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Natural Disasters and Social Capital: Evidence from a Field Experiment in Pakistan

Uzma Afzal, Ginger Turner and Farah Said

Centre for Research in Economics and Business
Lahore School of Economics

Centre for Research in Economics and Business (CREB)

Lahore School of Economics

Intersection Main Boulevard Phase VI, DHA and Burki Road
Lahore 53200, Pakistan
Tel: 042-36561230; 042-36560936
Email: creb@lahoreschool.edu.pk

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Uzma Afzal
Assistant Professor and Research Fellow, CREB

Ginger Turner
Senior Economist and Vice-President, Swiss Re
Global Governance Futures Fellow

Farah Said
Assistant Professor and Research Fellow, CREB

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Lahore School of Economics
Intersection of Main Boulevard, Phase VI, DHA, and Burki Road
Lahore 53200, Pakistan
Tel.: +92 42 3656 1230
www.creb.org.pk
creb@lahoreschool.edu.pk

Price: PRs100

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

Apart from the economic and structural losses associated with a natural disaster, the communities it affects also undergo a loss in social capital, which can affect perceptions, levels of trust, and social cohesion. This working paper examines the impact of a severe natural disaster (the heavy floods that affected large parts of Pakistan in 2010) on the social capital of disaster-stricken communities by conducting a series of behavioral experiments and household surveys three years afterward. It contributes to the current literature by combining household-level information with behavioral games and testing the impact of individual characteristics, perceptions, and external assistance on people's private contribution toward a pool of public goods in a post-disaster setting.

We find that social capital, measured by respondents' contribution toward a public good, is positively associated with a higher number of floods experienced. However, for individuals living in the 2010 flood-affected communities, contributions decline with each successive experience. This suggests that the experience of a severe natural disaster has a negative effect on social capital compared to frequent experiences of mild natural disasters where social capital is positively affected.

Natural Disasters and Social Capital: Evidence from a Field Experiment in Pakistan

1. Introduction

Given that the scale of destruction resulting from natural disasters has increased in recent decades, a growing body of literature has focused on the implications of natural disasters in a behavioral and economic development context. Economists are keen to look at the impact of natural disasters on selected macro- and microeconomic subjects such as output, income, migration, human capital, risk aversion, and trust (see, for example, Noy, 2009; Yang, 2008a, 2008b; Baez, de la Fuente, & Santo, 2010; Cameron & Shah, 2010; Zylberberg, 2010; Fleming, Chong, & Bejarano, 2011).

In the wake of a traumatic event, apart from economic and structural losses, communities also undergo a loss in social capital (Fleming et al., 2011), which can affect their perceptions, levels of trust, and social cohesion in the short, and possibly longer, term. Moreover, a loss in social capital tends to disrupt and slow down the recovery of disaster-stricken communities. Public and private relief efforts initiated immediately after a disaster can influence the volume of social capital, depending on how fair and effective such initiatives are. A public goods game, which allows participants to contribute voluntarily toward a common pool for the benefit of the community, helps capture the underlying social cohesion and interdependence and is, therefore, a good indicator of social capital.

The losses ensuing from natural disasters are more pronounced in developing countries, which bear a greater burden of death and damage, averaging around US$ 35 billion a year (Cameron & Shah, 2010). Historically, while Pakistan has witnessed floods of varying frequency and severity, in 2010 the country experienced its worst floods in over 60 years: exceptionally heavy monsoon rains led to a death toll of almost 2,000, leaving behind about 20 million affected individuals and about US$ 45 billion in damaged property and infrastructure (Webster, Toma, & Kim, 2011). In this context, the rare-flood event serves as a natural experiment to study the differences in the social capital of people who have undergone a traumatic event.

Of the few studies that look at how natural disasters affect social capital (see Toya & Skidmore, 2013; Fleming et al., 2011; Douty, 1972), there is no consensus on the latter's direction of change after a disaster. Moreover, studies such as Fleming et al. (2011), Andrabi and Das (2010), and Toya and Skidmore (2013) examine levels of social capital after a severe natural disaster or small, frequent natural disasters. This study is unique in that it distinguishes between frequent experiences of mild floods and a severe flood experience and draws conclusions based on these differences.

Combining household-level information with behavioral games for households from comparable communities located in the flood and nonflood clusters of 2010, we examine the impact of individual characteristics, perceptions, and external assistance on people's private contribution toward a pool of public goods. We believe that behavioral experiments provide a more accurate indication of behavioral social capital as responses determine real payoffs and participants take the exercise more seriously.

We find that social capital, as measured by participants' contribution toward public goods, is positively associated with the number of floods experienced. However, individuals living in the designated 2010 flood clusters contribute less with each successive experience. This is interesting because it suggests that the experience of a severe natural disaster has a negative effect on social capital compared to frequent experiences of milder floods where social capital is positively affected.

Our results show that one-time government assistance in the form of food results in higher contributions toward the community pool. Individuals who had received lump-sum monetary transfers under the Watan card scheme continued to contribute so long as they were not living in a flood cluster. Recipients living in a flood cluster (that is, those affected most by the 2010 floods) were less inclined to contribute. This is an important finding, given that there has been no systematic review of the Watan card scheme post-2010.

Individual characteristics such as positive expectations and resilience in the aftermath of a disaster are associated with greater contributions toward public goods in general. However, as people's experience of floods increases, their resilience can also result in smaller contributions, perhaps because their self-reliance surpasses their interdependence with the community. Consistent with the literature (Toya & Skidmore, 2013), we find that a shared sense of loss, measured by flood-related losses in the form of injury to friends or family, results in higher contributions and, therefore, expands the community's social capital.

The paper proceeds as follows. Section 2 presents a theoretical framework that draws on the related literature. Section 3 describes the study's econometric model and hypotheses. Section 4 explains the sampling method, data collection, and experimental design. Section 5 presents descriptive statistics. Section 6 analyzes the results obtained and Section 7 concludes the study.

2. Literature Review and Theoretical Framework

This section appraises the existing literature on the subject and presents a theoretical framework for the study's public goods game.

2.1. The Provision of Public Goods

There is an abundance of empirical and theoretical literature on the provision of public goods. Studies range across topics such as the private versus public provision of public goods, the efficacy of matching contributions from the state, pure versus impure altruism, how the provision of public goods can crowd out private charity (the neutrality theorem), and social capital and private contributions toward public goods (see Baker, Walker, & Williams, 2009; Anderson, Mellor, & Milyo, 2004; Chan, Mestelman, Moir, & Muller, 1996; Bergstrom, Blume, & Varian, 1986; Andreoni, 1989, 1990; Warr, 1982).

Anderson et al. (2004) draw on the relationship between social capital and public goods provision, where trust is presented as a measure of social capital. They combine results from the General Social Survey (GSS) on trusting behavior with the outcomes of a public goods experiment and find that trust, measured by the statement "most people can be trusted" (p. 375), is strongly associated with higher contributions in the public goods experiment. Similarly, Karlan (2005) finds that more positive responses to GSS questions predict higher repayment of loans and higher savings, although loan repayment is not correlated with higher contributions in a public goods game. In a panel data analysis, Toya and Skidmore (2013) study how the natural environment, particularly in the form of natural disasters, can affect trust levels in a community. They conclude that, aside from the devastating socioeconomic impact of a disaster, a positive spillover can be greater social trust.

Since the GSS responses that measure social capital do not necessarily match the behavior in an experimental research setup, recent studies are inclined to use laboratory experimental evidence to study behavior. However, the results obtained from a laboratory setting apply better to developed countries where the participants selected represent an educated population capable of working with computers. In order to study social capital in a developing countries context, behavioral experiments allow researchers to observe and understand behavior by using real-life examples and an interactive setup; this surpasses the quality of information gathered from responses to abstract survey questions. Giving people real incentives helps reveal the norms that guide their decision-making, which can, therefore, be analyzed with greater precision (Fleming et al., 2011).

Disasters that affect many people simultaneously can have opposite effects on community cooperation. On one hand, cooperation during relief efforts and reconstruction may enhance social cohesion, interdependence, and the shared benefits accruing from public goods in the affected community. On the other hand, the heterogeneous impacts of disasters and external assistance may cause jealousy and divide opinions as to the use of limited resources.

This is also likely to be true if the provision of public resources is insufficient or the response of the authorities is politically motivated. In the aftermath of a disaster, goodwill and trust may increase toward particular agents such as public officials, donors, and volunteers, but not necessarily among people from the same community. For example, Andrabi and Das (2010) have found that, after the 2005 earthquake in northern Pakistan, communities' trust toward foreigners in the earthquake zone increased substantially—primarily due to the inflow of foreign aid—while levels of mutual trust among locals remained much lower.

In the wake of the insecurity associated with a natural disaster, certain behavioral heuristics can help us understand the decisions individuals make. A popular approach to making judgments under uncertainty is to anchor them to preexisting impressions, perceptions, or values and then adjust such judgments until a plausible conclusion is reached. Often, the adjustment process is inadequate such that decision biases remain visible:

this is known as the "anchoring-and-adjustment" heuristic (Epley & Gilovich, 2006).

The "availability" heuristic is the propensity of individuals to judge the probability of events based on the most salient information. The "representativeness" heuristic leads individuals to overweigh salient events; the "conservatism" heuristic leads individuals to underestimate high values (Tversky & Kahneman, 1973). As an example of the availability heuristic, Deryugina (2010) cites the Gallup polls in the US to show that individuals are more likely to report a belief in climate change when the weather has been hot in the past week. According to Mullainathan (2002), when current events remind individuals of similar past events such that multiple events are compounded into their current perception, it gives rise to a heuristic of "associativeness."

Preferences are considered immutable individual characteristics while constraints are expected to change. This implies that, while constraints or circumstances can affect the choices individuals make, their underlying preferences remain unaffected. The literature on psychology and behavioral sciences indicates that individual experiences can alter preferences and allow behavioral learning over the course of time (Cassar, Healy, & von Kessler, 2011; Voors et al., 2010). In this context, Fleming et al. (2011) investigate the level of social capital in earthquake-stricken Chile and report a decline in trustworthiness among villagers in the affected areas. Studying a sample of Thai villages affected by the 2004 Asian tsunami, Cassar et al. (2011) find that individuals affected by the disaster were more trusting and trustworthy as well as more risk-averse than individuals living in similar communities not affected by the tsunami.

The importance of social capital in enhancing welfare and economic development through better public institutions, efficient markets, and greater accountability has already been established in the literature (see Fukuyama, 1995; Knack & Keefer, 1997; Alesina & La Ferrara, 2002; Uslaner, 2005; Dearmon & Grier, 2009). However, there is a lack of consensus on the role of social capital in post-disaster recovery and on whether the endowment of social capital is enhanced or diminished after a disaster. This can cause optimal policy responses to fail.

By utilizing the experience of the 2010 floods in Pakistan, we can determine if people who experienced these floods display similar patterns of contribution to a public good and, therefore, have similar levels of social capital relative to the control villages. Given that parts of Punjab are subject to perennial minor flooding, we can also compare the behavior of two categories of people: (i) individuals who have experienced numerous minor floods as well as the 2010 floods, and (ii) those who have experienced *either* minor floods *or* the 2010 floods. The household survey provides us with individual, household, and community-level information to match the individual responses obtained in the behavioral games. This enables us to investigate the mechanisms that underlie contributions made toward a public pool.

This paper makes a unique contribution to the literature by combining survey and experiment data to test whether the experience of different kinds of flood events have varied effects on people's perception of public goods and, therefore, on social capital in their community.

2.2. The Public Goods Experiment

In consonance with participants' literacy skills, we designed a game they could easily understand that would still elicit their behavioral social capital. In the experiment, each participant received an endowment of PRs 100 (equivalent to US$ 1); the game was played with pseudo-money. At the beginning of the experiment, participants were described a situation in which they had the opportunity to contribute toward a common pool of money that would be spent on a "community project" such as repairing a school building, installing a tube-well or paving a road—any expenditure from which the whole community could benefit. The game was designed as a typical public goods game where people's contributions were matched (doubled) and then divided among them to reflect the shared benefit accruing from the community project.

Participants were divided into groups of four. The identity of members in each group was not disclosed, but participants were told that each group's contributions would be doubled and then distributed among its members. They could choose to contribute any amount between 0 and 100 (in denominations of ten) and keep for themselves any money not contributed, along with the money they received from the common pool.

Apart from a demonstration and practice round, the experiment was conducted for three rounds. Participants received real payoffs at the end of the experiment for any one randomly selected round out of the three played. This was done to curtail the influence of winnings in earlier rounds on expectations and performance in later rounds.

Trust in other people indicates social capital and can be strongly associated with higher contributions in a public goods experiment (Anderson et al., 2004; Karlan, 2005). In consonance with the literature, we suggest that allowing participants to contribute voluntarily toward a common pool for the benefit of their community helps capture its underlying social cohesion, trust, and interdependence. Individual contributions are thus a good indicator of the level of social capital in a community.

3. Econometric Model and Hypotheses

To estimate the impact of a rare-flood event on individuals' contribution toward a public pool, we estimate the following equation using a linear regression model:

$$Contribution_{ij} = \alpha + \sum^{i} \sum^{j} \beta_1(Disaster_{ij}) + \sum^{i} \sum^{j} \beta_2(Individual_{ij}) + \varepsilon_{ij}$$

$Contribution_{ij}$ is the amount of money that individual i has contributed in round j of the game. The maximum a participant can contribute in each round is PRs 100 and the minimum is PRs 0 (in denominations of ten). Higher contributions reflect greater social capital. $Disaster_{ij}$ is a vector of flood-experience variables such as whether the individual lives in a village that experienced the severe 2010 floods, the number of times the individual has experienced floods, and other indicators that gauge the nature of such experience. $Individual_{ij}$ is a vector of participant characteristics such as individual and household information, external assistance, expectations about the future, and the adoption of different techniques.[1] ε_{ij} represents the standard errors that are heteroskedasticity-robust and clustered at the village level. Information on the control and explanatory variables has been gathered from a household survey conducted in April 2013.

[1] The control variables include age, gender, the log of monthly income, the log of household savings, and district and round dummies. The variables of interest are the types of government assistance (flood assistance in the form of cash, food, nonfood, and Watan cards and nonflood assistance in the form of BISP cash transfers), expectations concerning subsequent floods, expectations about oneself, the intention to migrate, and the adoption of new techniques (agricultural practices, cooking fuel, building materials).

3.1. Flood Experience: Incidence Versus Severity

We test if people with any or no experience of floods contribute differently toward public goods compared to those who live in areas that were affected by the 2010 floods (referred to as “flood clusters”). Individuals with greater experience of floods can be expected to react differently from those who have experienced fewer floods or only the 2010 floods.

Specifically, we use information from the survey to test for some interesting differences in the types of flood-related experience, for example, whether individuals who live in a 2010 flood cluster and have experienced floods make different contributions to public goods and, therefore, reflect different levels of social capital compared to those who have experienced a similar number of floods but not the 2010 floods. This enables us to isolate the impact of different flood-related experiences on people’s attitude toward public goods. However, if people’s experience of the 2010 floods varies across households in the flood clusters, the overall effect on social capital may be difficult to predict.

3.2. External Assistance

In a natural disaster, the role of the government is twofold: apart from immediate rescue and rehabilitation, a key task is to ensure that the benefits of government assistance are shared by the majority of those affected. Based on our data, we estimate the impact of government assistance for rehabilitation on private contributions to public goods. A negative coefficient (for government assistance) should support the neutrality theorem, which indicates that the private provision of public goods is being crowded out by government provision.

Andrabi and Das (2010) find that the humanitarian assistance provided by foreign agencies in the wake of the 2005 earthquake in Pakistan had a lasting impact on local individuals’ trust and attitudes toward foreigners. Thus, individuals who have received government assistance in the past or had regular interaction with government officials with respect to other types of transfer payments from the state are more likely to expect external assistance to compensate for their losses. Such individuals can, therefore, be expected to contribute less toward a public pool.

Negative contributions could also be due to a greater sense of personal loss, a sense of isolation from the rest of the country, or greater belief in self-reliance in difficult times. Anderson et al. (2004) argue that social capital, measured by trust in other people, may be strongly associated with higher contributions in public goods experiments. Similarly, Karlan (2005) finds that individuals who show more trust in a trust game are more likely to contribute toward the public good.

Some studies have looked at how attitudes toward risk change in the wake of a natural disaster. Cameron and Shah (2010) observe that individuals who have suffered a flood or earthquake in the last three years tend to be more risk-averse than those who have remained safe. Using the information on risk aversion (measured by a lottery game) and insurance demand from our experimental games, we test if risk aversion leads to greater contributions toward public goods. While this does not allow us to trace a relationship between risk aversion and social capital, it could yield an interesting result in itself. Similarly, we also test if greater insurance demand results in smaller contributions, reflecting greater self-sufficiency.

3.3. Self-Perception and Expectations

Individual perceptions about the future can also affect social capital. Tversky and Kahneman's (1973) "representativeness" heuristic, which indicates that individuals tend to overweigh salient events, may be relevant to people living in a flood cluster as the experience is likely to influence their expectations about floods in the future. Cameron and Shah (2010) find that individuals who have recently experienced a natural disaster report a greater probability of another (more severe) natural disaster occurring in the next 12 months compared to those who have not experienced a disaster. On the other hand, it is important to note that self-perception may not necessarily be affected by the experience of a flood.

Like preferences, self-perception can also be anchored and adjust slowly. According to Tversky and Kahneman's (1974) anchoring-and-adjustment heuristic, the initial information anchors or tends to draw out the subsequent adjustment process. Individuals who were optimistic about their future prior to a flood-event experience continue to carry the same perceptions even after a natural disaster. In this study, people with positive self-perceptions and expectations are expected to contribute more to public goods.

3.4. Adoption of New Practices

Resilience is "most frequently defined as positive adaptation despite adversity" (Fleming & Ledogar, 2008). We measure resilience at the individual level as the ability to adopt new practices such as the use of different cooking fuels or building materials and new agricultural practices. Our hypothesis will determine whether resilient individuals contribute more toward public goods, assuming that the contribution can be considered an investment in any local project. The assumption behind this hypothesis is that individuals already investing in ways to improve their daily lives or business are more likely to appreciate complementary investments at the community level compared to those who have not adopted new techniques. Greater contributions would, therefore, indicate more social capital.

However, it is also possible that some households will have adopted new techniques because of their frequent experience of floods. In this case, a second hypothesis to test is whether the contribution toward public goods by individuals who have adopted new techniques and experienced more floods is different from those who have experienced fewer floods. It is possible that, for the former, self-reliance surpasses interdependence.

4. Sampling, Data Collection, and Experimental Design

This section explains how the sample districts, flood clusters, and households were selected, and how the public goods experiment was carried out.

4.1. Sampling Strategy

This study focuses on Punjab, Pakistan's largest province. With five rivers flowing through Punjab, it serves as an advantageous site for sampling both flood-affected and unaffected households. Due to the geographic diversity of flood effects, there is considerable variation across the region in terms of rainfall levels, the extent of flooding, and external assistance.

Punjab comprises 36 districts subdivided into 127 *tehsils*.[2] Generally, a tehsil corresponds to one town, but can also span more than one. Each tehsil is further divided into union councils that serve as the local

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[2] http://www.punjab.gov.pk/?q=punjab quick stats

administrative unit and comprise multiple villages. For rural areas, it is standard practice for national surveys to divide villages into compact enumerator blocks of 200–250 proximate households, of which 16 households (called a "cluster") are randomly selected for the survey.

We have followed the framework of the Multiple Indicator Cluster Survey (MICS) for 2011, which comprises a sample of 30,000 households across Punjab and is representative at the tehsil level. The MICS is carried out every four years by the Punjab Bureau of Statistics. The most recent rounds were carried out in 2007/08 and 2011, thus providing representative household-level data prior to and shortly after the 2010 floods.

4.1.1. Selection of Districts

We selected a set of districts that allow sufficient variation in terms of flooding, ranging from nonflooded to low, moderate, and severe effects. In order to classify districts as either flooded or nonflooded, the 2011 MICS asked each respondent if the 2010 floods had affected their household. Based on the responses to this question, a cluster was classified as "flood-affected" in 2010 if *all* the randomly selected households in that cluster responded "yes" to the question and "nonflood-affected" if *any* of the households in that cluster responded "no."[3] Based on this list of flood-affected clusters, we determined the percentage of flood-affected clusters in each of the sample districts.[4] These clusters were affected more severely than others by the 2010 floods and, given their proximity to the rivers Indus and Chenab, they tend to be affected by floods more frequently than other clusters.

The Punjab Bureau of Statistics administered the United Nations Multi-cluster Rapid Assessment Mechanism (McRAM) in late August 2010 in eight of the eleven flood-affected districts.[5] The purpose of the survey was to gather detailed information on flood damage and rehabilitation needs.

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[3] These criteria were set to eliminate any errors due to the migration of households into or out of the cluster between 2010 and 2011 when the survey was being conducted; only clusters with a minimum likelihood of migration were deemed flood-affected.

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

[5] According to the MICS 2011, districts in which any household reported being affected by the 2010 floods included Rajanpur, Muzaffargarh, Jhang, Layyah, Dera Ghazi Khan, Sargodha, Multan, Rahimyar Khan, Bhakkar, and Bahawalpur.

Based on the 2011 MICS and 2010 McRAM, the five districts with the highest number of 2010 flood-affected clusters were Rajanpur, Muzaffargarh, Layyah, Dera Ghazi Khan, and Rahimyar Khan. Due to safety concerns, female staff and enumerators could not visit Rajanpur or Dera Ghazi Khan and, therefore, our survey was carried out in the three remaining districts: Muzaffargarh, Layyah, and Rahimyar Khan.

Flood maps obtained from the McRAM survey, the Punjab Provincial Disaster Management Authority, and the Lahore University of Management Sciences confirm that each of the three districts straddles both flooded and nonflooded areas. According to the 2011 MICS, 51 percent of the clusters sampled in Muzaffargarh, 18 percent in Layyah, and 9 percent in Rahimyar Khan were classified as "flooded" in 2010.

4.1.2. Selection of Village Clusters

A set of villages common to both rounds of the MICS (2007/08 and 2011) was drawn from the three districts. Eight pairs of flood and nonflood clusters were then selected based on their propensity scores. The pre-flood 2007/08 MICS was used to calculate the propensity score of characteristics correlated with the propensity for being flooded. The score is based on the distance to the river, household wealth, livestock, income, the household head's occupation, access to utilities, literacy, health, and access to public infrastructure.[6]

Using the propensity score, we created a control group of flood-affected villages with a similar propensity for being flooded based on geographic and socioeconomic factors; the control group was not flooded in 2010.[7] This technique of matching propensity scores helped us select a balanced sample with no significant differences in the mean of the key

[6] The three districts share similar environmental factors and terrain. Muzaffargarh and Layyah have received an annual historical mean of 200–400 mm of rainfall. Rahimyar Khan receives less than 200 mm per annum. However, the monsoon rains in 2010 were deemed the heaviest since 1994 and the sixth highest in the last 50 years (Pakistan Meteorological Department, www.pmd.gov.pk).

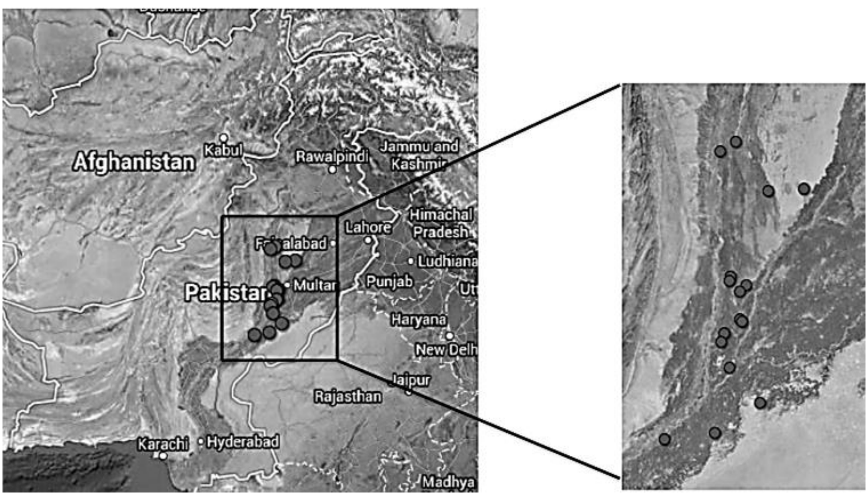
[7] Note that, in using both rounds of the MICS, we have effectively restricted our sample to villages that were common to both rounds. Since the samples for both years were completely random, any villages sampled in both rounds are also random. There is no reason to suspect any bias in the selection of these villages. Also, resampling the same villages in 2011 does not imply that the same households were sampled since the selection of households is random.

socioeconomic variables between the treatment and control groups (see Table A1 in the Appendix).

The flooded and unaffected villages were then mapped on the basis of their propensity scores. From the set of flood-affected villages, we randomly selected eight to constitute the treatment group. Of these, four villages were in Muzaffargarh, two in Layyah, and two in Rahimyar Khan. For half (four) the flood-affected villages, we selected as a control village whichever had a matching propensity score closest to the flooding site. For the remaining four villages, the control village chosen had a matching propensity score farthest from the flooding.[8] For the "nonflooded" villages, an additional check was performed using several map sources to verify that the village area was not considered "flooded" in 2010. Five nonflooded villages adjacent to the flooded villages were selected from Muzaffargarh, along with two from Layyah, and one from Rahimyar Khan.

Figure 1 maps the location of the 16 clusters visited. As we can see, the average distance between the treatment/control villages and any one of the three rivers (Indus, Jhelum, and Chenab) is comparable.

Figure 1: Map of sample clusters



Source: Google Maps.

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

4.1.3. Selection of Households

For each village it has surveyed, the MICS 2011 provides a complete list of households for a randomly selected block (a settlement or *basti* or a geographically concentrated group of households). For the purpose of our study, 20 households from this list were randomly selected and surveyed in each case; the enumerators were given a list of five additional randomly selected households from which to draw replacements in case they could not interview a particular household. In such cases, they recorded why a household could not be surveyed, for example, if (i) no one was available to provide household information, (ii) the house itself was uninhabited, or (iii) household members had declined to participate in the survey. Participants received no monetary compensation for the survey.

Community leaders were also interviewed to verify the village-level information collected. Since the 2010 floods had induced temporary out-migration, it was possible that a sample of flood-affected villages might underrepresent the flood-affected households. The interviews we conducted confirmed that the population composition had changed very little from before the 2010 floods. The average total attrition of individuals moving away from the village for any reason since 2010 was approximately 1.5 percent of the population. This small proportion supports the assumption that the flood propensity scores based on pre-flood data remain representative for the 2010 and post-flood population.

4.2. Survey and Experiment Participants

Our survey covered a total of 320 households across the three districts of Muzaffargarh, Layyah, and Rahimyar Khan. Two questionnaires—one targeting male respondents and the other, female respondents—were administered in each household, yielding 640 respondents in all. Of this group, 384 individuals (192 men and 192 women) participated in the public goods experiment.

Out of the 20 households surveyed in each village, a random subset of 15 households—comprising one male and one female participant each to maintain a gender balance—was invited to participate in the experiment. Participants were offered a fee for showing up on time. To fill the required number of slots (12 men and 12 women), we over-recruited by 20 percent; any excess arrivals were paid the minimum earning of PRs 150 (equivalent to US$ 1.50) and asked to leave before the session. There were no sessions for which fewer than 12 men and 12 women arrived.

In accordance with local custom, men and women interacted separately; female enumerators carried out the interviews and experiments involving female respondents. The experiment sessions for men and women were carried out simultaneously in different rooms or nearby venues to limit information sharing. Only one experiment session was held in each village to prevent any informal discussions outside the session venue, which might otherwise have influenced participants' behavior and expectations and affected our results.

5. Descriptive Statistics

For the purpose of this study, two kinds of surveys were carried out in each village: (i) interviews with community leaders and (ii) household and individual surveys. The interviews were conducted to gather village-level information such as the size of the village and its public infrastructure. The household-level surveys focused on household demographics, income, expenditure, and ownership of assets (land, livestock, durables).

The individual-level questions targeted adult male and female respondents who were invited to participate in the behavioral games. These questions focused on perceptions of self, resilience to change, traumatic experiences (e.g., crime, injury, death), experience of natural disasters, personal and neighbors' losses resulting from the 2010 floods, mitigation and prevention activities, the adoption of new techniques, flood information sources and warning times, community and external assistance including Watan cards, risk perception and risk-taking preferences in hypothetical situations, expectations concerning subsequent floods, financial and expenditure aspirations, and social networks and patronage. Table 1 presents the descriptive statistics collected for key variables of interest in our analysis.

Table 1: Summary statistics – household survey

Variable	Obs.	Mean	SD	Min.	Max.
Age (years)	384	37.77	12.58	16	80
Participant is female	640	0.50	0.50	0	1
Household total monthly income (PRs)	636	23,445.8	28,540	3,000	228,500
Household savings (PRs)	640	4,095.7	14,971.8	0	200,000
Household head's years of schooling	626	3.64	4.23	0	16
Lives in 2010 flood cluster	640	0.50	0.50	0	1
Has experienced floods (including in 2010)	640	0.79	0.40	0	1
Lives in 2010 flood cluster and has experienced floods	640	0.48	0.50	0	1
Lives in 2010 flood cluster and number of floods experienced	627	0.79	1.07	0	6
Number of floods experienced	627	1.16	1.04	0	6
Has adopted new practices: any of eight categories	640	0.51	0.50	0	1
Number of floods experienced and has adopted new practices	627	0.58	0.87	0	5
Has adopted new practices: new agricultural practices	634	0.10	0.30	0	1
Has adopted new practices: fuel/cooking techniques	635	0.17	0.38	0	1
Has adopted new practices: use of building materials	637	0.22	0.41	0	1
Flood-related livestock loss as a percentage of monthly income	640	0.64	7.30	0	180
Flood-related household possessions loss as a percentage of monthly income	640	0.69	3.60	0	60
Total flood-related loss as a percentage of monthly income	640	10.65	28.87	0	480
Has learned any mitigation methods from the 2010 floods	640	0.23	0.42	0	1
Has received government assistance	640	0.42	0.49	0	1
Has received government flood assistance (cash)	640	0.08	0.28	0	1
Has received government flood assistance (nonfood)	640	0.16	0.36	0	1

Variable	Obs.	Mean	SD	Min.	Max.
Has received government flood assistance (food)	640	0.30	0.46	0	1
Lives in 2010 flood cluster and has received flood assistance (food)	640	0.23	0.42	0	1
Has received government flood assistance under BISP	640	0.17	0.37	0	1
Lives in 2010 flood cluster and has received BISP assistance	640	0.10	0.30	0	1
Has received a Watan card	312	0.72	0.45	0	1
Lives in a designated flood cluster and has received a Watan card	312	0.58	0.49	0	1
Insurance game: insurance chosen in at least 1 out of 15 rounds	383	0.95	0.21	0	1
Average lottery game choice (higher value = riskier choice)	384	2.47	0.82	1	4
Prefers PRs 500 to game with 50% chance of winning PRs 1,000	640	0.58	0.49	0	1
Self-reported ability to recover faster from unexpected events	640	0.20	0.40	0	1
Has experienced hardships in life	640	0.86	0.35	0	1
Has had insurance in the past	640	0.10	0.30	0	1
Feels better prepared now than before the 2010 floods	640	0.31	0.46	0	1
Number of friends and family injured due to floods	640	4.17	18.9	0	200
Plans to move to another settlement	640	0.14	0.35	0	1
Lives in 2010 flood cluster and plans to move to another settlement	640	0.07	0.25	0	1
Willing to predict occurrence of the next flood	640	0.21	0.41	0	1
Lives in 2010 flood cluster and can predict number of seasons before the next flood	640	0.13	0.33	0	1
Expects to be better off in the future than today	640	0.45	0.50	0	1
Reports being in “good health today”	640	0.40	0.49	0	1
Thinks the next flood will be similar to the previous flood	640	0.08	0.27	0	1

Variable	Obs.	Mean	SD	Min.	Max.
Thinks the next flood will not be as bad as the previous flood	640	0.05	0.23	0	1
Thinks the next flood will be worse than the previous flood	640	0.34	0.47	0	1
Village flood propensity score	640	0.40	0.19	0.15	0.78
Muzaffargarh district	640	0.56	0.50	0	1
Layyah district	640	0.25	0.43	0	1
Rahimyar Khan district	640	0.19	0.39	0	1

Source: Authors' estimates.

From Table 2, we can see that, on average, participants contributed PRs 52 in all three rounds of the game. It is interesting to note that women consistently contributed less than men. However, both men and women increased their contributions in successive rounds. The contributions in the first round were the lowest, but rose in the second round for both men and women. There may have been a learning effect at work here, with participants initially contributing less but then understanding that they would receive higher payments if they increased their contributions, based on the payoffs received from the common pool in the first round. By the third round, the contributions had dwindled slightly compared to the second round, but were still higher than in the first round. One possible explanation for this is that participants were now trying to earn more by contributing less, based on the expectation that other participants would continue to contribute more: a classic example of the free-rider problem.

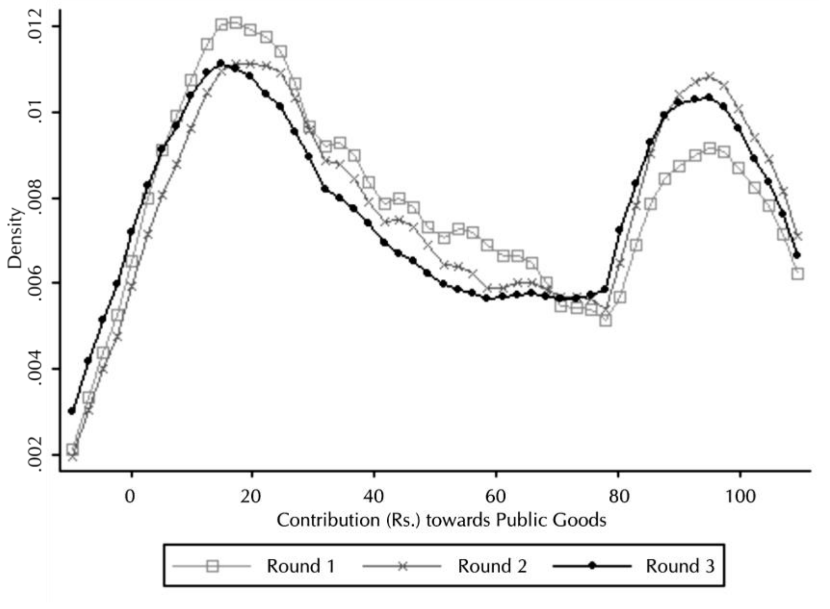
Table 2: Summary statistics – public goods game

Variable (PRs)	Obs.	Mean	SD	Min.	Max.
Average contribution in all rounds	384	52.13	32.40	0	100
Average contribution (men)	192	60.28	30.96	0	100
Average contribution (women)	192	43.98	31.82	0	100
Average contribution in round 1	384	50.47	34.49	0	100
Round 1 (men)	192	59.48	33.23	0	100
Round 1 (women)	192	41.46	33.43	0	100
Average contribution in round 2	384	53.83	35.20	0	100
Round 2 (men)	192	61.30	34.35	0	100
Round 2 (women)	192	46.35	34.54	0	100
Average contribution in round 3	384	52.08	36.24	0	100
Round 3 (men)	192	60.05	34.80	0	100
Round 3 (women)	192	44.11	35.98	0	100

Note: PRs 100 = US$ 1 approximately.
Source: Authors' estimates.

A t-test was performed to establish the difference in mean contributions across rounds as being statistically different from one another (Table A2 in the Appendix). The results indicate that the contributions in round 2 are statistically greater than those in rounds 1 and 3. Figure 2 displays the kernel density estimates of contributions across the three rounds. From the figure, we can see that there are two peaks in the contributions made across all three rounds: PRs 20 and PRs 100. There is a shift toward the higher contributions in rounds 2 and 3. The distribution of contributions in each round is illustrated in detail in Figures A1 to A3 in the Appendix. About 28 percent of the participants contributed PRs 100 in both rounds 2 and 3. There is a 75 percent correlation between participants who contributed PRs 100 in both rounds 1 and 2 and those who contributed PRs 100 in both rounds 2 and 3.

Figure 2: Kernel density estimates of participants' contributions across rounds



Source: Authors' estimates.

6. Results

Table 3 gives the linear regression results for the flood-related experience of people living in the flood clusters and in the control areas. It may be useful to reiterate that flood clusters comprise those villages where *all* households reported having been affected by the 2010 floods. All the regressions control for the age and gender of the participant, household income and savings, districts, propensity scores, and game rounds.

In order to isolate the impact of diverse flood-related experiences, we treat the frequency of floods experienced differently from the experience of a single flood-event. As Table 3 shows, individuals living in a flood cluster do not make significantly different contributions from those not living in a flood cluster. However, it appears that contributions increase with the number of floods experienced and that individuals pay, on average, PRs 4 more with each successive experience. People who have experienced only the 2010 floods contribute PRs 14.50 more, on average. Conversely, individuals living in a flood cluster behave differently from the control group, contributing significantly less as their experience of floods increases. Moreover, for individuals living in a flood cluster, any experience of floods results in higher contributions.

Table 4 includes external assistance variables. We test for the impact of different types of government assistance on contributions toward public goods. The results indicate that post-flood food assistance has a significant and positive effect on contributions, even after controlling for flood clusters. Individuals who received food assistance from the government are more likely to contribute toward public goods than those who did not receive food assistance, even though they may have received other types of government assistance during the floods.[9]

The Benazir Income Support Program (BISP) is a poverty alleviation fund that was initiated by the government in 2007 to help poor households by giving them monthly transfer payments of PRs 1,000. While this is not flood-related assistance, we control for households that have been receiving BISP assistance and find that those not belonging to a flood cluster contribute PRs 12 less, on average. This negative contribution might be explained by the fact that these are poorer households. To verify this, we perform a t-test for the difference in mean income levels of households who receive BISP payments and those who do not (Table A3 in the Appendix). Households receiving BISP payments have a mean income of PRs 18,469 while the other group has a mean income of PRs 24,463; from the t-test, we see that the two means are statistically different from each other. However, since we have already controlled for income in the regressions, there may be other exogenous factors driving this result.

In the wake of the 2010 floods, the provincial governments initiated the Citizens Damage Compensation Program under which flood-affected households were paid PRs 40,000 in two tranches (made accessible through individual ATM cards called "Watan cards") to provide financial relief. Column 2 of Table 4 shows that households with a Watan card

[9] The impact of food assistance is robust even when an interaction term comprising food assistance and flood clusters is included in the regression. The interaction term remains insignificant.

contribute PRs 19 more, on average, than households who do not have a Watan card. However, after controlling for flood clusters, contributions decline by PRs 28. The regression also includes risk aversion measured by the average of the responses obtained over three rounds of a lottery game; this has a positive but not significant effect on contributions. The same holds true for a survey question response measuring risk aversion in which individuals were asked if they preferred to receive PRs 500 now instead of a 50 percent chance of winning PRs 1,000.

We test for individuals' perceptions of self and the future in Table 5. In the survey, individuals were asked about their expectations for the future. In a cultural context, people are generally unwilling to predict adversity since it is considered a sign of pessimism.[10] Our results show that individuals who are willing to predict how many seasons before the next floods occur contribute less than those who do not want to make any predictions. Moreover, individuals who feel the next flood will be similar to—as opposed to better or worse than—the previous floods contribute significantly more.

Optimistic individuals who expect to be better off in the future make significantly positive contributions compared to those who are not hopeful about the future. Although the coefficient is insignificant, individuals who feel they are better prepared for floods now than in the past contribute more. Respondents planning to move to another settlement for any reason contribute less than their counterparts, which could be due to their diminished association with the existing community as they intend to migrate. A shared sense of loss stemming from the experience of a flood also affects social capital: we observe that individuals who have undergone such losses in the form of injury experienced by friends or family contribute significantly more toward public goods.

In Table 6, we test whether people who adapt to their circumstances and adopt new practices in their way of life contribute differently from others. While resilience can be measured in many ways and possibly through multiple characteristics, we consider the ability to adopt new techniques a suitable proxy for gauging resilience. Individuals who have adopted any new practice (in agriculture or in the use of cooking fuels or building materials) appear to contribute significantly more than those who have

[10] Only 21 percent of the respondents predicted when the next floods might occur.

not. However, this effect becomes negative as the number of floods experienced increases. This is an interesting result because it suggests that, while resilience may lead to higher contributions, resilient people are apt to contribute less when they experience more floods.

A more detailed analysis of the type of practice adopted reveals that individuals who have adopted new agricultural techniques contribute significantly more toward public goods. A larger flood-related loss as a percentage of total monthly income has a positive impact on contributions, although people who have lost their livestock as a consequence of floods make significantly negative contributions, controlling for income. The respondent's level of education does not affect contributions toward a common pool.

The round effects appear to be robust in all the regressions. Individuals make significantly larger contributions in round 2 than in round 1. The results support our discussion of the changes in behavior across rounds (Section 5). While we suggest the possibility of learning across rounds, three rounds (excluding a practice and demonstration round) may not be sufficient to establish the presence of a learning effect. It does, however, suggest that participants consciously change their contribution pattern across the three rounds.

From the district dummies, we see that participants from Layyah and, in selected cases, Muzaffargarh contribute significantly more than those in Rahimyar Khan. The control variables age and age-squared do not significantly affect contributions and neither do income or savings. Women contribute significantly less than men. This result is consistent with the findings of Brown-Kruse and Hummels (1993), who study the gender effect in public goods contributions in a laboratory setting. In another study by Carpenter, Daniere, and Takahashi (2004), women participants were seen to contribute significantly less toward public goods compared to men in Bangkok, Thailand, with the trend reversed for women in Ho Chi Minh City, Vietnam.

Table 3: Participants' experience of floods

Variable	Contribution					
	(1)	(2)	(3)	(4)	(5)	(6)
Age (years)	-0.029	-0.031	-0.064	-0.077	-0.022	-0.056
	(0.106)	(0.112)	(0.113)	(0.112)	(0.105)	(0.109)
Participant is female	-17.501***	-17.308***	-18.275***	-18.888***	-16.407***	-18.672***
	(5.433)	(5.468)	(5.251)	(5.507)	(5.512)	(5.443)
Log of monthly income	-1.271	-0.625	-0.370	-0.606	-0.112	-0.153
	(2.167)	(1.878)	(2.031)	(1.773)	(1.530)	(1.431)
Log of household savings	-0.359	-0.288	-0.373	-0.393	-0.450	-0.565
	(0.394)	(0.383)	(0.357)	(0.396)	(0.379)	(0.394)
Lives in 2010 flood cluster		7.299	3.502	14.585	-16.527	-21.209
		(8.944)	(8.982)	(10.560)	(11.948)	(12.190)
Number of floods experienced			4.046*	10.333***		9.963***
			(1.916)	(3.157)		(3.026)
Lives in 2010 flood cluster and number of floods experienced				-10.339**		-6.165**
				(3.673)		(2.381)
Has experienced floods (including in 2010)					6.232	-4.070
					(5.929)	(7.650)
Lives in 2010 flood cluster and has experienced floods					16.642*	25.661**
					(9.346)	(10.060)
Has only experienced the 2010 floods					14.556***	17.248***
					(4.509)	(3.765)
Muzaffargarh district	20.133	27.277	29.170	28.010*	20.174	22.040
	(12.329)	(17.297)	(17.712)	(15.138)	(13.279)	(12.914)

	Contribution					
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Layyah district	36.422***	39.375***	42.724***	42.828***	37.451***	39.744***
	(9.603)	(11.465)	(13.353)	(12.578)	(9.992)	(11.200)
Village flood propensity score	2.221	-13.174	-9.942	-15.750	-16.513	-17.186
	(27.944)	(37.634)	(35.659)	(29.496)	(25.648)	(20.864)
Round 2	3.403***	3.403***	3.440***	3.440***	3.403***	3.440***
	(1.021)	(1.021)	(1.034)	(1.035)	(1.023)	(1.036)
Round 3	1.623	1.623	1.653	1.653	1.623	1.653
	(1.407)	(1.407)	(1.452)	(1.453)	(1.409)	(1.455)
Constant	52.412*	43.722*	37.421	38.973*	36.840**	37.043**
	(25.713)	(23.314)	(25.155)	(21.724)	(16.832)	(15.633)
Observations	1,146	1,146	1,125	1,125	1,146	1,125
R-squared	0.172	0.179	0.184	0.201	0.223	0.240
Adjusted R-squared	0.165	0.171	0.176	0.192	0.214	0.230

Notes: Heteroskedasticity-robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
PRs 100 = US$ 1 approximately.
Source: Authors' estimates.

Table 4: External assistance received

	Contribution				
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Age (years)	-0.069	-0.365**	-0.066	-0.078	-0.089
	(0.109)	(0.156)	(0.116)	(0.115)	(0.103)
Participant is female	-18.891***	-21.592***	-18.734***	-18.990***	-18.678***
	(5.522)	(6.789)	(5.532)	(5.480)	(5.508)
Log of monthly income	-0.532	-4.142	-0.519	-0.600	-0.832
	(1.790)	(2.427)	(1.726)	(1.809)	(1.883)
Log of household savings	-0.373	-0.389	-0.413	-0.395	-0.360
	(0.397)	(0.322)	(0.415)	(0.387)	(0.384)
Lives in 2010 flood cluster	13.056	39.750***	9.235	14.548	14.154
	(10.990)	(10.127)	(10.261)	(10.708)	(10.193)
Number of floods experienced	10.323***	14.303***	8.825***	10.354***	10.312***
	(3.099)	(3.330)	(2.708)	(3.087)	(3.160)
Lives in 2010 flood cluster and number of floods experienced	-10.322**	-14.424***	-8.551**	-10.389**	-10.288**
	(3.661)	(3.277)	(3.483)	(3.597)	(3.620)
Has received government flood assistance (cash)			1.695		
			(5.587)		
Has received government flood assistance (nonfood)			-2.853		
			(3.833)		
Has received government flood assistance (food)			8.780**		
			(4.076)		
Has received government flood assistance under BISP			-11.751**		
			(4.694)		

	Contribution				
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Lives in 2010 flood cluster and has received BISP assistance			9.899		
			(6.891)		
Has received a Watan card		18.877*			
		(8.878)			
Lives in 2010 flood cluster and has received a Watan card		-28.649**			
		(9.586)			
Has received government assistance	3.785				
	(3.082)				
Insurance game: insurance chosen in at least 1 out of 15 rounds				1.265	
				(6.735)	
Has had insurance in the past				-0.319	
				(4.946)	
Average lottery game choice (higher value = riskier choice)					0.073
					(2.018)
Prefers PRs 500 to a game with 50% chance of winning PRs 1,000					2.181
					(3.494)
Muzaffargarh district	26.416*	24.506**	28.503*	27.978*	27.345*
	(14.771)	(9.991)	(14.151)	(15.248)	(14.397)
Layyah district	42.294***	41.321***	43.013***	42.750***	42.396***
	(12.412)	(7.316)	(12.115)	(12.633)	(11.887)
Village flood propensity score	-15.408	-16.716	-17.107	-15.729	-14.500
	(28.987)	(19.180)	(26.102)	(29.629)	(28.766)

Variable	Contribution (1)	(2)	(3)	(4)	(5)
Round 2	3.440***	4.242**	3.440***	3.440***	3.440***
	(1.035)	(1.693)	(1.037)	(1.036)	(1.036)
Round 3	1.653	1.818	1.653	1.653	1.653
	(1.454)	(2.187)	(1.456)	(1.454)	(1.454)
Constant	37.822	74.077**	39.599*	37.919	40.154
	(21.801)	(24.926)	(20.695)	(23.244)	(22.974)
Observations	1,125	594	1,125	1,125	1,125
R-squared	0.203	0.297	0.215	0.201	0.202
Adjusted R-squared	0.194	0.280	0.203	0.191	0.192

Notes: Heteroskedasticity-robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
PRs 100 = US$ 1 approximately.
Source: Authors' estimates.

Table 5: Self-perception and future expectations

	Contribution					
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Age (years)	-0.065	-0.040	-0.081	-0.063	-0.070	-0.076
	(0.112)	(0.111)	(0.106)	(0.108)	(0.113)	(0.109)
Participant is female	-18.296***	-18.009***	-18.510***	-18.574***	-18.346***	-19.093***
	(5.378)	(5.243)	(5.579)	(5.577)	(5.363)	(5.445)
Log of monthly income	-1.016	-0.124	-0.473	-0.338	-0.737	-0.848
	(1.747)	(1.830)	(1.819)	(1.798)	(1.811)	(1.735)
Log of household savings	-0.464	-0.374	-0.380	-0.353	-0.447	-0.401
	(0.395)	(0.393)	(0.394)	(0.399)	(0.392)	(0.399)
Lives in 2010 flood cluster	14.850	13.470	13.031	14.722	12.754	15.112
	(10.145)	(10.549)	(10.040)	(10.188)	(10.702)	(10.492)
Number of floods experienced	10.657***	9.736***	10.740***	10.428***	9.838***	10.231***
	(3.065)	(3.117)	(3.167)	(3.037)	(3.083)	(3.118)
Lives in 2010 flood cluster and number of floods experienced	-9.853**	-9.632**	-10.640**	-10.429***	-9.596**	-10.496**
	(3.596)	(3.669)	(3.641)	(3.506)	(3.762)	(3.606)
How many seasons from now do you expect the next flood to occur?	-10.345*					
	(5.135)					
Expects to be better off in the future than today	5.256*					
	(2.532)					
Household head's years of schooling		-0.080				
		(0.337)				

Variable	**Contribution**					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Self-reported ability to recover faster from unexpected events		-1.560				
		(3.684)				
Plans to move to another settlement			-12.021*			
			(6.063)			
Lives in flood cluster and plans to move to another settlement			11.262			
			(7.078)			
Thinks the next flood will be similar to the previous flood				9.597**		
				(4.181)		
Feels better prepared now than before the 2010 floods					3.914	
					(2.822)	
Reports being in "good health today"					0.723	
					(0.909)	
Has known friends and family who were injured due to floods						0.129***
						(0.042)
Muzaffargarh district	26.858*	27.325*	28.571*	28.252*	26.411*	29.014*
	(14.361)	(15.448)	(14.803)	(14.967)	(14.909)	(15.177)
Layyah district	39.331***	42.542***	42.899***	43.503***	42.137***	43.799***
	(12.287)	(12.752)	(12.369)	(12.590)	(12.463)	(12.667)
Village flood propensity score	-17.522	-10.834	-15.740	-16.582	-14.553	-17.071
	(28.905)	(28.937)	(27.925)	(28.599)	(29.472)	(29.342)
Round 2	3.440***	3.453***	3.440***	3.440***	3.440***	3.440***
	(1.036)	(1.123)	(1.036)	(1.035)	(1.036)	(1.035)

Variable	Contribution					
	(1)	(2)	(3)	(4)	(5)	(6)
Round 3	1.653	1.878	1.653	1.653	1.653	1.653
	(1.454)	(1.448)	(1.454)	(1.454)	(1.454)	(1.454)
Constant	43.930*	32.298	38.843*	34.825	39.268*	40.554*
	(22.353)	(23.314)	(21.379)	(22.272)	(21.977)	(21.938)
Observations	1,125	1,086	1,125	1,125	1,125	1,125
R-squared	0.218	0.197	0.209	0.206	0.204	0.206
Adjusted R-squared	0.208	0.187	0.199	0.197	0.194	0.197

Notes: Heteroskedasticity-robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

PRs 100 = US$ 1 approximately.

Source: Authors' estimates.

Table 6: Adoption of new practices

Variable	Contribution (1)	(2)	(3)	(4)	(5)
Age (years)	-0.086	-0.128	-0.097	-0.084	-0.090
	(0.120)	(0.123)	(0.126)	(0.118)	(0.122)
Participant is female	-19.022***	-19.313***	-19.130***	-18.569***	-18.912***
	(5.697)	(5.413)	(5.632)	(5.573)	(5.694)
Log of monthly income	-0.244	-0.237	0.260	-0.155	-0.553
	(1.613)	(1.812)	(1.675)	(1.609)	(1.681)
Log of household savings	-0.510	-0.494	-0.540	-0.572	-0.507
	(0.381)	(0.400)	(0.381)	(0.370)	(0.376)
Lives in 2010 flood cluster	15.959	13.876	13.212	14.834	15.627
	(10.418)	(10.076)	(10.283)	(11.000)	(10.504)
Number of floods experienced	14.417***	10.566***	13.967***	14.252***	14.049***
	(3.751)	(3.232)	(3.694)	(3.728)	(3.745)
Lives in 2010 flood cluster and number of floods experienced	-11.826***	-10.337**	-10.393**	-11.528***	-11.411***
	(3.715)	(3.601)	(3.599)	(3.790)	(3.827)
Has adopted new practices: any of eight categories	11.875***		11.908***	12.206***	11.730***
	(3.670)		(3.597)	(3.679)	(3.496)
Number of floods experienced and has adopted new practices	-8.102***		-8.273***	-8.357***	-8.250***
	(2.256)		(2.110)	(2.246)	(2.207)
Has adopted new practices: new agricultural practices		9.217**			
		(4.308)			
Has adopted new practices: fuel/cooking techniques		-1.479			
		(4.955)			

	Contribution				
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Has adopted new practices: use of building materials		2.225			
		(3.391)			
Flood-related livestock loss as a percentage of monthly income			-0.445***		
			(0.127)		
Total flood-related loss as a percentage of monthly income			0.108**		
			(0.050)		
Has learned any mitigation methods from the 2010 floods				3.432	
				(3.772)	
Number of years of education					0.342
					(0.334)
Has had insurance in the past					0.217
					(4.550)
Muzaffargarh district	28.845*	26.234*	28.438*	28.097*	27.975*
	(15.904)	(14.911)	(15.623)	(16.024)	(15.892)
Layyah district	43.799***	41.731***	43.215***	43.586***	43.068***
	(13.630)	(13.121)	(13.378)	(13.634)	(13.485)
Village flood propensity score	-13.195	-10.432	-11.567	-12.384	-12.858
	(28.911)	(28.968)	(28.552)	(29.227)	(29.263)
Round 2	3.440***		3.440***	3.440***	3.440***
	(1.036)		(1.037)	(1.036)	(1.037)
Round 3	1.653		1.653	1.653	1.653
	(1.454)		(1.456)	(1.455)	(1.456)

Variable	Contribution (1)	(2)	(3)	(4)	(5)
Constant	28.835	37.523	24.173	27.645	31.853
	(22.466)	(21.666)	(22.596)	(22.227)	(21.919)
Observations	1,125	1,098	1,125	1,125	1,125
R-squared	0.215	0.208	0.221	0.217	0.216
Adjusted R-squared	0.205	0.199	0.210	0.206	0.205

Notes: The interaction between "Has adopted new practices: any of eight categories" with "Lives in 2010 flood cluster" was included as a control, but is not shown in the results as it was statistically insignificant.
Heteroskedasticity-robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
PRs 100 = US$ 1 approximately.
Source: Authors' estimates.

7. Conclusion

Experiences of natural disasters have lasting effects on people's personal preferences and their relationship with other members of the community. By treating the 2010 floods in Pakistan as a natural experiment, we have studied the extent of social capital in communities by conducting a series of public goods behavioral games and observing contribution patterns across flood and nonflood clusters. By conducting incentivized games, we were able to measure behavioral social capital and test how behavior varies with monetary incentives after a rare-flood event.

Our results reveal a robust relationship between flood experiences and social capital. While other studies have looked at social capital after a severe natural disaster or frequent experiences of mild disasters, this study is unique because it makes a distinction between the two kinds of experience and draws conclusions based on these differences. Among our key results is that different kinds of flood-related experiences result in different levels of contribution to public goods. We find that having experienced more floods is associated with significantly larger contributions. Moreover, having experienced the 2010 floods results in larger contributions toward the community across the entire sample.

However, the behavior of individuals living in one of the 2010 flood clusters is different from that of the control group: while any experience of floods enhances their contribution, as the number of times they experience a flood increases their contribution declines. This is interesting because it suggests that the experience of a severe natural disaster (in this case, the 2010 floods) has a negative impact on social capital compared to frequent experiences of milder floods where social capital is positively affected.

The role of government assistance is crucial in the event of a natural disaster and can have a direct impact on social capital at the community level. Our results show that one-off government assistance in the form of food results in higher contributions toward the community pool. Individuals who had received lump-sum monetary transfers under the Watan card scheme made positive contributions so long as they did not live in a flood cluster. The fact that Watan card recipients living in a flood cluster made negative contributions indicates their limited appreciation for the scheme. This is an important finding, given that there has been no systematic review of the Watan card scheme following the 2010 floods. While our results suggest a negative relationship in terms of contributions toward public goods, an in-depth analysis of the scheme is needed to determine its utility as a policy instrument for the future.

Individual characteristics such as positive expectations and resilience in the aftermath of a disaster are associated with greater contributions toward public goods in general. However, as people's experience of floods increases, their resilience also results in smaller contributions. In consistence with Toya and Skidmore (2013), we find that a shared sense of loss, measured by flood-related losses in the form of injury experienced by friends or family, results in greater contributions and, therefore, in higher levels of social capital. While interesting per se, these results also suggest it is important to build social capital through measures such as skills development so that communities might develop better coping mechanisms and move toward self-reliance.

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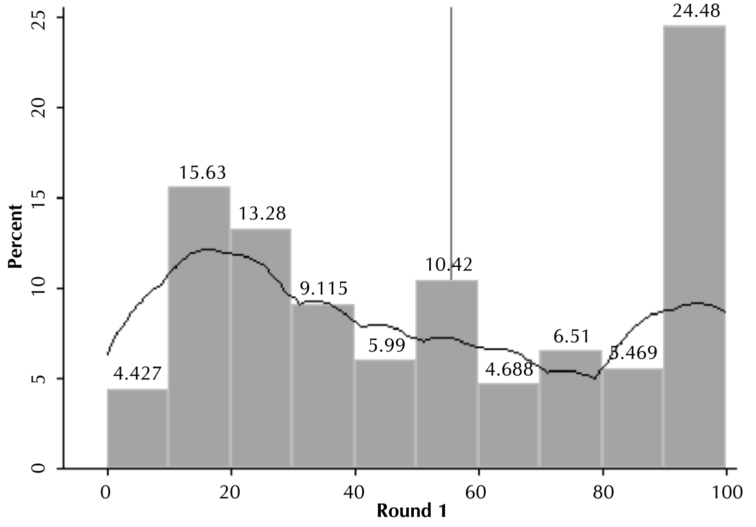
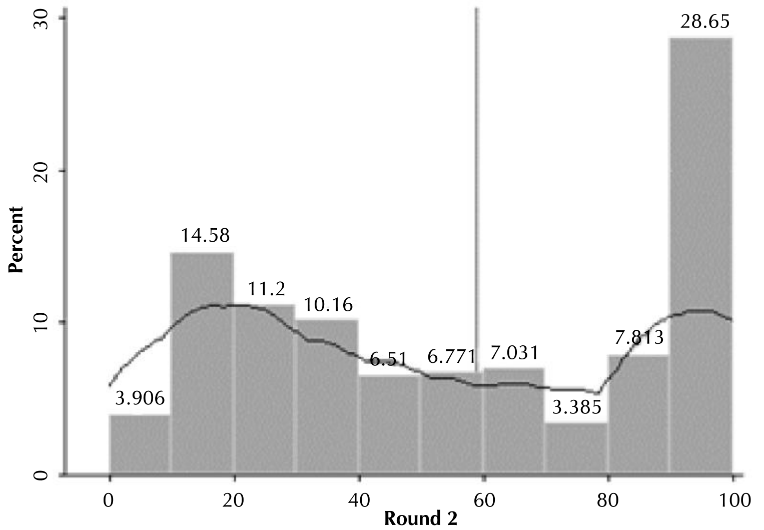
Appendix

Figure A1: Percentage distribution of contributions: round 1



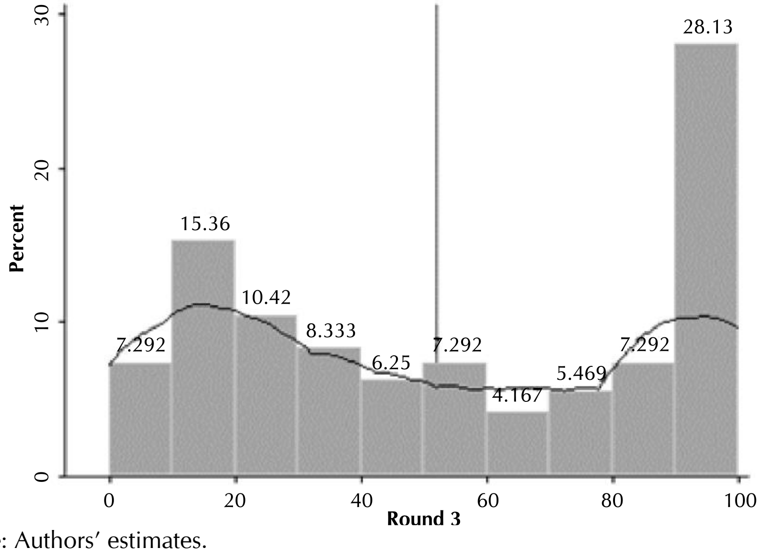
Source: Authors' estimates.

Figure A2: Percentage distribution of contributions: round 2



Source: Authors' estimates.

Figure A3: Percentage distribution of contributions: round 3



Source: Authors' estimates.

Table A1: t-test results for the difference in average contributions across rounds

```
Paired t test
------------------------------------------------------------------------------
Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
  Round1 |     384    50.46875    1.759895    34.48675    47.00849    53.92901
  Round2 |     384    53.82813     1.79652    35.20446    50.29585     57.3604
---------+--------------------------------------------------------------------
    diff |     384   -3.359375    1.234583    24.19279   -5.786784   -.9319662
------------------------------------------------------------------------------
     mean(diff) = mean(Round1 - Round2)                           t =  -2.7211
 Ho: mean(diff) = 0                              degrees of freedom =      383

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.0034         Pr(|T| > |t|) = 0.0068          Pr(T > t) = 0.9966

. ttest Round2= Round3

Paired t test
------------------------------------------------------------------------------
Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
  Round2 |     384    53.82813     1.79652    35.20446    50.29585     57.3604
  Round3 |     384    52.08333    1.849227     36.2373    48.44743    55.71924
---------+--------------------------------------------------------------------
    diff |     384    1.744792    1.200417    23.52328   -.6154414    4.105025
------------------------------------------------------------------------------
     mean(diff) = mean(Round2 - Round3)                           t =   1.4535
 Ho: mean(diff) = 0                              degrees of freedom =      383

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.9265         Pr(|T| > |t|) = 0.1469          Pr(T > t) = 0.0735

. ttest Round1= Round3

Paired t test
------------------------------------------------------------------------------
Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
  Round1 |     384    50.46875    1.759895    34.48675    47.00849    53.92901
  Round3 |     384    52.08333    1.849227     36.2373    48.44743    55.71924
---------+--------------------------------------------------------------------
    diff |     384   -1.614583    1.292255    25.32293   -4.155386    .9262192
------------------------------------------------------------------------------
     mean(diff) = mean(Round1 - Round3)                           t =  -1.2494
 Ho: mean(diff) = 0                              degrees of freedom =      383

 Ha: mean(diff) < 0           Ha: mean(diff) != 0           Ha: mean(diff) > 0
 Pr(T < t) = 0.1061         Pr(|T| > |t|) = 0.2123          Pr(T > t) = 0.8939
```

Source: Authors' estimates.

Table A2: t-test results for sample balance

	Mean			t-test	
Variable	**Treated**	**Control**	**Bias (%)**	**t**	**p > |t|**
Average monthly income	2,419.3	233.4	7.7	0.59	0.559
Literacy	0.232	0.219	11.2	0.54	0.593
Education level 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
Primary occupation: self-employed	0.019	0.020	-9.0	-0.47	0.642
Primary occupation: government employee	0.040	0.038	8.1	0.37	0.711
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	0.687	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
Households with electricity (percent)	0.766	0.748	7.6	0.37	0.716
Households with permanent flooring (percent)	0.244	0.255	-6.6	-0.36	0.721
Households with permanent roof (percent)	0.605	0.625	-10.1	-0.46	0.650
Households with permanent walls (percent)	0.411	0.442	-14.1	-0.69	0.491
Average number of households that receive a pension	2.007	1.997	12.3	0.61	0.546
Average number of cattle owned by households	3.374	3.294	6.1	0.23	0.816
Average number of goats owned by households	2.999	2.772	11.8	0.60	0.553
Average number of poultry owned by households	2.182	1.747	27.9	1.23	0.224
Wealth index	-1.050	-1.051	0.1	0.01	0.996
Measure of cluster size (weights)	0.947	1.052	-25.1	-0.79	0.432
		Mean	**SD**	**Min.**	**Max.**
Propensity scores		0.405	0.193	0.15	0.778

Source: Authors' estimates.

Table A3: t-test results for the difference in average income levels of households receiving BISP payments

```
Two-sample t test with equal variances
```

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	528	24463.75	1298.606	29839.7	21912.67	27014.83
1	108	18469.44	1968.1	20453.1	14567.92	22370.97
combined	636	23445.85	1131.685	28540	21223.55	25668.14
diff		5994.302	3007.04		89.33909	11899.26

```
    diff = mean(0) - mean(1)                                      t =   1.9934
Ho: diff = 0                                     degrees of freedom =      634

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9767         Pr(|T| > |t|) = 0.0466          Pr(T > t) = 0.0233
```

Note: Group 0 = not receiving payments, group 1 = receiving payments.

Source: Authors' estimates.

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Intersection Main Boulevard Phase VI, DHA and Burki Road
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