Risk-Taking Behavior in the Wake of Natural Disasters*

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Abstract

Globally, more and more individuals are living in a world of increasing natural disasters, and a disproportionate share of the damage caused by such environmental shocks is borne by people in developing countries. Three main categories of natural disasters account for 90% of the world's direct losses: floods, earthquakes, and tropical cyclones. In Indonesia, the two most commonly occurring natural disasters are earthquakes and floods. We study whether natural disasters affect risk-taking behavior. We investigate this issue using experimental data from rural Indonesian households which we collected in 2008. We play standard risk games (using real money) with randomly selected individuals and test whether players living in villages that have been exposed to earthquakes or floods exhibit more risk aversion. We find that individuals in villages that suffered a flood or earthquake in the past three years exhibit more risk aversion than individuals living in otherwise like villages that did not experience a disaster. This change in risk-taking behavior has important implications for economic development.

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Over the last decade, direct losses from natural disasters in the developing world averaged 35 billion USD annually. These losses are increasing. For example, these losses 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 there due to poor building practices and lack of adequate infrastructure. The enormity of these losses has focused attention on how natural disasters can undermine developing 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 term and possibly the longer term. We investigate the relationship between natural disasters and individuals' risk-taking behavior using data from experiments conducted in Indonesia in 2008. 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.

We find that individuals in villages that suffered a flood or earthquake in the past three years make choices that 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. We explore to what extent the result is an income effect. We find that some, but not all, of the effect is a consequence of a loss of income. The impact of natural disasters on risk aversion is found to be mitigated when households have access to insurance mechanisms such as remittances from people outside the home village.

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 from a development economics perspective 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 so prevalent in many developing countries. Twenty-six percent of Indonesian villages experienced a flood or earthquake from 2006-08 (PODES 2008). Therefore, the results from this paper have important ramifications for various household decisions that influence economic development.

We start with a brief description of ways in which natural disasters might affect risk-taking behavior. We then discuss natural disasters as they occur in Indonesia, the data and the experimental design, and present our main empirical results. We explore the extent to which experiencing a natural disaster affects people's perceptions of the probability and severity of such events. We conclude with an examination of whether access to informal insurance mechanisms reduces risk aversion in the face of a natural disaster and provide suggestive evidence that it does.

1 Why should natural disasters affect risk behavior?

It seems likely that natural disasters would affect individuals' risk choices. 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 Hurricane

Katrina 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 affects people's expectations and behavior in the short term. With time, the impact on their behavior dissipates (as long as they do not experience another one).

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 that wealth is negatively associated with risk aversion (CITE). Our data allow us to explore all of these potential avenues below.

Even if we accept that changing perceptions of risk are the most likely vehicle for behavioral change, theoretically the anticipated effect of these types of events on risk aversion remains unclear. On the one hand, it seems natural that adding a mean-zero background risk to wealth should 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) show that under certain conditions, an addition of background risk will cause a utility maximizing individual to make less risky choices. 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. 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.

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.

We argue that experiencing a natural disaster provides new information on the "riskiness" of living in a given area. While people have their 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 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. Moreover, 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 seem not to persist. Our data suggest that within 5 years of a disaster, individuals perceptions of the risk they face has returned to the pre-crisis levels.

As far as we know there are no 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) is the only paper of which we are aware that studies this issue, and it does so in the U.S. and focuses on the short term impact of Hurricane Katrina evacuees. Interestingly, our results differ from Eckel et al. (2009) 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.

2 Indonesia and natural disasters

Indonesia is particularly prone to natural disasters. It regularly experiences floods, earthquakes, volcanic eruptions, forest fires, tropical cyclones, and landslides. In this paper we focus on the two most commonly occurring natural disasters—floods and earthquakes. These occur most often and affect the highest number of people in Indonesia (EM-DAT, 2009).

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. 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.[1] 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.[2] The risk game (based on Binswanger (1980) and closely related to Eckel and Grossman (2002)) was played with an adult household member.[3] 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. A community level survey was also administered to the village head. This survey provides one measure of natural disasters affecting each village.

[1] East Java has 29 rural districts.

[2] This is because of the focus of the evaluation.

[3] The adult member with responsibility for sanitation decisions in the household was invited to play. This reflects the primary purpose of the data collection, as a tool for evaluating sanitation decisions.

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.[4] 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.[5]

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 as individuals are not expected to reveal their risk aversion when stakes are relatively small (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.

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

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

3.1 Estimating risk aversion parameters

We calculate our risk measures using two 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[6] 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 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 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 our 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.[7]

[6]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.

[7]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).

3.2 Measures of natural disaster

The main measures of natural disaster are obtained from a community level survey which was administered to the village head in each community in 2008. 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.

Though there is little reason to believe the village head would not provide accurate measures of natural disaster, we employ data from PODES (Potensi Desa) data to construct alternative measures of natural disaster for our villages. In addition, since the measure of natural disaster described above do not measure intensity, we use the PODES data to construct two measures of natural disaster for our villages which capture intensity. The PODES is a survey conducted by the Indonesian Statistical Agency in every village of Indonesia every three years. Using the 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. 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 for households that experienced a flood is 1.3 floods. None of the villages experienced more than one earthquake during this 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.[8]

Finally, we use data from the 2006, 2003, 2000, 1993, 1990, and 1983 PODES[9] to construct a historical measure of the mean number of earthquakes and floods in each of our villages. The mean number of floods from 1980-2005 is .23 floods and the mean number of earthquake 1980-2005 is 0.22. We use these means as measures which proxy for historical occurrences of natural disasters. We can think about these means as a measure of background risk and the occurrence of a new natural disaster as a change in the perception of background risk.

[8]If we correlate natural disaster reports from village heads relative to the 2008 PODES data reports, the correlation is quite high and significant at 0.5.

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

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.[10] 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 make less risky choices. Below, we investigate whether this remains the case once we control for a range of observable characteristics.

3.4 Potential Selection Bias

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 claim this is the causal effect of natural disaster on risk attitudes since the natural disaster is an unexpected shock. Since 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, 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.

One obvious concern with this empirical 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 negative correlation between flood and risk choice which is not causal. Similarly, villages that experienced a natural disaster in the past 3 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 negative correlation between natural disasters and risk aversion which is not causal.

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

To examine the extent of selectivity, 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. 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 second half of Table 3 we present summary statistics from the community level survey. We investigate whether the extent of public good provision and program access differ across village types since flooding is caused by poor drainage. Again we find no significant differences. Natural disaster and non-natural disaster villages 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.

A further concern is that wealthier households 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 6 we regress natural disaster on wealth and a polynomial of wealth and find no significant relationship between the occurrence of natural disasters and wealth. We return to the issue of wealth below.

Since village of residence in East Java is largely a function of family roots, we consider the potential for selection bias to be relatively small. Ties to the land and community are strong, though the potential for migration out of villages does exist.

3.4.1 Migration

To further examine the extent to which selectivity is likely to be a problem, we examine migration rates by natural disaster status. Since we do not have migration rates in our data, we use data from the first and second waves of the Indonesian Family Life Survey (IFLS). The IFLS is a panel of over 7000 Indonesian households.[11] 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 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).[12]

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.[13] The only characteristic that differs significantly across disaster and non-disaster

[11] 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/`.

[12] 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).

[13] 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)

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.

Finally, selectivity may operate within a village. More risk-averse households and wealthier families may choose to live farther from the river within their community. The IFLS data show that 10.3 percent of households in flood and earthquake affected villages in rural Indonesia moved house within the village versus 8.4 percent in villages with no disasters. This difference is statistically significant (p=0.01) and suggests that households are more likely to move within their village in disaster stricken villages. However, since our sample is a random sample of the community population and our estimates are derived from cross-village comparisons, this type of selectivity does not bias our results.[14]

4 Empirical results

In Table 4, we present the results from simple linear probability models where the dependent variable is "risk-loving" (a player who selected the riskiest choices, E or F, in the risk game).[15] 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 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 the mean amount of earthquakes and floods from 1989-2005 in each village as a measure of historical background risk.

Table 4 indicates that individuals who have experienced an earthquake in the past three years

[14]The figures for rural Java are 8.9 percent and 7.6 percent, p-value=0.13.
[15]The results are quantitatively similar if we estimate probit regressions.

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 insignificant 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 5-6 of Table 4, we introduce two different measures of natural disaster from the PODES data. Some of the villages in our sample experienced more than one flood in the past three years. Therefore, 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 in column 4 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 use a measure of the total amount of flood and earthquake damage (in log Indonesian rupiah). Again, we find that individuals in villages with more flood or earthquake damage, are less likely to choose the risky options. Therefore, regardless of the measure we use, 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 the mean occurrence of floods and earthquakes from 1980-2005 the main results are not affected. There also seems to be an additional effect on risk-taking behavior from the mean earthquakes. The coefficient is negative and statistically significant suggesting that people who lived in villages that experienced an earthquake from 1980-2005 exhibit even less risk loving behavior. The coefficient on mean floods is not statistically significant.

We now move to our other measures of risk, where the dependent variable is the log of the lower bound of the relative risk aversion parameter, calculated with and without income. In columns 1-6 of Table 5, the dependent variable is calculated assuming utility is only a function of the winnings from the game (column 6 of Table 1) and in columns 7-12 of Table 5 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 are the same as those described above in Table 4, and again, we build up to the final specification which includes all control variables.

Overall, the results in Table 5 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 5 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 4, 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 5-6 of Table 5, we include our alternative measures of floods: the number of floods in the past three years 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. Similarly, the greater the amount of damage caused by the floods, the greater the risk aversion.

In columns 7-12 of Table 5 we replicate the regressions in columns 1-6, 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.

4.1 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 5 control for wealth at the time of the survey. The results also stand if we add income as a control. (Income is not statistically significant and does not affect the other results. Results available on request.) 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 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.[16] Once we account for financial aid received, the reported lost 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 12 shows that the IFLS data produce similar results. We define a person as "risk-loving" if they picked the last, most risky option in the game.[17] 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. Details are given in the appendix.[18] 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 much 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 12 include additional controls for the log of household income, log 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.[19] 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 by the natural disaster, in terms of having lost a lot of income, act in a more risk-averse manner. The bottom line from 12 is that although there is evidence of income effects in the data, controlling

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

[17] The IFLS games were Holt and Laury (2002) type risk games where respondents are asked to make choices between a series of lottery pairs. Their choices reveal their risk preferences. The IFLS played two such games which differed in terms of the stakes employed. Though not central to their results, Andrabi and Das (2010) also find that individuals living closer to the 2005 Pakistani earthquake fault line are significantly more risk averse when playing hypothetical risk games. We also played Holt and Laury (2002) type hypothetical risk games. The results from the hypothetical games are consistent with our main results.

[18] 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.

[19] Table 13 shows the results when we use wealth instead of income. Wealth is not statistically significant. Otherwise the results are the same.

for both levels and changes of income does not affect our core result that experiencing a natural disaster 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.[20]

4.2 Robustness

4.2.1 Village Head Reporting Bias

One might be concerned that since the measures of natural disaster from our community survey are reported by village heads, the heads' characteristics might influence his or her response. Reporting bias of this type might then bias our coefficient estimates. While we do not believe this to be the case since the correlation between the PODES data and the data reported by village heads in the community survey is quite high, we re-estimate our regression models controlling for village head characteristics such as age, sex, length of tenure as village head, and education. The results are robust to the inclusion of village head characteristics and the main estimates do not change (results available upon request from authors).

4.2.2 Time Preferences

Another potential concern with our results is that we do not control for time preferences. To the extent that risk preferences are correlated with discount rates, the risk aversion results could be biased due to the omission of individuals' discount rates. In our survey we asked standard hypothetical questions about discounting behavior.[21] From those questions we can construct a minimum monthly discount factor for each individual. When we include the discount factor in the regressions as an additional control variable in the regressions (from Tables 4 and 5), the main risk aversion results do not change (results available upon request from authors). Therefore, it does not appear to be the case that time preferences are driving the main results.

4.3 Do past disasters predict current disasters?

Our identification assumptions requires the flood or earthquake to be an unexpected shock. To the extent floods and/or earthquakes are predictable, we would not expect their occurrence to change risk-taking behavior. We test to see if floods from the past predict floods today and similarly whether earthquakes from the past predict earthquakes today. The results of this exercise are

[20] 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.

[21] For example, "Would you prefer X today or Y in a month?" where Y is a greater amount.

presented in Table 7. In column 1, the dependent variable is flood occurrence in 2008 which we regress on flood occurrence in 2007, 2006, 2005, and 1980-2005. We also include district fixed effects and river dummies as additional control variables, and cluster standard errors at the village level. As the results in column 1 indicate, none of the coefficients on the previous flood measures are statistically significant. This implies that previous floods do not predict current floods. Column 2 in Table 7 presents similar regression results for earthquakes. Again, none of the coefficients are statistically significant suggesting that past earthquakes do not predict current earthquakes.

5 Do individuals update expectations after experiencing a natural disaster?

We also 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%) and slightly (but not statistically significantly) more likely to report that an earthquake will occur in the next year (18.2 vs. 16.8%). We also asked them to estimate how bad the impact of that flood or earthquake would be conditional on experiencing the disaster in the next year. The responses are coded into 5 categories with 0 being not bad at all and 4 being extremely bad and the results are displayed in Table 3.

In Table 8 we report OLS regression results where the dependent variable is the 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 1980-2005. In columns 3-4 of Table 8 we report ordered probit regressions where the dependent variable is the perceived impact of the flood if it were to occur (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). The results in columns 1-2 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 suggest that individuals update (and increase) the probability that another flood will occur 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. Interestingly, this probability decreases the further away the flood experience. 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, the coefficient even becomes negative.[22] Interestingly, this updating of expectations occurs even after we control for the mean background risk of floods in column 2, and the mean amount of floods over time has no impact on current day reports of expectations.

The ordered probit results in Table 8 are also very sensible. Individuals are much more likely to report that the flood impact will be bad if they have experienced a flood in the 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 9 we report the same regressions as in Table 8 except the measure of natural disaster is now earthquake. The coefficients are sensible. The more recent the earthquake experience, the higher the reported probability that an earthquake will occur in the next year. However, none of the coefficients are statistically significant. Experiencing a bad earthquake in the past also increases the likelihood that an individual will report that the severity of the future earthquake will be bad. However, again the coefficients on the year dummies are not statistically significant.

These results suggest that the updating of expectations at least in part explains the more risk-averse choices people make when they have been exposed to a disaster. Having experienced a disaster they perceive that they now face a greater risk and greater severity of future disasters and so are less inclined to take risks. The results in the previous section suggest this is irrational as past experiences of floods and earthquakes have no predictive power over the occurrence of such an event in the future. 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.

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

6 Do households self-insure?

So far the results presented are consistent with Gollier and Pratt's (1996) definition of risk vulnerability. One of the 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 friends and relatives meet monthly for a private lottery similar to a betting pool. 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.[23] However, this is more likely when the shock is idiosyncratic (only affects a household) and much more difficult in the 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 10 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 11 we examine whether having access to insurance can reduce some of the natural

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

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.[24]

In columns 1-2 of Table 11 the dependent variable is risk-loving and in columns 4-6 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 remittance receipt is positive and statistically significant. Receiving a remittance does provide some insurance against the impact of natural disasters. The positive .13 coefficient almost exactly offsets the negative .14 coefficient on natural disaster. Arisan participation however, 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 will be unable to insure villagers against shocks that affect the whole village.

In column 2, instead of using the dummy variable for remittance receipt, we use the log amount of remittances that a household receives (in Rp). Again, the interaction is positive and significant, suggesting that the greater the amount received, the less risk aversion we should observe when a natural disaster strikes.

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 of the effect which experiencing a natural disaster has on increased risk aversion. However, it is important to note that while insurance may offset some of the impacts on risk aversion, it does not completely wipe out the effect. This is consistent with our earlier results that show that income and wealth are determinants of risk-taking behavior but that the change in wealth and/or income does not fully explain the change in behavior. These results are consistent with DeSalvo et al. (2007) who find that 24.8% of Hurricane Katrina survivors without

[24]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.

property insurance suffered from post-traumatic stress disorder versus 17.8% of those who had property insurance (i.e. insurance had a small mitigating effect). In addition, Barr and Genicot (2008) find that villagers in Zimbabwe are willing to make more risky choices when playing a similar risk game when they know they have insurance.

7 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. Our data suggest that expectations 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. Although the impact of disasters on risk-taking behavior is mitigated when households have access to remittances or live in villages with access to health programs, changes in income do not fully explain the results.

Over 10 million people in Indonesia have been affected by an earthquake or a flood since 1990—this is approximately five percent of the total population (EM-DAT, 2009). 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 decide not to educate a child, 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 far higher than routinely estimated.

Finally, in terms of theory, this paper supports Gollier and Pratt's (1996) risk vulnerability hypothesis and rejects the hypothesis that independent risks are complementary.

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.

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.

Eckel, Catherine C. and Philip J. Grossman, "Sex Differences and Statistical Stereotyping in Attitudes Twoards Financial Risk," *Evolution and Human Behavior*, 2002, *23*, 281–295.

— **, Mahmoud A. El-Gamalb, and Rick K.Wilson**, "Risk loving after the storm: A Bayesian-Network study of Hurricane Katrina evacuees," *Journal of Economic Behavior & Organization*, 2009, *69*, 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.

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.

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.

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.

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

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, ∞)	(10.38, ∞)
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	(-∞, 0)	(-∞, 3.80e-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)** $\rightarrow$	**(C)**	**(D)** $\rightarrow$	**(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)
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	.78	.75	.03
	(.03)	(.01)	
Participates in conditional cash transfer	.03	.04	-.01
	(.01)	(.01)	
Health insurance for poor	.24	.22	.02
	(.04)	(.01)	
Subsidized rice buyer	.83	.83	0
	(.03)	(.01)	
Household on river bank	.02	.02	0
	(.003)	(.001)	
Village Characteristics:			
Health Care Program	.47	.42	.05
	(.04)	(.01)	
Deworming Program	.09	.09	0
	(.02)	(.01)	
Sanitation Program	.36	.35	.01
	(.04)	(.01)	
Village population	930	999	-69
	(38.5)	(15.5)	
Has river	.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 Natural Disasters Affect Risk Loving?

	(1)	(2)	(3)	(4)	(5)	(6)
Earthquake	-.09	-.10	-.10	-.10	-.11	
	(.01)***	(.03)***	(.03)***	(.04)***	(.04)***	
Flood	-.05	-.06	-.06	-.08		
	(.02)**	(.03)**	(.03)**	(.03)**		
Number of floods					-.03	
					(.01)***	
Total damage						-.004
						(.002)**
Mean earthquake(1980-2005)				-.03	-.02	-.03
				(.01)***	(.01)**	(.01)**
Mean floods(1980-2005)				.03	.04	.04
				(.03)	(.03)	(.04)
Married		.04	.03	.04	.04	.04
		(.05)	(.05)	(.05)	(.05)	(.05)
Female		-.11	-.11	-.11	-.12	-.12
		(.03)***	(.03)***	(.03)***	(.03)***	(.03)***
Madurese		.01	.00	-.01	-.03	-.03
		(.13)	(.13)	(.13)	(.13)	(.13)
Javanese		-.01	-.02	-.03	-.05	-.04
		(.14)	(.13)	(.13)	(.13)	(.13)
Age		-.002	-.003	-.003	-.002	-.003
		(.001)**	(.001)**	(.001)**	(.001)**	(.001)**
Education		.004	.003	.003	.003	.003
		(.003)	(.003)	(.003)	(.003)	(.003)
Rivers		.03	.03	.03	.02	.02
		(.03)	(.03)	(.03)	(.02)	(.02)
Wealth			.01	.01	.01	.01
			(.006)*	(.006)*	(.006)*	(.006)*
Constant	.17	.24	.08	.08	.11	.12
	(.01)***	(.17)	(.18)	(.18)	(.18)	(.18)
F statistic	29.64	5.51	3.97	4.22	3.55	2.42
Observations	1539	1539	1539	1539	1539	1539

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 5: Risk Coefficients and Natural Disaster

Dependent Variable:	$ln\gamma$						$ln\gamma$ with income					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Earthquake	2.26	2.69	2.6	2.49	2.76		2.45	2.81	2.72	2.61	2.88	
	(.57)***	(.99)***	(.92)***	(1.01)**	(.98)***		(.55)***	(.99)***	(.94)***	(1.02)**	(1.01)***	
Floods	1.28	1.53	1.65	2.29			1.31	1.63	1.75	2.39		
	(.68)*	(.85)*	(.86)*	(.95)**			(.69)*	(.88)*	(.88)**	(.99)**		
Number of floods					.90						.92	
					(.31)***						(.32)***	
Total damage						.13						.13
						(.05)***						(.05)***
Mean earthquake(1980-2005)				.77	.68	.73				.81	.72	.77
				(.26)***	(.28)**	(.27)***				(.27)***	(.3)**	(.29)***
Mean floods(1980-2005)				-1.24	-1.54	-1.72				-1.25	-1.54	-1.72
				(.93)	(.94)	(.96)*				(.97)	(.99)	(1.01)*
Married		-1.06	-1.02	-1.08	-1.11	-1.13		-1.05	-1.02	-1.08	-1.11	-1.12
		(1.34)	(1.36)	(1.36)	(1.35)	(1.35)		(1.38)	(1.39)	(1.39)	(1.38)	(1.38)
Female		3.29	3.31	3.28	3.3	3.33		2.94	2.96	2.93	2.95	2.98
		(.83)***	(.83)***	(.84)***	(.83)***	(.83)***		(.86)***	(.86)***	(.86)***	(.86)***	(.86)***
Madurese		1.18	1.41	1.67	2.39	2.42		1.01	1.24	1.5	2.24	2.27
		(4.57)	(4.38)	(4.37)	(4.41)	(4.39)		(4.6)	(4.43)	(4.41)	(4.47)	(4.44)
Javanese		1.15	1.47	1.7	2.33	2.13		1.11	1.42	1.65	2.3	2.1
		(4.69)	(4.52)	(4.5)	(4.53)	(4.53)		(4.72)	(4.55)	(4.54)	(4.57)	(4.56)
Age		.07	.08	.08	.07	.08		.08	.09	.09	.08	.09
		(.03)**	(.03)***	(.03)***	(.03)**	(.03)***		(.03)***	(.03)***	(.03)***	(.03)***	(.03)***
Education		-.2	-.15	-.14	-.15	-.14		-.17	-.12	-.12	-.12	-.11
		(.1)**	(.1)	(.1)	(.1)	(.1)		(.1)*	(.1)	(.1)	(.1)	(.1)
Rivers		-.89	-.95	-.89	-.49	-.53		-.96	-1.02	-.96	-.55	-.59
		(.71)	(.71)	(.71)	(.68)	(.69)		(.74)	(.73)	(.73)	(.7)	(.72)
Wealth			-.39	-.39	-.38	-.37			-.37	-.37	-.36	-.35
			(.16)**	(.16)**	(.16)**	(.16)**			(.17)**	(.17)**	(.17)**	(.17)**
Constant	-4.57	-6.74	-1.02	-.97	-1.99	-2.03	-4.55	-6.9	-1.42	-1.37	-2.43	-2.47
	(.33)***	(5.45)	(5.65)	(5.64)	(5.59)	(5.62)	(.35)***	(5.51)	(5.75)	(5.74)	(5.69)	(5.72)
F statistic	8.13	2.98	3.72	3.25	3.58	2.91	10.11	3.09	4.21	3.39	4.03	2.51
Observations	1538	1538	1538	1538	1538	1538	1539	1538	1538	1538	1538	1538

Notes: We report results from OLS regressions where the dependent variable is $ln\gamma$ in columns 1-6 (mean is -4.44) and $ln\gamma$ measured with income in columns 7-12 (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 6: 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. 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 7: Do Past Natural Disasters Predict Present Natural Diasters?

Dependent Variable:	Flood 2008	Earthquake 2007
	(1)	(2)
Flood (2007)	-.009	
	(.009)	
Flood (2006)	.003	
	(.004)	
Flood (2005)	-.009	
	(.009)	
Mean flood(1980-2005)	.02	
	(.02)	
Earthquake (2006)		-.04
		(.04)
Mean earthquake(1980-2005)		.002
		(.002)
Constant	-.01	.03
	(.01)	(.03)
Observations	1539	1539

Notes: We report results from OLS regressions where the dependent variable is Flood 2008 (column 1, mean is .01) Earthquake 2007 (column 2, mean is .01). All specifications are clustered at the village level and include district level fixed effects and river dummies. ***indicates significance at 1% level, ** at 5% level, * at 10% level.

Table 8: 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(1980-2005)		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 9: 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(1980-2005)		-.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 10: 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 11: Does "Insurance" Help?

Dependent Variable:	risk-loving		$ln\gamma$	
	(1)	(2)	(3)	(4)
Natural Disaster	-.14	-.14	3.39	3.35
	(.07)**	(.07)**	(1.44)**	(1.43)**
Arisan	.001	.001	-.23	-.23
	(.02)	(.02)	(.55)	(.55)
Arisan*natural Disaster	.05	.05	-1.18	-1.13
	(.07)	(.07)	(1.64)	(1.63)
Remittance	.008		-.55	
	(.03)		(.85)	
Remittance*natural disaster	.13		-2.58	
	(.06)**		(1.54)*	
Remittance amount		.0003		-.03
		(.002)		(.06)
Remittance amount*natural disaster		.01		-.22
		(.004)**		(.11)*
Constant	.08	.08	-1.13	-1.09
	(.18)	(.18)	(5.67)	(5.66)
F statistic	2.39	2.49	2.7	2.75
Observations	1547	1547	1547	1547

Notes: 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.

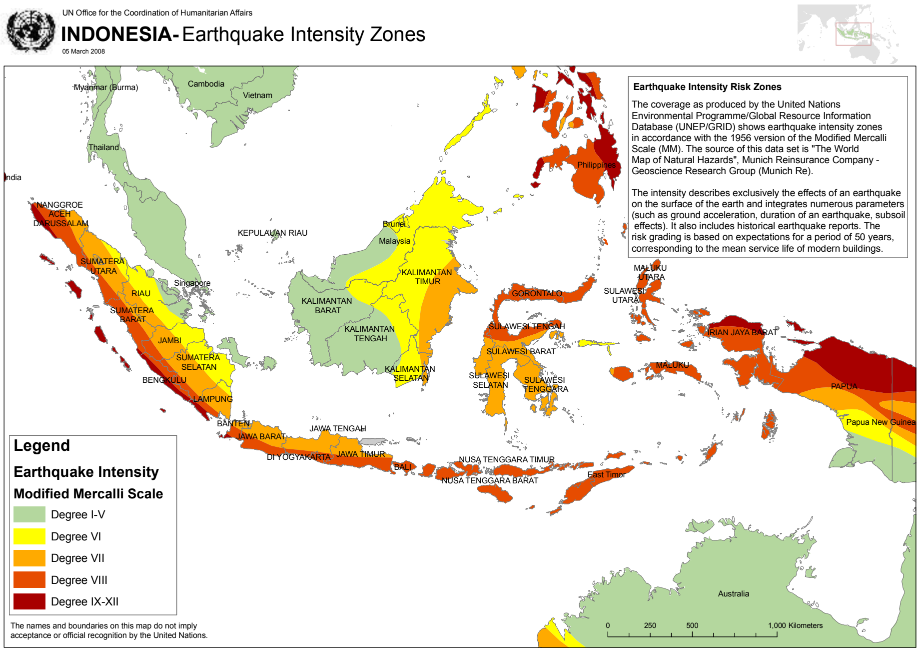

Figure 1: Earthquake Intensity

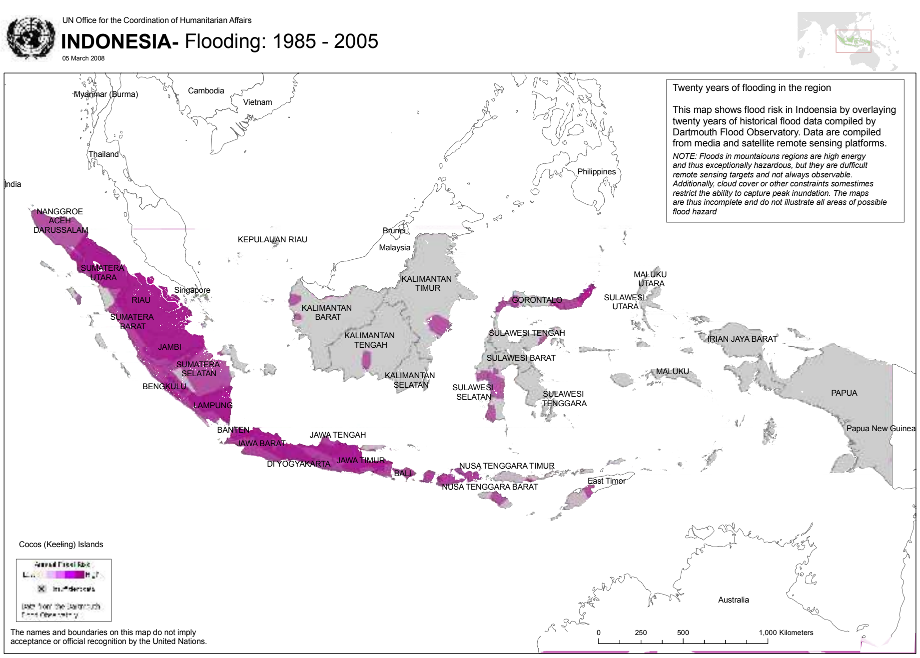

Figure 2: Flood Intensity

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:

$$U(B) \geq U(A) \quad \Leftrightarrow \quad U(B) - U(A) \geq 0 \tag{1}$$

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

$$0.5(\frac{19000^{(1-\gamma)}}{(1-\gamma)}) + 0.5(\frac{9000^{(1-\gamma)}}{(1-\gamma)}) - (\frac{10000^{(1-\gamma)}}{(1-\gamma)}) \geq 0 \tag{2}$$

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

$$-\frac{CU''(C)}{U'(C)} \tag{3}$$

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:

$$U(B) \geq U(C) \quad \Leftrightarrow \quad U(B) - U(C) \geq 0 \tag{4}$$

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

$$0.5(\frac{19000^{(1-\gamma)}}{(1-\gamma)}) + 0.5(\frac{9000^{(1-\gamma)}}{(1-\gamma)}) - 0.5(\frac{24000^{(1-\gamma)}}{(1-\gamma)}) - 0.5(\frac{8000^{(1-\gamma)}}{(1-\gamma)}) \geq 0 \tag{5}$$

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 12: 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 13: 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.