Unintended Consequences of Government Support: Impact of Pakistan's Flood Relief Program on Adaptation Behavior *

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Abstract

This paper examines the effect of government support in form of village-level cash transfers on adaptation behaviors. After the devastating 2010 floods, the Pakistan government initiated the Watan Card program, under which all households in a village that was more than 50 percent flooded got a cash transfer. I find that while cash transfer recipients are 20 percent more likely to invest in personal adaptation, they are 22 percent less likely to work with other villagers to invest in community adaptation. Non-damaged households who get the cash transfer just because they reside in a flood-affected village drive this negative effect. These findings hold even after conducting a series of robustness tests including a placebo test. Finally, I show that these findings are consistent with a simple economic model.

Keywords: Adaptation, Cash transfers, natural disasters

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1 Introduction

According to the UN, 1.3 billion people in developing countries live at risk of some kind of natural disaster (UNDP). Due to low state capacity, governments in low and middle-income countries are unable to reduce the disaster risk. Hence, people at risk resort to informal personal and community-level adaptations to protect themselves.[1] But, once there is a major disaster, the government with the support of international organizations steps in to provide relief. It can be difficult and time-consuming to survey affected areas and identify damaged households. A common practice is to provide relief to all households in a community or a village identified as calamity affected (also known as geographic targeting).[2] In this paper, I investigate how government relief in the form of village-level cash transfers affects people's adaptation behavior.[3]

I utilize the context of the 2010 monsoon floods in Pakistan and the subsequent government relief to study this question. Between July and September 2010, almost half of Pakistan was engulfed in historic floods that were described as one of the worst in the country's history. After the floods, the Pakistan government with the support of international donors launched a cash transfer program known as the Watan card program. Under the program, all households in villages that were more than 50 percent flooded received a cash transfer through a visa debit card. A survey was conducted by International Food Policy Research Institute (IFPRI) in 2012, which asked people about their adaptation behaviors. Using this dataset, I investigate how the Watan card influences people's adaptation behavior one and a half years after the floods.

I adopt multiple strategies to identify the effect of the cash transfer program on adapta-

[1] Personal adaptations could include people building houses on an elevated area to reduce flood risk. Community adaptations could include people working together to build small barrages to reduce flood risk, planting cork trees to prevent wildfires, or building *chowkas* (interconnected pits to hold rainwater) to prevent droughts.

[2] Some examples of such programs include the Philippines' Community Recovery and Livelihoods Program after 2013 Typhoon Haiyan, Haiti's Cash-for-Work Program after the 2010 earthquake, and Mozambique's Cash Transfer Program after Cyclone Idai in 2019.

[3] By village level, I mean all households in a village identified as calamity affected get the cash transfer instead of only the severely affected households.

tion. Among flooded villages, I compare the adaptation behaviors of households in Watan villages (cash transfer recipient) with those in non-Watan villages (non-recipient) while including a rich set of village-level controls. A potential worry is that these differences could be driven by confounders. I do two things to address this concern. First, using spatial data, I test whether Watan and non-Watan villages are different in potential confounder variables like nightlight and population density. Second, I use another province, Khyber Pakhtunkhwa (KPK), where the Watan card program was implemented at a household level instead of a village level, as a placebo to test whether the differences in adaptation between more and less than 50 percent flooded villages persist.

I find that the Watan card program encourages personal adaptation to floods, but it creates a disincentive for people to contribute towards community adaptation. Households in Watan villages are 20 percent more likely to invest in flood-resilient house infrastructure, send a household member as a migrant, or diversify income sources. But they are 22 percent less likely to help fellow villagers in building a barrage or protection around the village that will reduce the likelihood of the village being flooded in the future. I find that among flooded villages, there is no statistically significant difference between Watan and non-Watan villages in proxies for economic development like night lights and population density. Furthermore, I find that in the placebo province, while households in more than 50 percent of flooded villages are more likely to invest in personal adaptation, they are not less likely to invest in community adaptation than households in less than 50 percent of flooded villages. Thus, the negative effect of the village-level cash transfer on community adaptation cannot be explained by unobservable confounders.

Later, I turn to understand why village-level cash transfers discourage community adaptation. It seems unintuitive at first that while cash transfers have a positive effect on personal adaptation, they have a negative effect on community adaptation. I find that these effects are driven by the heterogeneous levels of damage that floods cause to different households in a village. Damaged households in a Watan village are 28 percent more likely to invest in personal adaptation than households of the same damage level in a non-Watan village, and there is an insignificant negative effect on their investments in community adaptation. The negative effect of the Watan card on community adaptation thus comes from non-damaged households who get the cash transfer just because they were situated in a more than 50 percent flooded village, but they were not personally affected by the floods. These non-damaged households are 49 percent less likely to contribute towards community adaptation when they get the Watan card. To confirm that these heterogeneous effects are not driven by unobservable socio-economic differences between more and less damaged households, I show that these heterogeneous effects are not present in the KPK province. I also conduct a series of robustness checks and try to rule out alternative explanations like substitution effect.

In the final section of the paper, I construct a simple two-period model to theoretically explain the negative effect of village-level cash transfer on community adaptation. Households derive utility from a potential future cash transfer that is conditional on the village getting flooded. Investing in community adaptation reduces the risk of flooding. Households get disutility from flood damage and investments in personal and community adaptation. Their belief about the risk of future damage in case of a flood depends on the damage they incurred in the past flood and their investments in personal adaptation. Deriving the effects of the cash transfer, the model shows that a village-level cash transfer discourages community adaptation with the non-damaged households being most strongly discouraged. Moreover, the model predicts that there would be no negative effect on community adaptation if cash transfers are provided at the household level.

The results of this paper generate important policy-relevant insights. It is not only important to provide relief but it is also important to carefully target it to the deserving population. Village-level cash transfers are a good policy option, for they can be implemented quickly, might incur low administrative costs, have short-term benefits, and encourage personal adaptation. But, they discourage people, particularly non-damaged people, from working together to protect the entire village from a future disaster. Since community efforts require everyone to chip in their share to prove effective, village-level cash transfers can undermine these community efforts. Overall, policymakers should realize that there are informal community-level adaptations to disasters that are already in place, so they should provide incentives to strengthen these adaptations while providing relief.

This paper contributes to three strands of literature. First, social scientists debate different targeting mechanisms for cash transfers i.e. proxy means testing, community-based targeting, and geographic targeting (Bigman and Fofack, 2000; Bigman and Srinivasan, 2002; Schady, 2002; Pritchett et al., 2002; Marito and Moore, 2009; Hagen-Zanker et al., 2016; Alatas et al., 2016). [4] The literature on targeting mechanisms focuses on important aspects like leakage rates, information accuracy, grievance rates, and initial conditions. However, a key aspect that is ignored in the literature is the subsequent behavioral response of beneficiary households. I contribute to the debate on the targeting mechanisms by showing that a particular design of the cash transfer program, geographic targeting in my case, can generate expectations about future transfers in the same manner and thus influence the recipient's behavior in a negative way. Thus, in evaluating different targeting mechanisms, it is not only important to consider which strategy identifies the deserving households best but also how the strategy would affect the household's future behavior.

Second, I contribute to the literature on the effects of cash transfer programs. Most of the research on cash transfers focuses on cash transfers as interventions to reduce poverty or to improve education and health outcomes (Haushofer and Shapiro, 2016; Rawlings and Rubio, 2005). While the research on cash transfers as a form of disaster relief is limited, it also focuses on short-term outcomes like hunger, poverty, sanitation, and shelter (Kosec and Mo, 2017; Asfaw et al., 2017; Bhalla et al., 2018; Skoufias, 2003). There has been very little attention paid to the effect of these cash transfers on long-term outcomes relating to

[4] Proxy means testing involves looking at a proxy such as household assets, education level, or house quality to identify low-income deserving households, whereas, in community-based targeting, communities are empowered to identify the most deserving households. In geographic targeting, geographic areas are identified based on aggregate indicators, and all households situated in the area are provided transfers.

people's behavior. Only a few scholars have studied the effects of post-flood cash transfers on migration patterns in the US and found that these cash transfers increase migration into flood risk areas (Pang and Sun, 2022; Henkel et al., 2022). I contribute to this literature by showing that cash transfers can influence important long-term adaptation behavior.

Third, I contribute to the broader literature on the interaction of formal and informal institutions. There exists a vast literature that discusses the effects of introducing formal institutions in contexts where informal arrangements are already in place (Williamson, 2009; Casson et al., 2010; Lin et al., 2014; Hartman et al., 2021). This literature covers a vast range of institutions associated with dispute resolution, insurance, governance, property rights, and many others. I contribute to this literature by showing how the introduction of formal relief programs can negatively affect informal institutions like community adaptation which can be vital for a community's long-term development.

The paper is structured as follows. In section 2, I explain the context. In section 3, I describe data sources and variables. In section 4, I show empirical results on the effects of cash transfer on adaptation behavior, test for the mechanism, conduct robustness checks, and explore alternative explanations. Finally, in section 5, I propose an economic model to explain my findings, and then I conclude in section 6.

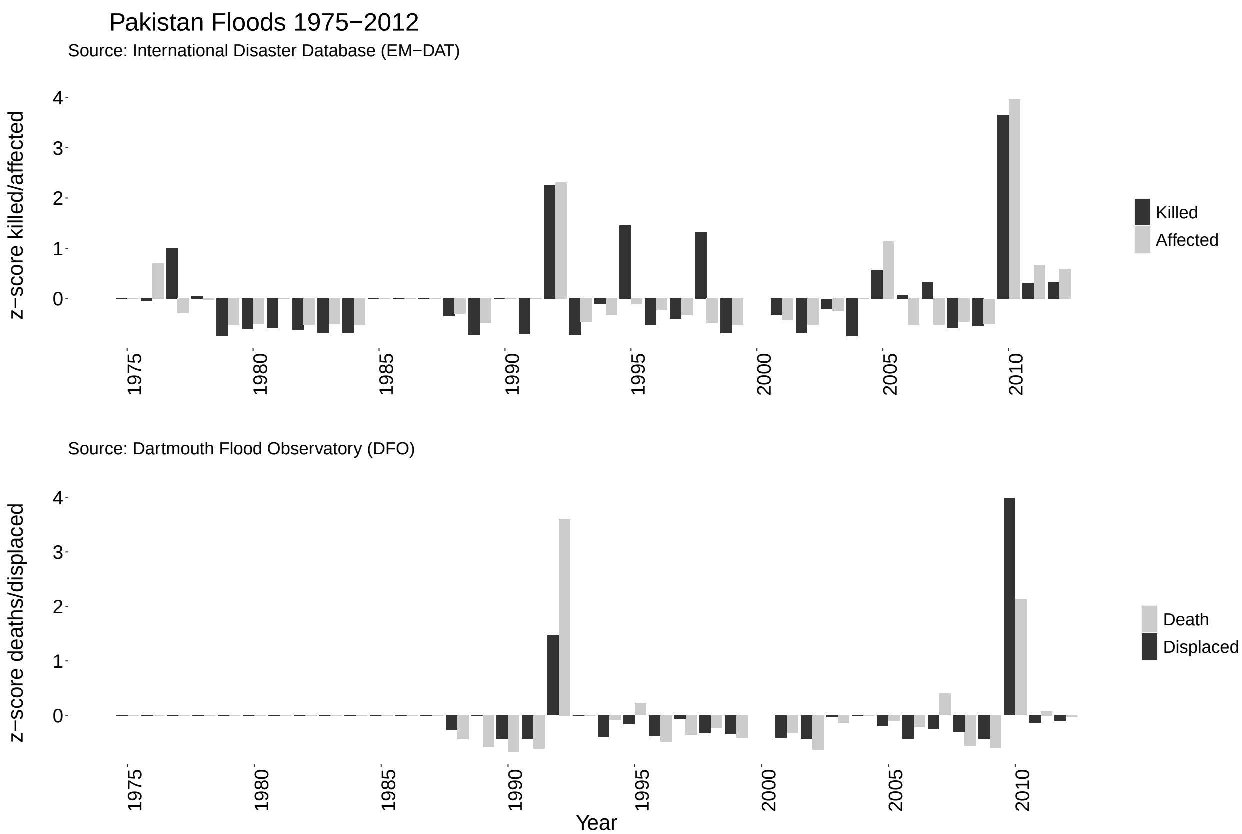
2 Context

2.1 Floods

Pakistan is a natural-disaster-prone country with floods accounting for almost 46 percent of all hazards (Larsen et al., 2014). Floods occur almost every year, but severe flooding events are rare (see figure 1). Floods are mainly caused by monsoon rainfall (Sayed and González, 2014), so there is a risk of flooding every year from July to October (monsoon season).

The response to small floods is mostly indigenous. Some of the common adaptation strategies included building homes on elevated land, migrating to other non-flooded cities and villages, and working with other villagers to plant trees around the village or improve river embankments or build a small barrage (Ahmed, 2022).[5]

Figure 1: Floods in Pakistan



Notes: This figure shows the impact of floods per year in Pakistan. The top panel shows the changes in people killed and affected per year by flooding using the EM-DAT database, whereas the bottom panel shows the changes in death and people displaced due to floods using the DFO database. Standardized z-scores are reported in each case. This figure has been reproduced with permission from Fair et al. (2017).

Figure 1 compares the 2010 floods with all other floods between 1975 and 2013, in terms of the number of people affected and killed. It shows that the 2010 floods were one of the worst floods in Pakistan's history, with the 1992 floods being the only other comparable flooding. According to official estimates and reports, the 2010 floods affected more than 20 million people (about 11 percent of the total population), displaced 10 million people, killed 1,980 people, destroyed 1.6 million homes, and damaged 2.4 million hectares of crops

[5]For some stories about how villagers in Pakistan resort to community methods for flood prevention, see (WEF; Shaikh and Tunio, 2015).

(around 11 percent of total crops) (CRED, 2013). Overall economic losses were estimated to be about US 10 billion (6 percent of GDP) (Asian Development Bank, 2011).

In the wake of the 2010 floods, the government stepped up relief efforts. The National Disaster Management Authority (NDMA) worked with government ministries and Pakistan Army to provide relief supplies in affected areas. The government made an international appeal for donations and managed to raise 1.8 billion USD by Nov 2010 for flood relief (UNOCHA, 2010). Since the bureaucracy was not too well trained for disaster management, NGOs and other community groups also played a very active role in the relief efforts (Shahbaz et al., 2012).

2.2 Cash Transfer Program (Watan Card)

In September 2010, the government launched the Watan card program in order to provide cash transfers to people affected by floods. The first phase of the program ran from September 2010 to August 2011. The government distributed US$ 400 million among 1.62 million households. Each transfer was 20,000 PKR (US$ 250), which is around two months' median rural income (World Bank, 2013).

The government distributed cash transfers through Watan cards. The Watan card was a visa direct debit card that was given to each beneficiary household. A beneficiary could cash out the money from an ATM or a designated point of sale. This method was preferred over other methods in order to make the process transparent, reduce the risk of corruption, and elite capture (World Bank, 2013).

Identifying the flood-affected families was a challenge as there had not been such an unprecedented flood before. Moreover, there was little time to train teams and do a house-by-house survey to enlist affected families into the program (World Bank, 2013).

In the two major provinces Punjab and Sindh, the government used a geographic targeting system to identify flood-affected villages (World Bank, 2013). Entire villages were declared as calamity hit and thus eligible for the Watan card if more than 50 percent of the cropland was covered by water.

While the official documents state that the government utilized satellite imagery obtained from Pakistan Space and Upper Atmosphere Research Commission (SUPARCO), I learned through interviews with the government officials in NDMA that things were done a bit differently (World Bank, 2013). If satellite imagery had been used to identify flood-hit villages, a regression discontinuity could be used at the 50 percent cutoff to identify the effects of the Watan card program. NDMA officials involved in the Watan card program informed me that the task of identifying flood-hit villages was transferred from the federal level to the district level. The district governments used middlemen *patwaris* to determine the proportion of village area flooded. Using the data gathered through these middlemen, district governments sent a list of flood-affected villages to the provincial government, who forwarded these notifications to the federal government. Therefore, it was also impossible for me to recover the data on the proportion of villages flooded as reported by the middlemen because the federal government only had the names of areas identified as flood-affected and the data on the proportion of areas flooded would have to be gathered at the district level. The federal government utilized the assistance of SUPARCO's satellite imagery to cross check if there were gross mistakes, but the final decision remained with district authorities.

A major weakness in the design of the Watan card program was that it led to large inclusion and exclusion errors. Affected households in villages that are less than 50 percent flooded were excluded from the cash transfer, and unaffected households in more than 50 percent flooded villages got the cash transfer even though they did not personally suffer from the floods. An independent impact evaluation of the program conducted by researchers at Hunt et al. (2011) found that "for every 100 potentially eligible family heads (flood affected), only 43 had received the Watan card."

In another province, Khyber Pakhtunkhwa (KPK), the government used an entirely different targeting system. Instead of declaring entire villages as eligible for Watan cards, the provincial government conducted a rapid housing survey. The survey teams visited all of the reported flood-affected villages and determined eligible households based on visual inspection if the house structure seems damaged by floods or not. The main reason for a different targeting mechanism in KPK was that there had been a massive earthquake in the KPK province a few years before the floods in 2005. Due to the earthquake, the disaster management authorities in KPK had more experience and a greater bureaucratic capacity to conduct a housing survey in little time(Hunt et al., 2011).

An important feature of the program in all provinces was that the payment was not supposed to be one-off. People were given the Watan visa debit cards so that it would be easier to make payments to these people in the future as well if there is a flood. During the time when the program was running, some politicians explicitly made commitments about this (Semple, 2011). There are also some news reports that mention that once the cash transfers had been completed, some people started selling their Watan cards if they had an urgent need of money because people expected future cash transfers in case of flooding (DAWN, 2010).

3 Data and Variable Construction

For the empirical analysis, I rely primarily on the data from Pakistan Rural Household Survey, and some other online sources for obtaining data on geospatial variables. To get qualitative insights about the Watan card program, I held interviews with government officials, who were involved in the program.

3.1 Pakistan Rural Household Survey (PRHS)

PRHS was a panel survey conducted by World Bank's International Food Policy research institute (, IFPRI). The survey consisted of three rounds. The first round was conducted in March-April 2012 (approximately one and a half years after the floods, and one year after the cash transfers), and the other two rounds were conducted in 2013 and 2014. In this paper, I only use the data from the first round of the survey. The survey covered 76 villages from three main provinces of Pakistan—Punjab, Sindh, and KPK. The survey consisted of both a household survey from a random sample of around 26 households per village and a three-member focus group survey with village elders. In total 2,090 households were interviewed, of which around 50 percent resided in flood-affected villages. It was a multi-topic survey, but since the first round of the survey took place soon after the biggest floods in Pakistan, one main part of the survey was dedicated to questions related to the experience of the households with floods and their subsequent adaptation-related response. The later rounds of the survey did not get follow-up information about flood-related adaptations, so these rounds were not useful for my analysis.

3.1.1 Variables

Dependent Variable: Adaptation

The main outcome variables I am interested in are household investments in flood-related adaptations. These adaptations could be categorized into personal adaptations, like improving house infrastructure, and community adaptations like building a barrage. In the floods section of the survey, households were asked if they had invested in a particular kind of adaptation after the 2010 floods. Households could respond with a "Yes" or "No" to each question.

Personal Adaptation

The survey asked about three main kinds of personal adaptations that will reduce a household's personal likelihood of either being damaged in the flood or getting an income shock in case the village is flooded. These personal adaptations include 1) rebuilding one's house with better concrete that is less likely to be damaged in case of flooding (*pacca* house), 2) sending some households members as migrants to areas with lower flood risk, and 3) moving away from farm income. There is abundant evidence in the existing literature that migration and income diversification reduce income and consumption shock if there is a natural disaster (Zhou et al., 2010; Black et al., 2011). To avoid problems with multiple hypothesis testing, I created an inverse covariance weighted index of the three kinds of personal adaptations. This technique of aggregating many variables into an index has been well-used in the existing economics literature (Anderson, 2008).

Community Adaptation

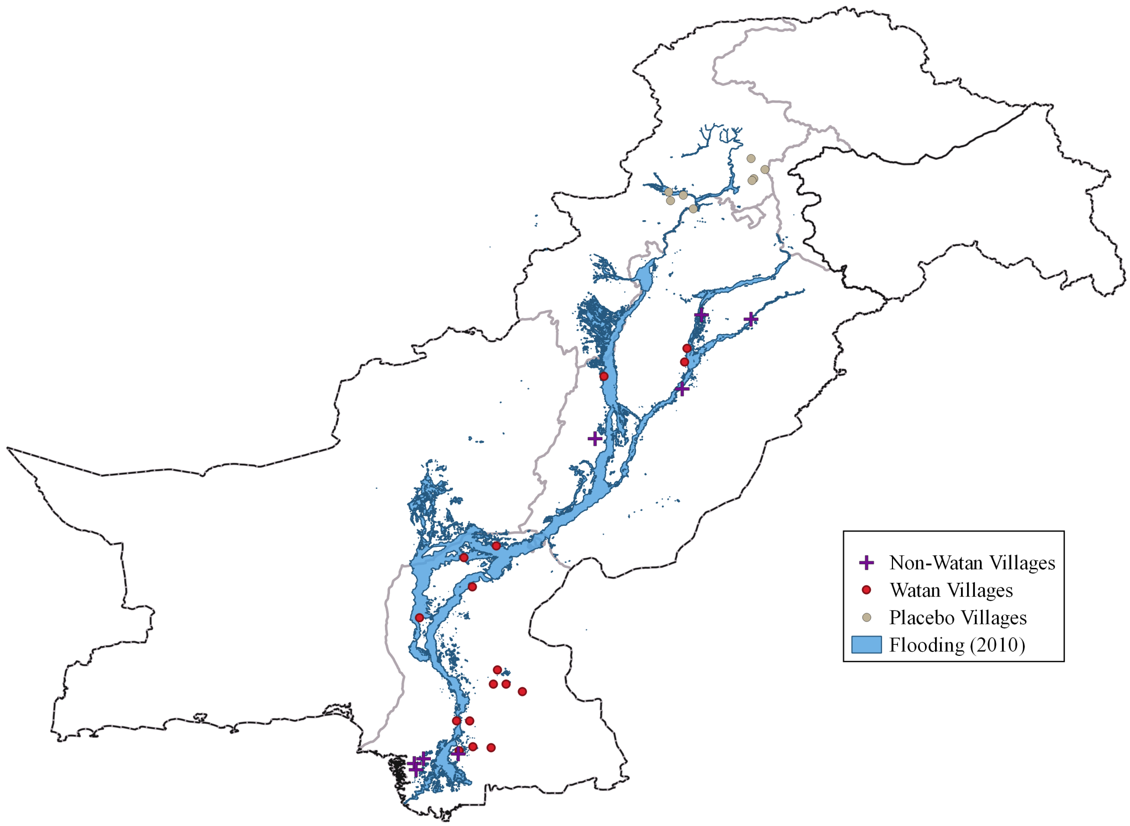
The survey only asked about one kind of community adaptation that is if the household helped the other villagers build a small barrage or another similar kind of protection near the village. A barrage can help to control water flow and prevent the village from being flooded in case there is excessive rainfall and water levels in the river increase to extraordinary levels.

Independent Variable: Watan Card

Both the village-level focus group survey and the household survey asks for information about the Watan card program. Since the Watan card was implemented at the village level in Punjab and Sindh, I use the response of the community elders if the Watan card program was active in the village. If the community elders respond that the Watan card program was active in the village, I code all households from the particular village as Watan card recipients and vice versa.[6] For the KPK province, since beneficiary households were identified through a rapid housing survey, I use household survey to determine which households got the Watan card. Figure 2 shows the locations of Watan and non-Watan villages for which I have data and the 2010 flood exposure.

[6]Kosec and Mo (2017) in their study on the effect of the Watan card on aspiration levels also use the same technique

Figure 2: Map of Pakistan



Notes: This figure shows the map of Pakistan with flood exposure and the location of Watan and non-Watan villages for which we have data. The placebo villages denote the villages from KPK where the Watan card program was implemented at a household level Flood extent data comes from UNOSAT.

Controls

Damage due to flooding

In the PRHS survey, they asked about damages suffered by a household across different dimensions: damage to house buildings, loss of lives, field flooding, diseases, and food insecurity. I create an index of all the damage-related variables and find an average for a village-level aggregate. As a robustness check, I also use just the house-building damage.

Other Household Controls

In the first round of the PRHS survey, they also ask retrospective questions for some household characteristics from before the floods. These include "Own House" (if the household owned their house), "Elite Connectedness" (the number of village elites or community leaders a household had a personal connection with), and "Family outside Village" (the number of relatives residing outside the village). These variable could affect a household's adaptation decisions, so I control for them to get precise results.

3.2 Geo-Spatial Data

Since there is no pre-flood survey data available, I use geospatial data to control for pre-flood differences in Watan and non-Watan villages. The sources and construction of these geospatial data sources have been discussed in the appendix section A.1

3.2.1 Proxies for economic activity: Night lights and Population Density

I use night light data (from DMSP-OLS) and population density data (from GPWv411) as proxies for economic activity in the village. Both are spatial data with a resolution of 1 km and are from 2009-one year before the flood. They are widely used as proxies for GDP and economic activity in the economics literature and have also been used in the case of Pakistan (Weidmann and Schutte, 2017; Abel et al., 2012; Rahman et al., 2020).

3.2.2 Flood risk

I use three variables for flood risk. Primarily, I use ex-ante flood risk data from United Nations Environment Programme (UNEP) that measures risk on a scale of 1 (low risk) to 5 (high risk) and elevation data from PRHS survey (UNEP, a). While UNEP's ex-ante flood risk data has been used before in the case of Pakistan, it has low spatial resolution (10 kms).[7] Therefore, I also use UNEP's another flood risk measure, the 100-year Flood Hazard, as well which has a better spatial resolution of 1 km (UNEP, b). Both measure flood risk of a place based on climatic factors unaffected by human interventions. On top of these two, I use elevation data from Kosec and Mo (2017).

[7]This data has been used previously by Fair et al. (2017) in their paper on floods and political engagement in Pakistan.

Table 1: Summary Statistics

	(1) Obs.	(2) Mean	(3) St. Dev.	(4) Min	(5) Max
Panel A: Household Level Data					
Improved house infrastructure	858	0.25	0.43	0	1
Send HH member as migrant	858	0.12	0.33	0	1
Move to non-farm income	858	0.17	0.37	0	1
Personal Adaptation (index)	858	0.18	0.25	0	1
Community Adaptation	858	0.17	0.38	0	1
Watan	858	0.56	0.50	0	1
Watan Eligible	858	0.64	0.48	0	1
Household Damage	858	0.11	0.29	-0.78	1.1
House Building Damage	858	0.87	1.2	0	3
No. of elite connections	858	0.32	0.69	0	5
No. of relatives outside village	858	47	110	0	1140
Education (HH head)	858	3.3	4.3	0	18
Own House	858	0.63	0.48	0	1
Panel B: Village Level Data					
Village Damage	32	0.11	0.14	-0.19	0.42
Night Light	32	13	11	0	57
Population density	32	294	161	58	539
Ex-ante flood risk	32	2	1.6	0	5
Flood hazard 100 years	32	94	121	0	379
Elevation (100m)	32	1.3	1.8	0.09	9.2
Flooding (2011)	32	0.47	0.51	0	1

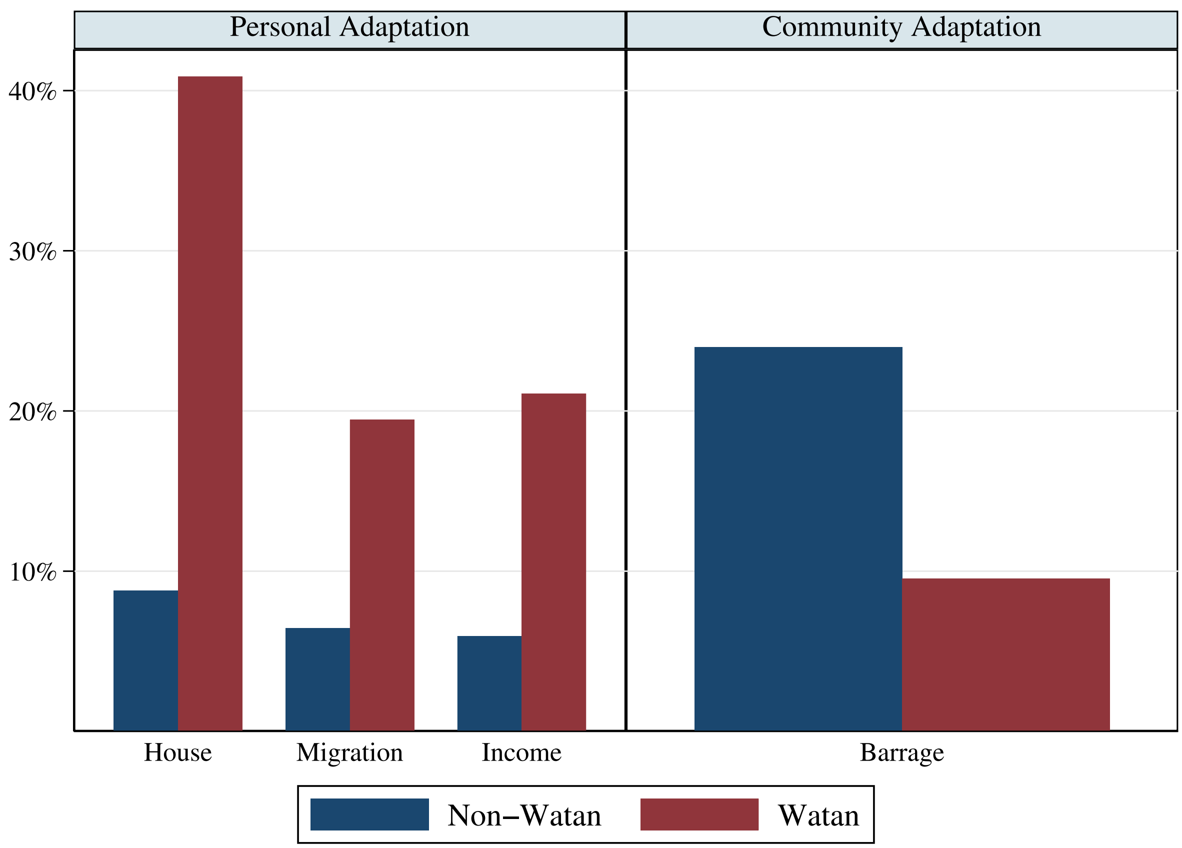
Table 1 reports the summary statistics for both the household-level and village-level data that we described earlier. For my analysis, I focus on 32 villages that were flooded in 2010 and were covered in PRHS.

4 Empirical Analysis

4.1 Effect of Cash Transfer on Adaptation

I first visually compare the Watan and non-Watan villages with regards to investments in different kinds of adaptation. Figure 3 presents this comparison. The left panel shows the differences in the three kinds of personal adaptations, whereas the right panel shows the difference in the community adaptation.

Figure 3: Adaptation in Watan vs Non-Watan Villages



Notes: This figure shows the difference between Watan and non-Watan villages with regards to adaptation. The y-axis here is the percentage of people per village who invest in a particular kind of adaptation (x-axis). The personal adaptations are House (Improving house infrastructure), Migration (sending a household member as a migrant to an area with lower flood risk), and Income (diversifying income sources by moving to non-farm income). The community adaptation is Barrage (assisting fellow villagers in building a barrage or other similar protection to protect the village from flood waters).

Figure 3 shows that people residing in Watan villages invest more in personal and less in community adaptations compared to the people in non-Watan villages. Moreover, community adaptation is the main kind of adaptation in non-Watan villages with more than 25 percent of households contributing towards community adaptation and less than 10 percent contributing towards any kind of personal adaptation. However, in Watan villages, personal adaptations are a lot more common. For instance, more than 40 percent of households work on improving house infrastructure, but less than 10 percent contribute towards community adaptation.

We cannot naively interpret these differences as the effect of the Watan card. Since eligibility for the Watan card depends on the extent of flooding, these differences could be attributed to two possible kinds of confounders. Firstly, the extent of flooding and thus the probability of Watan card could be associated with the damage caused by the flood in the village, which could also affect people's adaptation choices. Secondly, Watan villages could be different from non-Watan villages in pre-flood characteristics i.e. non-Watan villages could be more developed and more risk averse which could also affect people's adaptation behavior.

If I had data on people's adaptation before the 2010 floods, that would have resolved the worry about pre-flood confounders. I could compare the adaptation choices of people in the same village before and after 2010 floods to show that the differences observed in figure 3 are not due to pre-flood confounders. Since the first round of the survey was only conducted one and a half years after the floods, I cannot compare the same villages over time.

However, in order to test whether these differences are driven by pre-flood confounders, I compare Watan and non-Watan villages on possible confounders that can be measured using spatial data.

	Watan		Non-Watan		Difference
	Obs. (Villages)	Mean (SD)	Obs. (Villages)	Mean (SD)	Diff. (SE)
Night Light	441	13.1	193	12.1	0.99
	(16)	(13.6)	(8)	(6.2)	(1.0)
Population Density	441	237.8	193	227.7	10.16
	(16)	(123.6)	(8)	(127.4)	(10.8)
Ex-Ante Flood Risk	441	2.3	193	2.0	0.34***
	(16)	(1.5)	(8)	(1.3)	(0.1)
Flood Hazard 100 yrs	441	107.2	193	84.3	22.95**
	(16)	(129.7)	(8)	(87.7)	(10.2)
Elevation (100 m)	441	0.5	193	0.8	-0.26***
	(16)	(0.5)	(8)	(0.8)	(0.1)

Notes: This table reports the balance between Watan and non-Watan villages of Punjab and Sindh for possible village-level confounders. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 2 compares the Watan and non-Watan villages on five spatial variables from before 2010: nightlight, population density, ex-ante flood risk, flood hazard, and elevation. The first two rows of the table show that there is no statistically significant difference between Watan and non-Watan villages in night light and population density. Since night light and population density are proxies for a lot of important variables like economic activity, agricultural output, and overall development of a village, this implies that these variable cannot explain the differences we observed in figure 3. The bottom three rows show that Watan villages have higher ex-ante flood risk and lower elevation than non-Watan villages. These differences are reasonable because even though we are looking at flooded villages, more flooded villages are likely to have a higher ex-ante flood risk. Importantly, since we have data on these potential confounders, we can control for them to see if the differences persist.

In order to estimate the effect of the Watan card, I estimate the following equation in a regression framework:

$$Y_{ik} = \alpha + \beta watan_{ik} + \delta_k + \lambda_i + \epsilon$$

where Y_{ik} denotes adaptation, $watan_{ik}$ is a binary variable for whether household i is situated in a Watan village and δ_k, λ_i are a range of village level and household level controls respectively. The coefficient of interest is β, which reflects the average difference in the adaptation of households between Watan and non-Watan villages after controlling for other variables. Among these village-level controls, I include the spatial pre-flood variables shown in table 2. Additionally, I control for damage caused by the 2010 flood to the entire village, so that β does not capture the effect of flood damage. Since the Watan card's eligibility only depends on the proportion of the village area flooded, I can control for the damage caused by the floods to the village. The two variables are not too correlated to cause multicollinearity issues, because the proportion of the area where water stays after a flood depends on the topography of the village and the weather in the days after the flood. The damage caused by floods depends more on the intensity of the flood and the shock nature of flood.[8] I also add some pre-flood household-level controls for which they asked retrospective questions in the PRHS survey to get more precise estimates. I cluster the standard errors at the village level throughout the paper.

[8]For instance, in a village that is situated in a mountainous region, there might not be any flood water remaining a few days after the flood despite an intense flooding event.

Table 3: Effect of Watan Card on Adaptation

	Personal Adaptation			Community Adaptation		
	(1)	(2)	(3)	(4)	(5)	(6)
Watan	0.186***	0.216***	0.202**	-0.212***	-0.224***	-0.219***
	(0.061)	(0.068)	(0.083)	(0.049)	(0.041)	(0.066)
Village Damage		0.258	0.071		-0.247	-0.134
		(0.203)	(0.162)		(0.183)	(0.143)
Night Light (2010)		-0.000	-0.001		-0.001	-0.002
		(0.002)	(0.002)		(0.002)	(0.001)
Ex-Ante Flood Risk		-0.034	-0.028		-0.018	-0.013
		(0.026)	(0.024)		(0.012)	(0.012)
Elevation (100 m)		0.016	-0.020		0.054	-0.133***
		(0.073)	(0.069)		(0.150)	(0.043)
Household Damage			0.096**			-0.026
			(0.038)			(0.076)
Elite Connectedness			0.010			-0.123**
			(0.030)			(0.058)
Family out village			-0.000*			0.000
			(0.000)			(0.000)
Own House			0.178***			0.112**
			(0.047)			(0.042)
Education (HH Head)			-0.003			0.002
			(0.003)			(0.004)
Village Controls	No	Yes	Yes	No	Yes	Yes
Household Controls	No	No	Yes	No	No	Yes
Observations	634	634	634	634	634	634
Clusters	24	24	24	24	24	24
Non-Watan mean	0.079	0.079	0.079	0.275	0.275	0.275
R-Squared	0.10	0.15	0.22	0.08	0.10	0.13

Notes: This table compares household's investments in personal and community adaptation between Watan vs Non-Watan villages in Punjab and Sindh. Standard errors are clustered at the village level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 3 presents the regression results comparing the Watan and non-Watan villages. Columns (1) and (4) present results from baseline specification without any controls, whereas I add village-level controls in columns (2) and (5), and household-level controls in column (3) and (6). Table 3 confirms the general trend observed in figure 3. A household in a Watan village is about 20 percent more likely to invest in personal adaptations and 22 percent less likely to invest in community adaptation than a household in a non-Watan village. These effects are significant at the 5 percent level and are unaffected while controlling for various village and household level variables. The stability of the coefficients even after controlling for possible confounder variables also suggests that omitted variable bias is not a big concern (Altonji et al., 2005).

Still one might worry that there could be unobservable potential confounders. While I cannot control for these variables, I can use the KPK province as a placebo. The intuition behind the placebo is that if the adaptation differences between Watan and non-Watan villages in table 3 are due to unobserved confounders, then we should observe the same differences between more than 50 percent flooded villages and less than 50 percent flooded villages in a province where the cash transfer program was not present. The assumption here is that the unobserved confounders are not region fixed. An ideal placebo region would be a flood-affected region that is similar in terms of region-fixed factors to Punjab and Sindh, but the Watan card program was not rolled out in the province due to a random reason unrelated to floods or adaptation behavior. KPK province is not a perfect placebo, because the Watan card program was rolled out in KPK but instead of providing the cards to the entire villages, flood-affected households were identified through a household survey. Since the reason for the different design of the program was that there had been an earthquake in KPK 5 years before the floods due to which they had an apparatus in place to quickly conduct household surveys, there is not a big worry that the design of the program is correlated with adaptation.

Table 4: Effect of Watan Card on Adaptation (Placebo Province)

	Personal Adaptation			Community Adaptation		
	(1)	(2)	(3)	(4)	(5)	(6)
Watan Eligible	0.229***	0.104***	0.109***	0.631***	0.246***	0.332***
	(0.03)	(0.01)	(0.01)	(0.10)	(0.03)	(0.05)
Village Damage		2.480***	0.897		7.234***	6.269
		(0.31)	(0.60)		(0.89)	(3.58)
Night Light (2010)		-0.014***	-0.005		-0.039***	-0.031
		(0.00)	(0.00)		(0.01)	(0.02)
Ex-Ante Flood Risk		-0.029***	0.011		-0.081***	-0.084
		(0.01)	(0.02)		(0.02)	(0.09)
Elevation (100 m)		0.009**	-0.005		0.024**	0.026
		(0.00)	(0.01)		(0.01)	(0.03)
Watan			0.067**			-0.020
			(0.02)			(0.15)
Household Damage			-0.047			-0.081**
			(0.06)			(0.02)
Elite Connectedness			0.026*			-0.038
			(0.01)			(0.04)
Family out village			0.000			-0.001
			(0.00)			(0.00)
Own House			0.016			-0.159
			(0.02)			(0.11)
Education (HH Head)			0.003			0.005*
			(0.00)			(0.00)
Village Controls	No	Yes	Yes	No	Yes	Yes
Household Controls	No	No	Yes	No	No	Yes
Observations	224	224	224	224	224	224
Clusters	8	8	8	8	8	8
Non-Watan mean	0.05	0.05	0.05	0.15	0.15	0.15
R-Squared	0.47	0.51	0.56	0.52	0.57	0.59

Notes: This table compares households' investments in personal and community adaptation between Watan-eligible and Watan-ineligible villages in the KPK province. A village is coded as Watan eligible if more than 50 percent of the area is reported as flooded by the village heads. Standard errors are clustered at the village level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 4 presents the results from this placebo test. The "Watan Eligible" is a binary variable for whether the village was more than 50 percent flooded or not, which would have qualified it for a village-level cash transfer if the government had implemented the Watan card program at village level in KPK as well.[9] I also control for whether a household got the Watan card or not. Table 4 shows that a household in a Watan-eligible village is 11 percent more likely to invest in personal adaptation. It is not less likely but 33 percent more likely to invest in community adaptation than a household in a non-Watan eligible village.

These results show that while unobserved variables correlated with flooding could explain part of the positive effect of the Watan card on personal adaptation observed in table 3, they cannot explain the negative effect on community adaptation.

However, there is a caveat. The number of clusters is too small for the KPK province, as the PRHS survey covered only 8 flooded villages from KPK. Clustering standard errors with a small number of clusters can introduce a downward bias to the standard errors (Harden, 2011). Hence, I replicate table 4 in table A.11 with heteroscedasticity robust standard errors instead of clustered standard errors. The standard errors indeed increase if I do not cluster, but the effects observed are still statistically significant at least at the 10 percent level in the most strict specification.

4.2 Mechanism: Heterogeneous Effects by Household Damage

So far, I have shown that a village-level cash transfer positively affects personal adaptation and negatively affects community adaptation. However, it is unclear what is driving these results, especially in Punjab and Sindh. Do all households in Watan recipient villages invest more in personal adaptation while shirking on their communal responsibility or do some households shirk more than others? I explore this question using a heterogeneity analysis by damage levels in this section.

To understand the effects of the Watan card by damage levels, I do two things: firstly, I subset households by damage levels and compare the ones residing in Watan villages with those residing in non-Watan villages. However, this approach reduces the sample size. Therefore, I adopt another approach as well which is to include an interaction term for flood damage

[9] In the community level survey of village elders in PRHS, they were asked about the proportion of village flooded. I use this information to construct Watan Eligible variable.

caused to the household interacted with whether the household resides in a Watan village. The latter approach is very similar to a difference in difference setup, where instead of the time dimension we have the damage dimension. The benefit of this approach is that we can also incorporate village-fixed effects to get rid of all the village-fixed confounders. I estimate the following equation,

$$Y_{ik} = \alpha + \beta_1 damage_{ik} + \beta_2 watan_{ik} + \beta_3 damage_{ik} \times watan_{ik} + \delta_k + \lambda_i + \epsilon$$

where our coefficient of interest is β_3. Mathematically, β_3 captures the following difference,

$$\begin{aligned}\beta_3 =&(E[Y_{idk}|d = High, k = Watan] - E[Y_{idk}|d = High, k = Watan])\\ &- (E[Y_{idk}|d = Low, k = Non - Watan] - E[Y_{idk}|d = Low, k = Non - Watan])\end{aligned}$$

where d indicates the damage level of a household and k indicates whether it is situated in a Watan or non-Watan village. Hence, β_3 captures the differences in adaptation behavior of more and less damaged households in Watan vs non-Watan villages. The key identifying assumption here is that the differences between more and less damaged households in variables that could affect household adaptation decisions should be the same in both Watan and non-Watan villages (similar to parallel trend assumption).

Table 5: Heterogeneous Effects of the Watan Card by Damage in 2010 Floods

Panel A: Sub-Sample	(1) Personal	(2) Community	(3) Personal	(4) Community
Watan	0.281***	-0.067	0.167**	-0.490***
	(0.064)	(0.041)	(0.072)	(0.123)
Sample	Damaged HHs	Damaged HHs	Non-Damaged HHs	Non-Damaged HHs
Observations	361	361	273	273
Non-Watan mean	0.04	0.15	0.15	0.52
R-Squared	0.34	0.09	0.23	0.45
Panel B: Heterogeneity Analysis (Full Sample)				
Watan	0.202**	-0.219***	0.174**	-0.228**
	(0.083)	(0.066)	(0.078)	(0.100)
Household Damage	0.096**	-0.026	-0.081	-0.353*
	(0.038)	(0.076)	(0.082)	(0.189)
HH Damage x Watan			0.224*	0.410*
			(0.112)	(0.205)
Observations	634	634	634	634
R-Squared	0.22	0.13	0.23	0.11
Non-Watan mean	0.08	0.27	0.08	0.27
Clusters	24	24	24	24
Village Controls	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes

Notes: This table shows differences between households residing in Watan vs non-Watan across damage levels. Panel A reports results from the sub-sample analysis. In columns (1) and (2) of Panel A, I compare damaged households in Watan vs non-Watan villages. In columns (3) and (4) of panel A, I compare non-damaged households in Watan vs non-Watan villages. Panel B reports results from a heterogeneity analysis using a full sample. In columns (1) and (2) of panel B, I replicate the results from table 3, whereas in columns (3) and (4) of panel B, I include an interaction of household damage and Watan card. Standard errors are clustered at the village level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 5 presents the results from this analysis. In the top panel, I do a sub-sample analysis whereas, in the bottom panel, I use the full sample to do a heterogeneity analysis. In columns (1) and (2) of panel A, I subset the sample to only those households that report at least one kind of damage in any of the dimensions that contribute towards the index. In columns (3) and (4) of the top panel, I subset the sample to non-damaged households.

Table 5 shows that damaged households drive the positive effect of the Watan card on personal adaptation, whereas non-damaged households drive the negative effect on community adaptation. Column (1) of panel A shows that damaged households in Watan villages are 28 percent more likely to invest in personal adaptation than households of the same damage level in non-Watan villages. The interaction term in column (3) of panel B further confirms this by showing that the effect of the Watan card on personal adaptation is increasing in damage levels. The interaction term in column (4) of panel B is positive which seems to suggest that the effect of the Watan card on community adaptation is increasing in damage levels. But, if we read this together with columns (2) and (4) of panel A, we realize that it is not that damaged households in Watan villages contribute more towards community adaptation, but that non-damaged households contribute less.

Columns (3) and (4) show that the Watan card has a strong negative effect on non-damaged households' investments in community adaptations and a slight positive effect on their investments in personal adaptation. Moreover, the damage coefficient in column (4) of panel B is negative, but the interaction term is positive. This implies that independent of the Watan card, lesser damaged households are more likely to contribute towards community adaptations, but once given the Watan, they become less likely i.e. start shirking in their community contribution. It is as if non-damaged households are initially benevolent and more community-oriented, but once they get the cash transfer, they become selfish and start shirking on communal responsibility.

A worry in these heterogeneity results is that the differences between more and less damaged households might not be the same in Watan and non-Watan villages. To check if these differences drive the result, I conduct the same heterogeneity analysis for KPK province. The intuition here is that if there is another factor that varies across damage and village that explains the heterogeneity analysis results, then we should see the same effects in the KPK province.

Table 6: Heterogenous Effects - KPK

	(1) Personal	(2) Community	(3) Personal	(4) Community
Watan Eligible	0.109***	0.332***	0.096***	0.335***
	(0.011)	(0.053)	(0.017)	(0.070)
Household Damage	-0.047	-0.081**	0.081*	-0.020
	(0.058)	(0.025)	(0.042)	(0.088)
HH Damage x Watan Eligible			-0.131	-0.062
			(0.091)	(0.098)
Village Controls	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Observations	224	224	224	224
Clusters	8	8	8	8
Non-Watan mean	0.05	0.15	0.05	0.15
R-Squared	0.56	0.59	0.55	0.59

Notes: This table shows heterogeneity analysis results for the placebo province, KPK. Standard errors are clustered at the village level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 6 presents the results of the heterogeneity analysis for KPK. Unlike table 5, the interaction term here is not statistically significant. To understand what this means, we can refer to the mathematical framework of β_3. Since we are comparing Watan-eligible and ineligible villages, the first difference in the estimation of β_3 will be the difference between more and less damaged households in a Watan-eligible village, and the second difference will be between more and less damaged households in Watan-ineligible village. Since the non-damaged households do not get the cash transfer in KPK and damaged households do regardless of if they are situated in a more or less flooded village, β_3 will only capture the effect of other characteristic differences on adaptation between more and less damaged households in Watan vs non-Watan villages. The insignificant coefficients of the interaction term reported in table 6 show that these unobserved differences between more and less damaged households cannot explain the results we observed in the earlier heterogeneity analysis for Punjab and Sindh.

The results presented above suggest that the extent of damage a household faces in the 2010 floods is critical towards understanding the behavioral response of a household towards the Watan card. Households that are damaged by the 2010 floods benefit from the Watan card and invest in personal adaptations to secure themselves against future flooding events. The non-damaged households are generally very community oriented but once given the Watan card, they realize that investing in community adaptation will reduce the risk of village being flooded in the future and thus their chances of getting free money, so they do not contribute towards community adaptation. Damaged households on the other hand face a tradeoff. If they do not contribute to the community adaptation, they might expose themselves to personal damage in case the village gets flooded, but they also care about getting the cash transfer. Hence, there is only a small negative effect of the Watan card for damaged households on community adaptation.

4.3 Robustness Checks

Household Characteristics Heterogeneity (Parallel Trends)

A potential worry for the results in table 5 is that there could be a confounder that varies both across villages and damage levels, which could bias our results.[10] While table 6 for heterogeneous effects in placebo province shows that the effect of these characteristics on adaptation is unlikely, one could still worry that these differences might be province fixed. In order to test if such differences exist, I can estimate the same heterogeneity analysis equation as before but with observable household characteristics as outcome variables. Appendix table A.1 shows results from a heterogeneity analysis where the outcome variables are the various

[10] For instance, if we assume that the unaffected households have similar characteristics in both Watan and non-Watan villages, but the affected households in non-Watan villages are very different in their characteristics from those in Watan villages, and these characteristics could affect adaptation behavior, then these could bias our results.

household characteristics. All of the interaction term coefficients except for are statistically insignificant. This shows that most of the observable differences between more and less damaged households are similar in both Watan and non-Watan villages.

Heterogeneity Analysis for Non-Damaged and Slightly Damaged HHs

Another way in which we can counter the worry that damaged and non-damaged households might be very different in Watan vs non-Watan villages is to reduce the sample to only focus on non-damaged and slightly damaged households.[11] Since these households are similar in damage levels, they are also likely to be similar in terms of other characteristics. Table A.8 replicates the heterogeneity analysis for this subsample. The results are stronger for this sub-sample compared to the results using the full sample in table 5. This shows that the heterogeneity analysis results are not driven by other unobservable differences between more and less damaged households.

Construction of Watan Eligible Variable

In both tables 4 and 6, I used the “Watan eligible” variable to determine which villages would be eligible for a cash transfer if the government had implemented the Watan card program at a village level in the KPK province. To construct this variable, I used the responses from village elders on how much the village area was flooded. A potential worry could be that my construction of “Watan eligible” might not be too accurate. To check if my construction of this variable is correct, I construct a “Watan eligible” indicator for villages in Punjab and Sindh in the same way as I did for KPK. In appendix table A.6, I replicate my main results and heterogeneity results for Punjab and Sindh using the “Watan Eligible” variable instead of the actual Watan. The results show that both the main results and heterogeneity analysis results for Punjab and Sindh hold if I use the “Watan eligible variable”. Moreover, I also try to use the “Watan Eligible” variable in a two-stage least squares framework as an

[11] I regard households that report only minor damage to their house building as slightly damaged households.

instrument for the actual Watan card. Appendix table A.7 shows the results from the two-stage estimation. A "Watan Eligible" village is 72 percent likely to be an actual Watan, and other results on adaptation are unaffected if I instrument for Watan by "Watan Eligible." This confirms that my construction of the "Watan Eligible" variable is not the reason why we do not observe a heterogeneous response towards community adaptation in table 6 for KPK province.

Non-Damaged HHs in Punjab and Sindh vs KPK

The analysis presented in this section highlights that the negative effect of the Watan card on community adaptation is driven by households that are not damaged but get the Watan card because they reside in a village that is more than 50 percent flooded. These non-damaged households do not the cash transfer in the KPK province when a household survey is conducted. I can compare non-damaged households in Watan-eligible villages of KPK with those from Punjab and Sindh to more precisely test for the effect of a village-level cash transfer on their adaptation behavior. In table A.10, I do a sub-sample analysis to test for this. I find that indeed non-damaged households residing in Watan-eligible villages in Punjab and Sindh are 43 percent less likely to invest in community adaptation compared to non-damaged households in Watan eligible villages in KPK. This confirms that a village-level cash transfer disincentives non-damaged households from investing in community adaptation.

Heterogeneity Analysis across Province

Table 3 and 4 show that while Watan villagers in Punjab and Sindh have lower investments in community adaptation compared to non-Watan villagers, we do not observe the same difference between Watan eligible and Watan ineligible villagers in the KPK. It is possible to do a more formal test for this using an interaction between a Punjab and Sindh province dummy and Watan eligible variable. Appendix table A.9 shows the results. Column (4) shows that while households residing in Watan-eligible villages are generally more likely to invest in community adaptation, those in Punjab and Sindh are 89 percent less likely. This provides additional support that the design of the cash transfer program in Punjab and Sindh discourages adaptation.

Flooding 2011

Before the adaptation data was collected in 2012, floods hit Pakistan again in 2011. While the Watan cars were distributed based on the 2010 floods, it is likely that villages that were more flooded in 2010 and got the Watan card had a higher likelihood of being flooded again in 2011. Thus, we might be worried that the results in table 3 are driven by the 2011 floods. I do not control for the 2011 floods in the main specification, because the floods took place after the Watan cards were distributed, so it is possible that the 2011 floods might be affected by the Watan card program. However, I check if controlling for whether a village was flooded in 2011 affects the results. Appendix table A.4 shows that the results are not affected by whether I control for 2011 flooding or not.

Alternate Control Variables

Three of the control variables I include can be measured in different ways. First, I create an index of all flood damage-related variables and control for that instead of only controlling for house-building damage. Appendix table A.3 shows that the main results are unaffected by whether I control for damage as an index or for house building damage. Second, I control for nightlight activity as a proxy for economic activity. I do not control for nightlights and population density together, for it could cause multicollinearity issues as both are proxies for economic activity. Appendix table A.5 shows that my main results are unaffected by whether I control for nightlights or population density as a proxy for economic activity. Third, I control for categorical ex-ante flood risk variable, for it has been used in the context of Pakistan before by Fair et al. (2017)). But it has low spatial resolution. Another measure of flood risk, flood hazard, has a higher spatial resolution. Appendix table A.4 shows that my main results are unaffected by whether I use ex-ante flood risk or flood hazard 100 years as a control.

4.4 Alternative Explanations

Substitution effect.

One could argue that there is a positive effect of the Watan card on personal adaptation and a negative effect on community adaptation because people substitute from community to personal adaptation. The economic rationale behind this substitution effect would be that community adaptation is an inferior good whereas personal adaptation is a normal good, so once people get the cash transfer, they substitute from community to personal adaptation. Or, people in severely affected villages realize that community adaptations are actually not useful in preventing floods. An implication of the substitution effect would be that we should observe the same kinds of households reporting lower contributions to community adaptation and higher contributions toward personal adaptation. Table 5 shows that there might be some substitution effect, but the main drivers of positive and negative effects are households with different damaged levels.

Other explanations

One could argue that non-damaged households reduce community adaptation not because it would help them get a future cash transfer. Instead, they realize that if they were not damaged in a massive flood, then they are unlikely to be affected in any future smaller flood as well. Thus, they do not need to care about adaptations. I think this updating of beliefs about the likelihood of suffering personal damage could partly explain the heterogeneity in community contribution but not completely. Because if there were no disincentives caused by the Watan card, then non-damaged households in KPK should behave similarly and reduce community contribution. But, I do not find heterogeneous effects by damage levels in the KPK province.

One could propose many other explanations, but I think there are two aspects of the results that are difficult to explain without reference to the nature of the cash transfer program. First, that we observe households with different damage levels respond differently to cash transfers. Second that we do not find these different effects in the placebo province.

5 Model

In the paper, I have shown that Watan card at a village level positively affects personal adaptation but negatively affects community adaptation. To explain these effects theoretically, especially the effect on community adaptation, I construct a utility framework to understand adaptation decisions.

5.1 Model Setup

I consider a two-period setup. Flooding takes place in period 0 and there is a risk of flooding in period 1. Households make decisions about personal and community adaptation in period 0. Under a village-level cash transfer scheme, if there is flooding, everyone in the village gets the cash transfer. If the cash transfer is at the household level, conditional on flooding, households above a particular damage threshold get the cash transfer, and those below the damage threshold do not. A household derives utility only from net consumption in a given period. A household's expected utility for two periods is given by,

$$\mathbb{E}(U) = \mathbb{E}(U_0) + \rho\mathbb{E}(U_1)$$

where ρ is a discount factor for future.[12] A household's expected utility in period 0 will be

$$\mathbb{E}(U_0) = Y_0 + T - D_0 - qA_p - rA_c$$

[12]For simplification, I assume that $\rho = 1$ as it does not affect any of the predictions.

where Y_0 denotes a household's income, D_0 denotes the damage caused to the household due to the floods, A_p, A_c denotes the units of personal and community adaptation respectively, and q, r denote the prices of adaptation. T denotes the cash transfer, which is the same in both periods. To derive the utility in period 1, I consider four possible scenarios that a household could be in, with the probabilities and utilities associated with each scenario.

Table 7: Potential States for a Household in Period 1

State	**Probability**	**Utility**
(Flood, Damage)	$\pi(A_c)\tau(A_p, D_0)$	$Y_1 + T - D_1$
(Flood, No Damage)	$\pi(A_c)\,(1 - \tau(A_p, D_0))$	$Y_1 + kT$
(No Flood, Damage)	$(1 - \pi(A_c))\,(0)$	$Y_1 - D_1$
(No Flood, No Damage)	$(1 - \pi(A_c))(1)$	Y_1

Table 7 presents four different potential states for a household in period 1. The *Flood* in the state column refers to the village being flooded and *Damage* refers to whether the household suffers any personal damage.[13]

The second column in table 7 shows probabilities associated with each potential state. $\pi(A_c)$ denotes the probability of the village being flooded. From a household's perspective, it depends on a household's contribution to community adaptation A_c. I assume that $\pi(A_c)$ is concave up and decreasing in A_c ($\frac{\partial \pi}{\partial A_c} < 0$, $\frac{\partial^2 \pi}{\partial A_c^2} > 0$). $\tau(A_p, D_0)$ denotes the conditional probability of house being damaged in case the village is flooded. It is the subjective belief of the household that in case if the village is flooded, how likely is it that the household will suffer personal damages. This subjective belief depends on 1) the household's investments in personal adaptation and 2) the personal damages the household suffered in period 0 flooding. I assume $\tau(A_p, D_0)$ is concave up with respect to A_p and decreasing in A_p i.e. $\frac{\partial \tau}{\partial A_p} < 0$ and $\frac{\partial^2 \tau}{\partial A_p^2} > 0$. Moreover, I assume that $\frac{\partial \tau}{\partial A_p}$ is only a function of A_p and not D_0. This makes

[13]To simplify, I just denote households above the threshold for cash transfers under a household-level scheme as damaged households and those under the threshold as non-damaged.

sense, because how investing one more unit in personal adaptation affects one's self belief about future damage they might incur in case of flooding is unlikely to be affected by the damage they incurred in the past flood. However, I assume that independent of the personal adaptation, if a household suffered more damage in the past flood, it will have a higher belief that if the village gets flooded, it will be adversely affected ($\frac{\partial \tau}{\partial D_0} > 0$). But, I assume that one's conditional belief about damage in case of flooding is always greater than the amount of cash transfer ($\tau(A_p, D_0)D_1 > T$).

The third column in table 7 shows the potential utilities of a household in each scenario. A household's utility depends on its income in period 1, Y_1, cash transfer it will get if the village is flooded (T), and the damage it will incur in flood (D_1). The distinguishing feature for a village-level cash transfer compared to a household-level cash transfer is the utility for the second state. Under a village-level cash transfer, $k = 1$ and a household will get the cash transfer as long as it is in a flooded village regardless of whether it is personally damaged by the floods or not. Under a household-level cash transfer, $k = 0$ so only a damaged household will get the cash transfer.

A typical household's expected utility in period 1 will be given by,

$$\begin{aligned}
\mathbb{E}(U_1) = (\pi(A_c)\tau(A_p, D_0))\big(Y_1 + T - D_1\big) \\
+ \pi(A_c)(1 - \tau(A_p, D_0))\big(Y_1 + kT\big) \\
+ (1 - \pi(A_c))\big(Y_1\big)
\end{aligned}$$

which simplifies to

$$\mathbb{E}(U_1) = Y_1 - \pi(A_c)\tau(A_p, D_0)D_1 + k\pi(A_c)T + (1 - k)\pi(A_c)\tau(A_p, D_0)T$$

Therefore, a household's total expected utility will be,

$$\mathbb{E}(U) = W - \pi(A_c)\tau(A_p, D_0)D_1 - qA_p - rA_c + k\pi(A_c)T + (1-k)\pi(A_c)\tau(A_p, D_0)T \quad (1)$$

where $W = Y_0 + Y_1 + T - D_0$ and denotes the wealth of a household in the two periods after the damage caused in period 0.

Hence, a household's expected two period utility is given by its wealth (W), its future chances of getting the cash transfer ($\pi(A_c)T$ for village level and $\pi(A_c)\tau(A_p, D_0)T$ for household level), its subjective belief about future flood related damages ($\pi(A_c)\tau(A_p, D_0)D_1$), and the cost of personal and community adaptation ($qA_p + rA_c$).

5.2 Village Level Cash Transfer

I can find the first order condition (FOC) for how much a utility maximizing household will invest in community adaptation. Setting $k = 1$, and taking partial derivative of equation 1 with respect to A_c gives,[14]

$$\frac{\partial U}{\partial A_c} = \pi'(A_c)T - \pi'(A_c)\tau(A_p, D_0)D_1 - r$$

and setting it equal to zero, I get

$$r - \pi'(A_c)T = -\pi'(A_c)\tau(A_p, D_0)D_1$$

[14] Note about mathematical expressions. I use numerical subscripts in two ways. If it is a subscript to a capitalized letter like D_1, the subscript refers to the period i.e. in this case, it means damage in period 1. If it is a subscript to a greek letter like $\tau_1(A_p, D_0)$, it implies the partial derivative of *tau* with respect to A_p. Although I try to denote derivatives with either their full form like $\frac{\partial A_p}{\partial C}$ or with a superscript like π', I have to use a subscript to denote partial derivative as well when something is a function of more than one variables.

The left hand side is the marginal loss to the household of purchasing one more unit of community adaptation, which is the sum of the price of adaptation and the loss to the household in terms of reduced likelihood of future cash transfer. The right hand side is the marginal benefit to the household for an additional unit of community adaptation that comes from a reduced risk of flood related damage. A household will purchase units of A_c until the marginal loss equals marginal benefit.

I model the effect of the cash transfer in terms of a change in T. [15] Therefore, I take the partial derivative of the first order condition with respect to T.

$$-\pi''(A_c)T\frac{\partial A_c}{\partial T} - \pi'(A_c) = -\pi''(A_c)\tau(A_p, D_0)D_1\frac{\partial A_c}{\partial T} - \pi'(A_c)\tau_1(A_p, D_0)D_1\frac{\partial A_p}{\partial T}$$

$$\implies \frac{\partial A_c}{\partial T} = \frac{\pi'(A_c)\Big(1 - \tau_1(A_p, D_0)D_1\frac{\partial A_p}{\partial T}\Big)}{\pi''(A_c)\Big(\tau(A_p, D_0)D_1 - T\Big)} \tag{2}$$

Equation 2 models the effect of a village-level cash transfer on community adaptation. For the sake of simplicity, I can assume that the effect of the Watan card on personal adaptation is positive ($\frac{\partial A_p}{\partial T} > 0$).[16]. Given our other assumptions that $\pi' < 0, \tau_1 < 0, \pi'' > 0, \tau(A_p, D_0)D_1 > T$, the numerator will be negative, and the denominator will be positive. Hence, the overall effect will be negative. I can also relax the assumption that $\frac{\partial A_p}{\partial T} > 0$ and get the effect in the same direction.[17]

[15] While in reality some get the cash transfer and some do not, since we are interested only in the direction of the effect, it does not make a difference whether the effect is modeled as an increase in T or as a difference between $T = 0$ and $T > 0$.

[16] I assume this because in case of a village level cash transfer there is a straightforward relationship between the cash transfer and personal adaptation. People in a flooded village want to adapt to prevent themselves from damage in the future flood. Cash transfer easens the income constraint making personal adaptation more affordable, and investing in personal adaptation does not affect the likelihood of future cash transfer. Therefore, households receiving cash transfer are more likely to invest in personal adaptation

[17] Without the assumption, the effect is given by,

$$\frac{\partial A_c}{\partial T} = \frac{\pi'}{\pi''(\tau D_1 - T) - \frac{(\pi'\tau_1)^2}{\pi\tau_{11}}D_1} \tag{3}$$

The denominator in the equation above will be positive. Since $\pi' < 0$, the overall effect will be negative. See

While the overall effect is negative, its magnitude will not be the same for all households. There is a competing effect coming from the two terms in the denominator, $\tau(A_p, D_0)D_1$ and T. This captures the tradeoff a household faces. It might increase its chances of a future cash transfer by not investing in community adaptation which will increase the chances of flooding in the village. But if the village gets flooded, there is also an increased risk of a household being personally damaged by the flood. Importantly, what matters is the amount of damage a household suffered in the past flood D_0. For a household with low past damage, $\tau(A_p, D_0)$ will be small, so the overall negative effect of the cash transfer on community adaptation will be bigger and vice versa. As damage levels increase, the denominator grows bigger, so the overall negative effect becomes smaller. Intuitively, this means that a household that suffered a lot of damage in the past flood (D_0 high) will possess a higher self-belief that in case the village gets flooded, it will be definitely damaged, so it will have very little disincentive towards contributing to community adaptation. On the other hand, a household that suffered little damage in the past flood (D_0 is low), it will have a lower self-belief that in case of a future flood, they will be personally affected, so a cash transfer will create a bigger disincentive for them towards contributing to community adaptation.

5.3 Household Level Cash Transfer

To show how the negative effect of the cash transfer on community adaptation is a special feature of village-level cash transfer, I can also derive the effect cash transfer on community adaption under a household-level cash transfer. I set $k = 0$ in equation 1 and find FOC. However, unlike the village level cash transfer, here I cannot make the simplifying assumption that $\frac{\partial A_p}{\partial T} > 0$. Since investing in personal adaptation will reduce the chances of personal household damage, it will also reduce the chances of future cash transfer. Thus, it cannot be assumed ex-ante that providing people the cash transfer will make them more likely to invest in personal adaptation. [18] Therefore, I consider two FOCs, one with respect to A_c and

appendix section A.2 for the derivation.

[18] I also do the same for village level cash transfer earlier and derived equation 3.

another with respect to A_p and set them equal to zero. Then, I differentiate both equations with respect to T and substitute the expression for $\frac{\partial A_p}{\partial T}$ and derive the following equation for the effect of cash transfer on community adaptation.[19]

$$\frac{\partial A_c}{\partial T} = \frac{\pi'\tau_1\tau_{11} - \pi'\tau_1^2}{\Big(D_1 - T\Big)\Big(\pi''\tau_{11}\tau - \pi'\tau_1^2\Big)} \tag{4}$$

Given our usual assumptions that $\pi' < 0, \tau_1 < 0, \pi'' > 0, \tau_{11} > 0$, and $D_1 > T$, the numerator term, and the denominator will be positive, so the overall effect will be positive.

There are a few important things to note about this positive effect. First, there is no disincentive for less damaged households to contribute towards community adaptation. If anything, more damaged households are less likely to contribute towards community adaptation due to the τ term in the denominator.[20] Second, the overall effect of the cash transfer depends on the difference between the possible damage one could suffer in the flood and the amount of cash transfer. If the amount of cash transfer is larger than the damages a household could suffer in the flood $T > D_1$, then the overall effect of cash transfer on community adaptation will be negative. This makes sense, because if the government decides to compensate flood affectees more than the damage they suffered in the floods, then they will be disincentivized to protect themselves from future floods.

5.4 Extension: Effects on Personal Adaptation

Just as I derived the effects of the Watan card on community adaptation, I can similarly derive the effects on personal adaptation. The effect of village-level cash transfer on personal adaptation will be given by,

[19]For more detailed mathematical derivation, see appendix section A.2.

[20]This could be because of the wealth effect. Since adaptation is costly, more damaged households might have a stricter budget constraint due to flood damages, so they might use the cash transfer to spend on other things instead of community adaptation.

$$\frac{\partial A_p}{\partial T} = -\frac{\pi' \tau_1}{\pi'' \tau_{11}} \frac{\partial A_c}{\partial C} \tag{5}$$

and since the effect on community adaptation is negative, the effect on personal adaptation will be positive.

The effect of household level cash transfer on personal adaptation will be

$$\frac{\partial A_p}{\partial T} = \frac{\pi' \tau_1 \pi'' - \tau_1 \pi'^2}{\Big(D_1 - T\Big)\Big(\pi'' \tau_{11} \tau - \tau_1 (\pi')^2\Big)}$$

which is similar to equation 4 except that π' is interchanged with τ_1 and π'' is interchanged with τ_{11}. Moreover, since the signs of π' and τ_1 are the same and that of π'' and τ_{11} are the same, the effect of cash transfer on personal level adaptation will also be positive.

5.5 Model Predictions

The model generates three main predictions

First, the model predicts that under a village level cash transfer program, the overall effect of the cash transfer on the community adaptation will be negative and that on personal adaptation will be positive. In the model, the negative effect comes from the fact that investing in community adaptation reduces the likelihood of future flooding. While the reduced likelihood of future flooding reduces the chances of a household getting damaged in the future, it also reduces the chances of a household getting the cash transfer in the future. Since a household can reduce its chances of damage in case of flooding by investing in personal adaptation, it is still in the interest of a household to shirk on community contribution and allow flooding, so it can get the cash transfer.

Second, the model predicts that the negative effect will be lower for households who suffer greater damage in the past flood. This is because damages in the past flood generate a household's personal belief of how likely it is that it will be damaged if there is a flooding. If it is very likely that a household will be damaged in case of flooding, then a household will not shirk on community contribution.

Third, the model predicts that under a household level cash transfer program, there should be a positive effect on both community and personal adaptation. This effect comes from that while the household might increase its chances of a future cash transfer by investing less in personal and community adaptation, the risk of damage is greater, so it is in the household's interest to invest in both community and personal adaptation.

6 Conclusion

I have shown that providing cash transfers to households at the village level has a positive effect on personal adaptation but a negative effect on community adaptation. The positive effect is driven by households that have suffered damage due to floods, while the negative effect is driven by households that did not suffer damage but still received the cash transfer. This suggests that while cash transfers may be useful in enabling households to personally prepare for future floods, they may disincentivize investment in community adaptations

The findings suggest that policymakers need to be mindful of the design of disaster relief programs. While village-level cash transfers may have low administrative costs and be quick to implement, they can discourage households from investing in crucial community adaptations. These adaptations are the primary way communities at risk of disaster protect themselves in the absence of government support, and disincentivizing them can lead to greater disaster risk in the future.

There are three main limitations of this paper that can be improved in a future study. First, there may be some province-fixed factors that affect the adaptation behaviors that my empirical strategy cannot rule out. Second, while the study shows the direction of the effect of village-level cash transfers on personal and community adaptation, it cannot precisely estimate the magnitude of the effect, for part of the effect could be due to confounders. A better experimental setup is needed to better identify the magnitude of these effects. Third, the dataset used in the study is not large enough, especially for the KPK province, which may bias the standard errors in the regressions.

This project can inspire future research in a few ways. While I have shown that village-level cash transfers change adaptation behaviors, because they generate expectations that future cash transfers will be provided in the same manner, it will be useful to study how people change their behavior if these expectations are not fulfilled i.e. if the government does not provide the cash transfer in case of a future flood or provides it to only damaged households. Moreover, one could study how government cash transfers study adaptation behaviors in other disaster contexts like droughts or wildfires. Finally, one could also do a more rigorous replication my research with a better experimental setup. One possibility could be to gather data on the proportion of villages reported as flooded by relevant district authorities, subset villages that are reported as just above or below 50 percent flooded, conduct a household survey with a larger sample to ask about adaptations in these villages, and use a regression discontinuity to identify the effect of Watan card on adaptation.

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A Appendix

A.1 Additional Details on Data

Night lights

The data comes from images taken by US Air Force Defense Meteorological Satellite Program – Operational Linescan System (DMSP-OLS). The DMSP-OLS satellite captures visible and near infrared emissions from cities and villages, and creates a band measuring relative brightness on a scale of 0 to 63 with a spatial resolution of 927.67 meters. The satellite pictures are taken daily, and the data is later averaged by month and year. The night lights data is available from 1992 to 2013. The raw form of the data is in the avgvis band, but this can be noisy due to ephermal events like fire and other measuring errors. I use the stable lights band which is a cleaned version of avgvis band and is obtained after removing background noise and noise due to ephermal events. The stable lights band only captures the persistent lightning. To extract the village level night lights information, I extract the band score for the grid cell where the village GPS coordinate lies. I obtain the average of the stable lights band from 2009.

Population Density

I use the data on population density provided in Gridded Population of World Version 4 dataset (GPWv411). This is also a spatial dataset that comes from NASA SEDAC at the Center for International Earth Science Information Network. The data reports the estimated number of people per square kilometer with a spatial resolution of 927.67 meters. GPWv411 dataset provides yearly data from 2000 to 2020. To construct these yearly population estimates, they use national census data from the years when it is available and make projections for the years when there was no census. I use the data for the 2009 year and extract the population estimates for the pixels where village GPS coordinates were located.

Ex-ante flood risk

Flood risk data is provided by United Nations Environment Programme (UNEP)'s Global Global Assessment Report on Risk Reduction (GAR). It captures flood risk on a scale of 1 (low risk) to 5 (extreme risk) with a spatial resolution of around 10 kms. The risk score is calculated using hydrological models, data on historical disasters, rainfall patterns, topography, and soil type (Fair et al., 2017). I extract the risk score for the pixels where village GPS coordinates lie. This data has been used previously by Fair et al. (2017) in their paper on floods and political engagement in Pakistan.

100-year Flood Hazard

Since the resolution for ex-ante flood risk data is relatively big, I use another flood risk data with a finer spatial resolution. The 100-year Flood Hazard data is published by UNEP and uses similar techniques as the flood risk data to determine risk of flood events at a spatial resolution of around 1 km. The data captures risk of flood exposure indicating the potential water discharge depth in cm. It is called a 100 year flood hazard data, because the potential flood exposure is determined for flood events that have a one percent chance of taking place in a given year. These 100 year flood hazard maps identify areas with a greater flood risk. I extract the risk score for the pixels where village GPS coordinates lie.

A.2 Model Derivations

In this section, I explain in detail how I derive the effects of cash transfer at a village level vs household level on community vs personal adaptation.

To remind the utility function is given by,

$$\mathbb{E}(U) = W - \pi(A_c)\tau(A_p, D_0)D_1 - qA_p - rA_c + k\pi(A_c)T + (1-k)\pi(A_c)\tau(A_p, D_0)T \quad (6)$$

where $W = Y_0 + Y_1 + T - D_0$ and denotes the wealth of a household in the two periods after the damage caused in period 0, and k denotes whether the cash transfer is implemented at village level $k = 1$ or at a household level $k = 0$.

Village level Cash Transfer

I set $k = 1$ and get

$$\mathbb{E}(U) = W - \pi(A_c)\tau(A_p, D_0)D_1 - qA_p - rA_c + \pi(A_c)T+ \tag{7}$$

I differentiate w.r.t A_c and A_p to get the two FOCs.

$$r - \pi'(A_c)T = -\pi'(A_c)\tau(A_p, D_0)D_1 \tag{8}$$

$$q = -\pi(A_c)\tau_1(A_p, D_0)D_1 \tag{9}$$

Taking derivative of equation 9 with respect to T, I get,

$$\frac{\partial A_p}{\partial T} = -\frac{\pi'\tau_1}{\pi''\tau_{11}}\frac{\partial A_c}{\partial C} \tag{10}$$

Taking derivative of equation 8

$$-\pi''(A_c)T\frac{\partial A_c}{\partial T} + \pi' = -\pi''(A_c)\tau(A_p, D_0)D_1\frac{\partial A_c}{\partial T} - \pi'(A_c)\tau_1(A_p, D_0)D_1\frac{\partial A_p}{\partial T}$$

$$\implies \frac{\partial A_c}{\partial T} = \frac{\pi'(A_c)\left(1 - \tau_1(A_p, D_0)D_1\frac{\partial A_p}{\partial T}\right)}{\pi''(A_c)\left(\tau(A_p, D_0)D_1 - T\right)} \tag{11}$$

Substituting equation 10 this into equation 11, I get

$$\frac{\partial A_c}{\partial T} = \frac{\pi'}{\pi''(\tau D_1 - T) - \frac{(\pi'\tau_1)^2}{\pi\tau_{11}}D_1}$$

The denominator in the equation above will be positive. Since $\pi' < 0$, the overall effect will be negative. To see why the denominator will be positive, we can simplify the equation, and we get

$$\frac{\partial A_c}{\partial T} = \frac{\pi\pi'\tau_{11}}{D_1(\pi\pi''\tau\tau_{11} - (\pi'\tau_1)^2) - \pi\pi''\tau\tau_{11}T}$$

Here in the denominator, the coefficient for D_1 is slightly smaller than the coefficient for T. But given that cash transfer is a way small proportion of the possible damage, it would be justified to assume that still the D_1 term will be bigger than T term. Thus, the denominator will be positive. In the numerator, both π, τ_{11} will be positive, and π' will be negative, so numerator will be negative and overall the effect will be negative.

From equation 10, we can now also derive the effect of cash transfer on personal adaptation. Since $\frac{\partial A_c}{\partial T} < 0$, the overall effect of cash transfer on personal adaptation will be positive.

Household level Cash Transfer

The expected utility is given by,

$$\mathbb{E}(U) = W - \pi(A_c)\tau(A_p, D_0)\Bigg(D_1 - T\Bigg) - qA_p - rA_c$$

The two FOCs with repsect A_c and A_p will be,

$$r = -\pi'(A_c)\tau(A_p, D_0)\Bigg(D_1 - T\Bigg) \tag{12}$$

$$q = -\pi(A_c)\tau_1(A_p, D_0)\Bigg(D_1 - T\Bigg) \tag{13}$$

Taking derivative with respect to T in equation 12, we get

$$-(D_1 - T)\Bigg(\pi''\tau\frac{\partial A_c}{\partial T} + \pi'\tau_1\frac{\partial A_p}{\partial T}\Bigg) + \pi'\tau = 0. \tag{14}$$

Taking derivative of equation 13 with respect to T and separating out $\frac{\partial A_p}{\partial T}$, we get,

$$\frac{\partial A_p}{\partial T} = \frac{\tau_1}{\tau_{11}(D_1 - T)} - \frac{\pi'\tau_1}{\pi\tau_{11}}\frac{\partial A_c}{\partial T}$$

Substituting this equation into equation 14, and separating out $\frac{\partial A_c}{\partial T}$, we get

$$\frac{\partial A_c}{\partial T} = \frac{\pi'\tau_1\tau_{11} - \pi'\tau_1^2}{\Bigg(D_1 - T\Bigg)\Bigg(\pi''\tau_{11}\tau - \pi'\tau_1^2\Bigg)}$$

Thus, the overall effect will be positive. Moreover, by symmetry, if we derive the effect of household level cash transfer on personal adaptation, it will be the same as the effect on community adaptation except that π' will be interchanged with τ_1 and π'' will be interchanged with τ_{11}. Moreover, since the signs of π' and τ_1 are the same and that of π'' and τ_{11} are the same, the effect of cash transfer on personal level adaptation will also be positive.

A.3 Additional Tables

Table A.1: Heterogenous Effects - Balance

	(1) Elite Connectedness	(2) Relatives out village	(3) Own House	(4) Education
Watan	-0.32***	-129.28***	-0.18**	0.14
	(0.11)	(36.58)	(0.07)	(0.39)
Household Damage	0.10	37.82	-0.02	-1.54*
	(0.34)	(78.65)	(0.07)	(0.81)
HH Damage x Watan	a1 -0.05	-47.09	0.15	1.33
	(0.34)	(77.18)	(0.12)	(1.07) a1
Village Controls	Yes	Yes	Yes	Yes
Observations	634	634	634	634
Non-Watan mean	0.43	141.84	0.99	2.34

Notes: This table estimates the heterogenous effects equation but with the outcome variable as household characteristics instead of adaptation. This is to test the parallel trends assumption. Standard errors clustered at the village level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.2: Robustness Check - Flooding in 2011

	(1) Personal	(2) Community	(3) Personal	(4) Community
Watan	0.202**	-0.219***	0.182**	-0.274***
	(0.083)	(0.066)	(0.081)	(0.080)
Floods (2011)			-0.038	-0.108*
			(0.074)	(0.054)
Village Controls	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Observations	634	634	634	634
Clusters	24	24	24	24
Non-Watan mean	0.079	0.275	0.079	0.275
R-squared	0.22	0.13	0.22	0.14

Notes: This table checks if controlling for 2011 flooding affects the main results. Columns (1) and (2) replicate results from table 3, whereas in columns (3) and (4), I add control for whether the village was flooded in 2011. Standard errors clustered at the village level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.3: Robustness Check - House Damage vs Damage (Index)

	(1) Personal	(2) Community	(3) Personal	(4) Community
Watan	0.202**	-0.219***	0.156*	-0.226***
	(0.083)	(0.066)	(0.076)	(0.056)
Village Damage (Index)	0.071	-0.134		
	(0.162)	(0.143)		
Household Damage (Index)	0.096**	-0.026		
	(0.038)	(0.076)		
Village Damage (H)			0.081**	0.168***
			(0.030)	(0.051)
House Building Damage			0.000	-0.108**
			(0.019)	(0.041)
Village Controls	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Observations	634	634	634	634
Clusters	24	24	24	24
Non-Watan mean	0.079	0.275	0.079	0.275
R-squared	0.22	0.13	0.28	0.19

Notes: This table checks if how I construct the damage variable affects the results. Columns (1) and (2) replicate results from table 3, whereas in columns (3) and (4), I control for house building damage instead of damage as an index. Standard errors clustered at the village level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.4: Robustness Check - Ex-Ante Flood Risk vs Flood Hazard

	(1) Personal	(2) Community	(3) Personal	(4) Community
Watan	0.202**	-0.219***	0.217***	-0.228***
	(0.083)	(0.066)	(0.069)	(0.068)
Ex-Ante Flood Risk	-0.028	-0.013		
	(0.024)	(0.012)		
Flood Hazard (IHS)			0.018**	-0.006
			(0.008)	(0.007)
Village Controls	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Observations	634	634	634	634
Clusters	24	24	24	24
Non-Watan mean	0.079	0.275	0.079	0.275
R-squared	0.22	0.13	0.23	0.13

Notes: This table checks if how I measure flood risk affects the results. Columns (1) and (2) replicate results from table 3, whereas in columns (3) and (4), I control for flood hazard risk instead of ex-ante flood risk. Standard errors clustered at the village level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.5: Robustness Check - Night Light vs Population Density

	(1) Personal	(2) Community	(3) Personal	(4) Community
Watan	0.202**	-0.219***	0.187**	-0.220***
	(0.083)	(0.066)	(0.081)	(0.065)
Night Light (2010)	-0.001	-0.002		
	(0.002)	(0.001)		
Log(Pop Density)			0.092*	0.018
			(0.047)	(0.052)
Village Controls	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Observations	634	634	634	634
Clusters	24	24	24	24
Non-Watan mean	0.079	0.275	0.079	0.275
R-squared	0.22	0.13	0.25	0.12

Notes: This table checks if how I measure economic activity affects the results. Columns (1) and (2) replicate results from table 3, whereas in columns (3) and (4), I control for population density instead of nightlight as a measure of economic activity. Standard errors clustered at the village level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.6: Robustness Check - Construction of Watan Eligible

	(1) Personal	(2) Community	(3) Personal	(4) Community
Watan Eligible	0.24***	-0.18*	0.25***	-0.31**
	(0.06)	(0.10)	(0.05)	(0.11)
HH Damage	0.10**	-0.03	0.12	-0.46**
	(0.04)	(0.08)	(0.07)	(0.18)
HH Damage x Watan Eligible			-0.03	0.57***
			(0.10)	(0.20)
Village Controls	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Observations	634	634	634	634
Clusters	24	24	24	24
Non-Watan mean	0.08	0.27	0.08	0.27
R-squared	0.23	0.10	0.23	0.14

Notes: This table checks if my construction of Watan Eligible variable is correct. To do so, I replicate the heterogeneity analysis using Watan Eligible variable for Punjab and Sindh. The results are consistent with table 5 Standard errors clustered at the village level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.7: Robustness Check - Construction of Watan Eligible 2SLS

	(1) Watan	(2) Personal	(3) Community	(4) Personal	(5) Community
Watan Eligible	0.72***				
	(0.03)				
Watan		0.33***	-0.24**	0.28***	-0.39***
		(0.08)	(0.11)	(0.05)	(0.12)
HH Damage		0.09**	-0.03	-0.08	-0.64**
		(0.04)	(0.07)	(0.15)	(0.30)
HH Damage x Watan				0.22	0.78**
				(0.20)	(0.36)
Village Controls	No	Yes	Yes	Yes	Yes
Household Controls	No	Yes	Yes	Yes	Yes
Observations	634	634	634	634	634
Clusters		24	24	24	24
Non-Watan mean		0.08	0.27	0.08	0.27
R-squared	0.47	0.19	0.13	0.21	0.12
F-stat	562				

Notes: This table checks if my construction of Watan Eligible variable is correct. To do so, I replicate the heterogeneity analysis using Watan variable for Punjab and Sindh instrumented by Watan Eligible. The results are consistent with table 5 Standard errors clustered at the village level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.8: Heterogenous Effects of the Watan Card by Damage (Minor Damage vs Damaged)

Panel A: Sub-Sample	(1) Personal	(2) Community	(3) Personal	(4) Community
Watan	0.263**	0.031	0.170**	-0.491***
	(0.113)	(0.075)	(0.064)	(0.123)
Sample	Damaged HHs	Damaged HHs	Non-Damaged HHs	Non-Damaged HHs
Observations	133	133	273	273
Non-Watan mean	0.032	0.200	0.151	0.523
R-squared	0.417	0.203	0.231	0.454
Panel B: Heterogeneity Analysis (Full Sample)				
Watan	0.115	-0.259***	0.049	-0.353***
	(0.093)	(0.072)	(0.100)	(0.081)
Damage	0.100	0.015	-0.129	-0.252
	(0.125)	(0.111)	(0.088)	(0.207)
Damage x Watan			0.379*	0.497**
			(0.203)	(0.228)
Village Controls	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes
Clusters	23	23	23	23
Observations	406	406	406	406
Non-Watan mean	0.091	0.362	0.091	0.362
R-squared	0.181	0.292	0.206	0.315

Notes: This table replicates 5 using a subsample of only non-damaged and slightly damaged households. Standard errors clustered at the village level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.9: Effect of Watan Card on Adaptation (Punjab Sindh vs KPK)

	(1) Personal	(2) Community	(3) Personal	(4) Community
Watan Eligible	0.239***	0.101	0.281***	0.698***
	(0.064)	(0.104)	(0.090)	(0.115)
Punjab, Sindh	0.042	-0.268*	0.083	0.307**
	(0.063)	(0.142)	(0.082)	(0.117)
Punjab, Sindh x Watan Eligible			-0.063	-0.891***
			(0.096)	(0.162)
Village Controls	Yes	Yes	Yes	Yes
HH Controls	Yes	Yes	Yes	Yes
Clusters	32	32	32	32
Observations	858	858	858	858
Control mean	0.086	0.237	0.086	0.237
R-squared	0.25	0.07	0.25	0.23

Notes: This table conducts a heterogeneity analysis across province for being situated in a Watan Eligible village (more than 50 percent flooded). Standard errors clustered at the village level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.10: Effect of Watan Card on Adaptation of Non-Damaged Households (Punjab Sindh vs KPK)

	(1) Personal	(2) Community
Punjab, Sindh	-0.028	-0.427**
	(0.183)	(0.148)
Village Controls	Yes	Yes
HH Controls	Yes	Yes
Clusters	13	13
Observations	213	213
Control mean	0.166	0.400
R-squared	0.30	0.08

Notes: This table conducts a subsample analysis comparing non-damaged households in Watan eligible villages of KPK with those from Punjab and Sindh. Standard errors are clustered at the village level $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.11: Effect of Watan Card on Adaptation (KPK) Robust SE

	Personal Adaptation			Community Adaptation		
	(1)	(2)	(3)	(4)	(5)	(6)
Watan Eligible	0.229***	0.104*	0.109*	0.631***	0.246	0.332**
	(0.02)	(0.06)	(0.06)	(0.05)	(0.15)	(0.16)
Village Damage		2.480***	0.897		7.234***	6.269**
		(0.94)	(0.91)		(2.04)	(2.65)
Night Light (2010)		-0.014**	-0.005		-0.039***	-0.031**
		(0.01)	(0.01)		(0.01)	(0.02)
Ex-Ante Flood Risk		-0.029*	0.011		-0.081**	-0.084*
		(0.01)	(0.02)		(0.04)	(0.05)
Elevation (100 m)		0.009*	-0.005		0.024**	0.026
		(0.00)	(0.01)		(0.01)	(0.02)
Watan			0.067**			-0.020
			(0.03)			(0.09)
Household Damage			-0.047			-0.081
			(0.04)			(0.13)
Elite Connectedness			0.026**			-0.038*
			(0.01)			(0.02)
Family out village			0.000			-0.001
			(0.00)			(0.00)
Own House			0.016			-0.159**
			(0.03)			(0.07)
Education (HH Head)			0.003*			0.005
			(0.00)			(0.00)
Village Controls	No	Yes	Yes	No	Yes	Yes
Household Controls	No	No	Yes	No	No	Yes
Observations	224	224	224	224	224	224
Non-Watan mean	0.05	0.05	0.05	0.15	0.15	0.15
R-Squared	0.47	0.51	0.56	0.52	0.57	0.59

Notes: This table replicates table 4 using heteroscedasticity robust standard errors instead of clustered standard errors. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.