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Attitudes Towards Risk in the Wake of a Rare Event: Evidence from Pakistan

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Preface

The Centre for Research in Economics and Business (CREB) was established in 2007 to conduct policy-oriented research with a rigorous academic perspective on key development issues facing Pakistan. In addition, CREB (i) facilitates and coordinates research by faculty at the Lahore School of Economics, (ii) hosts visiting international scholars undertaking research on Pakistan, and (iii) administers the Lahore School's postgraduate program leading to the MPhil and PhD degrees.

An important goal of CREB is to promote public debate on policy issues through conferences, seminars, and publications. In this connection, CREB organizes the Lahore School's Annual Conference on the Management of the Pakistan Economy, the proceedings of which are published in a special issue of the *Lahore Journal of Economics*.

The CREB Working Paper Series was initiated in 2008 to bring to a wider audience the research being carried out at the Centre. It is hoped that these papers will promote discussion on the subject and contribute to a better understanding of economic and business processes and development issues in Pakistan. Comments and feedback on these papers are welcome.

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Abstract

This paper investigates the impact of rare-event experiences and observations on risk taking. Matching detailed individual, household, and community-level surveys with behavioral games data, we explore the mechanisms that underlie individual risk-taking after a natural disaster. Unlike the existing literature, which focuses mostly on community-level economic and disaster data, our unique dataset allows us to match detailed interviews on individual risk perceptions and loss experiences with game choices. In the context of rural Punjab, Pakistan, we find that having observed others' losses is as important as personal experience of loss, although the type of loss also matters. In multiple rounds of the game, we also find that the change in strategy between rounds depends on the severity of losses experienced or observed and on the number of floods experienced over one's lifetime.

Attitudes Towards Risk in the Wake of a Rare Event: Evidence from Pakistan

1. Introduction

While several studies have investigated the change in behavior that follows an extreme or traumatic natural disaster (see, for instance, Eckel, El-Gambal, & Wilson, 2009; Cameron & Shah, 2010; Zylberberg, 2011; Fleming, Chong, & Bejarano, 2011; Reynaud, Aubert, & Nguyen, 2013), there is no consensus on the direction of change. For instance, Eckel et al. (2009) have observed that Hurricane Katrina evacuees were more *risk-loving* than the control group in their study, though this difference declined over time. However, the authors divide their sample into hurricane-affected and unaffected groups without controlling for the impact of disaster losses. On the other hand, for Indonesian households affected by earthquakes and floods, Cameron and Shah (2010) report higher levels of *risk aversion* than for individuals in the unaffected villages—the higher the number of floods experienced, the higher was the level of risk aversion. They also find this differential to be long lasting, depending on the severity of the natural disaster. However, their study focuses on village-level rather than individual differences, ignoring the potential variation across individual experiences.

This paper enhances the external validity of the existing literature by combining data from behavioral games with information from a detailed household survey. Our data allows a comparison of flood-related effects not only across villages, but also across households and individuals. Given that flood risk is highly location-specific and flood effects more difficult to estimate parametrically than those of other natural disasters, such household- and individual-level survey data provide rich insights. We can therefore test for the impact of individual characteristics, perceptions, and losses on individual risk-taking behavior.

2. Updating Based on Experience or Observation and Heuristics

We draw on the broader literature on risk aversion and Bayesian updating under limited information.1 Kahneman and Tversky (1973) identify (i) the "availability" heuristic—the propensity of individuals to determine likelihood on the basis of prominent information; (ii) the "representativeness" heuristic, which causes individuals to overweigh salient events in determining the probability of an occurrence; and (iii) the "conservatism" heuristic, under which individuals are predisposed to give more weight to conservative values. Additionally, Mullainathan (2002) describes the "associativeness" heuristic under which current events remind individuals of similar past events such that multiple events are compounded into a single perception. An example of the availability heuristic is given by Deryugina (2010), who uses the US Gallup polls to provide evidence that individuals are more likely to report a belief in climate change when the weather has been hot over the past week.

2.1. Preferences versus Constraints

Although neoclassical economists generally assume that preferences are fixed while constraints change, there is a large body of literature in psychology and other behavioral sciences that examines the potential for behavioral learning. Voors et al. (2010) provide evidence that, several years after experiencing the traumatic conflict in Burundi, participants in behavioral games appeared to have shifted their risk-taking preferences. Similar studies highlight the possibility of risk-taking preferences changing over time when individuals experience traumatic events (see Dillenberger & Rozen, 2011). Natural disasters can be traumatic events that separate family members and destroy physical assets. Therefore, a rational agent might conceivably adjust his or her risk perceptions and mitigation plans for natural disasters when given new information.

Kahneman and Tversky's (1979) seminal work introduced the "prospect" theory, which deviates from other rational utility-maximizing utility models. Under the prospect theory, individuals consider potential gains or losses when making decisions rather than final outcomes. They set "reference" points: any potential outcome lower than the reference point is considered a loss. Moreover, the value function is steeper for losses

[1] For further discussion, see Deryugina (2010).

than for gains. In this context, Harrison, Humphrey, and Verschoor (2005) find that, in a sample of developing countries, just under 50 percent of the individuals behaved according to the prospect theory. Using data on affectees of the Australian floods of 2011, Page, Savage, and Torgler (2012) establish that the adoption of risk-seeking attitudes after large flood-associated losses is consistent with the prospect theory.

Identifying changes in risk preferences requires one to observe risk-taking behavior as well as to control for the constraints to risk taking. We consider two main areas of constraints: financial and psychological.

2.1.1. Financial Constraints

As demonstrated by Holt and Laury (2002), the level of financial assets at stake can determine the level of risk aversion. Cameron and Shah (2010), for instance, find that higher losses lead to higher risk aversion but that access to remittances mitigates the impact of floods on risk aversion. Orozco (2010) further demonstrates a change in risk aversion when subsistence is at risk. Falcon (1964), Mellor (1966), and Behrman (1968) have found that low-income and subsistence farmers are more risk averse. Kunreuther and Wright (1979) postulate that a behavioral kink emerges at a certain income level after which higher income leads to riskier choices. This finding is confirmed by Ortiz (1979): farmers tend to maximize their returns by taking risks after reaching a particular subsistence level. On the other hand, Tanaka, Camerer, and Nguyen (2006) find wealth effects to be insignificant in this context.

Expectations of external assistance can be an important factor in perceived financial constraints. In Pakistan's case, Andrabi and Das (2010) show the significant effect of earthquake-tied foreign aid on the public perception of foreign donors. Individuals who have received government aid for flood-related loss in the past, witnessed government aid being given to flood-affected neighbors, or interacted regularly with government officials to receive other types of nonflood-related government aid[2] may be more likely to expect external assistance to reduce their total losses in the case of a natural disaster.

[2] For example, the Benazir Income Support Program (BISP), which provides financial assistance to those below the poverty line through a variety of subprograms (see Pakistan, Ministry of Finance, 2013).

Nielsen, Keil, and Zeller (2013) have found that, for farmers in Vietnam, shocks that involved extensive ex-post assistance by the government (such as deaths and floods) led to an increase in risk aversion, while shocks that involved ex-post government coverage (such as livestock loss) led to no change in risk aversion. Similarly, we might expect network effects in receiving aid—for instance, through powerful patrons such as landlords—to influence individuals' risk levels.

2.1.2. Psychological Constraints

Psychological factors can be important determinants of risk choices. Specifically, psychological reasons may dictate how individuals perceive risk and, subsequently, how they mitigate it.

Loewenstein, Weber, Hsee, and Welch (2001) have put forward the *risk-as-feelings* hypothesis. Apart from conventional cognitive utility maximization, the emotional aspect of individual decision-making is more intuitive and automatic. Therefore, individual preferences may diverge from an economically rational utility maximization approach due to emotions. Following a trauma, an individual might put more weight on emotions (positive or negative) than on cognition. Eckel et al. (2009) attribute the increase in risk-*loving* behavior to greater importance being given to emotions immediately after the event, and the subsequent increase in risk aversion to the reassertion of cognitive reasoning. Similarly, Dillenberger and Rozen (2011) highlight two documented emotional biases in risk preferences: (i) the increase in risk *aversion* after a disappointing event and (ii) the stronger impact on risk averseness of earlier events.

Using household data from the Netherlands, Botzen, Aerts, and van den Bergh (2009) show that perceptions are different from actual risk; they find, for example, that individuals in unprotected areas consistently underestimate the risk of floods. Bubeck, Botzen, Suu, and Aerts (2012) note that even a high perception of flood risk does not necessarily lead one to take risk-mitigating actions because taking action also depends on the individual's perception of its cost effectiveness. In the context of Pakistan, even among villagers who have the financial resources needed to reduce risk, risk information and self-perception can vary, which, in turn, could determine the change in ex-post risk choices.

In particular, religious beliefs can play an important role in the perception of fate versus individual free will to influence the future. Although most people in rural Punjab are Muslim, individual interpretations of a natural disaster and its outcomes may vary, as can people's belief in their own ability to reduce future risk. The religious aspect may drive an individual toward risk-seeking behavior if they interpret future outcomes as acts of God. Cultural differences, even between people of the same religion, can further influence perceptions and mitigation. For example, subsistence farmers living in the Layyah district of Punjab, where the Indus riverbed stretches over several hundred kilometers, are economically dependent on small perennial floods to enrich arable land; they are, therefore, accustomed to being displaced briefly almost every year due to minor flooding. With perennial mobility, flood displacement may be a cultural norm.

2.2. Individual and Household Characteristics

Studies have found the level of risk aversion to differ by gender. Females tend to be more risk-averse (Riley & Chow, 1992; Jianakoplos & Bernasek, 1998; Weber, Blais, & Betz, 2002; Eckel et al., 2009; Cameron & Shah, 2010). On the other hand, Tanaka et al. (2006) report greater risk aversion in males. While many studies have explored the relationship between gender and risk preferences, they are largely silent on why risk aversion varies by gender among members of the same household. Bajtelsmit and Bernasek (1996) suggest a conceptual framework linking risk preferences to differences in labor market experiences, discrimination, human capital, socialization, and biological differences. Schubert, Gysler, Brachinger, and Brown (1999) argue that the difference in risk taking in lottery games arises because men and women face different opportunity sets.

Wang and Hanna (1997) and Bakshi and Chen (1994) present evidence for the "lifecycle risk aversion" hypothesis, according to which risk tolerance increases with age. Once again, there is a lack of consensus in the literature on the effects of age on risk tolerance. Older people are found to be more risk-averse in the Indonesian households sampled by Cameron and Shah (2010). Morin and Suarez (1983) and Pålsson (1996) observe similar results. Riley and Chow (1992) find nonlinear effects such that risk aversion decreases up to the age of 65 and then increases significantly.

The literature also explores the relationship between risk aversion and education. A concern with such analysis is that the correlation between education, wealth, and income might confound the interpretation of results. Once again, the literature does not agree on the expected direction of the relationship. Riley and Chow (1992) report a negative relationship between risk aversion and education, while Jianakoplos and Bernasek (1998) and Tanaka et al. (2006) find that risk aversion increases with education level.

Other studies investigate the relation between migration (Beegle, De Weerdt, & Dercon, 2011; Halliday, 2006; Yang, 2008; Paxson & Rouse, 2008), occupation (Tanaka et al., 2006), and risk aversion. Risk decisions are not made in isolation—background risk (or other risk sources) can increase risk aversion (Gollier & Pratt, 1996) or decrease it (Quiggin, 2003). This includes risk from occupation: Tanaka et al. (2006), for instance, show risk aversion to be lower among fisherfolk households (fishing is considered a risky occupation). Arrondel and Masson (1996) find that individuals in the private sector who are more exposed to risk are also likely to invest a greater proportion of their wealth in riskier assets than individuals who work in the public sector.

2.3. Motivation and Contributions

A better understanding of post-disaster risk-taking behavior is needed to provide more effective relief and insurance programs. (For instance, using data from the US, Gallagher (2012) finds that the demand for flood insurance increases significantly just after a flood but declines subsequently over the following decade.) This paper contributes to the literature by closely investigating both the financial and psychological mechanisms that underlie risk-taking, by matching detailed variation in individual experiences and observation of neighbors' experiences with behavioral game data.

Many regions in Pakistan are prone to minor perennial flooding and it is likely that some individuals will have experienced multiple floods, apart from the catastrophic 2010 floods. This has allowed us to ask questions about the number of floods experienced, their intensity, and the coping mechanisms adopted that may or may not have proved effective. We then use this information to estimate the differences in behavior between (i) those who have experienced multiple floods (including

2010) and those that experienced only the exceptional 2010 flood, or (ii) those who experienced the 2010 flood versus those who have experienced only minor floods.

Our first main result is that the observation of disaster losses is as important as the personal experience of loss in determining risk-taking behavior. Individuals who have experienced floods do not make significantly different choices from those who have not. However, individuals who live in areas designated as *flood clusters* make systematically more risk-averse choices than those who live elsewhere. Personal experience of floods in these areas increases the likelihood of more risk-*seeking* choices.

Our second contribution is to examine the impact of both severity and frequency in a region where minor floods occur perennially but a historically rare flood occurred recently. We find that frequency of experience is as important as severity, as individuals make significantly more risk-averse choices with the number of floods they have experienced. We isolate the psychological impact of individual flood experience from potential confounding factors (such as cumulative asset changes or unobserved geographic variation) by controlling for income effects and geographic flood propensity.

Our third main result is that the type of loss matters. While overall loss experience makes individuals more risk loving, we see that differences in risk behavior are driven mainly by those individuals who have either personal experience of floods or who have observed the loss of house structures as opposed to agricultural assets or personal possessions.

Our final contribution is to provide evidence that the process of risk learning depends on real-world disaster experience. In particular, learning between game rounds is influenced by the number of floods experienced and the severity of damage to the house structure.

3. Econometric Model and Hypothesis

The following section presents an econometric model of the determinants of game options.

3.1. Econometric Model

We are interested in the effects of flood experience on risk aversion decisions made by individuals. We estimate the following equation using an ordered probit regression:

$$\begin{aligned} Game\quad option_i &= \alpha + \beta_1(flood\quad experience_i) + \beta_2(flood\quad cluster_i) \\ &+ \beta_3(flood\quad experience.flood\quad cluster_i) + \beta_4 Round2_i + \beta_5 Round3_i \\ &+ \Sigma^j(\beta_j\, other\quad hhchars) + \varepsilon \end{aligned} \tag{1}$$

Game option is the choice made by participants in each round of the lottery game, where *game option* = 1 represents most risk-averse, 2 represents moderate risk aversion, 3 represents moderate risk-taking, and 4 represents most risk-taking. The higher the dependent variable, the more risk-*seeking* that choice will be. Explanatory variables include indicator variables for whether the individual belongs to a household that has experienced floods and for whether that household lives in an area that was severely affected by a flood (designated as *flood cluster*). Controls include the age and gender of the game participant and household characteristics collected from the survey. *Round2* and *Round3* are binary variables equal to 1 if the observation is from the second and third rounds of the game, respectively, and 0 otherwise. Standard errors are heteroskedasticity-robust and clustered at the village level.

All data was collected through a household survey administered to 640 individuals in 320 households (one male and one female per household). Of this group, 384 individuals (192 males and 192 females) also participated in a risk choice experiment. Lottery games involving 384 participants, as well as male and female questionnaires, were administered to the households to which they belonged. In total, there were 320 households that provided 640 observations at the household level. Table 1 provides summary statistics for the variables used.

A central question of this paper is whether individuals learn about risk, or change their risk-taking behavior, after rare events. First, we test whether the household flood experience, and particularly the 2010 flood experience, significantly determines the risk-taking behaviors measured by the game. We then test for how flood losses affect the risk-taking decisions, controlling for household and individual characteristics. This improves on the literature, which investigates the impact of natural disaster events on risk-taking in lottery games without controlling for individual or household-level losses. With our data, we are able to investigate how observation or experience of a natural disaster, the severity of the loss, as well as preparation and perceptions play a role in the process of learning from a disaster.

3.2. Hypothesis to be Tested

The following sections put forward the hypotheses for this study.

3.2.1. Observation versus Experience of Previous Events

Using survey questions that detail personal experience of floods versus only observation of flood damage incurred by others, we test whether risk aversion is different among individuals due to personal experience of a traumatic past event. According to Cameron and Shah (2010), people in communities who have experienced a natural disaster more recently report a higher probability of a natural disaster occurring in the next 12 months and expect it to be more severe than those who have not experienced a disaster. In contrast, Eckel et al. (2009) find that disaster-affected individuals make more risk-loving choices in a lottery game setting. The difference in findings could be due to differences between individual versus community loss experiences.

As discussed above, some households in designated flood villages had not suffered any flood damage. This allows us to test the location-specific aspect of flood risk. Individuals living in designated flood clusters may be more likely to make risk-averse choices even if they have not experienced a flood but have observed its negative impact on others. We will be able to test if individuals make decisions involving risk based on experience or on a summary description of outcomes related by others.

3.2.2. Updating Beliefs Based on Flood Frequency versus Severity

Under the "representativeness" heuristic, in determining the likelihood of an adverse event occurring, individuals tend to overweigh salient events. If true, this implies that individuals who recently experienced the severe floods of 2010 will make significantly different choices from those who did not experience the 2010 floods. On the other hand, according to Mullainathan (2002) and Deryugina (2010), current events remind individuals of similar past events, compounding their perceptions into a single perception of the event recurring in the future. This implies that individuals who have experienced multiple floods will make different choices from those individuals who have experienced a single flood, even if it were the 2010 flood. Our dataset also allows us to check for the differential impact of the frequency of floods versus the severity in areas designated as flood clusters versus those that are not.

3.2.3. Learning About Risk

According to Kahneman and Tversky (1973), individuals determine the likelihood of an event occurring by using prominent information. This implies that learning about risk (and potentially coping with it) depends on whether they encounter risk in other aspects of life. Under the "associativeness" heuristic, individuals learn about the risk of an event and form their perceptions of the event risk differently if it is easy to imagine or associate. Another example of associativeness is when individuals with risky livelihoods are more comfortable facing risk in other spheres of life. According to Çelen and Kariv (2004), individuals may be overconfident and overweigh personal information when making decisions. This implies that the options chosen in subsequent rounds of the game may depend on payoffs won in the last round: a higher payoff may encourage greater risk taken in the next round.

If the experience of previous events strengthens the effect of the most recent experience on behavior, this would be consistent with the *associativeness* heuristic. However, the memory of previous events experienced could make the impact of the 2010 event less significant had they already enhanced individual resilience to floods. Individuals with experience of other floods could also have a downward bias in reporting the comparative impact of the 2010 event.

We test for the likelihood of learning about risk by investigating the difference in decisions made by individuals who have experienced floods and/or live in designated flood clusters in subsequent rounds of the lottery game.

3.2.4. The Impact of Losses Incurred on Risk Aversion

Using data on the extent of loss incurred by flood-affected individuals from our survey, we will test if the level of risk aversion increases with losses. According to the prospect theory, individuals should become systematically more risk seeking after having incurred large flood losses (Page et al., 2012). On the other hand, Kunreuther and Wright (1979) propose a behavioral link at an income level under which lower income leads to more risk-averse choices. This is also consistent with the findings of Ortiz (1979). Cameron and Shah (2010) find that risk aversion increases with higher level of loss incurred.

Our data allows us to further disaggregate this effect by the type of loss. As discussed above, losses in terms of crop or structural damage tend to be more severe and variable than livestock damage or possessions lost due to a flood. We test if these relatively high losses also lead to significantly higher levels of risk-seeking behavior, consistent with the findings of Page et al. (2012).

4. Empirical Methodology and Data Collection

This section presents the methodology used and data collected.

4.1. Household and Individual Surveys

Our survey included a total of 640 individuals across three districts (Muzaffargarh, Layyah, and Rahimyar Khan) in the Punjab province of Pakistan during April 2013. This followed a province-wide household survey in 2008/09 that had included modules on the following categories:

- Household demographics, assets, land ownership
- Adoption of new practices, general adaption, perception of self- and others' resilience to change
- Experience of traumatic events (e.g., crime, injury)
- Risk perception and risk-taking preferences
- Savings, loans, gifts, financial and expenditure aspirations
- Patronage, social networks, relations to and assistance from powerful people

- Experience of natural disasters (floods, earthquakes, storms, droughts)
- 2010 flood losses (if any)
- Mitigation and prevention activities
- Information sources and warning times
- Perception of neighbors' 2010 flood losses
- Community assistance, assistance received or given to others
- External assistance, including government assistance and Watan cards
- Future expectations of flood timing, frequency, and severity
- Precautions taken against future floods; changes and learning in precautions taken
- Experience of and attitudes toward insurance products

4.2. Community Leader Interviews

In addition, interviews with a community leader in each village confirmed the village-level information collected.

The remainder of this section describes some particular elements of the survey and game. (A full copy of the survey instruments and game instructions can be obtained on request.)

4.3. Lottery Game

To elicit risk preferences, experimental games were conducted in groups of 12 males and 12 females from among the respondents of the household survey in each village. In the lottery game, participants were given four choices of paired lottery outcomes. The enumerator would randomly draw either a red or green ball from a bag, and participants would then receive the amount corresponding to that randomly chosen color for the choice they had made. The game was repeated in three rounds, with the second round offering higher payoffs with a similar spread, and the third round offering higher payoffs than the first two rounds and a wider spread.

The payoffs were slightly asymmetrical because the game design was constrained by the need to use payoffs in even units of currency so that participants could recognize bills immediately and did not have to perform addition sums to recognize the payoff choices. The level and spread of possible game outcomes in the three rounds is shown in Figures 1, 2, and 3. Negative payoffs are not possible, so loss aversion is not considered.

Figure 1: Round 1 payoffs based on participant choice and random-color ball drawn

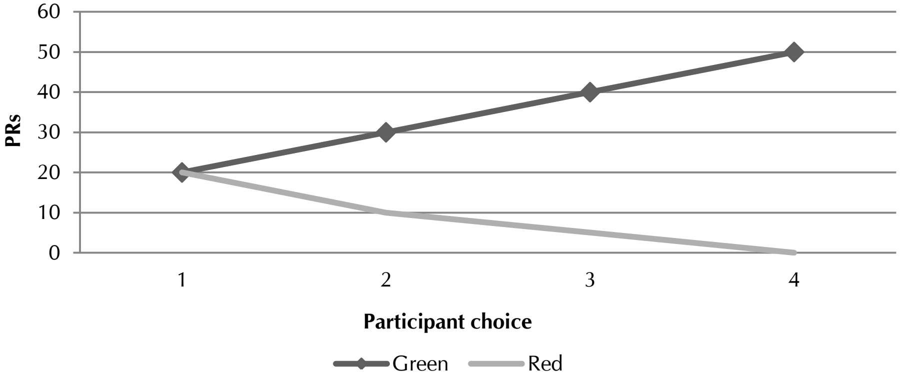


Figure 2: Round 2 payoffs based on participant choice and random-color ball drawn

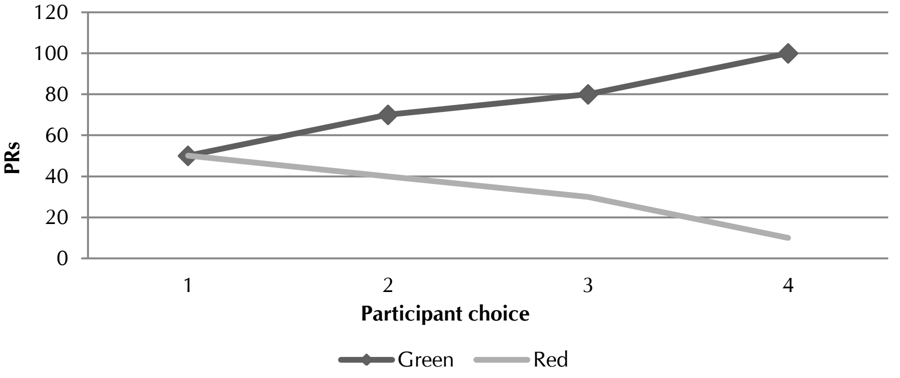
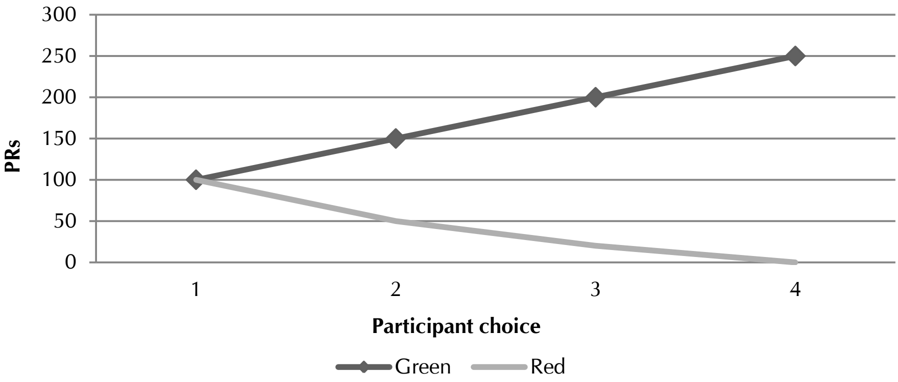


Figure 3: Round 3 payoffs based on participant choice and random-color ball drawn



We measure the lottery game choice variable in several ways: as the average across all rounds, as the variance in choices, and as the final-round choice. We can also estimate collectively over all three rounds to determine whether participant choices were consistent across the three rounds. We test whether each explanatory characteristic has a significant positive or negative impact on making more or less risky choices in the general lottery game setting.

Within each round, the dependent variable is defined as 1 = least risk taking and 4 = most risk taking. As an added measure, we also look at the return and risk characteristics of the choices given in each round. This would entail assigning higher levels of risk aversion to the choice that has a higher compensation for the risk undertaken (i.e., a higher Sharpe ratio). Individuals who are more risk-averse will opt for the choice that provides them with greater compensation for the spread between returns. For all rounds, the Sharpe ratio falls as we move from option 1 to 4. We can take this to mean that the level of risk aversion falls progressively as individuals move from opting for option 1 to 4 (Lettau & Uhlig, 2002).

4.4. Sampling Methodology and Data Construction

Our study focuses on Punjab, which is an advantageous location for sampling both flood-affected and unaffected households, given the five rivers that flow through the province and the geographic diversity of flood effects. There is considerable variation across the province in terms of rainfall levels, advent of floodwater, losses, and external assistance.

Punjab is divided into 36 districts, which are subdivided into 127 *tehsils*.[3] Tehsils generally correspond to towns, but within one tehsil, there may be multiple towns. Each tehsil is further divided into union councils that serve as the local administrative unit and can comprise multiple villages. The general methodology followed by national surveys for rural areas is to then divide these villages further into compact enumerator blocks of 200–250 proximate households out of which 16 are randomly selected for the survey (see the Punjab Bureau of Statistics' Multiple Indicator Cluster Survey [MICS] for 2008/09). Keeping in line with the terminology used in national surveys, these 16 randomly selected households are hereafter referred to as a "cluster."

Our sampling frame is taken from a representative survey of 30,000 households in Punjab that took place in 2011—about a year after the flood had occurred. We sample flood-affected ("treated") households and unaffected ("control") households with similar characteristics along other dimensions that could affect the outcome variables.

4.4.1. Selection of Districts

We test not only the direct impact of flood losses on risk perceptions and risk-taking behavior, but also the indirect impact of having observed a flood event that did not necessarily incur personal loss. We therefore select districts with variations in flood effects ranging from low/zero to moderate to severe.

To select districts that will allow a sufficient range of flood-affected and nonaffected villages, we have used the list of villages that were surveyed under the Multi-cluster Rapid Assessment Mechanism (McRAM) surveys in 2010 as well as information from the MICS 2011 implemented by the Punjab Bureau of Statistics. The McRAM survey, conducted in late August 2010, covered eight of eleven flood-affected districts,[4] and gathered detailed information on flood damage and rehabilitation needs

[3] http://www.punjab.gov.pk/?q=punjab_quick_stats

[4] According to the MICS 2011, the districts where any households reported having been affected by the 2010 floods were Rajanpur, Muzaffargarh, Jhang, Layyah, Dera Ghazi Khan, Sargodha, Multan, Rahimyar Khan, Bhakkar, and Bahawalpur.

(see Figure 4). In Pakistan, the MICS is implemented approximately every four years in Punjab and draws a sample of households from the province's total population, representative at the tehsil level. The most recent MICS took place in 2007/08 and 2011, providing representative household data for the periods preceding and following the 2010 floods.

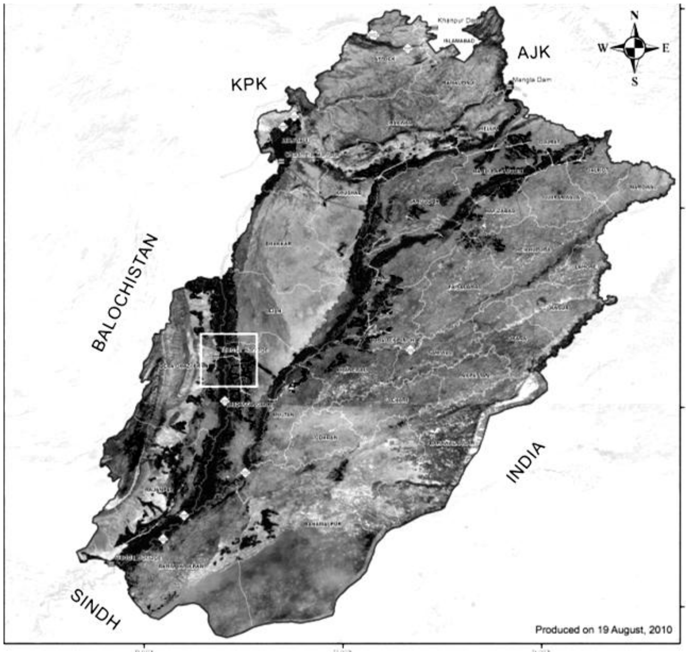
We obtained access to parts of the MICS data from the Punjab Bureau of Statistics—a provincial government agency that administers the survey on behalf of UNICEF.

The 2011 MICS asked each respondent if the 2010 floods had affected their household. Based on the responses to this question, the Punjab Bureau of Statistics designated a cluster as being "flood-affected" if all the randomly selected households in that cluster had responded "yes," and as being "nonflood-affected" if any of the households in the cluster had responded "no."[5] Based on this list of flood-affected clusters, we determine the percentage of flood-affected clusters in each district.[6] These clusters were not only affected more severely by the 2010 floods but, given their proximity to the rivers Indus and Chenab, also tend to be affected more frequently than other clusters.

[5] A cluster was designated as flood-affected only if all the households in that cluster had responded "yes" when asked if they had been affected by the 2010 flood. This was done to make sure there was no error due to the migration of households into and out of the cluster between 2010 and 2011 when the survey was conducted. Only clusters with a minimum likelihood of in- and out-migration were selected as flood-affected.

[6] Note that the MICS is a representative random sample of the total population, not a census of all households, so the percentage of flood-affected clusters calculated is approximate but based on the random sample.

Figure 4: Punjab flood map, August 2010



Source: Lahore University of Management Sciences (floodwaters in red). Available from http://floodmaps.lums.edu.pk/

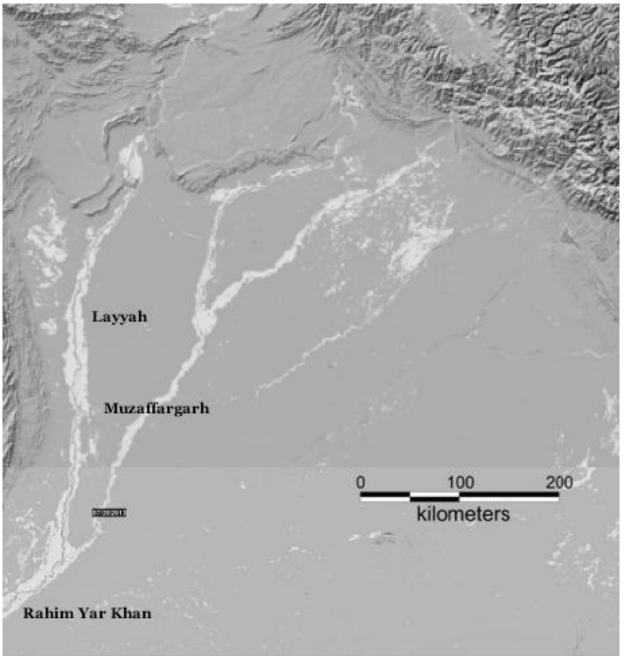
Based on information from both the MICS 2011 and the McRAM survey 2010, the five districts with the highest number of 2010 flood-affected clusters were Rajanpur, Muzaffargarh, Layyah, Dera Ghazi Khan, and Rahimyar Khan. For security reasons, female staff and enumerators could not visit Rajanpur and Dera Ghazi Khan, and so we concentrated our survey in the three remaining districts: Muzaffargarh, Layyah, and Rahimyar Khan. Flood maps obtained from the McRAM survey, the Punjab Provincial Disaster Management Authority, and Lahore University of Management Sciences confirm that each of the three districts lies across the border of flooded and nonflooded areas. According to the MICS 2011, 9 percent of the clusters sampled in Rahimyar Khan can be classified as flooded, while 18 percent of the clusters in Layyah and 51 percent in Muzaffargarh were "flooded" in 2010.

The terrain in these districts is mainly plain with *barani* (rain-fed) crops grown in the eastern half of Layyah. Layyah and Muzaffargarh are bounded to the west by the Indus and by the Chenab to the east. The

Indus flows across Rahimyar Khan's northwestern boundary (Figure 5). In Muzaffargarh and Layyah, the historical mean rainfall is 200–400 mm per annum, while the per annum mean rainfall in Rahimyar Khan is less than 200 mm.

Heavy rainfall in the north of the country causes the Indus and its tributaries to swell and overflow, leading to floods in the plains below. The monsoon rains in 2010 are considered to have been the heaviest (particularly in the north) since 1994 and the sixth heaviest in the last 50 years (Pakistan Meteorological Department, 2010).[7] Figure 5 below displays the surface water record maintained by the Dartmouth Flood Observatory, Colorado, for 2000 to 2013.[8] The blue areas indicate any reservoir or new body of water post-2000; the grey areas are those that have been inundated by floods in the past but where floodwaters have since then receded.

Figure 5: Surface water, 2000–13



[7] Wang, Davies, Huang, and Gillies (2011) attribute the 2010 floods to anomalies in wind circulation and the warming and moistening of the lower troposphere.
[8] http://floodobservatory.colorado.edu

4.4.2. Selection of Villages

Using a list of all the villages in the three focus districts, we sort out the flood-affected and nonflood-affected clusters. We then select clusters in terms of flooded and nonflooded *pairs* based on propensity scores. We use pre-flood data from the 2007/08 MICS (including household wealth and livestock, income, occupation of household head, access to utilities, literacy, health, and access to public infrastructure) to create a score of characteristics correlated with the propensity to be flooded. By matching propensity scores based on these characteristics, we obtain a control group that was not flooded in 2010 but is socioeconomically similar to those that were.[9] The propensity score matching provides us with a balanced sample: there are no significant differences in the mean of the key socioeconomic variables between the treatment and control groups (Table A5 in the Appendix).

Note that this list of flood-affected villages comprises those that were also randomly surveyed in the MICS 2011, when they reported having been flooded in 2010. Among the list of flood-affected villages, we randomly select eight villages as the treatment group: four in Muzaffargarh, two in Layyah, and two in Rahimyar Khan. Using the propensity scores, we map the flooded villages and unaffected villages.

For half (four) the flood-affected villages, we select a control village with a matching propensity score in closest proximity. For the other half (four), we select a control village with a matching propensity score that is located farthest from its paired flooded village.[10] For the "nonflooded" villages, an additional check is performed using our several mapping sources to verify that the village area was not considered flooded during 2010. Five nonflooded villages adjacent to the flooded villages are selected in Muzaffargarh, two in Layyah, and one in Rahimyar Khan. As can be seen in Figure 6, the average distance to one of the rivers (Indus,

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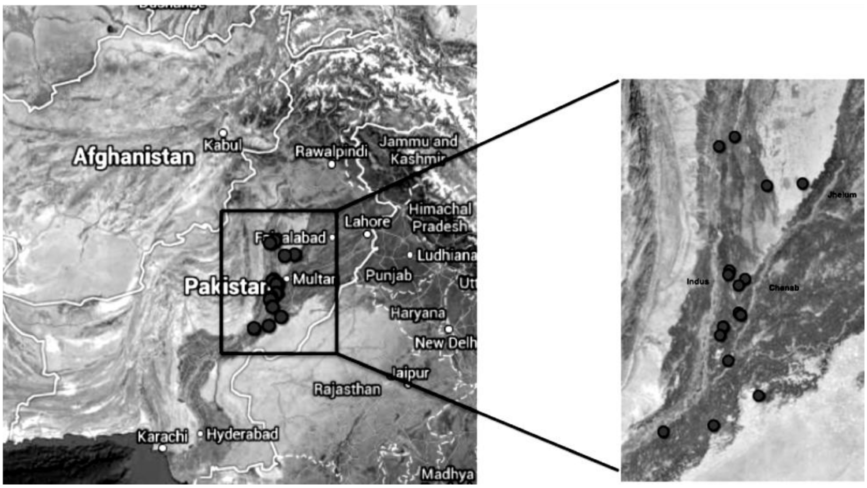
[9] Note that, in using both the 2007/08 and 2011 rounds of the MICS, we have effectively restricted our sample to villages that were common to both rounds. Since the samples in both years were completely random, any villages that were sampled in both rounds are also random. There is no reason to suspect any bias in the selection of these villages. Moreover, re-sampling the same villages in 2011 that were sampled in 2007/08 does not mean that the same households were sampled since the selection of households was random.

[10] The propensity scores of the nonflooded villages do not exceed those of the flooded villages by more than 30 percent of the standard deviation of the scores.

Jhelum, or Chenab) among the control and treatment villages (shown by the dots) is also comparable.

Figure 6: Sample villages selected



4.4.3. Selection of Households

The latest round of the MICS (2011) provides a complete list of households in one randomly selected village block (a settlement or *basti* or a geographically concentrated group of households). We have surveyed 20 households from each village.

Enumerators recorded reasons for why any household was not available for the survey. They were provided with a list of five additional randomly selected households to draw for replacement, which was used when (i) no one was available who could provide household information, (ii) the house was uninhabited, or (iii) household members declined to participate in the survey.

4.4.4. Addressing Potential Attrition Bias

Given that the 2010 floods induced temporary out-migration, there is a possibility that a sample of flood-affected villages might under-represent flood-affected households. We have used multiple sources to approximate village population changes and asked about migration directly in a separate survey module for village leaders who can give village-level estimates.

Although the most recent population census was performed in 1998, the Punjab Bureau of Statistics provides data for 2011 on the approximate number of households in a village. The MICS representative 2008 provincial survey also provides a count of the number of households in each block. Note that, since enumeration blocks within a village are selected randomly for survey in each round of the MICS, it is unlikely that the same enumeration block selected in 2008 would also have been selected in 2011. Comparing the available lists between these two surveys would not, therefore, reliably track households over time.

To collect direct information on village migration, we approached each settlement with the pre-existing MICS roster of households and asked the village leader and/or *numberdar* why any households on the list were missing and, specifically, the number of households that had moved away since 2010 due to the flood. In the household survey, we also asked participants about the extent of migration for various reasons, including the flood.

Characteristics such as risk perception and memory of past events were identified at the individual level. Other characteristics, such as assets and flood losses, which are identical for males and females from the same household, were identified at the household level. There was generally one male and one female from each household. Standard errors are heteroskedasticity-robust and clustered at the village (or census "cluster") level.

Note that the interaction term between living in a flood cluster and having experienced at least one flood captures the within-village variation. Some households that had suffered flood damage were located in villages not officially designated as flood-affected, and vice versa; some households in flood-affected villages had not suffered flood damage at all. This highly location-specific aspect of flood risk is one of the reasons our unique dataset with individual loss measurements is so important.

Household income and savings exhibit wide variation. While the poorest person lives on PRs 100 (approximately $1) per day, the richest in the sample has an annual income of nearly $83,000, with the average individual earning approximately $7,000 per annum.

5. Results

This section gives the results of our survey.

5.1. Summary Statistics

Table 1 provides the summary statistics of the variables used.

Table 1: Summary statistics

Variable	Obs.	Mean	SD	Min.	Max.
Age	384	37.77	12.58	16.00	80.00
Monthly savings (Rs)	640	4094	14,972	0.00	200,000
Monthly income (Rs)	640	27,750	61,315.5	3,000	724,000
Lives in a designated flood cluster	640	0.50	0.50	0.00	1.00
Has experienced floods (including 2010)	640	0.79	0.40	0.00	1.00
Lives in a designated flood cluster and has experienced floods (including 2010)	640	0.48	0.50	0.00	1.00
Has only experienced the 2010 floods	640	0.45	0.50	0.00	1.00
Lives in a designated flood cluster and has only experienced the 2010 floods	640	0.31	0.46	0.00	1.00
Experienced floods prior to 2010 only	640	0.06	0.24	0.00	1.00
Lives in a flood cluster and experienced floods prior to 2010 only	640	0.01	0.07	0.00	1.00
Has taken any mitigation action	640	0.33	0.47	0.00	1.00
Thinks the next flood will be worse	640	0.08	0.27	0.00	1.00
Lives in a designated flood cluster and thinks the next flood will be worse	640	0.04	0.20	0.00	1.00
Lives in a designated flood cluster and thinks nothing works to protect against	640	0.34	0.47	0.00	1.00
Flood crop loss as a percentage of monthly income	640	3.90	16.17	0.00	250.00
Flood house structure loss as a percentage of monthly income	640	5.42	12.38	0.00	133.33
Flood livestock loss as a percentage of monthly income	640	0.64	7.30	0.00	180.00
Flood possessions loss as a percentage of monthly income	640	0.69	3.60	0.00	60.00

Variable	Obs.	Mean	SD	Min.	Max.
Number of floods experienced	627	1.16	1.04	0.00	6.00 a
Number of floods experienced living in a designated flood cluster	627	0.79	1.07	0.00	6.00
Received government assistance	640	0.42	0.49	0.00	1.00
Received government flood BISP assistance	640	0.17	0.37	0.00	1.00
Received government flood cash assistance	640	0.08	0.28	0.00	1.00
Received government flood food assistance	640	0.30	0.46	0.00	1.00
Received government flood non-food assistance	640	0.16	0.36	0.00	1.00
Related to an influential local	640	0.19	0.39	0.00	1.00
Neighbors incurred damage to their houses	640	0.64	0.48	0.00	1.00
Lives in a designated flood cluster and neighbors incurred damage to their houses	640	0.45	0.50	0.00	1.00
Has held insurance in the past	640	0.10	0.30	0.00	1.00
Head of the household is a male	640	0.98	0.16	0.00	1.00
Ratio of males to females in the household	640	1.27	0.72	0.11	6.00
Ratio of members who are under 16 years old	640	0.42	0.16	0.00	0.78
Ratio of members who are migrants	640	0.18	0.25	0.00	1.00
Has experienced hardships in life	640	0.86	0.35	0.00	1.00
Education of household head	626	3.64	4.23	0.00	16.00
Has adopted new techniques	640	0.51	0.50	0.00	1.00
Ratio of members who have their own enterprise	640	0.05	0.08	0.00	0.44
Ratio of members who are in agriculture or livestock	640	0.06	0.09	0.00	0.67
Ratio of members who are laborers	640	0.11	0.11	0.00	0.60
Finished floor (house)	640	0.31	0.46	0.00	1
Finished roof (house)	640	0.77	0.42	0.00	1
House owned by member of household	640	0.87	0.33	0.00	1
Takes mitigation measures now	640	0.15	0.36	0.00	1
Has adopted new building material	637	0.22	0.41	0.00	1

Note: a = Respondents reported floods to have occurred in 1972/73, 1975, 1978, 1987, 1994, 1995, 2003, 2009, 2010, 2011, and 2012.
Source: Authors' calculations.

It is also interesting to note the distribution of different types of losses (Figures A1 to A4 in the Appendix). Note that all distributions are clustered around 0, with losses of personal possessions and livestock equal to 0 up to the 75th percentile. Losses in agriculture and household structure are much higher and more varied. However, apart from extreme values, losses in terms of house damage are, on average, higher and have a lower variation than losses incurred in the form of crop damage.

On average, total flood losses as a percentage of income are almost four times as high in the flooded areas as in the clusters that were designated "nonflooded." Specifically, the loss of crops as a percentage of income is more than three times as high in flooded areas (5.98 percent) as in the nonflooded areas (1.82 percent). On the other hand, losses incurred by household structures (as a percentage of income) are more than four times as high in the flooded clusters (8.82 percent) as in the nonflooded clusters (2.02 percent).

Table 2 provides summary statistics for the dependent variable used. On average, individuals made riskier choices in the second round, and this choice is statistically different in the second and third rounds at a significance level of 5 percent. Among individuals from the same household, females were seen to make marginally riskier choices in each round than their male counterparts, though the difference in choice made is not statistically significant. The correlation between options chosen by male and female individuals belonging to the same household is statistically insignificant at 14 percent.

The following section discusses the regression results from an ordered probit regression of *Game option* on a vector of independent variables. OLS regression was also carried out using the average game choice over the three rounds as the dependent variable. The OLS results are consistent with the results discussed below and are available on request.

Table 2: Summary statistics for game choice

Variable	Obs.	Mean	SD	Min.	Max.
Option – all rounds	1152	2.47	1.09	1	4
Option – Round 1	384	2.45	1.03	1	4
Option – Round 2	384	2.56	1.11	1	4
Option – Round 3	384	2.42	1.12	1	4
Choice made by males and females from the same household					
Option – all rounds, male	456 a	2.45	0.89	1	4
Option – all rounds, female	456	2.53	0.7	1	4
Option – Round 1, male	152	2.43	1.09	1	4
Option – Round 1, female	152	2.49	1.05	1	4
Option – Round 2, male	152	2.46	1.15	1	4
Option – Round 2, female	152	2.5	0.98	1	4
Option – Round 3, male	152	2.44	1.16	1	4
Option – Round 3, female	152	2.59	1.05	1	4
Correlation (average choice by male, average choice by female from the same household)	0.14				

Note: a = Out of the total 384 individuals who participated, only 304 belonged to the same household. Out of 40 households, only one individual, either male or female, participated in the games.
Source: Authors' calculations.

5.2. Regression Results

As shown in Table 3, individuals with flood-related experience do not make significantly different choices from those who have no experience of floods. However, individuals who live in areas designated as flood clusters make systematically more risk-averse choices than those who do not live in flood clusters. This is consistent with the findings of Cameron and Shah (2010).

The effect of flood experience on risk aversion is only significant for individuals who live in areas where floods are more frequent and more severe (the designated *flood clusters*). The positive and significant interaction term between flood clusters and flood experience implies that individuals with flood experience who live in designated flood clusters tend to make more risk-*loving* choices. However, this impact is insignificant for individuals in flood clusters who had only experienced the 2010 flood (columns 2 and 3, Table 3). Finally, individuals who have experienced any flood and those who had experienced floods only prior to 2010 (column 3 and 4, Table 3) show the same degree of risk aversion.[11]

Table 3: Risk aversion and flood experience

Variable	(1) GOption	(2) GOption	(3) GOption	(4) GOption	(5) GOption	(6) GOption
Lives in a designated flood cluster	-0.387**	-0.132	-0.050	-0.344*	-0.376*	-0.293
	(0.194)	(0.134)	(0.110)	(0.195)	(0.216)	(0.236)
Has experienced floods (including 2010)	-0.077				-0.078	-0.104
	(0.112)				(0.116)	(0.106)
Lives in a designated flood cluster and has experienced floods	0.384**			0.305**	0.396**	0.447**
	(0.168)			(0.145)	(0.174)	(0.197)
Has only experienced the 2010 floods		-0.079	0.037	0.036		
		(0.171)	(0.117)	(0.115)		
Lives in a designated flood cluster and has only experienced the 2010 floods		0.208				
		(0.270)				
Experienced floods prior to 2010 only			0.081	0.078		
			(0.133)	(0.133)		
Number of floods experienced					-0.027	
					(0.046)	
Number of floods experienced living in a designated flood cluster						-0.087**
						(0.040)
Round2	0.123**	0.122**	0.123**	0.123**	0.113**	0.114**
	(0.053)	(0.053)	(0.053)	(0.053)	(0.055)	(0.056)
Round3	-0.035	-0.036	-0.036	-0.035	-0.044	-0.044
	(0.086)	(0.086)	(0.086)	(0.086)	(0.088)	(0.088)

[11] Note that there are only three participants who live in a flood cluster and have only experienced floods prior to the 2010 floods. Therefore, an interaction term between pre-2010 flood experience and flood clusters has not been tested.

Variable	(1) GOption	(2) GOption	(3) GOption	(4) GOption	(5) GOption	(6) GOption
Cut1						
Constant	-0.289	-0.238	-0.268	-0.264	-0.067	-0.075
	(0.598)	(0.600)	(0.617)	(0.613)	(0.598)	(0.560)
Cut2						
Constant	0.402	0.453	0.424	0.429	0.623	0.616
	(0.598)	(0.600)	(0.617)	(0.613)	(0.597)	(0.558)
Cut3						
Constant	1.192*	1.243**	1.212*	1.218*	1.412**	1.406**
	(0.619)	(0.620)	(0.636)	(0.632)	(0.614)	(0.576)
Observations	1,152	1,152	1,152	1,152	1,131	1,131

Note: Control variables include: respondent age, respondent gender, household income, household savings, propensity score, and district dummies.
Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculations.

The greater the number of floods experienced, the greater is the likelihood of making risk-*averse* choices. However, this is only true for individuals who live in designated flood clusters, that is, risk-*seeking* behavior in individuals with flood experience in designated flood clusters decreases with each flood that they have experienced. Note also that the inclusion of the interaction term between flood clusters and the *number* of floods experienced renders the coefficient on flood clusters insignificant. Individuals who have experienced multiple floods appear to consistently make more risk-averse choices; this tendency can be attributed to the greater level of risk aversion exhibited in designated flood clusters (Table 3). These results are robust to the estimation methodology. Table A1 in the Appendix gives the OLS results taking the average risk choice over three rounds as the dependent variable.

The impact of perceptions and past mitigating actions is shown in Table 4. Participants who undertook actions to mitigate damage incurred after the 2010 floods, e.g., reinforcing the structure of their house or moving their possessions to a safer location, are also more likely to make more risk-averse choices. Similarly, participants who believed the floods would only worsen in terms of intensity in the future are more likely to make more risk-averse choices. However, individuals who believed that nothing could be done to reduce flood damage tend to make more risk-*seeking* choices (see Table A1, Appendix).

Table 4: Risk aversion and financial constraints

Variable	(1) GOption	(2) GOption	(3) GOption	(4) GOption	(5) GOption
Lives in a designated flood cluster	-0.440**	-0.564***	-0.462**	-0.397**	-0.441**
	(0.193)	(0.214)	(0.181)	(0.184)	(0.214)
Has experienced floods (including 2010)	-0.115	-0.232*	-0.278*	-0.078	-0.102
	(0.114)	(0.130)	(0.144)	(0.113)	(0.122)
Lives in a designated flood cluster and has experienced floods	0.423***	0.496***	0.568***	0.385**	0.441**
	(0.163)	(0.141)	(0.198)	(0.166)	(0.181)
Flood crop loss as a percentage of monthly income	-0.002				
	(0.001)				
Flood possessions loss as a percentage of monthly income	0.002				
	(0.011)				
Flood livestock loss as a percentage of monthly income	-0.000				
	(0.005)				
Flood house structure loss as a percentage of monthly income	0.009***				
	(0.003)				
Round2	0.123**	0.125**	0.125**	0.123**	0.123**
	(0.053)	(0.054)	(0.054)	(0.053)	(0.053)
Round3	-0.035	-0.036	-0.036	-0.035	-0.035
	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)
Neighbors incurred damage to their houses		0.262**	0.343**		
		(0.126)	(0.142)		
Lives in a designated flood cluster and neighbors incurred damage to their houses			-0.225		
			(0.227)		

Variable	(1) GOption	(2) GOption	(3) GOption	(4) GOption	(5) GOption
Received government assistance				0.030	
				(0.095)	
Related to an influential local					-0.158
					(0.143)
Cut1					
Constant	-0.032	-0.307	-0.348	-0.276	-0.237
	(0.637)	(0.612)	(0.606)	(0.589)	(0.598)
Cut2					
Constant	0.660	0.389	0.348	0.416	0.456
	(0.639)	(0.611)	(0.605)	(0.589)	(0.600)
Cut3					
Constant	1.454**	1.182*	1.142*	1.206**	1.248**
	(0.657)	(0.629)	(0.623)	(0.608)	(0.623)
Observations	1,152	1,152	1,152	1,152	1,152

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. These results are after controlling for age, gender, income, savings, propensity score, and district.
Source: Authors' calculations.

In sum, observation seems just as important as experience in determining the effect of floods on risk aversion: individuals who live in designated flood clusters are more likely to make risk-averse choices even if they have never experienced a flood. Personal experience of floods in these areas increases the likelihood of *less* risk-averse choices. Moreover, while the *frequency* of floods experienced has a positive impact on the likelihood of more risk-averse choices being made, the *severity* of floods experienced does not affect risk decision-making. Individuals who had just experienced the 2010 floods did not make significantly different decisions from those who had experienced prior floods.

The type of loss is relevant in estimating the impact of loss on an individual's risk preference. Risk aversion is lower among individuals who have sustained losses as a result of flood damage to their house structure. However, risk aversion is not affected by losses incurred to crops, livestock, or personal possessions (Table 4). Such losses have no differential impacts for individuals who live in designated flood clusters. Risk aversion is also lower for individuals who have observed their neighbors experience flood damage to their house structure. Levels of risk aversion are not different due to the receipt of patron or government assistance.

Losses incurred to house structure (as a percent of monthly income) in 2010 are significantly correlated with the current quality of the house, its ownership, and whether any mitigation measure is now being taken to reinforce the structure. Individuals who incurred lower losses now have better-quality houses though we do not have information to ascertain if this was because of the lower losses incurred earlier. Homeowners incurred higher losses; of these, 40 percent chose to move away to avoid the floodwaters, 14 percent chose to reinforce the house to protect it against flood damage, and only 5 percent did both. Individuals who had incurred higher household losses in the past were taking greater measures to protect against future floods and adopting better building materials (Table 5).

Table 5: Correlation of house loss (percent of monthly income) and house/owner characteristics

	House has a finished floor	House has a finished roof	Owned by a household member	Takes mitigation measures now	Reinforced house before 2010 flood	Believes reinforcing house is effective	Adopted new building materials
House structure loss (% of income)	-0.075*	-0.114*	0.070*	0.080*	0.044	0.063	0.140*

Note: * denotes significance at 10% level.
Source: Authors' calculations.

Risk aversion is significantly higher for individuals who have received cash assistance from the government (cash) but lower for those who are recipients of the Benazir Income Support Program (targeted towards the rural poor). Further, consistent with theory, individuals who have used insurance products in the past make more risk-averse choices. We can also see that individuals from households where a greater proportion of members work in agriculture, livestock, or as laborers, are more risk *loving* (Tables A2 and A3, Appendix).

Age and risk aversion are negatively related.[12] Older individuals tend to make more risk *loving* choices. Furthermore, while risk choices are insignificantly related to income, individuals who save more tend to be more risk-averse. Females tend to make more risk-seeking choices and, consistent with this, individuals from households with a male household head tend to be more risk-averse. Individuals are also more risk-averse the more educated is the household head (Tables A2 and A3, Appendix).

Statistically, individuals from households with a higher number of children (under 16 years of age) do not make more risk-loving or risk-seeking choices, whereas those from households with a larger proportion of members who have in-migrated from another location are more risk-averse. We also see greater risk aversion in individuals who report that their household has adopted new production or consumption techniques (cooking, schooling, agriculture, financing, construction).

The impacts of flood experience and living in a designated flood cluster (discussed above) are robust to adding these individual and household-level controls. Individuals consistently made riskier choices in the second round compared to the first (Tables 2, 3, and A1–A3) and then reverted to relatively more risk-averse choices in the last round.

Participants who had won the higher amount in any option chosen in round 1 made more risk-*seeking* decisions in the second round (Table A4, Appendix). Decisions in the second round were influenced by the number of floods experienced (greater risk aversion) and losses incurred as damage to the house (lower risk aversion), but were not influenced by either flood experience or living in a flood cluster (Table A4, Appendix). This implies that the number of floods experienced and the severity of house structure loss incurred influenced learning between games.

6. Discussion and Conclusion

The question of whether people learn about disaster risk is vital for future disaster risk reduction and preparation. With global flood risk on the rise, understanding individual risk-taking in the face of disaster is especially important because it affects individuals' ability to perceive, pool, and mitigate risks. When event experiences increase risk salience,

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[12] The nonlinear impact of age was tested for and found insignificant.

individuals might overestimate risks. Alternatively, if individuals adjust to coping with risk exposure, they may be less proactive about protecting themselves against potential disaster risk. The behavior of individuals ultimately affects the loss burden on themselves, their communities, and governments.

Risk taking is important for household investment in productive activities (agricultural techniques, education, entrepreneurship, migration). If individuals have fixed preferences, they will always return to their previous investment steady state as their income constraints recover after a shock. If, however, individual risk preferences can change with the experience of rare loss events, this could cause a permanent shift in behavior.

This paper provides evidence that individuals do experience persistent effects on risk-taking after a rare event. However, there is considerable individual variation within this and our unique dataset allows us to examine the effects of such variations in losses and observations, which has not been discussed in the existing literature. Although the direction of risk-taking effects is broadly consistent with the literature at the community level, we find that individuals who have suffered more severe recent flood losses make riskier choices on average, even after controlling for income and savings effects. Individuals with a greater number of lifetime flood experiences make more risk-averse choices, even when controlling for measures of geographic flood propensity to separate out potential unobserved characteristics that might lead risk-averse individuals to live in higher-risk areas. In sum, these results indicate that the timing, frequency, and severity of losses are important qualifiers.

Furthermore, observation of neighbor or community losses is a powerful mechanism in risk behavior. Those individuals who have observed their neighbors or community incur losses react in similar ways to those who have experienced personal losses, with stronger effects for those who have observed more severe neighbor losses.

Finally, using multiple game rounds has allowed us to examine the risk-learning process and to compare learning for people who have experienced or observed a real loss event. We find that real-world loss experience or observation strengthens the pattern of behavior changes after experiencing losses in the game situation. Those who had experienced or observed the most severe (house structure) actual losses tended to increase their risk-taking throughout the rounds of the game. Those who had experienced more pre-2010 floods tended to make less significant changes in strategy throughout the game. This finding points to an interesting parallel of the external validity of learning about risk in laboratory versus field environments.

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Appendix

Table A1: Ordered probit results for risk aversion and perceptions

Variable	(1) GOption	(2) GOption	(3) GOption	(4) GOption	(5) GOption
Lives in a designated flood cluster	-0.366*	-0.315	-0.404**	-0.391**	-0.551**
	(0.196)	(0.192)	(0.200)	(0.197)	(0.261)
Has experienced floods (including 2010)	-0.056	-0.082	-0.076	-0.081	-0.088
	(0.112)	(0.114)	(0.113)	(0.111)	(0.112)
Lives in a designated flood cluster and has experienced floods	0.373**	0.422**	0.402**	0.417**	0.378*
	(0.164)	(0.182)	(0.176)	(0.173)	(0.206)
Took any mitigation action	-0.096				
	(0.128)				
Round2	0.123**	0.124**	0.123**	0.123**	0.123**
	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)
Round3	-0.035	-0.035	-0.035	-0.035	-0.036
	(0.086)	(0.086)	(0.086)	(0.086)	(0.086)
Lives in designated flood cluster and took mitigation action		-0.260*			
		(0.138)			
Thinks the next flood will be worse			-0.237**		
			(0.110)		
Lives in a designated flood cluster and thinks the next flood will be worse				-0.349**	
				(0.145)	
Lives in a designated flood cluster and believes nothing protects against flood damages					0.263**
					(0.131)
Cut1					
Constant	-0.242	-0.224	-0.361	-0.353	-0.355
	(0.593)	(0.584)	(0.584)	(0.577)	(0.584)

Variable	(1) GOption	(2) GOption	(3) GOption	(4) GOption	(5) GOption
Cut2					
Constant	0.449	0.469	0.332	0.340	0.339
	(0.592)	(0.583)	(0.586)	(0.577)	(0.583)
Cut3					
Constant	1.240**	1.262**	1.123*	1.132*	1.132*
	(0.609)	(0.602)	(0.606)	(0.599)	(0.603)
Observations	1,152	1,152	1,152	1,152	1,152

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. These results are after controlling for age, gender, income, savings, propensity score, and district.
Source: Authors' calculations.

Table A2: Ordered probit results for risk aversion and household/individual characteristics

Variable	(1) GOption	(2) GOption	(3) GOption
Age	0.009*	0.009**	0.009*
	(0.005)	(0.004)	(0.005)
Participant is a female	0.150	0.154	0.163
	(0.101)	(0.105)	(0.106)
Log(savings)	-0.023*	-0.023*	-0.019
	(0.012)	(0.012)	(0.012)
Log(monthly income)	0.013	0.022	-0.006
	(0.059)	(0.061)	(0.062)
Lives in a designated flood cluster	-0.361**	-0.413**	-0.389**
	(0.177)	(0.194)	(0.174)
Has experienced floods (including 2010)	-0.036	-0.059	-0.080
	(0.104)	(0.105)	(0.123)
Lives in a designated flood cluster and has experienced floods (including 2010)	0.353**	0.382**	0.392**
	(0.151)	(0.163)	(0.169)
Received government flood cash assistance	-0.159*		
	(0.092)		
Received government flood nonfood assistance	-0.227		
	(0.185)		
Received government flood food assistance	0.132		

Variable	(1) GOption	(2) GOption	(3) GOption
	(0.087)		
Received government flood BISP assistance	0.216**		
	(0.096)		
Round2	0.125**	0.123**	0.122**
	(0.053)	(0.053)	(0.054)
Round3	-0.035	-0.036	-0.035
	(0.086)	(0.086)	(0.086)
Has had insurance in the past		-0.207**	
		(0.103)	
Head of the household is a male			-0.106
			(0.360)
Ratio of males to females in the household			0.021
			(0.052)
Ratio of members who are under 16 years old			0.214
			(0.175)
Ratio of members who are migrants			-0.282**
			(0.129)
Cut 1: Constant	-0.234	-0.137	-0.421
	(0.587)	(0.602)	(0.691)
Cut 2: Constant	0.462	0.557	0.272
	(0.588)	(0.601)	(0.690)
Cut 3: Constant	1.257**	1.348**	1.065
	(0.604)	(0.628)	(0.694)
Observations	1,152	1,152	1,152

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. These results are after controlling for propensity score, district and the experience of hardships such as crime, job loss, safety threats, and deaths in the family.
Source: Authors' calculations.

Table A3: Ordered probit results for risk aversion and household/individual characteristics

Variable	(1) GOption	(2) GOption	(3) GOption	(4) GOption
Age	0.009**	0.009*	0.009**	0.009**
	(0.004)	(0.005)	(0.004)	(0.004)
Participant is a female	0.141	0.139	0.224**	0.149
	(0.101)	(0.104)	(0.113)	(0.104)
Log(savings)	-0.019*	-0.023**	-0.017	-0.022*
	(0.011)	(0.011)	(0.012)	(0.011)
Log(monthly income)	-0.001	0.035	0.011	0.025
	(0.057)	(0.055)	(0.059)	(0.055)
	(0.315)	(0.325)	(0.327)	(0.342)
Lives in a designated flood cluster	-0.352**	-0.388*	-0.347	-0.426**
	(0.168)	(0.211)	(0.221)	(0.195)
Has experienced floods (including 2010)	-0.087	-0.050	-0.071	-0.074
	(0.116)	(0.113)	(0.113)	(0.109)
Lives in a designated flood cluster and has experienced floods (including 2010)	0.331**	0.341*	0.339*	0.431***
	(0.138)	(0.186)	(0.194)	(0.164)
Round2	0.123**	0.110*	0.124**	0.124**
	(0.053)	(0.057)	(0.053)	(0.053)
Round3	-0.035	-0.041	-0.036	-0.035
	(0.086)	(0.089)	(0.086)	(0.086)
Years of education attained by the household head		-0.035***		
		(0.011)		
Has adopted new techniques			-0.228***	
			(0.079)	
Ratio of members who have their own enterprise				0.818
				(0.627)
Ratio of members who are in the agriculture or livestock industry				0.936*
				(0.480)
Ratio of members who are laborers				1.048***
				(0.374)
cut1				
Constant	-0.205	-0.163	-0.322	0.088
	(0.620)	(0.582)	(0.611)	(0.588)

cut2				
Constant	0.488	0.537	0.374	0.786
	(0.622)	(0.587)	(0.611)	(0.592)
cut3				
Constant	1.279**	1.330**	1.169*	1.580***
	(0.641)	(0.604)	(0.633)	(0.610)
Observations	1,152	1,113	1,152	1,152

Note: Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. These results are after controlling for propensity score, district and the experience of hardships such as crime, job loss, safety threats, and deaths in the family.
Source: Authors' calculations.

Table A4: Risk preferences and learning between rounds

Variable	**(1)**	**(2)**	**(3)**	**(4)**
Lives in a designated flood cluster	-0.333*	-0.375*	-0.400**	-0.415**
	(0.187)	(0.221)	(0.192)	(0.199)
Has experienced floods (including 2010)	-0.093	-0.089	-0.128	-0.090
	(0.106)	(0.109)	(0.100)	(0.112)
Lives in a designated flood cluster and has experienced floods	0.384**	0.352	0.440***	0.405**
	(0.162)	(0.226)	(0.164)	(0.167)
Round2	-0.035	0.067	0.111	0.080
	(0.089)	(0.091)	(0.085)	(0.056)
Round3	-0.035	-0.035	-0.044	-0.035
	(0.086)	(0.086)	(0.088)	(0.086)
Lives in flood cluster. Round2		-0.034		
		(0.311)		
Has flood experience. Round2		0.036		
		(0.079)		
Lives in flood cluster and has flood experience. Round2		0.093		
		(0.319)		
Higher amount won in round1. Round2	0.381***			
	(0.122)			
Number of floods experienced. Round2			0.060	
			(0.056)	
Number of flood experienced and lives in flood cluster. Round2			-0.084*	
			(0.051)	

HH loss share of income. Round2				0.008**
				(0.004)
Cut1				
Constant	-0.310	-0.307	-0.121	-0.213
	(0.576)	(0.600)	(0.585)	(0.620)
Cut2				
Constant	0.386	0.384	0.569	0.479
	(0.577)	(0.600)	(0.585)	(0.621)
Cut3				
Constant	1.181**	1.175*	1.358**	1.270**
	(0.598)	(0.620)	(0.601)	(0.642)
Observations	1,152	1,152	1,131	1,152

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculations.

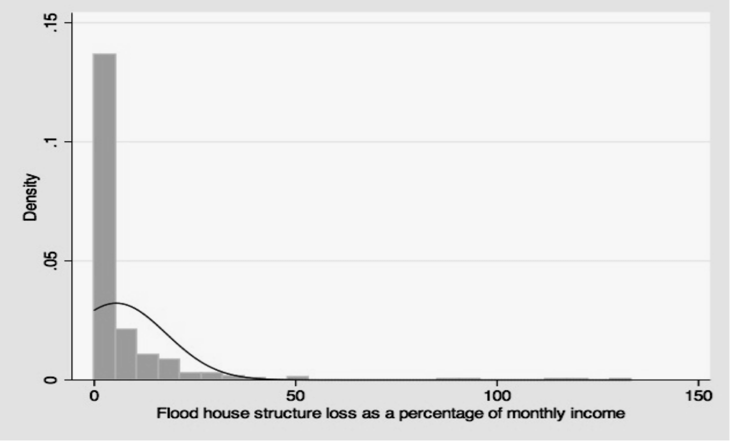
Table A5: Results of t-test to check sample balance

	Mean			t-test	
Variable	**Treated**	**Control**	**%bias**	**T**	**p> |t|**
Literacy	0.232	0.219	11.2	0.54	0.593
Education of household head (years)	3.011	2.721	19.0	0.92	0.361
Primary occupation					
Agriculture	0.065	0.071	-17.3	-0.75	0.454
Self-employed	0.019	0.020	-9.0	-0.47	0.642
Government employee	0.040	0.038	8.1	0.37	0.711
Average monthly Income	2419.3	233.4	7.7	0.59	0.559
Wealth index	-1.050	-1.051	0.1	0.01	0.996
Average distance to public health facility	0.280	0.243	11.2	0.49	0.622
Average distance to boys' primary school	0.757	0.770	-5.4	-0.23	0.818
Average distance to girls' primary school	0.6875	0.712	-8.8	-0.38	0.705
Average distance to boys' secondary school	0.243	0.204	11.0	0.51	0.612
Average distance to girls' secondary school	0.209	0.176	9.6	0.45	0.656
% of households with electricity	0.766	0.748	7.6	0.37	0.716
% of households with permanent floor	0.244	0.255	-6.6	-0.36	0.721
% of households with permanent roof	0.605	0.625	-10.1	-0.46	0.65
% of households with permanent walls	0.411	0.442	-14.1	-0.69	0.491
Average number of households who receive pensions	2.007	1.997	12.3	0.61	0.546
Average number of cattle owned by	3.374	3.294	6.1	0.23	0.816

households					
Average number of goats owned by households	2.999	2.772	11.8	0.60	0.553
Average poultry owned by households	2.182	1.747	27.9	1.23	0.224
Measure of cluster size (weights)	0.947	1.052	-25.1	-0.79	0.432

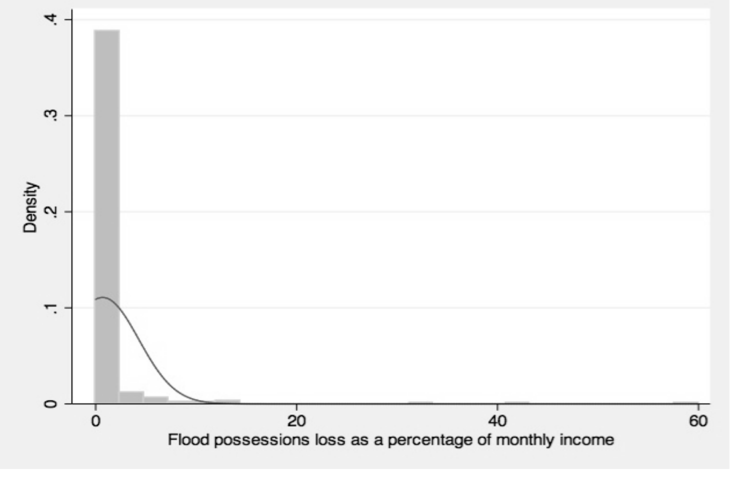
Source: Authors' calculations.

Figure A1: Distribution of household structure loss



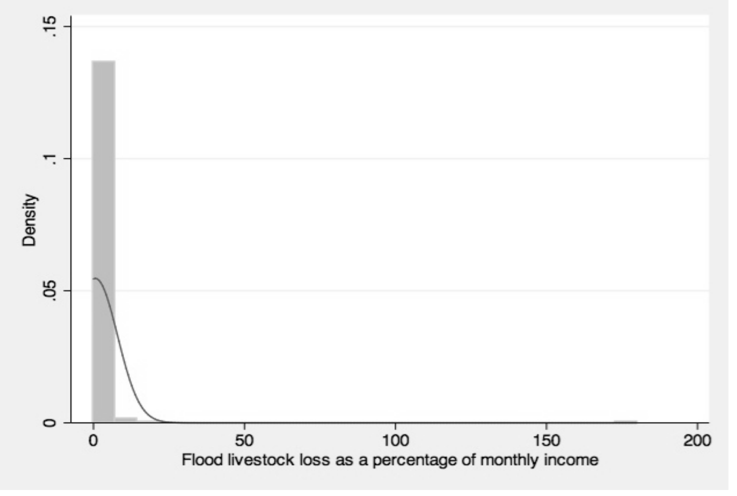
Source: Based on authors' calculations.

Figure A2: Distribution of personal possessions loss



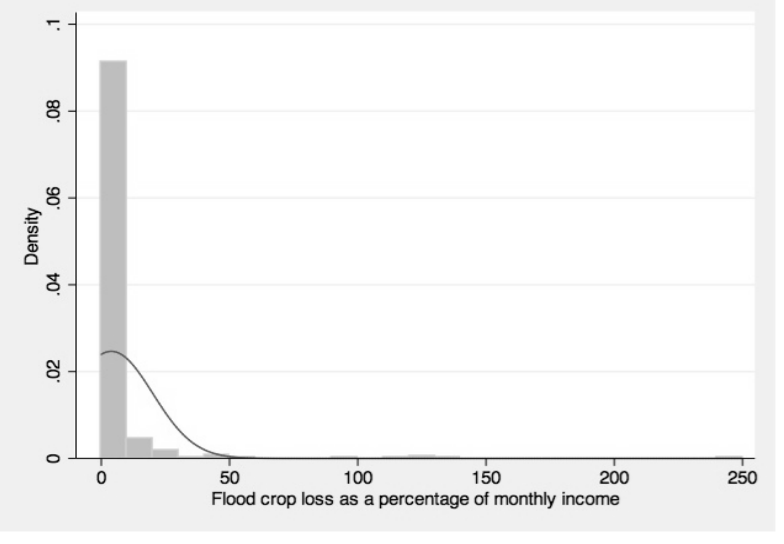
Source: Based on authors' calculations.

Figure A3: Distribution of livestock loss



Source: Based on authors' calculations.

Figure A4: Distribution of agricultural loss



Source: Based on authors' calculations.

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