The Voluntary Provision of Public Goods after a Natural Disaster: A Field Experiment from Pakistan[1]

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After a natural disaster, apart from economic and structural losses, communities also undergo a loss in social capital. This loss in social capital can affect perceptions, trusting behavior, and social cohesion. This paper examines the effect of a severe natural disaster on the social capital of disaster-stricken communities by conducting behavioral experiments and household surveys three years after the disaster took place. This paper contributes to current literature by combining household-level information with behavioral games, and testing the impact of individual characteristics, perceptions and external assistance on the private contribution towards a pool of public goods in a post disaster setting. We find that social capital, measured by contributions towards a public good, is positively associated with a greater number of floods experienced. However, for individuals residing in the 2010-flood affected communities, contributions decline with each successive experience of floods. This suggests that a severe experience with a natural disaster negatively affects social capital compared to frequent experiences with mild floods where social capital is positively affected.

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1 Introduction

As the scale of destruction from natural disasters has increased over the past decades there is a growing body of literature focusing on the implications of natural disasters in the behavioral and economic development context. Economists have investigated the impact of natural disasters on selective macro and microeconomic subjects such as output, income, migration, human capital, risk aversion and trust (Noy, 2009; Yang, 2008a and 2008b; Baez, Fuente and Santo 2010; Cameron and Shah, 2010; Zylberberg, 2010 and Fleming, Chong and Bejarano 2011). In the aftermath of a traumatic event, apart from economic and structural losses, communities also undergo a loss in social capital (Fleming, Chong and Bejarano, 2012). This loss in social capital can affect perceptions, trusting behavior, and social cohesion towards the community in the short and possibly longer term. Moreover a loss in social capital can disrupt and slow down the recovery process in disaster stricken communities. Immediately after a disaster, the public and private relief efforts can also influence the social capital levels depending on the fairness and effectiveness of these efforts. This study introduces the definition of social capital as the underlying feeling of cooperation, social cohesion and mutual interdependence in a community. By allowing participants to make voluntary contributions towards a common pool for the benefit of the community, a public goods game can capture these underlying feelings towards the community and therefore indicate the prevailing level of social capital.

Losses from natural disasters are more pronounced in developing countries, which bear a greater burden of deaths and damages, averaging around 35 billion USD each year (Munich Re, 2000). While Pakistan has historically experienced floods with varying frequency and severity; in 2010 the country experienced the worst floods in its history (National Disaster Management Authority, 2012). According to Webster, Toma and Kim (2011), the exceptionally high rainfall in the summer of 2010 led to a death toll of almost 2000 people, leaving behind about 20 million affected individuals and about 45 billion USD in damages. In this study, the rare flood event serves as a natural experiment to study the differences in social capital of people who have undergone a traumatic event. Of the few studies that look at how natural disasters affect social capital (Toya and Skidmore 2013; Cassar, Healy and von Kessler, 2011; Fleming et al., 2011; Whitt and Wilson, 2007; Douty 1972), there is no consensus on the direction of change in social capital after a disaster. Moreover, majority of the literature focuses on the community's level of social capital after a severe natural disaster or small frequent experiences with disasters, this study is unique as it makes a distinction between frequent experiences with mild floods and an extremely severe flood experience. This paper combines household-level survey data with behavioral games for households from comparable communities in the flooded and non-flooded clusters of 2010, and examines the impact of individual characteristics, perceptions and external assistance on the private contribution towards a common pool of public goods.

Our results show that social capital measured by contributions towards a public good is positively associated with a greater number of floods experienced. However, for individuals residing in the flooded communities of 2010, contributions decline with each successive experience of floods. This suggests that a severe experience with a natural disaster negatively affects social capital whereas frequent experiences with milder floods have a positive effect. Toyo and Skidmore (2013) find that among different kinds of natural disasters, floods negatively affect trust levels possibly because they occur in low lying areas where the lowest income groups afford living, hence giving way to social division. Our study takes the discussion further by differentiating between low intensity frequent floods and a severe disastrous flood and highlights the difference in social capital based on experiences. Whitt and Wilson (2007) in their study on the evacuees of Hurricane Katrina in the United States find that victims suffering from 'heightened stress' after the hurricane made lower contributions towards the public pool. Following a similar explanation, we attribute the lower contributions by individuals residing in flood clusters to their traumatizing experience of the worst floods.

In line with the literature, we find that contributions and external assistance are positively associated (Cassar et al., 2011). Flood-related government assistance in the form of food assistance results in higher contributions towards the community pool. Individuals who received lump-sum monetary transfers from the Watan card scheme made positive contributions as long as they were not residing in the flood clusters. The negative contributions from recipients of Watan cards residing in the flooded clusters of 2010 indicate the limited appreciation of the Watan card scheme by those who were most affected by the floods. This is an important finding, as there has not been much research on the utility of the Watan cards scheme post the 2010 floods. Moreover, there is evidence of non-flood government assistance crowding out private contributions in our sample. Individual characteristics such as having positive future expectations and being resilient in the aftermath of a disaster are associated with greater contributions towards public goods in general. However, as experience with floods increases, resilience also results in lesser contributions, perhaps because self-reliance surpasses interdependence for these individuals. In consistence with literature (Toyo and Skidmore, 2013), we find that a shared sense of loss, measured by flood losses in the form of injury experienced by friends or family results in greater contributions and therefore, social capital.

The paper proceeds as follows: Section 2 discusses the theoretical framework and related literature; section 3 describes the econometric model and hypotheses; section 4 explains the sampling, data collection and the experimental design; section 5 presents the descriptive statistics; section 6 discusses the results; and sections 7 concludes.

2 Theoretical Framework and Related Literature

The research on public goods encompasses empirical as well as theoretical studies ranging over topics such as such as private versus public provision of public goods, efficacy of matching contributions by the state, altruism in its pure and impure form, government assistance and crowding out of private charity (neutrality theorem) and social capital and private contributions towards public goods (Baker II, Walker and Williams, 2008; Anderson, Mellor and Milyo, 2004; Chan, Mestelman, Moir and Muller, 1996; Bergstrom, Blume and Varian, 1985; Adreoni, 1988 & 1990; Warr, 1982). The relationship between social capital and public goods is studied by Anderson et al. (2004), who use trust as a measure of social capital and combine the results from a General Social Survey (GSS) on trusting behavior with the outcomes of a public-goods experiment. They find that trust, measured by the statement "most people can be trusted" (p375) is strongly associated with higher contributions in the public goods experiment. Similarly, Karlan (2005) finds that more positive responses to GSS survey questions predict higher repayment of loans and greater savings, however higher contributions in a public goods game are not correlated to repayment of loans. By conducting a panel data analysis, Toya and Skidmore (2013) study how the natural environment, particularly in the form of natural disasters can affect the trust levels in a community. The study concludes that aside from the devastating socioeconomic impacts of a disaster, a positive spillover can be greater societal trust.

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

Disasters that affect many people simultaneously may have opposite effects on community cooperation: on one hand, cooperation during relief efforts and reconstruction may enhance feelings of social cohesion, mutual interdependence and shared benefit from public goods in the affected community, on the other hand, the heterogeneous impacts of disasters and external assistance may cause jealousy and divided opinions about 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. Goodwill and trust may be enhanced in the aftermath of a disaster towards particular agents such as public officials, donors and volunteers but not necessarily towards the people of the same community. For example, Andrabi and Das (2010) find that after the 2005 earthquake in Northern Pakistan, the trust in foreigners in the earthquake zone as measured by survey questions increased substantially, primarily due to foreign aid, however the trust levels of locals for each other remained much lower.

According to the neoclassical literature, preferences are considered as immutable individual characteristics while constraints are expected to change. This implies that while constraints or circumstances can affect the choices made by individuals, the underlying preferences remain unaffected. An often cited approach to make judgments under uncertainty is to anchor on preexisting impressions, perceptions or values and then adjusting it until plausible conclusion can be reached. Often the adjustment process is insufficient such that judgmental biases are visible, this is known as the "anchoring and adjustment" heuristic (Epley and 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, causes individuals to over-weight salient events, and the "conservatism" heuristic, causes individuals to under-estimate high values (Kahneman and Tversky, 1973). The different heuristics indicate that experiences can have lasting effects on people's perceptions about themselves, the future and their surroundings. More recently, literature on psychology and behavioral sciences suggests that individual experiences can alter preferences and allow behavioral learning over the course of time (Cassar, Healy and von Kessler, 2011; Voors et al., 2010). Fleming et al. (2011) investigate the level of social capital in earthquake stricken Chile and find that while trust levels are not affected, the trustworthiness amongst villagers of the affected areas had declined. On the other hand, Cassar, Healy and von Kessler (2011) study Thai villages affected in the 2004 Asian tsunami and find evidence that individuals affected by the disaster were more trusting, trustworthy and more risk averse compared to 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 been established in the literature (Fukuyama, 1995; Knack and Keefer. 1997; Alesina and La Ferrara, 2002, Uslaner, 2005, Dearman and Grier, 2009). However, there is a lack of consensus in the role of social capital in the post disaster recovery and whether the endowment of social capital is enhanced or diminished after a disaster. This results in the failure of optimal policy responses. By utilizing the experience of the 2010 floods in Pakistan we can determine if people who experienced the 2010 severe floods display similar contribution patterns and therefore share similar social capital levels as the control villages. Also, since parts of Punjab are subject to perennial minor flooding, the difference in behavior of those who have experienced numerous minor floods and the 2010 floods can be compared to those who only experienced minor floods or only the 2010 floods. The household survey provides us with individual, household and community level information to match the individual responses in the behavioral games and therefore investigate the underlying mechanisms for the contributions towards a public pool. This paper makes a unique contribution to the literature by combining survey and experiment data to test whether different kinds of flood experiences have varied effects on their perception of public goods and therefore, social capital in the community.

3 Econometric model and Hypothesis

To estimate the impact of a rare flood event on the contribution towards a public pool by individuals, we estimate the following equation using a linear regression model.

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

$Contribution_{ij}$ is the amount of money an individual i has contributed in round j of the game The maximum a participant can contribute in each round is Rs.100 and the minimum is Rs. 0, in denominations of ten. Higher contributions are reflective of greater social capital. $Disaster_{ij}$ is a vector of flood experience variables such as whether the individual is residing in a village that experienced the 2010 severe floods, the number of times the individual experienced floods in a lifetime and other indicators that gauge the nature of experience with floods. $Individual_{ij}$ is a vector of participant characteristics such as individual and household information, external assistance, expectations about the future and adoption of different techniques[4]. ε_{ij} represents the standard errors that are heteroskedasticity-robust and clustered at the village level. Information on control and explanatory variables has been gathered from the household survey conducted in April 2013.

3.1 Incidence versus severity of floods experience

We test if people with any or no previous experience of floods make different contributions towards public goods as compared to those who reside in areas that were affected by the 2010 severe floods (referred as flood clusters). Individuals with greater number of floods experience can be expected to react differently from those who experienced fewer floods, or only the 2010 floods. By using the information from the survey, we test for some interesting differences in the kind of experience with floods, for

[4] Control variables include age, gender, log of monthly income, log of household savings, propensity score, district and round dummies. Variables of interest: types of government assistance (flood assistance: cash, food, nonfood and Watan Cards; and non-flood assistance: BISP cash transfers), expectations about next floods, future expectations about self, intention to migrate, adoption of new techniques (agricultural practices, cooking fuel, building material).

example, we can further test if individuals residing in the 2010 flood clusters and with prior flood experience make different contributions compared to those who have experienced a similar number of floods, but not the 2010 severe floods. We hypothesize that there is distinction between frequent experiences with mild flood and a traumatic flood experience which can result in distinct outcomes in the public goods experiment and therefore reflect different levels of social capital

3.2 External assistance

The role of the government is twofold, apart from immediate rescue and rehabilitation, a major task is to ensure that the benefits of government assistance are shared by the majority of the affected. From our data we estimate the impact of government assistance for rehabilitation on the private contribution of public goods. A negative coefficient of government assistance should support the neutrality theorem that indicates crowding out of private provision of public goods by government provision. Andrabi and Das (2010) find that the humanitarian assistance by foreigners in the wake of the 2005 earth-quake has a lasting impact on the trust and attitudes of the locals towards foreigners. Individuals who have received government assistance in the past or have a regular interaction with government officials to receive other types of transfer payments from the government may be more likely to expect external assistance to compensate for their losses, and therefore can be expected to contribute less towards a public pool. Furthermore, 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. According to Anderson et al. (2004) social capital measured by trust in other people can have strong associations with higher contributions in the public goods experiments. Similarly, Karlan (2005) also finds that individual's who showed more trust in the trust games, were also likely to contribute towards the public good. According to Cameron and Shah (2010), individuals who suffered from a flood or earthquake in the past three years displayed more risk aversion than those who were safe from such a disaster. 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 contribution towards public goods. While this does not allow us to draw a relationship between risk aversion and social capital, a significant relationship can highlight risk aversion as an important covariate. Similarly, we will also test if greater insurance demand results in lesser contribution reflecting great self-sufficiency.

3.3 Self-perception and future expectations

Individual's perception about the future can also affect social capital. The Kahneman and Tversky's (1973) "representativeness" heuristic which indicates that individuals tends to over-weight salient events can be relevant for individuals residing in the flood clusters as this experience can influence their expectations about floods in the future. Cameron and Shah (2010) find that individuals who have experienced a natural disaster recently report a greater probability of a natural disaster occurring in the next twelve months, and expect it to be more severe 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 undergoing floods. Like preferences, self-perception can also be anchored and have a slow adjustment process. According to Tversky and Kahneman (1974) anchoring-and-adjustment heuristic, the initial information anchors or tends to drag on the subsequent adjustment process. Individual's who are optimistic about their future prior to any floods experience, can continue to carry the same perceptions even after a natural disaster. In this study, we test the hypothesis that people with positive self-perceptions and who have better expectations for the future make greater public goods contributions. The underlying assumption is that a positive self-perception and expectation of the future loosely reflects the human capital of an individual which in can positively affect contributions.

3.4 Adoption of new techniques

“Resilience has been most frequently defined as positive adaptation despite adversity” (Fleming and Ledogar, 2008). We measure resilience at the individual level as the ability to adopt new techniques such as cooking fuel techniques, building materials, agricultural practices etc. The hypothesis is to determine whether resilient individuals make greater contributions towards public goods, assuming that the contribution can be considered as an investment in any local project. The assumption behind this hypothesis is that individuals already investing in improvement of their daily lives or business are more likely to appreciate complementary investments at the community level compared to those who are not adopting new techniques; therefore greater contributions indicate more social capital. However, it is also possible that some households adopt new techniques because of the frequent experience with floods. In the latter case, a second hypothesis to test is whether the contribution towards public goods by individuals who have adopted new techniques and have experienced a higher number of floods is different from those who have experienced fewer floods; perhaps for these individuals self-reliance surpasses interdependence.

3.5 The Public Goods Experiment

In consonance with the participants’ literacy skills we designed a game which was easily comprehendible and could still elicit the behavioral social capital of the people taking part in the experiment. In each round of the experiment, participants received an endowment of PKR 100 (equivalent of USD 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 towards a common pool of money that would be spent on a ‘community project’ such as repairing a school building, installing a tubewell or paving roads; any expenditure from which the whole community could benefit. The game was designed as a typical public goods game, where the contributions by the participants were matched (doubled) and then divided equally -to reflect the shared benefit from the community project. The participants were divided between groups of four, the identity of the members in each group was not disclosed, however, the participants were informed that the group contributions would be doubled and then distributed amongst the group members. The participants could choose to contribute any amount between 0 to a 100, in denominations of ten. Any money not contributed could be kept for themselves, along with the money that they received from the common pool. Apart from a demonstration and a 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 the expectations and performance in the later rounds. According to literature, trust in other people indicates social capital and it can have strong associations with higher contributions in the public goods experiments (Anderson et al., 2004; Karlan, 2005). In accordance with literature, we suggest that by allowing participants to make voluntary contributions towards a common pool for the benefit of the community, the underlying feelings of cooperation, trust and social cohesion in the community can be captured and therefore the individual contributions are a good indicator of the level of social capital in a community.

4 Sampling, Data Collection and Experimental Design

4.1 Sampling Strategy

This study focuses on Punjab, the largest province of Pakistan. With five rivers flowing through Punjab, it provides an advantageous location for sampling both flood-affected and unaffected households. Due to the geographic diversity of the flood effects, there has been considerable variation across the region in terms of rainfall levels, extent of flood-water and external assistance.

Punjab is divided into 36 districts, which are further subdivided into 127 tehsils[5]. A tehsil in general, corresponds to one town but in it may comprise multiple towns. Each tehsil is further divided into union councils that serve as the local administrative units and can 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, out of which 16 households (called a "cluster") are randomly selected for the survey. We follow the framework of Multiple Indicator Cluster Survey (MICS) of 30,000 households in Punjab that took place in 2011 and is representative at the tehsil level. The MICS survey is carried out every four years by the Punjab Bureau of Statistics and the most recent waves were carried out in 2007-08 and 2011, hence providing representative household-level data prior to and shortly after the 2010 floods.

4.1.2 Selection of Districts

We select districts that allow sufficient variation in flood effects ranging from non-flooded to low, moderate and severely affected. In order the classify districts as flooded or non-flooded, the 2011 MICS survey asked each respondent if the 2010 floods had affected their household. Based on the responses to this question, a cluster was classified as being `flood-affected' in 2010 if all of the randomly selected households in the cluster responded `yes' to this question and `non-flood-affected' if any of the households in the cluster responded with a `no' to this question[6]. Based on the listing of flood-affected clusters, we determine the percentage of flood-affected clusters in each district[7]. These clusters were affected more severely by the 2010 floods, and due to proximity to the river Indus and Chenab, these clusters tend to be affected by floods more frequently than other clusters.

The Punjab Bureau of Statistics administered the United Nations 2010 Multi-cluster Rapid Assessment Mechanism (McRam) in late August 2010 in 8 out of the 11 flood affected districts[8]. The purpose of the survey was to gather detailed information on the flood damages and rehabilitation needs. Based on the 2011 MICS and 2010 McRam surveys, the five districts with the highest number of 2010 flood-affected clusters were Rajanpur, Muzaffargarh, Layyah, Dera Ghazi Khan, and Rahim Yar Khan. Due to safety concerns, female staff and enumerators could not visit Rajanpur and Dera Ghazi Khan, therefore the survey is carried out in the three remaining districts: Muzaffargarh, Layyah, and Rahim Yar Khan. Flood

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

[6] A cluster was designated as flood affected only if all the households in the cluster responded to the question of being affected by the flood in 2010 with a 'Yes'. This was done to make sure there are no errors due to the migration of households into and out of the cluster since 2010 to 2011, when the survey was conducted and only clusters where there is minimum likelihood of migration in and out are selected as flood affected.

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

[8] According to the MICS 2011, the districts where any households reported being affected by the floods in 2010 were Rajanpur, Muzaffargarh, Jhang, Layyah, DG Khan, Sargodha, Multan, Rahim Yar Khan, Bhakkar and Bahawalpur.

maps obtained from the McRam survey, the Punjab Provincial Disaster Management Authority (PDMA), and the Lahore School of Management Science (LUMS) [9] confirm that each of the three districts lie across the border of flooded and non-flooded areas. According to the 2011 MICS, 51% of the clusters sampled in Muzaffargarh, 18% in Layyah, and 9% in Rahim Yar Khan were classified as `flooded' in 2010.

4.1.3 Selection of Village Clusters

From the three districts, a list of villages common to both MICS 2008 and 2011 is drawn. From these villages, eight pairs of flooded and non-flooded clusters are selected based on propensity scores. Pre-flood 2007-08 MICS survey wave is used to calculate propensity score of characteristics correlated with the propensity to be flooded. The score is based on distance to the river, household wealth, livestock, income, occupation of household head, access to utilities, literacy, health, and access to public infrastructure[10]. With the help of the propensity score, we can create a control group for the flood-affected villages that had a similar propensity to be flooded based on geographic and socio-economic factors but was not flooded in 2010[11]. This technique of propensity score matching helps in selecting a balanced sample with no significant differences in the mean of the key socioeconomic observable variables between the treatment and control groups (See table A1 in the Appendix).

Using propensity scores, the flooded and unaffected villages are mapped. From the list of flood-affected villages we randomly select 8 villages as the treatment group. Of these, 4 villages are in Muzaffargarh, 2 in Layyah, and 2 in Rahim Yar Khan.

For half (4) of the flood-affected villages, we select the control village with a matching propensity score which is located at closest proximity. For the remaining 4 villages, we select the control village with a matching propensity score that is located at farthest proximity to flooding.[12] For the `non-flooded' villages, an additional check is performed using our several mapping sources to verify that the village area was not considered flooded during 2010. Five non-flooded villages adjacent to the flooded villages are selected from Muzaffargarh, 2 in Layyah and one in Rahim Yar Khan. From Figure 1, the location of the 16 clusters visited can be seen. Also, the average distance of the treatment and control villages from to any one of the three rivers (Indus, Jhelum and Chenab) is comparable, as shown in figure 1 below.

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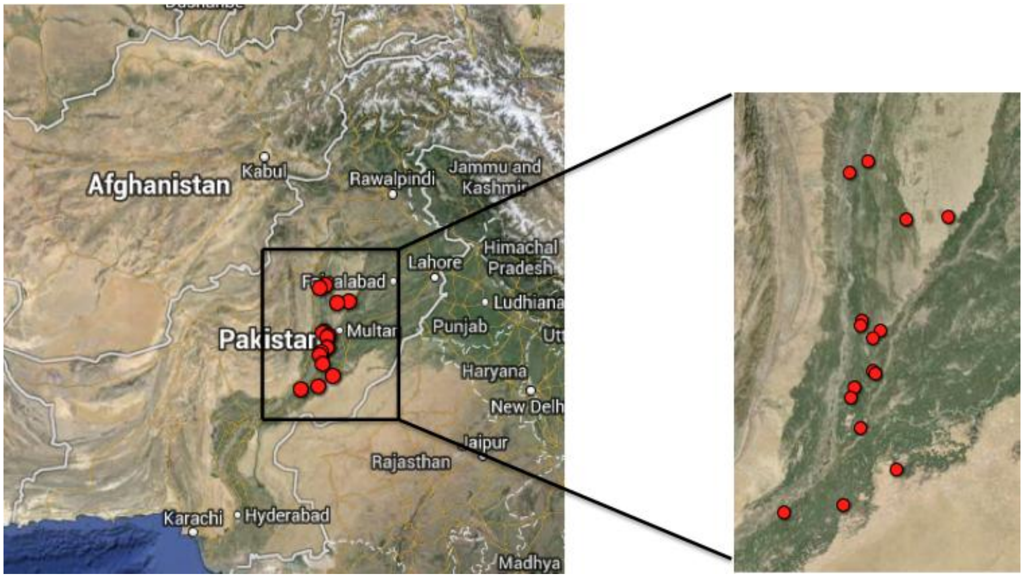
[9] http://floodmaps.lums.edu.pk

[10] The three districts share similar environmental factors and terrain. Muzzafargarh and Layyah have historically had mean rainfall of 200-400 mm per annum. Rahim Yar Khan has less than 200 mm per annum. However, the monsoon rains in 2010 were considered to be the worst in intensity since 1994 and 6th highest in the last 50 years. Source: Pakistan Meteorological Department (www.pmd.gov.pk)

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

[12] The propensity scores of the non-flooded villages do not exceed the propensity scores of the flooded villages by more than 30% of the standard deviation of the scores.

Figure 1: Map of Sample Clusters



Source: Google Maps

4.1.4 Selection of Households

The MICS 2011 contains complete listing of households for a randomly selected village block (a settlement or basti or a geographically concentrated group of households). From this list, 20 households were randomly selected and surveyed[13].

Community leader interviews were conducted to confirm village-level information collected. Since the 2010 floods induced temporary out-migration, there was the possibility that a sample of flood-affected villages would under represent the flood-affected households. The community leader interviews confirmed that the population composition 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% 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 covers a total of 320 households across the three districts of Muzaffargarh, Layyah and Rahimyar Khan. A male and female questionnaire was carried out in each household, resulting in 640 respondents of the survey. Of this group, 384 individuals -192 males and 192 females participated in the public goods experiment.

[13] Apart from the twenty households, enumerators were provided with a list of five additional randomly selected households to draw for replacement in case a household could not be interviewed. The enumerators recorded reasons for why any household was not surveyed, such as (i) no one was available who could provide household information, (ii) the house structure was uninhabited or (iii) household members declined to participate in the survey. Participants did not receive any monetary compensation for the survey.

For the experiment, out of the 20 households surveyed in each village, a random subset of 15 households was invited to participate in the experiment. To ensure gender balance, one male and one female was invited from each selected household. The invitees were incentivized by offering them a participation fee for showing up on time. To fill 12 male and 12 females spots we over-recruited by 20 per cent and any excess arrivals were paid the minimum earning of Pakistani Rupees (PKR) 150 (equivalent of USD 1.5) and asked to leave before the session. There were no sessions for which fewer than 12 males and 12 females arrived. In accordance with local practices, males and females interacted separately, women enumerators carried out the interviews of women as well as the experimental games sessions. The experiments sessions for men and women were carried out simultaneously in separate rooms of a venue in each village to limit information sharing. There was one experiment session in each village cluster to control informal discussion between sessions that could influence participant's behavior and expectations.

5 Descriptive Statistics

For the purpose of this study, two surveys were carried out: Community leader interview and household and individual survey. The community leader interview was carried out in each village to gather village-level information such as size of village and public infrastructure. The household survey focused on household demographics, income, expenditure and ownership of assets (e.g., land, livestock, durables). Individual level questions were asked from adult male and female respondents who were invited to participate in the behavioral games. These questions acquired about perceptions of self, resilience to change, traumatic experiences (e.g., crime, injury, death), previous experience of natural disasters, personal and neighbor flood losses from the 2010 floods, mitigation and prevention activities, adaptation of new techniques, information sources and warning times, community and external assistance including Watan Cards, risk perceptions and risk-taking preferences in hypothetical situations, future expectations of floods, future financial and expenditure aspirations, and social networks and patronage. Table 1A presents the descriptive statistics for key variables of interest in our analysis.

Table 1A: Summary Statistics –Household survey

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Age in years	384	37.77	12.58	16	80
Participant is a female	640	0.5	0.5	0	1
Household total monthly income	636	23445.8	28540	3000	228500
Household savings (PKR)	640	4095.7	14971.8	0	200000
Years of schooling attained by the household head	626	3.64	4.23	0	16
Lives in 2010 flood cluster	640	0.5	0.5	0	1
Has experienced floods (including 2010)	640	0.79	0.4	0	1
Lives in 2010 flood cluster and has experienced floods	640	0.48	0.5	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
Adopted new things: any of 8 categories	640	0.51	0.5	0	1
Number of floods experienced and adopted new things	627	0.58	0.87	0	5
Adopted new things: new agricultural practices	634	0.1	0.3	0	1
Adopted new things: fuel/cooking techniques	635	0.17	0.38	0	1

Adopted new things: building materials	637	0.22	0.41	0	1
Flood livestock loss as a percentage of monthly income	640	0.64	7.3	0	180
Flood household possession loss as percentage of monthly income	640	0.69	3.6	0	60
Total flood loss as a percentage of monthly income	640	10.65	28.87	0	480
Learn any mitigation methods from the 2010 floods?	640	0.23	0.42	0	1
Received government assistance	640	0.42	0.49	0	1
Received government flood cash assistance	640	0.08	0.28	0	1
Received government flood non-food assistance	640	0.16	0.36	0	1
Received government flood food assistance	640	0.3	0.46	0	1
Lives in 2010 flood cluster and received flood food assistance	640	0.23	0.42	0	1
Received government flood BISP assistance	640	0.17	0.37	0	1
Lives in 2010 flood cluster and received BISP assistance	640	0.1	0.3	0	1
Received Watan Card	312	0.72	0.45	0	1
Lives in a designate flood cluster and received 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
Prefer Rs.500 instead of a game with 50% chance of winning Rs. 1000	640	0.58	0.49	0	1
Self-reported ability to recover faster from unexpected events	640	0.2	0.4	0	1
Has experienced hardships in life	640	0.86	0.35	0	1
Has held insurance in the past	640	0.1	0.3	0	1
Feels better prepared now than before the 2010 flood	640	0.31	0.46	0	1
Number of friends and family who were injured due to floods	640	4.17	18.9	0	200
Plans to move to another settlement in the future	640	0.14	0.35	0	1
Lives in 2010 flood cluster and plans to move to another settlement in the future	640	0.07	0.25	0	1
Willing to predict when the next flood will occur?	640	0.21	0.41	0	1
Lives in 2010 flood cluster and predicts number of seasons before the next flood	640	0.13	0.33	0	1
Expect to be better off in the future compared to today	640	0.45	0.5	0	1
How is your health today: Good	640	0.4	0.49	0	1
Thinks the next flood will be similar to the previous flood	640	0.08	0.27	0	1
Thinks the next flood will be better than the previous flood	640	0.05	.218	0	1
Thinks the next flood will be worse than the previous flood	640	0.34	.47	0	1
Village flood propensity score	640	0.4	0.19	0.15	0.78
Muzaffargarh district	640	0.56	0.5	0	1
Layyah district	640	0.25	0.43	0	1
Rahim Yar Khan district	640	0.19	0.39	0	1

Note: PKR 100 =$1 approximately

Table 1B: Summary statistics –Public goods game

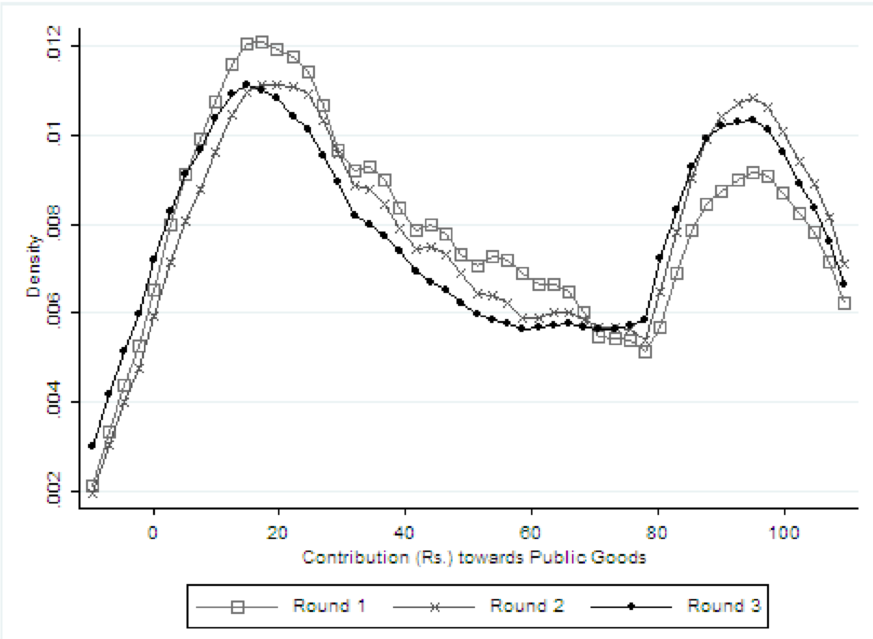
Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Average Contribution (Rs) in All Rounds	384	52.13	32.40	0	100
Average Contribution (Rs.) Male	192	60.28	30.96	0	100
Average Contribution (Rs.) Female	192	43.98	31.82	0	100
Average Contribution (Rs.) in Round 1	384	50.47	34.49	0	100
Round 1 (Rs.) Male	192	59.48	33.23	0	100
Round 1 (Rs.) Female	192	41.46	33.43	0	100
Average Contribution (Rs.) in Round 2	384	53.83	35.20	0	100
Round 2 (Rs.) Male	192	61.30	34.35	0	100
Round 2 (Rs.) Female	192	46.35	34.54	0	100
Average Contribution (Rs.) in Round 3	384	52.08	36.24	0	100
Round 3 (Rs.) Male	192	60.05	34.80	0	100
Round 3 (Rs.) Female	192	44.11	35.98	0	100

Note: PKR 100 =$1 approximately

From Table 1B we can see that on average participants contributed Rs. 52 in all three rounds. For the three rounds, on average, only 5.21 percent of the subjects kept all Rs.100 contributing nothing to the common pool whereas 23.1 percent of the participants on average put all Rs. 100 into the group pool.

Women consistently contribute less. However, both men and women increase their contributions in the successive rounds. The contributions in the first round are the lowest but they go up in the second round. A t-test is performed to establish the difference in mean contributions across rounds as statistically different from each other (Table A2 in appendix). The results show that contributions in round 2 are statistically greater from both, round 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 across all three rounds: Rs 20 and Rs.100. There is a shift towards the higher contributions in round 2 and 3. The distribution of contributions in each round can be studied in greater detail from figure A1 in the appendix. About 28 percent of the participants contribute Rs. 100 in both round 2 and round 3. There is a 75 percent correlation between participants who contributed Rs. 100 in both round 1 and 2 and those who contributed Rs. 100 in both round 2 and 3.

Figure 2: Kernel density estimates of participant contributions across rounds



6 Results

Table 2 shows the linear regression results for flood experience of people residing in the flood clusters and the control regions. It may be useful to reiterate that flood clusters comprise villages where all the households reported having been affected by the 2010 floods. All regressions control for age of participant, gender, income, savings, districts, propensity scores and game rounds.

In order to isolate the effects of diverse experiences with floods, we test whether frequency of floods experienced differently from a single experience of floods. From table 2, individuals residing in a flood cluster do not make significantly different contributions from those who are not living in flood clusters. Moreover, about 80 percent of the individuals in our sample had some previous experience of floods, including the 2010 floods, and the variable "*Has experienced floods*" does not significantly explain the variation in the contributions made by participants in the public goods experiment. Individuals who have only experienced the 2010 floods contribute Rs. 17 more on average. However, the frequency of floods experience impacts contributions differently. Individuals on average pay Rs. 4 more for each successive incidence of flood experience. The behavior of individuals residing in flood clusters is different from the control group as they make significantly lower contributions with increasing experience of floods. In other words, individuals who experienced multiple floods including the severe 2010 floods make negative contributions compared to those who experienced the same number of floods, but not the 2010 floods. As mentioned earlier, we attribute the lower contributions by individuals residing in flood clusters to their traumatizing experience of the worst floods.

Table 3 includes external assistance variables. We test for the impact of different types of government assistances on the contributions towards public goods. In line with findings of Cassar et al. (2011) contributions and external assistance are positively associated. Results indicate that food assistance after the floods 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 towards public goods as compared to individuals who did not receive food assistance, even though they may have received other types of government assistance during the floods[14]. The Citizens Damage Compensation Program (CDCP) initiated by the provincial government in the aftermath of the 2010 floods, provisioned for a transfer of Rs. 40,000 to flood affected households in two tranches through individual ATM cards called the “Watan cards”. Households that received a Watan card contributed Rs. 19 more (column 2), on average, than households not receiving a Watan card; however after controlling for flood clusters the contribution decline by Rs. 28. A t-test for difference in mean income levels (Table A3) shows that there is no difference in mean income levels of households receiving Watan cards. This indicates that flood assistance, unlike poverty assistance, has a strong positive impact on contributions barring those who experienced the 2010 floods.

The Benazir Income Support Programme (BISP) is a poverty alleviation fund which was initiated by the government in 2007 to assist poor households by making monthly transfers of Rs.1000. While this is not flood related assistance, we control for households that have been receiving the BISP assistance and find that households not belonging to the flood clusters contribute Rs. 12 less on average. Perhaps this negative contribution is because these are poorer households, and to verify this we do a t-test for difference in mean income levels for households who receive BISP compared to those who do not receive these payments (Table A4 in the Appendix). Households receiving BISP payments have a mean income of Rs. 18,469 while the other group has a mean income of Rs. 24,463, and from the t-test we see that the two means are statistically different from each other. However, since income is already being controlled for in the regressions, the negative contributions may also reflect a crowding out of private contributions as suggested by the neutrality theorem. Risk aversion measured by the average of responses in the three rounds of a lottery game is included in the regression and it has a positive but insignificant effect on contributions. The same holds true for a survey question response measuring risk aversion, in which individuals are asked if they prefer to receive Rs. 500 now instead of a 50 percent chance for winning Rs. 1000.

We test for individual’s perceptions of self and the future in Table 4. In the survey, individuals are asked about their expectations for the future. In a cultural context, people, in general, are unwilling to predict an adversity as it is considered to be a sign of pessimism[15]. In our results we find that individuals who are willing to predict the number of seasons before the next floods will occur make lower contributions compared to those who do not want to make any predictions. Moreover, individuals who feel the next flood will be similar, 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 make greater contributions

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

[15] Only 21 percent of the respondents made a prediction about when the next floods could be expected.

(Table 4). Respondents planning to move to another settlement for any reason contribute less compared to their counterparts. This may be due to a diminished association with the existing community as they intend to migrate. As observed by Toyo and Skidmore (2013), the effect of a shared sense of loss from floods captured by '*has known friends and family who were injured due to floods'* in this study, shows a positive effect on contributions.

In table 5, we test if people who adapt to their circumstances and adopt new techniques in their way of life make different contributions in comparison to others. While resilience can be measured in many different ways and possibly through multiple characteristics, we consider the ability to adopt new techniques as proxy for gauging resilience. It appears that individuals who adopted any new technique (in agriculture, cooking fuel, building material etc.) contribute significantly more compared to those who did not adopt any new techniques. However, this effect becomes negative as the number of floods experienced increases. This suggests that while resilience may lead to greater contributions, when resilient people experience more floods, they make lower contributions.

A more detailed analysis of the type of adoption technique reveals that individuals who adopted new agricultural practices make significantly greater contributions towards publics goods. A higher flood loss as a percentage of total monthly income has a positive effect on contributions however, people who lost their livestock as a consequence of the floods, make significantly negative contributions, controlling for income. In line with findings of Whitt and Wilson (2007), educational attained appears unrelated to contributions possibly because current and future prospects were not taken into account whilst making the experiment decisions.

The round effects appear robust in all the regressions[16]. Individuals make significantly greater contributions in round 2 compared to round 1. The regression results support the Section 5 discussion of the changes in behavior across rounds. While, we suggest the possibility of learning across rounds, three rounds (excluding a practice and demonstration round) may not be sufficient to establish a learning effect. It does however suggest that participants consciously change their contribution patterns across the three rounds. Among other control variables, age and the age-squared do not significantly affect contributions, neither do income and savings. Women contribute significantly less than their male counterparts. This result is consistent with the findings of Brown-Kruse and Hummels (1993) who study the gender effects in public goods contributions in a laboratory. In another study by Carpenter et al. (2004), female participants contributed significantly less towards public goods compared to men in Bangkok but the trend is reversed for women from Ho Chi Minh City.

[16] Results for control variables are shown in Table 2 only, however, they remain robust for all empirical estimations.

Table 2: Flood Experience

VARIABLES	(1) contribution	(2) contribution	(3) contribution	(4) contribution	(5) contribution	(5) contribution
Age in years	-0.029	-0.031	-0.064	-0.077	-0.080	-0.058
	(0.106)	(0.112)	(0.113)	(0.112)	(0.112)	(0.110)
Participant is a female	-17.501***	-17.308***	-18.275***	-18.888***	-18.286***	-17.847***
	(5.433)	(5.468)	(5.251)	(5.507)	(5.434)	(5.592)
Log of monthly income	-1.271	-0.625	-0.370	-0.606	-0.433	-0.133
	(2.167)	(1.878)	(2.031)	(1.773)	(1.698)	(1.488)
Log of Household savings	-0.359	-0.288	-0.373	-0.393	-0.400	-0.534
	(0.394)	(0.383)	(0.357)	(0.396)	(0.403)	(0.392)
Lives in 2010 flood cluster		7.299	3.502	14.585	10.657	0.650
		(8.944)	(8.982)	(10.560)	(10.306)	(7.682)
Number of floods experienced			4.046*	10.333***	8.112**	8.597***
			(1.916)	(3.157)	(3.479)	(2.406)
Lives in 2010 flood cluster and number of floods experienced				-10.339**	-8.275*	-4.545*
				(3.673)	(4.072)	(2.527)
Has experienced floods (including 2010 floods)					6.795	
					(6.494)	
Has only experienced the 2010 floods						16.880***
						(4.002)
Muzaffargarh district	20.133	27.277	29.170	28.010*	27.248*	21.750
	(12.329)	(17.297)	(17.712)	(15.138)	(14.475)	(13.138)
Layyah district	36.422***	39.375***	42.724***	42.828***	43.419***	40.199***
	(9.603)	(11.465)	(13.353)	(12.578)	(12.568)	(11.451)
Village flood propensity score	2.221	-13.174	-9.942	-15.750	-14.837	-15.721
	(27.944)	(37.634)	(35.659)	(29.496)	(28.347)	(22.209)
Round 2	3.403***	3.403***	3.440***	3.440***	3.440***	3.440***
	(1.021)	(1.021)	(1.034)	(1.035)	(1.035)	(1.035)
Round 3	1.623	1.623	1.653	1.653	1.653	1.653
	(1.407)	(1.407)	(1.452)	(1.453)	(1.454)	(1.454)
Constant	52.412*	43.722*	37.421	38.973*	34.576	34.566*
	(25.713)	(23.314)	(25.155)	(21.724)	(20.374)	(16.439)
Observations	1,146	1,146	1,125	1,125	1,125	1,125
R-squared	0.172	0.179	0.184	0.201	0.204	0.232
Adjusted R-squared	0.165	0.171	0.176	0.192	0.195	0.223

Note: Heteroskedasticity-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
PKR 100 =$1 approximately

Table 3 – External assistance

VARIABLES	(1) contribution	(2) contribution	(3) contribution	(4) contribution	(5) contribution
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)
Received government flood cash assistance			1.695		
			(5.587)		
Received government flood non-food assistance			-2.853		
			(3.833)		
Received government flood food assistance			8.780**		
			(4.076)		
Received government flood BISP assistance			-11.751**		
			(4.694)		
Lives in 2010 flood cluster and received BISP assistance			9.899		
			(6.891)		
Received Watan Card		18.877*			
		(8.878)			
Lives in 2010 flood cluster and received Watan Card		-28.649**			
		(9.586)			
Received government assistance	3.785				
	(3.082)				
Insurance game: insurance chosen in at least 1 out of 15 rounds				1.265	
				(6.735)	
Has held insurance in the past				-0.319	
				(4.946)	
Average lottery game choice (higher value = riskier choice					0.073
					(2.018)
Prefer Rs.500 instead of a game with 50% chance of winning Rs. 1000					2.181
					(3.494)
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

Note: Heteroskedasticity-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
All regressions are controlled for age, gender, log of monthly income, log of household saving, district dummies, propensity score and round variables.
PKR 100 =$1 approximately

Table 4- Self-perception and future expectations

VARIABLES	(1) contribution	(2) contribution	(3) contribution	(4) contribution	(5) contribution	(6) contribution
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 will occur?	-10.345*					
	(5.135)					
Expect to be better off in the future compared to today	5.256*					
	(2.532)					
Years of schooling attained by the household head		-0.080				
		(0.337)				
Self-reported ability to recover faster from unexpected events		-1.560				
		(3.684)				
Plans to move to another settlement in the future			-12.021*			
			(6.063)			
Resides in the flood cluster and plans to move to another settlement in the future			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 flood					3.914	
					(2.822)	
How is your health today: Good					0.723	
					(0.909)	
Has known friends and family who were injured due to floods						0.129***
						(0.042)
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

Note: Heteroskedasticity-robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
All regressions are controlled for age, gender, log of monthly income, log of household saving, district dummies, propensity score and round variables.
PKR 100 =$1 approximately

Table 5-Adoption of new techniques

VARIABLES	(1) contribution	(2) contribution	(3) contribution	(4) contribution	(5) contribution
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)
Adopted new things: any of 8 categories	11.875***		11.908***	12.206***	11.730***
	(3.670)		(3.597)	(3.679)	(3.496)
Number of floods experienced and adopted new things	-8.102***		-8.273***	-8.357***	-8.250***
	(2.256)		(2.110)	(2.246)	(2.207)
Adopted new things: new agricultural practices		9.217**			
		(4.308)			
Adopted new things: fuel/cooking techniques		-1.479			
		(4.955)			
Adopted new things: building materials		2.225			
		(3.391)			
Flood livestock loss as a percentage of monthly income			-0.445***		
			(0.127)		
Total flood loss as a percentage of monthly income			0.108**		
			(0.050)		
Learn any mitigation methods from the 2010 floods?				3.432	
				(3.772)	
Number of years of education					0.342
					(0.334)
Has held insurance in the past					0.217
					(4.550)
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

Note: An interaction of “Adopted new things: any of 8 categories” with “Lives in 2010 flood cluster” was included as a control but not shown in the results as it is statistically insignificant.
Heteroskedasticity-robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
All regressions are controlled for age, gender, log of monthly income, log of household saving, district dummies, propensity score and round variables.
PKR 100 =$1 approximately

7 Conclusion

Experiences with natural disasters have real lasting effects on personal preferences and relationships with other members of the community. By treating the 2010 floods in Pakistan as a natural experiment, we study the extent of social capital in communities by conducting public goods behavioral games and observing contributions patterns in the flood clusters of 2010 and the non-flooded communities. By conducting incentivized games we are 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 such as Fleming et al. (2011), Andrabi (2010) and Toyo and Skidmore (2013) have studied social capital after a severe natural disaster or small frequent experiences with disasters, this study is unique as it makes a distinction between frequent experiences with mild flood and an extremely severe flood experience and draws conclusions based on these differences. Among our main results, different kinds of experiences with floods resulted in difference levels of contributions. We find that experiencing a greater number of floods results in significantly larger contributions. Moreover, experiencing the 2010 floods increased contributions towards the community for the entire sample. However, the behavior of individuals who reside in the 2010 flood clusters is different from the control group as their contributions decline with the number of times they experience floods increases. In other words, mild floods experiences coupled with a severe flood can negatively affect social capital.

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 assistance results in higher contributions towards the community pool. Individuals who received lump-sum monetary transfers from the Watan card scheme made positive contributions as long as they were not residing in the flood clusters. The negative contributions from recipients of Watan cards residing in the flooded clusters of 2010 indicate the limited appreciation of the Watan card scheme by those who were most affected by the floods. While our results suggest a negative relationship in terms of contributions towards public goods, there is a need for an in-depth analysis of the scheme to determine its utility as a policy instrument for the future. Interestingly, for non-flood monetary transfers we find that private contributions are crowded out by government transfers. This is another area of research that has not been explored to its potential especially since the BISP programme is the largest safety net programme initiated by the government in 2008 and has been continued by the new government sworn in 2013.

Individual characteristics such having positive future expectations and being resilient in the aftermath of a disaster are associated with greater contributions towards public goods in general. However, as experience with floods increases, resilience also results in lesser contributions. In consistence with literature (Toyo and Skidmore, 2013), we find that a shared sense of loss, measured by flood losses in the form of injury experienced by friends or family results in greater contributions and therefore, social capital. While interesting on their own, these results also suggest the importance of building on social capital such as skills development so that the communities can develop coping mechanisms and move towards self-reliance.

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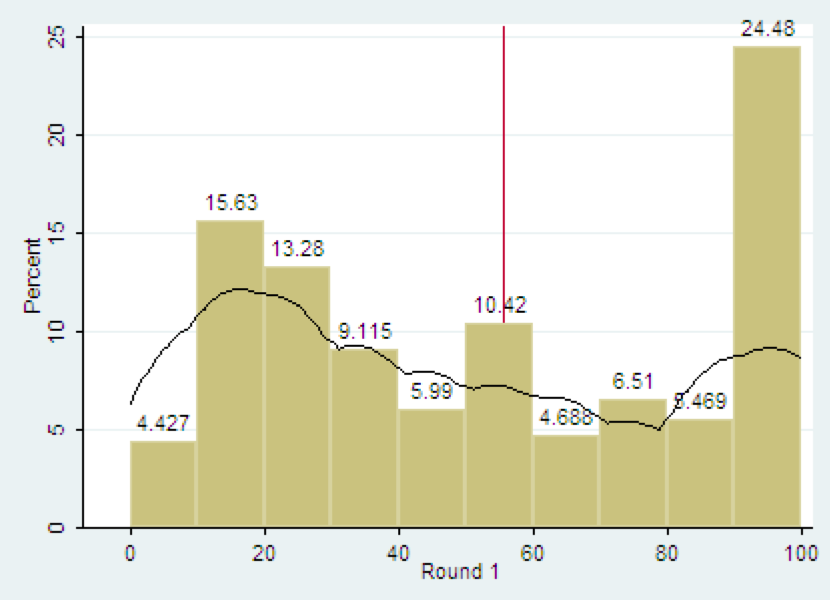
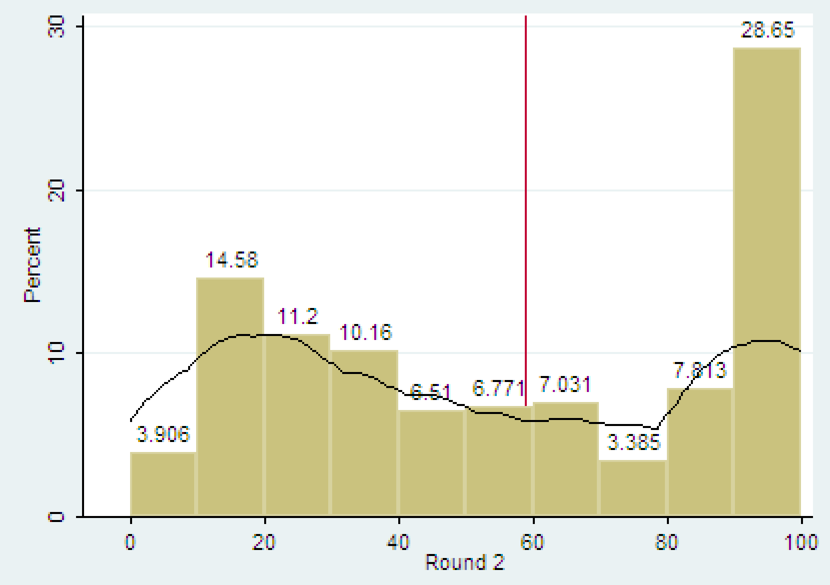
Appendix

Figure A1- Percentage distribution of contributions in each round





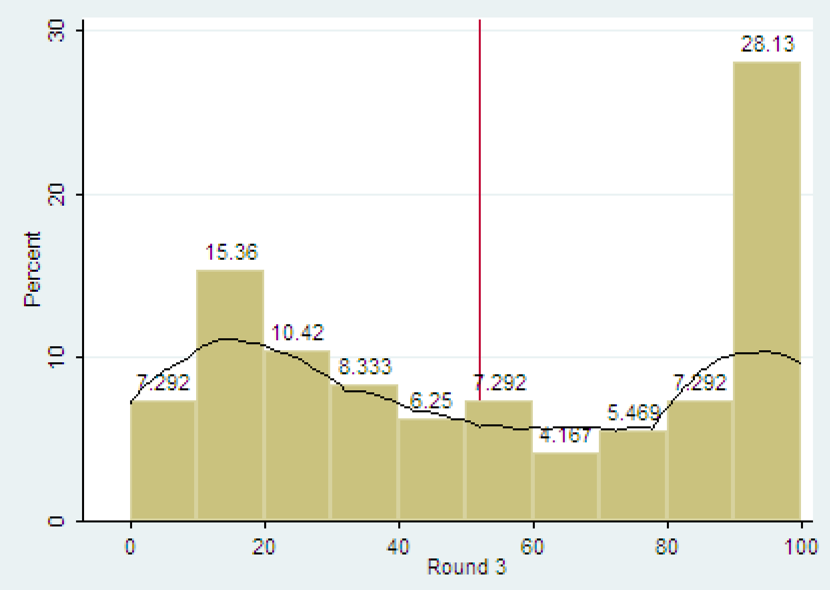


Table A2- T-test results for sample balance

	Mean			t-test	
Variable	Treated	Control	%bias	t	p> |t|
Average monthly Income	2419.3	233.4	7.7	0.59	0.559
Literacy	0.232	0.219	11.2	0.54	0.593
Education of household head (years)	3.011	2.721	19	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	-0.47	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 schools	0.757	0.770	-5.4	-0.23	0.818
Average distance to girls primary schools	0.6875	0.712	-8.8	-0.38	0.705
Average distance to boys secondary schools	0.243	0.204	11	0.51	0.612
Average distance to girls secondary schools	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 flooring	0.244	0.255	-6.6	-0.36	0.721
% of households with permanent roofs	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 households	3.374	3.294	6.1	0.23	0.816
Average number of goats owned by households	2.999	2.772	11.8	0.6	0.553
Average 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	Std. Dev.	Min	Max
Propensity scores		0.405	0.193	0.15	0.778

Table A1 – T-test result for 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
```

Table A3 – T-test result for difference in average income levels of households that received Watan Cards (Group 0: not receiving payments; Group 1: receiving payments)

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	88	18189.43	2469.428	23165.29	13281.18	23097.69
1	224	20060.85	1726.704	25842.94	16658.1	23463.59
combined	312	19533.01	1420.671	25094.06	16737.67	22328.36
diff		-1871.416	3160.361		-8089.888	4347.055

diff = mean(0) - mean(1)   t = -0.5922
Ho: diff = 0   degrees of freedom = 310

Ha: diff < 0   Ha: diff != 0   Ha: diff > 0
Pr(T < t) = 0.2771   Pr(|T| > |t|) = 0.5542   Pr(T > t) = 0.7229

Table A4 – T-test result for difference in average income levels of households receiving BISP payments (Group 0: not receiving payments; Group 1: receiving 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