated with self-employment. When demographic controls are included, the association is no longer statistically significant for migrating for work or smoking. I also run the probit using a dummy for being in the least risk averse category (risk category equals 1). Being in this category shows higher likelihood of engaging in risky behavior, and the results are statistically significant even when controls are included (except for smoking). This makes sense as those in the least risk averse category would be the individuals most likely to engage in risky behavior.

Table 21: Likelihood of Risky Behavior Based on Risk Category

	Migrated for Work		Self-Employed		Smoker	
	(1)	(2)	(3)	(4)	(5)	(6)
Risk Category	-0.008***	-0.004	-0.022***	-0.014***	-0.023***	-0.002
	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.003)
Demographic Controls	No	Yes	No	Yes	No	Yes
Observations	6,093	3,978	6,526	5,785	8,985	7,940
Pseudo R Squared	0.002	0.293	0.002	0.117	0.002	0.445
Least Risk Averse	0.020**	0.017**	0.058***	0.031**	0.066***	0.001
	(0.009)	(0.007)	(0.013)	(0.012)	(0.012)	(0.008)
Demographic Controls	No	Yes	No	Yes	No	Yes
Observations	4,559	3,978	6,526	5,785	8,985	7,940
Pseudo R Squared	0.003	0.295	0.002	0.116	0.003	0.445

Notes: Standard errors in parentheses, clustered at the district level. Results show average marginal effects of risk aversion on risky behavior from a probit model, controlling for interview month, sex, age, urban/rural, marital status, ethnicity, and religion, measured at wave 4. Most risky choice is a dummy for if the respondent is in risk category 1. The migrating for work probits only includes males. Smokers include people who used to smoke but have since quit. *** p<0.01, ** p<0.05, * p<0.1

A.3 Cross-sectional Results

Table 4 highlights the importance of using a fixed effects framework, showing the results of the cross sectional specification (separate results for IFLS 4 and IFLS 5), as well as the combined waves using individual and wave fixed effects. Columns 1 and 2 follow what much of the literature currently does, analyzing risk preferences at one point in time, comparing those who have experienced a disaster versus those who have not, without taking the time invariant exposure to disaster and other individual unobservables into effect. If individual unobserved heterogeneity was not an issue, the cross sectional results would not differ from the results using individual fixed effects. It is clear here that the results differ depending on which wave of data is being used, and by following individuals over time, I can observe changes in risk aversion and account for time invariant heterogeneity.[29]

In wave 4, individuals who were exposed to additional deaths are more risk averse, while in wave 5 individuals are more risk tolerant given higher levels of mortality, as seen in columns

[29] I use deaths from disaster in the district over 5 years for display purposes, but results do not change when I use deaths over 3 through 9 years (when deaths have a significant effect on risk aversion).

Table 22: Comparison of Cross-Sectional and Longitudinal Results

	Risk Category		
	Only IFLS4	**Only IFLS 5**	**IFLS 4 & IFLS 5**
	(1)	(2)	(3)
Deaths Past 5 Years	0.024**	-1.249**	0.085***
	(0.011)	(0.534)	(0.012)
Individual Fixed Effects	NO	NO	YES
Mean # Deaths	0.172	0.012	0.092
Observations	7,947	7,947	15894
Number of respondents			7,947
Adjusted R-squared	0.021	0.011	0.020

Notes: Standard errors in parentheses, clustered at the district level. Fixed Effects regressions also include wave fixed effects. All regressions include demographic controls including sex, age, urban/rural, marital status, ethnicity, and religion. Mean number of deaths are per 1,000 people in District. *** p<0.01, ** p<0.05, * p<0.1

1 and 2 of Table 4. These results may be driven by the specific timing of disasters during these two interview rounds, and do not consider differences in exposure that have existed for many years. Column 3 shows the results when both waves of IFLS data are included and accounts for individual and time fixed effects, and indicates that individual heterogeneity is likely a source of bias in the cross sectional approach. The impact of disasters on risk is now positive and significant at the 1% level. Table 5 shows that when the fixed effects approach is used, an additional 1 death per 1,000 people in the district in the last 5 years causes an increase in risk category of 0.085 (individuals become more risk averse).