DISCUSSION PAPER SERIES

IZA DP No. 6756

Risk-Taking Behavior in the Wake of Natural Disasters

Lisa Cameron
Manisha Shah

July 2012

Forschungsinstitut
zur Zukunft der Arbeit
Institute for the Study
of Labor

Risk-Taking Behavior in the Wake of Natural Disasters

Lisa Cameron
Monash University
and IZA

Manisha Shah
University of California-Irvine,
NBER and IZA

Discussion Paper No. 6756
July 2012

IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

IZA Discussion Paper No. 6756
July 2012

ABSTRACT

Risk-Taking Behavior in the Wake of Natural Disasters*

We study whether natural disasters affect risk-taking behavior exploiting geographic variation in exposure to natural disasters. We conduct standard risk games (using real money) with randomly selected individuals in Indonesia and find that individuals who recently suffered a flood or earthquake exhibit more risk aversion than individuals living in otherwise like villages. The impact persists for several years, particularly if the disaster was severe. Some, but not all, of this effect is due to income losses. While we cannot rule out fundamental changes in risk preferences, data on subjective beliefs of the probability of a disaster occurring and the expected severity of such a disaster suggest that changes in perceptions of background risk are driving the more risk-averse behavior we observe. We show that access to insurance can partly offset this effect. Finally, we relate the observed experimental behavior to the propensity of respondents to take risks in their daily lives and show that an increase in risk-aversion has important implications for economic development.

JEL Classification: Q54, O12, D81

Keywords: natural disasters, risk aversion, development

Corresponding author:

Manisha Shah
Department of Economics
3151 Social Science Plaza
University of California-Irvine
Irvine, CA 92697
USA
E-mail: m.shah@uci.edu

* We thank Abigail Barr, Ethan Ligon, Simon Loertscher, Mark Rosenzweig, Laura Schechter, John Strauss, and Tom Wilkening for helpful comments. Lucie Tafara Moore provided excellent research assistance. We are also indebted to Bondan Sikoki and Wayan Suriastini for assistance in the design and implementation of the survey.

Over the last decade, direct losses from natural disasters in the developing world averaged 35 billion USD annually. These losses are increasing and are more than eight times greater than the losses suffered as a result of natural disasters during the 1960's (EM-DAT, 2009). Three main categories of natural disasters account for 90% of the world's direct losses: floods, earthquakes, and tropical cyclones. A disproportionate share of the deaths and damage caused by such environmental shocks is borne by people in developing countries (Kahn, 2005). Developing countries are not necessarily more susceptible to natural disasters, but the impact is often more severe due to poor building practices and lack of adequate infrastructure. The enormity of these losses has focused attention on how natural disasters can undermine countries long-term efforts to attain and sustain economic growth (Freeman, 2000). This is becoming an increasingly important issue as climate change scientists have predicted an increase in the frequency of disasters like floods and tropical cyclones (IPCC, 2001).

Natural disasters are traumatic events and it is thus likely that they affect individuals' behavior in the short and possibly longer term. We investigate the relationship between natural disasters and individuals' risk-taking behavior using experimental data from Indonesia. If natural disasters affect people's perceptions of the riskiness of their environment, then we might expect them to exhibit more risk averse behavior after experiencing a natural disaster. However, psychological theories suggest that individuals who already live in high risk environments may not be particularly concerned about the addition of small independent risks or that individuals may react emotionally (as opposed to cognitively) and exhibit more risk-loving behavior.

Our identification strategy is simple. We exploit geographic variation in the timing of natural disasters in an area where any village could be hit by an earthquake or flood. Our study area - East Java - is highly vulnerable to such events. Seismology data going back to 1973 shows that 100 percent of the villages in our sample have been within 50 kilometers from an epicenter of an earthquake (measuring over 3.5 Richter Scale). Further, survey data shows that sixty-seven percent of the villages report having experienced a flood or an earthquake in the past 28 years. Therefore, while the exact timing is unpredictable, any village in the sample could experience a natural disaster.

We find that individuals in villages that suffered a flood or earthquake in the past three years exhibit higher levels of risk aversion compared to like individuals in villages that did not experience a disaster. Individuals who have experienced an earthquake (flood) in the past three years are 10 (6) percentage points less likely to be risk-loving. This is a large effect and translates into a 58 (35) percent decrease in risk tolerance. Recent disasters affect risk-taking behavior even after we control for the mean occurrence of earthquakes and floods over the previous 30 years. We also show that these results are not biased due to selection of residential location or migration patterns and that the effects of particulary severe shocks are long lasting.

Some, but not all, of the impact of a natural disaster is a consequence of a loss of income. In line with this, we show that access to informal insurance mechanisms only partially reduces risk aversion in the face of a natural disasters. Natural disasters also change people's beliefs. We show that individuals who recently experienced a natural disaster perceive the world to be a much riskier place. People (inaccurately) update their perception of background risk after experiencing a disaster. They report unrealistically high probabilities that another will occur in the next year and that it will be severe. These perceptions persist for several years. Our results are thus consistent with Di Tella et al. (2007) and Malmendier and Nagel (2011) in finding that different experiences (of land reform and macroeconomic shocks respectively) lead to differing beliefs and different behavior.

We conclude by examining the extent to which behavior in the risk experiments is correlated with "real life" risk-taking like opening a new business or changing jobs, and provide evidence that more risk averse individuals are less likely to take these types of risks. This clearly has important implications for economic development. Particularly since aid money is often infused into natural disaster sites just after the disaster occurs, and consequently the cost of more risk averse behavior at this time is heightened.

The economics literature on natural disasters is relatively new. However, recent papers have examined the impact of natural disasters on outcomes such as macroeconomic output (Noy, 2009), income and international financial flows (Yang, 2008a), migration decisions (Halliday, 2006; Paxson and Rouse, 2008; Yang, 2008b), fertility and education investments (Baez et al., 2010; Finlay, 2009; Portner, 2008; Yamauchi et al., 2009), and even mental health (Frankenberg et al., 2008). To our knowledge this is the first paper which attempts to examine the effect of natural disasters on risk-taking behavior in a developing country. This is an extremely important question as risk-taking behavior determines many crucial household decisions related to savings and investment behavior (Rosenzweig and Stark, 1989), fertility (Schultz, 1997), human capital decisions (Strauss and Thomas, 1995), and technology adoption (Liu, 2010); and natural disasters are becoming increasingly prevalent all over the world. Therefore, the results from this paper have important ramifications for various household decisions that influence economic development.

1 Why should natural disasters affect risk behavior?

It seems likely that natural disasters would affect individuals' risk choices. For example, disasters may change individuals' perceptions of the risk they face. In a world of perfect information, individuals will have accurately formed expectations as to the probability of such an event occurring. This constitutes their estimate of background risk associated with natural disasters. In this world, although a natural disaster imparts no new information, natural disasters affect behavior through their impact on estimates of background risk. So, in areas where disasters are more prevalent, background risk of this sort is higher and we might expect to see different risk-taking behavior than in areas with lower background risk.

Alternatively, a natural disaster may constitute a "shock" that contains new information and may cause estimates of background risk to be updated. We argue this is a more natural way to think of a disaster. For example, it is difficult to think of the victims of recent disasters such as the tsunami in Japan as not being shocked by the event and reappraising the world in which they live. Similarly, living through a large earthquake may make individuals perceive the world as a riskier place than prior to the event. In this case, even if one controls for the long term prevalence of disasters, recent disasters may affect risk-taking behavior. If this shock is incorporated in expectations of background risk then it will have a long-term effect on behavior. A possible alternative though is that the "shock" associated with a disaster only affects people's expectations and behavior in the short-term. With time, the impact on their behavior dissipates.

A further way in which disasters are likely to affect risk-taking behavior is through their effect on income and wealth. Disasters destroy physical property and reduce income-earning opportunities. It is well established in the economics literature that wealth is negatively associated with risk aversion. Our data allow us to explore all three of these potential avenues below.

Theoretically the anticipated effect of a natural disaster on risk aversion remains unclear. On the one hand, it seems natural that adding background risk to wealth will increase risk aversion to other independent risks (Eeckhoudt et al., 1996; Guiso and Paiella, 2008; Gollier and Pratt, 1996). Gollier and Pratt (1996) and Eeckhoudt et al. (1996) derive the necessary and sufficient restrictions on utility such that an addition of background risk will cause a utility maximizing individual to make less risky choices. Gollier and Pratt (1996) define this property as "risk vulnerability" and show that with such preferences, adding background risk increases the demand for insurance. However, psychological evidence of diminishing sensitivity suggests that if the level of risk is high, people may not be particularly concerned about the addition of a small independent risk (Kahneman and Tversky, 1979). Quiggin (2003), using non-expected utility theories based on probability weighting shows that for a wide range of risk-averse utility functions, independent risks are complementary rather than substitutes. That is, aversion to one risk will be reduced by the presence of an independent background risk.

Empirically, the evidence testing these theories is quite limited. Heaton and Lucas (2000), using survey data from the US find that higher levels of background risk are associated with reduced stock market participation. Guiso and Paiella (2008) show that the consumer's environment affects risk aversion and that individuals who are more likely to face income uncertainty or to become liquidity constrained exhibit a higher degree of absolute risk aversion. Lusk and Coble (2003) analyze individuals' choices over a series of lottery choices in a laboratory setting in the presence and absence of uncorrelated background risk. They find that adding abstract background risk generates more risk aversion, although they do not find the effect to be quantitatively large.

Our empirical findings are consistent with Gollier and Pratt's (1996) concept of risk vulnerability—the risk associated with natural disasters reduces people's propensity for risk-taking. We show that experiencing a natural disaster provides new information on the "riskiness" of living in a given area. While people have underlying beliefs about the likelihood a natural disaster will strike, we show that individuals are unable to adequately assess the underlying risk of these types of shocks and therefore consider the experience of a disasters as providing new information. Our data show that those who have experienced a natural disaster more recently, report significantly (and unrealistically) higher probabilities of a natural disaster occurring in the next twelve months and expect the disaster to be more severe than those who have not experienced a disaster. This is true even after we control for the mean occurrence of floods and earthquakes back to 1980. These results suggest that changes in expectations following a disaster likely play a role in explaining the differences in behavior. These changes persist for approximately five years after the disaster. After five years, individuals perceptions of the risk they face return to pre-disaster levels. This finding is strikingly similar to that of Gallagher (2010) who uses data on flood insurance take-up in the US over a 50 year period to examine the updating of expectations. He finds a spike in insurance take-up shortly after a flood which then dissipates over time, fully dissipating within ten years. He concludes that such behavior cannot be adequately explained by standard Bayesian updating and that the evidence is most consistent with a Bayesian model that allows households to to forget (or discount) past information. Kunreuther (1996) and Palm (1995) have also demonstrated that beliefs about the likelihood of a future natural disaster increase immediately following personal experience of such a disaster.

As far as we know there are no previous papers studying this phenomenon in a developing country where conceivably the risks faced by individuals on a daily basis are particularly high, individuals are extremely poor and a lowered willingness to take risks could have significant ramifications in terms of living standards and economic development. Eckel et al. (2009) examines this issue in the context of Hurricane Katrina in the US. They focus on the short-term impact of Hurricane Katrina evacuees. Their results differ from ours as they find that the evacuees exhibit risk-loving behavior. They subscribe such behavior to the emotional state of the participants shortly after the hurricane.[1]

2 Indonesia and natural disasters

Indonesia is particularly prone to natural disasters. It regularly experiences floods, earthquakes, volcanic eruptions, drought, forest fires, tropical cyclones, and landslides. In this paper we focus on the two most commonly occurring natural disasters both in terms of frequency of events and numbers of people afflicted—floods and earthquakes (EM-DAT, 2009).[2]

Our study site is rural East Java. The province of East Java covers approximately 48,000 square kilometers of land and is home to approximately 35 million people making it one of the most densely populated largely rural areas on earth with more than 700 people per square kilometer. Seventy percent of its population live in rural areas and farming is the main occupation. The population is predominantly muslim and ethnically Javanese with a significant Madurese minority. Village life is largely traditional with village heads and elders playing important roles in village decision-making.

The majority of East Java is flat (0-500m above sea level) and relatively fertile. Flooding generally occurs because water fills river basins too quickly and the rain water cannot be absorbed fast enough. Figures 1 and 2 show that the entire province of East Java (Jawa Timur on the map) suffers high intensity risk from both earthquakes (Figure 1) and floods (Figure 2). The figures illustrate that no region in our East Java sample is immune from these natural disasters.

[1] We have recently become aware of Cassar et al. (2011) which examines the impact of the 2004 tsunami on trust, time preferences and risk attitudes in Thailand. Their findings are consistent with ours - that the disaster is associated with increases in risk aversion.

[2] Droughts are important in some parts of Indonesia, but not in our study site. Floods and earthquakes are also more frequent events for the country as a whole than droughts. For example, from 1900-2011, the EM-DAT database recorded 97 earthquakes and 61 general floods compared to only 9 droughts in Indonesia. Similarly, during this same period, more individuals were affected by earthquakes and floods relative to drought. The same is true for dollar amounts in damage due to earthquakes and floods relative to drought. Data extracted from `www.emdat.be/database` on September 20, 2011.

However, whether an earthquake and/or flood strikes a village in a given time period is obviously unpredictable.

3 Data and experimental design

Our sample consists of approximately 1550 individuals spread across 120 rural communities, in six districts of the province of East Java.[3] These individuals participated in experimental games which will be explained in detail below. The individuals were members in households that had previously been surveyed as part of a randomized evaluation. The baseline survey was conducted in August 2008 and the experiments were conducted in October 2008. Both were conducted prior to the program being introduced and so for our purposes constitute a random sample of the population, except that only households with children were sampled.[4] The risk game (based on Binswanger (1980)) was played with an adult household member. An important advantage of this game design is that it is easily comprehended by subjects outside the usual convenient sample of university students. In addition, our sample size is much larger than previous research using similar risk games with real stakes. The survey collected information on the standard array of socio-economic variables, including income and wealth. A community level survey was also administered to the village head. This survey provides one of our measures of natural disasters affecting each village.

The risk game was conducted as follows. Individuals were asked to select one gamble from a set of six possible gambles. Each gamble worked as follows. The experimenter showed the player he had two marbles, a blue and a yellow one. He would then put the marbles behind his back and shake them in his hands. Then he would take one marble in each hand and bring them forward telling the player he had one marble concealed in each hand. The player would pick one hand. If the player picked the hand containing the blue marble, she would win the amount of money shown on the blue side of the table. If she picked the hand containing the yellow marble, the player would win the amount of money shown on the yellow side of the table.[5] Before playing the risk game, the experimenter went through a series of examples with each player. When it was clear that the player understood the game, money was put on the table to indicate the game for real stakes would begin.[6]

[3]East Java has 29 rural districts.

[4]This is because of the focus of the evaluation. Although we endeavored to have as many male participants as possible, women are over-represented in our sample as they were more often at home with children and available to participate.

[5]More detailed instructions for the risk game including the protocol are given in the appendix.

[6]Only 11 players (0.70%) got the two test questions wrong. We proceeded with two more test questions for those 11 players. Four players (out of 11) still got the next two questions wrong. In 3 of the cases, we switched to another

The six 50-50 gamble options each player was given are summarized in Table 1. Gamble A gives the participant a 50% chance of winning Rp10,000 and a 50% chance of winning Rp10,000, hence it involves no risk. The risk associated with each gamble increases as the player progresses down the table, with choice F being the riskiest. The expected values of the winnings in this game range from Rp10,000 to Rp20,000 where the expected value also increases until choice E. Note that Choice E and F have the same expected return, but F has a higher variance, so only a risk-neutral or risk-loving person would take the step from E to F. In terms of the magnitude of the stakes, one day's wage in this region is approximately Rp10,000. Therefore, the potential winnings are quite substantial. Players can win anywhere from one to four days income. Since the stakes are substantial, we expect individuals to exhibit risk aversion (Arrow, 1971; Rabin, 2000).

Table 1 also summarizes the frequency of gamble choices that players made. Overall, the distribution is quite similar to other studies that have played similar risk games (for example, see Binswanger (1980); Barr and Genicot (2008); Cardenas and Carpenter (2008) for a review.) Barr and Genicot (2008) play the same risk game based on Binswanger (1980) in a number of Zimbabwean villages and interestingly, both of the tails on our distribution are slightly fatter than their round 1 data, especially on the lower end. This heavier lower end may be consistent with the large number of natural disasters in East Java increasing risk aversion.

3.1 Estimating risk aversion parameters

We calculate our risk measures using three different methods. We first use a simple measure of risk attitudes. We define those individuals who selected choice E or F as exhibiting "risk-loving"(=1) behavior[7] and all others are defined as "non risk-loving"(=0). We choose choices E and F as they are the riskiest choices an individual can make, and have the same expected value. This measure does not require any assumptions about individuals utility functions. In addition, we then construct an alternate measure of risk aversion (following much of the experimental economics literature) by estimating risk aversion parameters for each person assuming constant relative risk aversion (CRRA) CES utility: $U(c) = \frac{c^{(1-\gamma)}}{1-\gamma}$.

Most studies which estimate risk aversion parameters from experiments in developing countries ignore income outside the experiment (Cardenas and Carpenter, 2008). However, an exception to this is Schechter (2007) who defines utility over daily income plus winnings from the risk experiment

player within the same household and we did not play the risk game in one household.

[7] Given this is a sample or poor, rural Indonesians, these individuals are probably more correctly defined as exhibiting "risk-tolerant" behavior however for ease of exposition we use the term risk-loving.

in Paraguay. In column 6 of Table 1, we generate risk aversion parameters by defining utility only over winnings from the risk experiment. Column 7 of Table 1 follows Schechter (2007) and reports risk-aversion parameters for each choice when utility is defined over daily income plus winnings from the game. We generate household-specific risk-aversion intervals from the different risk game choices and report the mean values of the upper and lower bound for each choice. Both methods assume that the amount received is consumed. We describe the method in more detail in the appendix.

In our regressions we take the lower bound of the risk aversion parameter as the dependent variable. We use the lower bound of the interval as this is the most conservative estimate of the risk aversion parameter and thus gives us an estimate which is a lower bound. Some scaling decisions need to be made for choices E and F since the lower bounds are 0 and $-\infty$ respectively. To use the log of the lower bound of the risk aversion parameter as the dependent variable, we set the value of choice F to some arbitrarily small number. We similarly set the value for choice E which has a lower value of 0 to just above zero. Our empirical results are not sensitive to the choice of the small number.[8]

3.2 Measures of natural disaster

The measures of natural disaster are obtained from three different datasets: a community level survey which was administered to the village head in each community in 2008, the PODES (Potensi Desa) which is a survey conducted by the Indonesian Statistical Agency in every village of Indonesia every three years, and seismology data from the USGS website.[9] We use three different datasets as they measure natural disasters in different ways (e.g. occurrence, frequency, total damage in dollar amount, distance from epicenter); but our results are consistent regardless of the dataset and measure of natural disaster we employ, illustrating the robustness of our results. In the community level survey heads responded yes/no as to whether their village had experienced an earthquake and/or flood and if yes, when it occurred. Approximately 10 percent of our villages experienced a flood or earthquake between 2005 and 2008. None of the villages experienced both types of natural disasters during this period.

We also employ data from PODES to construct measures of the intensity of natural disasters for our villages. The respondent is a village representative, most often the village head. Using the

[8] Following Binswanger (1980), we can also use the log of the geometric mean of each *interval* as an alternative dependent variable. This avoids the need to add arbitrarily small figures to the zero amounts. The empirical results are qualitatively similar (results available upon request).

[9] `http://earthquake.usgs.gov/earthquakes/eqarchives/epic/epic_global.php`

2008 PODES, we generate a measure of the total value of material damage due to floods and/or earthquakes from 2005-2008 for each village. The average amount of damage during this period was reported as 46 million rupiah (or 4650 USD) with the maximum damage reported at approximately 122,000 USD. In addition, some of the villages in our sample experienced more than one flood from 2005-2008. Therefore, we also construct a continuous measure of flood (which varies from 0 to 6) for the same time period using the PODES data. The mean number of floods 0.4 floods. None of the villages experienced more than one earthquake during this 3 year period. In addition, there were no reported deaths caused by earthquakes or floods during this period in our sample villages. While these are disasters severe enough to cause material damage, none were severe enough to cause death.

We also construct an additional measure of earthquake intensity using seismology data from the USGS, restricting the data to every earthquake that occurred between 2005-2008 (the same years as our other natural disaster data described above) and that registered above 3.5 on the Richter scale. We restrict earthquake occurrences to the latitude and longitude of the province of East Java ($7°16'S, 112°45'E$). Distance between each village in the sample and the earthquake epicenter is calculated for the largest magnitude earthquake each year and then we take the average over the three years to generate one measure of earthquake intensity per village per year.

There are many reasons to use this seismology data in addition to the PODES and community level survey data. Firstly, although there is little reason to believe the village head would not provide accurate information on natural disasters, using the seismology data removes any concerns about reporting errors and/or measurement error and also the possible subjectivity of the information given.[10] Secondly, different villages might engage in different ex-ante disaster mitigation strategies such as building structures so that they are more able to withstand earthquakes and investing in drainage infrastructure.[11] This raises the potential for unobserved factors associated with disaster prevention and risk attitudes to drive our results. Using the seismology data means such unobservables cannot be driving our results because treatment is simply a function of geographic location, and is not a function of infrastructure investment or biased reporting.

Ideally we would also use rainfall data as a similar proxy for flooding. However, Indonesia only has a small number of rainfall stations. As our sample is geographically clustered across only 6

[10] To further examine this issue we include controls for village head characteristics such as age, sex, length of tenure as village head, and education in the specifications reported below. The results are robust to the inclusion of village head characteristics and the main estimates do not change (results available upon request from authors).

[11] Although the ability of communities to invest in such measures is severely constrained by the general poverty of the area.

of Indonesia's over 400 districts, the measured rainfall data does not vary enough to be closely correlated with flooding which we have at the village level. In fact due to missing data and few rainfall stations, the rainfall data generates a maximum of only 3 different values across our 120 villages each year of our sample periods. Note that this is the same source of rainfall data used by Maccini and Yang (2009) but they have approximately 166 districts in their sample, so a lot more geographic variation that they can exploit.

Finally, we construct historical measures of the mean number of earthquakes and floods in each of our villages. We use data from the PODES in 2008, 2006, 2003, 2000, 1993, 1990, and 1983 to construct a measure going back 28 years to 1980.[12] The mean value of floods from 1980-2008 is .26 floods and 0.23 earthquakes. We use these means as measures of the historical occurrence of natural disasters in each village. We can think of these means as measuring background risk. The coefficients on recent earthquakes/floods will then tell us if these recent events have an additional effect.

The USGS data also allow us to construct another historical measure of earthquake intensity back to 1973. The same method described above is employed: distance between each village in the sample and the earthquake epicenter is calculated for the largest magnitude earthquake each year and then we take the average over all years back to 1973. We use this an an additional historical measure of earthquakes instead of the PODES data. Using this historical seismology data gives us the same benefits described above in that USGS earthquake occurrences cannot be biased by reporting, infrastructure investments, etc.

3.3 Summary statistics

Summary statistics by risk game choice are presented in Table 2. Risk choices do not vary by marital status. However, females are less likely to choose the riskier options which is consistent with the experimental literature.[13] In addition, as we might expect, younger, more educated, and wealthier individuals are more likely to select riskier options. We define "wealth" as the sum of the value of all assets the household owns (e.g. house, land, livestock, household equipment, jewelry, etc.) and then take the natural log. In terms of natural disasters, the summary statistics in Table 2 indicate that individuals who have experienced an earthquake or flood in the past three years, are less likely to choose more risky options. Further, individuals who live in villages that have been flooded more frequently in the last three years choose less risky choices. In addition, individuals in

[12] Questions about natural disaster were not asked in the 1986 and 1996 PODES.

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

villages further away from the epicenter of large earthquakes are more likely to choose the riskier options. Below, we investigate whether these trends remain once we control for a range of observable characteristics.

4 Empirical Strategy

Our empirical strategy is simple. We regress the risk measure on the various natural disaster measures, while controlling for household, individual, geographic characteristics, and district fixed effects. We cluster all specifications at the village level. More specifically, we estimate OLS regressions:

$$y_{iv} = \alpha + \beta_1 E_v + \beta_2 F_v + \beta_3 X_i + \gamma + \epsilon_{iv} \tag{1}$$

where i indexes individuals and v villages. The dependent variable, y_{iv} is the risk measure (we use 3 different measures); γ is district fixed effects. Control variables in X_i include age, education, marital status, ethnicity, wealth, river dummy, etc. The coefficients of interest are β_1 and β_2 on the Earthquake and Flood measures.

We exploit geographic variation in the timing of natural disasters in a region where any of the villages in the sample could be hit by an earthquake or flood. Figures 1 and 2 show that the entire province of East Java (Jawa Timur on the map) suffers high intensity risk from both earthquakes (Figure 1) and floods (Figure 2). The figures illustrate that no region in our East Java sample is immune from these natural disasters. However, when one will occur is unpredictable. The historical data support this conjecture. Using the USGS data going back to 1973, our entire sample of villages was within 50 kilometers from an epicenter of an earthquake (over 3.5 Richter Scale). This means no village was immune from an earthquake going back to 1973. Further, sixty-seven percent of the sample villages report having experienced a flood or an earthquake in the preceding 28 years (using PODES data).

4.1 Potential Selection Bias

One obvious concern with this identification strategy is that individuals who live in villages that experienced earthquakes and floods in the past three years might be different from individuals who live in villages that did not experience these natural disasters. For example, it is possible that wealthier individuals choose to live in villages that do not experience flooding and are more likely to choose the riskier option (because of their wealth). This could introduce a correlation between flood and risk choice which is not causal. Similarly, villages that experienced a natural disaster in the past three years might be different from villages which did not. For example, villages which experienced a natural disaster might provide worse public goods than villages which did not, again introducing a correlation between natural disasters and risk aversion which is not causal.

We argue that such selectivity is unlikely because village of residence in East Java is largely a function of family roots, and ties to the land and community are strong. Furthermore, all of rural East Java is in an earthquake and flood zone (see Figures 1 and 2), and experts are unable to predict when and where an earthquake will occur and no village in our sample is immune from the risk of these shocks. Flooding is also widespread in East Java. Exposure to flooding risk is however largely governed by proximity to rivers and poor drainage. However, again as the map indicates, all villages in East Java are susceptible to high annual flood risk.

We also empirically examine the extent of selection bias, Table 3 presents the mean and standard deviation of many individual, household, and village characteristics by natural disaster status (columns 1-2). Column 3 shows that marital status, age, gender, and education are not significantly different from one another by natural disaster. A further concern is that wealthier households may choose to live in safer areas or build houses on higher ground, implying that wealthy households will be less likely to be affected by the natural disasters. In Table 4 we regress natural disaster on wealth and a polynomial of wealth and find no significant relationship between the occurrence of natural disasters and wealth. Therefore, it seems unlikely that the wealthier households can escape natural disasters in these regions. We return to the issue of wealth below. Thus there is no indication of a selection effect along these observable characteristics—those who experienced a natural disaster in the past three years are no different to those who did not. We do find a different ethnic composition in these villages by natural disaster as more Madurese individuals live in natural disaster villages than Javanese. This is likely a reflection of geographic clustering of different ethnic groups and is unlikely to be related to natural disaster activity. All of our regressions control for ethnicity. We also test various measures of household poverty, such as whether the household participates in the conditional cash transfer program (Keluarga Harapan), health insurance program for the poor (Askeskin), and whether they have access to subsidized rice. None of these measures are significantly different from one another suggesting households are equally poor across the types of villages. Since living on the river bank is the riskiest place to live in terms of risk of flood, we also test if that differs by natural disaster status—it does not.

In the middle part of Table 3 we present summary statistics from the community level survey. We investigate whether the extent of public goods provision and program access differ across village types since some part of flooding is caused by poor drainage. Again we find no significant differences. Natural disaster and non-natural disaster villages in the past three years provide the same health and sanitation programs and have similar population sizes. We do find that natural disaster villages are significantly more likely to have a river in close proximity. All of the empirical specifications below include a variable which indicates whether the village is on a river. If risk-averse individuals are less likely to settle in flood-prone areas then we would expect this variable to be positive and significant. However, it is not statistically significant in any of the specifications. We also check for other infrastructure differences such as electrification. Ninety-nine percent of our sample villages have electric lighting in the main street regardless of natural disaster status. Further, all households in both natural disaster and non-natural disaster villages use electricity.

4.1.1 Migration

To further examine the extent to which selectivity is likely to be a problem, we examine migration rates by natural disaster status. A follow up survey on these same households was conducted in December 2010. Therefore we know which households moved and dropped out of the sample between 2008 and 2010. Approximately 5 percent of the sample moved outside the village during this period. Therefore, we can test whether experiencing a natural disaster from 2005 to 2008 impacted the decision to move during this period. In Table 5 we regress the decision to migrate on our various measures of natural disaster. All specifications are clustered at the village level and include district level fixed effects. Columns 2-5 include additional controls for ethnicity, gender, age, education, wealth, marriage, and river dummies. We find that regardless of the natural disaster measure we use, experiencing a natural disaster is never significantly associated with the probability of moving. Therefore, it does not seem to be the case that there is differential migration due to natural disasters.

To further examine this issue, we examine migration rates using data from another dataset: the first and second waves of the Indonesian Family Life Survey (IFLS). The IFLS is a panel of over 7000 Indonesian households.[14] The 1993 wave provides information on natural disasters between 1990 and 1993. The 1997 wave identifies what percentage of individuals have moved between 1993 and 1997, both within the village and beyond the village. Between 1990 and 1993, 14.4 percent of IFLS communities in rural Indonesia experienced a flood or an earthquake. In villages that experienced a flood or an earthquake in rural Indonesia, 16.2 percent of individuals over the age of

[14] IFLS 1 (1993) and IFLS 2 (1997) were conducted by RAND in collaboration with Lembaga Demografi, University of Indonesia. For more information, see `http://www.rand.org/labor/FLS/IFLS/`.

15 (n=1752) migrated in the following 3 years versus 16.7 percent in villages that did not (n=9897). This difference is not statistically significant (p-value=0.63).[15]

We also investigate the composition of migrants to check whether different types of individuals are migrating by disaster status, thus changing the composition of rural communities. We look at various characteristics such as age, gender, marital status, education, and employment in rural Indonesia and test whether characteristics of migrants differ by natural disaster status. For example, our results might be biased if we find that younger men are more likely to be migrating from disaster areas (because they are generally more risk-loving) relative to non-disaster areas. This would imply that more risk-averse individuals are left behind in the villages that experience disasters, biasing our findings upward. We find that migrants from disaster villages are 25.4 years old on average (compared to 25.7 years old in non-disaster villages), and 52.2 percent are male (compared to 53.8 percent in non-disaster villages). Therefore it is not the case that migrants from villages that experienced disasters are more likely to be male or younger. In addition, migrants from villages which experienced a disaster completed 3.07 years of education on average compared to 3.30 years in non-disaster villages and 72 percent of migrants from disaster villages are currently employed (compared to 65.2 percent in non-disaster villages). None of these differences are statistically significant.[16] The only characteristic that differs significantly across disaster and non-disaster villages is marital status. Married individuals (both male and female) are more likely to migrate when the village experiences a natural disaster (51.2 percent of migrants from disaster villages are married versus 42.2 percent, p-value=0.04). Note though that our regressions indicate that being married does not affect risk aversion. Thus compositional differences in migrants are unlikely to be driving our results.[17]

5 Empirical results

In Table 6, we present the results from simple linear probability models where the dependent variable is "risk-loving" (a player who selected one of the two riskiest choices, E or F, in the risk

[15]To check the migration statistics for a sample closer to our rural East Java sample, we conduct the same analysis for rural Java. In villages that experienced a flood or an earthquake in rural Java, 15.6 percent of individuals over the age of 15 (n=1006) migrated in the following three years versus 13.9 percent in villages that did not (n=4742). Though the point estimate suggests that natural disasters may increase the likelihood of migration, again, this difference is not statistically significant (p-value=0.16).

[16]The p values for these tests are age (p-value=0.84), male (p-value=0.73), education (p-value=.25), and currently working (p-value=.10)

[17]Additionally, if it is the case that people who dislike living in natural disaster environments have been migrating out over time (for many years), then it is likely that our results are lower bounds. These individuals who have left are more likely to be risk averse individuals since they dislike living in risky, natural disaster environments.

game).[18] All specifications allow for clustering of standard errors at the village level and include district level fixed effects. We include district fixed effects to control for any potential differences at the district level which might affect our results such as public goods provisions, government programs, and/or geographic differences. Column 1 does not include any individual or household level controls; in column 2 we include age, marital status, gender, education, ethnicity, and a dummy indicating whether the village is on a river; and in column 3 we show the full model which includes the previous set of controls as well as the measure of mean number of earthquakes and floods (1980-2008) and a measure of wealth. While the consensus view is that absolute risk aversion should decline with wealth, including a measure of wealth could be endogenous since the higher returns that accompany riskier decisions may make risk-loving individuals more wealthy. The results show wealth to be associated with riskier behavior but its inclusion in the regression does not change our main results. In column 4 we include an alternative measure of floods (the number of floods) in each village which captures intensity, and in column 5 we use the alternative seismology measure of earthquakes (distance to epicenter). In column 6 we use the measure of monetary total damage caused by floods and earthquakes.

Table 6 indicates that individuals who have experienced an earthquake in the past three years are 10 percentage points less likely to choose option E or F. This is a large effect (58 percent) since the mean of the dependent variable is 0.17. Similarly, individuals who experienced a flood in the past three years are 6 percentage points less likely to choose option E or F. Though this effect is slightly smaller (35 percent decrease), it is qualitatively similar. Both of these results are statistically significant at the .01 and .05 level. As mentioned above, the variable indicating proximity of the community to a river is not statistically significant and suggests that selectivity of residence on the basis of risk attitudes is not a problem. As we might expect, women and older individuals are less likely to be risk-loving. Wealthier individuals are more likely to be risk-loving. These results are consistent with findings in the experimental economics literature.

In columns 4-6 of Table 6, we introduce the three different measures of natural disaster from the PODES and USGS data described above. When we include the continuous measure of flood (which varies from 0 to 6) in column 4, instead of the flood dummy in columns 1-3, the results indicate that for a one standard deviation increase in floods (which is equivalent to one flood), individuals are two percentage points less likely to choose option E or F. In column 5 we show that the further away from the epicenter of the earthquake, the more likely the individual is to choose

[18] The results are quantitatively similar if we estimate probit regressions.

one of the risky options. In column 6, using the measure of the total amount of monetary flood and earthquake damage (in log Indonesian rupiah), again we find that individuals with more flood or earthquake damage are significantly less likely to choose the risky options. Therefore, regardless of the natural disaster measure we employ (and whether it is our community data, PODES or USGS data), individuals who suffered an earthquake or a flood are significantly less likely to choose the riskier options in the risk game.

Interestingly, when we control for our measure of background risk—the mean occurrence of floods and earthquakes from 1980-2008 (in columns 3-6) using PODES data—the main results are not affected. That is, even controlling for actual background risk, current disasters affect risk-taking behavior. Mean background risk of an earthquake further reduces risk-taking behavior. The coefficient is negative and statistically significant suggesting that people who live in villages that experienced an earthquake from 1980-2008 exhibit even less risk loving behavior. In Table 16 of the appendix, we also regress the risk measures on the mean distance to epicenter (1973-2008) using the USGS seismology data. The results are similar. A one standard deviation increase in distance to the epicenter (approximately 30 kilometers) during the period 1973-2008, makes a person 9 percent less likely to choose the risky option (column 1). This result is statistically significant at the .01 percent level. The same is true when the dependent variable is the lower bound of the risk aversion parameter measured with or without income (column 2-3). The coefficient on mean floods is not statistically significant in either of these tables.

We now move to the other measures of risk which are more standard in the experimental economics literature, where the dependent variable is the log of the lower bound of the relative risk aversion parameter, calculated with and without income. In Table 7, the dependent variable is calculated assuming utility is only a function of the winnings from the game (column 6 of Table 1) and in Table 8 the dependent variable is calculated using the winnings from the game plus household daily income (column 7 of Table 1). We estimate OLS regressions, and all specifications allow errors to be clustered at the village level and include district fixed effects. The control variables in each column are the same as those described above in Table 6, and again, we build up to the final specification which includes all control variables.

Overall, the results in Table 7 indicate that individuals who experience earthquakes or floods are significantly more likely to exhibit a higher degree of risk-aversion. The magnitude of the results are slightly difficult to interpret due to the non-linearity of the risk aversion parameters. For example, moving from choice B to A is a 331 percent increase in the risk aversion parameter while moving from choice C to B is a 115 percent increase. Column 3 of Table 7 displays the model with the full set of control variables. The results indicate that experiencing an earthquake in the past three years increases the risk parameter by 260 percent. This implies that a person who would have chosen D is now more likely to choose the less risky option C. The maximum movement possible given the magnitude of the effect is one choice. The coefficient on the flood variable is also positive, though the magnitude is smaller than the earthquake coefficient. An individual who experiences a flood will have a 165 percent larger risk parameter.

The coefficients on the control variables are also sensible. As in the previous regressions in Table 6, females and older players are significantly more likely to have higher risk parameters (i.e. exhibit greater risk aversion). Education is statistically significant in these regressions (until we control for wealth in column 3), and we find that more educated players take more risk. This is also true for the wealthier players. In columns 4-6 of Table 7, we include our alternative measures: the number of floods in the past three years, distance to epicenter, and the total damage caused by earthquakes or floods. Again, the results are consistent and statistically significant. The greater the number of floods, the greater the risk aversion we observe in player choices. The closer to the epicenter of an earthquake means risk averse choices. Similarly, the greater the amount of damage caused by floods and earthquakes, the greater the risk aversion.

In Table 8 we replicate the regressions from Table 7, however we use the risk parameter that was generated including income in the utility function. Again individuals who experience earthquakes or floods exhibit more risk aversion, and the results are quantitatively similar to the results described above. In fact, the flood results are stronger and more significant.

6 Does history matter?

To examine the longevity of the impact we regress our measures of risk on the historical measures of natural disaster constructed from our data and the PODES data. The results are presented in Table 9. In columns 1-2 the dependent variable is risk-loving and in columns 3-4 the dependent variable is the log of the lower bound of the relative risk aversion parameter. All models have errors clustered at the village level, include district fixed effects, and include the full set of control variables.

In column 1 of Table 9 we include dummy variables generated from our survey data for both the types of disaster (earthquake or flood) for each year 2005-2008. We also construct a measure of the number of floods and earthquakes in the period 2000-2004 from the PODES data. In column 2, we group earthquakes and floods together (in case the small number of observations in each year is driving our results). The two sets of results are similar. Focusing on column 2, an economically significant effect is found for each of the four years, 2005-2008, although disasters in 2007 are not statistically significant. The coefficient on natural disasters over these years varies from 17 percentage points to 3 percentage points less risk-loving. While the magnitude of the effect decreases from 2008 to 2006, the effect of natural disasters on risk aversion is largest in 2005. The coefficient on the number of disasters 2000-2004 is negative but not significant.[19]

Recall that we have information on the total value of damage in each village from the PODES data. The mean value of total damage is 3.74 ln Rp; but in the villages that experienced a natural disaster in 2005, the mean value of total damage is 16.5 ln Rp. This is almost the maximum value of damage for the entire sample (the maximum is 20.9 ln Rp). Therefore, it seems likely that the large effect on risk aversion in 2005 is caused by the severity of the shocks in that year. Experiencing a disaster in 2005 reduces the probability of being risk-loving by 16 percentage points. This is a very large effect given the mean of risk-loving is 0.17.

In columns 3-4 of Table 9 we replicate the regression in columns 1-2, but with the other dependent variable: the log of the lower bound of the relative risk aversion parameter. The results are similar using this alternate measure of risk aversion.

Thus, the results suggest that natural disasters affect risk attitudes beyond the year in which they occur. The longevity of the effect appears to vary with the severity of the experience with more severe damage or trauma leaving a deeper and longer lasting imprint on people's risk attitudes.

7 Income Effects

One possible interpretation of our results is that the behavioral differences are driven by the changes in income or wealth that accompany natural disasters. Note however that the specifications in Table 6, 7, and 8 control for wealth at the time of the survey. The results also stand if we add income instead of wealth as a control. (Income is not statistically significant and does not affect the other results.) Unfortunately, we do not have income or wealth pre-natural disaster in our dataset so it is difficult to investigate whether a change in income or wealth is driving the results. However, to examine the role played by income and wealth changes more closely we turn to another data set. Unlike our data set, the fourth round of the Indonesian Family Life Survey (IFLS4) asked

[19] This variable is constructed from the PODES data and even if we separate it by years, it is not statistically significant.

households to report the value of income and assets lost due to natural disasters as well as the amount of financial aid received (if any). The reported income lost is approximately 5 percent of annual income.[20] Once we account for financial aid received, the reported loss decreases to 2 percent of annual income.

IFLS4 respondents also played games designed to elicit risk preferences. Unlike our game, the IFLS risk games were not played for real money. However, Table 10 shows that the IFLS data produce similar results.[21] We define a person as "risk-loving" if they picked the last, most risky option in the game. The IFLS4 respondents played two games, which we call Game 1 and Game 2. The games differed in terms of the payoffs in the lotteries.[22] Columns 1 and 4 show that for both games, the more disasters experienced by the household, the more risk averse their behavior. While the magnitude of the impact of natural disasters on risk aversion is smaller in the hypothetical games (as expected since there are no real stakes), the negative signs on the coefficients are consistent with our results.

Columns 2 and 5 of Table 10 include additional controls for the log of household income,[23] log of income lost due to natural disaster, and the log of financial assistance received. This allows us to examine if the income shock (controlling for the level of income) can explain our result. As anticipated, the log of household per capita income is positively associated with the probability of being risk-loving, but only significantly so for Risk Game 1.[24] Total assistance received is also positive, and again only significantly so in Game 1. Total amount lost is not significant in either specification. In both specifications, the coefficient on the number of disasters is unaffected by the inclusion of these controls. In column 3 and 6, we include an indicator of whether there was a large loss of income (the top 5 percentile of amount lost). The more assistance a household receives, the less risk averse were the choices made. Consistent with this, households that were severely affected

[20] This is 0.004 percent of the value of household assets.

[21] Though not central to their results, Andrabi and Das (2010) also played hypothetical risk games and found that individuals living closer to the 2005 Pakistani earthquake fault line were significantly more risk averse.

[22] The IFLS games were Holt and Laury (2002) type risk games where respondents are asked to make choices between a series of lottery pairs. Game 1 asks respondents to choose between Rp800,000 with certainty and lotteries with an equal chance of: 1) Rp1.6 million and Rp500,000; 2) Rp1.6 million and Rp400,000; and 3) Rp1.6 million and Rp200,000. The choices in Game 2 are between Rp4 million with certainty and lotteries with an equal chance of: 1) Rp8 million and Rp0; 2) 12 million and Rp0 ; and 3)16 million and a loss of Rp2 million. To be consistent with our sample, we limit the IFLS4 sample to rural households. We also exclude players who answered either of two test questions incorrectly. We also define natural disaster in a similar manner: the experience of a flood and/or earthquake.

[23] Again we note that including income is endogenous. The main results hold regardless of whether we control for baseline income or not.

[24] Table 17 in the appendix shows the results when we use wealth instead of income. Wealth is not statistically significant. Otherwise the results are the same.

by the natural disaster, in terms of having lost *a lot* of income, act in a more risk-averse manner. The bottom line from Table 10 is that although there is evidence of income effects in the data, controlling for both levels and changes of income does not affect our core result that experiencing a natural disaster, ceteris paribus, causes one to act in a more risk-averse manner. That is, changes in income do not fully explain the more risk-averse behavior of households that experienced natural disasters.[25]

8 Do individuals update expectations after experiencing a natural disaster?

The section above suggests that income effects cannot fully explain the change in risk-taking behavior associated with a natural disaster. A potential alternative mechanism is that a natural disaster impacts upon individuals' perceptions of the background risk they face. To examine this mechanism, in a later survey of the same respondents we asked households to report the probability (or likelihood) that a flood and/or earthquake would occur in their village in the next year. We report the mean results of their responses by natural disaster status in Table 3. Individuals who experienced a flood are significantly more likely to report a higher probability that a flood will occur in the next year (42.6 vs. 12 percent). Those that had experienced an earthquake reported a slightly higher (but not statistically significantly) probability that an earthquake will occur in the next year (18.2 vs. 16.8%). All of these figures are higher than the actual historical probabilities. The figure reported by those who had recently experienced a flood is however an order of magnitude higher than the actual probability of a flood occurring in these villages (approximately 3 percent per year).

In Table 11 we report OLS regression results where the dependent variable is the reported probability that a flood will occur (columns 1-2) regressed on year dummies for past flood experiences. All results are clustered at the village level and include district fixed effects. Column 1 does not include any control variables and column 2 reports results which include controls for ethnicity, gender, age, education, marriage, rivers, and mean flood (or earthquake) occurrence from 1980-2008. The results indicate that the more recent the flood experience, the more likely the individual will report a higher probability of occurrence in the next year. Therefore, it appears that past flood experiences cause individuals to update (and increase) the probability that another flood will occur

[25]We also control for income changes and test for an income effect by using the information on household income for the same households in the IFLS3 2000. The coefficient on income changes is not statistically significant. Similarly we interacted the change in income with natural disaster but again, the coefficient is not statistically significant. These results are available upon request.

in the next year. For example, a person who experienced a flood in 2008-09 reports a probability of occurrence in the next year that is 34 points higher than an individual who did not experience a flood in the preceding 7 years. This probability decreases the further away the flood experience (although not monotonically). For example, an individual who experienced a flood in 2004-05 reports a probability of occurrence in the next year that is 23 points higher than an individual who did not experience a flood. In 2002-03, the coefficient falls to 0.8 and loses statistical significance in column 2.[26] This updating of expectations occurs even after we control for the mean background risk of floods, and the mean number of floods over time has no impact on current day reports of expectations.

Given the true probability of a flood occurring is approximately 3 percent, these results suggest that the perceptions of risk reported by individuals who have recently experienced a disaster are irrationally high. However similarly "irrational behavior" has been well-documented in different settings. For example, "hot hand beliefs" where after a string of successes of say, calling heads or tails to the flip of a coin, individuals believe they are on a winning streak and give subjective probabilities of guessing the next flip correctly that are in excess of 50 percent (Croson and Sundali, 2005). The Indonesian data similarly suggests positive autocorrelation in the perceived probability of negative events.

We also asked respondents to estimate how bad the impact of that flood or earthquake would be conditional on experiencing a disaster in the next year (scale of 0-4 with 4 being the worst outcome, i.e. an extremely bad flood and the mean for both variables is approximately 1). Columns 3-4 of Table 11 report ordered probit regressions where the dependent variable is the perceived impact of the flood. These results are also very intuitive and show a similar pattern to the probabilities. Individuals are much more likely to report that the flood impact will be bad if they have experienced a flood in the recent past. In addition, we include a dummy variable if they have experienced a bad flood in the past and it is both positive and significant. We define a "bad flood impact" if the individual reports they had a bad or extremely bad flood experience. This implies that an individual who experienced a bad flood in the past is significantly more likely to report that the future flood impact will be bad.

In Table 12 we report the same regressions as in Table 11 except the measure of natural disaster is now earthquake. The pattern is similar. The more recent the earthquake experience, the higher the reported probability that an earthquake will occur in the next year. However, none of the

[26] We test for the equality of the year coefficients and can reject equality.

coefficients are statistically significant. Having experienced an earthquake in the past does not affect the predicted severity of an earthquake but having experienced a bad earthquake in the past significantly increases the likelihood that an individual will report that the severity of the future earthquake will be bad.[27]

These results suggest that the updating of expectations help explain the more risk-averse choices people make when they have been exposed to a disaster. Having experienced a disaster people perceive that they now face a greater risk and/or greater severity of future disasters and so are less inclined to take risks. Note that the longevity of the effect is similar to that on risk-taking behavior in Table 9—approximately 5 years—and there is similarly a larger impact on perceptions of the likely severity of another disaster occurring if previous disasters have been severe.[28]

9 Do households self-insure?

Our results are so far consistent with the prediction of Gollier and Pratt's (1996) "risk vulnerability" that (perceived) exposure to greater background risk decreases risk-taking. A further implications of risk vulnerability is that individuals demand more insurance in the presence of increased risk. We examine this using various measures of "insurance." Given the setting is rural Indonesia, individuals do not have access to formal earthquake or flood insurance. However, rural households have other informal methods of self-insuring against risk.

Our data provide information on households' participation in "arisan" and their receipt of remittances. Arisan is the Indonesian version of rotating savings and credit associations (ROSCAs) which are found in many developing countries. It refers to a social gathering in which a group of community members meet monthly for a private lottery. Each member of the group deposits a fixed amount of money into a pot, then a name is drawn and that winner takes home the cash. After having won, the winner's name is removed from the pot until each member has won and the cycle is complete. The primary purpose of the arisan is to enable members to purchase something beyond their affordability, but it is occasionally used for smoothing shocks.[29] However, this is more likely when the shock is idiosyncratic (only affects a household) and much more difficult in the

[27] These results suggest that earthquakes are more likely to affect behavior by altering individuals' perceptions of the severity of earthquakes, while floods affect the perception of the probability of the a flood occurring and the severity. This difference may reflect a perception that earthquakes are inherently more random.

[28] Ideally we would use the predicted probabilities and severity indices as explanatory variables in the natural disaster regressions. They were however collected in an additional survey approximately 12 months after the original survey and so will also reflect natural disasters that occurred after the experimental games were conducted.

[29] For example, if a member falls ill, she might be given the pot of money that month even if her number was not selected.

presence of an aggregate shock (which affects the whole village).

In addition to arisan participation, households were asked whether they receive remittance income from outside their village—this could be money sent from urban migrants within Indonesia or money sent from overseas Indonesian migrants. A literature exists on the role of gifts and remittances which households use for insurance and risk-coping strategies (Lucas and Stark, 1985; Rosenzweig and Stark, 1989; Yang and Choi, 2007). We use arisan participation and remittance receipt to test for informal methods of self-insurance.

In Table 13 we test whether we observe greater incidence of insurance in villages that are hit by natural disasters. In columns 1-2, we report the mean of the insurance measure by natural disaster status, and in column 3, we test whether the means are statistically different. Consistent with Gollier and Pratt (1996), individuals who live in villages which experienced a natural disaster in the previous three years are more likely to receive remittances and participate in arisan. The amount of remittances received is also higher in villages that have experienced a natural disaster, but not statistically significantly so.

In Table 14 we examine whether having access to insurance can reduce some of the natural disaster induced risk aversion. We regress our measures of risk on the different measures of insurance and interact our measure of insurance and natural disaster. To the extent our results are driven by income effects, we would expect this impact to be mitigated by insurance. Note that the analysis presented in this section is only suggestive as the results may be biased due to endogeneity and/or reverse causality.[30]

In column 1 of Table 14 the dependent variable is risk-loving and in column 2 the dependent variable is the log of the lower bound of the relative risk aversion parameter. All models have errors clustered at the village level, include district fixed effects, and include the full set of control variables. In column 1 we report the effect of remittance receipt and arisan participation on risk aversion. The coefficient on the interaction of natural disaster and the remittance amount (in log Rp) is positive and statistically significant. Receiving a remittance does provide some insurance against the impact of natural disasters. The greater the amount received, the less risk aversion we should observe when a natural disaster strikes. This is consistent with Barr and Genicot (2008) who find that villagers in Zimbabwe are willing to make more risky choices when playing a similar

[30]For example, remittances may be received by households that have experienced more severe disasters and so are expected to be more risk-averse. More risk averse individuals may also seek out more insurance. Both of these effects would however bias the coefficients against our finding that remittance receipt ameliorates the impact of natural disasters on risk preferences.

risk game when they know they have insurance. Note however that while insurance may offset some of the impacts on risk aversion, it does not completely wipe out the effect. At the mean, remittances offset only 16 percent of the impact of a natural disaster. In order to completely offset the effect of a disaster, log remittances need to be *six times* larger than this. Only 13 percent of our sample receive remittances of this magnitude. This is consistent with our earlier results that show that income and wealth are determinants of risk-taking behavior but that the changes in wealth and/or income do not fully explain the changes in behavior. (It is also consistent with DeSalvo et al. (2007) who find that 24.8 percent of Hurricane Katrina survivors without property insurance suffered from post-traumatic stress disorder versus 17.8 percent of those who had property insurance i.e. insurance had a small mitigating effect.)

Arisan participation has no statistically significant effect on on risk aversion. Though the interaction is positive and .06, it is not statistically significant. This is consistent with arisan being a within village insurance mechanism and so unable to insure villagers against shocks that affect the whole village.[31]

In columns 3-4 we repeat the regressions from columns 1-2 with our alternate measure of risk as the dependent variable. The results are very similar. Therefore, our findings are consistent with individuals demanding more insurance when experiencing natural disasters and suggest that access to insurance can help ameliorate some, but not all of the effect which experiencing a natural disaster has on risk aversion.

10 Do Risk Averse People Take Fewer Risks in Their Daily Lives?

So far we have examined risk-taking within the experimental setting. In this section we explore whether the experimental game choice predicts actual decisions that individuals make about technology adoption, opening a new business, and/or changing jobs. In a survey of the same participants conducted two years after the risk games were conducted we ask them whether they have done any of the above in the intervening period. We then examine the relationship between this behavior and their behavior in the risk games. The results of this exercise are shown in Table 15. Odd-numbered columns do not include any additional controls (except for regional fixed effects) and show that regardless of which risk measure we use, more risk loving individuals are more likely to open a new business and change jobs. They are also more likely to adopt new technologies though

[31] The greater level of arisan participation in natural disaster villages may reflect demand for arisan as a savings mechanism post-disaster.

the standard errors become large. Even numbered columns add a control for years of education. Education is the only socio-demographic variable that has a statistically significantly relationship with any of the dependent variables in Table 15. Controlling for education affects the coefficients on the risk-aversion variables only very slightly.

These findings are important in that they suggest that natural disasters can impact real life behavior through decreased risk taking behavior. If people are less likely to open businesses or switch jobs, this has obvious ramifications for economic growth and development. In addition, the period right after a natural disaster is often when aid money is infused into disaster stricken areas. If individuals are not investing optimally, again this has the potential for negative consequences.[32]

11 Conclusion

This paper shows that individuals living in villages that have experienced a natural disaster behave in a more risk averse manner than individuals in otherwise like villages. Some, but not all, of this impact is a function of households losing income as a result of the disaster. Our data suggest that beliefs about the likelihood of such shocks occurring and their severity change as a result of having experienced a natural disaster. People who have recently experienced a disaster attach a higher probability to experiencing another in the next twelve months and expect the impact to be more severe than people who have not experienced one. They thus behave as though they face greater background risk. Thus, in terms of theory, this paper supports Gollier and Pratt's (1996) risk vulnerability hypothesis and rejects the hypothesis that independent risks are complementary.

Our finding that people's beliefs changed as a result of their experience is similar to that of Di Tella et al. (2007) who find that people who benefited from land reform developed more materialist and individualist beliefs than others. While people's subjective beliefs changed, they found no evidence of changes in underlying preferences. Empirically in our context it is difficult to identify and isolate changes in preferences, and though we present evidence that income and beliefs play a role in determining risk-taking behavior, we cannot rule out that changes in underlying risk preferences may also play a role.

Over 10 million people in Indonesia have been affected by an earthquake or a flood since 1990—

[32]We also examine the role played by time preferences. To the extent that risk preferences are correlated with discount rates, the risk aversion results could be reflecting changes in time preferences. In our survey we asked a series of questions along the lines of "Would you prefer X today or Y in a month?" where Y is a greater amount. From those questions we construct a minimum monthly discount factor for each individual. When we include the discount factor as an additional control variable in the regressions (from Tables 6, 7, and 8), the main risk aversion results do not change (results available upon request from authors). Hence it is risk-aversion, not discounting behavior that is driving these results.

this is approximately five percent of the total population (EM-DAT, 2009). Even larger numbers of individuals face these shocks on a global level each year. That natural disasters result in more risk-averse choices, coupled with the large number of people affected, make this an important finding. It suggests that the adverse consequences of natural disasters stretch beyond the immediate physical destruction of homes, infrastructure and loss of life. Increased risk aversion very likely impairs future economic development. For example, if farmers choose less risky technologies (as shown in Liu (2010)) or are less likely to open a business or change jobs as suggested by our data, such decisions can have long-term consequences even if risk attitudes later rebound. While the exact longevity of these effects is difficult to ascertain, one thing is clear. Exposure to significant damage has large impacts on people's risk-taking behavior that extend well beyond the year in which the disaster occurs.

The results on insurance presented above point to one potential policy solution. The provision of insurance to counter the impact of natural disasters can partly stem this type of behavior. The analysis also suggests that the potential benefits from infrastructure investments aimed at reducing the likelihood of floods and mitigating the impacts of natural disasters are higher than routinely estimated.

References

Andrabi, Tahir and Jishnu Das, "In Aid We Trust: Hearts and Minds and the Pakistan Earthquake of 2005," *World Bank Policy Research Working Paper 5440*, October 2010.

Arrow, K., *Essays in the Theoty of Risk-Bearing*, Chicago, IL: Markham Publishing Company, 1971.

Baez, Javier, Alejandro de la Fuente, and Indhira Santos, "Do Natural Disasters Affect Human Capital? An Assessment Based on Existing Empirical Evidence," *IZA Discussion Paper No. 5164*, 2010.

Barr, Abigail and Garance Genicot, "Risk Sharing, Commitment, and Information: An Experimental Analysis," *Journal of the European Economic Association*, December 2008, *6* (6), 1151–1185.

Binswanger, Hans P., "Attitudes toward Risk: Experimental Measurement in Rural India," *American Journal of Agricultural Economics*, August 1980, *62*, 395–407.

Cardenas, Juan Camilo and Jeffrey Carpenter, "Behavioural Development Economics: Lessons from Field Labs in the Developing World," *Journal of Development Studies*, 2008, *44* (3), 311–338.

Cassar, A., A. Healy, and C. von Kessler, "Trust, Risk, and Time Preferences after a Natural Disaster: Experimental Evidence from Thailand," August 2011. University of San Francisco Working Paper.

Croson, Rachel and James Sundali, "The Gambler's Fallacy and the Hot Hand: Empirical Data from Casinos," *Journal of Risk and Uncertainty*, 2005, *30* (3), 195–209.

— **and Uri Gneezy**, "Gender Differences in Preferences," *Journal of Economic Literature*, 2009, *47* (2), 448–474.

DeSalvo, Karen B., Amanda D. Hyre, Danielle C. Ompad, Andy Menke, L. Lee Tynes, and Paul Muntner, "Symptoms of Posttraumatic Stress Disorder in a New Orleans Workforce Following Hurricane Katrina," *Journal of Urban Health*, 2007, *84* (2), 142–152.

Di Tella, R., S. Galiani, and E. Schargrodsky, "The Formation of Beliefs: Evidence from the Allocation of Land Titles to Squatters," *Quarterly Journal of Economics*, 2007, *122* (1), 209–241.

Eckel, C., M. El-Gambal, and R. Wilson, "Risk Loving after the Storm: A Bayesian-Network Study of Hurricane Katrina Evacuees," *Journal of Economic Behavior and Organization*, 2009, *69* (2), 110–124.

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

EM-DAT, "The OFDA/CRED International Disaster Database," Technical Report, Universite Catholique de Louvain, Belgium 2009.

Finlay, Jocelyn E., "Fertility Response to Natural Disasters The Case of Three High Mortality Earthquakes," March 2009. World Bank Policy Research Working Paper 4883.

Frankenberg, Elizabeth, Jed Friedman, Thomas Gillespie, Nicholas Ingwersen, Robert Pynoos, Umar Rifai, Bondan Sikoki, Alan Steinberg, Cecep Sumantri, Wayan Suriastini, and Duncan Thomas, "Mental Health in Sumatra after the Tsunami," *American Journal of Public Health*, September 2008, *98* (9).

Freeman, Paul K., "Estimating Chronic Risk from Natural Disasters in Developing Countries: A Case Study on Honduras," 2000. Working Paper.

Gallagher, J., "Learning about an Infrequent Event: Evidence from Flood Insurance Take-up in the US," November 2010. University of California at Berkeley Working Paper.

Gollier, Christian and John W. Pratt, "Risk Vulnerability and the Tempering Effect of Background Risk," *Econometrica*, September 1996, *64* (5), 1109–1123.

Guiso, Luigi and Monica Paiella, "Risk Aversion, Wealth, and Background Risk," *Journal of the European Economic Association*, December 2008, *6* (6), 1109–1150.

Halliday, Timothy, "Migration, Risk, and Liquidity Constraints in El Salvador," *Economic Development and Cultural Change*, July 2006, *54* (4), 893–925.

Heaton, J. and D. Lucas, "Portfolio Choice in the Presence of Background Risk," *Economic Journal*, 2000, *110* (460), 1–26.

Holt, Charles A. and Susan K. Laury, "Risk Aversion and Incentive Effects in Lottery Choices," *American Economic Review*, December 2002, *92*, 1644–55.

IPCC, *Climate Change 2001: Synthesis Report*, Cambridge University Press, 2001.

Kahn, Matthew E., "The Death Toll from Natural Disasters: The Role of Income Geography and Institutions," *The Review of Economics and Statistics*, May 2005, *87* (2), 271–284.

Kahneman, Daniel and Amos Tversky, "Prospect Theory: An Analysis of Decision Under Risk," *Econometrica*, 1979, *47*, 263–291.

Kunreuther, H., "Mitigating Disaster Losses through Insurance," *Journal of Risk and Uncertainty*, 1996, *12* (2-3), 171–187.

Liu, Elaine, "Time to Change What to Sow: Risk Preferences and Technology Adoption Decisions of Cotton Farmers in China," *University of Houston working paper*, 2010.

Lucas, Robert E.B and Oded Stark, "Motivations to Remit: Evidence from Botswana," *Journal of Political Economy*, 1985, *93* (5), 901–18.

Lusk, Jayson L. and Keith H. Coble, "Risk Aversion in the Presence of Background Risk: Evidence from the Lab," 2003. Working Paper.

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

Malmendier, U. and S. Nagel, "Depression Babies: Do Macroeconomic Experiences Affect Risk-Taking?," *Quarterly Journal of Economics*, 2011, *126*, 373–416.

Noy, Ilan, "The Macroeconomic Consequences of Disasters," *Journal of Development Economics*, 2009, *88*, 221231.

Palm, L., "The Roepke Lecture in Economic Geography Catastrophic Earthquake Insurance: Patterns of Adoption," *Economic Geography*, April 1995, *71* (2).

Paxson, Christina and Cecilia Elena Rouse, "Returning to New Orleans after Hurricane Katrina," *American Economic Review Papers and Proceedings*, May 2008, *98* (2), 38–42.

Portner, Claus C., "Gone with the Wind? Hurricane Risk, Fertility and Education," February 2008. Working Paper.

Quiggin, J., "Background Risk in Generalized Expected Utility Theory," *Economic Theory*, 2003, *22*, 607–611.

Rabin, Matthew, "Risk Aversion and Expected-Utility Theory: A Calibration Theorem," *Econometrica*, September 2000, *68* (5), 1281–1292.

Rosenzweig, Mark and Oded Stark, "Consumption Smoothing, Migration, and Marriage: Evidence from Rural India," *Journal of Political Economy*, 1989, *97* (4), 90526.

Schechter, Laura, "Risk Aversion and Expected-utility Theory: A Calibration Exercise," *Journal of Risk Uncertainty*, 2007, *35*, 67–76.

Schultz, T.P., "Demand for Children in Low Income Countries," in M. R. Rosenzweig and O. Stark, eds., *Handbook of Population and Family Economics*, Vol. 1A, Elsevier Science B.V., 1997, pp. 349–430.

Strauss, John and Duncan Thomas, "Human Resources: Empirical Modeling of Household and Family Decisions," in J. Behrman and T. N. Srinivasan, eds., *Handbook of Development Economics*, Vol. 3A, Elsevier Science, 1995, pp. 1883–2023.

Yamauchi, Futoshi, Yisehac Yohannes, and Agnes R Quisumbing, "Natural Disasters, Self-Insurance and Human Capital Investment : Evidence from Bangladesh, Ethiopia and Malawi," April 2009. World Bank Policy Research Working Paper 4910.

Yang, Dean, "Coping with Disaster: The Impact of Hurricanes on International Financial Flows, 1970-2002," *The B.E. Journal of Economic Analysis & Policy*, 2008, *8* (1).

— , "Risk, Migration, and Rural Financial Markets: Evidence from Earthquakes in El Salvador," *Social Research*, Fall 2008, *75* (3), 955–992.

— **and HwaJung Choi**, "Are Remittances Insurance? Evidence from Rainfall Shocks in the Philippines," *The World Bank Economic Review*, 2007, *21* (2), 219–248.

Table 1: Payoffs and Corresponding Risk Coefficients

Gamble Choice (1)	Frequency (2)	Percent (3)	Low Payoff (4)	High Payoff (5)	Partial Risk Aversion Coefficient^{+} (6)	Partial Risk Aversion Coefficient^{++} (7)
A	274	18%	10000	10000	$(7.51, \infty)$	$(10.38, \infty)$
B	223	14%	9000	19000	(1.74, 7.51)	(2.23, 10.18)
C	353	23%	8000	24000	(0.81, 1.74)	(1.12, 2.42)
D	444	28%	6000	30000	(0.32, 0.81)	(0.47, 1.15)
E	138	9%	2000	38000	(0, 0.32)	(2.21e-10, 0.45)
F	119	8%	0	40000	$(-\infty, 0)$	$(-\infty, 3.80e\text{-}16)$

Notes: We report two different risk aversion coefficients: $^{+}$ defines utility over the gamble, $^{++}$ defines utility over household daily income plus the gamble.

Table 2: Summary Statistics by Risk Choice

Choice:	**(A)** Least Risky	**(B)** →	**(C)**	**(D)** →	**(E)**	**(F)** Most Risky
Married(=1)	0.96	0.96	0.97	0.96	0.97	0.97
	(.20)	(.20)	(.18)	(.20)	(.17)	(.16)
Female(=1)	0.85	0.85	0.85	0.83	0.76	0.75
	(.35)	(.36)	(.35)	(.37)	(.43)	(.44)
Javanese(=1)	0.57	0.54	0.59	0.59	0.53	0.66
	(.50)	(.50)	(.49)	(.49)	(.50)	(.48)
Madurese(=1)	0.43	0.45	0.41	0.41	0.47	0.34
	(.50)	(.50)	(.49)	(.49)	(.50)	(.47)
Age(years)	31.5	31.1	30.1	30.9	30.1	29.8
	(10.6)	(9.36)	(9.33)	(9.59)	(8.81)	(8.14)
Education(years)	7.74	7.47	7.88	7.81	7.44	8.94
	(3.03)	(2.93)	(3.23)	(3.11)	(2.88)	(3.51)
Wealth(ln Rp)	16.87	16.99	17.04	17.0	17.0	17.4
	(1.49)	(1.47)	(1.45)	(1.56)	(1.54)	(1.41)
Earthquake(=1)	0.01	0.02	0.02	0.02	0.01	0.01
	(.10)	(.13)	(.15)	(.13)	(.09)	(.09)
Flood(=1)	0.08	0.11	0.07	0.08	0.04	0.06
	(.27)	(.31)	(.25)	(.27)	(.20)	(.25)
Number of floods	.53	.43	.39	.44	.24	.33
	(1.29)	(.88)	(.91)	(.99)	(.66)	(.97)
Distance epicenter(km)	161.6	162	163.9	163.9	164.5	166.6
	(24.7)	(24.1)	(26.1)	(23.9)	(25.8)	(25.8)
Total damage(ln Rp)	3.82	4.4	3.7	3.8	2.7	3.3
	(7.38)	(7.6)	(7.3)	(7.4)	(6.4)	(7.0)
Observations	274	223	353	444	138	118

Notes: We report the means and standard deviations by risk category. The risk categories A-F correspond to the choices in Table 1.

Table 3: Summary Statistics by Natural Disaster

	Natural Disaster	**No Natural Disaster**	**Difference**
	(1)	(2)	(3)
Individual and Household Characteristics:			
Married(=1)	0.97	0.96	0.01
	(0.16)	(.19)	
Female(=1)	0.87	0.83	0.04
	(.34)	(.37)	
Javanese(=1)	0.49	0.58	-0.09**
	(.50)	(.49)	
Madurese(=1)	0.51	0.41	0.10**
	(.50)	(.49)	
Age(years)	29.7	30.8	-1.1
	(8.3)	(9.6)	
Education(years)	7.8	7.8	0
	(2.79)	(3.2)	
Number of friends	6.01	5.7	.30
	(.18)	(1.41)	
Has friends to borrow money(=1)	.78	.75	.03
	(.03)	(.01)	
Participates in conditional cash transfer(=1)	.03	.04	-.01
	(.01)	(.01)	
Health insurance for poor(=1)	.24	.22	.02
	(.04)	(.01)	
Subsidized rice buyer(=1)	.83	.83	0
	(.03)	(.01)	
Household on river bank(=1)	.02	.02	0
	(.003)	(.001)	
Village Characteristics:			
Health Care Program(=1)	.47	.42	.05
	(.04)	(.01)	
Deworming Program(=1)	.09	.09	0
	(.02)	(.01)	
Sanitation Program(=1)	.36	.35	.01
	(.04)	(.01)	
Village population	930	999	-69
	(38.5)	(15.5)	
Households have electricity(=1)	1.0	1.0	0
	(0)	(0)	
Has river(=1)	.91	.76	.15***
	(.01)	(.02)	
Dependent Variables:			
Risk-loving	0.11	0.17	-0.06*
	(0.32)	(0.38)	
ln risk aversion	-3.12	-4.57	1.45
	(9.4)	(10.7)	
Probability of flood in next year	42.6	12.0	30.6***
	(32.4)	(15.9)	
Probability of earthquake in next year	18.2	16.8	1.4
	(18.8)	(20.8)	
Perceived flood impact	1.79	0.93	.86***
	(1.07)	(0.93)	
Perceived earthquake impact	.84	.96	-.12
	(1.18)	(1.3)	
Observations	144	1395	

Notes: We report the means and standard deviations by natural disaster. A “risk-loving” individual is someone who picked category E or F in the risk game. ***indicates difference is statistically significant at 1% level, ** at 5% level, * at 10% level.

Table 4: Do Wealthier Escape Natural Disasters?

Dependent Variable:	Natural Disaster		
	(1)	(2)	(3)
Wealth	.005	.008	.003
	(.005)	(.01)	(.01)
Wealth squared		-.001	.0001
		(.001)	(.001)
Constant	-.09	-.11	-.3
	(.09)	(.11)	(.17)*
F statistic	2.07	1.78	.95
Observations	1539	1539	1538

Notes: We report results from OLS regressions where the dependent variable is Natural Disaster (mean is .10). All specifications are clustered at the village level and include district level fixed effects. Column 3 includes additional controls for ethnicity, gender, age, education, marriage, and river dummies. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table 5: Natural Disasters and Migration

Dependent Variable:	Household Migrated				
	(1)	(2)	(3)	(4)	(5)
Earthquake	.07	.09	.09		
	(.08)	(.08)	(.07)		
Flood	.02	.02		.02	
	(.02)	(.02)		(.02)	
Distance to epicenter				-.0007	
				(.0009)	
Number of floods			.004		
			(.007)		
Total damage					.0002
					(.0009)
Constant	.05	.14	.31	.4	.3
	(.007)***	(.15)	(.17)*	(.19)**	(.17)*
Observations	1539	1538	1538	1538	1538

Notes: We report results from OLS regressions where the dependent variable is migrated (mean is .05). All specifications are clustered at the village level and include district level fixed effects. Columns 2-5 includes additional controls for ethnicity, gender, age, education, wealth, marriage, and river dummies. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table 6: Do Natural Disasters Affect Risk Loving?

	(1)	(2)	(3)	(4)	(5)	(6)
Earthquake	-.09	-.10	-.10	-.11		
	(.01)***	(.03)***	(.04)***	(.04)***		
Flood	-.05	-.06	-.08		-.08	
	(.02)**	(.03)**	(.03)**		(.03)**	
Distance to epicenter					.004	
					(.002)**	
Number of floods				-.03		
				(.01)***		
Total damage						-.004
						(.002)**
Mean earthquake(1980-2008)			-.02	-.02	-.02	-.02
			(.01)**	(.01)*	(.01)*	(.01)**
Mean flood(1980-2008)			.02	.03	.03	.03
			(.03)	(.03)	(.03)	(.03)
Married		.04	.04	.04	.04	.04
		(.05)	(.05)	(.05)	(.05)	(.05)
Female		-.11	-.11	-.12	-.11	-.12
		(.03)***	(.03)***	(.03)***	(.03)***	(.03)***
Madurese		.007	-.006	-.03	-.02	-.03
		(.13)	(.13)	(.13)	(.12)	(.13)
Javanese		-.01	-.02	-.05	-.03	-.04
		(.14)	(.13)	(.13)	(.12)	(.13)
Age		-.002	-.003	-.002	-.003	-.003
		(.001)**	(.001)**	(.001)**	(.001)**	(.001)**
Education		.004	.003	.003	.002	.003
		(.003)	(.003)	(.003)	(.003)	(.003)
Rivers		.03	.03	.02	.04	.02
		(.03)	(.03)	(.02)	(.02)	(.02)
Wealth			.01	.01	.01	.01
			(.006)*	(.006)*	(.006)*	(.006)*
Constant	.17	.24	.08	.11	-.43	.12
	(.01)***	(.17)	(.18)	(.18)	(.26)	(.18)
F statistic	29.64	5.51	3.9	3.35	2.29	2.3
Observations	1539	1538	1538	1538	1538	1538

Notes: We report results from OLS regressions where the dependent variable is a dichotomous variable if the individual is risk-loving (mean is 0.17). All specifications are clustered at the village level and include district level fixed effects. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table 7: Risk Coefficients and Natural Disaster

	(1)	(2)	(3)	(4)	(5)	(6)
Earthquake	2.26	2.69	2.45	2.71		
	(.57)***	(.99)***	(1.01)**	(.98)***		
Flood	1.28	1.53	2.26		2.38	
	(.68)*	(.85)*	(.95)**		(.94)**	
Distance to epicenter					-.13	
					(.05)***	
Number of floods				.90		
				(.31)***		
Total damage						.13
						(.05)**
Mean earthquake(1980-2008)			.72	.64	.7	.7
			(.27)***	(.3)**	(.31)**	(.29)**
Mean flood(1980-2008)			-1.02	-1.33	-1.24	-1.42
			(.84)	(.88)	(.82)	(.88)
Married		-1.06	-1.09	-1.12	-1.09	-1.14
		(1.34)	(1.36)	(1.35)	(1.37)	(1.35)
Female		3.29	3.29	3.31	3.01	3.34
		(.83)***	(.84)***	(.83)***	(.82)***	(.83)***
Madurese		1.18	1.67	2.42	2.03	2.41
		(4.57)	(4.36)	(4.41)	(4.14)	(4.39)
Javanese		1.15	1.69	2.33	1.75	2.11
		(4.69)	(4.5)	(4.53)	(4.24)	(4.52)
Age		.07	.08	.07	.08	.08
		(.03)**	(.03)***	(.03)**	(.03)***	(.03)***
Education		-.2	-.14	-.14	-.13	-.14
		(.1)**	(.1)	(.1)	(.1)	(.1)
Rivers		-.89	-.9	-.49	-1.11	-.54
		(.71)	(.71)	(.68)	(.69)	(.69)
Wealth			-.4	-.38	-.4	-.38
			(.16)**	(.16)**	(.16)**	(.16)**
Constant	-4.57	-6.74	-1	-2.02	14.94	-2.05
	(.33)***	(5.45)	(5.64)	(5.59)	(7.21)**	(5.62)
F statistic	8.13	2.98	3.21	3.68	2.95	2.79
Observations	1539	1538	1538	1538	1538	1538

Notes: We report results from OLS regressions where the dependent variable is $ln\gamma$ (mean is -4.44). All specifications are clustered at the village level and include district level fixed effects. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table 8: Risk Coefficients with Income and Natural Disaster

	(1)	(2)	(3)	(4)	(5)	(6)
Earthquake	2.45	2.81	2.58	2.84		
	(.55)***	(.99)***	(1.03)**	(1.01)***		
Flood	1.31	1.63	2.36		2.48	
	(.69)*	(.88)*	(.98)**		(.98)**	
Distance to epicenter					-.13	
					(.05)***	
Number of floods				.92		
				(.32)***		
Total damage						.13
						(.05)**
Mean earthquake(1980-2008)			.76	.68	.74	.73
			(.29)***	(.32)**	(.33)**	(.31)**
Mean flood(1980-2008)			-1.01	-1.32	-1.24	-1.4
			(.88)	(.92)	(.86)	(.92)
Married		-1.05	-1.09	-1.12	-1.09	-1.14
		(1.38)	(1.39)	(1.38)	(1.4)	(1.38)
Female		2.94	2.94	2.96	2.65	2.99
		(.86)***	(.87)***	(.86)***	(.85)***	(.86)***
Madurese		1.01	1.5	2.26	1.87	2.25
		(4.6)	(4.41)	(4.46)	(4.19)	(4.44)
Javanese		1.11	1.64	2.3	1.71	2.07
		(4.72)	(4.53)	(4.57)	(4.27)	(4.56)
Age		.08	.09	.08	.09	.09
		(.03)***	(.03)***	(.03)***	(.03)***	(.03)***
Education		-.17	-.11	-.12	-.1	-.11
		(.1)*	(.1)	(.1)	(.1)	(.1)
Rivers		-.96	-.97	-.55	-1.19	-.6
		(.74)	(.73)	(.71)	(.71)*	(.72)
Wealth			-.38	-.37	-.38	-.36
			(.17)**	(.17)**	(.17)**	(.17)**
Constant	-4.55	-6.9	-1.41	-2.46	14.81	-2.48
	(.35)***	(5.51)	(5.74)	(5.69)	(7.49)**	(5.72)
F statistic	10.11	3.09	3.47	4.17	2.53	2.39
Observations	1539	1538	1538	1538	1538	1538

Notes: We report results from OLS regressions where the dependent variable is $ln\gamma$ measured with income (mean is -4.41). All specifications are clustered at the village level and include district level fixed effects. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table 9: Do Past Natural Disasters Matter?

Dependent Variable:	risk-loving		$ln\gamma$	
	(1)	(2)	(3)	(4)
Earthquake (2007)	-.11		3.17	
	(.04)**		(1.19)***	
Earthquake (2006)	-.14		2.86	
	(.04)***		(1.13)**	
Flood (2008)	-.1		2.63	
	(.04)**		(1.14)**	
Flood (2007)	.01		.03	
	(.05)		(1.4)	
Flood (2006)	-.03		1.12	
	(.03)		(.94)	
Flood (2005)	-.15		3.77	
	(.04)***		(1.01)***	
Number earthquakes(2000-2004)	.07		-1.77	
	(.07)		(1.63)	
Number floods(2000-2004)	-.02		.45	
	(.02)		(.61)	
Natural disaster (2008)		-.13		3.22
		(.04)***		(1.04)***
Natural disaster (2007)		-.02		.96
		(.03)		(1.08)
Natural disaster (2006)		-.09		1.96
		(.04)*		(.94)**
Natural disaster (2005)		-.16		4.1
		(.04)***		(1.02)***
Number disasters(2000-2004)		-.005		.03
		(.02)		(.53)
Mean natural disaster (1980-2008)	-.02	-.03	.41	.61
	(.04)	(.03)	(1.1)	(1.04)
Constant	.09	.08	-1.24	-1.01
	(.18)	(.18)	(5.69)	(5.66)
Observations	1538	1538	1538	1538

Notes: We report results from OLS regressions where the dependent variable is risk-loving (columns 1-2); $ln\gamma$ (columns 3-4). All specifications are clustered at the village level and include controls for ethnicity, gender, age, education, marriage, wealth, river, and district level fixed effects. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table 10: Hypothetical Risk Game and Natural Disaster (Income)

Dependent Variable:	Hypothetical risk-loving IFLS4 1			Hypothetical risk-loving IFLS4 2		
	(1)	(2)	(3)	(4)	(5)	(6)
Number of disasters	-.007	-.007	-.007	-.003	-.003	-.003
	(.003)**	(.003)**	(.003)**	(.001)**	(.001)**	(.001)**
Income		.006	.006		.001	.001
		(.003)**	(.003)**		(.002)	(.002)
Total assistance received		.02	.02		.007	.007
		(.006)**	(.006)***		(.005)	(.004)
Total amount lost		-.002			-.0004	
		(.001)			(.001)	
Lost a lot of income			-.06			-.001
			(.04)*			(.04)
Constant	.4	.32	.31	.15	.14	.14
	(.05)***	(.06)***	(.06)***	(.03)***	(.04)***	(.04)***
Observations	4536	4536	4536	4536	4536	4536

Notes: We report results from OLS regressions where the dependent variable is risk-loving as measured by the hypothetical risk loving game 1 from IFLS4 in columns 1-3 (mean is .24), and hypothetical risk loving IFLS4 4 as measured by the hypothetical risk game 2 from IFLS4 data in columns 4-6(mean is .08). All specifications are clustered at the village level, include district level fixed effects, and controls for age, ethnicity, marital status, gender, and education. ***indicates difference is statistically significant at 1% level, ** at 5% level, * at 10% level.

Table 11: Probability Flood will Occur and Perceived Impact

Dependent Variable:	Probability flood will occur		Perceived flood impact	
	(1)	(2)	(3)	(4)
Flood (2008-09)	35.29	33.78	.55	.54
	(8.44)***	(8.38)***	(.16)***	(.16)***
Flood (2006-07)	19.19	19.07	.14	.19
	(6.86)***	(6.9)***	(.27)	(.25)
Flood (2004-05)	24.47	23.28	.58	.6
	(8.62)***	(8.33)***	(.31)*	(.3)**
Flood (2002-03)	-3.41	.88	.02	.03
	(1.64)**	(2.71)	(.26)	(.29)
Mean flood(1980-2008)		1.33		-.04
		(3.4)		(.22)
Bad flood impact			1.3	1.3
			(.22)***	(.21)***
Control Variables	N	Y	N	Y
Test Statistic	96.0	57.4	113.7	136.4
Observations	1508	1485	1505	1482

Notes: We report results from OLS regressions where the dependent variable is the probability that a flood will occur in the next year in columns 1-2 (mean is 14.9); and ordered probit regressions where the dependent variable is the perceived impact of the flood if it occurs in columns 3-4 (mean is 1.0). All specifications are clustered at the village level and include district level fixed effects. "Control Variables Y" indicates results include controls for ethnicity, gender, age, education, marriage, and rivers. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table 12: Probability Earthquake will Occur and Perceived Impact

Dependent Variable:	Probability earthquake will occur		Perceived earthquake impact	
	(1)	(2)	(3)	(4)
Earthquake (2008-09)	5.27	5.52	-.1	-.08
	(5.0)	(5.06)	(.24)	(.24)
Earthquake (2006-07)	3.39	2.73	.18	.21
	(6.12)	(5.93)	(.21)	(.21)
Earthquake (2004-05)	-1.26	-.46	.25	.24
	(8.18)	(7.33)	(.31)	(.31)
Mean earthquake(1980-2008)		-.6		-.09
		(.77)		(.14)
Bad earthquake impact			1.29	1.27
			(.19)***	(.18)***
Control Variables	N	Y	N	Y
Test Statistic	9.66	5.69	88.4	135.2
Observations	1503	1480	1495	1472

Notes: We report results from OLS regressions where the dependent variable is the probability that an earthquake will occur in the next year in columns 1-2 (mean is 16.9); and ordered probit regressions where the dependent variable is the perceived impact of the earthquake if it occurs in columns 3-4 (mean is 0.95). All specifications are clustered at the village level and include district level fixed effects."Control Variables Y" indicates results include controls for ethnicity, gender, age, education, marriage, and rivers. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table 13: Insurance Measures by Natural Disaster

	Natural Disaster	**No Natural Disaster**	**Difference**
	(1)	(2)	(3)
Receives remittance(=1)	0.19	0.13	0.06**
	(0.39)	(0.34)	
Remittance amount(ln Rp)	2.3	1.7	0.6
	(4.9)	(4.6)	
Participates in arisan(=1)	0.88	0.66	0.22***
	(.33)	(.47)	
Observations	144	1404	

Notes: We report the means and standard deviations by natural disaster. ***indicates difference is statistically significant at 1% level, ** at 5% level, * at 10% level.

Table 14: Does "Insurance" Help?

Dependent Variable:	risk-loving	$ln\gamma$
	(1)	(2)
Natural disaster	-.14	3.35
	(.07)**	(1.43)**
Arisan	.001	-.23
	(.02)	(.55)
Arisan*Natural disaster	.05	-1.13
	(.07)	(1.63)
Remittance amount	.0003	-.03
	(.002)	(.06)
Remittance amount*Natural disaster	.01	-.22
	(.004)**	(.11)*
Constant	.08	-1.09
	(.18)	(5.66)
F statistic	2.49	2.75
Observations	1547	1547

Notes: We report results from OLS regressions where the dependent variable is risk-loving (column 1); $ln\gamma$ (column 2). All specifications are clustered at the village level and include controls for ethnicity, gender, age, education, marriage, wealth, river, and district level fixed effects. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table 15: Do Risk Averse Participants Take Fewer Real Life Risks?

Dependent Variable:	Opened new business				Changed jobs				Adopted new technology			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Risk-loving	.03	.03			.03	.03			.02	.01		
	(.02)*	(.02)			(.02)*	(.02)			(.03)	(.03)		
$ln\gamma$			-.001	-.001			-.001	-.001			-.001	-.001
			(.0007)*	(.0007)			(.0007)*	(.0007)*			(.001)	(.001)
Education		.01		.01		.005		.005		.01		.01
		(.002)***		(.002)***		(.002)**		(.002)**		(.003)***		(.003)***
Constant	.1	-.001	.1	.000	.1	.06	.1	.06	.33	.22	.32	.22
	(.02)***	(.03)	(.02)***	(.03)	(.02)***	(.03)**	(.02)***	(.03)**	(.11)***	(.11)**	(.11)***	(.11)**
Observations	1432	1432	1432	1432	1432	1432	1432	1432	1432	1432	1432	1432

Notes: We report results from OLS regressions where the dependent variable is opened a business in the past two years (columns 1-4, mean is .08); changed jobs in last two years (columns 5-8, mean is .08); and adopted new technology in past two years (columns 9-12, mean is .14). All specifications include district level fixed effects. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

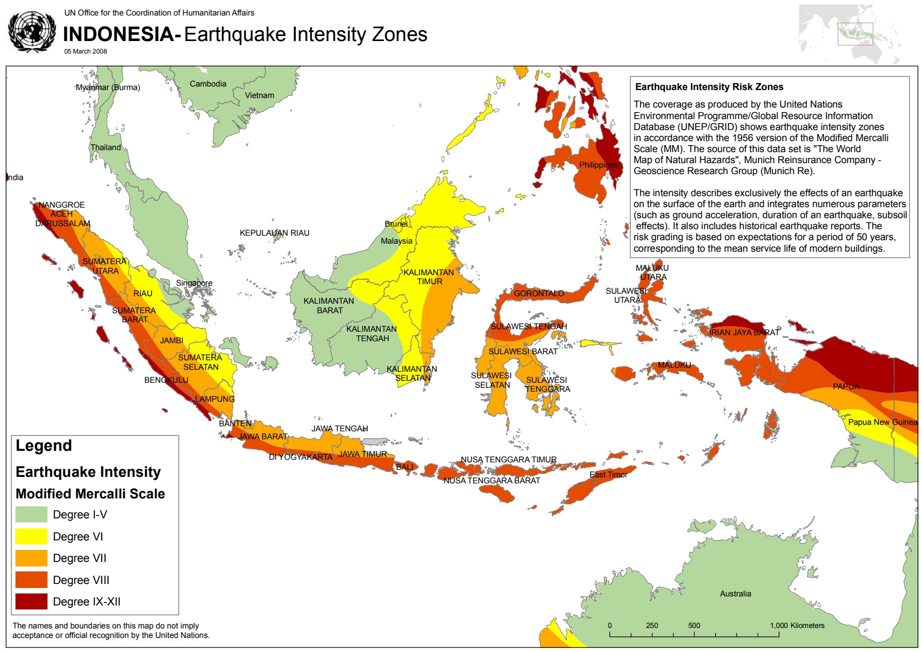

Figure 1: Earthquake Intensity

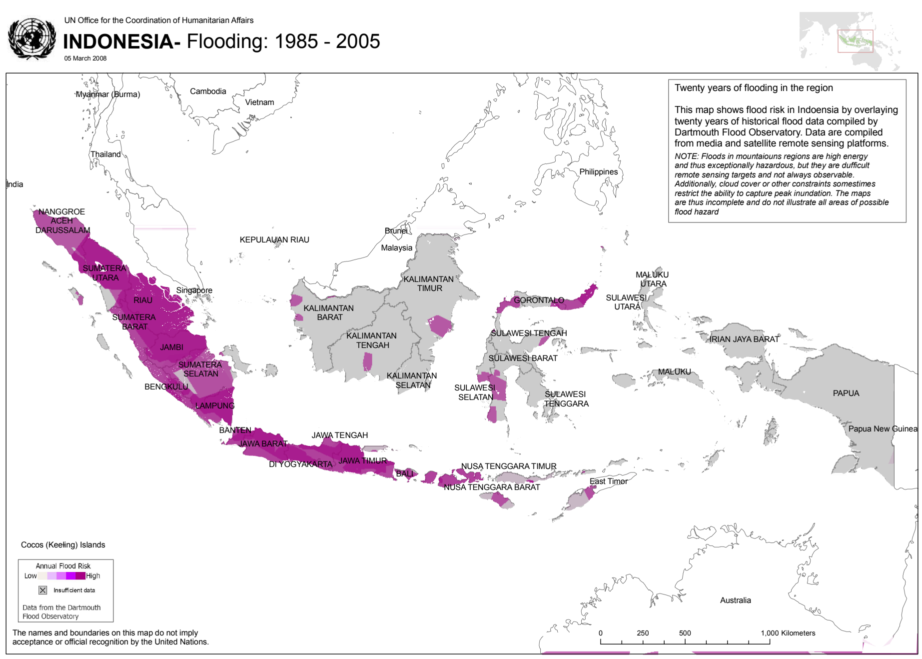

Figure 2: Flood Intensity

Appendix

In order to estimate a risk coefficient for each person we implement the following method. If a person chose B then we assume she prefers B to all other choices (A, C, D, E, F). Starting with the knowledge that she prefers B to A we have:

$$U(B) \geq U(A) \quad \Leftrightarrow \quad U(B) - U(A) \geq 0 \tag{2}$$

If we assume a constant risk aversion (CRRA) utility function this becomes:

$$0.5(\frac{19000^{(1-\gamma)}}{(1-\gamma)}) + 0.5(\frac{9000^{(1-\gamma)}}{(1-\gamma)}) - (\frac{10000^{(1-\gamma)}}{(1-\gamma)}) \geq 0 \tag{3}$$

Where γ is the Arrow-Pratt coefficient of relative risk aversion defined as:

$$-\frac{CU''(C)}{U'(C)} \tag{4}$$

The solution is 7.51. Therefore we conclude that the solution to the above inequality is $\gamma \leq 7.51$ Similarly given we know that she prefers B to C we have:

$$U(B) \geq U(C) \quad \Leftrightarrow \quad U(B) - U(C) \geq 0 \tag{5}$$

Again, if we assume a constant risk aversion (CRRA) utility function this becomes:

$$0.5(\frac{19000^{(1-\gamma)}}{(1-\gamma)}) + 0.5(\frac{9000^{(1-\gamma)}}{(1-\gamma)}) - 0.5(\frac{24000^{(1-\gamma)}}{(1-\gamma)}) - 0.5(\frac{8000^{(1-\gamma)}}{(1-\gamma)}) \geq 0 \tag{6}$$

The solution is 1.74. We find that an estimate for the coefficient of relative risk aversion for a person who chose B is such that $1.74 \leq \gamma \leq 7.51$. We use the same method to estimate the coefficient of relative risk aversion for all choices.

Table 16: Using Historical USGS Seismology Data

Dependent Variable:	risk-loving	ln γ	ln γ income
	(1)	(2)	(3)
Earthquake	-.12	2.99	3.12
	(.05)**	(1.05)***	(1.12)***
Flood	-.08	2.34	2.43
	(.04)**	(.96)**	(1.01)**
Mean distance epicenter (1973-2008)	.003	-.1	-.1
	(.001)***	(.04)***	(.04)***
Mean flood (1980-2008)	.03	-1.26	-1.26
	(.03)	(.82)	(.86)
Married	.03	-1.02	-1.02
	(.05)	(1.37)	(1.4)
Female	-.1	2.98	2.62
	(.03)***	(.82)***	(.84)***
Madurese	-.005	1.65	1.48
	(.12)	(4.13)	(4.19)
Javanese	-.02	1.55	1.49
	(.12)	(4.24)	(4.27)
Age	-.003	.07	.08
	(.001)**	(.03)**	(.03)***
Education	.003	-.15	-.13
	(.003)	(.1)	(.1)
Rivers	.04	-1.13	-1.2
	(.02)*	(.67)*	(.69)*
Wealth	.01	-.37	-.35
	(.006)*	(.16)**	(.17)**
Constant	-.29	10.72	10.53
	(.22)	(6.19)*	(6.4)*
Sample size	1538	1538	1538

Notes: We report results from OLS regressions where the dependent variable is risk-loving in column 1, $ln\gamma$ in column 2, and $ln\gamma$ measured with income in column 3. All specifications are clustered at the village level and include district level fixed effects. ***indicates difference is statistically significant at 1% level, ** at 5% level, * at 10% level.

Table 17: Hypothetical Risk Game and Natural Disaster (Wealth)

Dependent Variable:	Hypothetical risk-loving IFLS4 1			Hypothetical risk-loving IFLS4 2		
	(1)	(2)	(3)	(4)	(5)	(6)
Number of disasters	-.007	-.006		-.003	-.003	
	(.003)**	(.003)**		(.001)**	(.001)**	
Wealth		.002	.002		.003	.003
		(.005)	(.005)		(.002)	(.002)
Total assistance received		.02	.02		.007	.007
		(.006)**	(.005)***		(.005)	(.004)*
Total amount lost		-.002			-.0004	
		(.001)			(.001)	
Lost a lot of income			-.07			-.007
			(.04)*			(.04)
Constant	.40	.36	.41	.15	.11	.1
	(.05)***	(.1)***	(.1)***	(.03)***	(.05)**	(.05)*
Observations	4536	4536	4536	4536	4536	4536

Notes: We report results from OLS regressions where the dependent variable is risk-loving as measured by the hypothetical risk loving game 1 from IFLS4 in columns 1-3 (mean is .24), and hypothetical risk loving IFLS4 4 as measured by the hypothetical risk game 2 from IFLS4 data in columns 4-6(mean is .08). All specifications are clustered at the village level, include district level fixed effects, and controls for age, ethnicity, marital status, gender, and education. ***indicates difference is statistically significant at 1% level, ** at 5% level, * at 10% level.

RISK GAME INSTRUCTIONS (To be read to respondent. Notes in bold are not to be read but give the enumerator instructions.)

I am now going to ask you to play a game. The game forms part of our research. We are interested in understanding how people make decisions. There are no right and wrong decisions. You just make the decision that feels right to you. This is what we are going to do.

1. First, I am going to describe six options to you. A little later you will be asked to choose one of the options.
2. Second, we are going to work through some examples together.
3. Third, you are going to make your choice.
4. Fourth, we are going to calculate your winnings.
5. And finally, I will pay you according to what happened in the game. Any money you receive is real money and is yours to keep. **[SHOW THEM THAT YOU HAVE THE MONEY WITH YOU].**

Take a look at this card. It shows the six options that you have to choose between **[*point and count, 1, 2, 3, 4, 5, 6*]**. Whichever option you choose, your winnings are going to be decided by us playing "which-hand-is-it-in". Here, I have two marbles, a blue one and a yellow one. **[*RA holds both marbles in one hand to show them to the subject.*]** I am going to put them behind my back and shake then about in my hands. Then, I am going to take one in each hand and bring them forward. **[Do this.]** So, now I have one marble concealed in each hand. You must pick one hand. If you pick the hand containing the blue marble you win the amount of money shown on the blue side of the table. If you pick the hand containing the yellow marble you win the amount of money shown on the yellow side of the table. Before we go any further, which do you think is more likely, that you pick the hand with the blue marble in or the hand with the yellow marble in?
[*Correct answer - neither, they are equally likely. If they got it wrong, explain correct answer to them.*]
[*While teaching the game refer to the tables all the time. Point to the appropriate images on the tables and make sure that the player is looking, seeing, and concentrating.*]

So, if you choose option B and then pick the hand with the blue marble in you win Rp19000. If you choose option B and then pick the hand with the yellow marble in you win Rp9000.

If you choose option C and then pick the hand with the blue marble in you win Rp24000. If you choose option C and then pick the hand with the yellow marble in you win Rp8000.

If you choose option D and then pick the hand with the blue marble in you win Rp30000. If you choose option D and then pick the hand with the yellow marble in you win Rp6000.

If you choose option E and then pick the hand with the blue marble in you win Rp38000. If you choose option E and then pick the hand with the yellow marble in you win Rp2000.

If you choose option F and then pick the hand with the blue marble in you win Rp40000. If you choose option F and then pick the hand with the yellow marble in you win nothing.

If you choose option A and then pick the hand with the blue marble in you win Rp10000. If you choose option A and then pick the hand with the yellow marble in you win

Rp10000. So, in option A you win Rp10000 whatever happens.

EXAMPLES
So, now let us work through some examples together.
1. First, imagine that you choose D. Then we play which-hand-is-it-in **[*play*]**. You have found the yellow (blue) marble so you win how much? **[*Correct answer is Rp6000 (Rp30000)*]** And what if you had found the blue (yellow) marble, how much would you win then? **[*Correct answer is Rp30000 (Rp6000).*]**

2. Now, imagine that you choose F. Then we play which-hand-is-it-in [*play*]. You have found the yellow (blue) marble so you win how much? **[*Correct answer is nothing (Rp40000)*]** And what if you had found the blue (yellow) marble, how much would you win then? **[*Correct answer is Rp400000 (nothing).*]**

IF BOTH CORRECT, NO MORE EXAMPLES. CONTINUE WITH EXAMPLES UNTIL GETS TWO CORRECT IN A ROW.

3. Now, imagine that you choose A. Then we play which-hand-is-it-in [*play*]. You have found the yellow (blue) marble so you receive how much? **[*Correct answer is Rp10000 (Rp10000).*]** And what if you had found the blue (yellow) marble, how much would you win then? **[*Correct answer is Rp10000 (Rp10000).*]**

4. Now, imagine that you choose C. Then we play which-hand-is-it-in [*play*]. You have found the yellow (blue) marble so you win how much? **[*Correct answer is Rp8000 (Rp24000).*]** And what if you had found the blue (yellow) marble, how much would you win then? **[*Correct answer is Rp24000 (Rp8000).*]**

5. Now, imagine that you choose E. Then we play which-hand-is-it-in [*play*]. You have found the yellow (blue) marble so you win how much? **[*Correct answer is Rp2000 (Rp38000).*]** And what if you had found the blue (yellow) marble, how much would you win then? **[*Correct answer is* Rp*38000 (Rp20000).*]**

6. Now, imagine that you choose B. Then we play which-hand-is-it-in [*play*]. You have found the yellow (blue) marble so you win how much? **[*Correct answer is Rp9000 (Rp19000).*]** And what if you had found the blue (yellow) marble, how much would you win then? **[*Correct answer is Rp19000 (Rp9000).*]**

IF RESPONDENT SEEMS INCAPABLE OF UNDERSTANDING. FINISH INTERVIEW AND DON'T PLAY. MARK THIS ON THE QUESTIONNAIRE.

Now it is time for you to make your choice. Which option do you pick, A, B, C, D, E, or F? **[*Record their answer in Q SC15c on the questionnaire.*]**

Now, we play which-hand-is-it-in**. [*Record the outcome.*]**
So, you have won Rp.... I will write that amount in the box on the survey sheet on this piece of paper. **[*Write their winnings on the questionnaire at QSC15d.*]** Here is your money.

Thank you for playing. Thanks for your time today.

	If Blue marble	If Yellow marble
A	10,000	10,000
B	19000	9000
C	24000	8000
D	30000	6000
E	38000	2000
F	40000	0

	If Blue marble	If Yellow marble
A	❶❶❶❶❶❶❶❶❶❶	❶❶❶❶❶❶❶❶❶❶
B	❶❶❶❶❶❶❶❶❶❶ ❶❶❶❶❶❶❶❶❶	❶❶❶❶❶❶❶❶❶
C	❶❶❶❶❶❶❶❶❶❶ ❶❶❶❶❶❶❶❶❶❶ ❶❶❶❶	❶❶❶❶❶❶❶❶
D	❶❶❶❶❶❶❶❶❶❶ ❶❶❶❶❶❶❶❶❶❶ ❶❶❶❶❶❶❶❶❶❶	❶❶❶❶❶❶
E	❶❶❶❶❶❶❶❶❶❶ ❶❶❶❶❶❶❶❶❶❶ ❶❶❶❶❶❶❶❶❶❶ ❶❶❶❶❶❶❶❶	❶❶
F	❶❶❶❶❶❶❶❶❶❶ ❶❶❶❶❶❶❶❶❶❶ ❶❶❶❶❶❶❶❶❶❶ ❶❶❶❶❶❶❶❶❶❶	