# HOW DO RAINFALL SHOCKS AFFECT RURAL HOUSEHOLD WELFARE, LABOR SUPPLY AND MIGRATION DECISIONS?

A Dissertation

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by

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## Abstract

This study examines the effect of extreme weather events on rural households in a developing country. Such events pose a threat to the livelihood of farmers and have wider ramifications for food security which may not necessarily be confined to the rural areas. In that light, such a study of extreme weather-related disasters and their impact on economies is essential for the formulation of effective government policy response.

This dissertation consists of mainly two parts. First part examines the relationship between rainfall shock and household welfare outcomes, that is, per capita income and per capita consumption by exploiting a three-year panel data with the help of fixed effect model. This study finds that extraordinary rainfall reduces per capita income of the rural households mainly because of the reduction in crop income. Evidence of consumption smoothing is also observed which is mainly channelized through liquid assets such as savings, selling of livestock, and lastly through borrowing – which is mostly from informal sources. Heterogeneity analysis also found that the impact of disasters for the households living in communities having better access to physical or financial infrastructure seem to be at an advantage and show resilience in the event of shocks.

The second part deals with the impact of rainfall shocks on labor supply and temporary migration decisions. The results of estimating the logit fixed effects model and linear probability model suggest that the extraordinary shocks diminish non-farm work opportunities, thereby decreasing farm wages and creating excess supply of labor. As a coping strategy, adult males are found to temporarily migrate for remittances, particularly in areas without direct access to urban areas. This implies that those individuals whose daily commuting costs out of disaster hit area in search of non-farm wages are greater are more likely to migrate.

**Key Words:** Rainfall disasters, Household welfare, Consumption smoothing, Temporary migration, Labor supply, Remittances

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## 1. Introduction

The destruction and economic damage caused by natural calamities can be on such a large scale that even the developed countries feel the heat of such events despite having strong economies and robust safety nets. Hurricane Katerina, for example, not only resulted in mass displacement of people but also considered as 'the most costly hurricane in terms of property damage in the US history' (Gallagher and Hartley, 2017: 203). The population of New Orleans fell by 29% from 2005 to 2011[1] with '400,00 people permanently displaced by the storm'[2] and the recovery is still considered incomplete[3]. The toll that such extraordinary weather events can take on the developing economies can be fathomed by this single example. This can be of particular concern given the established scientific evidence that such weather phenomenon is not only going to persist but likely to worsen in the coming years.

Such calamities can be addressed by two broad approaches, namely, ex-ante precautionary measures or ex-post damage reduction strategies. However, in case of covariate shocks which affects entire communities the ex-ante insurance strategy, for example, for crops; or ex-post strategy of households to get loans from banks is likely to fail as everyone is approaching the insurer or bank which simply can't deal with such huge claims and even if they try, they will default (Sawada, 2007).

Considering such complex issues, the study of the impact of weather events on the economies of developing countries is very important for better understanding and formulation of possible policy solution for the less developed economies to deal with such issues. I choose Pakistan, a developing

[1] https://www.britannica.com/event/Hurricane-Katrina accessed on June 19, 2021
[2] https://www.nationalgeographic.com/environment/article/hurricane-katrina accessed on June 19, 2021
[3] https://www.pennlive.com/nation-world/2019/08/new-orleans-still-a-work-in-progress-14-years-after-hurricane-katrina.html accessed on June 19, 2021

country for this study as Pakistan is the sixth most populous country in the world with population at 199.7M out of which 59% are still living in rural areas.[4] The contribution of agriculture in the Gross Domestic Product has fallen over the years and was recorded at 19.5 during 2016-17, however, still 42.3% of total labor force, which is disproportionately much higher, is employed in agrarian economy.[5] Therefore, the impact of climate on agricultural economy is likely to hurt a large number of people. Moreover, Pakistan is among the top ten countries which are predicted to be worst hit by weather changes.[6]

This dissertation studies the impact of rainfall shocks on the rural household welfare and the coping strategies adopted by the affected households, for example, selling livestock or opting to go out of affected areas, that is, migrate. The study is structured as follows:

Chapter 2 discusses the exponential rise in the natural disasters during last few decades and accompanied human and economic loss. Chapter 3 gives an overview of the data used in this study. As the explanatory and outcome variables have been drawn from common data sources for chapters 4 and 5 – main chapters of this dissertation – the explanation of common variables has been combined in one chapter for sake of brevity.

Chapter 4 is the first main chapter which analyses the rural household welfare in terms of income and consumption in the aftermath of rainfall disasters. Previous literature seems to have dealt with such issues showing mixed results but leaves a room for further research on the heterogeneity analysis of such weather incidents. The study particularly contributes by looking at the resilience of households in covering their food consumption through dissaving and credit uptake and finds

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[4] Economic Survey of Pakistan (2016-17), Statistics Division, Government of Pakistan, 2017
[5] ibid
[6] https://germanwatch.org/sites/default/files/Global%20Climate%20Risk%20Index%202021_1.pdf accessed on June 09, 2021

heterogeneity in the resilience of the household, for example, those who were able to get loans in order to smooth out their consumption.

Chapter 5 then looks at the coping behavior of those household whose income is affected by the shocks. Starting with literature review, it lays down this study’s unique methodology for analysis using both logit and OLS side by side which is followed by results. First it looks at the response of rural labor market indirectly by analyzing the farm and non-farm wages and finds an increase in migration as coping strategy and also a consequent increase in remittances. It is to be highlighted that no previous study seems to have looked at the possible channels and possible links of rural labor market with migration decisions and increase in remittances. This is the original contribution of this paper.

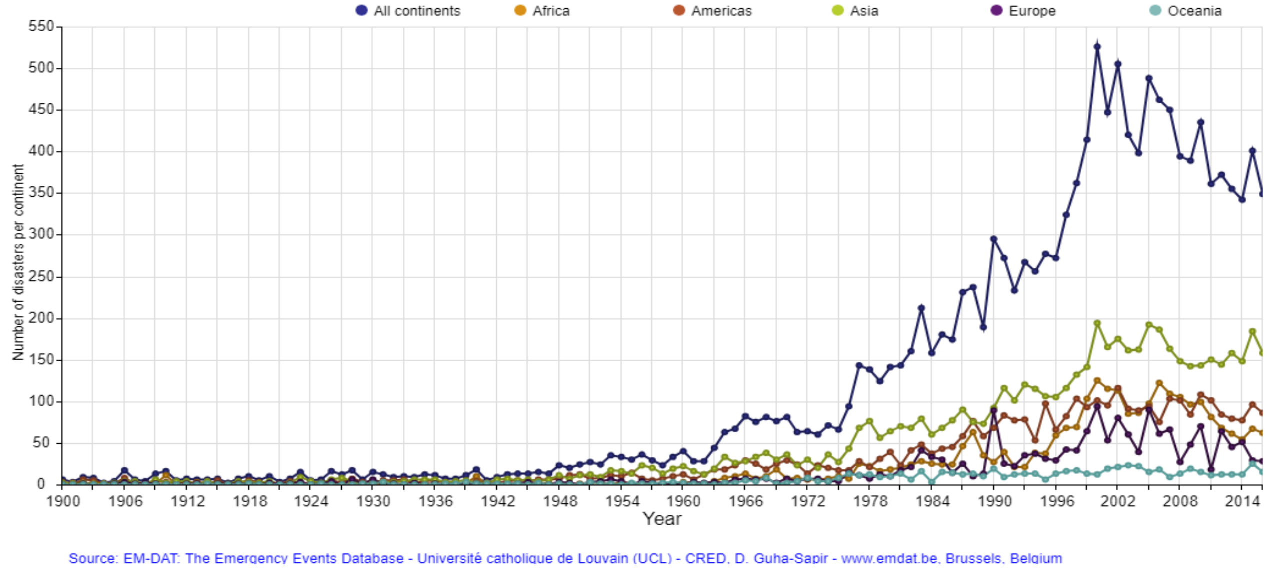
Last chapter closes the discussion by concluding and laying down certain policy solution to deal with or reduce the weather impact on the developing economies like Pakistan.

## 2. Natural Disasters[7]

Variability in rain and temperature, which in extreme cases causes dangerous events such as floods, cyclones, storms, etc., is a natural phenomenon. Since the time immemorial human life has adjusted to these natural disasters and adapted their lives to the vagaries of nature. Wherever human life was not able to adjust, nature took its course and many civilizations deteriorated or affected adversely, for example, Maya Civilization, Andean Civilization or Roman Empire (Binford et al, 1997; McCormick et al, 2012; Peterson and Haug, 2005). However, the speed and scale of this climate change, posing a collective challenge to this world recently, is unprecedented. The manifold increase in the number of reported natural disasters since the second half of the 20th century across the globe highlights the unusual intensification and recurrence of natural disasters due to extraordinary environmental variations. The figure 2.1 shows the number of yearly reported disaster since 1900 for every continent which remained less than 50 per year till 1960s. However, marked increase (green line) since then can be observed. Historically devastating floods in Pakistan in 2010 were followed by floods again in 2011 and 2012 which were more intense and damaging than the usual seasonal flooding. Similarly, Hurricane Katrina in the US (2005), typhoon Yolanda in Philippines (2013), Hurricanes Harvey, Irma and Maria in Americas (2017), floods in Japan and Kerala, India (2018) are some of the incidents which point to the fact that extreme weathers incidents are becoming a regular feature of our lives lately.

[7] Natural disasters include biological, climatological, extra-terrestrial, geophysical, hydrological and meteorological disasters in the Em-dat database. This study only looks at the floods as manifestation of climate change measured objectively by using publicly available precipitation data from, NASA.

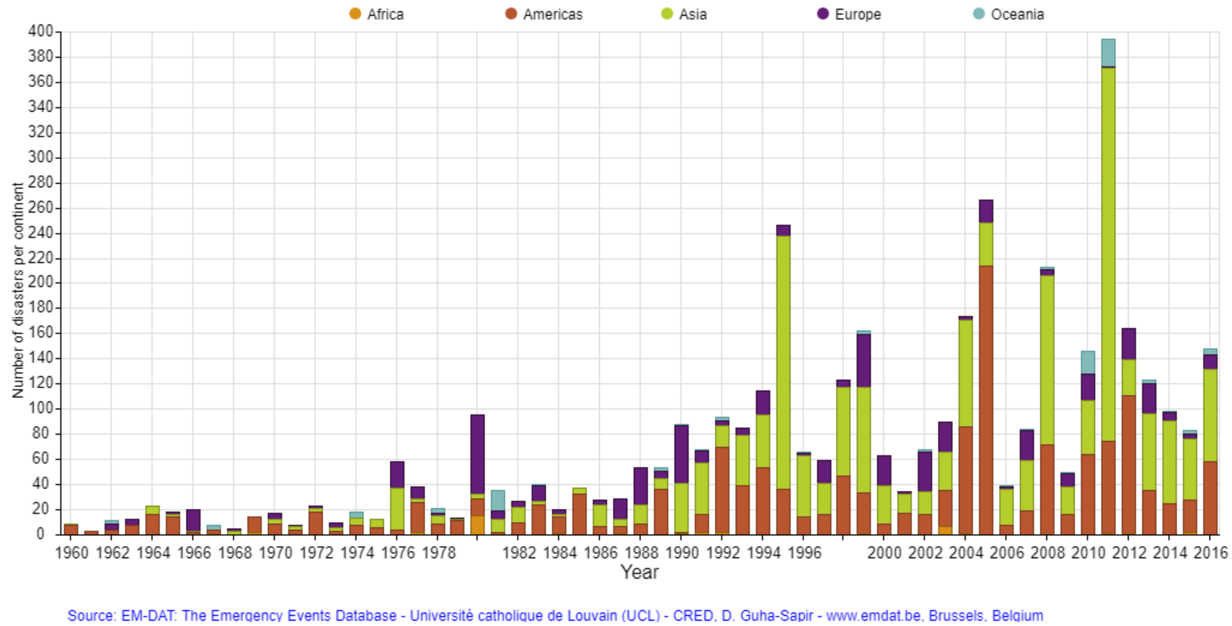
**Figure 2.1 Total number of reported natural disasters from 1900-2016[8]**




This steep rise in the number of incidents of natural calamities is accompanied by rising economic losses too. The Figure 2.2 reports yearly reported disasters and different colors in columns depicts different continent, green is for example, for Asia. A meteoric rise in economic damages in the recent years can be observed; major share of which had to be borne by Asia, the most diverse and populous part of the world.

[8] **https://www.emdat.be/emdat_db/ Database was updated on August 01, 2018. Accessed on August 02, 2018**

**Figure 2.2 Reported economic damage caused by Natural disasters between 1960 and 2016 (Scaled to 2016 US$)9**

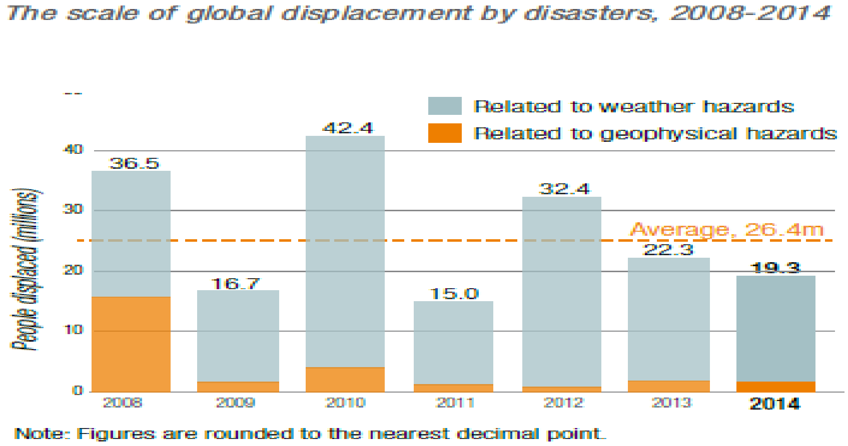



These reported economic costs in the past 20 years at $1.891 trillion, according to UNISDR report are much lower and actual economic damages might be around $250 to $300 billion annually.[10] The floods alone, same report says, accounted for the 47% of these natural disasters during 1995-2015 which affected around 2.3 billion people and accounted for the 40% of weather-related deaths.[11]

The impact of the disasters can also be gauged by the fact that population displaced due to disasters is not only on the rise but now the likelihood of being displaced by natural disasters is 60% higher than it used to be 40 years ago even after adjusting for population growth[12]. Figure 2.3 (IDMC, 2015; Page 08) shows that in 2014 alone, of the 19.3 Million people displaced by disasters in 100 countries, 17.5 Million were due to climate change or weather-related hazards.

[9] ibid
[10] UNISDR. (2015). The human cost of weather-related disasters, 1995–2015. *United Nations*, *Geneva*.
[11] ibid
[12] Internally Displacement Monitoring Center. (2015). Global estimates. People displaced by disasters. Norwegian Refugee Council, *Châtelaine: IDMC*.

**Figure 2.3 Global displacement since 2018 is depicted in the picture. Yellow colour shows weather related displacement of people and it can be seen that major displacement is due to weather related incidents.**



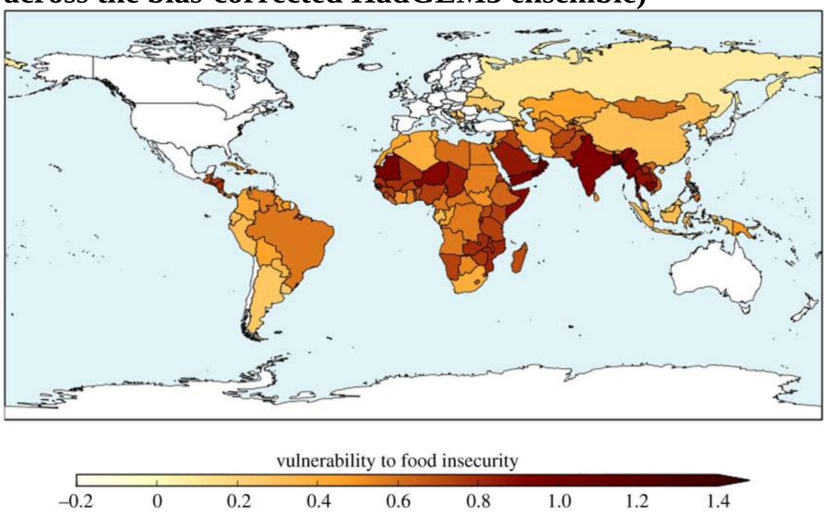

In case of Pakistan parallel increase in natural disasters has been observed over the years as discussed above, in fact, the contrast in the physical and economic damage between 1950-2000 and 2001-2018 is alarming. There were 89 reported incidents of natural disasters from 1950 to 2000 causing 29,080 deaths, affecting 36 Million people and costing $2.543 Billion to the economy. However, in the past 18 years since 2001 the number of such reported events numbered 113 affecting 49.5 Million people, causing 84,298 deaths and cost to the economy was, even higher, at $25.86 Billion.[13]

It is also emphasized that climate change will increase the number of disasters affecting not only human lives directly but also the only source of their food, that is, the agriculture (IPCC 2014). The direct and immediate impact of climate change resulting in the colossal damage to life and economy is astounding, however, the slow and creeping change that rising temperatures and irregular rain patterns will bring in the form of increasing food insecurity is even more disturbing. In a recent study based on an advanced climate model, Sub-Saharan Africa and South Asia, later includes Pakistan, will be the hardest hit regions, shown in Fig 2.4, due to weather extremes and

[13] https://www.emdat.be/emdat_db/ Database was updated on August 01, 2018. Accessed on August 02, 2018

natural disasters resulting in severe food insecurity for these regions (Betts et al, 2018). This all points to the importance of studying impacts of such disasters on the economy of a country which will help in devising policies either to check the speed of change through a visionary climate policy or to adapt everyday lives to the changed environmental realities which would reduce the physical and economic damage accompanied by such disasters.

**Figure 2.4 Hunger and Climate Vulnerability Index for 1981-2010 climate (ensemble mean across the bias-corrected HadGEM3 ensemble)**

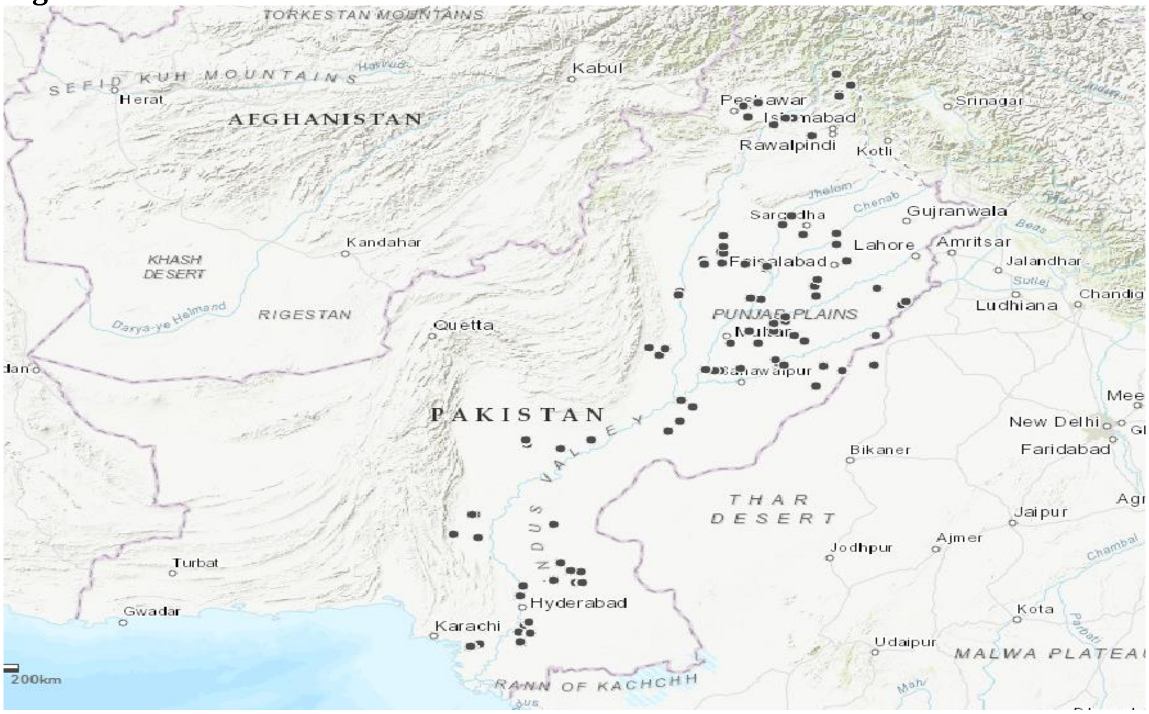



Source: Betts et al, 2018

## 3. Data

This study utilizes panel data collected through Pakistan Rural Household Panel Survey (PRHPS)[14] under Pakistan Strategy Support Program (PSSP) launched in July 2011. The survey was designed and administered by IFPRI. The survey includes three out of four provinces of Pakistan, namely, Punjab, Khyber Pakhtunkhwa (KPK) and Sindh plotted in the Figure 3.1 below. Due to security reasons Balochistan, a thinly populated province, constituting only 5% of total population of Pakistan, could not be included in the survey.

**Figure 3.1 Households' location across Pakistan**




Source: Household PRHS, 2012 data plotted by the Author using ArcGIS

The survey collected multi-topic information from 2090 households in 76 villages during March-April 2013 (Round 1), April-May 2013 (Round 2) and April-May 2014 (Round 3, publicly

[14] International Food Policy Research Institute (IFPRI); and Innovative Development Solutions (IDS). 2014. Pakistan Rural Household Panel Survey (RHPS), 2012. Washington, DC: International Food Policy Research Institute (IFPRI). http://dx.doi.org/10.7910/DVN/28558

available since April, 2017) through a multistage, stratified sampling technique to select the sample (Nazli and Haider, 2012). The latest third round survey covered 1876 households out of 2090 households interviewed for the first wave, which brings attrition rate at 10%.[15] This study uses balanced panel of 1786 households from PRHPS 2012, 2013 and 2014. The survey covers wide ranging topics which allows the examination of income from different sources, analyze spending on different items and enables this study to investigate rainfall shock from the perspective of heterogeneity.

Table 3.1 shows that the summary stats of indicator variables used in the heterogenous analysis which shows that 61% of households take more than median time to commute to nearest commercial center. Similarly, the percentage of population residing far from credit facilities is around 45%.

Household characteristics show that 53% of households are engaged in agricultural activity which takes the value of 1 if households grow crops on their own plots or land is shared or rented. If those household who are indirectly engaged in agriculture, for example, farm labor, are included the percentage of those engaged in farm related activities will be around 60% which will be explained while discussing the outcome variables for first topic in chapter 4.

In the chapter 5, this study also uses balanced panel of 11,934 individuals from PRHPS 2012, 2013 and 2014. Table 3.1 below also present summary statistics of individual having average working age of 31 years who are equally divided between males and females and working age individuals – those greater than 14 years and less than 65 years of age – constitute 59% of the total sample.

[15] The attrition rate is not likely to affect the results on account of time invariant characteristics as the fixed effects strategy is used in this paper. Community characteristics were reported only for 2011-12 in the data and therefore will be taken care of by the fixed effects. Some household characteristics, such as, household size or age are checked as control variable as robustness test and those are also not found affecting the results which rules out any attrition bias. Appendix IV deals with it in detail.

**Table 3.1 Summary Statistics: Community and Household Level Variables**

| Variables | | All Households | |
|---|---|---|---|
| **Community characteristics**[16] | **Observations** | **Mean** | **SD** |
| 1 if railway station is within 5 KM of a community | 5,358 | 0.150 | 0.357 |
| 1 if it takes more than median commute time to nearest city | 5,358 | 0.330 | 0.470 |
| 1 if it takes more than median commute time to nearest market | 5,358 | 0.391 | 0.488 |
| 1 if the distance to the nearest city is less than or equal to the median | 5,358 | 0.515 | 0.500 |
| 1 if the distance to the nearest commercial market is less than or equal to the median | 5,358 | 0.552 | 0.497 |
| 1 if it takes more than median commute time to nearest commercial bank | 5,358 | 0.450 | 0.498 |
| 1 if it takes more than median commute time to nearest Regd. Cooperative | 5,358 | 0.481 | 0.500 |
| I if the formal credit institutions are situated within a community | 5,358 | 0.152 | 0.359 |
| 1 if there is no water in canal for more than median number of weeks for a community | 5,358 | 0.535 | 0.499 |
| 1 if canal is opened officially for more than median number of weeks for a community | 5,358 | 0.600 | 0.490 |
| 1 if a community is situated in areas less than the median elevation | 5,358 | 0.487 | 0.500 |
| 1 if a community is situated in areas less than the median population density | 5,358 | 0.513 | 0.500 |
| **Household Characteristics** | **Observations** | **Mean** | **SD** |
| 1 if household engaged in agricultural activity | 5,358 | 0.533 | 0.499 |
| 1 if household owns agricultural land | 1,786 | 0.350 | 0.477 |
| 1 if a household possess equal to or greater than the median value of initial farm assets | 1,786 | 0.362 | 0.481 |
| 1 if a household possess equal to or greater than the median value of initial assets | 1,786 | 0.494 | 0.500 |
| 1 if a household possess equal to or greater than the median value of initial livestock | 1,786 | 0.501 | 0.500 |
| 1 if a household possess equal to or greater than the median value of household initial savings | 1,786 | 0.125 | 0.331 |
| 1 if a household has more than or equal to the median of 7 households members | 5,358 | 0.659 | 0.474 |
| **Individual Characteristics** | | | |
| 1 if the individual is married | 35,802 | 0.379 | 0.485 |

[16] These characteristics were reported only once in the first year PRSP data during March-April, 2012

| | | | |
|---|---|---|---|
| 1 if the individual 's age is greater than the median working age (>= 15 & <= 64) of 31 Years | 35,802 | 0.312 | 0.463 |
| Adult (working Age), 1 if a person is >= 15 and <= 64 | 35,802 | 0.591 | 0.492 |
| Dependent, 1 if a person is<= 15 and >= 64 | 35,802 | 0.409 | 0.492 |
| Gender, 1 if Male, 0 otherwise | 35,802 | 0.514 | 0.500 |

**Source**: Authors' computation from the PRHS 2012, 2013 and 2014

Table 3.2 below present summary statistics of household and community characteristics. Community characteristics show that on average 454 people live per square kilometer in a sub-district, however it varies among different regions. The most populous Tehsil or Sub-district in our sample is Khanewal with population density of 3727 and De-Excluded Area DG Khan Sub-district is the most sparsely populated with population density of 40 person per square Km. It takes, on average, 34 or 39 minutes to reach nearest city or commercial center, respectively. As the agriculture or agricultural related activities are very important for rural life, access to irrigation can be instrumental for village economy. There are large number of districts with access to irrigation, for example, 100% areas in Sangahar and Tando Muhammad Khan in Sindh; and Sargodha, Khanewal and Faisalabad in Punjab have access to irrigation means, such as, Canals or Tube wells. According to government statistics on average 83% sub-districts included in the data have access to irrigation means.[17] . Even if the areas have access to canal water, the canal may not be operating throughout the year. The efficacy of irrigation canal can be measured by the information available in the survey regarding the number of weeks the canal in a village is full, half full or empty. The data used in study, reported in Table 3.2 below, reveals that around 23 weeks in a year a canal is opened on average and for 29 weeks of the year there is no water in these canals.

From the household summary statistics it appears that the land owned on average is only 1.57 acres which is not very big, however, considering the fact that the ownership of land is relevant only for those involved in growing crops, the average land holding among agricultural households is around 3 acres. The inequality in agricultural land ownership among those who are engaged in growing crops is also conspicuous, as of the 892 agricultural households in 2012, top 25 % hold around 10

[17] These figures are on district level and pertains to 19 districts included in the household data. The information was reported in the Agricultural Census of Pakistan, 2010 available online: http://www.pbs.gov.pk/content/agricultural-census-2010-pakistan-report accessed on September 01, 2018

acres of land and bottom 25% has no land of their own.[18] Lastly, the average family size is 7 members, 3 of which are dependents – below 15 years of age or above 64 years of age – and 4 of which are male.

Summary statistics for individuals show that the sample is, not only, relatively young having average age of 25 years, but also have low literacy rates with mean education of 2.4 years only. This also points to the low skilled population which is more likely to be engaged in low-paying unskilled wage-earning activities which will be discussed later.

**Table 3.2 Summary Statistics: Community, Household and Individual Level Continuous Variables**

| Variable | Observations | Mean | SD |
|---|---|---|---|
| **Community** | | | |
| Time it takes to reach nearest city (Minutes) | 76 | 34.316 | 25.121 |
| Time to nearest commercial center (Minutes) | 76 | 39.159 | 26.710 |
| Empty Canal (Weeks) | 76 | 29.136 | 19.255 |
| Canal Officially Opened (Weeks) | 76 | 23.483 | 19.664 |
| Population density | 48 | 454.192 | 467.260 |
| **Household** | **Observations** | **Mean** | **SD** |
| Agricultural area owned (Acre) | 1786 | 1.571 | 4.701 |
| Total Assets owned (Rs.) | 1786 | 1,590,397 | 3,332,205 |
| Household savings (Rs.) | 1786 | 4779 | 44278 |
| HH Size | 5,358 | 6.883 | 3.184 |
| Male members of family | 5,358 | 3.494 | 1.879 |
| Dependents | 5,358 | 2.917 | 2.118 |
| Adults | 5,358 | 3.967 | 2.256 |
| Age of HH Head | 5,358 | 47.446 | 13.480 |
| **Individuals** | | | |
| Age of Individuals (Continuous) | 35,802 | 25.145 | 19.035 |
| Education level (Continuous) | 35,802 | 2.487 | 3.756 |

**Source**: Authors' computation from the PRHS 2012, 2013 and 2014

[18] Author's calculation from data

**Rainfall Data**

Rainfall data, available publicly, from NASA website has been used to calculate severity of covariate seasonal shocks, such as, extraordinary rainfalls likely to cause floods. More specifically, this study utilizes the NASA MEERA-2[19] monthly precipitation data in millimeters with high spatial resolution at 0.5° latitude x 0.5° longitude degree intervals[20]. Unlike some studies which used rainfall data at district or state level (Giesbert and Schindler, 2012; Gilmont et al, 2018; Karim, 2018; Skoufias et al, 2017), I have used village level rainfall data for more accuracy.

Average rainfall data since 1981 to 2010 has been used as reference period for survey years of 2012 to 2014 to calculate the deviation from the mean. Monthly rainfall of the major rainy season, monsoon[21], during June through September has been normalized using 30-year mean, as mainly the variation during these four months affects agriculture and, therefore, more relevant for analysis (Gao and Mills, 2018; Kosec and Mo, 2017; Menon, 2009; Skoufias et al, 2017; Grimard and Hamilton, 1999). For this study, I have adopted the standardization technique used by Grimard and Himilton, 1999. Normalized rainfall was calculated as shown in equation 3.1 below. Where, $X_{it}$ is the standardized precipitation in community / village i, during year t (2011, 2012 and 2013), on the left-hand side. $x_{imt}$ is the total rainfall during monsoon months, m in year, t; $\mu_{im}$ and $\sigma_{im}$ are the 30 year mean and standard deviation, respectively (1981 through 2010) of moonsoon

[19] Modern Era Retrospective-Analysis for Research and Applications (MERRA-2) is reanalysis data which combines information from ground stations, satellite-based readings and other climate variables through a climate model. The areas where the ground gauges are thinly spread have more input from satellite data (https://power.larc.nasa.gov/docs/methodology/).

The results from the climate data have been found to be qualitatively same as the ground station data (Ebert, 2007) and MEERA-2 is also found to be optimal among other satellite-based data sources (Sun et al, 2020).

[20] https://power.larc.nasa.gov/data-access-viewer/ (NASA/POWER SRB/FLASHFlux/MERRA2/GEOS 5.12.4 (FP-IT) 0.5 x 0.5 Degree Interannual Averages/Sums) accessed and downloaded on December 06, 2018.

[21] Rainfall of past 12 months, that is October through September, was also used for the analysis (not reported) which returned qualitatively same but weaker results.

months, m in village, i. Based on following equation categorical shock variable for 2011, 2012 and 2013, is calculated separately.

$$X_{it} = \frac{x_{imt} - \mu_{im}}{\sigma_{im}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Eq. 3.1}$$

Standardized monthly / seasonal rainfall data take into consideration not only the seasonal variations but also the uneven rainfall in a particular month or season over the years (Mitchell, 2003). It will also take care of household's employment practices – for example, whether or not engaged in agricultural sector – adapted to the average rainfall in a particular village and, therefore, comparable across regions meaningfully (Hidalgo et al, 2010). Using the standardized data, the extraordinary rain fall shock measure, is defined as an indicator variable that equals 1 if the monsoon rainfall is more than 1 standard deviation above 30-year historical mean, whereas 0, means the rainfall is within 1 SD, implying a normal rainfall year.[22]

Table 3.3 shows not only the standardized rainfall explanatory variable used for this analysis but also compares it with household and community level disaster responses. Around 28% of households were affected from 2012 to 2014 due to extraordinary rains on average. Year-wise break down further highlights that the rainfall shocks affected more households during 2012 and least in 2014 which also corroborates with the disaster figures reported by the households or community elders.[23]

The extreme events in Pakistan are mostly related to extraordinary floods or rainfall incidents. Some areas face droughts, for example, Thar in Sindh. The data which I am using for this paper do not show that households faced drought or famine like situation, and not even a single

[22] No observation in the NASA rainfall normalized data is less than negative 1 SD, or in other words, no reported incidence of extraordinary poor rainfall likely to result in a drought like situation

[23] Data was collected in 2012 for past one year, therefore, data for 2012 reports the events or figures for past 12 months, that is April 2011 to March 2012.

standardized rainfall observation in respect of any of 76 villages show the rainfall below standard deviation negative 1.

**Table 3.3 Summary Statistics: Outcome Variable**

| | | | | 2012 | | | 2013 | | 2014 | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Observations** | **Mean** | **SD** | **Observations** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** |
| 1 if normalized rainfall is above 1 SD | 5,358 | 0.282 | 0.450 | 1,786 | 0.580 | 0.494 | 0.207 | 0.405 | 0.059 | 0.235 |
| 1 if households reported foods, 0 otherwise | 5,358 | 0.109 | 0.312 | 1,786 | 0.170 | 0.375 | 0.097 | 0.297 | 0.060 | 0.237 |
| 1 if community reported floods, 0 otherwise | 5,358 | 0.140 | 0.347 | 1,786 | 0.215 | 0.411 | 0.134 | 0.341 | 0.072 | 0.258 |

**Source**: **Rainfall**: Rainfall Shock calculated by author from the data downloaded from NASA website https://power.larc.nasa.gov/data-access-viewer/

## 4. How do rainfall shocks affect welfare of rural households in Pakistan?

### 4.1 Introduction

The evidence on the adverse social and economic impacts of climate change is increasing over the years (Emdat, 2018; IPCC, 2014) but the required collective and individual efforts are minuscule compared to the huge challenge faced by the world. This study is an effort to see how a populous developing country can deal with the economic damages of irate weather events, which pose a threat to food security through temperature or precipitation changes[24] resulting in productivity declines or increased number of extreme weather-related disasters, such as, floods.[25]

Change in temperature and rainfall directly affect agriculture which is not only important for the food security but its contribution as of 2017 to the Gross Domestic Product (GDP) of low and middle-income countries at 36% is still significant.[26] Despite substantial decrease in the share of agriculture in developing economies over the years, disproportionately high percentage of people is still living in rural areas of developing economies and in one way or other are reliant on agricultural sector. This is evident by the fact that 51% of 6.252bn[27] people of low and middle-income countries are not only living in rural areas but 32% are still employed in agricultural sector.[28]

Economic literature has tried to document the harmful effects of natural disasters along with the possible suggestions to minimize the damages. The methodology varies largely in these studies. Some research studies look at the impacts of disasters measured subjectively (Bui et al, 2014;

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[24] NASA claims climate change has increased global temperatures by 1.8° F since 1880, decreasing Arctic ice by 13.2 percent every decade and expected to raise sea level by 3.2 mm per year. ( https://climate.nasa.gov/ accessed on August 2, 2018)
[25] http://www.fao.org/3/a-i6372e.pdf accessed on August 12, 2018
[26] https://data.worldbank.org/indicator/SL.AGR.EMPL.ZS accessed on August 12, 2018
[27] https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS accessed on December 17, 2017
[28] https://data.worldbank.org/indicator/NV.AGR.TOTL.ZS accessed on December 17, 2017

Kurosaki, 2014) where possibility of reporting error due to differences in judgement, literacy rates or reference dependence can't be ruled out (Bertrand and Mullainathan, 2001; Hoffmann & Muttarak, 2017). Rainfall measure is objective as compared to self-reported disaster impact, however, measurement at district or state level (Lewin et al, 2012; Gilmont et al, 2018), may include, in some studies, unaffected areas or villages in the study resulting in the underestimation of the results.

This study intends to improve on the existing research in this area by analyzing the impact of natural disasters in terms of rainfall variability measured at the village level which will not only avoid the reporting error likely to be present in the subjective data but by measuring the rainfall disaster at village level, the data more relevant to the study area is likely to be included in the study. Moreover, this study focuses on heterogeneity among different community characteristics – for example, variations in household's access to areas having better access to urban centers or irrigation facilities – highlighting their respective capacity to withstand the disastrous impacts of variability in rainfall. This will make it a unique study, particularly, on Pakistan.

I intend to study the impact of disasters with reference to Pakistan due to various reasons. Pakistan is one of the countries vulnerable to climate change which is likely to affect agriculture adversely resulting in food insecurity (FAO, 2016: Page 35). Global Climate Risk Index, 2021 describes Pakistan as frequently affected country placing Pakistan among the most affected countries by extraordinary weather events from 2000 to 2019.[29] One such notable event was the historically extraordinary floods of 2010 which affected around 18M people (Deen, 2015).[30]

[29] https://germanwatch.org/sites/default/files/Global%20Climate%20Risk%20Index%202021_1.pdf accessed on June 09, 2021

[30] Online Encyclopaedia Britannica quotes the figure of 20M. ( https://www.britannica.com/event/Pakistan-Floods-of-2010 accessed on December 24, 2017 )

There is no proper study on the impact of natural disasters on the agricultural sector of Pakistan and its rural economy, using objective rainfall disaster measure, in recent years which necessitates a research to find out the impact of natural disasters on the welfare of rural households (HHs).

### 4.2 Literature Survey

Several research studies have tried to analyze the impact of weather changes and accompanied natural disasters on wide-ranging social, political and economic outcomes (Gallagher and Hartley, 2017) including economies of developed (Dell and Olken, 2014) as well as developing (Sawada and Takasaki, 2017) countries.

The methodologies employed by these researchers to measure the shocks varies and resultantly the results for developing countries also show variations. Levine and Yang (2014) using historical mean of over 40 years defined shock as the deviation of annual rainfall from the norm. Similarly, research on Ghana by Akobeng (2017) used absolute amount of rainfall. The studies using unstandardized rainfall may not be appropriate for big countries like Ethiopia or Pakistan, having diverse climatic or agroecological regions where same amount of rain may have varied impact depending on whether the region is temperate or arid (Hidalgo et al, 2010) and fails to take into consideration the seasonal variations (Mitchell, 2003). In order to avoid such criticism, studies often use standardized rainfall with historical mean (Karim, 2018; Kosec and Mo, 2017; Menon, 2009).

Gao and Mills (2018), working on data on Ethiopia also show positive impact of rainfall on the real consumption of Households. This study used historical mean of five years to compute the standardized rainfall, but there are also some studies which used long-term mean of at least 30 years.

Karim (2018) uses dichotomous standardized rainfall shock constructed with historical data of last 64 years 1948 and finds adverse impact of standardized rainfall at district level on non-food expenditure and crop income in Bangladesh. Similarly, Amare et al (2018) and Skofias et al (2014) find positive correlation of rainfall with agricultural productivity and per capita expenditure, respectively. Amare et al (2018) construct rainfall shock from last 30-year average which is used as an instrument variable and show in the first stage result that negative shock reduced agricultural production significantly in Nigeria, which, in turn, reduce household consumption in second stage. These studies, however, do not explore heterogeneity with respect to household or community characteristics, except Amare et al, 2018 who showed the adverse impact of rainfall shock on asset-poor households was greater than it was for asset-nonpoor households (Amare et al (2018).[31]

Heterogeneity analysis is also made in some macroeconomic time-series studies where objective rainfall or temperature data was used to investigate the impact of weather variations on the national economy (Gilmont, 2018; Olayide et al, 2016. For example, Gilmont (2018) concludes that heavy rainfalls adversely affect income and the sensitivity to rainfall is less in states having better irrigation infrastructure. The macro-level studies, however, are good for analyzing economy wide impact of disasters, however, in order to understand heterogeneity at household or community level microeconomic analysis is required (Kurosake, 2014); which at the same time can also be important for the governments to focus on particular communities which are more vulnerable and show limited capacity to deal with weather variations.

[31] The research used IV of rainfall shock, where agricultural income was calculated in first stage and subsequently the results was used to calculate its impact on consumption. This type of strategy is not preferred for this paper as the agricultural income impact on consumption may not be exclusive and expenditures could have been affected directly by rainfall which is also pointed out by Akobeng, 2017 in his study.

Several microeconomic studies which try to analyze how the variability in weather patterns impact the welfare of households by using subjective measures of disaster show detrimental consequences of natural disasters on the welfare of the households (Arouri, 2015; Bui et al, 2014; Keethiratne et al, 2018; Kurosaki 2014 & 2017; Lewin et al, 2012). Similarly, adverse impact of natural disasters on consumption (Khandker, 2007; Lewin et al, 2012), business income (Noy, Nguyen, and Patel, 2014); agricultural income and farm input expenditure (Karim, 2018), was found by other researchers highlighting the harmful nature of weather-related impacts on the welfare of households. Among these studies, heterogeneous impact of weather-related disasters can also be found.

Kurosaki (2014), for example, finds that the younger households or those having more land can alleviate the adverse impact of covariate shocks. Keethiratne et al (2018) finds that economic losses are borne by relatively rich household due to natural disasters, who earn major portion of income from non-agricultural sources. Arouri et al (2015) find that relatively educated households and wealthy communities are more resilient to disasters.

These studies provide useful insight; however, subjective measure of disaster can be criticized on several grounds. First of all, the self-reported measures can have measurement errors due to problems, such as, cognitive bias, reference dependence or the possibility that respondents may try to look socially desirable in their responses (Bertrand and Mullainathan, 2001; Gutteras et al, 2015; Hoffmann & Muttarak, 2017). For example, the self-reported data collected from the households that suffered financially or physically due to floods or natural disasters may differ from the actual damage they endured. The perception of the intensity of damage from similar tragic circumstances can differ from person to person even in the same neighborhood due to differences in reference dependence or cognitive bias. This would lead to measurement errors in the survey data. Guiteras et al (2015) showed that people adapt to weather related disasters and their response, therefore, is influenced by their previous exposure to such incidents. Similarly, subjective response regarding damage can be correlated with ownership of assets or access to infrastructure. Households living in same community might respond differently to the intensity of disaster depending on the impact it had on their consumption.

Furthermore, these studies, though, try to measure disaster but every study seems to measure different variable which makes it difficult to compare these studies meaningfully. For example, from Table 1, it is clear that each study is using not only different types of sources but also diverse disaster types and more importantly, varied response scales.

**Table 4.1 Studies using Subjective Explanatory Variable**

| Research | Source | Level at which disaster is measured | Type of Disaster | How disaster is measured | Who responded |
|---|---|---|---|---|---|
| Kurosaki (2014) | Survey | Community | Floods and Droughts | 1-5 point scale | Village Elders |
| Keethiratne and Tol (2018) | Govt. Data | District | Weather (floods, earthquakes). Biological (epidemics) | %age of affected (Govt. Data) | N/A |
| Bui et al (2014) | Survey | Households | Floods, storms, landslides, climate (too hot or too cold) | Y/N | Households |
| Arouri et al (2015) | Survey | Commune | Storm, flood and drought | Y/N | Commune leaders |

**Source**: Author’s compilation from studies mentioned in table 1

There are a couple of studies which analyzed the impact of natural disasters in Pakistan. One is by Kurosaki (2014), which finds adverse impact of shocks on consumption, though the misaligned timing of data collection makes it difficult to interpret the results.[32] The other is Eskander et al (2018), which employed DID estimation technique, using first two waves of PRHS, 2012 and 2013, and found negative impact of disaster on the farm income, savings and migration.[33] However, the EM-DAT database they use for the disaster indicators excludes economic damages,[34] and, therefore, omits some affected districts.[35]

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[32] Kurosaki (2014) research included panel data comprising two waves, that is, 2001 and 2004. The first wave collected data, including consumption, during September to January of 2001-02, and second wave collected data during August to October of 2004. This means consumption data in 2001-02 was collected during and after harvest of Kharif crop, whereas it was just before harvest in 2004. Consumption may vary due to different harvesting periods, seasonality of production, wages and economic activity (Gao and Mills, 2018: 270; Lewin et al, 2012: 196), which, in other words, means consumption pattern of households alters just because of different data collection periods.

[33] I will also be using the same PRHS data, but I use all three waves (2012, 2013 and 2014), instead of two waves. Further my study uses objective measures of disaster and focuses on the heterogeneity analysis of the impact of exogenous rainfall related disasters.

[34] The use of EM-DAT may not be very accurate or relevant for economic research due to the definition and criteria it uses for the people affected by disaster. It defines 'affected' as, "People requiring immediate assistance during a period of emergency, i.e. requiring basic survival needs such as food, water, shelter, sanitation and immediate medical assistance (https://www.emdat.be/Glossary).
However, this definition may exclude crop loss due to weather disaster which may not require immediate emergency assistance but is likely to have negative economic effects resulting in adverse welfare consequences for the households. Moreover, the results in this study are difficult to be compared with Eskender et al (2018) as they do not explain what their farm or non-farm income includes, for example, non-farm income can include business profits, non-farm wages, remittances and other income, but they do not explain what their non-farm income constitutes. Whereas this study explicitly divides these into constituents and analyses each one by one. Similarly, this study finds disaster reducing income which compels some individuals to migrate out of disaster hit areas whereas Eskender et al (2018) find decrease in migration despite decreasing agricultural income which is difficult to explain.

[35] Owing to definition quoted in end note 18, they missed out some affected districts. For example, Dadu, Jacobabad, Hyderabad and Sanghar districts in Sindh province were included as affected in 2011. For 2012 they include Dadu and Jacobabad from Sindh and DG Khan from Punjab Province as disaster affected. However, during 2012 along with DG Khan, Rahim Yar Khan, included in the survey but omitted in the research paper, was also severely affected. Though the persons affected in DG Khan according to official Punjab Govt. figures are much higher 616,623 than Rahim Yar Khan's 93,211 which could have been the reason of inclusion of former as affected district in EM-DAT database, however, the crop affected in case of DG Khan according to same source was 48,250 Acres and in case of Rahim Yar Khan it was 76,953 Acres. (http://pdma.gop.pk/system/files/LossesDmages_2012_%28punjab%29%5B1%5D_1.pdf accessed on August 10, 2018). Villages affected were 1150 and 103 and cattle perished were 552 and Nil in case of Rahim Yar Khan and DG Khan respectively. It seems economic damage is much higher in case of Rahim Yar Khan which has not been included in the analysis resulting in severe loss of data which could have resulted in erroneous estimate of disaster impact. Furthermore, village level focus survey in the dataset used in the research, reported 80-90% of 2 of the 4 villages chosen from district Jhang were also affected due to the floods of 2012 but the same were considered not affected following only EM-DAT reported districts. Similarly, no district from KPK province is included in their study due to usage of disaster data from EM-DAT.

This study is different from the previous literature on the subject in several other ways too. I plan to use objective rainfall data which is exogenous and normalized at more disaggregated village or community level, which will make the results more accurate and unbiased. Normalization will make comparison at village level meaningful by accounting not only the seasonal variations but also by taking into account the villagers' adaptations of their agricultural production to the average rainfall levels. The studies which used rainfall objective data previously, in majority of cases, normalized the rainfall at district level (Giesbert and Schindler, 2012; Karim, 2018; Lewin et al, 2012). Lastly, household or community heterogeneity has not been investigated thoroughly in a microeconomic study by using exogenous rainfall data which will make it a first study of its kind. Variations in disaster impacts with respect to infrastructure availability or household savings and corresponding coping strategies, for example, selling livestock, borrowing or dissaving found in this study, sheds some light on the heterogeneity of the impacts of extraordinary disasters / floods. From the perspective of policy implications, the heterogeneity is very important as it enables the government to focus on vulnerable communities or households.

### 4.3 Outcome Variables

This chapter is trying to look at the impacts of extraordinary rainfall on the household welfare. Two major outcome variables, namely, real per-capita income and real per-capita consumption, have been used as measures of household welfare. Annual inflation rates from the Economic Survey of Pakistan have been used to deflate these variables.

Per capita household income is comprised of income from selling crops, wages from working on farms and non-farm employment and business income. The disaggregated analysis of these components of income, that is, crop income, wage income – further separated into farm and non-farm wage income – and business income has also been made.[36] Crop income includes income earned from selling value of crop and by-product value and excludes input costs incurred on seed, fertilizers, irrigation and labor, both manual and mechanical. Business income is the net profit, that is, gross profit net of operational and fixed costs.

Second welfare variable is per capita household consumption. The use of consumption data as the measure of welfare has an edge over income data which can be misreported but consumption figures are relatively more accurate (Lanjouw and Lanjouw, 2001; Scharf and Rahut, 2014). However, there is also some evidence that households tries to smooth their consumption in case of disaster by taking loans, selling assets or through private or governmental safety nets (Carter and Lybbert, 2012; Thied, 2014), therefore, it can also be argued that the impact of weather changes or irregular rains may not be clearly reflected in consumption, if households are able to maintain their consumption despite the fall in their earnings. Therefore, I keep both consumption and income in the analysis and see how both outcomes respond and differ from one another.

Per capita real consumption includes money spent on food and non-food items for 12 months period preceding to the households' interviews for collection of original data conducted during the months of March, April and May of 2012, 2013 and 2014. Per capita real consumption is disaggregated into food and non-food consumption. The food consumption data has been computed and annualized from the 15-day recall period, whereas the non-food data is annualized from monthly data. Non-food expenditures include money spent on utilities, clothing, medicine, travelling, schooling, repairing of houses, etc. Some economists advise for non-inclusion of non-food items, such as, health, as these are lumpy and transitory (Deaton and Zaidi, 2003: 32). The expenditure on health as well as on repair of houses – which can also be lumpy – is included in the

[36] Minor items of remittances and other income which constitute 4.2% and 3.9% respectively of the total income had to be excluded from this analysis due to data problems across three waves. Discussed in detail in Appendix II

analysis. Disasters can result in accidents and necessitates the incidental emergency expenditure on health or house repair. Kurosaki (2017) showed in a study on Pakistan that those household whose houses were damaged during a disaster were slow to recover as they used productive assets for repairing their houses instead of replenishing the income.

It is obvious from Table 4.2 below that the major constituents of total income are crop income and non-farm wage income, though, the former is greater than the latter, implying that rural population is overwhelmingly dependent on agricultural sector. This is also corroborated by the fact that, 53% of the households are associated with growing crops, which, increases to 60%, if total households employed in farm related sector are taken into consideration.[37] It is also noticeable from the breakup of total consumption expenditure that rural society, being relatively poor, spends major part of their earning on food, that is, 63% of total consumption.

The Table also shows increase in nominal income and consumption from 2012 to 2014. Household income increased from Rs.169,504 in 2012 to Rs.240,515 in 2014. Total consumption showed an increase from Rs.182,793 in 2012 to Rs.245,351 in 2014. There is not much difference in crop income from 2013 to 2014, standing at 132,021 and 138,947 respectively. However, in 2012 it is disproportionately low at 84,980 which might be due to super floods of 2010 followed again by unusually high floods in 2011. This explanation is supported by the incidence of floods reported by households, which was highest in 2011-12 at 15% and afterwards decreased to 10% and 6% during 2012-13 and 2013-14 respectively, reported in Table 3.3.

[37] Author’s calculations from the PRHPS, 2012-2014

**Table 4.2 Summary Statistics: Outcome Variables**

| Panel I | | | | 2012 | | | 2013 | | 2014 | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Nominal Variables** | **Obs** | **Mean** | **SD** | **Obs** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** |
| Total Income (Rs.) | 5358 | 208567 | 362517 | 1786 | 169504 | 319761 | 215682 | 382697 | 240515 | 378287 |
| Crop Income (Rs.) | 5358 | 118649 | 351111 | 1786 | 84980 | 310767 | 132021 | 369718 | 138947 | 367399 |
| Paid farm Income (Rs.) | 5358 | 15688 | 36161 | 1786 | 14215 | 35392 | 16708 | 35906 | 16142 | 37135 |
| Paid non-farm Income (Rs.) | 5358 | 59385 | 104928 | 1786 | 56371 | 82609 | 56654 | 108836 | 65130 | 119678 |
| Business Income (Rs.) | 5358 | 14844 | 63900 | 1786 | 13938 | 65571 | 10299 | 49567 | 20296 | 73800 |
| Total Consumption (Rs.) | 5358 | 213268 | 155057 | 1786 | 182793 | 101098 | 211659 | 142482 | 245351 | 199177 |
| Food Consumption (Rs. | 5358 | 134893 | 83518 | 1786 | 110344 | 67312 | 139625 | 77496 | 154710 | 96844 |
| Non-Food Consumption (Rs. | 5358 | 78375 | 110166 | 1786 | 72450 | 60448 | 72034 | 96410 | 90641 | 152474 |
| **Panel II** | | | | | | | | | | |
| **Per-Capita Inflation Adjusted Values** | | | | | | | | | | |
| Per-capita Total Income (Rs.) | 5358 | 29001 | 46105 | 1786 | 26916 | 42087 | 30392 | 52153 | 29694 | 43373 |
| Per-capita Crop Income (RS.) | 5358 | 16064 | 45105 | 1786 | 12937 | 40758 | 18462 | 51753 | 16792 | 41832 |
| Per-capita Paid Farm Income (Rs.) | 5358 | 2316 | 5254 | 1786 | 2368 | 5739 | 2485 | 5417 | 2093 | 4525 |
| Per-capita Paid Non-Farm Income (Rs.) | 5358 | 8406 | 14799 | 1786 | 9192 | 13173 | 7882 | 13991 | 8145 | 16941 |
| Per-capita Business Income (Rs.) | 5358 | 2215 | 9981 | 1786 | 2419 | 11836 | 1564 | 7650 | 2663 | 9985 |
| Per capital Total Consumption (Rs.) | 5358 | 30785 | 20281 | 1786 | 31469 | 22667 | 30455 | 18336 | 30430 | 19588 |
| PC Food Consumption (Rs.) | 5358 | 19555 | 12803 | 1786 | 19000 | 17216 | 20176 | 9567 | 19490 | 10165 |
| PC Non-Food Cons. (Rs.) | 5358 | 11229 | 13479 | 1786 | 12469 | 11410 | 10280 | 13442 | 10939 | 15226 |

**Source**: Authors' computation from the PRHS 2012, 2013 and 2014
Panel I shows summary stats with nominal values and Panel II shows per capita real inflation adjusted variables

**Relationship between rainfall shock and Income / Consumption**

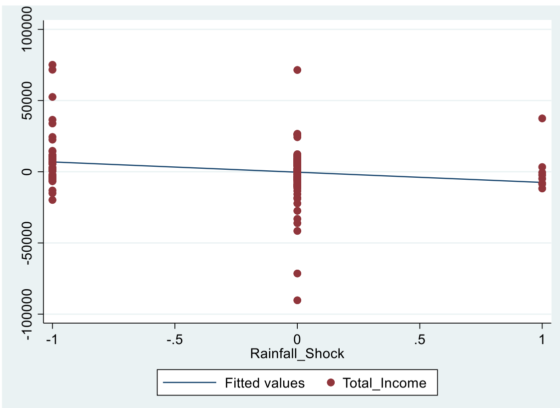
The correlation between the main explanatory variable, rainfall shock, and outcome variables of per capita income, per capita consumption and their various components can be seen in Figure 5. The analysis is carried out at village level by summing up the outcome variables at community level. Horizontal-axis shows rainfall shock, which is computed by subtracting dummy rainfall variable for previous year, t-1 (for example 0, or no rain in 2012) from current year, t (for example 1 or deviation of rainfall for 2013 from 30 year mean greater than 1 SD), which is 1, similarly, this year, -1 is disaster last year but current normal rainfall year; and 0 means consecutive normal / disaster years. Vertical-axis shows the total income and consumption and their constituents – summed up at the village level – calculated in the same way as the disaster variable, that is subtracting income / consumption of previous year from current year, for example, income of 2012 subtracted from income of 2013.

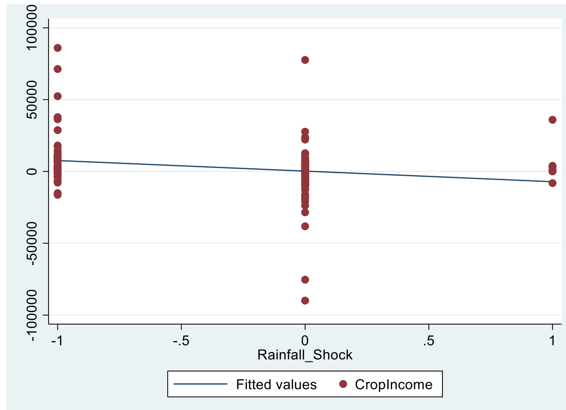
Panel 1A shows that as a result of extraordinary shocks per capita income decreases. When the correlation is observed in panel 1B to 1E, it can be seen that the negative correlation is mainly due to disaster suffered by farm related income, that is, crop income and farm wages (Panel 1A to 1C). Non-crop related income components in Panel 1 (D & E) apparently show very small increase in income, for example, non-farm wages in figure 4. These small increases are, anyway, not able to offset the income losses borne by farm sector as the Panel 1A shows overall falling trend in per capita income.

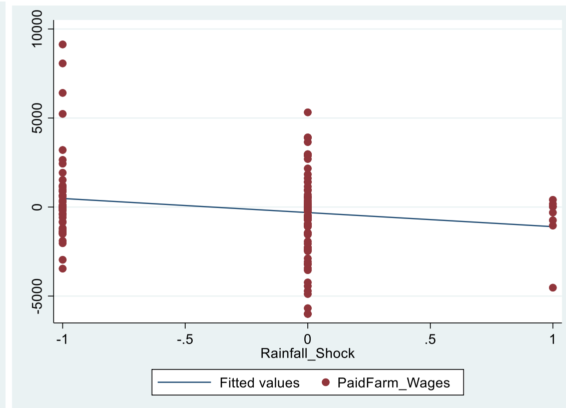
This falling trend in per capita income is strikingly not reflected in the corresponding figures of per capita food consumption in Panel 2G of Figure 5. The small increase in total consumption (Panel 2 F) seems to be on account of non-food consumption (Panel 2H). This points to the consumption smoothing of food consumption by the rural households.

**Figure 4.1 Relationship between rainfall shock and Income / Consumption**
X-axis: Shock as deviation from long-term mean
Y-axis: Income / Consumption and its various components

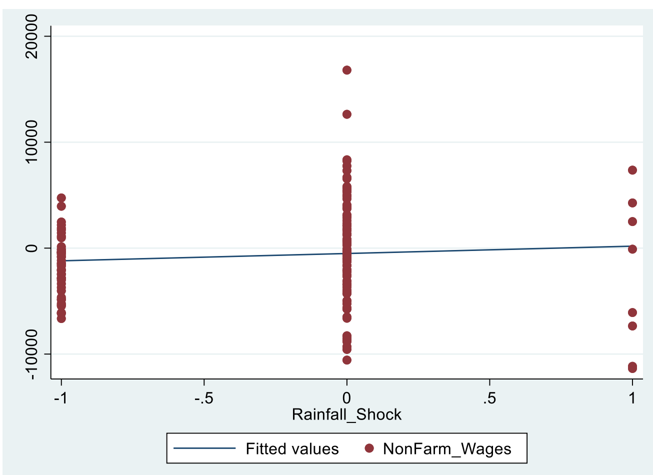
**Panel 1: Income**

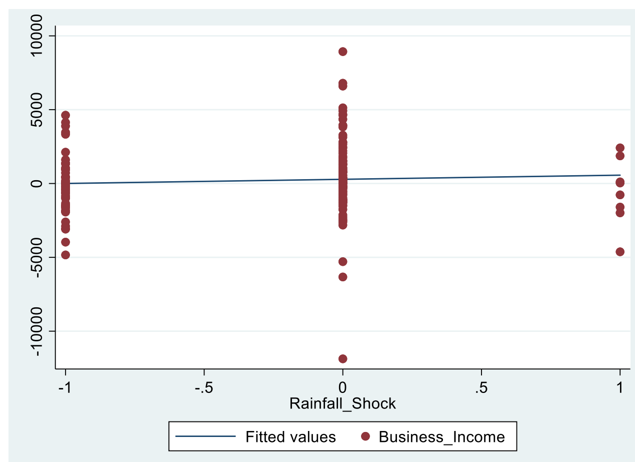


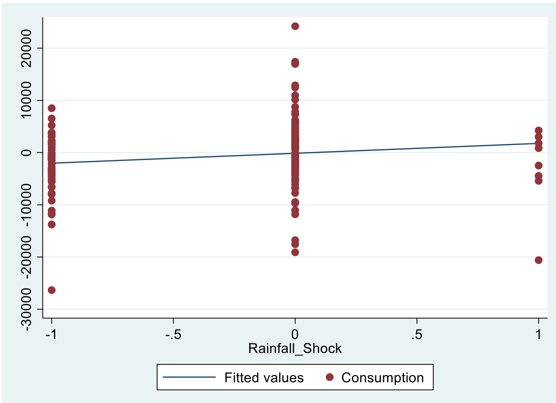

**A:Total Income** **B: Crop Income** **C: Farm wages**

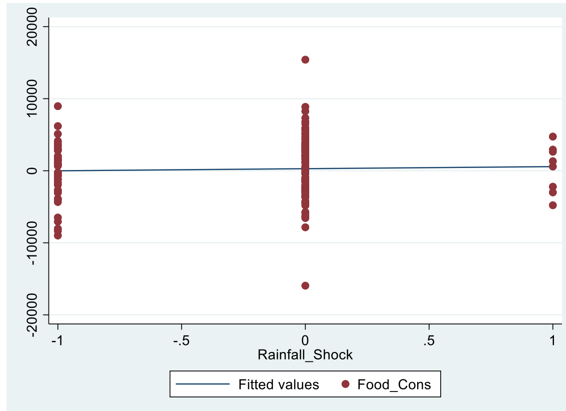


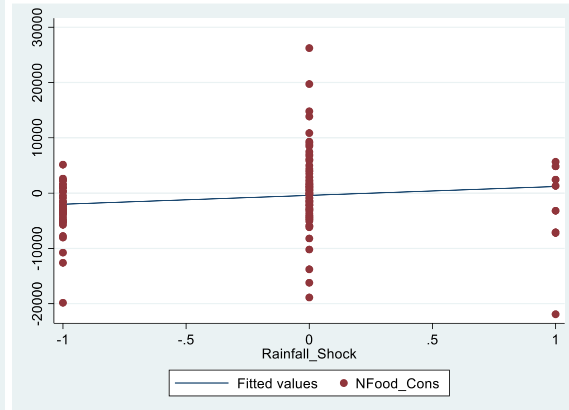




**D: Non-farm wages** **E: Business Income**

**Panel 2: Consumption**




**F: Total per capita consumption** **G: Per capita food consumption** **H: Per capita Non-food consumption**

**Source:**

Household data on income and consumption plotted against rainfall shock by the author

Authors' computation of income and consumption measures from the PRHS 2012, 2013 and 2014; and rainfall from Nasa rainfall data

### 4.4 Methodology

In order to calculate the impacts of rainfall shocks on household income and consumption more rigorously, I estimate the following household-level fixed effects model using the three waves of panel data set:

$$Y_{hvt} = \alpha_1 S_{vt} + \gamma_{pt} + \delta_{dt} + \mu_h + \lambda_t + \varepsilon_{ihvt} \ldots \ldots\ldots \text{Eq. 4.1}$$

Where, Y, for household, h in village, v, at time t is a continuous welfare measure, and represents real per capita household income and real per capita consumption in alternate specifications. The main explanatory variable, S, indicates binary rainfall shock indicator in village v at time t, which takes the value of one if the amount of rainfall during the monsoon months is greater than 1 SD above the historical mean of 30 years (1980-2010). In order to control regional differences and area specific characteristics affecting outcomes endogenously over time, province interactions with year dummies and district specific time trends have been introduced in the specifications. That is, $\gamma$ stands for the province-year interaction, where subscripts p and t represent the set of dummy variables for each province and year, respectively; and $\delta_{dy}$ is the district-specific linear trends for each district, d and year, t. which control district-wide shocks / events probably restricted to a particular district. Household-level fixed effects, $\mu$, remove time-invariant unobserved heterogeneity emanating from household factors; year effects, $\lambda$, take care of any unobserved common trends over the years and robust standard error, $\varepsilon_{ihvt,}$ is clustered around villages.

Moreover, there are certain channels or coping mechanisms through which households can show resilience when faced with shrinking income levels due to shocks, such as, credit access or social allowances provided by the government or non-governmental organizations (Arouri et al, 2015). For example, ex-ante risk reduction by farmers – according to Kazianga and Udry, 2006 – can take the form of grain storage for self-consumption; and ex-post coping mechanism may manifest itself in increased loans by farmers – which may be from formal or informal sources – to smooth out the consumption (Sawada and Takasaki, 2017). Equation 4.2 tries to capture the heterogeneity in the impacts of extraordinary rainfalls as well as in the responses / risk reduction strategies – to deal with such disasters – of different households and communities.

$$Y_{hvt} = \alpha_1 S_{vt} + \alpha_2 (S_{vt} W_{ht}) + \gamma_{pt} + \delta_{dt} + \mu_h + \lambda_t + \varepsilon_{ihvt} \quad \text{…. Eq. 4.2}$$

Where, S in the interaction term is disaster indicators and W is the household or community characteristics, for example, plot ownership, household savings; community access to credit, roads, irrigation facilities, main market/commercial center. Interactions help to capture the heterogeneous impacts of rainfall shock across households and communities depending upon their respective personal or regional peculiarities.

## 4.5 Results

### 4.5.1 Overall Analysis

Regression results for equation 4.1 indicate that extraordinary rainfall shocks decrease per capita total income, largely due to reduced crop income. Column 1 of Table 4.3 shows the results for per capita total income, which is decreased significantly by Rs.8,061 due to rainfall shock. This amounts to 28% of the average per capita income of Rs.29,001. Column 2 of the same Table also indicates that the decline in total income is largely due to decrease in crop income, which is expected as the successful crops depends on good rainfall and those associated with this sector are more likely to be affected by natural disasters (Betts et al, 2018, IPCC 2014). Agriculture or crop related earning activities are also a major constituent of the total income in rural areas, accounting for approximately 63% of the total income.[38]

There is also a reduction in farm related wages, though the coefficient is small. The drop in the farm wage activities is also probable since demand for farm wage workers is contingent upon the agriculture sector performance. Lastly, the consumption increases, mainly, on account of non-food expenses, which in turn is due to increased medical and travel expenses (disaggregated analysis of non-food consumption is not reported). Medical expenses may refer to injuries or illness resulting from the floods and travel expenses can be the outcome of displacement or migration in the aftermath of natural disaster. The fall in income does not seem to be reflected in consumption pattern of the households, which can be explained in term of consumption smoothing behaviour of households (Giesbert and Schindler, 2012; Mogues, 2011; Carter et al, 2007; Carter and Barret, 2006). I will discuss this later in the section on consumption and savings.

**Table 4.3 Impact of Rainfall Shock on Rural Household Income and Consumption in Pakistan**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | PC Income | Crop Income | FarmWage Income | Non-Farm Wage | Business Income | Cons | Food Cons | NFood Cons |
| 1 if standardized monsoon rain is > 1 | -8,061** | -6,842* | -585.6** | 99.13 | -732.1 | 2,141** | 319.2 | 1,822* |
| | (3,812) | (3,728) | (286.0) | (764.1) | (455.2) | (994.7) | (632.2) | (1,048) |
| Observations | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 |
| Number of hid | 1,786 | 1,786 | 1,786 | 1,786 | 1,786 | 1,786 | 1,786 | 1,786 |

Source: Authors' estimation from the PRHS 2012, 2013 and 2014
Note: Robust standard errors, clustered around villages, are in parentheses. Table results are based on specification explained in equation 4.1 which uses household fixed effects, province-year interactions and district specific time trends.

*** p<0.01, ** p<0.05, * p<0.1

[38] Author's calculation from data

Overall results suggest that extraordinary rainfall shocks in the rural areas of Pakistan decrease income mainly on account of reduction in the crop income. The drop in income, apparently, does not seem to be big enough to force households to cut down their necessary consumption expenditures as evident from the insignificant coefficients for food expenditure in column 7 of Tables 4.3.

The standardized rainfall greater than 1 SD may be a good rainfall for arid and dry agroecological areas. In order to absolutely rule out such possibility, shock variable with standardized rainfall greater than 2 SD is also checked and the results are qualitatively same with higher coefficient and significance level reported in Appendix Table A1.1. This also rules out the possibility of non-linear impact of rainfall shock.

**Measurement Error: Some Concerns**

The accuracy of the rainfall data may be challenged on account of measurement errors likely to be present in the data interpolated from observatory data.[39] However, the measurement error in the rainfall shock variable is not expected to be correlated with true shock variable, though, it is likely to result in attenuation bias, whereas, the correlation of subjective household responses with the true shock variable is not clear and thus the sign of the bias in case of measurement error is also vague.

It will, nevertheless, be interesting, to see whether the results of extraordinary rainfall disasters reported in Table 4.3 are comparable with the subjective measures of disasters based on household or community level responses. The results presented in Table 4.3, based on the household

[39] Climate Data Processing Centre (CDPC) of Pakistan Meteorological Department (PMD) informed that out of 19 districts, observatories data are not available from 7 districts, namely, Faisalabad, Multan, Rahim Yar Khan, Bahawalnagar, DG Khan, Hyderabad and Jacobabad

responses regarding disaster, are not very different from Table 4.4, except that the severity of floods seems to have decreased food consumption which is not comparable with table 4.3 and that difference is likely due to the attenuation bias present in objective rainfall data.

**Table 4.4 Comparison of Rainfall Shock with Household Level Subjective Disaster Variable**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | PC Income | Crop Income | FarmWage Income | Non-Farm Wage | Business Income | Cons | Food Cons | NFood Cons |
| 1 if households responded they had flood | -7,228*** | -6,421*** | -477.9 | 311.0 | -640.1* | -155.3 | -1,733** | 1,577** |
| | (1,958) | (1,707) | (395.2) | (557.0) | (339.6) | (1,181) | (678.9) | (735.9) |
| Observations | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 |

Source: Authors' estimation from the PRHS 2012, 2013 and 2014
Note: Robust standard errors, clustered around villages, are in parentheses. Table results are based on specification explained in equation 4.1, which uses household fixed effects, province-year interactions and district specific time trends – except the rainfall disaster variable which is replaced by household level disaster variable.
*** p<0.01, ** p<0.05, * p<0.1

Similarly, community level responses[40], depict the same picture with a reduction in crop income by Rs.7498 which is comparable not only with Table 4.3 but also with Table 4.4

**Table 4.5 Comparison of Rainfall Shock with Village Level Subjective Disaster Variable**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | PC Income | Crop Income | FarmWage Income | Non-Farm Wage | Business Income | Cons | Food Cons | NFood Cons |
| 1 if community affected > 90 % | -7,648** | -7,498** | -545.3 | 454.9 | -58.73 | -665.7 | -1,208 | 542.1 |
| | (3,122) | (2,920) | (499.2) | (564.5) | (449.8) | (1,550) | (886.1) | (1,065) |
| Observations | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 |

Source: Authors' estimation from the PRHS 2012, 2013 and 2014
Note: Robust standard errors, clustered around villages, are in parentheses. Table results are based on specification explained in equation 4.1, which uses household fixed effects, province-year interactions and district specific time trends – except the rainfall disaster variable which is replaced by community level disaster variable.
*** p<0.01, ** p<0.05, * p<0.1

[40] Community elders report at least 90% of the community is damaged. The result is same if the elders report 75% or between 10 to 25% of community affected. However, if median value, which is zero, is adopted the adverse impact is significant only for farm wages earned.

The results reported in Table 4.3 to 4.5 are qualitatively similar which overrules the presence of any serious measurement error in the explanatory variable.[41]

**Consumption**

The results thus far suggest robust evidence for the negative impact of extraordinary rainfall on the income, particularly for agriculture-related components. The main results in Table 4.3 show adverse impact on income is not, apparently, comparable with relatively small positive coefficient of consumption. Further disaggregated analysis of consumption shows there was no impact of shock on food consumption and the increase in consumption was owing to the rising non-food expenditure, notably, on account of medical expenses, which is expected during any disastrous event.

The absence of a loss in food consumption and the increase in non-food consumption might be explained by investigating the impact of rainfall shocks on savings behavior. That is, households can smooth consumption by using intertemporal resource allocation (Aldrich, Oum and Sawada, eds., 2014; 342). This is particularly important when households face borrowing constraints (Deaton, 1991), such as lack of access to formal banking channels and high collateral requirements for the formal loans, which is also the case for rural Pakistan. In order to examine consumption smoothing behavior, a number of outcome variables have been used in this section. First, the impact of rainfall shocks on household savings is reported in column 2 of Table 4.7, which shows highly significant decrease over three years from 2012 to 2014 by Rs.13,311. This suggest that

[41] Some households report droughts but the impact of droughts (not reported) is insignificant on income as well as on consumption. Moreover, no village elder reported famine like situation in the three years for which data is collected.

households used savings for consumption purposes in the event of shock, which points to their ex-ante precautionary behavior.

Similarly, credit received reported in column 1, from both formal and informal sources, increases significantly by Rs.6928 as a result of rainfall shock.[42] The results show an increase in borrowings and consequently, it can be conjectured that these financial resources have also been used in maintaining consumption expenses.

**Table 4.7 Possible Explanation of Consumption Smoothing Behavior**

| | (1) | (2) | (3) |
|---|---|---|---|
| **Variables** | **Credit Received** | **Household Savings** | **Livestock Sold** |
| 1 if standardized monsoon rainfall is > 1 | 6,928* | -13,311*** | 4,953** |
| | (3,741) | (4,269) | (2,039) |
| Observations | 5,358 | 5,358 | 5,358 |
| Number of hid | 1,786 | 1,786 | 1,786 |

Source: Authors' estimation from the PRHS 2012, 2013 and 2014
Note: Robust standard errors, clustered around villages, are in parentheses. Table results are based on specification explained in equation 4.1 (except the outcome variable changed to the column titles) which uses household fixed effects, province-year interactions and district specific time trends. *** p<0.01, ** p<0.05, * p<0.1

Furthermore, there is some evidence that the extraordinary rainfalls forced the households to sell their relatively liquid asset, the livestock, to smooth out their consumption or to cope with income losses. Column 3 of Table 4.7 shows that the value of livestock sold during 2012-14 has significantly increased.

In sum it can be said that extraordinary rainfall reduces per capita income of the rural households mainly because of the reduction in crop income. Evidence of consumption smoothing is also observed which is mainly channelized through liquid assets such as savings, increase in the sale of livestock, and lastly through borrowing – which is mostly from informal sources.

[42] The credit received is mainly composed of informal loans from relatives, money lenders, friends, etc., which make up to 81% of the total borrowings during three years on which this analysis is based.

### 4.5.2 Heterogeneity Analysis: Household Characteristics

The impact of rainfall shock on households is not necessarily homogeneous, across different groups of households and communities exhibiting different characteristics, which I have assumed so far. Households with different levels of wealth or having different education achievements may show variations in their responses to disasters and some groups of households may be more resilient as compared to others. For example, the household with more assets may be more resilient or the number of male adult members could mean more labor supply available to a particular household.

This study, however found no particular heterogeneity due to household characteristics. Variables, such as, dependents to adult ratio, household head education, households possessing more assets, the ratio of male to female members in a household, age of household head or the household size had no significant impact on consumption or income of a household. Initial household savings is found to have significantly enabled the households to smooth their consumption. However, the result is not reported out of the concern of time variant nature of household savings. Ownership of agricultural land in case of an extraordinary shock, estimated by interaction between rainfall shock and agricultural area owned (not reported), is found insignificant, but the possibility that the agricultural land ownership may be relevant for the agricultural households only is explored in appendix III by restricting the sample to only those household who are engaged in growing crops.

### 4.5.3 Heterogeneity Analysis: Community Characteristics

Heterogeneity analysis with respect to differences in community characteristics is as important as it is for household characteristics. The households, for example, with different irrigation facilities may be affected differently owing to differentiated access to irrigation water and drainage facility for flood waters. Similarly, credit facilities or road infrastructure can help in timely access to relief or borrowing to manage rainfall disasters. Heterogeneity analysis is essential from this perspective as it will helps in suggesting policy implications for enabling communities to minimize disaster in future.

I am particularly focusing on the physical infrastructure, such as, roads, commercial banks and transport, which indicate relatively more developed nature of an area and in case of emergency, such as floods, such regions can have early access to relief services. Good infrastructure and institutional access are also very important to gauge the resilience of a community against any natural disasters (Cutter et al, 2008; Khandker, 2007). Access to urban areas not only helps in early relief assistance but may also offer non-farm work opportunities in case of floods. The importance of different types of infrastructure, therefore, is investigated in the subsequent discussion

### Irrigated vs Non-Irrigated Households

The results thus far have demonstrated that the damaging consequences of rainfall shocks particularly affected agricultural production. An extensive irrigation infrastructure is the hallmark of the agriculture sector of Pakistan. Agricultural production, particularly, the four major crops, namely, wheat, cotton, rice, and sugarcane are heavily dependent on its canal network (World Bank, 2019). Moreover, the irrigation system can be a defense against not only droughts (Thomas et al, 2010) but also floods (Arouri et al, 2015) by providing an organized system for drainage of excess water in an area. Therefore, the rainfall shock is likely to affect the communities differently depending upon whether they have access to better managed irrigation system or not.

These observations are examined by using a variable indicating the irrigation facilities available to various communities. I use the dummy variable of empty canals or poorly managed canals[43], that takes the value of 1, if the communities do not have water in their canals more than the median number of weeks in a year, and ‘0’ otherwise. This variable, not only, implies relatively less access to water but also acts as a proxy for the better management which can make it possible to have more water for a longer period of time in a year for some communities.

The results in the column 3 of Table 4.8 show that the impact of rainfall shocks on real per capita wages earned from farm related activities is significantly negative for those households having poor irrigation facilities, which implies shrinking farm labor demand due to adverse impact on the agriculture sector. Conversely, those households having relatively better irrigation facility are not affected by the rainfall shock as suggested by the insignificant coefficient of the uninteracted indicator for shock. Net loss of farm wages for the households living with poor irrigation facilities is Rs. -521 (472 - 993) which is not significant.

The coefficient of consumption, particularly, food consumption is positive in Table 4.8, for those households which lack better irrigation facilities. The positive food consumption is not seen throughout this study in any other specification. The result, however, appears irrational and as a robustness check the specifications in Table 4.8 were estimated, which is reported in appendix Table A1.2, with crop-zones specific time trends instead of district specific time trends and the food consumption was found insignificant as a result, whereas. at the same time farm related wages earned decrease by Rs.1200 significantly at 1 %. Income related results are not only similar but

[43] Community characteristics usually do not change every year, therefore, community module reports most of the community characteristics only once and these are not calculated in fixed effect models therefore no results for uninteracted empty canals. Other interactions where community characteristics are reported in the original data only for the initial year, similar pattern.

robust, the increase in food consumption, therefore, can be dismissed as an aberration due to some endogeneity bias in that particular specification.

It can, therefore, be deduced that the impact of rainfall shock is more damaging for the household living in areas with poorly managed irrigation facilities, but the overall results are not convincing and strong enough to come to any meaningful conclusion which may point to the problems in data. The negative impact of shock on the areas with poor access to irrigation waters, though evidence is weak, might be due to overall poor maintenance of irrigation system which is also affecting the agricultural sector of Pakistan over the years (World Bank, 2019; Waqas et al, 2019; Ahmad et al, 2007).

Long neglect of irrigation system has resulted in decreasing capacity of dams and canals due to accumulation of silt which seriously affects the operational capacity of the system. The neglected canal infrastructure is not only lacking the capacity to distribute the water for agriculture, but it also fails to provide effective drainage of flood water[44] resulting in frequent breaches of dikes, canal headworks and consequent physical and economic loss both at micro and macro level during extraordinary rains. Therefore, the positive but weak impact of irrigation is not surprising.

**Urban Access**

The time it takes to reach the nearest city or commercial center / market area is important in number of ways. It, not only, signifies the distance, but also the condition of road and availability of transport, therefore, the variable is preferred over actual distance to city. Urban Access, defined in terms of time it takes to reach the nearest market, equals 1, if it takes more than 30 minutes to

[44] Larkin, K. Pakistan faces long-term damage to irrigation system. *Nature* (2010) https://doi.org/10.1038/news.2010.424 Assessed on September 07, 2020

reach the nearest commercial center / market and 0 otherwise. Table 4.8 shows that those areas which are relatively away from urban areas have significant adverse impact on total income, farm wages and business income. The highly significant impact of urban access on the business income during rainfall disaster shows not only the adverse impact of rainfall shock in the areas which are away from the urban centers but the net adverse impact of disaster, that is the F-test for rainfall shock and interaction terms, is also significant, in other words, the null hypothesis that the effect of shock for the households having poor urban access is zero can be rejected significantly as indicated by the p-value of the F test in the Table 4.8. This implies that being located away from urban centers increases the risk attached with the rainfall shock.

These results signify the importance of access in terms of transport, distance and quality of road to nearest commercial center or city. For example, if a community has easy access to city, it could mean access to better quality seeds, pesticides, or fertilizers for agricultural households as the better accessible areas likely to have more markets offering such services / commodities.

Similarly, the proximity to cities is also important for businesses as the 68%[45] of communities responded in the survey that main business constraint is the lack of access to road infrastructure. Households running business enterprises can benefit not only from market access for their products but also from an easy availability of inputs or other externalities of economies of agglomeration, even, if those are not in very advanced or organized form.

[45] Author calculation from the community level data

**Table 4.8 Heterogeneity in the Impact of Rainfall Shocks by Community Characteristics**

| VARIABLES | PC Income | Crop Income | FarmWage Income | Non-Farm Wage | Business Income | Cons | Food Cons | NFood Cons |
|---|---|---|---|---|---|---|---|---|
| 1 if standardized monsoon rain is > 1 | 1,358 | 1,552 | 472.1 | -726.4 | 59.58 | -861.0 | -1,064 | 202.6 |
| | (4,227) | (3,881) | (384.2) | (1,121) | (547.5) | (1,888) | (1,252) | (1,495) |
| 1 if standardized monsoon rainfall is > 1 * 1 if canal is empty ($\alpha_2$) | -5,810 | -3,942 | -992.8** | -304.4 | -570.2 | 4,418** | 2,338** | 2,080 |
| | (4,684) | (4,717) | (408.9) | (916.0) | (491.4) | (1,766) | (1,050) | (1,267) |
| 1 if standardized monsoon rainfall is > 1* 1 if Railway station is within 5 Km ($\alpha_3$) | 4,077 | 1,214 | 172.9 | 2,839*** | -149.1 | 1,214 | -1,164 | 2,378* |
| | (3,105) | (2,844) | (554.7) | (1,055) | (548.8) | (1,778) | (1,082) | (1,319) |
| 1 if standardized monsoon rainfall is > 1 * 1 if it takes greater than equal to median time to reach the nearest market ($\alpha_4$) | -7,233* | -6,364 | -1,201*** | 1,527* | -1,194*** | -1,705 | -250.9 | -1,455 |
| | (4,214) | (4,287) | (405.4) | (772.2) | (394.0) | (1,416) | (1,098) | (995.8) |
| 1 if standardized monsoon rainfall is > 1 * 1 if a community located more than median distance from Bank ($\alpha_5$) | -9,767** | -9,507** | -180.7 | -95.21 | 15.72 | 2,534 | 912.6 | 1,622 |
| | (4,581) | (4,651) | (389.8) | (888.3) | (449.9) | (1,856) | (1,155) | (1,282) |
| Observations | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 |
| Prob > F ($\alpha_1 + \alpha_2$) | 0.250 | 0.526 | 0.161 | 0.406 | 0.321 | 0.005 | 0.126 | 0.041 |
| Prob > F ($\alpha_1 + \alpha_3$) | 0.124 | 0.430 | 0.283 | 0.081 | 0.890 | 0.874 | 0.195 | 0.075 |
| Prob > F ($\alpha_1 + \alpha_4$) | 0.160 | 0.237 | 0.049 | 0.480 | 0.045 | 0.261 | 0.340 | 0.520 |
| Prob > F ($\alpha_1 + \alpha_5$) | 0.066 | 0.0725 | 0.535 | 0.329 | 0.885 | 0.230 | 0.896 | 0.170 |

Source: Authors' estimation from the PRHS 2012, 2013 and 2014

Note: Robust standard errors, clustered around villages, are in parentheses. Table results are based on specification explained in equation 4.2 which uses household fixed effects, time dummies, province-year dummy interactions and district specific time trends.

*** p<0.01, ** p<0.05, * p<0.1

**Rainfall shocks and access to transportation facility: Railways**

Access to railways could mean an efficient means of transport which might mitigate the negative impact of rainfall shocks on income. Railways stations are likely to provide an easy access to basic amenities required for businesses and crop production. Alternatively, they can allow the affected households to offset the loss in agricultural income by finding non-farm employment opportunities. This is examined using the indicator variable for a railway station; that is, 1 if there is a railway station within a range of 5Km from the village / community and equals 0 otherwise. Column 4 of Table 4.8 indicate that better transport facilities increase or encourage households to diversify into non-farm employment when there is a rainfall shock.[46] F-test indicates the overall positive impact of rainfall shocks on non-farm wage income in the areas located near railway station.

An alternate interpretation can also be in terms of more developed nature of the area near railway station which in itself can be a hub of non-farm activities. However, earlier explanation seems plausible as the shock can be big enough to reduce local employment activities.

The increase in non-farm wages in case of availability of transport, can also be considered in terms of income smoothing. The households tend to increase their time allocation to non-farm wage market to smooth their income which, in turn, is an effort to smooth their consumption during a shock (Kochar, 1999). In case of communities which are located away from urban centers reported in column 4 of Table 4.8 same behavior of non-farm wage income was observed, which also suggests that crop income shock encouraged the allocation of time to non-farm wages when households were located relatively away from the urban areas in case of a natural calamity: a

[46] The majority of these non-farm wage jobs are low paying temporary jobs, with around 56% of individuals associated with non-farm wages are construction labor. The second and third categories are government and private enterprise salaried workers, who account for 10% and 9%, respectively.

rainfall shock. An interaction term between three variables, namely, rainfall shock, presence of railway station and urban access (not reported) showed positive and bigger significant coefficient having, at the same time, significant non-zero impact for those located away from urban centers but residing near railway station during shocks, which further supports these results suggesting agriculture income shocks encourage time allocation to non-farm wage income.

**Rainfall shock and Financial Institutions**

In addition to irrigation facilities and physical infrastructure of roads, household or communities may also benefit due to the presence of formal credit facilities, for example, banks, registered cooperatives, microfinance banks (NGOs) or Agricultural Banks. However, the credit access in the rural areas of Pakistan is limited particularly for small landholders lacking collateral assets (Abid and Thapa, 2012), I examine, therefore, whether credit institutions benefit households in the rural areas of Pakistan, by measuring the absence of credit facility with the dummy variable, banks, that takes the value of 1 if the communities are located at the distance exceeding 13 Km from commercial banks, and '0' otherwise. The results suggest that the absence of commercial banks has negative influence aggravating the rainfall disaster, that is, if commercial bank is located at more than median distance from a community the households are likely to suffer more. The coefficient of the interaction term, reported in column 1 and 2 of Table 4.8, between the bank indicator and the rainfall shock variable shows heterogeneous reduction for both total per capita income and crop income, and the net effect for households living away from banks is also significantly negative, as indicated by the F-test in the column 1 and 2 of Table 4.8.

This suggests that the lack of credit coupled with a rainfall shock can aggravate the impact of shock on crop income. Apparently, the result appears surprising given the fact mentioned in the beginning of discussion that small farmers usually do not have an easy access to formal credit due to difficult collateral requirements in Pakistan. However, if this variable of distance from bank is interpreted in terms to distance to market or urban area – banks are more likely to be present in urban or relatively more developed areas – the results will be easy to interpret. In that sense the results are comparable to urban access which discussed the impact of shocks with respect to distance from the nearest commercial center.

**Heterogeneity in Credit Uptake**

In table 4.7 increase in credit uptake is observed in case of extraordinary rainfall shock. The result showed the possible channel of maintaining food consumption and increase in non-food consumption. Table 4.11 also pointed to the likely disadvantage of household living in communities with areas relatively far from the commercial banks with decrease in their income significantly.

In this section credit uptake or total loans received by the household are used as an outcome variable. To investigate the role of credit institutions in the coping mechanism an interaction term between rainfall shock and commercial bank is introduced where latter takes the value of 1 if the commercial bank is located at less than the median distance as compared to other communities. The result shows that in the event of shocks the household living in communities which are located near commercial bank are able to take more credit which included credit from both formal and informal sources. As explained earlier that 81% of the loans are from informal sources, this may not be easy to explain, but an inference can be drawn that proximity to credit institutions may be benefiting the informal sources who are extending loans to the households affected during the shocks. The estimate of the total credit received when there is a shock for the household which are located near commercial banks is Rs. 10608 (8841 + 1767), which is also significant indicated by the p-value in the last row of the Table. The uninteracted term is not significant which shows that those households which are located away from banks are not affected by the shock. The increase in credit is likely to help the household to smooth their consumption or take care of their non-food consumption which may increase due to shock.

**Table 4.9 Heterogeneity in the Impact of Rainfall Disaster on Credit Uptake by Access to Commercial Banks**

| VARIABLES | (1)<br>Loans |
|---|---|
| 1 if standardized monsoon rainfall is > 1 ($\alpha_1$) | 1,767 |
| | (3,565) |
| 1 if standardized monsoon rainfall is > 1 * 1 if a community located less than the median distance from commercial bank ($\alpha_2$) | 8,841** |
| | (4,262) |
| Effect for households lacking credit facilities $\alpha 1 + \alpha 2 = 0$ | 10608 |
| F-test ($\alpha_1 + \alpha_2$) | 5.051 |
| Prob > F | 0.0276 |

Source: Authors' estimation from the PRHS 2012, 2013 and 2014
Note: Robust standard errors, clustered around villages, are in parentheses. Table results are based on specification explained in equation 4.2 (except the outcome variable is changed to the column title) which uses household fixed effects, province-year interactions and district specific time trends.
*** p<0.01, ** p<0.05, * p<0.1

## 4.6 Robustness Checks

So far, the income data used in this study was collected from March to May during 2012-14 and included income earned in the previous year. For example, in the 2012 survey, crop income during the Kharif harvest in fall 2011 and Rabi harvest income in spring 2011 were recorded (The Rabi income in 2012 was not included since it was still being harvested at the time of the survey). However, since the 2011 Rabi income realized before the monsoon months in 2011, this portion of annual income should not be affected by our measure of rainfall shocks. In order to see whether this measurement error in the outcome variable causes any problem, I estimate the impact on the Kharif crop income only, excluding the Rabi income.

**Table 4.10 Robustness Check – Impact of Rainfall Shock on Kharif Crop Only**

| VARIABLES | (1) Total Income | (2) Crop Income | (3) FarmWage Income |
|---|---|---|---|
| 1 if standardized monsoon rainfall is > 1 ($\alpha_1$) | -7,903*** | -7,259*** | -11.78 |
| | (2,712) | (2,700) | (159.5) |
| Observations | 5,358 | 5,358 | 5,358 |

Source: Authors' estimation from the PRHS 2012, 2013 and 2014
Note: Robust standard errors, clustered around villages, are in parentheses. Table results are based on specification explained in equation 4.1 which uses household fixed effects, province-year interactions and district specific time trends.

*** p<0.01, ** p<0.05, * p<0.1

It can be seen the results in the Table 4.10 above are robust and comparable with those reported in Table 4.3.[47]

Additionally, I also constructed an alternative income variable that combine crop income realized in Kharif and Rabi seasons that both followed the monsoon period. For example, the 2011 monsoon rain was assigned to Kharif crop income in 2011 and Rabi crop income in 2012. This resulted in the loss of data pertaining to Rabi crop income in 2011 and Kharif crop income in 2014. Per capita crop income is adjusted for inflation, however, to keep the analysis simple the analysis is restricted to the agricultural households engaged in growing crops only.[48] The results are once again not very different from the main results despite the smaller sample.

[47] The robustness checks have been carried only for those components of income which are related to agriculture / farm income. Business income, non-farm wage income and consumption can't be broken into Rabi / Kharif seasons as the same were collected only for the last 12 months.
[48] Including non-agricultural households can complicate the results as in this analysis I am not including non-farm wages and business income as the data pertaining to these constituents of income were collected on yearly basis and therefore could not be segregated between Rabi and Kharif crop seasons.

**Table 4.11 Robustness Check – Impact of Rainfall Shocks on Crop Income from Rabi & Kharif Combined across Three Waves**

| **VARIABLES** | 1 if standardized monsoon rainfall is > 1 | **SE** | **Observations** | **R-squared** | **Number of hid** | **HH FE** | **Cluster Village** |
|---|---|---|---|---|---|---|---|
| Crop Income | -14759** | (7493) | 1,851 | 0.081 | 1,045 | Yes | Yes |
| FarmWage Income | 176 | (339) | 1,851 | 0.076 | 1,045 | Yes | Yes |

Source: Authors' estimation from the PRHS 2012, 2013 and 2014

Note: Robust standard errors, clustered around villages, are in parentheses. Table results are based on specification explained in equation 4.1 which uses household fixed effects, province-year interactions and district specific time trends.

*** p<0.01, ** p<0.05, * p<0.1

Furthermore, the impact of the Rabi rain (December to March) on the Rabi crop income was found insignificant, which is expected due to very limited variations and the small amount of rainfall in those months.[49] These results indicate the robustness of the main results reported above.

## 4.7 Falsification Test

In order to rule out the possibility that the significant impact of rainfall shock on per capita income and consumption is a mere happenstance lacking any systematic causal relationship, I am also performing a falsification test. In the Table 4.12 one-year lag as well as one year lead is added along with the contemporaneous standardized rainfall shock greater than 1 Standard Deviation.

[49] Result not reported

**Table 4.12 Falsification Test Using Explanatory Variable of Rainfall Shock Along With its Leads and Lags**

| VARIABLES | (1) PC Income | (2) Crop Income | (3) FarmWage Income | (4) Non-Farm Wage | (5) Business Income | (6) Cons | (7) Food Cons | (8) NFood Cons |
|---|---|---|---|---|---|---|---|---|
| 1 if standardized rainfall shock is > 1 | -8,575* | -7,377 | -712.3* | 268.2 | -754.1 | 1,125 | 245.9 | 879.4 |
| | (5,121) | (5,023) | (421.7) | (1,076) | (565.4) | (1,364) | (667.0) | (1,251) |
| 1 if standardized rainfall shock (lead) is > 1 | 1,769 | -1,700 | -23.77 | 3,469* | 23.58 | -176.4 | 1,046 | -1,222 |
| | (5,144) | (5,305) | (340.9) | (1,882) | (794.7) | (2,075) | (995.0) | (2,166) |
| 1 if standardized rainfall shock (lag) is > 1 | -2,841 | 183.3 | -292.7 | -2,656*** | -75.27 | -2,358 | -1,109 | -1,250 |
| | (6,741) | (6,765) | (507.1) | (883.1) | (640.5) | (1,644) | (843.0) | (1,450) |
| Observations | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 |

Source: Authors' estimation from the PRHS 2012, 2013 and 2014

Note: Robust standard errors, clustered around villages, are in parentheses. Table results are based on specification explained in equation 4.1 which uses household fixed effects, province-year interactions and district specific time trends.

*** p<0.01, ** p<0.05, * p<0.1

It is evident when results in Table 4.12 are compared with the main results in the Table 4.3 that values of contemporaneous variable do not change to great extent. Direction of results is same across all specification, though the significance level slightly changes. Moreover, lead rainfall shock does not show any placebo effect on the outcome variables which seem unaffected in general. Overall, it can be deduced from this test that the main results reported in Table 4.3 are not due to some coincidence.

## 4.8 Conclusions

This paper examined the relationship between rainfall shock and household welfare outcome, such as, per capita income and consumption. The overall results suggest that positive rainfall shocks lead to loss in income, particularly for those engaged in growing crops. However, evidence for consumption smoothing behavior was confirmed. That is, in the event of shocks households' savings decreased, sale of livestock and credit uptake – mostly informal loans – increased. At the same time, the rainfall shocks have no significant impact on food consumption. These results suggest that households are able to protect or shield their food consumption from rainfall shocks. For non-food consumption, the increasing trend on account of medical and travelling costs was observed.

The heterogeneity results also shed light on how some household or communities are in better position to withstand the disasters. Communities with relatively better access to irrigation systems seem to get an advantage, though the evidence is weak and therefore not conclusive, which points to the possible inefficiency of irrigation system.

Likewise, the absence of road infrastructure seems to affect the resilience of households in coping with the natural shocks, which result not only in shrinkage of crop related income but also the income from non-agricultural enterprises. This implies that road infrastructure is also important for better access to markets for farm output or business goods and procurement of inputs for small businesses. Moreover, financial infrastructure, for example, banks, are very important as their absence also reduces crop income as an easy access to credit can help farmers to deal with the unfavorable circumstances, including natural calamities.

Lastly. the impact of shock on the agriculture sector is likely to create excess labor in the rural areas due to diminishing employment opportunities in farm sector. It appears that non-farm wage income increases, particularly, in the areas having some transport access to the urban areas.

## 5. Disruptions caused by weather shocks in the rural labor-markets and consequent temporary migration decisions.

### 5.1 Introduction

Economists have been studying the links between extraordinary weather events, particularly, rainfall and temperature, and household welfare. The link between agricultural economy and weather shocks is established in a number of studies (Arouri et al, 2015; Karim, 2018) which in turn can adversely affect the welfare of the households, for example, household consumption (Khandker, 2007; Lewin et al, 2012). However, if the rural economy – which is overwhelmingly dependent on agriculture – is affected by the natural disasters, for examples, famine or floods, how communities or households respond to such calamities potentially affecting their livelihoods? One strategy to deal with such calamities is to migrate which is also investigated this paper.

Migration in agricultural economies is recurring and seasonal phenomenon as the farming is directly affected by the vagaries of nature. However, the extraordinary variations in weather observed in the last couple of decades are not temporary in nature but are going to be a new normal in the coming years (IPCC, 2019). Understanding the scale of environmental impact and the consequent modes of adaptation and coping strategies employed by the rural household can be very important for the policy makers, particularly in the developing countries where a vast population is still living in rural areas and directly or indirectly participates in agriculture which is directly affected by such weather changes. For example, the percentage of rural population in 2019 was 66%, 60%, 47% and 19% in South Asia, lower-middle income countries, middle income countries, and high-income countries, respectively.[50] In the absence of enough absorptive capacity

[50] https://data.worldbank.org/indicator/SP.RUR.TOTL.ZS?locations=XN-XP-XD-8S accessed on May 02, 2021

in the urban areas of developing countries such migration episodes forced by the nature can be of grave concern for urban planners.

Economist study migration mainly from two perspectives, namely, permanent and temporary, where the former points to the change of residence or leaving the household for good and later refers to short-term or frequent movement to a place outside the village / city of origin in search of livelihood, aptly referred as the practice of ‘station keeping’ in biological migration literature (DaVanzo, 1976: 116). I am investigating phenomenon of internal temporary migration in Pakistan. Permanent migration or international, long-distance migration has been analyzed in number of studies (Chen et al, 2019; Grey and Muller, 2012; Muller and Osgood, 2009; Munshi and Rozenberg, 2016; Feng et al, 2010; 2012; Halliday, 2006; 2012; Dustmann and Mestres, 2008), however, internal temporary migration is not widely studied, perhaps, due to its relatively limited importance (against international migration phenomenon).

Two recent studies discussed the temporary migration based on the data collected in East Africa (Grace et al, 2018; Mueller et al, 2020). In Africa weather conditions are relatively dry and extreme weather events are often related to absence of rainfall resulting in famine like conditions. The extraordinary rainfall may, in fact, be a good event in this background and research results in East Africa may lack the external validity for regions like South Asia where extreme events, in most cases, cause floods. Perhaps, that can be the reason that both studies find no impact of rainfall variations in East Africa on the temporary out-migration.

Besides, the study by Grace et al uses rainfall measures which take into consideration the annual rainfall, onset of rain season and quality of rainfall season during the past year which may be measuring rainfall stress but still does not correspond with the measurement of extraordinary weather events usually based on the deviations from historical mean employed in various studies, such as, Gao and Mills, 2018; Grimard and Hamilton, 1999; Kosec and Mo, 2017; Menon, 2009 and Skoufias et al, 2017. Study on Bangladesh by Cell et al (2017), which does not find any impact of floods on temporary migration, can be more relevant as the Bangladesh does not have dry conditions but the study has the same issue of not using rainfall variations as the explanatory variable as floods are not derived from precipitation data.[51]

Moreover, quantitative discussion on what forces the migrants out of rural economy or the channels through which floods affect household necessitating a decision to send a member of their house outside the village is scant in literature. Agriculture is dependent on many seasonal factors, including climate. One of the major motivations for non-farm work in the rural economies is the strategy to reduce ex-post or ex-ante risks attached with agricultural income (Barret et al, 2001). In case of floods or dry season, farmers have to rely on non-agricultural sources to earn their living or they may diversify into non-farm sector, ex ante, to have an income source on which they can rely during such shocks. Moreover, agricultural households may engage into non-farm activities to generate finance or capital, owing to the absence of credit markets, to invest into modern agricultural technology for increasing production (Barret et al, 2001; Ellis and Freeman, 2004; Shiferaw et al 2015).

However, this is the normal course of events for a rural economy and agricultural economy is hardwired to follow such routes to adjust to the vagaries of nature. What happens when the weather shocks are greater than the adjusted lifestyles to the regular and ordinary shocks? If the local rural economy can’t deal with excess labor supply in the event of crop failure, how do rural households respond? Analysis of labor markets at origin can be informative for such questions.

[51] Moreover, Bangladesh is not only lower riparian but has to drain water of entire Ganges-Brahmaputra-Meghna basin (Guitera et al, 2015; Page 233). The flooding in Bangladesh, therefore, may not be attributed to rainfall in Bangladesh only, and thereforethe study may also lack the external validity.

Study by Muller et al (2020) tried to discuss it but it was more focused on labor markets in case of urban out-migration and did not discuss this important aspect with respect to rural economy, perhaps due to its finding that rainfall variations do not result in rural out-migration. Changes in labor markets, for example, diversification into non-farm income, though, has been widely studied as an alternative employment and risk reduction strategy in case of floods / rainfall disasters (Menon, 2009; Rijkers and Soderbom, 2013; Skoufias et al, 2017), but these studies do not delve into the discussion with respect to labor mobility – such as, shrinking employment opportunities at the origin – through which migration is affected. The investigation of these channels is even more important if it is assumed that disasters are likely to make local conditions unfavorable for the non-farm employment too, for example in case of extreme floods construction activities can also be affected (Bryan et al, 2014: 24).

Lastly, if individuals migrate, do they help the family back home? This study will not only discuss the channels which compels the rural households to migrate, but another contribution of this study is to investigate the channels through which migrants contribute to welfare of household at the origin in the rural areas through exploiting the available remittances data. These channels have not been studied together simultaneously in any other study.

There are few studies which investigated the links between migration and consequent impact on remittances, for example, Halliday (2006) while investigating migration from El Salvadore to the US and concluded that self-reported floods not only increased migration but also resulted in increased remittances. However, it is difficult to find even a single study investigating natural disasters and migration, as well as the channels which result in migration – for example, changes in farm and non-farm employment – and the channels which can contribute to household welfare at the origin, that is, remittances.

There are some migration studies on Pakistan, but they also fail the answer all these questions econometrically. Most of recent studies on migration did not tackle the environmental factors (Chen et al, 2016; 2019; Ilhan and Jafery, 1999) except two: by Mueller et al (2014) and Eskander et al (2018). Study by Mueller et al was on long-term migration using three waves of Pakistan Panel Survey (1986-2012) data and the explanatory variable of flooding was derived from the number of deaths in a flood at provincial level which seems to be very broad in nature. Similarly, the study by Eskander et al (2018), though was on temporary migration using the first two waves of Pakistan Rural Household Survey, 2012, but they used subjective floods data by Emdat as explanatory variable. Former study showed insignificant impact of floods on migration and later showed decrease in migration in response to extreme flooding events. Both did not use the exogeneous explanatory variable and subjective variables can have reporting errors.

This study fills the visible gap in the existing literature by investigating econometrically the internal temporary migration in response to extraordinary weather shocks as well as the channels through which weather forces migration and whether this out-migration, in turn, contributes to the welfare of the households in a single study.

### 5.2 Outcome Variables

Three major outcome variables, namely, temporary migration, wages earned which includes both farm and non-farm wages, and remittances have been used in this study. A migrant is defined as an adult individual aged between 15 to 64 (both included) years, who leaves his village during or after monsoon rains at least for one month. The survey period covers 12 months starting from April to March for 2012-13 and 2013-14. It covered the period from March to February for 2011-12. The months prior to the setting of monsoon period are excluded to include only the duration during which an individual was likely to migrate due to extraordinary rains of Monsoon. In order to keep harmony across 3 waves of data, 9 months – starting from June till February next year – have been included in the analysis. Table 5.1 shows that a little less than 2% of the sample was away from home for at least 1 month during the period 2012-14.

Second variable is the remittances sent by the migrants. It can be very informative to see if the individuals who migrate due to extraordinary shocks were able to contribute to family income and resultantly contributed to the welfare of the household at origin. Due to limitations of data remittances could be analyzed on household level only. The data for 2011-12 reported the remittances sent back by the individuals who migrated due to current year floods or extraordinary rains, however, the data collected in later years did not connect the remittances with migrants. Moreover, data collected for 2012-13 and 2013-14 has the figures for transfer payments received by the household – both in cash and in kind – from different sources, including from those household residing in the same village. Due to the detailed information available on the types, sources and origin of transfers – for example, cash or in kind, received from relatives or neighbors sent from within or outside the village – it was possible to segregate the transfers received in cash only from the immediate household members from outside the village only. This made it possible to use these payments as proxy for remittances received by the household. In order to check the robustness of my analysis, results were also obtained by excluding 2011-12 as the questionnaire had similar questions and pattern for data collection related to remittances for the last two years, namely, 2012-13 and 2013-14. Table 5.2 shows that on average migrants send back Rs.915 if all the years and values are included. However, due to differences of recording across years just discussed above I have reported the results by excluding 2012. The figures for 2012-13 and 2013-14 show average per capita remittances of Rs.1075 have been received by the households which further reduces to 996 if extreme values are excluded from the analysis. Net remittances, which subtracts transfers sent out from the remittances received, also seems to have increased in response to extraordinary rainfalls.

The migration decision is the likely outcome of the falling employment opportunities or rising labor supply due to weather shocks or extraordinary rains. People are likely to go in search of employment opportunities elsewhere. The overwhelming percentage of population in rural areas is attached with agricultural economy, therefore, in the event of natural shock, agricultural economy, crop income and farm wages are affected. The only option available to less educated and low-skilled labor is to look for unskilled wages or non-farm wages elsewhere. In addition to the continuous variable for farm and non-farm wages, I have also used a dummy variable separately for farm and non-farm wages as outcome variable, that is, 1 if an individual earned any farm (non-farm) wage, 0 otherwise. This analysis was possible due to availability of individual level data in respect of wages.

The disaggregated analysis of the composition of non-farm employment shows that these are mainly composed of low paying temporary jobs such as factory workers, earth work labor, maids / servants, street vendors or construction labor. Of the total individuals associated with non-farm wages, overwhelming number, around 56% is associated with construction labor. The second and third category is government and private enterprise salaried jobs, at 10% and 9% respectively, which are relatively permanent in nature.[52] Table 5.1 shows that overall 10% of individuals were engaged in non-farm activities and it showed some variation from 2012 at 12% and lowest at 10% during 2014. Wages earned from farm related activities includes agricultural labor hired by the landlords for sowing, weeding, harvesting, picking, thrashing or for the application of inputs, such as, fertilizers / pesticides application. Around 12% of the individuals were engaged with the farm

[52] Author's calculation from PRSP, 2012-14 survey data

activities during 2012 to 14 and the percentage did not change much even if observed separately for each year. The wages have also been used as continuous variable and it can be observed from the last two rows of Table 5.1 that roughly non-farm wages earned in terms of monetary value are four times higher than the farm wages.

**Table 5.1 Summary Statistics: Outcome Variables of Employment and Wages Earned**

| | | | | | 2012 | | | 2013 | | 2014 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Observations** | **Mean** | **SD** | **Observations** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** |
| Migration | 1 if an adult was away from home for at least one month | 35,802 | 0.019 | 0.136 | 11,934 | 0.020 | 0.139 | 0.015 | 0.123 | 0.022 | 0.147 |
| Non-Farm Employment | 1 if an individual earned any non-farm wage | 35,802 | 0.106 | 0.308 | 11,934 | 0.122 | 0.327 | 0.097 | 0.297 | 0.100 | 0.300 |
| Farm employment | 1 if an individual earned any farm wage | 35,802 | 0.127 | 0.333 | 11,934 | 0.121 | 0.326 | 0.134 | 0.341 | 0.125 | 0.330 |
| Non-Farm Wage | Non-farm wages earned (Rs.) | 35,802 | 8284 | 32466 | 11,934 | 8698 | 31162 | 7853 | 32710 | 8300 | 33480 |
| Farm Wage | Farm Wages earned (Rs.) | 35,802 | 2165 | 9176 | 11,934 | 2199 | 9835 | 2361 | 9142 | 1935 | 8499 |

**Source**: Author's calculation from PRSP, 2012-14 survey data

**Table 5.2: Summary Statistics: Outcome Variable of Remittances**

| **Variable** | **Observations** | **Year** | **Observations** | **Mean** | **SD** |
|---|---|---|---|---|---|
| Remittances | All values | All Years | 5,358 | 916 | 6133 |
| Remittances | Excluding extreme values | All Years | 5,358 | 915 | 6132 |
| Remittances | All values | Excl 2012 | 3,572 | 1075 | 6493 |
| Remittances | Excluding extreme values | Excl 2012 | 3,572 | 996 | 5635 |
| Net Remittances | All values | Excl 2012 | 3,572 | 887 | 6429 |
| Net Remittances | Excl extreme values | Excl 2012 | 3,572 | 1048 | 5974 |

Source: Author's calculation from PRSP, 2012-14 survey data

The Figure 5.1 below is instructive to understand the apparent correlation between the outcome variables discussed above and extraordinary rainfall during 2012-14. Panel 1A & B show striking difference between farm and non-farm activities in response to the rainfall shock.

Horizontal-axis shows the differences in rainfall shock, which is computed by subtracting dummy rainfall variable for previous year, t-1 (for example 0, or no rain in 2012) from current year, t (for example 1 or deviation of rainfall for 2013 from 30 year mean greater than 1 SD), which is 1, similarly, this year, -1 is disaster last year but current normal rainfall year; and 0 means consecutive normal / disaster years. The vertical-axis shows the variables farm / non-farm employment, farm / non-farm wages, migration and remittances calculated in the same way as the disaster variable, that is subtracting wages / remittances of previous year from current year, for example, wages of 2012 subtracted from wages of 2013.

It is clearly seen in Panel 1A & B that in response to shock, employment in the non-farm sector increases but shrinks in the farm sector. The similar pattern is seen in Panel 2, where continuous variable replaces the dummy variables on the vertical axis, showing apparent increase in non-farm wages and decrease in farm related wages.

Panel 3 gives us some hint how this is happening. Apparently, due to the shock agriculture sector is likely to be affected adversely reducing farm-related activities and wages earned. This can not only push workers into non-farm sector but also has the potential to increase the rural unemployment rate due to excess labor supply in the local labor market at the time when shock may also be adversely affecting the non-farm activities during floods. This is, therefore, conceivable that such conditions will drive the labor out of their place of residence, thereby increasing the number of individuals making decisions to migrate in search of employment. The analysis of remittances also gives some evidence that these decisions, in turn increase welfare of the households implying that these individuals transferred some of the wages back to the origin. Panel 4 shows this correlation. Panel 4A shows positive correlation between shock and remittances, which does not change when extreme values are excluded from the analysis in Panel 4B.

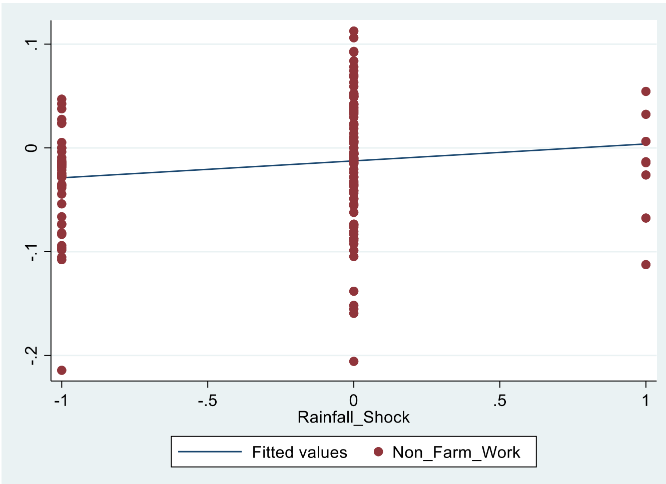
Owing to variation of recording data in 2012 and later years, the analysis was also made excluding 2012 and the relationship is same in panel 4C & D.[53] Lastly, the net remittances, which excluded transfer payments sent out of the home are shown in Panel 4E and F.[54] When extreme values from transfer payment sent out are excluded the relationship becomes positive in Panel 4F.

So, in short, from the above discussion it can be inferred that due to rainfall shock employment opportunities seems to have fallen in the villages which pushes the excess unemployed labor, exacerbated by floods and failure of crops, out of villages / communities of origin. The resultant migration seems to have contributed household income through remittances sent by those moved out. In the next sections I will try to find out whether the apparent correlation between extreme weather events and Migration / non-farm wages / remittances has any causality or some unobserved events / factors are driving this correlation.

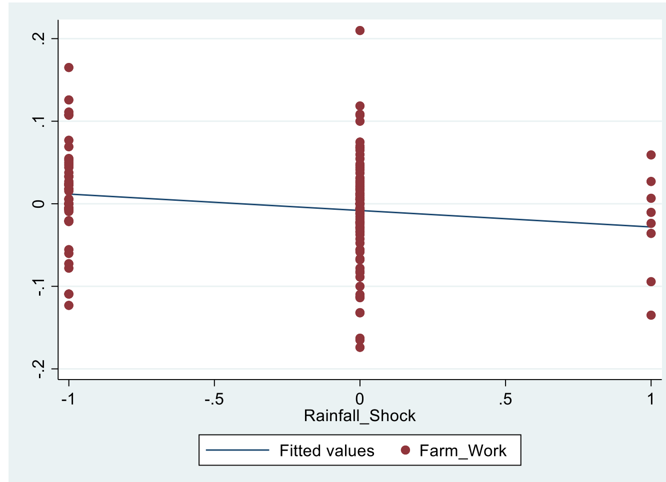
[53] As the data is compiled at the village level for these graphs, that's why the panels 4A & B and 4C & D show little variation when extreme values are excluded.
[54] This data is available only for 2012-13 and 2013-14

**Figure 5.1 Relationship between rainfall shock and Farm & Non-farm Work / Farm & Non-farm wages / Migration decisions**

**Panel 1: Farm & Non-farm Work**

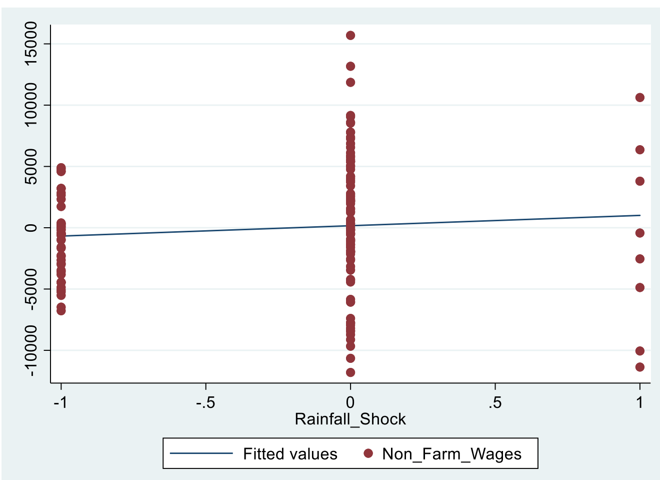



**A: Non-Farm Employment**

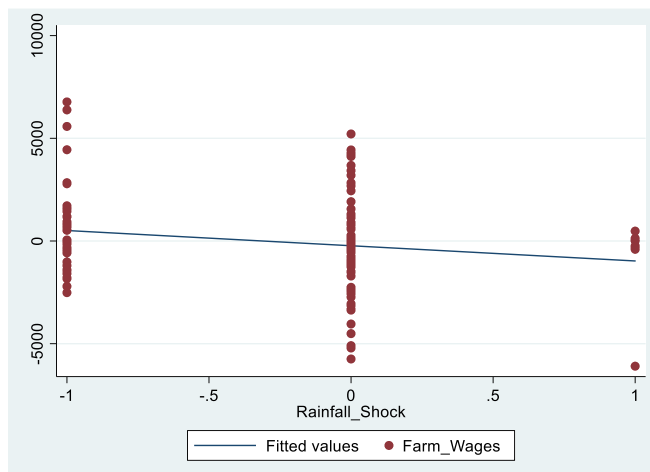



**B: Farm Employment**

**Panel 1: Farm & Non-farm Wages**

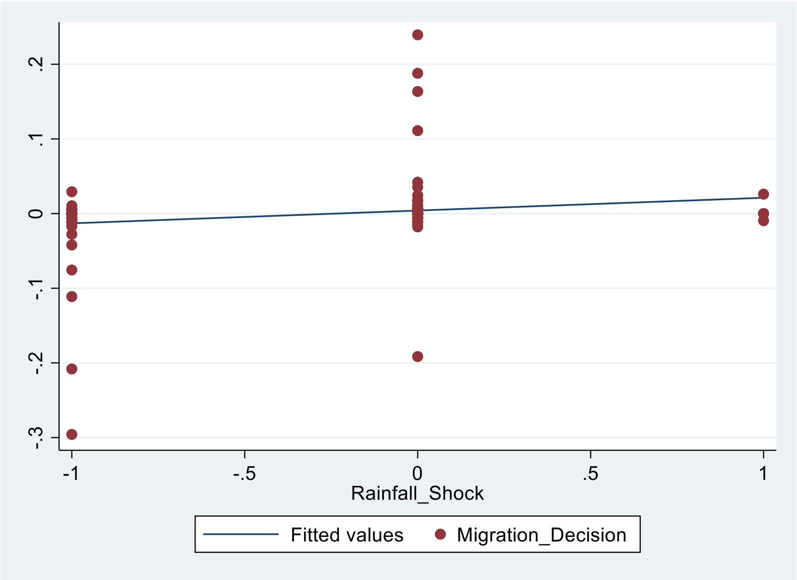



**A: Non-Farm Wages**

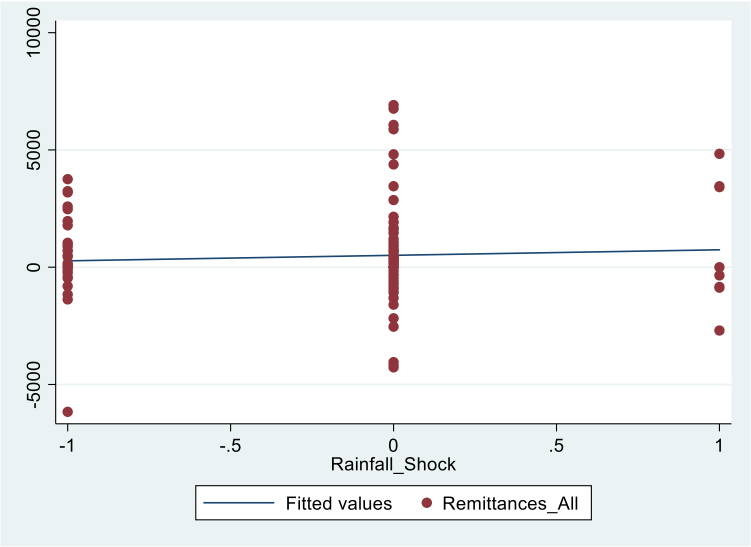



**B: Farm Wages**

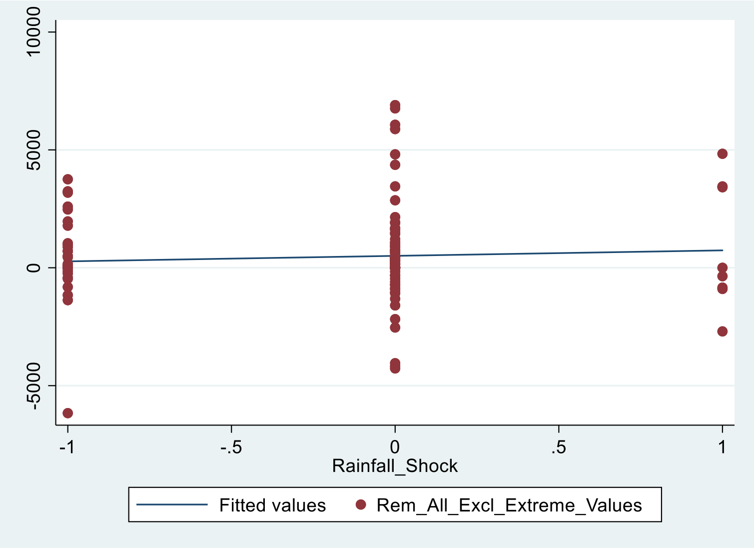
**Panel 3: Migration Decisions**



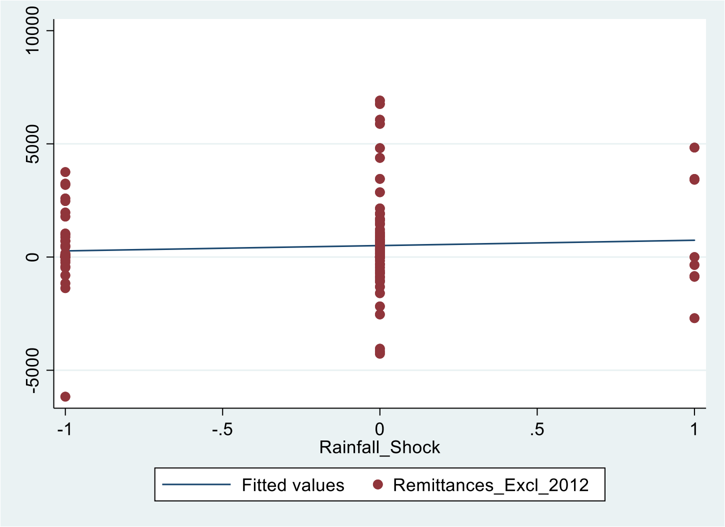
**Panel 4: Remittances**



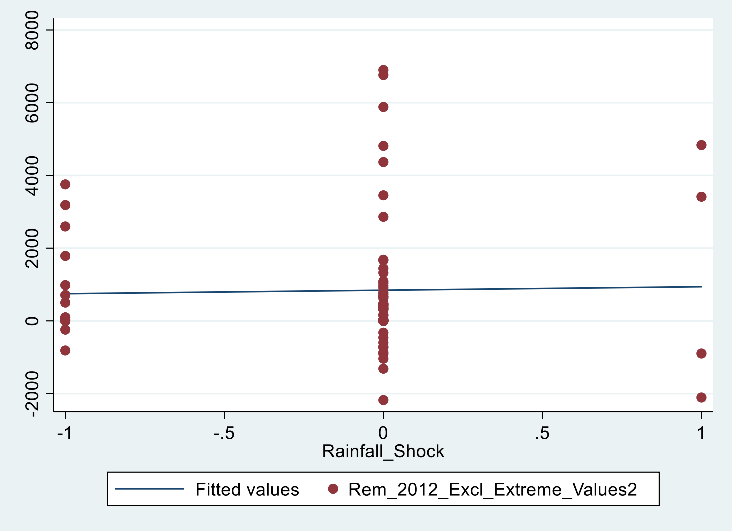

A. Remittances including all years



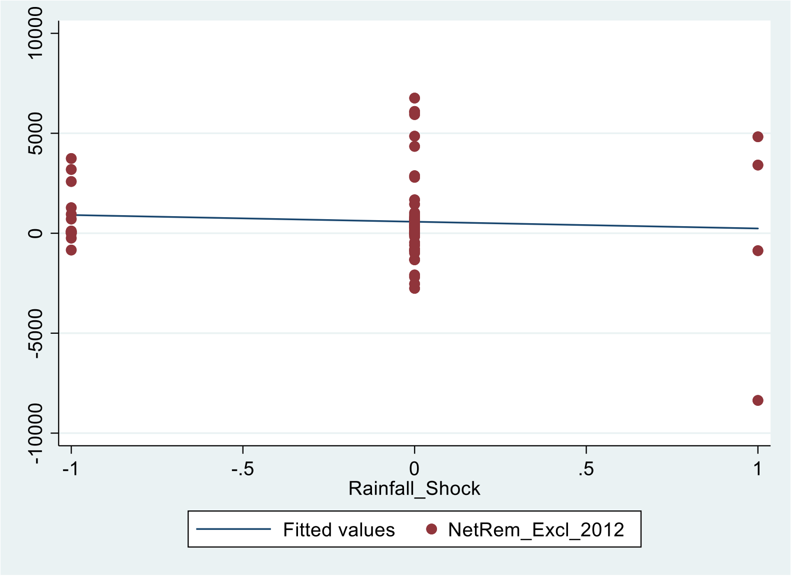

B. Remittances all years but excluding extreme values

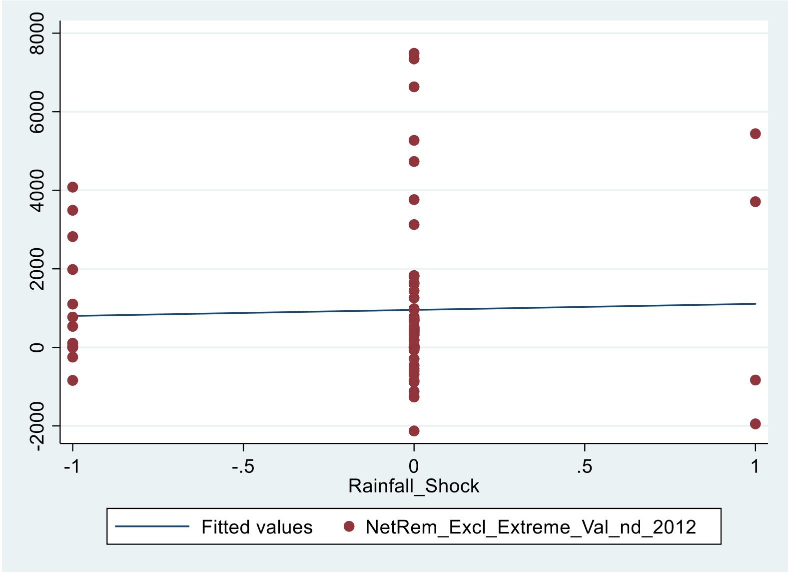



C. Remittances all values excluding 2012




D. Remittances excluding extreme values and 2012




Net Remittances: All values excluding 2012

F. Net Remittances: Excluding 2012 and extreme values

Horizontal-axis: Shock as deviation from long-term mean
Vertical-axis: Farm / Non-farm wages / Migration Decisions

**Source:**

Household data on employment, migration and remittances collected by IFRPI http://dx.doi.org/10.7910/DVN/28558
Rainfall data is collected from NASA

## 5.3 Methodology

The choice of methodology, linear probability model vs discreet choice model, is very important and at the same time difficult to decide in case of categorical outcome variables.[55] Where the discreet choice models, for example, logit or probit, allow estimation of non-linear probabilities, they are difficult to be interpreted. On the other hand, the linear probability is very easy for interpretation but problematic where probability is less than 0 or greater than 1 (Stock and Watson, 2006; 389, 396; Wooldridge, 2010). It is difficult and beyond the scope of this paper to argue whether logit specification is better than linear probability models. In order to address such methodology issues, I intend to use logit fixed effects regression along with linear probability model simultaneously as robustness check throughout the paper.

First, I intend to analyze how the rainfall shocks affect the village labor market which is one of the major channels through which migration decision are made. The research question I am trying to probe is that whether the labor markets are affected due to rainfall disasters diminishing the farm and non-farm employment opportunities? I use fixed effects logit model given in equation 5.1, with categorical outcome variable *w*, of farm / non-farm work for individual i, in village v during year t in alternate specifications. Fixed effects model is used as a major estimation strategy which is preferred for removing time-invariant unobserved heterogeneity emanating from individual factors.

$$\log \left(\frac{w_{ivt}}{1-w_{ivt}}\right) = \zeta S_{vt} + \gamma_{pt} + \delta_{dt} + \eta_j + \lambda_t + \varepsilon_{ihvt} \ldots \ldots\ldots \text{Eq. 5.1}$$

I use exogeneous rainfall measure as explanatory variable, S, in village v at time t, to rule out any personal biases often present in subjective disaster data. In order to control for regional differences

[55] For detailed discussion see chapter 15 of 'Econometric Analysis of Cross Section and Panel Data' by Wooldridge (2010)

and area specific characteristics affecting outcomes endogenously over time, province interactions with Time dummies, $\gamma_{pt;}$ and district specific time trends, $\delta_{dy}$ have been introduced in the specifications. District specific time trends control for district-wide shocks probably restricted to a particular district. Lastly, η indicates individual fixed effects to control time-invariant factors and the year fixed effects, λ, take care of any unobserved common trends over the years, such as, El Nino or La Nina phenomenon[56], which can affect the temperatures globally lasting, typically, for 9-12 months. Robust standard error, $\varepsilon_{ihvt,}$ is clustered around villages.

Second question that how rainfall disasters impact rural individual migration decisions, is probed through equation 5.2, to investigate the null hypothesis that rainfall disaster do not affect individual migration decisions.

$$\log\left(\frac{\rho_{ivt}}{1-\rho_{ivt}}\right) = \zeta S_{vt} + \gamma_{pt} + \delta_{dy} + \eta_j + \lambda_t + \varepsilon_{ihvt} \ldots \ldots\ldots\text{Eq. 5.2}$$

Where, $\rho_{ivt}$, for individual, i in village, v, at time t is a dichotomous migration measure, capturing the probability of an individual deciding to migrate or not in response to rainfall shock, S. Both equation 1 & 2 are same with the exception of outcome variable. This equation used crop-zone specific time trends instead of district-specific time trends, as the equation with latter could not be estimated by Stata.[57]

Equation 5.3, introduces an interaction term for capturing heterogeneity among households or villages.

$$\log\left(\frac{\rho_{ivt}}{1-\rho_{ivt}}\right) = \zeta_1 S_{vt} + \zeta_2 (S_{vt} W_{hv}) + \gamma_p + \delta_{dy} + \eta_j + \lambda_t + \varepsilon_{ihvt} \ldots \ldots\ldots\text{Eq. 5.3}$$

[56] https://oceanservice.noaa.gov/facts/ninonina.html accessed on March 10, 2021

[57] Stata reported a warning, namely: 'variance matrix is nonsymmetric or highly singular'.

Where, S in the interaction term is disaster indicators and W is an individual or community characteristics, for example, age on an individual, community access to credit, roads, etc. Interactions help to capture the heterogeneous impacts of rainfall shock across households and communities depending upon their respective personal or regional peculiarities.

As I have used logistic probability model for analyzing migration, one flip side of this estimation strategy is the inability of usual Stata command which rules out robust standard errors in the fixed effects models, which may result in underestimating of standard errors due to presence of certain factors common to a particular group, for example, village in this study. The possibility of within village correlation of unobserved factors can be taken care of by 'clogit' command, which enables the use of Heteroskedasticity and Autocorrelation-Consistent (HAC) standard error along with fixed effect specification, in other words, standard errors can be grouped across villages.

Lastly, the third research question that how rainfall affects migration decisions contribute to the household welfare at the origin is investigated through equation 5.4. The analysis of remittances, as explained in data section, was not possible at individual level and hence carried out at household level by fixed effect model.

$$R_{hvt} = \zeta S_{vt} + \gamma_{pt} + \delta_{dy} + \mu_h + \lambda_t + \varepsilon_{hvt} \quad \ldots \ldots\ldots \text{Eq. } 5.4$$

Where, R is the remittance received by the household, h in village, v in year, t and $\mu_h$, the household fixed effects replaces η, the individual fixed effects. Remaining model is not very different from equation 5.2 and 5.3.

**5.4 Results**

Before moving to the migration question, I start discussing the impact of shock on farm / non-farm wages and work opportunities in rural economy.

### 5.4.1 Farm and Non-Farm Wages

The results in Table 5.3 suggest that extraordinary rainfall events not only significantly reduce farm related work and farm wages but also gives rise to the non-farm work engagements. Column 1 of Table 5.3 is fixed effects OLS regression which reports farm wages, a continuous outcome variable. In response to a one-SD increase in the rainfall above the 30-year historical mean, farm wages reduced by Rs.689 significantly at 5%. Columns 3 and 5 show fixed effects logit regression results – while latter also uses robust standard errors – with odd ratios in column 4 and 6 respectively, showing that in response to shock the odds of engaging in farm work reduced due to rainfall shock. More specifically the probability of an individual staying in farm related work decreases and the odds of someone living in shock affected community and still engaged in farm work are only 74 % of those who were lucky enough to live in community spared by the natural disaster. So not only non-farm-work decreased but it also suppresses the wages earned.

Results regarding non-farm work and wages are reported in specification 5 to 8. The results are not as robust as in the case of farm wages. However, the direction of results shows increase in farm wages (column 7) and non-farm work (column 8 to 12). The Stata inbuilt command reports results in column 9 which allows the use of conditional fixed effects at the cost of robust SE, shows that the odds of an individual staying or switching to the non-farm sector are 1.3 times in a community hit by shock as compared to those individuals whose village of residence is not affected by the shock. However, the use of, clogit command, which allows the use of robust SE in column 11, turns the results insignificant.

It can be said confidently that farm wages and farm employment decrease as these are directly related with agriculture which is affected due to extra-ordinary rainfall. The non-farm related specifications though are not significant consistently but show positive sign from column 7 to 12.

Though the results are weaker, the combined analysis of both farm and non-farm works shows that there is some evidence that extraordinary rains push farm labor out of agriculture sector, and pulls into the non-farm employment sector, which mostly offers temporary employment and pays only subsistence wages.

The non-farm market is also unlikely to absorb all the potential non-farm labor inside the village which is supposed to be having excess labor freed from rain-hit farm activities. Even the floods conceivably make it impossible to work in construction sites which may have been affected due to rains. However, owing to data-limitation the information related to the place of non-farm work is not available. This aspect, however, can be probed indirectly by studying migration, which is thought to be a coping strategy when there is a crop-failure and implies search of non-farm work in the urban areas which are less affected by rains/ floods.

**Table 5.3 Impact of Rainfall Disaster on Individual Employment Levels and Wages**

| Panel 1: Farm Sector | | | | | | | Panel 2: Non-farm Sector | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Column | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| VARIABLES | Farm Wages | Farm Work | Farm Work | odds ratio | Farm Work | odds ratio | Non_Farm Wages | Non_Farm Work | Non_Farm Work | odds ratio | Non_Farm Work | odds ratio |
| Methodology | OLS | | Logit | | | | OLS | | Logit | | | |
| 1 if standardized monsoon rainfall is > 1 | -689.1** | -0.0161 | -0.297*** | 0.743*** | -0.297* | 0.743* | 348.5 | 0.0111 | 0.262** | 1.300** | 0.262 | 1.300 |
| | (323.3) | (0.0110) | (0.0946) | (0.0703) | (0.159) | (0.118) | (789.8) | (0.00739) | (0.113) | (0.147) | (0.187) | (0.242) |
| Observations | 35,802 | 35,802 | 7,176 | 7,176 | 7,176 | 7,176 | 35,802 | 35,802 | 5,016 | 5,016 | 5,016 | 5,016 |
| Cluster Village | Yes | yes | No | | Yes | | Yes | Yes | No | | Yes | |

Source: Authors' estimation from the PRHS 2012, 2013 and 2014

Note: Robust standard errors, clustered around villages, are in parentheses. Table results are based on equation 5.1 which uses individual fixed effects, province-year interactions and district specific time trends. Column 1 and 7 use continuous outcome variable of farm and non-farm wages respectively, whereas, remaining columns use dummy outcome variables of employment while using both OLS and Logit regression mentioned against each column.

*** p<0.01, ** p<0.05, * p<0.1

**Table 5.4 Impact of Rainfall Disaster and Migration Decisions**

| Column | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Migration | Migration | Migration | odds ratio | Migration | odds ratio |
| Methodology | **OLS** | | **Logit** | | | |
| 1 if standardized monsoon rainfall is > 1 | 0.00819* | 0.0113** | 2.188** | 8.921** | 2.330** | 10.28** |
| | (0.00442) | (0.00553) | (0.958) | (8.550) | (0.965) | (9.916) |
| Observations | 35,802 | 35,802 | 828 | 828 | 828 | 828 |
| Ind FE | Yes | Yes | Yes | | Yes | |
| Crop-Zone time Trends | No | Yes | No | | Yes | |
| Year Dummies | Yes | Yes | Yes | | Yes | |

Source: Authors' estimation from the PRHS 2012, 2013 and 2014

Note: Robust standard errors, clustered around villages, are in parentheses. Table results are based on equation 5.2 which uses individual fixed effects, province-year interactions and district specific time trends. However, different strategies ranging from simple OLS without time trends and crop-zone specific time trends to using trends have been used mentioned in respective columns. Column 2 and 5 use the preferred models using robust SE and crop-zone time trends and province year interactions

*** p<0.01, ** p<0.05, * p<0.1

### 5.4.2 Migration

It appears that out-migration from villages hit by extraordinary shocks not only rises but the results are also highly robust – and qualitatively same – whether logit or LPM specifications.

Column 5 reports the main model which includes individual fixed effects and robust standard error centered around villages. It shows that the chances of adult individuals – aged equal to or greater than 15 years and less than or equal to 64 years – living in the communities which receive an extraordinary rainfall – which is one standard deviation above 30 years historical mean – are 10 times greater than those individuals who reside in villages where deviation of rainfall is less than 1 SD. The result significant at 5% significance level reported in column 3 to 6. The results based on the OLS model (Columns 1& 2) are also robust and significant at 5% in the specification 2 where fixed effect and robust SE are used.

Results reported in Table 5.6 strongly indicate that the individuals decide to migrate out of the village which are affected by the rainfall shocks. The apparent reason of migration decision in response to rainfalls / floods is evident from the Table 5.3 which earlier showed the evidence that employment opportunities associated with agriculture are reduced due to rainfall shocks which pushed them into non-farm wage activities. Also, it can be conjectured from the Migration analysis that adults seek non-farm opportunities outside of their villages by migrating in order to cope with the devastating impact of shocks. The labor market conditions in the places of origin could be unfavorable either due to limited work opportunity or reduced wages due to excess labor, ultimately pushing excess labor out of the shock hit villages, hence increased migration is the result.

#### 5.4.2.1 Heterogeneity in the impacts of rainfall shocks on the migration Decisions

Heterogeneity analysis shows that the likelihood to migrate is higher if households are engaged in located further from the urban areas.

Migration in search of non-farm employment is influenced by distance. Table 5.5 shows that those individuals originating from villages located relatively far from the urban areas are more likely to migrate. The preferred variable of commute time to the nearest commercial market, which takes the value of 1 if commute time to the nearest commercial center is more than or equal to the median, 0 otherwise, was used as proxy for the nearness to urban areas. The coefficient is positive and significant, implying the heterogeneous difference between those areas located near urban centers and those which are not.

That is if the distance to the nearest urban areas is greater, there are increased chances of individuals migrating outside the village hit by the rainfall disaster. This implies that those who can daily commute to cities or areas unharmed by the shocks in search of non-farm work they adopt the behavior of station-keeping and do not migrate. The nearness to urban areas can also be interpreted in terms of transportation costs. As long as the costs are not high the decision to migrate is not made. But with rising distance, apparently, daily costs outweigh the cost attached with migrating from household, at which point the decision is made to migrate in search of non-farm labor.

Another interaction, between rain shock and variable Railway station which is 1 if a railway station is located within 5 km radius of the village, adds further credibility to the above analysis. Figure 5.3 shows that the difference between areas located near or far from the railway station is significantly heterogeneous. The individuals from areas where a railway station is situated nearby are less likely to migrate which implies that due to easy transport availability – which apparently reduces the transportation costs – individuals are likely to commute daily instead of migrating to urban areas. Net effect for the above two interactions is also significant denoted by the last three rows of Table 5.5. The financial institutions seem not to affect the overall migration decisions as the net effect is non-zero.

**Table 5.5 Heterogeneity in the Impacts of Rainfall Shock on Migration Decisions by Community Characteristics**

| VARIABLES | (1) Migration | (2) odds ratio |
|---|---|---|
| 1 if standardized Rainfall is > 1 | 0.615 | 1.850 |
| | (0.846) | (1.566) |
| 1 if standardized monsoon rainfall is > 1 * 1 if a community located more than the median distance from commercial center ($\alpha_2$) | 1.595*** | 4.930*** |
| | (0.571) | (2.815) |
| 1 if standardized monsoon rainfall is > 1 * 1 if a community located within 5 Km of a Railway Station ($\alpha_3$) | -3.257** | 0.0385** |
| | (1.266) | (0.0487) |
| 1 if standardized monsoon rainfall is > 1 * 1 if a community located less than the median distance from formal credit institutions ($\alpha_2$) | 1.612* | 5.013* |
| | (0.906) | (4.543) |
| Observations | 828 | 828 |
| | | |
| Prob > chi2 ($\alpha_1 + \alpha_2$) | 0.0257 | |
| Prob > chi2 ($\alpha_1 + \alpha_3$) | 0.0248 | |
| Prob > chi2 ($\alpha_1 + \alpha_4$) | 0.0102 | |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Lastly, individual characteristic of age is very important in migration decisions. Those who migrate to cope with the devastating impact of extraordinary rains, include all working age adults above 31 years of age, reported in Table 5.6. It can be observed that results are also robust with OLS estimations.

**Table 5.6 Heterogeneity in the Impacts of Rainfall Shocks on Migration Decisions by Individual Characteristic of Age**

| | (1) | (2) |
|---|---|---|
| VARIABLES | Migration | Migration |
| | Logit | OLS |
| 1 if standardized monsoon rainfall is > 1 ($\zeta$ 1) | 2.047** | 0.00791 |
| | (0.920) | (0.00488) |
| 1 if standardized monsoon rainfall is > 1 * 1 if age of adult is > median (31) ($\zeta_2$) | 0.585** | 0.0107* |
| | (0.276) | (0.00593) |
| 1 if the Age > 31 | -0.0464 | 0.00552 |
| | (0.460) | (0.00657) |
| Observations | 828 | 35,802 |
| chi-test | 6.914 | |
| Prob > chi2 | 0.00855 | |
| F-test | | 5 |
| Prob > F ($\zeta_1 + \zeta_2$) | | 0.0284 |

Source: Authors' estimation from the PRHS 2012, 2013 and 2014
Note: Robust standard errors, clustered around villages, are in parentheses. Table results are based on equation 5.3 which uses individual fixed effects, province-year interactions and crop-zone specific time trends.
*** p<0.01, ** p<0.05, * p<0.1

### 5.4.3 Welfare Impact of Migration: Remittances

Once it is established that the individuals migrate due to extraordinary shock which seem to reduce employment opportunities in their communities of residence, the question arises, whether they contribute anything to the welfare of their homes at origin. It was pointed out in data section that due to peculiar way the data was collected this analysis can't be done on the individual basis. Furthermore, the variations exist in the way the data was collected in 2011-12 and in later years, namely, 2012-13 and 2013-14. The data in the later years has been extrapolated with 2011-12 by restricting the transfers sent back home from outside the villages in cash form by the immediate members of family only. However, the analysis was also carried out excluding 2011-12 to check the robustness of my analysis.

**Table 5.7 Impact of Rainfall Shocks on Remittances**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Remittances | Remittances | Remittances | Remittances | Net Remittances | Net Remittances |
| Years | All (2012 to 2014) | | Excluding 2012 | | | |
| Observations | All | Above 2000 | All | Excluding: below 1000 and above 60000 | All | Excluding: below 1000 and above 60000 |
| 1 if standardized monsoon rainfall is > 1 | 543.2* | 541.4* | 1,754** | 1,387** | 981.4 | 1,496** |
| | (301.2) | (301.5) | (815.2) | (635.6) | (764.2) | (684.5) |
| Observations | 5,358 | 5,358 | 3,572 | 3,572 | 3,572 | 3,572 |

Source: Authors' estimation from the PRHS 2012, 2013 and 2014

Note: Robust standard errors, clustered around villages, are in parentheses. Table results are based on equation 5.4 which uses household fixed effects, province-year interactions and district specific time trends.

*** p<0.01, ** p<0.05, * p<0.1

Columns 1 & 2 report the remittances sent back home including all years, latter excludes extreme values which do not seem to affect the results. In the villages which receive extraordinary rainfall, the immediate family members living outside the village of their residence significantly increase the money sent back home by Rs.543. Column 3 & column 4 report results excluding 2011-12, where the latter excludes extreme values exceeding Rs. 600,000 and less than Rs.1000. Column 3 shows the migrants sent Rs.1754 back homes situated in the villages affected by the extraordinary shocks.

The data collected after 2011-12 also recorded the information regarding transfers out of the home, so the net remittances could also be calculated. The column 6, where extreme values were excluded show net remittances received by the household increased by Rs.1496 significantly. It can be confidently concluded from this section that the migration adopted as a coping strategy to deal with the disastrous impacts of rainfall shocks is helpful and the migrants contribute to the welfare of the households at origin.

#### 5.4.3.1 Heterogeneity in the impact of rainfall shocks on the remittances received

Heterogeneity results correspond to the heterogeneity analysis of migration, as comparing Table 5.5 with Table 5.8, it can be observed that the individuals migrate due to greater distance from the urban areas and the household located in the communities which are further away from the urban areas also receive more remittances.[58]

[58] Remittances and net remittances definition correspond to the column 4 and 6 of Table 5.7, respectively

**Table 5.8 Heterogeneity in the Impact of Rainfall Disaster on the Remittances by Access to Urban Areas**

| VARIABLES | (1)<br>Remittances | (2)<br>Net Remittances |
|---|---|---|
| 1 if standardized monsoon rainfall is > 1 | 1,259** | 1,359** |
| | (614.7) | (663.2) |
| 1 if standardized monsoon rainfall is > 1 * 1 if commute time to city is greater than median | 1,006* | 1,072* |
| | (562.5) | (610.0) |
| Observations | 3,572 | 3,572 |
| F-test | 10.51 | 10.41 |
| Prob > F | 0.00178 | 0.00187 |

Source: Authors' estimation from the PRHS 2012, 2013 and 2014
Note: Robust standard errors, clustered around villages, are in parentheses. Table results are based on equation 5.4 which uses household fixed effects, province-year interactions and district specific time trends.
*** p<0.01, ** p<0.05, * p<0.1

In the absence of corresponding data of remittances and migrants, inference from this analysis can be drawn that the villages from where the migrants move out are the same areas which received the remittances, corollary to which is another deduction that the migrants who migrate due to extraordinary rainfall shocks contribute to the welfare of the households at origin.

## 5.5 Conclusions

Using a panel data this study finds the extraordinary shocks affects agricultural sector in the rural area adversely resulting, not only, in fall in farm wages but excess supply of labor coupled with floods seems to diminish even the non-farm work. Further probing of data highlights the coping strategy the rural households are forced to adopt – which is the increase in seasonal or temporary migration. This migration is particularly used as strategy in areas which lack direct access to urban areas, either it is the owing to the absence of proper transport facility or road infrastructure.

The migration also results in the increase of remittances back home, particularly, in the areas which are away from urban areas and give credence to the assumption that the increase is in the areas which sent more migrants outside the shock hit villages.

## 6. Conclusions and Policy Implications

This dissertation examined the impact of extraordinary rainfalls on the rural household welfare, that is, household income and consumption. The study also tried to find whether some households and areas are more resilient than others and how the affected households cope with these disasters. Migration and the sending home of remittances were the main coping mechanisms examined.

First topic investigated the link between rainfall shocks and rural household income and consumption and found that although the household income reduced, largely on account of crop income, but the households were able to smooth their consumption adopting both ex-ante – that is, household savings – and ex-post – such as, loans and selling relatively liquid assets of livestock – strategies. The impact on income was also mitigated for those having relatively easy access to urban areas or financial means.

The results have certain policy implications for the government. The enhancement of physical and financial infrastructure is likely to increase the capability of rural households to withstand the rainfall shocks. The infrastructure includes the improvement of inefficient irrigation system which possibly could be used by the powerful elites to their advantage. As well, the improvement of drainage and dyke system and running system with merit could reduce the impact of flood on the small farmers.

This study also shows strong spatial variations in the disastrous impact of floods. The areas which are less developed in terms of road and transport infrastructure which increase the travel time to the urban centers ae more likely to face the difficulties while coping with the disasters. Reducing travel time to urban areas gives advantage to communities to transport their agriculture and business output to cities in addition to help in finding alternate work opportunities. The government needs to spread its development programs away from cities which helps bring urban utilities and amenities near rural areas.

Second major topic discussed the impact of rainfall shock on the rural labor markets and resultant strategy of households to migrate which also seems to contribute to the household welfare at the origin.

It appears from the analysis that alternate employment opportunities, other than farm related jobs in the rural area are insufficient to absorb the excess farm labor during rainfall shocks. Most of the non-farm jobs are concentrated in construction labor which is also low-paying, temporary and uncertain in nature. Government initiatives in bringing small enterprises and industry to backward areas can reduce the migration to and resultant congestion in cities. This analysis shows that the absence of infrastructure and transport can result in migration decisions. Equitable development projects which cover rural areas also can help the rural areas to escape the worst consequence of rainfall disasters, such as floods.

## References


Akobeng, E. (2017). The Invisible Hand of Rain in Spending: Effect of Rainfall-Driven Agricultural Income on Per Capita Expenditure in Ghana. *South African Journal of Economics*, *85*(1), 98-122.

Aldrich, D. P., Oum, S., & Sawada, Y. (Eds.). (2014). *Resilience and recovery in Asian disasters: Community ties, market mechanisms, and governance* (Vol. 18). Springer.

Amare, M., & Shiferaw, B. (2017). Nonfarm employment, agricultural intensification, and productivity change: empirical findings from Uganda. *Agricultural Economics*, *48*(S1), 59-72.

Amare, M., Jensen, N. D., Shiferaw, B., & Cissé, J. D. (2018). Rainfall shocks and agricultural productivity: Implication for rural household consumption. *Agricultural systems*, *166*, 79-89.

Arouri, M., Nguyen, C., & Youssef, A. B. (2015). Natural disasters, household welfare, and resilience: evidence from rural Vietnam. *World development*, *70*, 59-77.

Banerjee, A. V., & Duflo, E. (2007). The economic lives of the poor. *Journal of economic perspectives*, 21(1), 141-168.

Barrett, C. B., Reardon, T., & Webb, P. (2001). Nonfarm income diversification and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications. *Food policy*, 26(4), 315-331.

Bashir, M. K., Mehmood, Y., & Hassan, S. (2010). Impact of agricultural credit on productivity of wheat crop: Evidence from Lahore, Punjab, Pakistan. *Pakistan Journal of Agricultural Science, 47*(4), 405-409.

Bertrand, M., & Mullainathan, S. (2001). Do people mean what they say? Implications for subjective survey data. *American Economic Review*, *91*(2), 67-72.

Betts, R. A., Alfieri, L., Bradshaw, C., Caesar, J., Feyen, L., Friedlingstein, P., ... & Papadimitriou, L. (2018). Changes in climate extremes, fresh water availability and vulnerability to food insecurity projected at 1.5° C and 2° C global warming with a higher-resolution global climate model. *Phil. Trans. R. Soc. A*, *376*(2119), 20160452.

Binford, M. W., Kolata, A. L., Brenner, M., Janusek, J. W., Seddon, M. T., Abbott, M., & Curtis, J. H. (1997). Climate variation and the rise and fall of an Andean civilization. *Quaternary research*, *47*(2), 235-248.

Bohra-Mishra, P., Oppenheimer, M., & Hsiang, S. M. (2014). Nonlinear permanent migration response to climatic variations but minimal response to disasters. *Proceedings of the National Academy of Sciences*, 111(27), 9780-9785.

Bryan, G., Chowdhury, S., & Mobarak, A. M. (2014). Underinvestment in a profitable technology: In case of seasonal migration in Bangladesh. *Econometrica*, 82(5), 1671-1748.

Bui, A. T., Dungey, M., Nguyen, C. V., & Pham, T. P. (2014). The impact of natural disasters on household income, expenditure, poverty and inequality: evidence from Vietnam. *Applied Economics*, *46*(15), 1751-1766.

Call, M. A., Gray, C., Yunus, M., & Emch, M. (2017). Disruption, not displacement: Environmental variability and temporary migration in Bangladesh. *Global Environmental Change*, 46, 157-165.

Carnaje, G. P., & Cabanilla, L. S. (Eds.). (2009). *Development, Natural Resources & the Environment*. Department of Economics, College of Economics and Management, University of the Philippines at Los Baños.

Carter, M. R., & Barrett, C. B. (2006). The economics of poverty traps and persistent poverty: An asset-based approach. *The Journal of Development Studies*, *42*(2), 178-199.

Carter, M. R., Little, P. D., Mogues, T., & Negatu, W. (2007). Poverty traps and natural disasters in Ethiopia and Honduras. *World development*, *35*(5), 835-856.

Carter, M. R., & Lybbert, T. J. (2012). Consumption versus asset smoothing: testing the implications of poverty trap theory in Burkina Faso. *Journal of Development Economics*, *99*(2), 255-264.

Chandio, A. A., Jiang, Y., Gessesse, A. T., & Dunya, R. (2019). The nexus of agricultural credit, farm size and technical efficiency in Sindh, Pakistan: A stochastic production frontier approach. *Journal of the Saudi Society of Agricultural Sciences*, *18*(3), 348-354.

Chen, J. J., Kosec, K., & Mueller, V. (2019). Temporary and permanent migrant selection: Theory and evidence of ability-search cost dynamics. *Review of Development Economics*, 23(4), 1477-1519.

Cutter, S. L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E., & Webb, J. (2008). A place-based model for understanding community resilience to natural disasters. *Global environmental change*, *18*(4), 598-606.

DaVanzo, J. (1976). Differences between return and nonreturn migration: An econometric analysis. *International Migration Review*, 10(1), 13-27.

Deen, S. (2015). Pakistan 2010 floods. Policy gaps in disaster preparedness and response. *International journal of disaster risk reduction*, 12, 341-349

Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature*, *52*(3), 740-98.

Deschênes, O., & Greenstone, M. (2007). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American Economic Review*, *97*(1), 354-385.

Donaldson, D., & Storeygard, A. (2016). The view from above: Applications of satellite data in economics. *Journal of Economic Perspectives*, *30*(4), 171-98.

Dorosh, P., Wang, H. G., You, L., & Schmidt, E. (2012). Road connectivity, population, and crop production in Sub-Saharan Africa. *Agricultural Economics*, *43*(1), 89-103.

Dustmann, C., & Mestres, J. (2010). Remittances and temporary migration. *Journal of Development Economics*, 92(1), 62-70.

Ebert, E. E. (2007). Methods for verifying satellite precipitation estimates. In *Measuring precipitation from space* (pp. 345-356). Springer, Dordrecht.

Ellis, F., & Freeman, H. A. (2004). Rural livelihoods and poverty reduction strategies in four African countries. *Journal of development studies*, 40(4), 1-30.

Eskander, S., Fankhauser, S., Jha, S., Batool, S., & Qaisrani, A. (2018). *Do natural disasters change savings and employment choices: evidence from Pakistan.* Grantham Research Institute on Climate change and the Environment Working Paper No.293.

Fafchamps, M. (1999). *Rural Poverty, Risk and Development* (No. 144). Food & Agriculture Org.

Fafchamps, M., Udry, C., & Czukas, K. (1998). Drought and saving in West Africa: are livestock a buffer stock?. *Journal of Development economics*, *55*(2), 273-305.

Feng, S., Krueger, A. B., & Oppenheimer, M. (2010). Linkages among climate change, crop yields and Mexico–US cross-border migration. Proceedings of the national academy of sciences, 107(32), 14257-14262.

Feng, S., Oppenheimer, M., & Schlenker, W. (2012). Climate change, crop yields, and internal migration in the United States (No. w17734). National Bureau of Economic Research.

Gallagher, J., & Hartley, D. (2017). Household finance after a natural disaster: The case of Hurricane Katrina. *American Economic Journal: Economic Policy*, *9*(3), 199-228.

Gao, J., & Mills, B. F. (2018). Weather Shocks, Coping Strategies and Consumption Dynamics in Rural Ethiopia. *World Development*, *101*, 268-283.

Giesbert, L., & Schindler, K. (2012). Assets, shocks, and poverty traps in rural Mozambique. *World Development*, *40*(8), 1594-1609.

Gilmont, M., Hall, J. W., Grey, D., Dadson, S. J., Abele, S., & Simpson, M. (2018). Analysis of the relationship between rainfall and economic growth in Indian states. *Global Environmental Change*, *49*, 56-72.

Grace, K., Hertrich, V., Singare, D., & Husak, G. (2018). Examining rural Sahelian out-migration in the context of climate change: An analysis of the linkages between rainfall and out-migration in two Malian villages from 1981 to 2009. *World Development*, 109, 187-196.

Gray, C. L., & Mueller, V. (2012). Natural disasters and population mobility in Bangladesh. *Proceedings of the National Academy of Sciences*, 109(16), 6000-6005.

Grimard, F., & Hamilton, B. (1999). Estimating the elderly's returns on the farm: evidence from Cote d'Ivoire. *Journal of Development Economics*, *58*(2), 513-531.

Guiteras, R., Jina, A., & Mobarak, A. M. (2015). Satellites, self-reports, and submersion: exposure to floods in Bangladesh. *American Economic Review*, *105*(5), 232-36.

Haggblade, S., Hazell, P., & Reardon, T. (2010). The rural non-farm economy: Prospects for growth and poverty reduction. *World Development*, *38*(10), 1429-1441.

Halliday, T. (2006). Migration, risk, and liquidity constraints in El Salvador. *Economic development and cultural change*, 54(4), 893-925.

Halliday, T. J. (2012). Intra-household labor supply, migration, and subsistence constraints in a risky environment: Evidence from rural El Salvador. *European Economic Review*, 56(6), 1001-1019.

Hidalgo, F. D., Naidu, S., Nichter, S., & Richardson, N. (2010). Economic determinants of land invasions. *The Review of Economics and Statistics*, *92*(3), 505-523.

Hirashima, S. (2001). *Rural Poverty and the Landed Elite: South Asian Experience Revisted* (No. 642-2016-44210).

Hirashima, S. (2008). The land market in development: a case study of Punjab in Pakistan and India. *Economic and Political weekly*, 41-47.

Hoffmann, R., & Muttarak, R. (2017). Learn from the past, prepare for the future: Impacts of education and experience on disaster preparedness in the Philippines and Thailand. *World Development*, *96*, 32-51.

Hunter, L. M., Murray, S., & Riosmena, F. (2013). Rainfall patterns and US migration from rural Mexico. *International Migration Review*, 47(4), 874-909.

Rahman, Saeed Ur, Hussain, A., & Taqi, M. (2014). Impact of agricultural credit on agricultural productivity in Pakistan: An empirical analysis. *International Journal of Advanced Research in Management and Social Sciences*, *3*(4), 125-139.

Hussain, A., & Thapa, G. B. (2012). Smallholders' access to agricultural credit in Pakistan. *Food Security*, *4*(1), 73-85.

Ilahi, N., & Jafarey, S. (1999). Guestworker migration, remittances and the extended family: evidence from Pakistan. *Journal of development Economics*, 58(2), 485-512.

Karim, A. (2018). The household response to persistent natural disasters: Evidence from Bangladesh. *World Development*, *103*, 40-59.

Karim, A., & Noy, I. (2016). Poverty and natural disasters: A regression meta-analysis. *Review of Economics and Institutions*, *7*(2), 26.

Kazianga, H., & Udry, C. (2006). Consumption smoothing? Livestock, insurance and drought in rural Burkina Faso. *Journal of Development economics*, *79*(2), 413-446.

Keerthiratne, S., & Tol, R. S. (2018). Impact of natural disasters on income inequality in Sri Lanka. *World Development*, *105*, 217-230.

Khan, N., & Khan, M. (2019). Effects of Zarai Tarqiaiti Bank Limited Credit Program on Desi Tenda (Squash) Production in Rural Area of District Mardan-Pakistan. *International Journal of African and Asian Studies www. iiste. org ISSN*, 2409-6938.

Khandker, S. R. (2007). Coping with flood: role of institutions in Bangladesh. *Agricultural Economics*, *36*(2), 169-180

Kochar, A. (1999). Smoothing consumption by smoothing income: hours-of-work responses to idiosyncratic agricultural shocks in rural India. *Review of Economics and Statistics, 81*(1), 50-61.

Kosec, K., & Mo, C. H. (2017). Aspirations and the role of social protection: Evidence from a natural disaster in rural Pakistan. *World Development*, *97*, 49-66.

Kurosaki, T. (2014). Vulnerability of household consumption to floods and droughts in developing countries: evidence from Pakistan. *Environment and Development Economics*, *20*(2), 209-235.

Kurosaki, T. (2017). Household-Level Recovery after Floods in a Tribal and Conflict-Ridden Society. *World Development, 94*, 51-63.

Lanjouw, J. O., & Lanjouw, P. (2001). The rural non-farm sector: issues and evidence from developing countries. *Agricultural economics*, *26*(1), 1-23.

Levine, D. I., & Yang, D. (2014). *The impact of rainfall on rice output in Indonesia* (No. w20302). National Bureau of Economic Research.

Lewin, P. A., Fisher, M., & Weber, B. (2012). Do rainfall conditions push or pull rural migrants: evidence from Malawi. *Agricultural Economics*, 43(2), 191-204.

McCormick, M., Büntgen, U., Cane, M. A., Cook, E. R., Harper, K., Huybers, P., ... & Nicolussi, K. (2012). Climate change during and after the Roman Empire: reconstructing the past from scientific and historical evidence. *Journal of Interdisciplinary History*, *43*(2), 169-220.

Menon, N. (2009). Rainfall uncertainty and occupational choice in agricultural households of rural Nepal. *The Journal of Development Studies*, *45*(6), 864-888.

Mitchell, T. (2003). Northeast Brazil Rainfall Anomaly Index, 1849-2002. *Joint Institute for the Study of the Atmosphere and Ocean.* http://research.jisao.washington.edu/data_sets/brazil/ accessed on December 05, 2019

Mogues, T. (2011). Shocks and asset dynamics in Ethiopia. *Economic Development and Cultural Change, 60*(1), 91-120.

Mueller, V. A., & Osgood, D. E. (2009). Long-term consequences of short-term precipitation shocks: evidence from Brazilian migrant households. *Agricultural Economics*, 40(5), 573-586.

Mueller, V., Gray, C., & Kosec, K. (2014). Heat stress increases long-term human migration in rural Pakistan. Nature climate change, 4(3), 182-185.

Mueller, V., Sheriff, G., Dou, X., & Gray, C. (2020). Temporary migration and climate variation in eastern Africa. *World development*, 126, 104704.

Munshi, K. (2003). Networks in the modern economy: Mexican migrants in the US labor market. *The Quarterly Journal of Economics*, 118(2), 549-599.

Munshi, K., & Rosenzweig, M. (2016). Networks and misallocation: Insurance, migration, and the rural-urban wage gap. *American Economic Review*, 106(1), 46-98.

Mustafa, D. (2002). To each according to his power? Participation, access, and vulnerability in irrigation and flood management in Pakistan. *Environment and planning D: Society and space*, *20*(6), 737-752.

Nazli, Hina; Haider, Syed Hamza. 2012. Pakistan Rural Household Panel Survey 2012 (Round 1): Methodology and community characteristics. PSSP Working Paper 7. Washington, D.C.: International Food Policy Research Institute (IFPRI). http://ebrary.ifpri.org/cdm/ref/collection/p15738coll2/id/127365

Noy, I., Nguyen, C., & Patel, P. (2021). Floods and spillovers: Households after the 2011 great flood in Thailand. *Economic Development and Cultural Change*, *69*(2), 000-000

Olayide, O. E., Tetteh, I. K., & Popoola, L. (2016). Differential impacts of rainfall and irrigation on agricultural production in Nigeria: Any lessons for climate-smart agriculture?. *Agricultural water management*, *178*, 30-36.

Peterson, L. C., & Haug, G. H. (2005). Climate and the collapse of Maya civilization: A series of multi-year droughts helped to doom an ancient culture. *American Scientist*, *93*(4), 322-329.

Radel, C., Schmook, B., Carte, L., & Mardero, S. (2018). Toward a political ecology of migration: Land, labor migration, and climate change in Northwestern Nicaragua. *World Development*, 108, 263-273.

Rigaud, K. K., de Sherbinin, A., Jones, B., Bergmann, J., Clement, V., Ober, K., ... & Midgley, A. (2018). *Groundswell: preparing for internal climate migration*. World Bank.

Rijkers, B., & Söderbom, M. (2013). The effects of risk and shocks on non-farm enterprise development in rural Ethiopia. *World Development*, *45*, 119-136.

Rosenzweig, M. R., & Stark, O. (1989). Consumption smoothing, migration, and marriage: Evidence from rural India. Journal of political Economy, 97(4), 905-926.

Sawada, Y., & Takasaki, Y. (2017). Natural disaster, poverty, and development: An introduction. *World Development*, *94*, 2-15.

Sawada, Yasuyuki, Estudillo, J. P., Fuwa, Nobuhiko., Kajisa, K., Carnaje, G., & Cabanilla, L. (2009). How Do People Cope With a Natural Disaster? The Case of Super-Typhoon Milenyo in the Philippines. *Development, Natural Resources and the Environment*, 116-150.

Scharf, M. M., & Rahut, D. B. (2014). Nonfarm employment and rural welfare: evidence from the Himalayas. *American Journal of Agricultural Economics*, *96*(4), 1183-1197.

Shiferaw, B., Kebede, T., Kassie, M., & Fisher, M. (2015). Market imperfections, access to information and technology adoption in Uganda: challenges of overcoming multiple constraints. *Agricultural economics*, 46(4), 475-488.

Shoji, M. (2010). Does contingent repayment in microfinance help the poor during natural disasters? *The Journal of Development Studies*, *46*(2), 191-210.

Skoufias, E., Bandyopadhyay, S., & Olivieri, S. (2017). Occupational diversification as an adaptation to rainfall variability in rural India. *Agricultural Economics*, *48*(1), 77-89.

Sun, S., Shi, W., Zhou, S., Chai, R., Chen, H., Wang, G., ... & Shen, H. (2020). Capacity of satellite-based and reanalysis precipitation products in detecting long-term trends across Mainland China. *Remote Sensing*, *12*(18), 2902.

Thiede, B. C. (2014). Rainfall shocks and within-community wealth inequality: Evidence from rural Ethiopia. *World Development*, *64*, 181-193.

Thomas, T., Christiaensen, L., Do, Q. T., & Trung, L. D. (2010). *Natural disasters and household welfare: evidence from Vietnam*. Policy Research Working Paper 5491. The World Bank.

Waqas, M. M., Awan, U. K., Cheema, M. J. M., Ahmad, I., Ahmad, M., Ali, S., ... & Iqbal, M. (2019). Estimation of canal water deficit using satellite remote sensing and GIS: A case study in lower chenab canal system. *Journal of the Indian Society of Remote Sensing*, *47*(7), 1153-1162.

Young, W. J., Anwar, A., Bhatti, T., Borgomeo, E., Davies, S., Garthwaite III, W. R., ... & Saeed, B. (2019). *Pakistan: Getting more from water*. World Bank.

**Surveys / Data / Reports**

Food and Agricultural Organization of the United Nations (2016). The state of food and agriculture: Climate change, agriculture and food security. Accessed online dated August 18, 2018: http://www.fao.org/publications/sofa/sofa2016

Fedeal Bureau of Statistics. (2017). Economic Survey of Pakistan, 2016-17, Government of Pakistan.

Internally Displacement Monitoring Centre. (2015). Global estimates. People displaced by disasters. Norwegian Refugee Council, *Châtelaine: IDMC*.

International Food Policy Research Institute (IFPRI); and Innovative Development Solutions (IDS). 2014. Pakistan Rural Household Panel Survey (RHPS), 2012. Washington, DC: International Food Policy Research Institute (IFPRI). http://dx.doi.org/10.7910/DVN/28558

IPCC, 2019: Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems [P.R. Shukla, J. Skea, E. Calvo Buendia, V. Masson-Delmotte, H.-O. Pörtner, D. C. Roberts, P. Zhai, R. Slade, S. Connors, R. van Diemen, M. Ferrat, E. Haughey, S. Luz, S. Neogi, M. Pathak, J. Petzold, J. Portugal Pereira, P. Vyas, E. Huntley, K. Kissick, M. Belkacemi, J. Malley, (eds.)]. In press.

Pakistan Rural Household Panel Survey (PRHPS), 2012. Administered by International Food Policy Research Institute (IFPRE) and Innovative Development Strategies (IDS)

UNISDR. (2015). The human cost of weather-related disasters, 1995–2015. *United Nations, Geneva*.

World Bank; *IFC; MIGA. 2016.* World Bank Group Climate Change Action Plan 2016-2020. *World Bank*, Washington, DC. https://openknowledge.worldbank.org/handle/10986/24451 License: CC BY 3.0 IGO

## Appendix I: Some Robustness Checks

### Table A1.1 Robustness Check: Main Results using standardized monsoon rainfall which is greater than 2

| VARIABLES | (1) PC Income | (2) Crop Income | (3) FarmWage Income | (4) Non-Farm Wage | (5) Business Income | (6) Cons | (7) Food Cons | (8) NFood Cons |
|---|---|---|---|---|---|---|---|---|
| 1 if standardized monsoon rainfall is > 2 | -12,085*** | -10,018** | -865.7** | -178.0 | -1,023* | 1,908* | -750.9 | 2,659*** |
| | (4,562) | (4,749) | (329.8) | (728.6) | (596.2) | (1,067) | (530.5) | (890.0) |
| Observations | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 |

Source: Authors' estimation from the PRHS 2012, 2013 and 2014

Note: Robust standard errors, clustered around villages, are in parentheses. Table results are based on specification explained in equation 4.1 which uses household fixed effects, province-year interactions and district specific time trends.

*** p<0.01, ** p<0.05, * p<0.1

### Table A1.2 Robustness Check: Heterogeneity in the Impact of Rainfall Disaster by Access to Canals Using Crop Zone- Year interaction instead of District-Year interactions

| VARIABLES | (1) PC Income | (2) Crop Income | (3) FarmWage Income | (4) Non-Farm Wage | (5) Business Income | (6) Cons | (7) Food Cons | (8) NFood Cons |
|---|---|---|---|---|---|---|---|---|
| 1 if standardized monsoon rainfall is > 1 | -8,291** | -8,187** | 341.5 | 309.8 | -755.1 | 1,190 | 619.8 | 570.2 |
| | (4,118) | (3,654) | (377.8) | (792.2) | (595.0) | (1,290) | (593.9) | (1,163) |
| 1 if standardized monsoon rainfall is > 1 * 1 if canal is empty | -2,192 | -296.6 | -1,200*** | -953.3 | 258.3 | 2,084 | 402.2 | 1,682 |
| | (3,976) | (4,016) | (402.4) | (848.6) | (517.5) | (1,744) | (946.8) | (1,133) |
| Effect for communities when Empty Canal = 1 $\alpha_1 + \alpha_2 = 0$ | -10483 | -8484 | -859 | -644 | -497 | 3274 | 1022 | 2252 |
| F-test($\alpha_1 + \alpha_2$) | 8.752 | 8.509 | 6.218 | 0.563 | 0.0477 | 1.361 | 0.205 | 0.732 |
| Prob > F | 0.00417 | 0.00469 | 0.0149 | 0.456 | 0.828 | 0.247 | 0.652 | 0.395 |

Source: Authors' estimation from the PRHS 2012, 2013 and 2014

Note: Robust standard errors, clustered around villages, are in parentheses. Table results are based on specification explained in equation 4.2 which uses household fixed effects, province-year interactions and district specific time trends.

*** p<0.01, ** p<0.05, * p<0.1

## Appendix II: Minor items excluded from per capita income

I had to exclude livestock farming / poultry products from agriculture income due to serious issues in the data collection across three years. The questionnaire related to costs incurred on livestock changed in the third years in such a way which inflated costs for 2014 disproportionately and incomprehensibly rendering the comparison of 2014 with 2012 and 2013 illogical and futile as reflected in Table A2.1.

**Table A2.1 Livestock Expenses by Year**

| Year | Mean (Livestock Expense) |
|---|---|
| 2012 | 3397 |
| 2013 | 3110 |
| 2014 | 41796 |

Source: Author computation from original data

Similarly, other income, which comprised of building / land / equipment rent, gifts, pension, pension and others in 2012. However, income from sharing of land and animals were also included in 2013; gifts and pension were excluded from 2014 data. If these two components, that is, livestock income and other income, are included in the total income the analysis due to such issues will be unreliable. However, these components, namely, livestock income and other income constitute only 3.6% and 3.9%, respectively of overall income, reported in Table A2.2, and form a very small part of overall income and excluding them will not affect the overall analysis qualitatively.

**Table A2.2 Composition of Household Income**

| Components | Mean |
|---|---|
| Total Income | 1 |
| Crop Selling | 0.500 |
| Farm Wages | 0.066 |
| Non-Farm Work | 0.254 |
| Business Income | 0.064 |
| Remittances | 0.042 |
| Livestock Farming | 0.036 |
| Other Income | 0.039 |

Source: Authors' estimation from the PRHS 2012, 2013 and 2014

## Appendix III: Ownership of Agricultural Land

The results of impact of shock for those households who own agricultural land are reported here. As this aspect is important for agricultural households, therefore, this section is based on only agricultural households, that is, those households who are engaged in growing crops on their own, shared or rented land.

The HHs who are engaged in agricultural activity, possession of land can be an important variable to see how natural disaster affects those households who possess land and those who prefer risk sharing by opting for sharecropping (Fafchamps. 1999: 30). Possession of land can be used as collateral for securing loans, on the other hand, some growers may opt for sharecropping with those who own land as an ex-ante risk reduction strategy – which can benefit both by sharing costs.

Therefore, the households who are engaged in agricultural activity, possession of land can be an important variable and it can be instructive to see how natural disasters affect those households who possess land and more likely to engage in agriculture related activities. This analysis is done only for agricultural households. The binary variable, Land, takes the value of 1, if a household owns agricultural land, and ‘0’ otherwise. The uninteracted term show a big significant decrease in per capita income, crop income and farm wages for those engaged in agriculture but having no land of their own.  The net estimate for agricultural households possessing land during a shock is significant but negative in column 1-3 of Table 4.7, which also means the increase in income for landowners is not strong enough to fully mitigate the large negative effect of rainfall shock. The gap in the two coefficients is also significant in these columns.

**Table A3.1 Heterogeneity in the Impact of Rainfall Disaster by Ownership of Agricultural Land (Only agricultural households)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | PC Income | Crop Income | FarmWage Income | Non-Farm Wage | Business Income | Cons | Food Cons | NFood Cons |
| 1 if standardized monsoon rainfall is > 1 ($\alpha_1$) | -22,496*** | -21,178*** | -1,191*** | 42.44 | -169.0 | 1,743 | -412.1 | 2,155 |
| | (6,385) | (6,422) | (354.0) | (804.6) | (699.0) | (1,797) | (1,013) | (1,567) |
| 1 if standardized monsoon rainfall is > 1 * 1 if household owns land | 11,832** | 11,115** | 591.5** | 257.4 | -132.0 | 818.4 | 1,375** | -556.5 |
| ($\alpha_2$) | (5,109) | (4,944) | (252.8) | (621.1) | (583.0) | (1,324) | (684.2) | (1,054) |
| Effect of shock for landowners $\alpha_1 + \alpha_{2\ =\ 0}$ | -10664 | -10063 | -599.5 | 299.84 | -301 | 2561.4 | 962.9 | 1598.5 |
| F-test($\alpha_1 + \alpha_2$) | 3.117 | 2.659 | 3.510 | 0.123 | 0.341 | 2.734 | 1.202 | 1.043 |
| Prob > F | 0.0816 | 0.107 | 0.0650 | 0.727 | 0.561 | 0.103 | 0.276 | 0.310 |
| Observations | 2,854 | 2,854 | 2,854 | 2,854 | 2,854 | 2,854 | 2,854 | 2,854 |

Source: Authors' estimation from the PRHS 2012, 2013 and 2014

Note: Robust standard errors, clustered around villages, are in parentheses. Table results are based on specification explained in equation 4.2 which uses household fixed effects, province-year interactions and district specific time trends.

*** p<0.01, ** p<0.05, * p<0.1

The positive coefficient of interaction of shock with agricultural land ownership may be difficult to interpret as these households are more likely to be associated with agricultural sector which is severely affected due to natural shocks observed in Table 4.3. The similar results were reported by Kurosaki (2014) for Pakistan, who speculated the possibility of interpreting the results indirectly in terms of political power wielded by the big landowners. These landlords, according to him, can maneuver irrigation system to their advantage and thus mitigate the impact of disaster for themselves. The interpretation is convincing as the theft of canal water as well as maneuvering of irrigation department to the advantage of influential landlords is well known characteristic of Pakistan's irrigation system (World Bank, 2019; 62-65; Mustafa, 2002).

Unlike land ownership, the possession of relatively liquid agricultural assets, for example, farm assets and livestock, as well as the household assets, in terms of their initial monetary value, does not provide any cushion to households in the event of rainfall shock.[59] This might be due to the reason that households in developing countries are reported to avoid selling their assets and, instead, prefer to mitigate their income losses by participating in non-farm income activities or through borrowing from credit markets (Fafchamps, Udry and Czukas. 1998; Kazianga and Udry, 2006). The favorable impact of land ownership as discussed above seems to be its political power attached with it.

[59] Results not reported

## Appendix IV: Attrition

The total number of households interviewed for each wave of the Pakistan Rural Household Panel Survey (PRHPS) data is reported in the Table A4.1. Though the attrition is not more than 10%, however, the possibility of attrition causing any attrition bias resulting in sample selection bias is checked.

**Table A4.1 Households Interviewed in Different Years**

| Year | Freq. | Household Interviewed (Percent) |
|---|---|---|
| 2012 | 2,090 | 100 |
| 2013 | 2,002 | 95.789 |
| 2014 | 1,876 | 89.761 |

**Source**: Authors' computation from the PRHS 2012, 2013 and 2014

In order to check the attrition bias which may possibly be present in the three-year sample data, attrition regressions are exploited in which household or community characteristics are used as explanatory variables. The outcome variable of Attrition is created for this purpose, which takes the value of 1, if a household shows up in all three waves of three-year data and, 0, if the households is present in first wave for year 2011-12 and absent from one or both of the next waves of 2012-13 or 2013-14. It is evident from the Table A4.2 that 1842 households are present in all three waves.

**Table A4.2 Households Present in All Three Waves**

| Attrition | Freq. | Percent | Cum. |
|---|---|---|---|
| 0 | 248 | 11.87 | 11.87 |
| 1 | 1,842 | 88.13 | 100 |
| Total | 2,090 | 100 | |

**Source**: Authors' computation from the PRHS 2012, 2013 and 2014

It will be useful to see if this attrition results in any attrition bias or sample selection bias. In the table A4.4 the household and community characteristics are used as explanatory variables for the outcome variable of Attrition.

**Table A4.3 Attrition Regressions to Check Attrition Bias**

| VARIABLES | (1)<br>Attrition | (2)<br>Attrition | (3)<br>Attrition |
|---|---|---|---|
| Household Savings | -4.45e-09 | | 2.95e-08 |
| | (8.14e-08) | | (7.80e-08) |
| Household head education | 0.00116 | | 0.00116 |
| | (0.00185) | | (0.00183) |
| Dependency Ratio | 0.0480 | | 0.0450 |
| | (0.0339) | | (0.0336) |
| Agricultural Area Owned | 0.00205* | | 0.00188* |
| | (0.00108) | | (0.00106) |
| Household head age | 0.00168*** | | 0.00165*** |
| | (0.000577) | | (0.000571) |
| Gender Ratio | 0.0158** | | 0.0182*** |
| | (0.00633) | | (0.00624) |
| Household Size | 0.00484** | | 0.00402* |
| | (0.00244) | | (0.00241) |
| Urban Access | | -0.00116*** | -0.00116*** |
| | | (0.000270) | (0.000272) |
| No Canal | | -0.00236*** | -0.00231*** |
| | | (0.000358) | (0.000358) |
| Railway Station | | -0.0679*** | -0.0697*** |
| | | (0.0214) | (0.0213) |
| Observations | 2,090 | 2,090 | 2,090 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Column 1 of Table A4.3 reports the regression estimates where all the household characteristics have been used. It can be seen that the households owning more than the median agricultural area are more likely to attrit. Similarly, household with relatively larger household size or relatively older household heads have more tendency to attrit.

Column 2 of Table A4.3, similarly, reports community characteristics of living near railway station, away from urban area or having poor irrigation facilities, and all three seem to have significant tendency to attrit. The estimates are not very different in column 3 where all the household and community characteristics have been cumulatively checked.

The time invariant household characteristics can be addressed by the strategy of household fixed effects used in this study. Community characteristics – urban access, location of railway station or irrigation facilities – and household ownership of agricultural land have been reported only once for the first wave data collected for 2011-12 and, therefore, are less likely to be a cause of concern. However, time variant characteristics of household size, gender and the age of household head can be problematic, out of which, the variable of age is not affected by any social or human decisions that leaves household size and gender ratio only which can be problematic.

All the time variant characteristics – which have been reported for more than one year – are checked in Table A4.4 where all of them are used as control variable along with explanatory variable of rainfall shock and they do not seem to change the main results reported in Table 4.3

**Table A4.4 Main Results with Time Variant Household Characteristics as Controls**

| VARIABLES | (1)<br>PC Income | (2)<br>Crop Income | (3)<br>FarmWage Income | (4)<br>Non-Farm Wage | (5)<br>Business Income | (6)<br>Cons | (7)<br>Food Cons | (8)<br>NFood Cons |
|---|---|---|---|---|---|---|---|---|
| 1 if standardized rainfall shock is > 1 | -7,860** | -6,740* | -596.0** | 182.0 | -705.7 | 2,051** | 264.5 | 1,787* |
| | (3,827) | (3,731) | (285.0) | (742.3) | (450.6) | (983.5) | (662.3) | (1,038) |
| Dependency Ratio[1] | 5,180 | -2,779 | 102.6 | 3,822 | 4,034 | -28,030*** | -11,860*** | -16,170*** |
| | (11,724) | (6,088) | (974.6) | (9,740) | (2,711) | (5,576) | (3,548) | (3,789) |
| Age of Household Head[2] | 277.4 | 198.8 | -148.2 | 195.6* | 31.19 | 156.2 | 142.4 | 13.80 |
| | (1,032) | (842.3) | (136.5) | (99.18) | (99.19) | (99.13) | (213.9) | (151.9) |
| Household Size[3] | -1,830** | -681.1 | -211.5** | -933.3* | -3.986 | -759.5* | -1,070*** | 310.2* |
| | (909.5) | (570.3) | (105.9) | (499.3) | (138.1) | (381.2) | (287.4) | (182.1) |
| Gender Ratio[4] | 1,517 | 623.9 | -621.5** | 89.77 | 1,425** | -2,475*** | 14.79 | -2,489*** |
| | (1,560) | (1,448) | (254.1) | (622.3) | (542.6) | (867.6) | (477.8) | (670.7) |
| Marital Status[5] | 11,848*** | 6,030* | 90.22 | 5,267*** | 460.5 | -6,550 | -6,307 | -243.9 |
| | (3,176) | (3,217) | (340.2) | (1,272) | (743.3) | (7,000) | (6,837) | (2,083) |
| Observations | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 | 5,358 |

Source: Authors' estimation from the PRHS 2012, 2013 and 2014
Note: Robust standard errors, clustered around villages, are in parentheses. Table results are based on specification explained in equation 2 which uses household fixed effects, province-year interactions and district specific time trends.
*** p<0.1, ** p<0.05, * p<0.1
[1] Dependency Ratio is the ratio of number of dependents in a household to the total household size
[2] Age of household head
[3] Household size
[4] Gender ratio is the ratio of number of male members to the number of female members in a household
[5] Marital Status takes the value of 1 if married and otherwise 0

The results reported in above table are not only qualitatively same with the main results of Table 4.3, but even the coefficients do not differ much, for example, the coefficient of rainfall shock for per capita income shows that if there is rainfall shock, or if standardized rainfall is greater than 1 standard deviation, the reduction in per capita income is 7860 which is significant at 5%. The main table reports, without household controls, the coefficient as 8061 with same significance level. Therefore, the possibility of attrition bias can be ruled out.