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

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ABSTRACT:

Many economic decisions are influenced by individual risk preferences, and new evidence challenges the immutability of these preferences. This paper explores the impact of disasters on individual risk attitudes using longitudinal data from Indonesia, focusing on the heterogeneity of disasters by type, severity and timing. I find risk aversion increases for a decade following disasters, and high-mortality disasters, namely earthquakes, are more salient to individuals than higher frequency, lower-mortality disasters. These outcomes shed light on how survivors in a developing country respond to and internalize disaster shocks and are informative to policymakers in addressing the increasing threat of disasters.

JEL Classification: D12, D81, O12, Q54

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1 Introduction

It is well documented that risk and uncertainty play a significant role in determining economic choices such as savings (Dohmen et al., 2011; Rosenzweig and Stark, 1989; Lawrance, 1991), investment in education and health (Dasgupta et al., 2015; Shaw, 1996; Strauss and Thomas, 1998), as well as technology adoption (Liu, 2013; Feder, 1980; Kebede, 1992). However, it is unclear if risk preferences are immutable throughout an individual's life. There is little conclusive evidence on whether and to what extent shocks, including natural disasters, financial crises, and conflict, impact individual risk preferences. This could have particularly important consequences for individuals in developing countries given that poorer households display higher levels of risk aversion, as a result of ineffective institutions, lack of educational opportunities, poor health, exposure to violence and crime, and other economic challenges (Guiso and Paiella, 2008; Haushofer and Fehr, 2014; Rosenzweig and Binswanger, 1993). This higher level of risk aversion may lead to under-investment in risky but potentially rewarding behavior and activities, and therefore have negative economic consequences, and shocks may compound the consequences of credit constraints and uninsurable risks that exist for these individuals (Haushofer and Fehr, 2014).[1] Because the poor face considerable credit constraints and uninsurable risks, they are also particularly vulnerable to income and health shocks (Haushofer and Fehr, 2014).

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

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

This paper contributes to the literature on shocks and risk attitudes in the following important ways. First, it is the first to use panel data from a developing country to examine the impact of disasters on risk attitudes, accounting for time-invariant unobservables in order to address an important source of selection bias. I can therefore 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, I find that the measure of disaster severity, the type of disaster (earthquake, flood, etc.), and timing of disasters are important 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, I am able 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.

Cameron and Shah (2015), Cassar, Healy, and Kessler (2017), Brown et al. (2018), and Beine et al. (2020) find that natural disaster shocks increase risk aversion in developing countries.[2] However, all of these studies rely on cross-sectional experiments post-disaster and assume that the disasters are not correlated with time-invariant and time-varying unobservables, such as residential sorting. In contrast, studies by Hanaoka, Shigeoka, and Watanabe (2018), Eckel, El-Gamal, and Wilson (2009), Bchir and Willinger (2013), and Page, Savage, and Torgler (2014) find the opposite result: natural disasters cause individuals to become more risk tolerant or have no impact on risk preferences. Cameron and Shah (2015) provide detailed background on why both an increase in risk aversion or an increase in risk tolerance could be plausible, because of both increased background risk (Guiso and Paiella, 2008) and prospect theory (Kahneman and Tversky, 1979), respectively.

Cross-sectional and single-event studies are unable to capture variation over time and the heterogeneous impact of different disasters by severity and type. It is unlikely that all disasters impact individuals in the same way. This paper shows that the results are more nuanced than a "yes" or "no" answer to whether an individual has experienced a natural disaster. In fact, both time and severity matter greatly in determining changes in risk attitudes following disasters. Because the IFLS follows the same individuals over time, I am able to address concerns about unobserved heterogeneity using individual fixed effects. I find that individuals become more risk averse as the cumulative district mortality rate and district destruction from disasters increase. Results indicate that individuals are most affected from three to nine years following disasters. Individuals are not significantly impacted in the short term (one to two years), where despite the higher magnitude on the coefficient, the results are statistically insignificant. Additionally, while the impact is long-lived, the effect of disasters on risk fades to zero after about a decade and is no longer significant, with some evidence of long-run increases in risk tolerance.

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

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

The rest of the paper is organized as follows. Section 2 describes the data, including a background of disasters in Indonesia. Section 3 describes the empirical specification. Results are discussed in Section 4, and includes the heterogeneous impacts of disaster on risk attitudes. I investigate pathways in Section 5 and conduct Robustness checks in Section 6. Section 7 concludes the paper.

2 Data & Background

2.1 IFLS Data

The Indonesian Family Life Survey is a household survey conducted in Indonesia that started in 1993 and at that time covered individuals in 13 out of the country's 26 provinces. The survey was representative of 83% of Indonesia's population in 1993, and because of the extensive effort to find and survey individuals that had moved or migrated, the IFLS was able to re-interview close to 90% of the original households, including split-off households. Since the initial survey wave in 1993, there have been 5 waves of surveys, the most recent of which was completed in 2015. The IFLS initially surveyed over 30 thousand individuals from seven thousand households and to the best of their ability attempted to track these individuals over all five waves. 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, as respondents from split-off households are added. The survey includes data on a variety of socioeconomic and demographic indicators at the individual, household and community levels including age, ethnicity, religion, migration history, household expenditures, availability of facilities in the community, etc. This paper primarily uses the individual data from waves four (2007/8) and five (2014/15) as risk questions were only introduced in wave four.

Beginning in fourth wave of the IFLS, a section on risk and time preferences was added to the questionnaire. In the risk section, hypothetical lottery choices are presented to all household members above the age of 15. The respondent is told, "Suppose you are offered two ways to earn some money." The respondent is then presented a scenario that provides two options, one where the payoff is certain, and one where the payoffs are uncertain. The uncertain option includes two possible payoffs with equal probability.[3] There were two different sets of questions, one where the return was always positive (Game A) and one where there were possible zero outcomes or losses (Game B). See Table 1 for the specific scenarios that were presented to the individuals.[4] From the respondent's decision between the safe choice (certain payment) versus the risky choice (the gamble between a higher and lower amount than the certain choice with equal probability), I can estimate the individual's attitude towrds risk. 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, and there may be differing interpretations of results when considering losses.

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 meant to be a logic check). An illustration of how the 1 to 4 scale is composed is shown 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.[5]

2.1.1 Defining Risk Attitudes and Sample Summary Statistics

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

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

If the risk measures from the IFLS lottery choices are a true representation of risk attitudes, they should be able to predict risky behavior of individuals. Before I examine the impacts of disasters on risk attitudes, I first validate the measures of risk obtained from the hypothetical lottery. I use IFLS data on risky behavior and analyze whether this behavior is correlated with the individual's risk attitude from the lottery choices. Following Jakiela and Ozier (2019), Hanaoka, Shigeoka, and Watanabe (2018) and Brown et al. (2019), I use a probit model to evaluate whether risk choices influence the likelihood of migrating for work, being self-employed, or smoking.[7] Owning your own business and seeking out job opportunities away from home are both behaviors that may result in higher returns in the long run but are risky in the short run, and smoking is generally considered a health risk and as such we would expect individuals with a higher risk tolerance to be more likely to smoke. The results of this analysis are shown in Online Appendix Table A.2 and indicate that risk category based on lottery choices predicts observed risky behaviors.

2.2 Disaster Data

2.2.1 Background on Indonesian Disasters

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

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

2.2.2 Historical Disaster Data

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

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

Figure 2 shows the cumulative number of people killed by disasters between 1998 and 2015 by district (including non-IFLS districts). The distribution of disaster deaths is quite varied across the country, with a concentration in the densely populated districts of West Java and fewer disaster fatalities occurring in South Kalimanten. The data is also heavily skewed. There are frequent disasters that occur on a small scale, killing anywhere from zero to 10 people and are relatively minor events, such as 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 displays a timeline of disaster events (that apply specifically to the districts that appear in the sample) where the size and frequency of different types of disasters can be observed. The y-axis plots the four digit district code and is meant to display the geographic variation of the disasters. The largest of these events was the 2006 Yogyakarta Earthquake that killed thousands of individuals.[8]

The summary statistics for the disaster variables are shown in Table 3. Disaster deaths in the district in the past 1 year are low, with an average of less than 2 deaths in the year preceding the wave 4 and wave 5 interviews. In wave 4, the average deaths in the last 5 years is driven up by a few larger disasters, the most significant of which was the 2006 Yogyakarta Earthquake. In wave 5 the deaths in the past 5 years is 9, but again once the Earthquake and other big disasters are captured at the 10 year time frame, the average is driven up to over 160 deaths. These numbers also reflect the large number of individuals that did not experience any fatal disasters during these time periods. The other categories follow a similar 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 for the 5-year time frame, and then to over 4,500 at the 10 year time frame and beyond. Average evacuations are close to 7,000 and over 3,000 in the past 1 year at wave 4 and wave 5, respectively. This jumps to over 50,000 in the 5 year time frame for wave 4 and for wave 5, average evacuations increase to 12,000 in the past 5 years, 68,000 in the past 10 years, and 73,000 in the past 15 years. Average damages in the past year are 4.8 million USD in wave 4 and 6.4 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 60.8 million USD. In wave 5, average damages are driven by a Sumatra earthquake, the 2015 wildfires, and a few severe floods and average 57.7 million USD. As mentioned, 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.

3 Empirical Specification

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

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

Natural disasters are a plausibly exogenous shock. While there have been substantial advances in early warning systems and evacuation procedures, experts are still not able to tell exactly when or where a disaster will hit. Early warning systems in Indonesia were completed in 2008, so they are fairly new to the country, and are not perfect. For instance, the system failed in the 2018 Sulawesi earthquake due to destruction of cell phone towers (people were unable to receive evacuation text alerts), a nonoperational buoy network from lack of maintenance and vandalism, and lack of observation equipment in the area. Because of this, residents were not prepared for the earthquake and subsequent tsunami that hit the shores of Palu. While there are certain areas that are more prone to certain types of disasters (e.g., close proximity to fault lines and volcanoes, peat forests prone to wildfires, and flood-prone areas during monsoon), the timing and severity of disasters can't be known by the individuals living in these areas. As such, disasters can be treated as a random shock, given I control for selection caused by decisions made to live in a particular location.

For comparison purposes, it is useful to look first at the results from the cross-sectional results from both waves of the IFLS, which is the focus of the current literature in the developing country context. I run separate regressions for waves 4 and 5 of the IFLS using equation [1] below, controlling for individual demographic characteristics.[10] 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 as the risk preference parameter. D_{jt} is a continuous variable that measures the cumulative district mortality rates from disasters over 1 to 15 years. I additionally include other measures to capture disaster severity, including house destroyed and economic damages. δ_i and σ_t represent individual and wave fixed effects, respectively. All standard errors are clustered at the district level. The main specification in equation [2] shows the individual impact of an increase in district mortality from disaster on risk attitudes, where β_3 represent the increase (or decrease if negative) in risk aversion category given additional exposure of 1 death per 1,000 people in the district.

4 Results

4.1 Intent to Treat Effects of Disasters on Risk Aversion

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

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

The pattern appears more clearly when each coefficient is plotted from three to 15 years, as seen in Figure 4. The results from one and two years are removed because of their outsized and statistically insignificant coefficient sizes.[14] There is a clear pattern that arises when looking over the fifteen-year time frame for 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, with some possibility of individuals becoming even more risk tolerant in the long run (likely due to some resilience that is built over the long run).

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

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

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

While it may be hard to measure the direct impacts of an increase in risk aversion in Indonesia, previous literature suggests that higher risk aversion impacts risk taking behavior. Dohmen et al. (2011) finds that a one standard deviation in an individual's willingness to take risks results in 3% increased participation in the stock market, and 2.4% increase in self-employment. Jaegar (2010) find that a one standard deviation increase in the willingness to take risks increases the likelihood of migration by 1.7%, and by 3.1% for individuals who are relatively more willing to take risks (using an indicator dummy for those who are more risk tolerant). Additionally, and more appropriate to the developing country context, Liu (2013) finds that a one standard deviation increase in loss aversion lowers the probability of adopting new technology by 12%. These results show that even a half a standard deviation increase risk aversion can have large impacts for those exposed to high-fatality disasters.

There are two potential explanations for the lack of a significant effect in the shorter term: that there is a threshold of severity that needs to be met in order to have a change in risk attitude (and the sum of deaths over one year (measured in 2007 and 2015) is not sufficient for this threshold) or that there is an immediate emotional response to the disaster which conflicts with the change in risk in the longer term. Eckel, El-Gamal, and Wilson (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 severe disasters as defined by EM-DAT.[15] Table 5 shows that increases in deaths from significant deaths have a positive and significant impact on risk even in the short run.[16] The results for disasters measured over a longer time frame mirror the direction and significance displayed in the main specification using all disasters. Figure 5 shows that for severe disasters, the initial increase in risk aversion is higher, and the subsequent decrease in risk aversion over the longer term is more negative. This would indicate that individuals who experienced severe disasters 15 years ago are then more risk tolerant than if they had not experienced the disaster. There is very little evidence on the long-term impacts of natural disasters, and it is somewhat confounding why individuals would be less risk averse many years after the disaster occurred. However, Frankenberg, Sumantri, and Thomas (2020) do find that mortality risks increase 10 years after the 2004 Indian Ocean Tsunami and Gennaro, Bhagwat, and Rau (2017) find that moderate disaster fatality experiences in childhood lead to riskier decisions by CEOs later in life. It is possible that individuals face higher mortality risks in the long term following disasters which impacts their perception of risk and uncertainty, or that making it through the disaster experience somehow desensitizes individuals to risk in the long-term. This may also point to additional resilience among the most affected people, where surviving such a serious life shock means that you are able to bounce back to the point of becoming even more risk tolerant than before experiencing the disaster.

4.2 Threshold Effects

Using a spline regression, I further test the theory that more fatal and destructive disasters are more salient to individuals and therefore more likely to change risk attitudes. 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 specification, where T is the threshold tested depending on the disaster measure (deaths, damages, houses destroyed).[17]

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

I find that below the threshold of 7 deaths per one million 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 6. I also do alternative measures of the spline where economic damages and houses destroyed are used in place of deaths and a similar threshold effect exists above $114,000 in damages and above 0.170 houses destroyed (both population adjusted).[18] 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 may not be salient enough to cause a shift. Interestingly, there is an increase in risk tolerance below the damages threshold, although the effect is small.[19] This result is consistent with Gennaro, Bhagwat, and Rau (2017) who find that CEOs who experienced disasters that were not hugely negatively consequential were more risk-taking later in life. It could be true that individuals who experienced disasters but were lucky enough that their communities did not suffer drastically from an economic standpoint had a reaction that was in contrast to those who were not so lucky. Additionally, to distinguish between a frequency and severity effect, I 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 main 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 constant exposure to smaller threats that become part of daily life.

4.3 Heterogeneity: Severity Measurements, Disaster Types, and Subgroups

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. Alternative measurements from the BPS database include evacuations, houses destroyed, and number of people affected. Additionally, EM-DAT, the international database for disasters, reports both deaths and damages from disasters for each country. I find that damages and the number of houses destroyed broadly follow the patterns seen using disaster mortality, but the impacts are not as large in magnitude and the effects on risk from houses destroyed are quicker to fade. In the case of damages, the results are not statistically significant, but both deaths and damages follow a similar pattern over 15 years as the BNPB results (see Figure 6). Evacuations and the number of people affected seem to have little effect on individual risk attitudes, showing some short run increases in risk tolerance, but virtually no effect afterward. See the Online Appendix Section A.4, including Tables A.4-A.6 for more detailed discussion of these results.

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. Death has a more significant influence on risk than other measures, such as evacuations and destruction from disasters. This may indicate that while risk attitudes change following the trauma of the natural disaster, there is evidence of resilience or a return to the status quo, after a certain amount of time has passed. There is evidence in the psychological literature that suggests that those who have longer lasting psychological effects from natural disasters stem from the traumatic experience of injury and death, specifically the fear of death or death of a loved one, as well as personal property loss (Briere and Scott, 2015).

Another source of differential impact of disaster on risk attitudes is the type of disaster. I run analyses on extensive and intensive disasters[20], and also for floods and earthquakes, as they are the most frequent and deadly disasters, respectively, that Indonesia faces. Larger, more intensive disasters affect risk attitudes more than extensive disasters with lower mortality. Earthquakes clearly drive the main results of the paper, and emphasize the narrative that unexpected, high-mortality events are causing the changes in risk preferences in the sample. More discussion and detailed results can be found in the Online Appendix Section A.5, Table A.7.

While many studies document the fact that women 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, Shigeoka, and Watanabe (2018) find that men become more risk tolerant following the Earthquake and women are unaffected, while Eckel, El-Gamal, and Wilson (2009) finds that women are more risk tolerant compared to men immediately after Hurricane Katrina. Results for both males and females in the IFLS are consistent with the main results, but the increase in risk aversion is higher for women in the sample. More interesting are the results by age and gender. Risk aversion of older women (50+) is not statistically significantly impacted by disasters at any time frame, while there is a significant and large impact for older men at the 5-year time frame. Additionally, younger men are significantly impacted in the short-term, with the effect fading more quickly than for women. Women between the ages of 35-50 are also affected for longer, displaying statistically significantly higher risk aversion at the 10-year time frame. Again, more discussion and numerical results can be found in the Online Appendix Section A.6, Tables A.8 and A.9.

5 Pathways

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

As explored by Hanaoka, Shigeoka, and Watanabe (2018) and Eckel, El-Gamal, and Wilson (2009), individuals may have an emotional response to disasters, which impact how they answer the lottery questions. It is likely that severe disasters cause fear, as lives are threatened and there is worry about recovery. This fear may result in individuals displaying higher risk aversion. Additionally, depression and PTSD have been closely linked to the experience of disaster and these conditions may also impact emotions and perceptions of risk. The IFLS includes information on mental health. There is a module that asks the respondents a series of questions about their current emotional state, including if they are fearful, hopeful, have trouble sleeping, etc. The IFLS instructs that the 10 questions on mental health and emotions can be indexed into a depression score, where individuals are considered depressed if they are above a score of 10, which I have standardized for the sample. Table 7 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. The results of the same analysis at the 10- and 15-year time frames are insignificant, indicating that these feelings are not lasting over the long term.

The second pathway through which disasters are inducing a change in risk aversion is through income, where disasters cause a loss in wealth and that loss in wealth drives 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 may appear more risk averse because their risk is evaluated at a lower income level. In fact, Table 8 shows that district disaster mortality is generally negatively correlated with household income (except for the 10-year time frame), and is significant for five-year mortality, when we see the most significant impacts on risk aversion. Individual income impacts are even more persistent, with the most significant decline for the 5-year mortality, with highly negative impacts (significant at the 10% level) persisting even when using 15-year mortality statistics. This is strong evidence that higher disaster mortality in a district causes loss of income, which in turn affects an individuals' risk aversion.

The third possibility, as cited by Cassar, Healy, and Kessler (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 the sample. This result is also found by Gibson and Mullins (2020), who find that the decrease in property values resulting from Hurricane Sandy and updated FEMA maps are driven by belief-updating regarding flood risk in the area. They emphasize the importance of belief-updating, especially as climate change is increasing the risk of disaster events.

Belief-updating could have important implications for policy-makers, as the demand for insurance may increase following disasters and there is evidence that the distribution of disaster losses may be fat-tailed in nature. Conte and Kelly (submitted) explore the implications of fat-tailed events, where disaster events measured by damages and mortality may not follow a normal distribution, and tail events may occur with higher frequency than expected. One property of these events is that the largest observations in the data are poor predictors for subsequent tail events. The fact that disasters are fat-tailed may be driving the change in risk perceptions which requires belief updating, since this would be unexpected if these losses were normally distributed.

6 Robustness

I examine the robustness of my results to a number of concerns. I test for selective attrition, analyze possible bias from endogenous migration, and compare results to regressions that include individuals who are "gamble averse." Additionally, the relationship between risk and time preference is discussed in the Online Appendix Section A.8 to validate the results of changes in individual risk aversion.

6.1 Selective Attrition

There were 28,859 individuals that answered the lottery questions in 2007.[21] 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.[22] This is due to a variety of reasons, which I have partial information on. Out of those who were not re-interviewed, 1,561 refused to answer the questions, 1,381 died between waves, 1,089 individuals had a proxy answering questions for the person (risk and time preference questions were not asked on behalf of the individual), and the rest were not interviewed for a variety of other reasons.[23] This may indicate selective attrition and may confound the main results if individuals who drop out of the sample have inherently different risk preference or have differential experiences with natural disasters. First, I analyze whether individuals who drop out of the sample in wave 5 are inherently different from panel individuals in terms of demographics. The two groups do differ significantly in terms of demographics, and attritors are more likely to be older (logical as a substantial portion died), female, less educated, unmarried, living in rural areas, Javanese, and muslim. While this may be some cause for concern, the main preoccupation is whether these individuals are different in terms of their risk attitudes and exposure to disasters.

In order to determine whether individuals who attrite are inherently different in terms of risk preference, I test the null hypothesis that risk attitudes of panel respondents and attritors are the same at the baseline wave (wave 4, conducted in 2007). I cannot reject the null hypothesis (p-value=0.51), suggesting that respondents who are not re-interviewed do not have significantly different risk preferences than those appear in both waves of data. Additionally, I regress an attrition dummy on risk category in wave 4 and the resulting coefficient (see Table 9) is not statistically significant, further confirming that differences in risk preference are not driving the probability of attrition.[24] It may also be that individuals that experience natural disasters are more likely to drop out of the sample (due to displacement, death, etc.). To determine whether disasters are correlated with attrition, I regress an attrition dummy on deaths from disasters in both waves. Table 9 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 9). The exception is 1-year mortality measured at wave 5 which is significant at the 10% level, but the relationship is negative, so those hit by a shock are less likely to attrite and should not bias the main results.

6.2 Endogenous Migration

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

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

It is possible that the change in risk preferences would induce migration following disasters, where individuals become more risk averse and want to move away from the area after the disaster hits. If a disaster experience forced an individual to migrate and this in turn influenced the individual's risk preference, the impact of disasters on risk could be upward biased by not properly accounting for migration in the identification strategy. However, Table 10 shows that higher disaster mortality has no significant effect or results in less migration away from the district, addressing the concern that it is migration driving the increase in risk aversion, not the shock itself. Additionally, I test whether the results differ for those who have never moved from the district. While coefficient estimates are higher at the five-year mortality and insignificant for 15-year mortality, the results are largely similar.

6.3 Gamble Averse Respondents

There is a group of individuals that has been only briefly mentioned thus far and I address them more directly here. There is a substantial portion of the IFLS sample who can be labeled "gamble averse" based on their answer to the first lottery questions they are asked, meant as a comprehension check. They are asked to choose between 800,000 rupiahs and a 50-50 chance of receiving 800,000 rupiahs or 1,600,000 rupiahs. If they choose the 800,000 for certain the interviewer asks, "Are you sure? In option 2 you will get at least Rp 800 thousand per month and you may get Rp 1.6 million per month. In option 1 you will always get Rp 800 thousand per month." If the respondent sticks with the certain choice, they are not asked any further questions. This could be indicative of a lack of comprehension, but it could also indicate an extreme aversion to uncertainty. It may be that individuals would rather know with certainty the amount they will receive rather than any uncertain outcome, regardless of the possible amounts. Brown et al. (2019) encounters a similar issue in the Mexican Family Life Survey and includes these individuals in their "most risk averse" category, showing that his results are robust when these individuals are excluded. I remain unconvinced it would be appropriate to include all of these individuals as a separate risk category in the main results (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 11.

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

7 Conclusion

Economists have long sought to understand the factors that influence our economic decision-making and lifetime earnings. There has been substantial debate over whether risk preferences are immutable throughout one's life or if experiences can shape these preferences. As Schildberg-Hörisch (2018) emphasizes, this question can largely be framed as an empirical one. This paper analyzes the impact of natural disasters on risk preferences in Indonesia, a country highly exposed to disasters.

As nations build programs and policies around disaster preparedness and risk reduction, it is important to understand the factors that affect our decision-making following disasters and how we recover from these shocks. While the frequency and intensity of disasters across the world can be variable, the burden of these events is not equally shared. In recent years, developed countries have made significant strides in reducing the death toll and economic loss from disaster, while developing countries continue to bear the highest human costs due to exposure, poor infrastructure and building construction, low household savings, and the tendency of the poorest populations to live in remote areas where it is hard to receive aid.[25] While the costs of these disasters can be substantial for all countries, extreme weather events can affect those in developing nations more acutely.[26] Natural disasters leave the most vulnerable populations even more impoverished by increasing food insecurity, water insecurity, and health risks, as well as causing physical damage, agriculture loss, and income loss (*CRED & USAID*, 2016). While physical damage and health impacts are explicit and have been widely estimated in both a developing and developed context,[27] there is much to be explored in the indirect impacts of natural disasters for those in developing countries, such as psychological and behavioral effects.

Because disasters can be severe and traumatic events causing death and property loss, it is plausible that they impact our individual risk preferences. Using longitudinal data from a household survey and national disaster statistics in Indonesia, I evaluate how disasters impact risk attitudes, removing time-invariant individual heterogeneity by including individual fixed effects. The literature has produced mixed results on the impact of disasters on risk preferences due to primarily ex-post disaster analysis and differences between developing and developed countries.

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

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

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

Figures

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

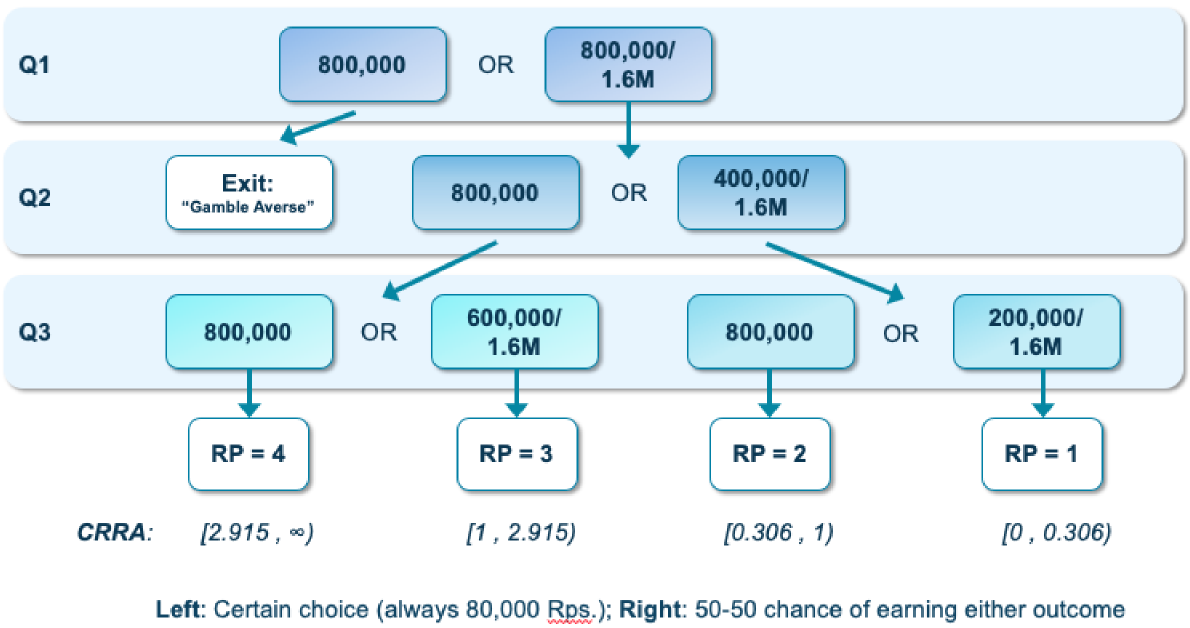


Figure 2: Cumulative Number of People Killed by Natural Disasters By District
By District, 1998-2015

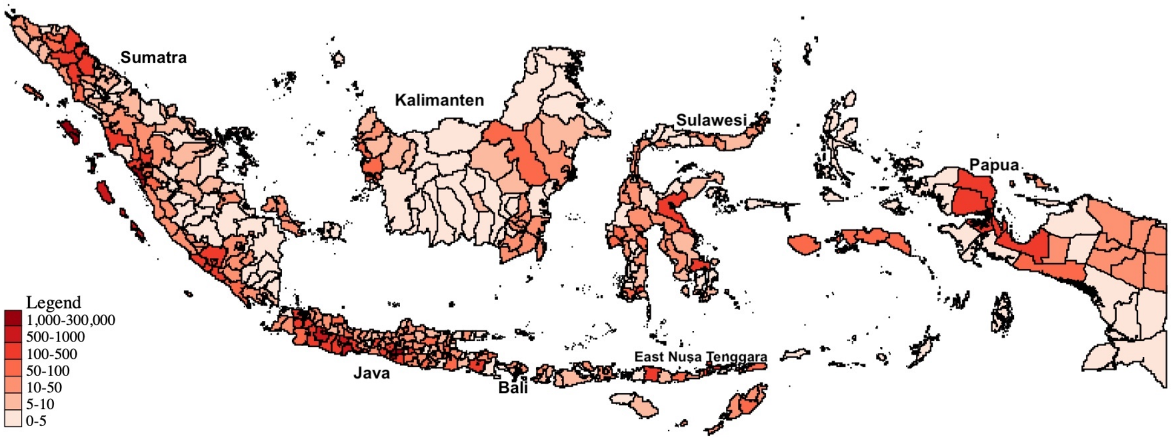
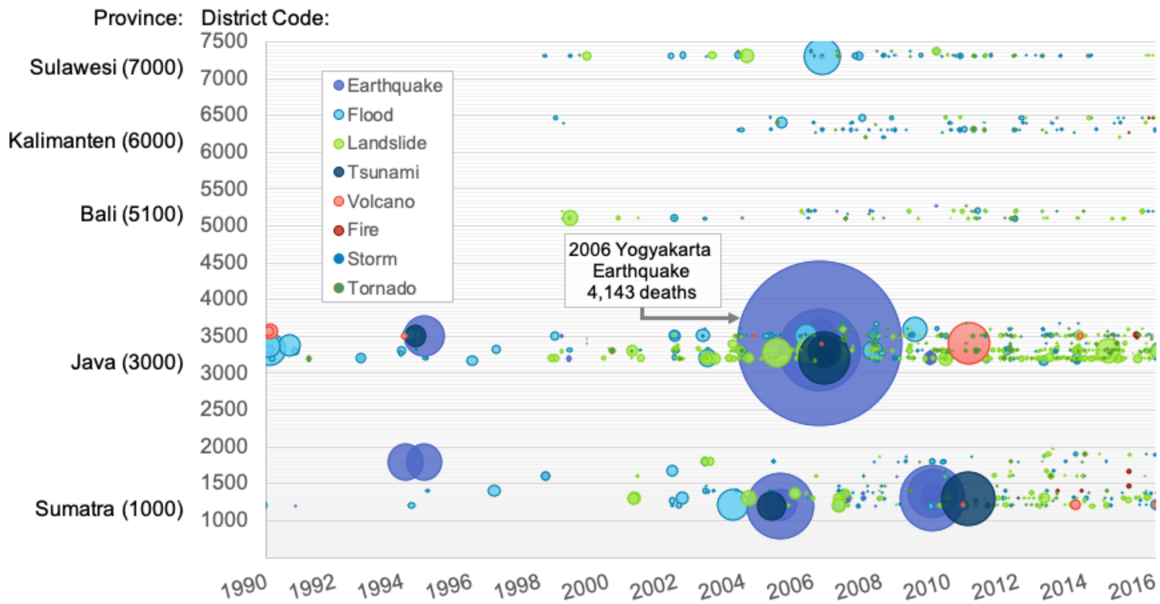


Figure 3: Indonesian Natural Disaster Events

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.

Figure 4: Coefficient Estimates for Risk on Disaster Deaths, all disasters and severe disasters

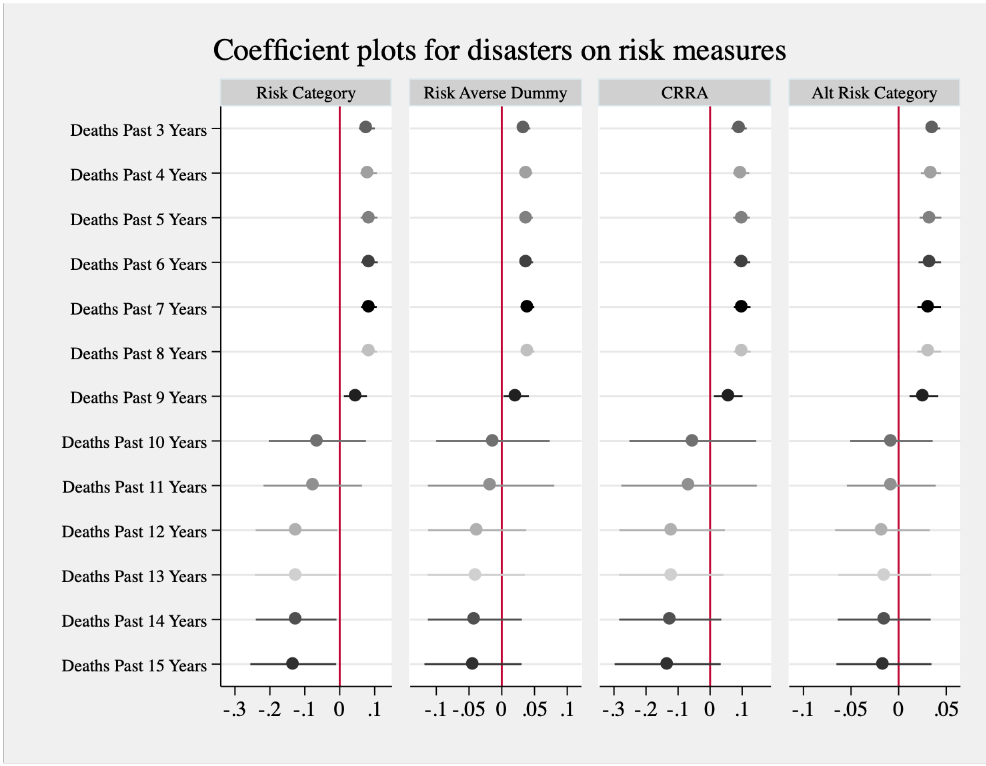


Figure Notes: Coefficient estimates and confidence intervals for separate regressions using district deaths from disaster as primary independent variable. Standard errors are clustered at the district level. All regressions use individual and wave fixed effects and control for demographic characteristics.

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

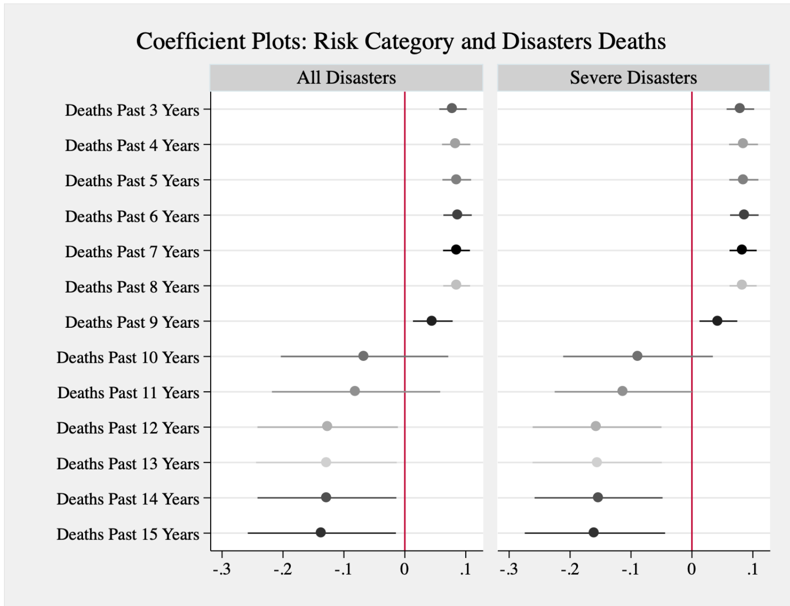


Figure Notes: Coefficient estimates and confidence intervals for separate regressions using district deaths from severe disaster as primary independent variable. Standard errors are clustered at the district level. All regressions use individual and wave fixed effects and control for demographic characteristics.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

Figure 6: Coefficient Estimates for EM-DAT Mortality and Damages on Risk Category

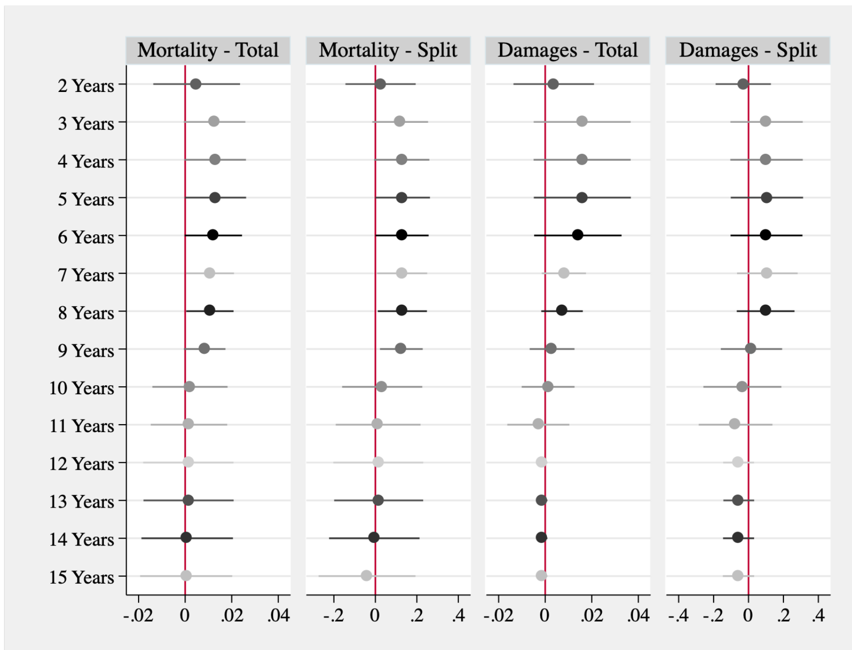


Figure Notes: Coefficient estimates for separate regressions using risk category as the outcome variable. Standard errors are clustered at the district level. All regressions use individual and wave fixed effects and control for demographic characteristics. Mortality rate is per 1,000 residents in a district, damages are measured in millions of US dollars and also adjusted for population (per 1,000 residents). EM-DAT reports statistics at the disaster level, and lists affected districts, not district-specific statistics. Therefore Columns (1) and (3) show the effect when the total disaster impact is assigned to each affected district, and Columns (2) and (4) show the effects when the disaster impact is split equally among the affected districts.

Tables

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.

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
Per Capita HH Income (2007 USD)	8,990	2,006.77	2,459.81	0.00	46,165.63
Individual Income (2007 USD)	8,990	934.39	2,097.76	0.00	19,691.50
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 Indonesian Rupiahs to USD at the average 2007 exchange rate (9,141 IDR/USD).

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, millions USD				
Past 1 Year	4.79	22.62	0.00	161.83
Past 5 Years	57.46	151.62	0.00	630.00
Past 10 Years	60.84	151.75	0.00	641.50
Past 15 Years	88.77	187.49	0.00	1,550.36
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, millions USD				
Past 1 Year	6.42	39.15	0.00	300.00
Past 5 Years	57.68	204.60	0.00	1,100.00
Past 10 Years	120.82	260.21	0.00	1,733.96
Past 15 Years	125.05	264.83	0.00	1,733.96

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).

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

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

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

Table 5: Impact of Severe Disasters

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

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

Table 6: Spline Regressions

	Risk Category		
	Deaths	Damages	Houses
	(1)	(2)	(3)
Spline Cutoff:	=0.007	=0.114	=0.170
Below Cutoff	-8.833	-1.100**	0.040
	(13.12)	(0.454)	(0.446)
Above Cutoff	0.093***	0.025**	0.003***
	(0.019)	(0.011)	(0.001)
Maximum value	7.5	23.6	345.0
Observations	15,894	15,894	15,894
Number of Respondents	7,947	7,947	7,947
Adjusted R-squared	0.021	0.021	0.021

Notes: Spline Cutoffs determined by sample median among those who experienced any deaths, damages, and houses destroyed, respectively. 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, adjusted for population. 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

Table 7: Impact of Disasters on Mental Health

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

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

Table 8: Impact of Disasters on Income

	Log Household Income				Log Individual Income			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-Year Mortality	-2.233				7.484			
	(1.391)				(9.019)			
5-Year Mortality		-0.011*				-0.203***		
		(0.007)				(0.040)		
10-Year Mortality			0.028				-0.312*	
			(0.074)				(0.185)	
15-Year Mortality				-0.013				-0.331*
				(0.063)				(0.197)
Observations	15,894	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	7,947
Mean Mortality	0.002	0.092	0.186	0.190	0.002	0.092	0.186	0.190
Adjusted R-squared	0.004	0.004	0.004	0.004	0.062	0.062	0.062	0.062

Notes: Standard errors in parentheses, clustered at the district level. Log of household income is annual and per capita; log of individual income is a sum of all annual labor income, non-labor income, and transfers. All regressions include individual fixed effects, wave dummy, and demographic controls. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9: Selective Attrition

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

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

Table 10: Effects of Disaster Deaths on Migration

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

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

Table 11: Most Risk Averse on Total District Deaths from All Disasters, with and without Gamble Averse Individuals
adjusted for district population (per 1,000)

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

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

Footnotes

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

2. Cameron and Shah (2015) specifically explore whether floods and earthquakes affect risk preferences in Indonesia and find that individuals living in villages that had experienced a 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, which limits their sample to a small geographical area of the country. Risk attitudes may differ from individuals in other provinces, as well as from non-heads of household and from people residing in different types of households (i.e., without children).

3. While in other experiments and surveys this question is typically phrased as a gamble between two choices, due to the substantial Muslim population in Indonesia among whom gambling is prohibited, it is phrased in a way that the respondent would earn money with the option of becoming "lucky" and earning extra if the uncertain option is chosen.

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

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

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

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

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

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

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

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

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

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

14. While the coefficients appear large, the one- and two-year mortality rates from disaster are small, and when this is taken into consideration, the coefficients are in line with the results for other time frames

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

16. The coefficient on the one-year mortality rate seems impossibly large, but this simply reflects the steep slope of the regression. Given the one-year mortality rate is below 1, an 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

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

18. Spline Cutoffs determined by sample median among those who experienced any deaths, damages, and houses destroyed, respectively.

19. Maximum effect of -1.10*0.114 = -0.125 in risk category compared to the maximum effect above the threshold of 0.59 (=0.025*23.6).

20. Extensive disasters are higher frequency, typically lower-severity disasters, while intensive disasters are lower frequency and typically higher in severity

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

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

23. 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.

24. All attrition regressions include district fixed effects.

25. 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).

26. See *CRED & UNISDR* (2018), as well as *UNSD* (2016).

27. See, for example, Stern (2008); Frankenberg, Thomas, and Laurito (2014); Maccini and Yang (2009); Brando

and Santo (2015); Datar et al. (2013); Desbureaux and Rodella (2019).

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