Risk-Taking Behavior in the Wake of Natural Disasters

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ABSTRACT

We investigate whether experiencing a natural disaster affects risk-taking behavior. We conduct standard risk games (using real money) with randomly selected individuals in rural Indonesia. We find that individuals who recently suffered a flood or earthquake exhibit more risk-aversion. Experiencing a natural disaster causes people to perceive that they now face a greater risk of a future disaster. We conclude that this change in perception of background risk causes people to take fewer risks. We provide evidence that experimental risk behavior is correlated with real-life risk behavior, highlighting the importance of our results.

I. Introduction

Over the last decade, direct losses from natural disasters in the developing world averaged US$35 billion annually. These losses are increasing and are more than eight times greater than the losses suffered as a result of natural disasters during the 1960s (EM-DAT 2009). Three main categories of natural disasters account for 90 percent 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

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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. If natural disasters affect people's perceptions of the riskiness of their environment, then experiencing a disaster can be thought of as an addition of background risk, and if people are "risk-vulnerable," in the sense of Gollier and Pratt (1996), they will then exhibit more risk-averse behavior. This could have potential dampening effects on post recovery growth if, for example, people are less willing to be entrepreneurial, particularly because 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. Psychological theories, however, 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. Thus, the question is an empirical one.

We investigate the relationship between natural disasters and individuals' risk-taking behavior using experimental data from Indonesia. 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.

Our results are consistent with the concept of risk-vulnerability. 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 or a flood in the past three years are seven percentage points less likely to make risky choices. This is a large effect and translates into a 41 percent decrease in the probability of making a risky choice. 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 likely not biased due to selection of residential location or migration patterns and that the effects of particularly severe shocks are long lasting.

Natural disasters change people's beliefs. We show that individuals who recently experienced a natural disaster perceive the world to be a 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 consistent with Di Tella, Galiani, and Schargrodsky (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. Even more in line with our results is Callen et al. (2014), which finds that fearful recollections of individuals exposed to violence in Afghanistan trigger changes in risk and certainty preferences.

We conclude by examining the extent to which behavior in the risk experiments is correlated with such "real-life" risk-taking as opening a new business or changing jobs, and provide evidence that more risk-averse individuals are less likely to take these types of risks.

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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, de la Fuenta, and Santos 2010; Finlay 2009; Portner 2008; Yamauchi, Yisehac, and Quisumbing 2009), and even mental health (Frankenberg et al. 2008). A small number of working papers examine the effect of natural disasters on risk-taking behavior and discount rates in various developing countries (Callen 2011; Cassar, Healy, and von Kessler 2011; van den Berg, Marrit, and Burger 2009) with similar results to what we find here—that risk-taking decreases as a result of natural disasters. Our paper aims to provide greater certainty that these results are not simply due to selection and examines pathways that might explain this result. This is an 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 2013), 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.

II. 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 average background risk.

Alternatively, a natural disaster may constitute a "shock" that contains new information and may cause estimates of risk to be updated. We argue this is a more natural way to think of a disaster. It is difficult to think of victims of recent disasters as not being shocked by the event and reappraising the world in which they live. For example, 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 current 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

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increase risk-aversion to other independent risks (Eeckhoudt, Gollier, and Schlesinger 1996; Guiso and Paiella 2008; and Gollier and Pratt 1996). Gollier and Pratt (1996) and Eeckhoudt, Gollier, and Schlesinger (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) defines this property as "risk vulnerability" and shows 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). Lerner and Keltner (2001) shows that fearful people express more pessimistic and risk-averse choices. Quiggin (2003), using nonexpected 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 United States, finds that higher levels of background risk are associated with reduced stock market participation. Guiso and Paiella (2008) shows 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 (2008) analyzes individuals' choices over a series of lottery choices in a laboratory setting in the presence and absence of uncorrelated background risk. It finds that adding abstract background risk generates more risk-aversion, although it does not find the effect to be quantitatively large. Eckel et al. (2009) examines risk-aversion in the context of Hurricane Katrina evacuees in the United States. Its results differ from ours as it finds that the evacuees exhibit more risk-loving behavior. It subscribes such behavior to the emotional state of the participants shortly after the hurricane.

III. 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).[1]

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 37 million people, making it one of the most densely populated largely rural areas on earth with almost

1. 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 compared to droughts. For example, from 1900–2011, the EM-DAT database recorded 97 earthquakes and 61 general floods compared to only nine 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. Note also that although Indonesia was severely affected by the 2004 Indian Ocean tsunami, East Java was not. The floods captured in the data used in this paper are a result of excess rainfall not ocean flooding.

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800 people per square kilometer. Seventy percent of its population lives 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 (0–500 meters above sea level) and relatively fertile. Flooding generally occurs because water fills river basins too quickly and the rainwater cannot be absorbed fast enough. The entire province of East Java suffers high-intensity risk from both earthquakes and floods (see Figures 1 and 2 in the online appendix, associated with this article at http://uwpress.wisc.edu/journals). Our sample covers six districts that span the length of the province of East Java.[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.

IV. Data and Experimental Design

Our sample consists of approximately 1,550 individuals spread across 120 rural villages in six districts of the province of East Java. These individuals participated in experimental games that 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.[3] 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 socioeconomic variables. A community-level survey was also administered to the village head.

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 one and a yellow one. He would 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

2. Our sample is drawn from the district of Ngawi in the west of the province; Jombang and Blitar in the center; and Probolinggo, Bondowoso, and Situbondo in the west. The sample does not include any districts on the island of Madura, which is part of East Java province.

3. This is because of the focus of the survey, which was for a randomized controlled trial of an intervention that aimed to improve child health. The 120 villages included in the survey were randomly selected from lists provided by district officials. A listing was made of all households within the community with children under the age of two and 12 households were then randomly selected from this listing to participate in the sample. If a household refused or was unable to participate, another household was randomly selected from the listing. Refusal was not common. Although we endeavored to have as many male participants as possible, women are overrepresented in our sample as they were more often at home with children and available to participate.

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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 percent chance of winning Rp10,000 and a 50 percent 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 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. Because 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) plays the same risk game based on Binswanger (1980) in a number of Zimbabwean villages. 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.

A. Estimating Risk-Aversion Parameters

We calculate two different risk measures. We first use a simple measure of risk attitudes. We define those individuals who selected Choice E or F as exhibiting "risk-tolerant" (=1) behavior and all others are defined as "non-risk-tolerant" (= 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 assuming constant relative risk-aversion (CRRA) CES utility: $(c) = c^{(1-\gamma)} / (1 - \gamma)$. These are presented in Column 8 of Table 1. For each individual, we solve for his/her γ based on the choice made in the game. [6]

4. More detailed instructions for the risk game, including the protocols, are given in the online appendix.

5. Only 11 players (0.70 percent) 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 three of the cases, we switched to another player within the same household and we did not play the risk game in one household.

6. Most studies that estimate risk-aversion parameters from experiments in developing countries ignore income outside the experiment (Cardenas and Carpenter 2008). An exception to this is Schechter (2007), which defines utility over daily income plus winnings from a risk experiment in Paraguay. We also followed this approach. We generated risk-aversion intervals for each participant when utility is defined over winnings plus the participant's daily wage. The results are similar to the results that do not take income into account and are available upon request from the authors.

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Table 1
Gamble Choices: Payoffs, Expected Values, and Levels of Risk-Aversion

Gamble Choice	Frequency (Percentage) (Disaster=1)	Frequency (Percentage) (Disaster=0)	Low Payoff	High Payoff	Expected Value	Variance in Payoffs	Partial Risk-Aversion Coefficient
1	2	3	4	5	6	7	8
Gamble A	16.7	17.7	10,000	10,000	10,000	0	$(7.51, \infty)$
Gamble B	19.4	13.8	9,000	19,000	14,000	5,000	(1.74, 7.51)
Gamble C	22.2	22.9	8,000	24,000	16,000	8,000	(0.81, 1.74)
Gamble D	30.6	28.5	6,000	30,000	18,000	12,000	(0.32, 0.81)
Gamble E	4.9	9.3	2,000	38,000	20,000	18,000	(0, 0.32)
Gamble F	6.3	7.8	0	40,000	20,000	20,000	$(-\infty, 0)$

Notes: Gamble A is the least risky but has the lowest expected value. Gamble F is the most risky but has the joint (with Gamble E) highest expected value.

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B. Measures of Natural Disaster

The measures of natural disaster are obtained from three different data sets: a community-level survey that was administered to the village head in each community in 2008; the PODES (Potensi Desa), a survey conducted by the Indonesian Statistical Agency in every village of Indonesia every three years; and seismology data from the U.S. Geological Survey (USGS) website.[7] We use three different data sets as they measure natural disasters in different ways (occurrence, frequency, total damage in dollar amount, distance from epicenter), but our results are consistent regardless of the data set and measure of natural disaster we employ, illustrating the robustness of the 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 but a few experienced more than one flood.

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 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 $4,650) with the maximum damage reported at approximately $122,000. 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 number of disasters (which varies from zero to six) for the same time period using the PODES data. The mean number of disasters is 0.43. There were no reported deaths caused by earthquakes or floods during this period in our sample villages. Although these are disasters severe enough to cause material damage, none were severe enough to cause death.[8]

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 and 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. First, 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.[9] Second, different villages might engage in different ex ante disaster mitigation strategies, such as building struc-

7. See http://earthquake.usgs.gov/earthquakes/eqarchives/epic/epic_global.php.

8. In a previous version of the paper, we constructed separate variables for earthquakes and floods. Here we group the two categories. The results are largely unaffected.

9. 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 (results available upon request from authors).

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tures so that they are more able to withstand earthquakes and investing in drainage infrastructure. 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 six of Indonesia's over 400 districts, the measured rainfall data does not vary enough to be closely correlated with flooding that we have at the village level. In fact, due to missing data and few rainfall stations, the rainfall data generates a maximum of only three different values across our 120 villages each year of our sample periods.

Finally, we construct historical measures of the mean number of disasters 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.[10] 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 disasters 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 as 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 and/or infrastructure investments.

V. 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.[11] 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 (such as house, land, livestock, household equipment, jewelry) 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 experienced more disasters in the last three years make less risky choices. In addition, individuals in villages farther 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.

10. Questions about natural disasters were not asked in the 1986 and 1996 PODES.
11. For a review of the literature on gender and risk, see Croson and Gneezy (2009).

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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
	(0.20)	(0.20)	(0.18)	(0.20)	(0.17)	(0.16)
Female(=1)	0.85	0.85	0.85	0.83	0.76	0.75
	(0.35)	(0.36)	(0.35)	(0.37)	(0.43)	(0.44)
Javanese(=1)	0.57	0.54	0.59	0.59	0.53	0.66
	(0.50)	(0.50)	(0.49)	(0.49)	(0.50)	(0.48)
Madurese(=1)	0.43	0.45	0.41	0.41	0.47	0.34
	(0.50)	(0.50)	(0.49)	(0.49)	(0.50)	(0.47)
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)
Number of natural disasters	0.55	0.45	0.42	0.46	0.25	0.34
	(1.30)	(0.89)	(0.92)	(1.0)	(0.67)	(0.97)
Earthquake(=1)	0.01	0.02	0.02	0.02	0.01	0.01
	(0.10)	(0.13)	(0.15)	(0.13)	(0.09)	(0.09)
Flood(=1)	0.08	0.11	0.07	0.08	0.04	0.06
	(0.27)	(0.31)	(0.25)	(0.27)	(0.20)	(0.25)
Number of floods	0.53	0.43	0.39	0.44	0.24	0.33
	(1.29)	(0.88)	(0.91)	(0.99)	(0.66)	(0.97)
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	271	221	351	441	137	118

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

VI. 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 regressions:

$$y_{iv} = \propto + \beta_1 DISASTER_v + \beta_2 X_i + \delta + \epsilon_{iv}$$

where i indexes individuals and v villages. The dependent variable, y_{iv}, is the risk measure (we use two different measures); control variables in X_i include age, education, marital status, ethnicity, river dummy, and the mean of natural disasters over

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time; and δ is district fixed effects. The measures of natural disasters (at the village level) are denoted by $DISASTER_v$.

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. The figures in the online appendix 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). Further, 67 percent of the sample villages report having experienced a flood or an earthquake in the preceding 28 years (using PODES data).

A. 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 that is not causal. Similarly, villages that experienced a natural disaster in the past three years might be different from villages that did not. For example, villages that experienced a natural disaster might provide worse public goods than villages that did not, again introducing a correlation between natural disasters and risk-aversion that 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 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. Exposure to flooding risk is, however, largely governed by proximity to rivers and poor drainage. However, again, 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 errors 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 status from 2005–2008. 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. Ideally, we would conduct this exercise with predisaster wealth but we do not have that measure. However, the results from Table 4 suggest that it is unlikely that the wealthier households can escape natural disasters in these regions. We return to the issue of wealth below. It appears 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

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Table 3
Summary Statistics by Natural Disaster

	Natural Disaster 1	No Natural Disaster 2	Difference 3
Individual and household characteristics:			
Married(=1)	0.97	0.96	0.01
	(0.13)	(0.005)	(0.02)
Female(=1)	0.87	0.83	0.04
	(0.028)	(0.01)	(0.03)
Javanese(=1)	0.49	0.58	–0.09**
	(0.041)	(0.013)	(0.04)
Madurese(=1)	0.51	0.41	0.10**
	(0.041)	(0.013)	(0.04)
Age(years)	29.7	30.8	–1.1
	(0.69)	(0.258)	(0.83)
Education(years)	7.8	7.8	0.05
	(0.23)	(0.08)	(0.27)
Number of friends	6.01	5.7	.30
	(1.4)	(0.18)	(0.73)
No friends to borrow money(=1)	0.22	0.25	0.03
	(0.03)	(0.01)	(0.04)
Participates in conditional cash transfer(=1)	0.03	0.04	–0.01
	(0.013)	(0.005)	(0.02)
Subsidized rice buyer(=1)	0.83	0.83	0.004
	(0.03)	(0.01)	(0.03)
Household on river bank(=1)	0.02	0.02	0.001
	(0.003)	(0.001)	(0.01)
Village characteristics:			
Health care program(=1)	0.47	0.42	0.05
	(0.04)	(0.01)	(0.04)
Deworming program(=1)	0.09	0.09	0.001
	(0.02)	(0.01)	(0.03)
Sanitation program(=1)	0.36	0.35	0.01
	(0.04)	(0.01)	(0.04)
Has river(=1)	0.91	0.76	0.15***
	(0.01)	(0.02)	(0.04)
Dependent variables:			
Risk-tolerant	0.11	0.17	–0.06*
	(0.026)	(0.01)	(0.03)
ln risk-aversion	–3.12	–4.57	1.45
	(0.779)	(0.285)	(0.09)
Probability of flood in next year	42.6	12.0	30.6***
	(2.73)	(0.458)	(1.67)
Probability of earthquake in next year	18.2	16.8	1.4
	(1.58)	(0.571)	(1.83)
Perceived flood impact	1.79	0.93	0.86***
	(0.089)	(0.33)	(0.106)
Perceived earthquake impact	0.84	0.96	–0.12
	(0.099)	(0.036)	(0.115)
Observations	144	1,394	

Notes: We report the means and standard errors by natural disaster. A "risk-tolerant" individual is someone who picked Category E or F in the risk game. ***indicates difference is statistically significant at 1 percent level, ** at 5 percent level, * at 10 percent level.

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Table 4
Do the Wealthier Households Escape Natural Disasters?

	Dependent Variable: Natural Disaster		
	1	2	3
Wealth	0.005	0.008	0.003
	(0.005)	(0.01)	(0.01)
Wealth squared		−0.001	0.0001
		(0.001)	(0.001)
District fixed effects	Y	Y	Y
Control variables	N	N	Y
R^2	0.05	0.05	0.08
Observations	1,538	1,538	1,538

Notes: We report results from OLS regressions where the dependent variable is Natural Disaster (mean is 0.10). 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 percent level, ** at 5 percent level, * at 10 percent level.

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. Because 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 because some part of flooding is caused by poor drainage. Again, we find no significant differences. Natural disaster and nonnatural 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 that 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 nonnatural disaster villages use electricity.

B. Migration

To further examine the extent to which selectivity is likely to be a problem, we examine migration rates by natural disaster status. A followup survey on these same

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Table 5
Natural Disasters and Migration Behavior

Dependent Variable: Household Migrated (2008–2010)				
	1	2	3	4
Natural disaster (2005–2008)	0.03			
	(0.02)			
Number of disasters (2005–2008)		0.004		
		(0.007)		
Distance to epicenter (2005–2008)			−0.0007	
			(0.0009)	
Total damage (2005–2008)				0.0002
				(0.001)
District fixed effects	Y	Y	Y	Y
Control variables	Y	Y	Y	Y
R^2	0.02	0.02	0.02	0.02
Observations	1,538	1,538	1,538	1,538

Notes: We report results from OLS regressions where the dependent variable is migrated from 2008–2010 (mean is 0.05). 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, marriage, and river dummies. ***indicates significance *** at 1 percent, ** at 5 percent level, * at 10 percent level.

households was conducted in December 2010, thereby informing us 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 2005–2008 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, include district level fixed effects, and control for ethnicity, gender, age, education, marriage, and river dummies. We find that regardless of the natural disaster measure we use, experiencing a natural disaster is not 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 data set: the first and second waves of the Indonesian Family Life Survey (IFLS). The IFLS is a panel of over 7,000 Indonesian households.[12] The 1993 wave provides information on natural disasters between 1990 and 1993. The 1997 wave identifies what percentage of individuals has 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

12. IFLS1 (1993) and IFLS2 (1997) were conducted by RAND in collaboration with Lembaga Demografi, University of Indonesia. For more information, see http://www.rand.org/labor/FLS/IFLS/.

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of 15 (n=1,752) migrated in the following three years versus 16.7 percent in villages that did not (n=9,897). This difference is not statistically significant (p-value=0.63).[13]

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 nondisaster 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 nondisaster villages) and 52.2 percent are male (compared to 53.8 percent in nondisaster 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 that experienced a disaster completed 3.07 years of education on average compared to 3.30 years in nondisaster villages, and 72 percent of migrants from disaster villages are currently employed (compared to 65.2 percent in nondisaster villages). None of these differences are statistically significant. The only characteristic that differs significantly across disaster and nondisaster 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.[14]

VII. Empirical Results

Columns 1–4 in Table 6 present the results from simple linear probability models where the dependent variable is "risk-tolerant" (a player who selected one of the two riskiest choices, E or F, in the risk game).[15] All specifications cluster 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 that might affect our results such as public goods provisions, government programs, and/

13. 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 migrated in the following three years versus 13.9 percent in villages that did not. 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).

14. A further possibility is that people who dislike living in natural disaster environments have been migrating out over time (for many years). If this is the case, 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. In addition, we examine whether disasters cause contemporaneous long-term migration. We do this using our main data set and the USGS data on earthquakes between 2008 and 2010 and also using the IFLS data on migration and floods and earthquakes between 1994 and 1997. Both sets of results show no relationship between disasters and contemporaneous migration.

15. The results are quantitatively similar if we estimate probit regressions.

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or geographic differences. The control variables include age, marital status, gender, education, ethnicity, and a dummy indicating whether the village is on a river. We also control for the mean number of natural disasters in the village between 1980 and 2008. The coefficient on disasters between 1980 and 2008 will tell us the effect of mean background risk on behavior. The coefficient on recent disasters will tell us whether recent disasters affect risk-taking, controlling for background risk.[16]

In Column 1, we include an indicator for whether the village experienced a natural disaster in the previous three years. It indicates that individuals who have experienced a flood or an earthquake in the past three years are seven percentage points less likely to choose Option E or F. This is a large effect (41 percent) because the mean of the dependent variable is 0.17. This result is statistically significant at the 0.05 level.

In Columns 2–4 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 disasters in Column 2 instead of the disaster dummy in Column 1, the results indicate that for a one standard deviation increase in disasters (which is equivalent to one disaster), individuals are 2 percent less likely to choose Option E or F. In Column 3, we show that the further away from the epicenter of the earthquake, the more likely the individual is to choose one of the risky options. In Column 4, we include the measure of the total amount of monetary flood and earthquake damage (in log Indonesian rupiah). This variable is negatively signed but not statistically significant at standard levels.

Interestingly, the coefficient on the measure of background risk, the mean occurrence of floods and earthquakes from 1980–2008, is negative. This is consistent with people who live in villages that experienced more disasters between 1980 and 2008 being less likely to take risks, but it is not statistically significant. We also regress the risk measures on the mean distance to epicenter (1973–2008) using the USGS seismology data. Being closer to earthquake epicenters is significantly associated with making less risky choices. A one standard deviation increase in distance to the epicenter (approximately 30 kilometers) during the period 1973–2008 makes a person 9 percent more likely to choose the risky option. This result is statistically significant at the 0.01 percent level. The coefficient on mean floods in this specification is not statistically significant (results available upon request).

Columns 5–8 present the coefficients from tobit interval regression where the dependent variable is the natural log of the interval of the relative risk-aversion parameters. All specifications allow errors to be clustered at the village level and include district fixed effects and the same set of control variables as Columns 1–4. The results are very similar except that now the coefficient on total damage is significant at the 0.10 level. Experiencing a disaster is on average associated with an 86 percent increase in the relative risk-aversion parameter. Education is also now statistically significant in these regressions, and we find that more educated players take more risk. As we might expect, women and older individuals are less likely to be risk-tolerant in all specifications. Note also that the variable indicating proximity of the community to a river is

16. Although the consensus view is that absolute risk-aversion declines with wealth, wealth is potentially endogenous as the higher returns that accompany riskier decisions may make risk-loving individuals wealthier. In unpublished results, we did include a measure of wealth as a control. It was associated with riskier behavior but its inclusion did not change our main results.

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Table 6
Do Natural Disasters Affect Risk-Taking?

Dependent Variable:	Risk-Tolerant				Interval of $ln\gamma$			
	1	2	3	4	5	6	7	8
Natural disaster (2005–2008)	–0.07				0.86			
	(0.03)**				(0.52)*			
Number of disasters (2005–2008)		–0.02				0.51		
		(0.01)**				(0.21)**		
Distance to epicenter (2005–2008)			0.004				–0.07	
			(0.002)**				(0.03)**	
Total damage (2005–2008)				–0.003				0.06
				(0.002)				(0.03)*
Mean natural disasters (1980–2008)	–0.03	–0.02	–0.03	–0.02	0.36	0.17	0.33	0.24
	(0.03)	(0.04)	(0.03)	(0.04)	(0.61)	(0.72)	(0.62)	(0.69)
Married	0.04	0.04	0.04	0.04	–0.66	–0.67	–0.66	–0.67
	(0.05)	(0.05)	(0.05)	(0.05)	(0.95)	(0.95)	(0.95)	(0.95)
Female	–0.12	–0.11	–0.11	–0.12	2.15	2.14	2.02	2.18
	(0.03)***	(0.03)***	(0.03)***	(0.03)***	(0.58)***	(0.57)***	(0.56)***	(0.57)***
Madurese	0.008	–0.01	–0.009	–0.01	1.63	2.03	1.88	1.91
	(0.13)	(0.13)	(0.13)	(0.13)	(3.12)	(3.13)	(3.02)	(3.13)
Javanese	–0.008	–0.03	–0.01	–0.02	1.1	1.45	1.18	1.25
	(0.14)	(0.14)	(0.13)	(0.14)	(3.24)	(3.25)	(3.13)	(3.25)

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Age	−0.002	−0.002	−0.002	−0.002	0.05	0.05	0.05	0.05
	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.02)**	(0.02)**	(0.02)**	(0.02)**
Education	0.004	0.004	0.004	0.004	−0.14	−0.14	−0.14	−0.14
	(0.003)	(0.003)	(0.003)	(0.003)	(0.07)**	(0.07)**	(0.07)**	(0.07)**
Rivers	0.04	0.03	0.03	0.03	−0.68	−0.53	−0.68	−0.56
	(0.02)	(0.02)	(0.02)	(0.02)	(0.47)	(0.45)	(0.47)	(0.45)
District fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.03
Observations	1,538	1,538	1,538	1,538	1,538	1,538	1,538	1,538

Notes: We report results from OLS regressions (Columns 1–4) where the dependent variable is a dichotomous variable if the individual is risk-tolerant (mean is 0.17) and tobit interval regressions (Columns 5–8). All specifications are clustered at the village level and include district level fixed effects. ***indicates significance at 1 percent level, ** at 5 percent level, * at 10 percent level.

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Table 7
Do Past Natural Disasters Matter?

	1	2
Natural disaster (2008)	–0.12	1.72
	(0.04)***	(0.75)**
Natural disaster (2007)	–0.03	0.68
	(0.04)	(0.83)
Natural disaster (2006)	–0.08	0.43
	(0.04)*	(0.51)
Natural disaster (2005)	–0.16	1.57
	(0.04)***	(0.73)**
Number of natural disaster (2000–2004)	–0.003	–0.07
	(0.02)	(0.32)
Mean natural disaster (1980–2008)	–0.03	0.37
	(0.03)	(0.64)
District fixed effects	Y	Y
Control variables	Y	Y
R^2	0.02	0.03
Observations	1,538	1,538

Notes: We report results from an OLS regression where the dependent variable is risk-tolerant (Column 1); and a tobit interval regression where the dependent variable is the interval of $ln\gamma$ (Column 2). All specifications are clustered at the village level and include controls for ethnicity, gender, age, education, marriage, river, and district level fixed effects. ***indicates significance at 1 percent level, ** at 5 percent level, * at 10 percent level.

not statistically significant and suggests that selectivity of residence on the basis of risk attitudes is not a problem.[17]

A. Does History Matter?

To examine the longevity of the impact, we regress the measures of risk on the historical measures of natural disaster constructed from our data and the PODES data. The results are presented in Table 7. In Column 1, we estimate OLS regressions where the dependent variable is risk-tolerant, and in Column 2 we estimate interval regressions and the dependent variable is the interval of $\ln \gamma$. All models have errors clus-

17. Callen et al. (2014) finds that individuals exposed to violence exhibit an increased preference for certainty. We examine whether exposure to natural disasters has the same effect by defining a dependent variable to equal 1 if the individual chose Gamble A, which paid Rp 10,000 with certainty and 0 otherwise. Experiencing a natural disaster has no significant effect on the probability of choosing this gamble.

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 (in Table 6), 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.

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tered at the village level, include district fixed effects, and include the full set of control variables.

We include dummy variables generated from our survey data that indicate whether the village experienced a disaster for each year 2005–2008. We also include a measure of the number of disasters in the period 2000–2004 from the PODES data. 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 16 percentage points to three percentage points less likely to be risk-tolerant. Although 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 statistically significant. Even if we separate this variable into dummies by year, none are statistically significant.

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.

Column 2 in Table 7 replicates the regression in Column 1 but estimates an interval regression for the risk-aversion parameters. 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.

VIII. Potential Pathways

A. Do Individuals Update Beliefs After Experiencing a Natural Disaster?

One reason a natural disaster may affect risk-taking behavior is that experiencing a disaster may impact individuals' perceptions of the background risk they face. To examine this mechanism, in a survey of the same respondents conducted approximately a year after the original survey 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 the bottom panel of 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 versus 12 percent). Those who had experienced an earthquake reported a slightly higher (but not statistically significant) probability that an earthquake will occur in the next year (18.2 versus 16.8 percent). 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 8, 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

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Table 8
Probability Natural Disaster Will Occur and Perceived Impact

Dependent Variable:	Probability Flood Will Occur		Perceived Flood Impact	
	1	2	3	4
Flood (2008–2009)	35.29	33.78	0.55	0.54
	(8.44)***	(8.38)***	(0.16)***	(0.16)***
Flood (2006–2007)	19.19	19.07	0.14	0.19
	(6.86)***	(6.9)***	(0.27)	(0.25)
Flood (2004–2005)	24.47	23.28	0.58	0.6
	(8.62)***	(8.33)***	(0.31)*	(0.3)**
Flood (2002–2003)	–3.41	0.88	0.02	0.03
	(1.64)**	(2.71)	(0.26)	(0.29)
Mean flood (1980–2008)		1.33		–0.04
		(3.4)		(0.22)
Bad flood impact			1.3	1.3
			(0.22)***	(0.21)***
District fixed effects	Y	Y	Y	Y
Control variables	N	Y	N	Y
	Probability Earthquake Will Occur		Perceived Earthquake Impact	
Earthquake (2008–2009)	5.27	5.52	–0.1	–0.08
	(5.0)	(5.06)	(0.24)	(0.24)
Earthquake (2006–2007)	3.39	2.73	0.18	0.21
	(6.12)	(5.93)	(0.21)	(0.21)
Earthquake (2004–2005)	–1.26	–0.46	0.25	0.24
	(8.18)	(7.33)	(0.31)	(0.31)
Mean earthquake (1980–2008)		–0.6		–0.09
		(0.77)		(0.14)
Bad earthquake impact			1.29	1.27
			(0.19)***	(0.18)***
District fixed effects	Y	Y	Y	Y
Control variables	N	Y	N	Y
Observations	1,503	1,503	1,503	1,503

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 include controls for ethnicity, gender, age, education, marriage, and rivers. ***indicates significance at 1 percent level, ** at 5 percent level, * at 10 percent level.

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for past flood experiences.[18] 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 that include controls for ethnicity, gender, age, education, marriage, rivers, and mean flood 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 in the next year. For example, a person who experienced a flood in 2008–2009 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 seven years. This probability decreases the further away the flood experience (although not monotonically). For example, an individual who experienced a flood in 2004–2005 reports a probability of occurrence in the next year that is 23 points higher than an individual who did not experience a flood. In 2002–2003, the coefficient falls to 0.8 and loses statistical significance in Column 2. We test for the equality of the year coefficients and can reject equality. 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 significant impact on current day reports of expectations though the coefficient is positive.

Given the true probability of a flood occurring is approximately 3 percent per year, these results suggest that the perceptions of risk reported by individuals who have recently experienced a disaster are irrationally high. Similar "irrational behavior" has been well documented in different settings: For example, "hot hand beliefs" in which, 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 suggest 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, for example, an extremely bad flood and the mean for both variables is approximately 1). Columns 3–4 of Table 8 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 the bottom panel of Table 8, we report the same regressions, 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 coefficients are statistically significant. Having experienced an earthquake in the past does not affect the predicted severity

18. We need to look at floods and earthquakes separately here because the survey asked about these two types of disasters separately and it is not trivial to combine the responses into one measure.

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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.

These results suggest that the updating of expectations may help explain the more risk- averse choices people make when they have been exposed to a disaster. People who have experienced disaster 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 7—approximately five years—and there is similarly a larger impact on perceptions of the likely severity of another disaster occurring if previous disasters have been severe.[19] 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. Gallagher (2010), which uses data on flood insurance takeup in the United States over a 50-year period, finds spikes in insurance takeup shortly after floods that then diminish over time, fully diminishing within ten years.

B. Income and Wealth Effects

An alternative interpretation of our results is that the behavioral differences we observe are driven by the changes in income or wealth that accompany natural disasters. We have not included income or wealth as controls in the regressions in Table 6 as they are potentially endogenous. We do not have income or wealth prenatural disaster in our data set so it is difficult to investigate whether a change in income or wealth is driving the results or affecting the coefficient on natural disaster.[20] However, to examine the role played by income and wealth changes we turn to another data set. Unlike our data set, the fourth round of the Indonesian Family Life Survey (IFLS4) was conducted in 2007–2008 and asked households to report the value of financial loss due to natural disasters as well as the amount of financial aid received (if any). The reported loss is approximately 3 percent of the value of household assets (which we call wealth). We can also use wealth from the previous round of the IFLS3 (conducted in 2000) to control for predisaster wealth.

IFLS4 respondents also played games designed to elicit risk preferences. Unlike our game, the IFLS4 risk games were not played for real money. However, Table 9 shows that the IFLS4 data produce similar results.[21] We define a person as "risk-tolerant" 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

19. 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 a year after the original survey and so will also reflect natural disasters that occurred after the experimental games were conducted.

20. A regression of wealth today on natural disasters in the previous three years suggests that wealth is not an important channel; we find no statistically significant relationship and the coefficient on natural disaster is positive (that is, the wrong sign). If we do include contemporaneous wealth or income in the regressions in Table 6, we find that they are positively associated with risk-tolerance and do not affect the other coefficients in the regression.

21. Though not central to its 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.

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Table 9
Testing for Income Effects Using IFLS3 and IFLS4 Data

Dependent Variable:	Risk-Tolerant IFLS4 1			Risk-Tolerant IFLS4 2		
	1	2	3	4	5	6
Number of disasters (2001–2008)	–0.006	–0.006	–0.006	–0.002	–0.002	–0.003
	(0.003)**	(0.002)**	(0.003)**	(0.001)**	(0.001)**	(0.001)**
Baseline wealth (2000)		–0.0002	0.003		0.0008	0.002
		(0.004)	(0.004)		(0.002)	(0.002)
Total assistance received (2001–2008)		0.02	0.02		0.009	0.009
		(0.007)**	(0.006)**		(0.006)	(0.006)
Total amount lost (2001–2008)		–0.002			0.0001	
		(0.001)			(0.001)	
Change in wealth (2000–2008)			–0.003			–0.003
			(0.006)			(0.004)
District fixed effects	Y	Y	Y	Y	Y	Y
Control variables	Y	Y	Y	Y	Y	Y
R2	0.06	0.07	0.07	0.04	0.04	0.04
Observations	4,150	4,150	4,150	4,150	4,150	4,150

Notes: We report results from OLS regressions where the dependent variable is risk-tolerant as measured by the hypothetical risk Game 1 from IFLS4 in Columns 1–3 (mean is 0.24), and as measured by the hypothetical risk Game 2 from IFLS4 data in Columns 4–6 (mean is 0.08). All specifications are clustered at the village level, include district level fixed effects, and controls for age, ethnicity, marital status, gender, and education. ***indicates significance at 1 percent level, ** at 5 percent level, * at 10 percent level.

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payoffs in the lotteries.[22] Columns 1 and 4 show that for both games, the more disasters experienced in the seven years prior to the survey by the household, the more risk-averse the 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 and statistically significant signs on the coefficients are consistent with our results.

Columns 2 and 5 of Table 9 include additional controls for baseline wealth. This is log wealth from the 2000 round of the IFLS3 (and so predisaster). We also include log of financial assistance received and log of the total amount lost due to natural disaster (reported in IFLS4). This allows us to examine if the income effect (controlling for the level of baseline wealth) can explain our result. The coefficient on baseline assets is close to zero and insignificant in all specifications.[23] Total assistance received is positive in both games and statistically significant in Game 1. The total amount lost is negative in Game 1: The more one loses due to natural disasters, the less likely one is to be risk-tolerant though this result is not statistically significant in either specification. In Columns 3 and 6, we include a control for the change in wealth between 2000 and 2007. The coefficient while negative is not statistically significant.

In both specifications, the coefficient on the number of disasters is unaffected by the inclusion of these controls. We include different measures of potential income effects and the only income effect that seems to be statistically significant is when the household receives money due to natural disasters. This increase in income makes individuals more risk-tolerant. However, the bottom line from Table 9 is that there is little evidence of strong income/wealth effects in the data: Controlling for both levels and changes of wealth 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 explain the more risk-averse behavior of households that experienced natural disasters.

Below, we present results showing that having insurance may reduce some, but not all, of the natural disaster-induced risk-aversion.

C. Insurance

A further implication of Gollier and Pratt's (1996) "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 that are found in many developing countries. It refers to a social gathering in

22. The IFLS games asked respondents 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) Rp12 million and Rp0; and (3) Rp16 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 define natural disasters in a similar manner: the number of floods and/or earthquakes experienced from 2001–2008.

23. We also include a measure of baseline log income (instead of log assets) and the results are qualitatively similar.

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Table 10
Insurance Measures by Natural Disaster

	Natural Disaster 1	No Natural Disaster 2	Difference 3
Receives remittance(=1)	0.19	0.13	0.06**
	(0.03)	(0.01)	
Remittance amount (ln Rp)	2.3	1.7	0.6
	(0.41)	(0.12)	
Participates in arisan (=1)	0.88	0.66	0.22***
	(0.03)	(0.01)	
Observations	144	1394	

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

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. 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 such as a natural disaster.

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 migrants. A literature exists on the role of gifts and remittances that 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. Arisan and remittances are distinct in that an arisan provides a form of ex ante insurance with involvement being irrespective of experiencing a disaster, whereas remittances are a form of ex post support that can respond to the occurrence of a disaster.

In Table 10, we test whether we observe greater incidence of insurance in villages that are hit by natural disasters from 2005–2008. 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. Individuals who live in villages that 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.[24]

24. Note that the analysis presented in this section is only suggestive as the results may be biased due to endogeneity and/or reverse causality. 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.

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Table 11
Does "Insurance" Help?

Dependent Variable	Risk-Tolerant 1	Interval of $ln\gamma$ 2
Natural disaster	–0.14	1.05
	(0.07)*	(0.65)
Arisan	0.003	–0.45
	(0.02)	(0.34)
Arisan*natural disaster	0.05	0.31
	(0.07)	(0.77)
Remittance amount	–0.0001	–0.02
	(0.002)	(0.05)
Remittance amount*natural disaster	0.01	–0.14
	(0.004)**	(0.07)*
Constant	0.14	0.04
	(0.04)***	(0.59)
R^2	0.01	0.01
District fixed effects	Y	Y
Observations	1,538	1,538

Notes: We report results from OLS regressions where the dependent variable is risk-tolerant (Column 1) and a tobit interval regression where the dependent variable is the interval of $ln\gamma$ (Column 2). All specifications are clustered at the village level and include river and district level fixed effects. ***indicates significance at 1 percent level, ** at 5 percent level, * at 10 percent level.

In Table 11, 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.

In Column 1 of Table 11, the dependent variable is risk-tolerant. In Column 2, the dependent variable is the natural log of the interval of the relative risk-aversion parameters and we estimate tobit interval regressions. 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), which finds that villagers in Zimbabwe are willing to make more risky choices when playing a similar 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 receives remittances of this magnitude. This is consistent with our earlier results that changes in wealth and/or income are not strong determinants of changes in behavior following a natural disaster.

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Arisan participation has no statistically significant effect on risk-aversion. Though the interaction is positive and 0.06, 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.[25]

IX. Do the Experimentally Risk-Averse Take Fewer Risks in Daily Life?

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 game. The results of this exercise are shown in Table 12. Odd-numbered columns do not include any additional controls (except for district fixed effects) and show that, regardless of which risk measure we use, more risk-tolerant individuals are more likely to open a new business and change jobs. They are also more likely to adopt new technologies though the standard errors become large. Even numbered columns add a control for years of education. Education is the only sociodemographic variable that has a statistically significantly relationship with any of the dependent variables in Table 12. 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.

X. Conclusion

This paper shows that individuals living in villages that have experienced a natural disaster recently behave in a more risk-averse manner than individuals in otherwise like villages. 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 12 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.

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

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Table 12
Is Experimental Risk-Tolerance Correlated with Real Life Risk-Taking?

Dependent Variable:	Opened New Business		Changed Jobs		Adopted New Technology	
	1	2	3	4	5	6
Risk-tolerant	0.03	0.03	0.03	0.03	0.003	−0.001
	(0.02)*	(0.02)	(0.02)*	(0.02)	(0.02)	(0.02)
Education		0.01		0.005		0.01
		(0.002)***		(0.002)**		(0.003)***
R^2	0.01	0.03	0.01	0.01	0.01	0.02
District fixed effects	Y	Y	Y	Y	Y	Y
Observations	1,432	1,432	1,432	1,432	1,432	1,432

Notes: We report results from OLS regressions where the dependent variable is opened a business in the past two years (Column 1, mean is 0.08); changed jobs in last two years (Column 2, mean is 0.08); and adopted new technology in past two years (Column 3, mean is 0.14). All specifications include districts fixed effects and no other controls except for education in Columns 2, 4, and 6. ***indicates significance at 1 percent level, ** at 5 percent level, * at 10 percent level.

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Our finding that people's beliefs changed as a result of their experience is similar to that of Callen et al. (2014), which finds that individuals who experienced violence in Afghanistan become more risk-averse. Empirically in our context it is difficult to identify and isolate changes in preferences, and though we present evidence 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—this is approximately 5 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 2013), 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.

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