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

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ABSTRACT:

It is well documented that risk preferences influence many individual economic decisions, and new evidence suggests that life shocks may impact 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 individual risk aversion are high. Using data from Indonesia, a large developing country highly exposed to disasters, I evaluate the impact of several types of disasters over multiple measurements and time periods on risk attitudes. I combine data on risk attitudes from the Indonesian Family Life Survey (IFLS), a longitudinal household survey, with national natural disaster statistics reported by Indonesia's National Disaster Management Authority (BNPB), and I address possible selection bias using an individual fixed effects framework that accounts for individual time-invariant heterogeneity. I find that risk aversion increases following a disaster for a sustained period of time, but the effect fades after a decade, indicating an eventual recovery from the shock. Additionally, I find that more severe disasters with high mortality rates are most salient to individuals, and earthquakes and tsunamis have more impact than higher frequency, lower mortality disasters like floods and landslides. The results are robust to attrition, migration, inclusion of "gamble averse" individuals, and time preference. These outcomes shed light on how individuals in a developing country respond to disasters, specifically how survivors internalize the aftermath of these shocks, and can be informative to how policymakers can address the increasing threat of severe disasters due climate change and increasing 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 significant roles in determining economic choices, and risk attitudes influence important individual and household decisions such as savings, investment in health and education, entrepreneurship, and technology adoption (see, for example, Dohmen et al., 2011; Rosenzweig and Stark, 1989; Lawrance, 1991; Strauss and Thomas, 1998; Liu, 2013; Frankenberg et al., 2013; Maccini and Yang, 2009). Additionally, poorer households display higher levels of risk aversion, which can lead to under-investments and over-saving, compounding the consequences of credit constraints and uninsurable risks that these individuals face (Haushofer and Fehr, 2014). 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 less certainty surrounding the impact of shocks, including natural disasters, financial crises, and conflict, on individual risk preferences.

Given the traumatic nature and devastating human costs of natural disasters, it is plausible that disasters would impact how individuals view risk and uncertainty. The frequency and intensity of disasters across the world can be variable, but 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.[1] While the costs of these disasters can be substantial for all countries, extreme weather events can affect those in developing nations more acutely.[2] 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

[1] 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.

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

and health impacts are explicit and have been widely estimated in both a developing and developed context,[3] there is much to be explored in the indirect impacts of natural disasters for those in developing countries, such as psychological and behavioral effects. 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.

I investigate the impact of several types of disasters over multiple measurements and time periods on risk attitudes in Indonesia, a large developing country that is highly exposed to disasters. To do this, 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 the Indonesia's National Disaster Management Authority (BNPB) at the district level. Indonesia is located on the Pacific Ring of Fire, and is frequently plagued by major disaster events such as earthquakes, tsunamis, volcanic eruptions, wildfires, floods, landslides, tornadoes, etc. Additionally, there is substantial regional heterogeneity of economic and social development. This makes Indonesia an ideal research setting for exploring the varied ways in which natural disasters may influence risk attitudes and decision making.

Using an individual fixed effects framework, I find that individuals become more risk averse as the cumulative district mortality rate and district destruction from disaster increases over the past three to nine years. These results don't hold in the short term (one to two years), where despite the higher magnitude on the coefficient, the results are statistically insignificant. While the impact is long-lived, after 10 years the effect of disasters on risk fades to zero and is no longer significant. 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. Finally, I find evidence that the changes in risk attitude may be driven by specific types of

[3]See, for example, Stern, 2008; Frankenberg et al., 2014; Maccini and Yang, 2009; Brando and Santo, 2015; Datar et al., 2013; Desbureaux and Rodella, 2019.

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).

Currently, the literature on risk and disasters is conflicted on whether natural disasters change individual risk attitudes, and also the direction of the changes. It is unclear whether these extreme weather shocks would ultimately result in higher or lower levels of risk aversion. In the developed context, Hanaoka et al., 2018, Eckel et al., 2009 and Page et al., 2014 find that individuals become more risk tolerant following disasters in Japan, United States, and Australia, respectively. Cameron and Shah, 2015, P. Brown et al., 2018, and Cassar et al., 2017 find the opposite in developing countries and conclude that individuals that have experienced a disaster in Indonesia, Fiji, and Thailand, respectively, become more risk averse.[4] 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.

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. My 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 attitudes following disasters. Mortality is 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 natural disasters to psychological impacts such as Post-Traumatic Stress

[4]The exception to this is Bchir and Willinger, 2013 who find that individuals in Peru become less risk averse, however this paper focuses on exposure and background risk, not experience of disaster.

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).

My paper contributes to the literature on shocks and risk attitudes in the following important ways. First, my paper is the first to use panel data from a developing country to examine the impact of disasters on risk attitudes, allowing me to remove 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 includes a detailed literature review. Section 3 describes the data and methodology, including a background of disasters in Indonesia. Section 4 describes the empirical specification. Results are discussed in Section 6, including the heterogeneous impacts of disaster on risk attitude. I investigate pathways in Section 7 and conduct Robustness checks in Section 8. Section 9 concludes the paper.

2 Literature Review

Risk and uncertainty inform most economic decisions we make as individuals and households. As such, analyzing risk preferences is important for understanding economic behavior and household decisions regarding savings (Dohmen et al., 2011; Rosenzweig and Stark, 1989; Lawrance, 1991), investment in education and health (Dasgupta et al., 2016; Shaw, 1996; Strauss and Thomas, 1998), as well as technology adoption (Liu, 2013; Feder, 1980; Kebede, 1992). In the developing context, previous literature has found that poor households and individuals in developing countries tend to be more risk averse (Guiso and Paiella, 2008; 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 (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.[5] Because the poor face considerable credit constraints and uninsurable risks, they are also particularly vulnerable to income and health shocks (Haushofer and Fehr, 2014).

Given that underlying risk preferences may differ among populations based on a country's economic growth stage and the type of social safety nets citizens are provided, risk responses to negative life shocks may also vary across these contexts. This underscores the importance of having studies on risk attitudes from both developing and developed countries. While the literature on formation of risk preferences is quite established, there is still a lack of evidence on the impact of shocks on risk preferences. There is an emerging literature that has attempted to measure the behavioral consequences of individual shocks by assessing changes in individual risk attitudes following natural disasters and conflict.[6]. As natural

[5]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.

[6]Conflict includes wars, violence, or increases in crime rates. See, for example, Jakiela and Ozier, 2015 and R. Brown et al., 2017

disasters are traumatic events, cause physical damage and income loss,[7] and often result in adverse health outcomes (Frankenberg et al., 2013; Maccini and Yang, 2009; and Baez et al., 2010), it is conceivable that these shocks would be significant enough to induce changes in risk preference.

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 shortcoming in this literature is reliance on cross sectional data, where individuals can only be viewed at one point in time. The most notable exception to this is Hanaoka et al., 2018, who use panel data to evaluate risk attitudes before and after the Great Japanese Earthquake, however, they focus on a single event in Japan. 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.

Cameron and Shah, 2015, Cassar et al., 2017, and P. Brown et al., 2018 find that natural disaster shocks increase risk aversion in developing countries. Cameron and Shah, 2015 explore whether floods and earthquakes affect risk preferences in Indonesia and find that individuals living in villages that had experienced a flood or earthquake in the last 3 years are more risk averse than those who did not. 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,[8] which limits their sample to a small geographical area of the country. Risk attitudes may differ from individuals in other provinces, and from non-heads of household and from people residing in different types of households (i.e., without children). Cassar et al., 2017 similarly

[7]Physical damage to buildings & equipment, infrastructure loss, and lost profits are explicit and significant, often exceeding $1 billion dollars per event. In the US, 16 extreme weather events passed this threshold in 2017 alone, and the total cost of 279 weather and climate disasters since 1980 exceeds $1.825 trillion, as estimated by the National Center for Environmental information Smith and Information, 2020.

[8]East Java is one of 34 provinces in Indonesia.

show that the 2004 tsunami lead to long-lasting increases in risk aversion, prosocial behavior and impatience in Thailand. P. Brown et al., 2018 analyze the consequences of Cyclone Evan on risk attitudes and expectations regarding the likelihood of future disasters in Fiji and find that the responses differ among the two ethnic groups studied. Indo-Fijans hit by the cyclone are more risk averse and more pessimistic following the storm, while there is no effect for indigenous Fijans. Again, the challenge of these three studies is the reliance on cross sectional experiments post-disaster and the reliance on the assumption that the disasters are not correlated with time invariant and time varying unobservables, such as residential sorting. Jakiela and Ozier, 2015, in a different context, also find that risk aversion increases after experiencing a shock. They study the effect of Kenya's post-election crisis on individual risk preferences, using the timing of a survey interrupted by the conflict as an exogenous shock to show that those who were interviewed after exposure to the conflict displayed higher levels of risk aversion. In Mexico, R. Brown et al., 2017 use panel data from the Mexican Family Life Survey to analyze the impact of Mexican Drug War on risk attitudes, finding that individuals exposed to higher rates of crime during the Drug War become more risk averse. All of the above literature is 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. Hanaoka et al., 2018 use panel data to analyze the impact of the Great Japanese Earthquake on risk and find that men living in areas that were more severely hit by the earthquake become more risk tolerant following the Earthquake, while there was no change for women. Eckel et al., 2009 use Bayesian networks and show that women evacuees interviewed shortly after Katrina display more risk-loving preferences compared to a sample of evacuees interviewed a year after and a comparable sample of Houstonians. Bchir and Willinger, 2013 find that poor

Peruvians living in areas more exposed to lahars (mudflows) are more risk-loving than those that are not as exposed. Page et al., 2014 find that Australians who suffered direct property damage chose riskier gambles in an experiment than their unaffected neighbors. Finally, Voors et al., 2012 find that individuals who experienced violence or live in communities that have been more exposed to violence from the long-standing civil war in Burundi display more risk-seeking behavior. These results more closely corroborates 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.

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 has 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.

3 Data & Methodology

3.1 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 percent 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) because 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. While in other experiments and surveys this question is typically phrased as a gamble between two choices, because of the substantial Muslim population in Indonesia among whom gambling is prohibited, it is 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. See Table 1 for the scenarios that were presented to the individuals. There were two 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). 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.[9]

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.

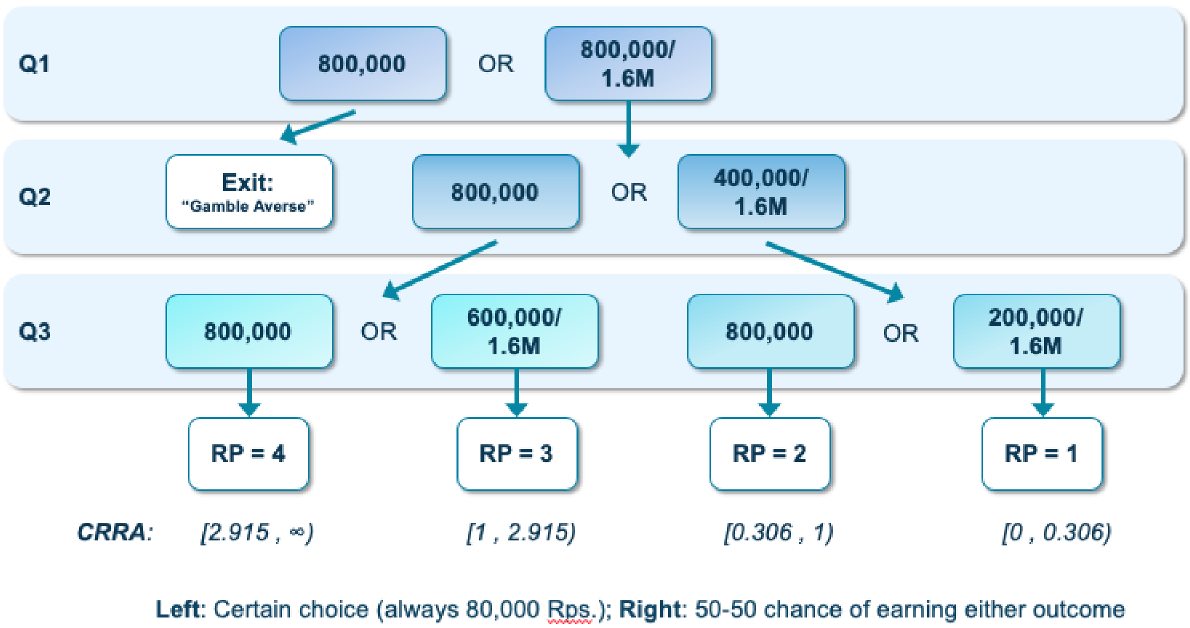
The responses to these questions put individuals on a risk scale from 1 to 4, where 1 is always choosing the certain option, and 4 is always choosing the gamble (excluding the Q1 response which is a logic check). An illustration on how the 1 to 4 scale is composed is

[9] 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., 2017, I consider alternative specifications where these individuals are included as "gamble averse," with similar results to the main analysis which exclude these respondents.

shown below in Figure 1.

A total of 17,980 individuals have risk data for both wave 4 and wave 5 of the IFLS. These individuals form the basis of my analysis as I am able to measure the change in risk over the two waves.[10]

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



3.1.1 Defining Risk Attitudes and Socioeconomic factors

I use three measures of risk aversion as my dependent variable: (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 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

[10]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.

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 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 1 below).

Table 2 shows summary statistics of the overall sample. On average, individuals fall between Category 2 and 3 on the four-point scale, and that half of the sample falls in the most risk averse category. About half 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 3/4 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 A1 in the appendix, which most importantly shows that males tend to make riskier lottery choices, consistent with the current literature (Eckel et al., 2009).[11]

3.1.2 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,

[11]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.

2015, Hanaoka et al., 2018 and R. Brown et al., 2017, I use a probit model to evaluate whether risk choices influence the likelihood of migrating for work, being self-employed, or smoking.[12] 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 Appendix Table A2 and indicate that risk category based on lottery choices predicts certain risky behavior.

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

3.2 Disaster Data

3.2.1 Background of 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.[13]

Earthquakes (and often the tsunamis that follow) have caused the most deaths overall in Indonesia, as evidenced by the 2018 Sulawesi Earthquake and 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

[13] *Population Exposed to Natural Hazards*, 2015

1997, when lower than expected rainfall was exacerbated by El Niño, killing over 600 people and affecting close to a million. 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.[14]

Figure 2: District Population in IFLS communities from 2010 Census

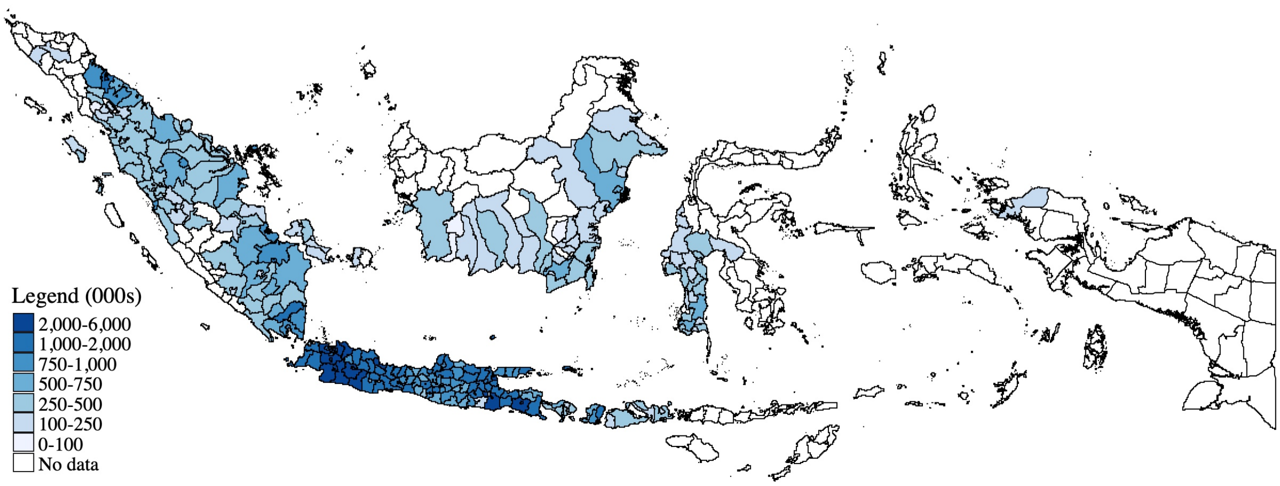


Figure 2 shows the population for IFLS districts as of the 2010 census. The population is heavily concentrated on the island of Java, where over half of the total population of the country resides. The island of Java is considered one of the most densely populated regions on the planet. Otherwise, population 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.

3.2.2 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,

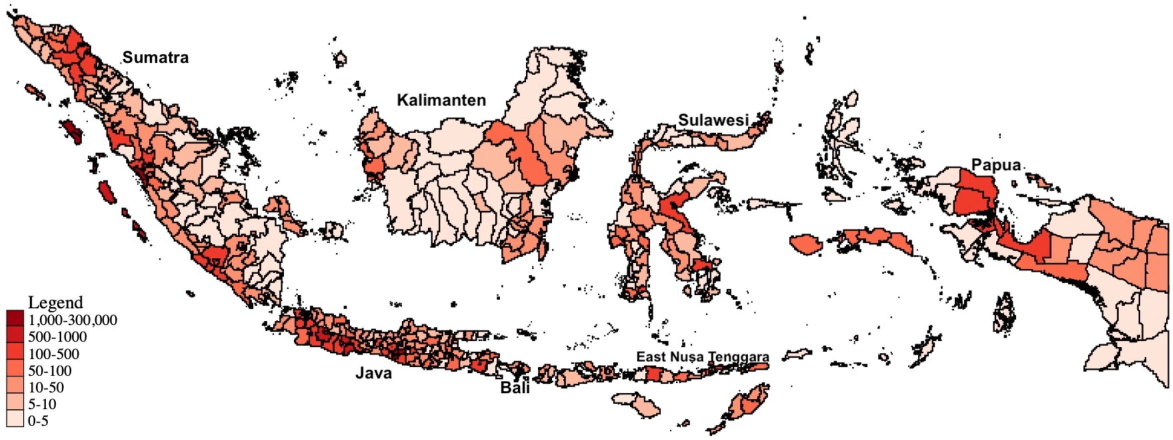
[14] *CFE-DMHA Report*, 2015.

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, 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 will 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 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.

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



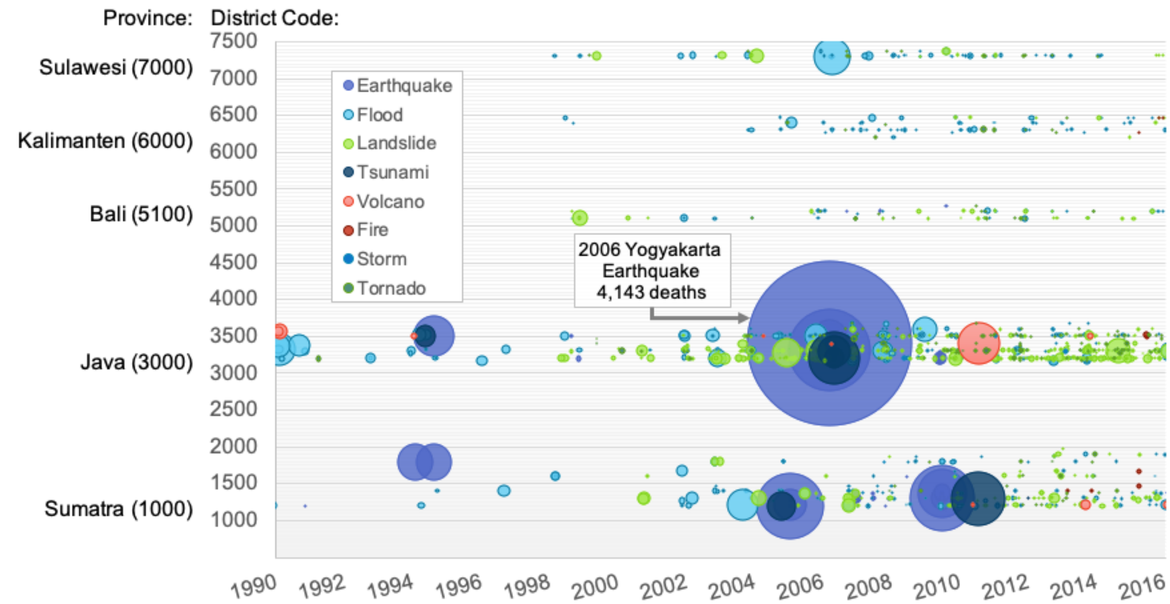
The below displays a timeline of disaster events (that apply specifically to the districts that appear in my sample) where the size and frequency of different types of disasters can be observed. The variability on the y-axis is only to display geographic variation and plots the four digit district code. The largest of these events was the 2006 Yogyakarta Earthquake that killed thousands of individuals.[15]

The summary statistics on the disaster variables are shown below in Table 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 in the last 5 years is driven up by a few bigger 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. The other categories follow a similar 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

[15]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.

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).

4 Empirical Specification

I use an individual fixed effects framework to evaluate the impact of natural disasters on risk attitudes. The use of fixed effects addresses an important source of selection bias. This strengthens the case for drawing causal claims between disasters and risk, relying on weaker stochastic assumptions compared to the current literature.

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), nonoperational buoy network from 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, as long as I control for selection caused by decisions made to live in a particular location.

As mentioned above, 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. This can include the environment within which individuals live, and these differences are not captured in a cross sectional model. For instance, it may be 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 may live in areas that experience less disasters. For additional evidence that a fixed effects model is preferred to a random effects model, I use a form of the Hausman test that is cluster-robust, proposed by 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.[16]

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 [1] below, controlling for individual demographic characteristics.[17] Equation [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 [2]. This specification relies on weaker stochastic assumptions than equation [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. D_{jt} is a continuous variable that measures the number of district deaths in the past one to fifteen years. The cross sectional results show only deaths from the last 5 years as that is the main result from the fixed effects specification, but there are similarly contrasting results between waves for all years. δ_i and σ_t represent individual and wave fixed effects, respectively. All standard errors are clustered at the district level. The main specification

[16]The Sargan-Hansen statistic (similar to the chi squared statistic in the Hausman test) is 22.547 with a p-value < 0.01.

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

in equation [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.

5 Results

5.1 Intent to Treat Effects of Disasters on Risk Aversion

As discussed earlier, there are multiple ways to measure whether an individual has been exposed to a natural disaster. 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 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.[18]

[18] 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 4: 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

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 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).

Table 5 shows the impact of an additional district death from disaster on an individual's risk category (1-4) over multiple time periods. At first glace there does not seem to be a consistent pattern in how disaster deaths impact risk attitudes. The table shows that disasters measured by mortality rate in the past 1 year do not have a significant impact on risk aversion, over 5 years has a positive impact and is significant at the 1% level, at 10 years is slightly negative and no longer statistically significant, while increases in mortality rates over the past 15 years appear to make individuals more risk tolerant and is statistically

Table 5: Risk Category on Total District Deaths from All Disasters
adjusted for district population (per 1,000)

	Risk Category			
Disaster Deaths:	(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)
Mean # Deaths	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. Mean number of deaths are per 1,000 people in District. *** p<0.01, ** p<0.05, * p<0.1

significant.

The pattern appears more clearly when each coefficient is plotted from three to 15 years, as seen in Figure 5. The results from 1-2 years are removed because of their out-sized and 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. To put the coefficient size into context, the average deaths in the last 5 years in the sample was 0.092. When multiplied by the coefficient of 0.085, this impact is small. The impact is large when individuals experience a high amount of deaths. 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

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

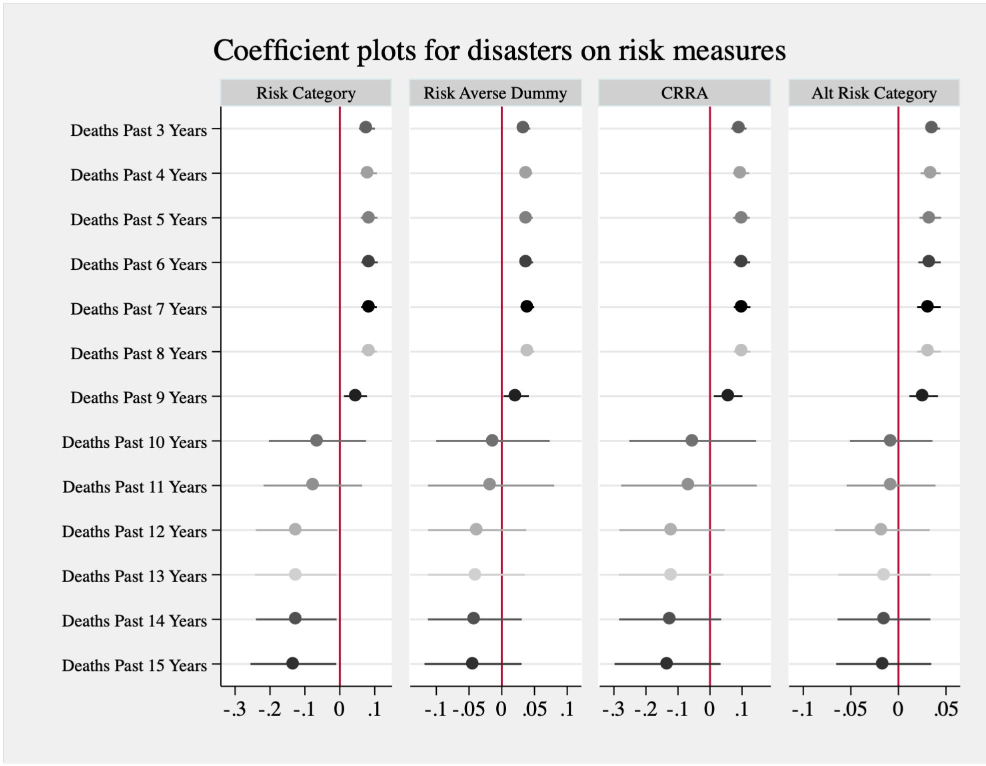


Figure Notes: Coefficient estimates for separate regressions using district deaths from disaster as primary independent variable and confidence intervals. Standard errors are clustered at the district level. All regressions use individual and individual fixed effects and control for demographic characteristics.

0.63 (0.085*7.45), which equates to half of a standard deviation increase in risk. This result is robust to different risk measurements. 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 reversion in the long term, while the other measure are negative but statistically insignificant.

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

Table 6: Impact of Severe Disasters

	Risk Category			
	(1)	(2)	(3)	(4)
Deaths Past 1 Year	8.806***			
	(1.528)			
Deaths Past 5 Years		0.0852***		
		(0.012)		
Deaths Past 10 Years			-0.0885	
			(0.062)	
Deaths Past 15 Years				-0.159***
				(0.058)
Mean # Deaths	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	0.0197	0.021	0.0196	0.0198

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. Mean number of deaths are per 1,000 people in District. *** p<0.01, ** p<0.05, * p<0.1

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 [2] to only include disaster deaths for significant disasters.[19] Table 6 shows that increases in deaths from significant deaths have a positive and significant impact on risk even in the short run. [20] The results for disas-

[19]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)

[20]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

ters measured over longer time frame mirror the sign and significance displayed in the main specification using all disasters. Figure 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 that if they had not experienced the disaster. This may point to additional resilience among the most affected people, where surviving such a serious life shock means that in the long term you experience bouncing back to the point of becoming even more risk tolerant than before experiencing the disaster.

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

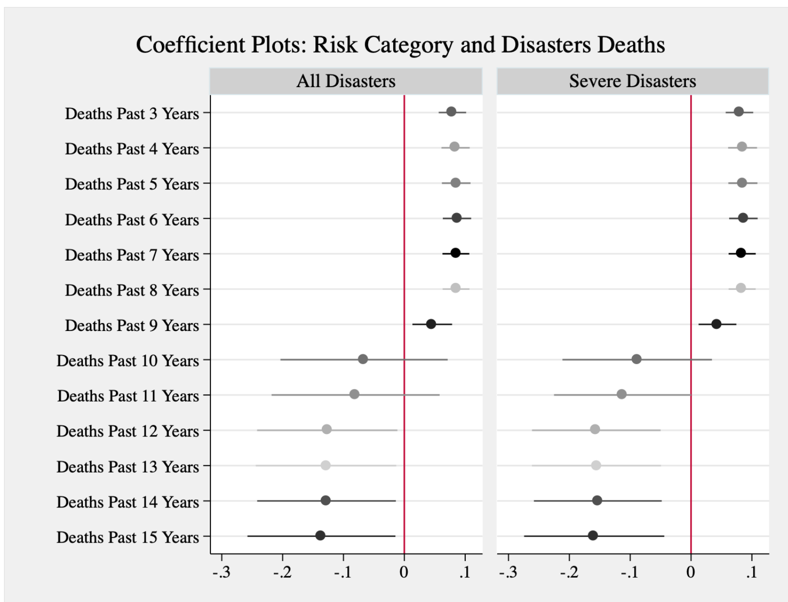


Figure Notes: Coefficient estimates for separate regressions using district deaths from disaster as primary independent variable and confidence intervals. Standard errors are clustered at the district level. All regressions use individual and individual fixed effects and control for demographic characteristics.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

5.2 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 [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.[21] Most districts have a population between 500,000 and 1 million people so this would equate to about 5-10 people dying in disasters over the last 5 years.

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

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 8. 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

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

are constantly exposed to small threats that become part of daily life.

Table 7: 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	.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

5.3 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 government 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 that the Indonesian database. I assume that each district listed is affected equally, and divide the damages among the affected districts.

Table 8: *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		0.0421***				
		(0.0151)				
Deaths Past 10 Years			0.0291***			
			(0.00390)			
Damages Past 1 Year				0.0810		
				(0.0883)		
Damages Past 5 Years					0.0243**	
					(0.0119)	
Damages Past 10 Years						0.00387
						(0.00487)
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

When I run equation [2] using the deaths from EM-DAT instead of the BNBP, 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 9. 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 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 de-

Table 9: 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

stroyed and evacuations, and I use these as alternative disaster severity measurements, see Tables 9 and 10. 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 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 the 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 1% level. Generally, when looking over

Table 10: 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	3.98	35.08	67.8	70.72
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 number of evacuations are per 1,000 people in District. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

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 and therefore risk is not affected. It appears 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.

5.4 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 earthquake are the most common and deadly intensive disaster.

When equation [2] uses floods and earthquake deaths as the D_{jt} measure, the results contrast each other. Table 12 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.[22]

Table 11: 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)
Deaths Past 1 Year	6.141**				-26.970			
	(3.059)				(23.010)			
Deaths Past 5 Years		3.526				0.084***		
		(2.363)				(0.012)		
Deaths Past 10 Years			0.365				-0.095*	
			(1.217)				(0.056)	
Deaths Past 15 Years				0.276				-0.142**
				(1.261)				(0.058)
Mean # Deaths	0.001	0.004	0.007	0.009	0.0002	0.079	0.162	0.162
Number of 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. Mean number of deaths are per 1,000 people in District. *** p<0.01, ** p<0.05, * p<0.1

5.5 Heterogeneous Effects

Next I 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

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

Table 12: 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)
Deaths Past 1 Year	5.475				0.995			
	(3.658)				(5.671)			
Deaths Past 5 Years		0.079***				0.092***		
		(0.011)				(0.016)		
Deaths Past 10 Years			-0.115				0.083	
			(0.091)				(0.097)	
Deaths Past 15 Years				-0.129				-0.124
				(0.094)				(0.165)
Mean # Deaths	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. Mean number of deaths are per 1,000 people in District. *** p<0.01, ** p<0.05, * p<0.1

that women are more risk tolerant compared to men immediately after Hurricane Katrina. Table 13 shows that when equation [2] is estimated separately for women and men, the results generally hold for both. The results at the 1- and 10-year time frame are insignificant. The coefficient on deaths from disasters in the district over the last 5 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).[23] This differs from Hanaoka et al., 2018 who find significant gender differences in their results.

More interesting than the slight overall differences between men and women is the difference among age groups by gender, as shown in Table 14. 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 five 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

[23] 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.

Table 13: 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)
Deaths Past 1 Year	-0.576	12.710***	0.571	-0.704	4.270	1.711
	(6.215)	(4.814)	(8.460)	(4.328)	(8.542)	(8.697)
Deaths Past 5 Years	0.095***	0.087***	0.126***	0.034**	0.003	0.169***
	(0.014)	(0.015)	(0.035)	(0.015)	(0.026)	(0.035)
Deaths Past 10 Years	-0.042	-0.109	0.343**	-0.139	-0.653	-0.449
	(0.118)	(0.079)	(0.168)	(0.194)	(0.745)	(0.576)
Deaths Past 15 Year	-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, round dummy, and demographic controls. *** p<0.01, ** p<0.05, * p<0.1

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.

Results appear in Table 14. While increased mortality causes increased risk aversion in the 5 year time frame for both genders and most age groups, surprising patterns appear. Younger men are affected earlier, becoming more risk averse 1-5 years after experiencing a disaster and the effect fades after 5 years, while women aged 35-50 have a later onset affect, becoming more risk averse 5-10 years after the disaster, but not in the short term nor at the 15 year time frame. Additionally, the largest impact appears for men over 50 years old at the 5 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.

6 Pathways

There are 3 plausible pathways through which disasters can impact risk preference, and plausible cases for all three are made in the current literature. They are (1) emotional response, (2) income loss, and (3) probability updating.

The first is an

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 and that fear may cause an increase in risk aversion. 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 15 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 is the income pathway, where disasters cause a loss in wealth and that loss in wealth drives 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 16 shows that district disaster mortality is negatively correlated with income, and is significant when measured as 5-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. Interestingly, the short term results differ based on gender. Males

Table 14: Impact of Disasters on Mental Health

	Standardized Score for Depression					
	Full Sample	Females	Males	Full Sample	Females	Males
	(1)	(2)	(3)	(4)	(5)	(6)
Deaths Past 1 Year	33.05*	47.91*	22.31*			
	(17.07)	(27.41)	(13.28)			
Deaths Past 5 Years				0.171***	0.280***	0.0845**
				(0.0411)	(0.0566)	(0.0369)
Observations	15,894	7,736	8,158	15,894	7,736	8,158
Mean Deaths	0.002	0.002	0.002	0.092	0.089	0.094
Max Deaths	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, round dummy, and demographic controls. *** p<0.01, ** p<0.05, * p<0.1

are much more likely to see a loss of income, and the results are significant. As stated above, younger males were the cohort that had the most significant change in risk aversion in the 1 year time frame, so it is plausible that income loss is the driving factor for the change in risk, at least in the short term.

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 events or expectations so it would be difficult to test for my sample.

Table 15: 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)
Deaths Past 1 Year	-1.195	-0.192	-2.006*			
	(1.027)	(1.406)	(1.137)			
Deaths Past 5 Years				-0.019***	-0.020***	-0.016***
				(0.004)	(0.004)	(0.006)
Mean Deaths	0.002	0.002	0.002	0.092	0.089	0.094
Max Deaths	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	0.0188	0.0183	0.0198	0.0190	0.0187	0.0197

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

7 Robustness

To test the robustness of my results, I test for selective attrition, examine endogenous migration, compare results to regressions that include individuals who are "gamble averse," and discuss the inclusion of Time Preference.

7.1 Selective Attrition

There were 28,859 individuals that answered the lottery questions in 2007.[24] 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.[25] 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

[24]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.

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

on behalf of the individual), and the rest were not interviewed for a variety of other reasons.[26] 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. As Table 17 shows, the two groups do differ significantly in terms of demographics. Attritors are more likely to be older (makes sense since a significant 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.

Table 16: Selective attrition: demographic comparison

	Attritors		**Panel Resondents**			
	Mean	*SD*	*Mean*	*SD*	*Difference*	*p-value*
Age	40.533	19.407	35.365	13.536	-5.168	0.000
Sex	0.535	0.499	0.456	0.498	-0.079	0.000
Years of Schooling	7.794	5.073	8.284	4.478	0.49	0.000
Married	0.595	0.491	0.733	0.442	0.138	0.000
Urban	0.599	0.49	0.509	0.5	-0.09	0.000
Javanese	0.4	0.49	0.426	0.495	0.027	0.000
Sundanese	0.151	0.358	0.119	0.324	-0.032	0.000
Muslim	0.882	0.323	0.898	0.302	0.017	0.000
Observations	28,859					

Note: Demographics measured in wave 4, and includes individuals who are gamble averse. Attritors are those who have risk data in wave 4 but not in wave 5.

[26] 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.

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 our 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 18) is not statistically significant, further confirming that differences in risk preference are not driving the probability of attrition.[27] 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 attrition, I regress an attrition dummy on deaths from disasters in both waves. Table 19 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 that disasters are not driving attrition (see columns 6-9 in Table 19). 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.

7.2 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 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

[27] All attrition regressions include district fixed effects.

Table 17: 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)								
Deaths Past 1 Year		2.435				-2.078*			
		(1.828)				(1.165)			
Deaths Past 5 Years			-0.022				0.002		
			(0.055)				(0.446)		
Deaths Past 10 Years				-0.00775				-0.006	
				(0.041)				(0.015)	
Deaths Past 15 Years					-0.0253				-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. Deaths from disaster are adjusted for district population (per 1,000 inhabitants) and only pertain to disasters for IFLS 5. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

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 19 shows that higher disaster mortality has no significant effect or results in less migration

Table 18: Effects of Disaster Deaths on Migration

	Migration Dummy						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Deaths Past 1 Year	-0.423						
	(0.560)						
Deaths Past 2 Years		-0.0209					
		(0.135)					
Deaths Past 3 Years			-0.00377**				
			(0.002)				
Deaths Past 4 Years				-0.00337*			
				(0.002)			
Deaths Past 5 Years					-0.00313		
					(0.002)		
Deaths Past 6 Years						-0.00449**	
						(0.002)	
Deaths Past 7 Years							-0.00771*
							(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	0.00562	0.00823	0.00868	0.009	0.0114	0.0131	0.0157

Note: Standard errors in parentheses, clustered at the district level. Adjusted for district population, measured in 1 death per 1,000 people in district. All regressions include individual fixed effects, round 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 5 year mortality and insignificant for 15 year mortality, the results are largely similar.

7.3 Gamble Averse Respondents

There is a group of individuals that has been only briefly mentioned and I will them address 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 R. Brown et al., 2017 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. While I am 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 20. 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 (1 and 10 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.

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

Table 19: 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)
Deaths Past 1 Year	0.789	0.655						
	(1.433)	(1.373)						
Deaths Past 5 Years			0.038***	0.021***				
			(0.005)	(0.004)				
Deaths Past 10 Years					-0.014	0.026		
					(0.044)	(0.028)		
Deaths Past 15 Years							-0.044	-0.006
							(0.038)	(0.026)
Includes Gamble Averse	NO	YES	NO	YES	NO	YES	NO	YES
Mean # Deaths	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. Mean number of deaths are per 1,000 people in district. *** p<0.01, ** p<0.05, * p<0.1

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). I 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.

7.4 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 risk preferences. One way to test whether the main results on risk preferences are robust 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 1 or 5 years from now. The specific questions can be found below in Table 21.

Table 20: 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

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 3 to 9 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 results are summarized in Table 22 and Figure 7. 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 7: Coefficient Estimates for Time on Disaster Deaths, all disasters and severe disasters

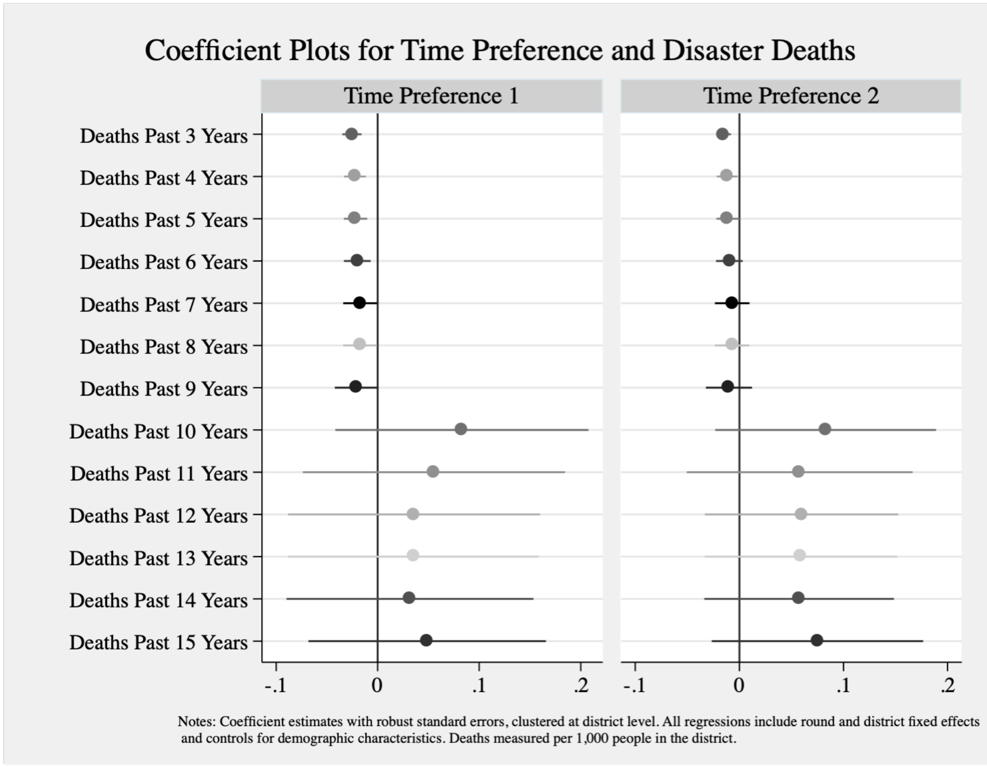


Table 21: Time Preference Category on Total District Deaths from All Disasters
adjusted for district population (per 1,000)

	Time Category			
	(1)	(2)	(3)	(4)
Deaths Past 1 Year	-5.521**			
	(2.493)			
Deaths Past 5 Years		-0.0218***		
		(0.006)		
Deaths Past 10 Years			0.083	
			(0.063)	
Deaths Past 15 Years				0.0487
				(0.059)
Mean # Deaths	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. Mean number of deaths are per 1,000 people in District.
*** p<0.01, ** p<0.05, * p<0.1

8 Conclusion

Disasters can be severe and traumatic events that have the capacity to impact our risk preferences. Using longitudinal data from a household survey and national disaster statistics in Indonesia, I evaluate how disasters impact risk attitudes. 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. Indonesia is a developing country that is highly exposed to natural disasters, including tsunamis, earthquakes, floods, volcanoes, etc. Due to rich data on disaster impact and individual data from the IFLS, I am able to account for time invariant individual unobservables and remove the bias that exists when doing a cross sectional analysis. While cross sectional studies assume disasters are uncorrelated with any individual heterogeneity, we know that disaster exposure that has existed for many years and other time invariant individual characteristics can be important for determining both disaster experience and formation of risk attitudes. Because the disaster data I have is extensive, covering several types of disaster severity measurement and disaster types, I can evaluate several aspects of disaster that may be more salient to individuals than a simple "yes" or "no" question. 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 has 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 and 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 (3-9 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. 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.

References

Baez, J., de la Fuente, A., & Santos, I. (2010). Do Natural Disasters Affect Human Capital? An Assessment Based on Existing Empirical Evidence. *IZA Discussion Paper*, *No. 5164*.

Bchir, M. A., & Willinger, M. (2013). Does the exposure to natural hazards affect risk and time preferences? Some insights from a field experiment in Perú. Laboratoire Montpelliérain d'Economie Théorique et Appliquee (LAMETA) Document de Recherche.

Brando, J. F., & Santo, R. J. (2015). La Niña y los Niños: Effects of an unexpected winter on early life human capital and family responses. *CEDE*, *2015*(5).

Briere, J., & Scott, C. (2015). *Principles of trauma therapy: A guide to symptoms, evaluation, and treatment* (2nd ed.). Los Angeles, SAGE Publications.

Brown, P., Daigneault, A. J., Tjernström, E., & Zou, W. (2018). Natural disasters, social protection, and risk perceptions. *World Development*, *104*, 310–325.

Brown, R., Montalva, V., Thomas, D., & Velásquez, A. (2017). Impact of Violent Crime on Risk Aversion: Evidence from the Mexican Drug War. *National Bureau of Economic Research (NBER)*, (Working Paper 23181).

Cameron, L., & Shah, M. (2015). Risk Taking Behavior in the Wake of Natural Disasters. *Journal of Human Resources*, *50*(2), 484–515.

Cassar, A., Healy, A., & von Kessler, C. (2017). Trust, Risk, and Time Preferences After a Natural Disaster: Experimental Evidence from Thailand. *World Development*, *94*, 90–105.

Croson, R., & Gneezy, U. (2009). Gender Differences in Preferences. *Journal of Economic Literature*, *47*(2), 448–474.

Dasgupta, U., Mani, S., Sharma, S., & Singhal, S. (2016). Eliciting Risk Preferences: Firefighting in the Field. *IZA Discussion Paper*, *No. 9765*.

Datar, A., Liu, J., Linnemayr, S., & Stecher, C. (2013). The Impact of Natural Disasters on Child Health and Investments in Rural India. *Social Science & medicine (1982)*, *76*(1), 83–91.

Desbureaux, S., & Rodella, A.-S. (2019). Drought in the city: The economic impact of water scarcity in Latin American metropolitan areas. *World Development*, *114*, 13–27.

Dohmen, T., Huffman, D., Schupp, J., Falk, A., Sunde, U., & Wagner, G. G. (2011). Individual Risk Attitudes: Measurement, Determinants, and Behavioral Consequences. *Journal of the European Economic Association*, *9*(3), 522.

Eckel, C. C., El-Gamal, M. A., & Wilson, R. K. (2009). Risk loving after the storm: A Bayesian-Network study of Hurricane Katrina evacuees. *Journal of Economic Behavior & Organization*, *69*(2), 110–124.

Economic Losses, Poverty, & Disasters: 1998-2017. (2018). Centre for Research on the Epidemiology of Disasters (CRED), UNISDR.

Eeckhoudt, L., Gollier, C., & Schlesinger, H. (1996). Changes in Background Risk and Risk Taking Behavior. *Econometrica*, *64*(3), 683–689.

Feder, G. (1980). Farm Size, Risk Aversion and the Adoption of New Technology under Uncertainty. *Oxford Economic Papers*, *32*(2), 263–283.

Frankenberg, E., Sikoki, B., Sumantri, C., Suriastini, W., & Thomas, D. (2013). Education, Vulnerability, and Resilience after a Natural Disaster. *Ecology and society : a journal of integrative science for resilience and sustainability*, *18*(2), 16.

Frankenberg, E., Sumantri, C., & Thomas, D. (2020). Effects of a natural disaster on mortality risks over the longer term. *Nature Sustainability*, *3*(8), 614–619.

Frankenberg, E., Thomas, D., & Laurito, M. (2014). The Demography of Disasters. *North Holland, Amsterdam*.

Global Climate Change Initiative for a Clean, Safe, and Prosperous World. (2016). Centre for Research on the Epidemiology of Disasters (CRED), USAID. Retrieved January 14, 2020, from https://pdf.usaid.gov/pdf_docs/PBAAE329.pdf

Gollier, C., & Pratt, J. W. (1996). Risk Vulnerability and the Tempering Effect of Background Risk. *Econometrica*, *64*(5), 1109–1123.

Guiso, L., & Paiella, M. (2008). Risk Aversion, Wealth and Background Risk. *Journal of the European Economic Association*, *6*(6), 42.

Hanaoka, C., Shigeoka, H., & Watanabe, Y. (2018). Do Risk Preferences Change? Evidence from the Great East Japan Earthquake. *American Economic Journal: Applied Economics*, *10*(2), 298–330.

Haushofer, J., & Fehr, E. (2014). On the psychology of poverty. *Science*, *344*(6186), 862–867.

Indonesia Disaster Management Reference Handbook. (2015). Center for Excellence in Disaster Management and Humanitarian Assistance (CFE-DMHA).

Jakiela, P., & Ozier, O. (2015). *The Impact of Violence on Individual Risk Preferences: Evidence from a Natural Experiment*. The World Bank.

Kahneman, D., & Tversky, A. (1979). Prospect Theory. *Econometrica*, *47*(2), 263–292.

Kebede, Y. (1992). Risk Behavior and New Agricultural Technologies: The Case of Producers in the Central Highlands of Ethiopia. *Quarterly Journal of International Agriculture*, *31*, 269–284.

Kihlstrom, R. E., & Laffont, J.-J. (1979). A General Equilibrium Entrepreneurial Theory of Firm Formation Based on Risk Aversion. *Journal of Political Economy*, *87*(4), 719.

Lawrance, E. C. (1991). Poverty and the Rate of Time Preference: Evidence from Panel Data. *Journal of Political Economy*, (1), 54.

Lerner, J. S., & Keltner, D. (2001). Fear, Anger, and Risk. *Journal of Personality and Social Psychology*, (1).

Liu, E. (2013). Time to Change What to Sow: Risk Preferences and Technology Adoption Decisions of Cotton Farmers in China. *The Review of Economics and Statistics*, (4), 1386.

Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as Feelings. *Psychological Bulletin*, *127*(2), 267–86.

Maccini, S., & Yang, D. (2009). Under the Weather: Health, Schooling, and Economic Consequences of Early-Life Rainfall. *American Economic Review*, *99*(3), 1006–1026.

Natural Disasters, 2018: An Opportunity to Prepare. (2018). Centre for Research on the Epidemiology of Disasters (CRED), USAID, UCLouvain.

Page, L., Savage, D. A., & Torgler, B. (2014). Variation in risk seeking behaviour following large losses: A natural experiment. *European Economic Review*, *71*, 121–131.

Population Exposed to Natural Hazards. (2015). UNFPA, BNPB, BPS. Jakarta. Retrieved October 27, 2020, from https://indonesia.unfpa.org/sites/default/files/pub-pdf/Population_Exposed_0.pdf

Report: Inequalities exacerbate climate impacts on poor. (2016). Retrieved January 14, 2020, from https://www.un.org/sustainabledevelopment/blog/2016/10/report-inequalities-exacerbate-climate-impacts-on-poor/

Rosenzweig, M. R., & Binswanger, H. P. (1993). Wealth, Weather Risk and the Composition and Profitability of Agricultural Investments. *The Economic Journal*, *103*(416), 56–78.

Rosenzweig, M. R., & Stark, O. (1989). Consumption Smoothing, Migration, and Marriage: Evidence from Rural India. *Journal of Political Economy*, *97*(4), 905–926.

Shaw, K. (1996). An Empirical Analysis of Risk Aversion and Income Growth. *Journal of Labor Economics*, *14*(4), 626–653.

Smith, A. B., & Information, N. N. C. F. E. (2020). U.S. Billion-dollar Weather and Climate Disasters, 1980 - present (NCEI Accession 0209268) [type: dataset]. NOAA National Centers for Environmental Information. https://doi.org/10.25921/STKW-7W73

Stern, N. (2008). The Economics of Climate Change. *American Economic Review*, *98*(2), 37.

Strauss, J., & Thomas, D. (1998). Health, nutrition, and economic development. *Journal of Economic Literature*, *36*(2), 766.

Voors, M. J., Nillesen, E. E. M., Verwimp, P., Bulte, E. H., Lensink, R., & Van Soest, D. P. (2012). Violent Conflict and Behavior: A Field Experiment in Burundi. *The American Economic Review*, (2), 941.

Woolridge, J. M. (2002). *Analysis of Cross Section and Panel Data*. Cambridge, MA, MIT Press.

A Appendix

A.1 Summary statistics by risk category

Unsurprisingly, males tend to make riskier lottery choices (Eckel et al., 2009). There is not much variation in education based on risk category, and older individuals are more likely to fall in the most risk tolerant category (however, those who are gamble averse are older and less educated than any other category). Because the vast majority of the sample is Muslim, Risk category does not differ greatly based on religion. Javanese respondents and people residing in urban areas make less risky choices, while Sundanese respondents vary little by risk. Finally, there is no clear association between deaths from disaster in a district and risk category, except that the most risk averse individuals have the highest levels of reported deaths from disaster in the last 5 years. The relationship between risk and gender, education, marital status and age are in line with previous findings.

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

Table 22: Summary Statistics by risk category

	Full Sample	Risk = 1 *Most Risky*	Risk = 2 →	Risk = 3	Risk = 4 *Least Risky* →	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)
Disaster Deaths, Last 5 Years	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 deaths are adjusted for district population per 1,000 residents.

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 23: 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