Vulnerability of Households to Weather Shocks and the Mitigating Role of Workfare Programs

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September 2018

Abstract

What impact do adverse weather shocks have on household living standards? Using a large household panel survey in India and geo-coded climate data, I find that rainfall shocks lower household income by 6%. Consumption declines by 3%, albeit with a lag, while household debt rises by 51%. Rainfall shocks affect rural households and the asset-poor. It shrinks agricultural and non-agricultural wage incomes and exhibit heterogeneous impact across states. A related policy question is the effectiveness of public safety nets in mitigating weather-induced impact. Using a difference-in-difference strategy and the nationwide roll-out of a public workfare program in India, I find that, participating in the program raises household income by 10% in districts affected by rainfall shocks. Moreover, its impact on female-headed households is nearly five times as large. Thus, by acting as public safety nets, workfare programs can increase climate resilience.

1 Introduction

Increasing variability in the weather poses major economic and non-economic challenges (see IPCC 2014, Fischer and Knutti 2015, Morton 2007, Mani et al. 2018, Rigaud et al. 2018, etc.). The effects are most conspicuous in the rural areas of developing countries (Loayza et al. 2012, Skoufias 2012). There are three reasons for this: first, rural households

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predominantly depend on agriculture for their livelihood. Second, absent or incomplete financial markets constrain farmers from insuring against crop failures, which increase vulnerability (Rose 2001, Dercon 2002, Cole et al. 2013). Third, negative weather shocks might reinforce existing socioeconomic disadvantages that lower adaptive capacity (Flatø et al. 2017). For the rural poor facing multiple socioeconomic stressors, negative weather shocks can reduce earnings, increase the debt-burden and adversely affect the quality of life, sometimes with fatal consequences (Mani et al. 2018, Carleton 2017, Burke et al. 2018). Hence, to build a climate-resilient future, it is imperative that we understand how negative weather shocks affect lives at the most granular level.

Yet, our understanding of the heterogenous impact of weather shocks on households, the different coping measures these households adopt, and the role of public safety nets in moderating its effect, is far from complete. To fill this knowledge gap, I use a large household panel survey in India administered in 2005 and 2012 along with geo-coded climate data, to examine the causal effect of weather shocks on household living standards. Identification comes from within-household variations in unanticipated weather shocks that are orthogonal to time-invariant determinants of household living standards. In this study, I concentrate on a specific source of weather shocks – unanticipated variation in rainfall – which mainly affect rural households. I then examine the impact of the phasewise roll-out of a nationwide public workfare program – the Mahatma Gandhi Rural Employment Guarantee Scheme (NREGS) – on household income in districts affected by adverse rainfall shocks.[1] To measure impact, I compare the change in income for households that participated in NREGS with the change in income for households that were eligible, but did not participate. In estimating the results, I address the non-random selection of districts into NREGS phases.

To preview the main results, I find that rainfall shocks reduce household income by around 6%. The weather-induced loss in income is equivalent to about one month's earnings for the average-income household. This result is robust to a placebo treatment of a series of randomly drawn rainfall shocks, including higher order lags of rainfall shocks, sample selection due to permanent out-migration, using alternative measures of rainfall shocks, winsorising the data to guard against outliers and varying the empirical specification to accommodate the length of exposure to shocks or, controlling for time-varying factors such as temperature. I find that rainfall shocks impact the rural poor. It mainly affects agriculture income and non-agricultural wage income. Although socioeconomic barriers

[1] An institutional feature of NREGS is that it 'guarantees' 100 days of unskilled manual work. The National Rural Employment Guarantee Act (NREGA), 2005 clearly says that the state government is mandated to provide work within fifteen days of receiving the application to work, failing which the applicant will be entitled to an unemployment allowance. Thus, the seasonality of NREGS work is less of a concern in this study.

are associated with lower household income, I find no evidence to suggest that rainfall shocks exacerbate existing socioeconomic barriers, once its direct effect is accounted for. With regard to debt-burden and consumption, rainfall shocks increase the former by about 51%, while it reduces the latter by slightly more than 3%, albeit with a one-period lag. Another interesting result is the positive role that public safety nets play in mitigating rainfall-induced impact. I find that participating in NREGS increases household income by 10% in districts affected by rainfall shocks. Its impact on female-headed households is nearly five times as large. Furthermore, to ensure that the estimates are representative of all the states and union territories in India, I use the sampling weights provided in the household survey in all the regressions.

In general, negative weather shocks lower household living standards (Mani et al. 2018). For instance, erratic rainfall might lead to crop failures that shrink agricultural income. The shock-income gradient might however differ by household characteristics. In South Africa, for example, the weather-induced decline in income is steeper for female-headed households (Flatø et al. 2017). The extent to which shocks affect households might be correlated with asset-ownership. In India, rainfall shocks affect landless farmers but not the landed (Townsend 1994). In this study, I test this empirically by interacting rainfall shocks with socioeconomic characteristics of households in section 4.1. I also re-estimate the primary relationship between rainfall shocks and income on different sub-samples to identify the groups most vulnerable to weather shocks.

Households adopt several coping measures to insulate consumption from fluctuations in income (Wolpin 1982). They make important trade-offs between saving, consumption and debt.[2] Against this background, how do rainfall shocks affect household consumption expenditure and debt-burden in India? Understanding this is important because of its high human cost. For instance, a recent study suggests that weather adversities claimed as many as 60,000 farmer deaths over a span of 30 years in India (Carleton 2017).[3] I engage with these questions in section 4.2. With incomplete risk-pooling, as is often the case in informal economies (Townsend 1994, Ligon et al. 2002), public safety nets can

[2]Households draw down their savings or assets such as cash, grain, livestock or farm implements to smooth consumption (Paxson 1992, Rosenzweig and Wolpin 1993, Udry 1995). They diversify income *ex-ante* (Morduch 1995). They invest more in low-risk low-return activities and less in activities that enhance productivity but are more risky (Dercon 2002, Dercon and Christiaensen 2011, Gebremariam and Tesfaye 2018). To cope with weather shocks, households adjust their labour supply and reallocate hours worked from farm to off-farm employment (Rose 2001, Kochar 1995, 1999). In the absence of formal insurance and credit markets, common in high-risk informal environments, loans based on family or kinship ties fill this gap, allowing households to smooth consumption. In Nigeria, for example, Udry (1994) finds that loan contracts are state-contingent, with more favourable repayment terms for those affected by a negative shock.

[3]Weather-induced suicides are not just limited to developing countries. In the United States and Mexico, suicide rates rise with increasing temperature (Burke et al. 2018).

insure households against weather-induced income volatility (Dercon 2002). In section 4.3, I analyse the impact of a public workfare program in moderating the effect of weather shocks.

India provides rich ground to study the impact of variations in weather at the micro-level. First, India's land area encompasses several climatic conditions. Three-fourths of its cropped area is in the semi-arid tropics and much of it is drought-prone (CED 2011). Secondly, with almost one-half of its population affected by climate change (Mani et al. 2018), India accounts for a sizeable share of the climate-vulnerable population in developing countries. Thus, the results from this study will be directly relevant to a substantial share of the population vulnerable to climate change.

While the literature has made significant advances in understanding how weather variability affects households, gaps still exist. First, there is relatively little quantitative evidence on the heterogeneous impact of weather-related shocks. To efficiently target adaptation policies, identifying the groups most vulnerable to weather shocks is extremely important. Second, I study the impact of an aggregate shock – variation in rainfall at the district level – on household living standards. Aggregate shocks affect the entire village or district. In contrast, idiosyncratic shocks such as death or disease affect an individual or household. As covariate shocks are harder to insure than idiosyncratic shocks, this study sheds light on an important source of risk for low-income households. Third, I examine the impact of weather shocks on different sources of income. Besides revealing the pathways of impact, I test the feasibility of *ex-ante* income diversification as an effective coping measure. Finally, the role of public workfare programs in acting as safety nets during times of weather-induced hardship has not been studied widely. By examining the impact of NREGS in rainfall affected districts, this study sheds light on an important policy question.

I make three important contributions in this study. First, I examine the relationship between weather shocks and living standards using household-level panel data, which controls for unobserved household-specific heterogeneity. In contrast, cross-sectional studies are unable to control for this, which might result in omitted variables bias. This might arise, for instance, if better-informed households proactively invest in climate-resilient crops. Not accounting for such unobserved differences will downward bias the impact of rainfall shocks. Moreover, the large sample size ensures that the coefficients are precisely estimated. Second, inspired by Burke et al. (2015), I construct an exogenous measure of rainfall shocks to analyse impact. To this end, I fit a statistical distribution of monsoon rainfall for every district during 1980-2012 and define the realisation of a shock to be one where a district's rainfall is either below the 20^{th} percentile or exceeds the 80^{th}

percentile of its rainfall distribution over past 30 years. As this captures unanticipated variation in rainfall, it is exogenous by design and orthogonal to time-invariant determinants of household living standards, which allows for clear identification. The results from this study contribute to the literature on the relationship between weather shocks and household living standards in a developing country context. Finally, I analyse the impact of NREGS in mitigating rainfall-induced impact, which highlights the important role that public safety nets play in increasing climate resilience.

The rest of the paper is organised as follows: In section 2, I outline the framework that connects rainfall shocks to household living standards and introduce the dataset. In section 3, I discuss the empirical strategy. Section 4 presents regression results, illustrates the effectiveness of NREGS as a safety net, discusses the implications of the results, and presents extensions to gain deeper analytical insight. Section 5 presents several robustness checks. Section 6 concludes.

2 Climate Change and Household Living Standards

The weather exerts a strong influence on income (see discussion in Dell et al. 2014). Although today we understand a great deal about the science behind the different weather phenomena, the vagaries of the weather affects the lives of millions. To add some details, a recent World Bank report suggests that climate change will result in 143 million 'climate migrants', predominantly in developing countries, if no immediate action is taken to combat its impact (Rigaud et al. 2018). It also suggests optimistically that with adequate development planning the number of climate-migrants can be reduced by 80% to about a manageable 40 million. Achieving this target however will require adaptation policies informed by micro-level evidence on the impact of weather shocks on households.

Figure 1 illustrates how, for a particular weather shock, households might experience varying degrees of weather-induced burden. In this study, a weather shock constitutes variation in rainfall during the preceding monsoon season (more on this in section 2.2). If households are homogenous in all respects they would each experience a shock of equal magnitude for a given severity of rainfall shock. However, this is not realistic. In fact, households face different 'mitigating' and 'intensifying' factors that affect weather-induced impact. For example, weather shocks might exert a larger impact on rural households that depend on agriculture. The impact might be worse if they are asset-poor. On the other hand, access to public safety nets might moderate the intensity of weather shocks. This might, in itself, be influenced by household characteristics such as the household-head's gender. Thus, it is the combined effect of all these factors that determine the actual

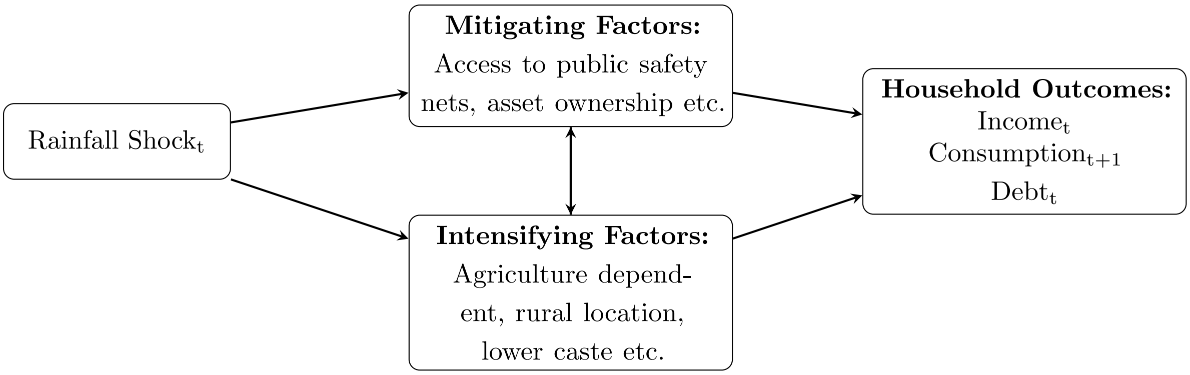

Figure 1: Conceptual framework of the relationship between rainfall shocks and its burden on households.

weather-induced burden on households. To what extent are the different mitigating and intensifying factors salient in India? To address this question, I combine panel data on more than 40,000 Indian households per survey round with high-resolution gridded climate data.

I am guided by economic theory in selecting the household-level economic variables – the dependent variables in the empirical model. Since income affords purchasing power, it is instrumental in gaining access to a wide array of resources. This has first order impact on household living standards and is therefore a natural choice. But, as Deaton (2005) argues, consumption better approximates direct living standards of households. To explore how weather shocks affect them, I include household-level consumption expenditure in the analysis. To smooth weather-induced income variability, households might take-up more debt which might drag them deeper into poverty. Hence, I examine the effect of rainfall shocks on household debt-burden and its consequences on household-level poverty.

Next, I introduce the data and discuss the variables created to conduct the empirical analysis.

2.1 Household Level Data

I obtained data on household income, consumption, debt, poverty status and several other household-specific characteristics from two consecutive rounds of the India Human Development Survey (IHDS). IHDS is a nationally representative, multi-topic survey jointly conducted by the University of Maryland and the National Council of Applied Economic Research (NCAER). It covers 33 states and union territories and 384 districts. The IHDS sampling frame is divided into two samples: a rural sample and an urban sample. The rural sample is a stratified random sample of rural households in India. The urban sample is a stratified random sample of towns and cities within states (or groups of states) which are selected by probability proportional to population. The first round (IHDS-I), conducted in 2005, interviewed 41,554 households in 1503 villages and 971 urban blocks. The follow-up survey in 2012 (IHDS-II) re-interviewed 83% of the households from 2005, and covered 1420 villages and 1042 urban blocks.[4] IHDS-II provides information on 42,152 households, which includes an additional replacement sample of 2,134 households.[5] One main advantage of using the IHDS survey is its panel structure, which allows to control for unobservable household-specific heterogeneity in a regression analysis.

IHDS provides data on income, consumption, and debt are in nominal prices. To obtain their real equivalents, I multiply the values of the respective variables in 2012 with the deflator provided in IHDS-II. This yields 2012 values in 2005 constant prices. In addition, while IHDS reports monthly per capita consumption expenditures (MPCE) in 2005, it reports annual household consumption in 2012. To maintain consistency across the two survey rounds, I divide the 2012 consumption values by 12 to arrive at its monthly equivalent. Finally, I transform the dependent variables to a log scale. Among the three continuous economic variables that I examine in this study – income, consumption, and debt – debt has many zero values. This is expected since only a small fraction of the households take-up debt. To deal with missing values, I use the log transform on (1 + Debt) to avoid omitting a bulk of the data, which might otherwise lead to selection bias.

Table 1 presents summary statistics. The average log household income, log (Income), was 10.4 in 2005, increasing to 10.6 in 2012. The overall income across the two survey rounds was 10.5 on a log scale with significant variation across households. Figure 2 maps districtwise variations in average household income (in logs) across IHDS rounds I and II. With regard to consumption. the average log consumption expenditure, log(MPCE), was about 7 across the two survey rounds. Figure 3 maps districtwise varaitions in log(MPCE). Not surprisingly, the maps show regional differences in income and consumption. Households in the Central and Eastern regions in India have lower income and consumption per capita than other districts in the country. In contrast, districts in South India have higher levels of income and consumption.

With regard to household debt, the table shows that the average log household debt was around 5 with significant variability amongst households. IHDS also provides information

[4] One concern is the bias arising from sample attrition due to out-migration of households that are worst affected by weather shocks. Although weather-induced migration in India is quite low to be a significant concern (see Viswanathan and Kumar 2015), I address this problem head-on in section 5.3.

[5] IHDS-I was administered between November 2004 and October 2005, while IHDS-II was administered between January 2011 and May 2013. The majority of the interviews however were conducted during 2004 and 2012 for IHDS-I and IHDS-II, respectively. I take the interview date into account to match rainfall data to respective districts. See section 2.2 for details.

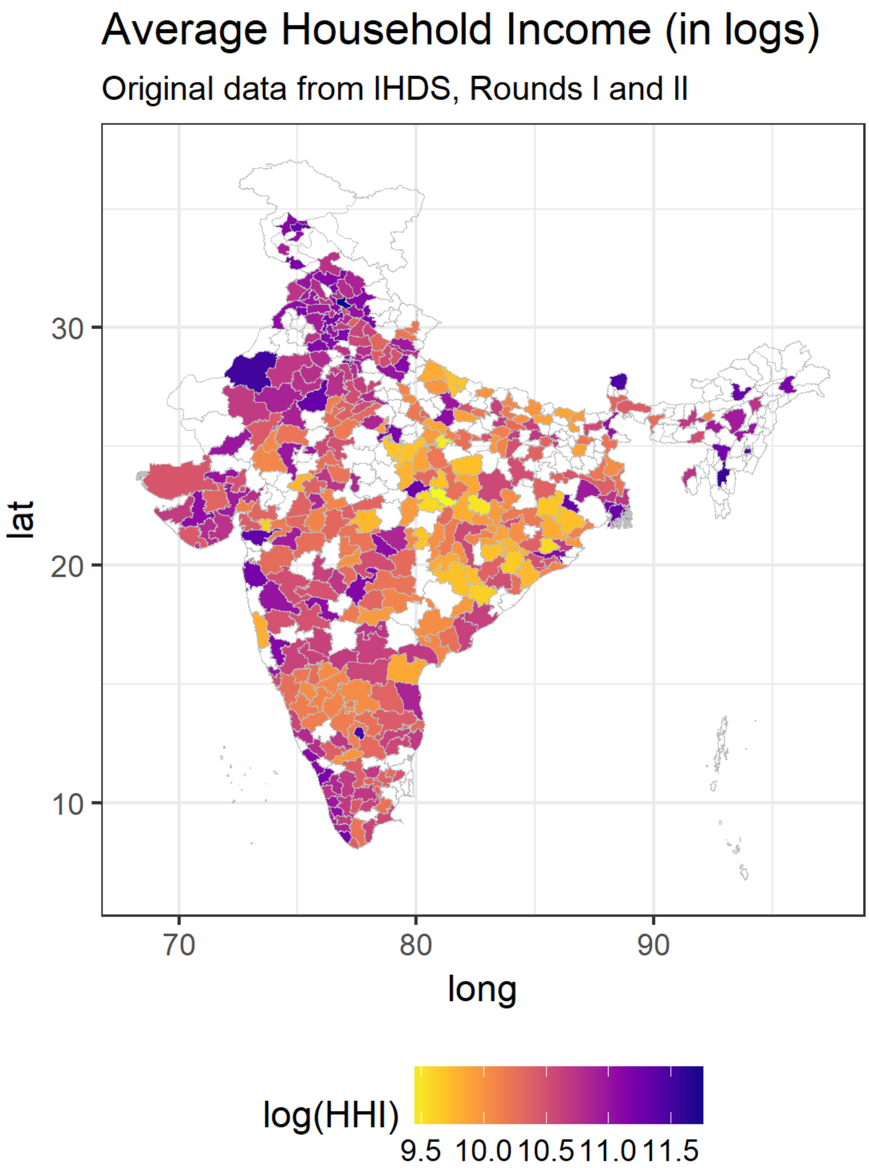

Figure 2: Districtwise average household income in logs (log(HHI)).
Notes: Figure illustrates districtwise log(HHI) averaged over IHDS survey rounds I and II. The scale ranges from low to high where districts shaded yellow report low log(HHI) whereas, districts shaded dark blue report higher values. Unshaded regions are districts not covered in the IHDS survey.

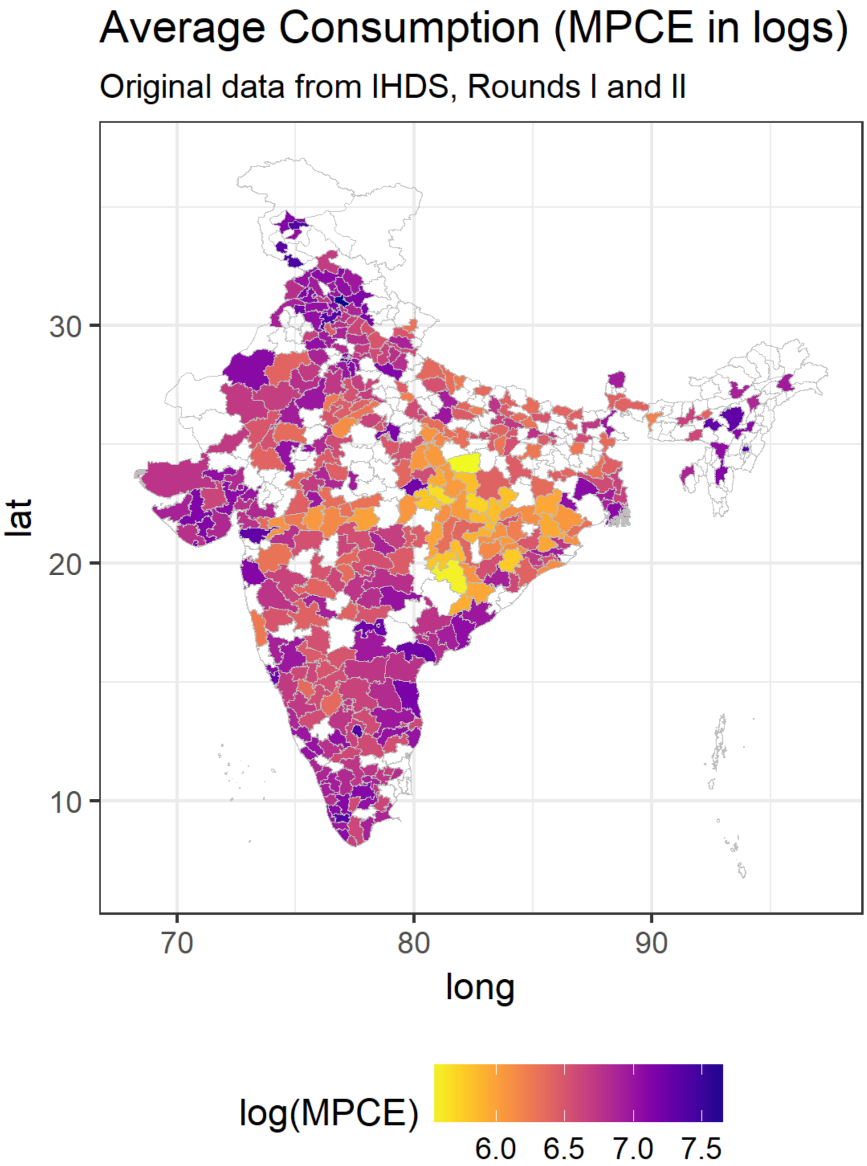

Figure 3: Districtwise monthly per capita consumption expenditure in logs (log(MPCE)). Notes: Figure illustrates districtwise log(MPCE) averaged over IHDS survey rounds I and II. The scale ranges from low to high where districts shaded yellow report low log(MPCE) whereas, districts shaded dark blue report higher values. Unshaded regions are districts not covered in the IHDS survey.

Table 1: Descriptive Statistics

Variable	2005		2012		Total	
	Mean	SD	Mean	SD	Mean	SD
Dependent variables:						
log(Income)	10.40	1.017	10.59	1.068	10.50	1.047
log(MPCE)	6.50	0.688	6.82	0.691	6.66	0.708
log(1+Total Debt)	5.25	4.932	4.84	5.033	5.03	4.990
BPL Households	0.22	0.415	0.17	0.374	0.19	0.396
Main covariates:						
$\text{Rainshock}_{\text{t}}$	0.31	0.462	0.35	0.476	0.33	0.469
NREGS_{2012}	-	-	0.16	0.362	-	-
Household Controls:						
No. of Members	5.85	3.029	4.87	2.341	5.36	2.751
Agriculture Dep.	0.43	0.495	0.37	0.483	0.40	0.490
Urban	0.29	0.456	0.32	0.466	0.31	0.461
Low Caste (SC/ST)	0.30	0.457	0.30	0.459	0.30	0.458
Muslim	0.12	0.319	0.11	0.318	0.11	0.319
Assets Index	11.79	6.046	15.19	6.601	13.49	6.553
Household-Head Controls:						
Female Headed	0.09	0.292	0.14	0.352	0.12	0.324
Age of Household Head:						
Age$\leq$25	0.03	0.162	0.02	0.142	0.02	0.152
25$<$Age$\leq$40	0.31	0.463	0.26	0.440	0.29	0.452
40$<$Age$\leq$60	0.49	0.500	0.50	0.500	0.49	0.500
Age$\geq$60	0.17	0.380	0.22	0.414	0.20	0.398
Literate	0.64	0.481	0.67	0.470	0.65	0.476

Notes: Table shows descriptive statistics. BPL=Below Poverty Line. BPL is based on a state-specific poverty line that determines whether a household is poor. NREGS=National Rural Employment Guarantee Scheme. In this table, NREGS, shows the fraction of households receiving positive income from NREGS in 2012 whereas, $\text{Rainshock}_{\text{t}}$ is the fraction of households living in districts affected by unanticipated rainfall shocks. A rainfall shock is defined as a dummy variable that takes a value of 1 if the rainfall during the preceding monsoon within a particular district either falls below the 20^{th} percentile or exceeds the 80^{th} percentile.

on whether a household is poor. This variable takes a value of 1 if the household's income falls below the poverty line (BPL), while it takes a value of zero if its income is above the poverty line.[6] In the sample, about 20% of the households were below the poverty line.

Besides the economic variables facing households, I also gathered information on several indicators of socioeconomic status. A household on average had 5.4 members. Nearly 40% of the households were agriculture dependents i.e. households that reported agriculture as their main source of income. The predominance of agriculture as a source of livelihood in India illustrates the widespread impact that weather variations might result. About 31% of households were urban-based. With regard to socioeconomic conditions, nearly 30%

[6]IHDS-I followed the official Planning Commission poverty line of 2005 based on monthly per capita consumption, whereas IHDS-II followed the Tendulkar poverty line estimates of 2012.

of the households belonged to the disadvantaged sections of society i.e. the Scheduled Castes or the Scheduled Tribes. Around 11% of households were Muslims. The average asset-index, measured on a 0–33 points scale, with higher values indicating more assets owned, was 11.8 in 2005 increasing to 15.1 in 2012, and averaging 13.5 over the two survey rounds.

I also gathered information on household heads from individual-level IHDS data files for both the survey rounds. This included information on whether the household head was a female, their age classified into four groups: less than 25 years, between 25-40 years, between 40-60 years and above 60 years, and whether the household head was literate. I find that nearly 12% of the households were female-headed; the majority of the household heads belonged to the 40-60 age group; and, about 65% of the household heads were literate. IHDS-II also provides information on whether households received any income from NREGS work. Data shows that 16% of the sample received payment for NREGS work in 2012.[7]

2.2 Weather Data and Construction of Shocks

To create the rainfall shock series, I obtained gridded data on monthly rainfall during 1980-2012 from Willmott and Matsuura (2015). This database provides global high-resolution monthly rainfall data in centimetres on 0.5 degree latitude x 0.5 degree longitude grids. I then overlaid the gridded rainfall data on India's district GIS boundaries to obtain an area-weighted average value of monthly rainfall for each of the districts from 1980-2012. In this study, I focus on 'annual monsoon rainfall' or the rainy season, which spans the months of June to September in India. This is because rainfall during the monsoon season is absolutely critical for Indian agriculture. Figure 4 plots the distribution of annual monsoon rainfall during 2005-2012.

However, rainfall is location-dependent and therefore endogenous to a model that determines variation in economic variables. The literature presents different ways to estimate weather shocks (see Dell et al. 2014 for a detailed list of measures used in the literature). Most commonly, however, weather shocks are measured as deviations from a location's long term mean, computed either in levels or in percentage. In this study, inspired by Burke et al. (2015), I fit a gamma distribution to every district's monsoon rainfall during 1980-2012 to compute the relative monsoon rainfall experienced by a district during a year. I then define a rainfall shock to be a dummy variable that takes a value of one if

[7]Note that NREGS began implementation in 2006 and hence there is no data for the 2005 survey period. See Figure 7 for the timeline on NREGS implementation and the adminsitration of the IHDS survey rounds.

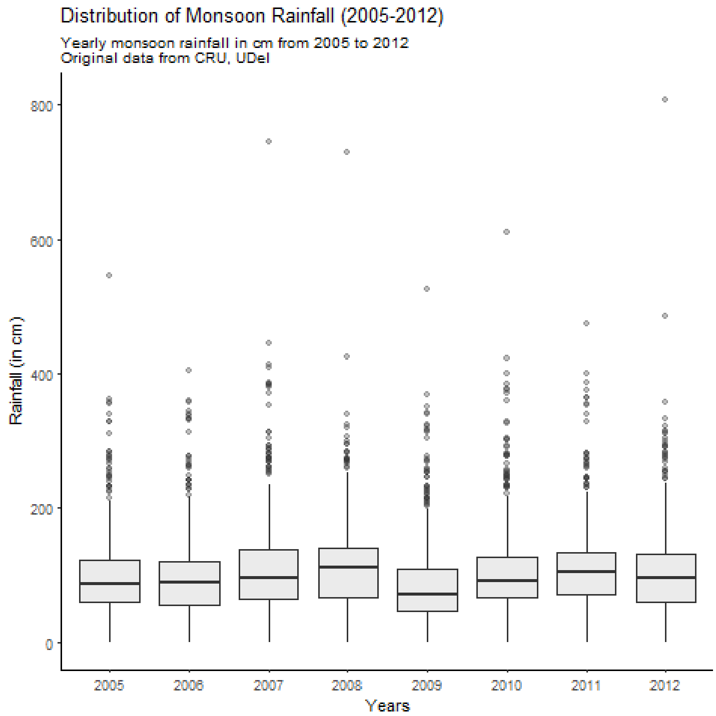

Figure 4: Distribution of Annual Monsoon Rainfall in India During 2005-2012.
Notes: Figure shows annual distribution of rainfall during the months of June to September in a calendar year during 2005-2012.

a district's monsoon rainfall is either below its 20th percentile (a drought-like condition) or exceeds its 80th percentile (a flood-like condition) during past 30 years, and is zero otherwise (normal rainfall).[8] The location-specific shock is defined relative to its past rainfall distribution, and uses the same (lower and upper) percentile thresholds (rather than absolute cut-offs), which makes it exogenous to time-invariant factors that affect household living standards. Defining rainfall shocks in this way captures the unanticipated variation in rainfall that affects households, which aids identification. One advantage of using a binary variable to capture rainfall shocks is that it imposes weaker functional form assumptions in the regression analysis.[9]

I match rainfall shocks with information on households using a simple timing-rule. For households interviewed on or after the onset of the monsoon season, I attribute the rainfall shocks corresponding to the interview-year. However, if households were interviewed before the onset of that year's monsoon i.e. if they were interviewed during January-May of the

[8] The 20th percentile and 80th percentile thresholds to define rainfall shocks are used in Jayachandran (2006), although they code shocks differently. On the other hand, Burke et al. (2015) consider rainfall below the 15th percentile as a rainfall shock in sub-Saharan Africa and focus on the number of shocks in the last 10 years.

[9] In sections 4.5.4 and 5.4.4, I show that the main results are robust to alternative definitions of rainfall shocks.

interview-year, I attribute the rainfall shocks for the preceding rainy season. Because rainfall shocks are at the district-level, changes in district boundaries between the survey years need to be accounted for. Both IHDS rounds I and II provide district identifiers for every household that correspond to the 2001 census year. I use this to attribute rainfall shocks to more than 370 districts in the sample.

Referring back to the descriptive statistics in Table 1, it shows that one-third of the households experienced a rainfall shock in at least one of the survey rounds. While 31% of the households experienced a rainfall shock in 2005, it was higher at 35% in 2012. Figure 5 maps districtwise rainfall shocks in 2005 whereas, Figure 6 maps districtwise rainfall shocks for 2012. In both the figures, districts shaded green experienced a normal monsoon whereas, those in either blue or yellow experienced a rainfall shock. Moreover, the blue-shaded districts experienced a positive rainfall shock (a flood-like situation), while the yellow-shaded districts experienced a negative rainfall shock (a drought-like situation).

I now turn to discuss my empirical strategy.

3 Empirical Strategy

The main objective of this study is to examine the effect of variation in rainfall on household living standards. To this end, I estimate the following regression:

$$y_{idt} = \beta Rainshock_{dt} + \gamma X_{idt} + \alpha_i + \phi_t + u_{idt} \tag{1}$$

where y_{idt} is a dependent variable (income, consumption, debt, all in log scale, and poverty status), for household i in district d at time t. $Rainshock_{dt}$ is a dummy variable that takes a value of 1 if the district is exposed to a rainfall shock, with β its coefficient. Thus, $Rainshock_{dt}$ is a covariate shock that applies to all the households within district d. X_{idt} is a vector of household-level controls. It includes information on the caste, religion or location of households. It also controls for household head's gender, age and literacy with corresponding coefficient vector, γ. The variables contained in X_{idt} directly affect the dependent variables. Hence, they are included in the regression to avoid omitted variables bias.

I also include household fixed effect, α_i, to control for unobservable household-specific factors.[10] ϕ_t is the year fixed effect that absorbs year-specific shocks. u_{idt} is an error term

[10]Note that household fixed effects subsume district and state fixed effects since households do not move across districts or states in our sample.

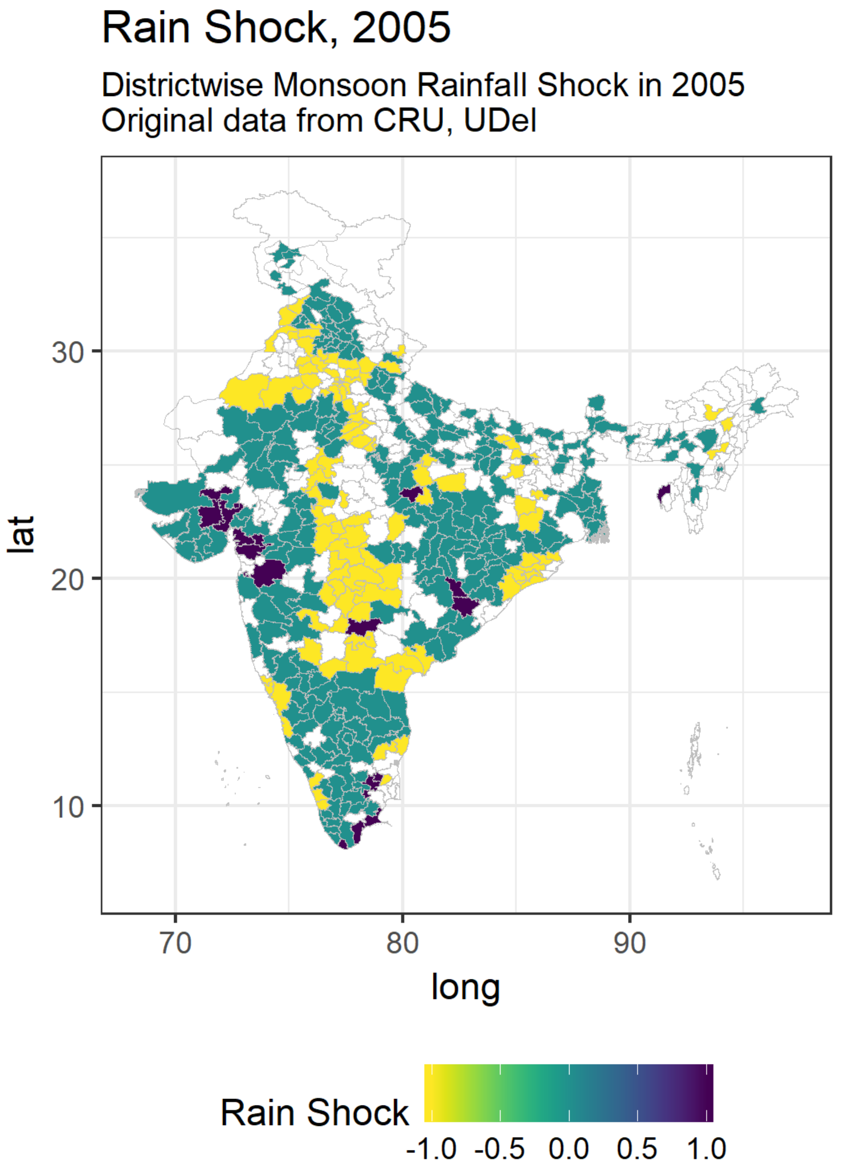

Figure 5: Districtwise monsoon rainfall shocks in 2005.
Notes: Monsoon rainfall is the total rainfall during the months of June-September in a year. Districts shaded yellow experience a negative rainfall shock (or, drought), those in dark blue experience a positive rainfall shock (or, flood), whereas those shaded green record normal rainfall. Unshaded regions are districts not covered in the IHDS survey.

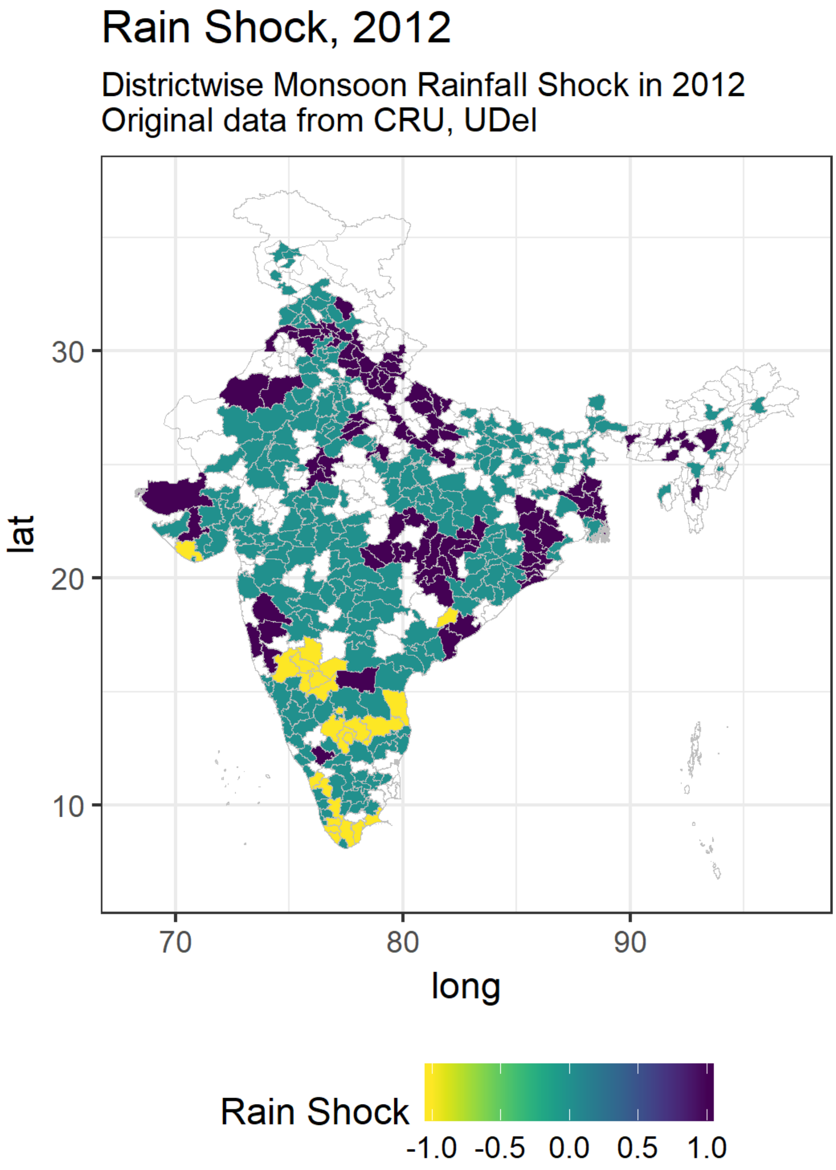

Figure 6: Districtwise monsoon rainfall shocks in 2012.
Notes: Monsoon rainfall is the total rainfall during the months of June-September in a year. Districts shaded yellow experience a negative rainfall shock (or, drought), those in dark blue experience a positive rainfall shock (or, flood), whereas those shaded green record normal rainfall. Unshaded regions are districts not covered in the IHDS survey.

clustered at the district level. The clustering takes into account possible serial correlations arising from district-level rainfall shocks. IHDS also provides sampling weights that specify the probability that a household is included in the sample based on the survey sampling design. To obtain coefficient estimates that are representative of the population, I use the sampling weights in 2005 supplied by IHDS.[11] In equation (1), the main coefficient of interest is β. It measures the impact on the dependent variable, y_{idt}, if the district where the household lives experiences a rainfall shock, $Rainshock_{dt}$ (treatment), as described in section 2.2 above, relative to households in districts that do not receive a rainfall shock i.e. experiences a normal monsoon season (control or base category). Because $Rainshock_{dt}$ is exogenous by construction, it results in a clear causal identification. Conditioning on the list of controls adds to the precision of the obtained estimates.

I now turn to present findings from the regression analysis.

4 Results

In this section, I first examine how rainfall shocks affect household income and then trace its impact on consumption, debt-burden and poverty status. I then assess the effectiveness of NREGS, a public workfare program, in mitigating the impact of weather-induced variability in household income.

4.1 Effect on Income: Benchmark Results

A reasonable *ex-ante* hypothesis is that negative weather shocks adversely affect household income. The impact is likely to be particularly severe on agricultural income since unanticipated variation in rainfall can ruin harvest. Further, absent or incomplete insurance markets in developing countries add to farmers' woes. With no insurance to protect against downside risks, a crop failure can lead to significant variability in income with follow-on impact on consumption and debt-burden.

Table 2 shows the effect of rainfall shocks on household income on a sample of nearly 40,000 households in each of the two survey rounds. Column 1 presents estimates from a model that regresses log household income on rainfall shocks, $Rainshock_T$, controlling for household and year fixed effects. The point estimate of β shows that a rainfall shock reduces household income by 6.6% on average. It is also statistically significant at the 5% level. I cluster the standard errors at the district level to take into account possible serial

[11] Using the sample weights for 2005 in panel estimates is recommended by IHDS.

Table 2: Main Results: Impact of Rainfall Shock on Income

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Rainshock_T	-0.066**	-0.058**	-0.065**	-0.056**	-0.062**	-0.056*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Agriculture Dependent		-0.148***	-0.153***	-0.148***	-0.148***	-0.149***
		(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Female Headed		-0.087***	-0.087***	-0.079***	-0.087***	-0.087***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Muslim		-0.218**	-0.218**	-0.217**	-0.227**	-0.218**
		(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
Low Caste (SC/ST)		-0.012	-0.012	-0.012	-0.012	-0.010
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Rainshock_T x Agriculture Dep.			0.015			
			(0.03)			
Rainshock_T x Female Headed				-0.022		
				(0.04)		
Rainshock_T x Muslim					0.033	
					(0.04)	
Rainshock_T x Lower Caste						-0.007
						(0.03)
Household Controls	No	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-Square	0.027	0.160	0.160	0.160	0.160	0.160
Households	39681	39680	39680	39680	39680	39680
Observations	78062	77999	77999	77999	77999	77999

Notes: Dependent variable is log of total household income. $Rainshock_T$ is a dummy variable that is 1 if the district is exposed to a rainfall shock during the last monsoon season and is zero otherwise. Household controls include dummies for agriculture dependence, if the household is female headed, four age categories ($\leq$25, 26-40, 41-60 and >60), if the household head is literate, the number of household members, its assets index, whether the household belongs to a lower caste (i.e. scheduled caste or scheduled tribe), if the household head is Muslim and it is located in an urban area. All regressions include a constant term along with household and year fixed effects. Estimates are weighted to be representative of 35 states and union territories in India. Standard errors clustered at the district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

correlations arising from rainfall shocks. The results suggest that, for the average-income household earning Rs. 36,315 (=exp(10.5) from Table 1), experiencing a rainfall shock, reduces household income by around Rs. 2,397 (=0.066 x exp(10.5)). This amounts to a little less than one month's earning. For poor households, a decline in income of such magnitude can potentially affect living standards, as will be discussed in section 4.2.

Households face several socioeconomic barriers that affect earnings. I consider four such disadvantages: whether the household depends on agriculture as its primary source of income, if the household is female-headed, whether the household belongs to a lower caste or if the household head identifies herself as a Muslim. Each of these variables enters into the regression model as a dummy variable that takes a value of 1 if the respective condition is satisfied and is zero otherwise. Column 2 presents results once

I add these household-specific socioeconomic characteristics to the model in column 1. This results in a substantial gain in the model fit as the adjusted R-squared rises from 0.03 in column 1 to 0.16 in column 2. The point estimates in column 2 show that, after accounting for these factors, a rainfall shock lowers income by 5.8%, on average. Three of the four socioeconomic variables included in the model in column 2 turn out to be statistically significant. Household income is about 22% lower for Muslims, 15% lower for agriculture-dependents and about 9% lower if the household is female-headed. However, I do not find any significant difference in income for lower caste households (i.e. the group consisting of Scheduled Castes and Scheduled Tribes).

I then investigate if these socioeconomic disadvantages, affect household income beyond their direct influence. Columns 3 to 6 present results where I interact $Rainshock_T$ with each of the four disadvantages in separate columns. For instance, in column 3, I interact $Rainshock_T$ with *Agriculture Dependent*, a dummy variable for whether the household is agriculture-dependent, controlling for the other disadvantages and including household and year fixed effects. The result in column 3 shows that the interaction term is not statistically significant. In fact, it is not significant in any of the four cases considered. Hence, it suggests that although socioeconomic barriers lower household earnings, they do not exacerbate the impact of rainfall shocks once the direct impact of these disadvantages are factored into the model.[12]

4.2 Effect on Consumption, Debt and Poverty

In this section, I consider the impact of a rainfall shock on household consumption, debt-burden and poverty status. I run regressions with two different specifications for each of the three dependent variables: In the first specification, I include only the contemporaneous shock, $Rainshock_T$ i.e. the rainfall shock faced by the household during the last monsoon season along with household-specific controls, household fixed effects and year fixed effects. In the second specification, I include lagged rainfall shock, $Rainshock_{T-1}$, as an additional covariate.

Wolpin (1982) suggests that consumption is less volatile than income as households attempt to smooth consumption by dissaving. Consumption also better approximates direct living standards than income (Deaton 2005). To examine if past shocks affect consumption, I include lagged rainfall shock as an additional covariate. If the proposition

[12] Flatø et al. (2017), for example, find that female-headed households in South Africa experience greater income loss due to a rainfall shock i.e. the interaction of rainfall and female-headed indicator is significant. However, they do not include female-headed households independently and it is possible that the interaction term is biased due to omitted variables.

Table 3: Impact of Rainfall Shock on Consumption, Debt and Poverty

	log(MPCE)		log(1+Debt)		BPL	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Rainshock}_{\text{T}}$	-0.029	-0.030	0.513***	0.507**	-0.009	-0.008
	(0.02)	(0.02)	(0.20)	(0.20)	(0.01)	(0.01)
$\text{Rainshock}_{\text{T-1}}$		-0.034*		-0.198		0.016
		(0.02)		(0.19)		(0.01)
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-Sq	0.289	0.290	0.015	0.015	0.069	0.069
Households	39714	39714	38987	38987	39714	39714
Observations	79187	79187	68605	68605	79187	79187

Notes: Dependent variables are log monthly per capita consumption expenditure (cols.(1) and (2)), log (1+total household debt) (cols.(3) and (4)) and BPL status (columns (5) and (6), an indicator for whether the household is below poverty line (BPL). $Rainshock_T$ is a dummy variable that is 1 if the district is exposed to a rainfall shock during the last monsoon season and is zero otherwise. Even numbered columns introduce one-period lags of rainfall shock, $\text{Rainshock}_{\text{T-1}}$. All regressions include a constant term, the full set of controls (see Table 2 for a list of conditioning variables) along with household and year fixed effects. Estimates are weighted to be representative of 35 states and union territories in India. Standard errors clustered at the district level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

is indeed true, and households smooth consumption by dissaving, $Rainshock_T$ will not affect consumption but impact household income and debt.

Table 3 shows that while rainfall shocks raise household debt (in logs) by more than 51% (in column 3), there is no statistically significant effect on log monthly consumption expenditure (in column 1). Reading this result in conjunction with columns 2 and 4 which include lagged rainfall shocks is particularly insightful. Column 2 shows that while contemporaneous rainfall shocks have no effect on log(MPCE), its one period lag lowers consumption levels by slightly more than 3%. On the other hand, in column 4, while contemporaneous rainfall shocks increase debt, lagged rainfall shocks exert no significant influence on debt. These results clearly indicate some attempt to smooth consumption by taking-up loans to absorb income volatility. It also points out the limitation of debt as a consumption smoothing instrument as households face borrowing constraint after just one period. And, once households reach the credit ceiling, rainfall shocks start affecting consumption.

What implication does this have on household's poverty status? In column 5, I examine the impact of rainfall shocks on household's poverty status (BPL). BPL is a dummy variable that takes a value of 1 if a household is below the poverty line and is zero otherwise. In column 6, I add lagged rainfall shocks into the model. In both the models in columns 5 and 6, rainfall shocks turn out to be statistically insignificant. Thus, neither contemporaneous

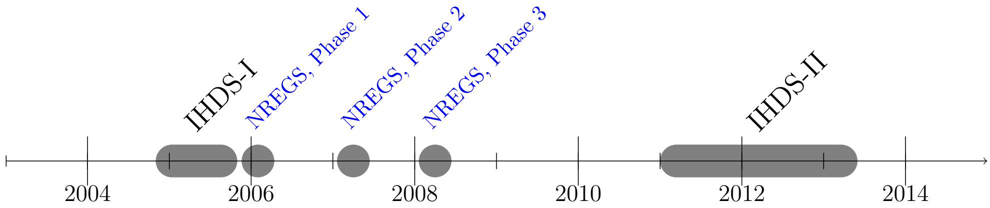

Figure 7: Timeline for NREGS and IHDS implementation.

rainfall shocks nor its one period lag affect household's poverty status. Although, this does not rule out the effect that higher order lags might have on household-level poverty, it is beyond the scope of this paper.

Thus, if loans provide short-term consumption-buffer to credit-constrained households, as observed in Table 3, a related policy question is whether public safety nets reduce vulnerability to weather-induced shocks. In the next section, I examine this question in the context of the introduction of NREGS.

4.3 Mitigating Role of NREGS

NREGS is a demand-driven, rights-based workfare program with a mandate to provide 100 days of unskilled manual work to every household in rural India. It is a demand-driven program where people have to first register their interest to work at village-level Gram Sabha meetings. NREGS is also a rights-based program. The state government must provide unskilled manual work to anyone who registers her interest to work within a reasonable timeframe under NREGS. Men and women are paid equally. Moreover, one-third of the work is reserved for women. Implemented at a cost of 1% of India's GDP, the overarching objective of the workfare program is to provide livelihood-security. To what extent does NREGS insulate households from adverse income shocks? And, does its impact differ by household-head's gender?[13] In this section, I address these questions by exploiting the phasewise roll-out of NREGS.

NREGS is a nationwide program that was implemented in three phases. Phase 1 began in February 2006 covering the 200 most backward rural districts. Phase 2 added an

[13]One possible concern is that NREGS work might be correlated with weather-shocks. While such correlations might impact monthly wages or the tightness of the labour market during a season, its impact on household living standards – the main focus of this study – would be much lower. This is because first, adverse weather events do not invalidate the state's mandate to provide 100 days of guaranteed unskilled work per year to every household that seeks employment. Secondly, to safeguard against delays in providing work, the NREGA Act of 2005 has in-built provisions for mandatory compensation in the form of unemployment allowance to the job-seeker if the state government fails to provide work within fifteen days of receiving a job application. Thus, the seasonality of NREGS work is less of a concern in this study.

additional 130 districts in April 2007, while Phase 3 covered the remaining 296 districts in April 2008. Figure 9 in Appendix B maps the phasewise implementation of NREGS for districts covered in the IHDS survey.

Figure 7 illustrates the key milestones in the implementation of NREGS and the administration of the IHDS survey rounds. The first round of the IHDS survey was conducted in 2005 i.e. before the roll-out of NREGS whereas, the second round of the IHDS survey took place in 2012 after NREGS had been completely extended to entire rural India. The timing of the events is critical in identifying the impact of NREGS on household living standards. To understand how NREGS performs in the face of adverse rainfall shocks, I focus on a sub-sample of households in districts affected by rainfall shocks. I use a difference-in-difference (DD) strategy to estimate the impact of NREGS on household living standards. I compare the average change in income for the treatment group – households without NREGS in 2005 that have NREGS in 2012 – relative to the average change in income for the control group – households without NREGS in both 2005 and 2012. One concern, however, is that workers self-select into the program. To reduce self-selection bias, I compare treated households with eligible but untreated counterpart i.e. households that have a NREGS jobcard, but do not receive NREGS income.

Table 4 presents the preperiod or the baseline characteristics of the treatment and control groups in columns 1 and 2, respectively. The treatment and control groups are similar in terms of income (in logs) at the baseline. As already mentioned, NREGS was rolled-out in three phases. The phasewise roll-out of the program is useful in identifying the impact of NREGS because it ensures that the estimates are not confounded with another separate policy intervention that affects all districts in the post-NREGS regime.

Many studies have looked at the impact of NREGS on economic and non-economic outcomes. Using the phased roll-out of NREGS, Imbert and Papp (2015) adopt a DD strategy and find that NREGS increased casual earnings. Another study by Berg et al. (2018) uses a DD strategy, similar to the one used here, and finds that NREGS increased agricultural wages by 4.3%. While the increase in wages was gender-neutral, it predominantly affected unskilled work.[14] Taking a different methodological approach which pre-supposes that NREGS phases were assigned by an algorithm based on an underlying score of a district's backwardness, Zimmermann (2013) uses the cut-off as a

[14]NREGS also impacts household consumption. For instance, Bose (2017) finds that NREGS implementation raised consumption by about 6.5%-10%, with a more pronounced increase for the marginal caste groups. In another study, Ravi and Engler (2015) find higher expenditure on food and non-food consumables, more food security, a higher propensity to save and improved mental health due to NREGS. Other studies on the impact of NREGS on non-economic outcomes include the positive impact of NREGS implementation on child health in regions affected by drought (Dasgupta 2013) and a higher intake of calories and proteins in three Indian states (Jha et al. 2011).

Table 4: Baseline Household Characteristics in 2005

Variable	Treatment (1)	Control (2)	Diff. (3)=(1)-(2)
Dependent variable:			
log(Income)	10.03	9.99	0.045
Household Controls:			
No. of Members	6.19	6.07	0.112
Agriculture Dep.	0.73	0.69	0.040**
Urban	0.02	0.01	0.010*
Low Caste (SC/ST)	0.41	0.49	-0.076***
Muslim	0.03	0.02	0.006
Assets Index	8.28	7.94	0.339**
Household-Head Controls:			
Female Headed	0.06	0.09	-0.026***
Age of Household Head:			
Age≤25	0.03	0.04	-0.011*
25<Age≤40	0.32	0.35	-0.034**
40<Age≤60	0.48	0.47	0.013
Age≥60	0.17	0.13	0.033**
Literate	0.56	0.42	0.140***

Notes: Table shows baseline summary statistics of households in districts affected by rainfall shocks and having an NREGS job card in 2005. Treatment group=Households without NREGS in 2005 that have NREGS in 2012. Control group=Households without NREGS in 2005 and 2012. $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

threshold in a regression discontinuity (RD) framework and finds a significant increase in private sector wages for women. Thus, past studies have examined the impact of NREGS on a range of outcomes. However, with the exception of Dasgupta (2013) who focuses on the impact of NREGS on child health in drought-affected districts in Andhra Pradesh in India, none of the other studies explicitly test whether NREGS acts as an effective public safety net in the face of adverse weather events. To fill this knowledge gap, I study the impact of NREGS on household income in districts affected by rainfall shocks using a nationally representative panel dataset. Furthermore, I analyse if the impact of NREGS is different for female-headed households.

I estimate the following regression to evaluate the impact of NREGS on household living standards:

$$y_{idt} = \delta T_{idt} + \sum_{j=1,2} \eta_j (T_{idt} * Phase_j) + \gamma X_{idt} + \alpha_d + \phi_t + v_{idt} \tag{2}$$

where y_{idt} denotes household income. i denotes households with at least one NREGS jobcard. d denotes districts, and t denotes time. T_{idt} is a dummy variable that indicates if any of the household members received NREGS income – the treatment – with δ its corresponding coefficient. η_j is a vector which captures the phasewise interaction with

Table 5: Impact of NREGS on log of Households Income

	All Districts		Rainfall Affected	
	All	Female-headed	All	Female-headed
Variables	(1)	(2)	(3)	(4)
Treated	0.136***	0.377***	0.097*	0.475***
	(0.03)	(0.08)	(0.05)	(0.15)
Treated x Phase 1	-0.155***	-0.217**	-0.046	-0.323
	(0.04)	(0.10)	(0.08)	(0.22)
Treated x Phase 2	-0.244***	-0.461***	-0.178**	-0.702***
	(0.05)	(0.12)	(0.08)	(0.21)
Household Controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj R-Sq	0.327	0.428	0.351	0.485
Districts	292	245	188	134
Observations	23225	2336	7078	717

Notes: Table shows the impact of participating in NREGS (Treated) on household income. Columns (1) and (2) consider households with NREGS jobcards in all districts in the sample whereas, columns (3) and (4) consider households with NREGS jobcards in districts affected by rainfall shocks. Even numbered columns focus on 'female-headed' households within the respective sub-samples whereas, odd-numbered columns consider all observations within the respective sub-samples. Treated is a dummy variable that takes a value of 1 if households did not received NREGS income in 2012. All regressions include a constant term, the full set of controls (see Table 2 for a list of conditioning variables) along with district and year fixed effects. Estimates are weighted to be representative of 35 states and union territories in India. Standard errors clustered at the household level. $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

treatment, $\sum_j (T_{idt} * Phase_j)$, where $j \in \{1, 2\}$ indexes NREGS phases. The vector X_{idt} is a list of household-specific controls as defined in equation (1).

The selection of districts into different phases was however not random. In fact, the 200 districts in Phase 1 were the most economically backward. Phase 2 extended NREGS to the next 130 backward districts, while Phase 3 covered the remaining rural districts. To address selection bias arising from unobservable time-invariant district-specific characteristics, I include district fixed effect α_d. I also include year fixed effect, ϕ_t, to control for unobservable year-specific factors. v_{idt} is an error term, which might be correlated within households over time.

Table 5 presents results from estimating equation (2). Columns 1 and 2 relate to the impact of the treatment i.e. NREGS participation, on log of income of households with NREGS jobcards across all districts in the sample. On the other hand, columns 3 and 4 focus on households with NREGS jobcards in rainfall-affected districts. While columns 1 and 3 present results on all households in the respective sub-samples, columns 2 and 4 focus on female-headed households within those sub-samples. Table 5 show that NREGS participation ('Treated') raises log household income by around 14% (column 1). For female-headed households, the corresponding rise is about 38% (column 2). In rainfall affected districts, NREGS participation raises household income by around 10% (column

3). Furthermore, for female-headed households, it increases income by nearly 48% (column 4). In addition, relative to Phase 3 districts, the effect is lower in both Phase 2 and Phase 1 districts (in columns 1 and 2), but only lower in phase 2 districts (in columns 3 and 4).

As already mentioned, I include district fixed effects to rule out selection of districts into one of the three NREGS phases. Additionally, to ensure that selection is not a concern, I run placebo checks on a sub-sample of high asset-index households in rainfall-affected districts, for which there is strong theoretical reason that NREGS will not have an impact. Table 11 in Appendix A presents results from re-estimating equation (2) on a sub-sample of households that satisfy the following characteristics: they have an asset-index that exceeds the median value of asset-index in a district-year, they have an NREGS jobcard, and they live in districts affected by rainfall shocks. The premise is that NREGS will have negligible impact on households that are non-poor in terms of asset holdings in the face of income shocks. The results in Table 11, Appendix A confirm this. I find no statistically significant impact of NREGS on income for households with higher than median asset-index. This holds true not only for this sub-sample, but also to a further restricted set of female-headed households within this sub-sample.[15]

4.4 Discussion

Overall, the results suggest that rainfall shocks reduce log household income by about 5.6%-6.6% (see Table 2). This translates to a loss of earnings between Rs.2,106 (=exp(10.5)*0.058 from Tables 1 and 2, respectively) and Rs.2,397 (=exp(10.5)*0.066) for the average-income household across different model specifications. In other words, rainfall shocks cost the average household the equivalent of one month's earnings. Hence, rainfall shocks are a source of significant variability in income. And, as shown below in section 4.5, rural households and the asset-poor are most vulnerable to rainfall shocks. In addition, while socioeconomic barriers are associated with lower average earnings, they do not reinforce the impact of rainfall-induced shocks.

Do rainfall shocks affect consumption in a similar way? This is important because consumption better approximates direct living standards. The results from Table 3 show that while contemporaneous rainfall shocks have no significant impact on household consumption, its one period lag reduces per capita consumption by more than 3%.

[15] I consider another estimation strategy where I group Phase 1 and Phase 2 districts into 'early' implementers of NREGS and Phase 3 districts as 'late' implementers similar to Imbert and Papp (2015). Tables 12 in Appendix A presents results that relate to this classification scheme. Table 13 presents corresponding placebo checks on high asset-index households. The results are qualitatively similar to those in Tables 5 and 11, respectively.

Given that the average household consumption per capita in this sample is about Rs.781 (=exp(6.66) from Table 1), a reduction of 3% shrinks it by Rs.26 or annually by Rs.318. A little algebra show that for an average sized household, this represents a reduction of Rs. 1,708. To get a sense of its importance, I compare this reduction with average medical expenses per episode of sickness obtained from National Sample Survey (NSS) report. The average total expenditure for a non-hospitalised treatment per ailment in rural areas is about Rs.509 (NSSO 2014, pp.41). Thus, the rainfall-induced contraction in consumption expenditure is non-trivial and represents the equivalent of at least three foregone medical treatments a year for an average-sized household. The loss is actually much greater since the erosion of human capital affects future earning streams. With regard to debt, rainfall shocks raise household debt-burden by Rs.78 (=exp(5.03)*0.51 from Tables 1 and 3). The timing of the impact on income, consumption, and debt suggests that, on average, households smooth consumption by taking-up debt in response to a negative income shock.

But increasing the debt-burden to smooth consumption is an unsustainable coping strategy. As Carleton (2017) points out, rising debt-burden is a major cause of weather-related farmer suicides in India. Against this backdrop, can public safety nets such as NREGS reduce vulnerability to weather shocks? The results from Table 12 is quite encouraging. It shows that participating in NREGS increases income 10% in rainfall affected districts. Moreover, the impact of NREGS on income for female-headed households is nearly five times as large. Thus, by providing income-buffer in times of weather-induced shocks, workfare programs act as public safety nets that increase climate resilience.

In the next section, I consider extensions of the benchmark model presented in section 4.1 above.

4.5 Extensions

This section illuminates the heterogeneous impact of rainfall shocks, examines the pathways through which rainfall shocks affect income and tests whether income diversification is a feasible *ex-ante* coping measure.

4.5.1 Heterogeneous Impact by Asset-Index and Location

Here, I examine if the impact of a rainfall shocks differs by household's wealth and location. To investigate the role of wealth, I divide the sample into two groups: households with assets-index above the median value of asset-index in a district-year, and households with assets-index below the median value in a district-year. Columns 1 and 2 in Table 6 present results corresponding to households with assets above and below the median, respectively. I find that a rainfall shocks lower income by around 7% for asset-poor households i.e. for those with assets-index below the median (column 1), but has no impact on households with assets above the median (column 2). This might be due to asset-rich households drawing down assets to reinstate lost income that offset the negative impact of rainfall shocks. But, since this is not feasible for the asset-poor, rainfall shocks reduces household income.

Table 6: Impact of Rainfall Shock on Income by Household Asset-Index and Location

	Asset-Index		Location	
	<Median	>Median	Rural	Urban
Variables	(1)	(2)	(3)	(4)
Rainshock_T	-0.065*	-0.039	-0.060*	-0.037
	(0.03)	(0.03)	(0.03)	(0.03)
Household Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj R-Sq	0.158	0.131	0.154	0.183
Households	26183	22739	28213	12414
Observations	42410	35589	54347	23652

Notes: Dependent variable is log of household income. Cols.(1) and (2) show results for households with asset-index below and above the median value of assets index respectively, within a survey round. Cols.(3) and (4) relate to rural and urban residents, respectively. $Rainshock_t$ is a dummy variable that is 1 if the district is exposed to a rainfall shock during the last monsoon season and is zero otherwise. All regressions include a constant term, the full set of controls (see Table 2 for a list of conditioning variables) along with household and year fixed effects. Estimates are weighted to be representative of 35 states and union territories in India. Standard errors clustered at the district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Rural households depend on agriculture for their livelihood. Hence, a rainfall shock is much more likely to affect income in rural areas than in urban areas. This is what columns 3 and 4 in Table 6 indicate. A rainfall shock reduces household income in rural areas by 6% (column 3) whereas, I do not observe any statistically significant effect on income in urban areas (column 4).

4.5.2 Heterogeneous Impact by State

The impact of rainfall shocks might differ across states. States might be differently predisposed to weather shocks. The percentage of people living below the poverty line or engaged in agriculture might also vary widely, which result in heterogeneous impact. To understand how wide the disparities are, I estimate equation (1) for income and consumption by different states in the sample. Figure 8 plots the coefficients of rainfall shocks on log of household income for different states. In a similar way, Figure 10 in Appendix B plots the coefficients of rainfall shocks on log of consumption. Both the figures indicate that the overall effect masks significant heterogeneity in the distribution of impact of rainfall shocks across Indian states.

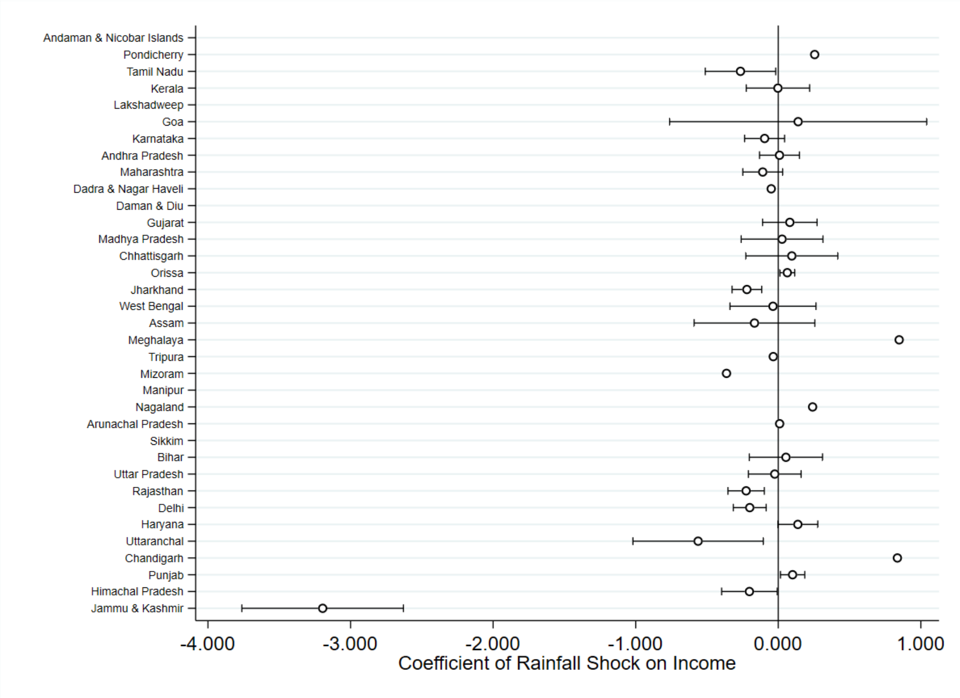

Figure 8: Heterogeneous Impact of Rainfall Shocks on Income.
Notes: Figure plots the coefficient on rainfall shocks by estimating equation (1) with log income as the dependent variable separately for each of the states in the sample. There are no plots for some states due to missing data.

4.5.3 Pathways and Coping Measures

What are the pathways through which rainfall shocks affect household income? And, how effective is income-diversification as a coping measure to combat weather shocks? Using an empirical specification similar to that in equation (1), Table 7 presents results relating to the impact of rainfall shocks on household income for different primary sources of income. Column 1 examines the impact on agricultural income, column 2 on non-agricultural wage income whereas, columns 3 to 5 consider the effect on business, salary and other income sources, respectively. Column 6 considers the effect on public benefits such as insurance income, pensions etc., while column 7 looks at remittance income. It shows that the main pathway through which rainfall shocks affect income is expectedly through agriculture and non-agricultural wages. I find that rainfall shocks negatively impact agricultural income and non-agricultural wage income. The point estimates in Table 7 in columns 1 and 2, show that rainfall shocks reduce agricultural income by 18% and non-agricultural wage income by 12%. The negative impact on agricultural income is expected as agricultural success is tied to normal rainfall. On the other hand, the reduction in non-agricultural wage income might be due to farmers reallocating labour supply to off-farm employment, as evidenced in Kochar (1995). The increase in labour supply is likely to depress non-agricultural wage rates, which result in lower income from this source.

Table 7: Impact of Rainfall Shock on Income by Primary Source

Variables	Agri (1)	Non-agri (2)	Business (3)	Salary (4)	Other (5)	Benefits (6)	Remittance (7)
$\text{Rainshock}_{\text{T}}$	-0.177**	-0.117**	-0.043	-0.069	-0.093	0.067	-0.128
	(0.07)	(0.05)	(0.05)	(0.05)	(0.07)	(0.06)	(0.09)
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-Sq	0.085	0.070	0.061	0.136	0.087	0.118	0.166
Households	21289	19740	12184	16141	6722	16437	6684
Observations	32831	26893	16500	22716	8595	19451	7485

Notes: Dependent variables are log household income by main source of income for the household as shown in column headings. Agri=Agriculture income (col.(1)); Non-agri=Non-agricultural wage income (col.(2)); business, salary and other income in cols.(3)-(5) respectively; Income from government benefits such as pensions, allowances etc. (col(6)); and, remittance income (col.(7)). $Rainshock_t$ is a dummy variable that is 1 if the district is exposed to a rainfall shock during the last monsoon season and is zero otherwise. All regressions include a constant term, the full set of controls (see Table 2 for a list of conditioning variables) along with household and year fixed effects. Estimates are weighted to be representative of 35 states and union territories in India. Standard errors clustered at the district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The table also shows that rainfall shocks have no statistically significant impact on alternative sources of income – business, salary or other sources (columns 3 to 5). Moreover, neither publicly provided benefits nor remittances are associated with rainfall shocks. In addition, Table 14 in Appendix A, provides pairwise cross-correlations coefficients between different sources of income. The low degree of correlation, along with the results in columns 3 to 5 in Table 7, suggest that income-diversification might be an effective strategy to build climate resilience.

Thus far, a rainfall shock is treated as a binary variable that indicates the presence or absence of the shock. But, if shocks recur frequently, its effect might accumulate over time, limiting its adaptation capacity and permanently lowering a household's earning potential. I examine this next.

4.5.4 Impact of Accumulated Shocks

What is the impact of accumulated rainfall shocks on household income? Here, I study this question by considering the number of rainfall shocks experienced by a district within the last five years. The idea is to test if successive shocks leave a lasting impact on household living standards (see Alderman 1996, Karim 2018, etc.). Column 1 in Table 8 shows result from regressing log household income in 2012 on the number of rainfall shocks experienced in the last five years controlling for initial household characteristics from the 2005 survey round and including district fixed effects. It shows that an additional episode of shock reduces household income in 2012 by 21%. The estimate is significant at the 1% level of signficance. The standard errors are clustered at the district level. In column 2, I regress the change in log income between 2005 and 2012 i.e. on the growth rate of income and find that an additional shock, on average, reduces the growth rate of household income by 22%. Thus, accumulated shocks impact not only the level of income, but also reduces its rate of growth.

Table 8: Impact of Recurring Rainfall Shocks on Income

	$\log(\text{Income})_{2012}$	$\Delta\log(\text{Income})$
	(1)	(2)
No. of Rain Shocks in last 5 years	-0.210***	-0.221**
	(0.07)	(0.09)
Initial Household Controls	Yes	Yes
Adj R-Sq	0.321	0.123
Districts	371	371
Observations	39265	38645

Notes: Dependent variables in column headings. Col.(1) regresses log household income in 2012 on the number of rainfall shocks experienced by a district in the last 5 years. Col.(2) shows results from long differenced regression which regresses the change in log household income between 2005 and 2012 on the number of shocks experienced by a district in the last 5 years. Both regressions control for the initial values of the full set of conditioning variables and district fixed effects. Estimates are weighted to be representative of 35 states and union territories in India. Standard errors clustered at the district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In the next section, I present results from several robustness checks.

5 Robustness Checks

5.1 Placebo Treatment

To ensure that the effect of rainfall shock is not merely an artefact of the data used, I conduct 100 placebo runs whereby, in each run, I randomly draw a weather shock from a uniform distribution – the placebo – for each district in the sample. I then iteratively regress household income on this placebo shock 100 times controlling for the true rainfall shock[16], the socioeconomic barriers that households face along with household and year fixed effects in each regression.

Table 15 in Appendix A shows results from one such placebo run. It shows that the placebo rainfall shock is not significant in explaining variations in income, as expected. Figure 11 in Appendix B plots the cumulative distribution function of the coefficients obtained from the 100 placebo regressions with log income as its dependent variable. It reveals that the coefficients on the placebo shocks mostly have the wrong sign (i.e. they are positive), and even when they do have the correct sign (i.e. when they are negative) they are of much smaller magnitudes than the true coefficient in Table 2. The insignificance of the results in Table 15 suggests that the benchmark result in Table 2 in section 4.1 systematically captures the impact of location-specific rainfall shocks, while random placebos exert no significant impact.

5.2 Higher Order Lags of Rainfall Shocks

How important are lagged shocks in explaining variations in income? Table 3 in section 4.2 included one-period lagged rainfall shocks along with contemporaneous rainfall shocks to show that the lag affects consumption but not debt or poverty status. But do higher order lags (of rainfall shocks) affect household income? This is important because, if they do, it would indicate that not only do rainfall shocks affect the level of income, but it also affects its growth rate. In Table 9 column 1, I regress log household income on contemporaneous rainfall shocks and its one-period lag, while conditioning on the full set of controls. In column 2 of the same table, I introduce the second lag of rainfall shocks to the model in column 1. In both cases, I find that only the contemporaneous rainfall shock turns out to be statistically significant and has a negative sign, while its lags have no discernible impact.

5.3 Sample Selection

Rainfall shocks might force affected households to permanently out-migrate. If weather-induced migration systematically affects attrition, it might lead to spurious correlation between weather shocks and income. To understand if weather-induced migration affects

[16]Because the 'true' distribution of rainfall shock cannot be ruled out, including the true shock controls for it.

Table 9: Lagged Rainfall Shock on Income

Variable	(1)	(2)
$\text{Rainshock}_{\text{T}}$	-0.058**	-0.056**
	(0.03)	(0.03)
$\text{Rainshock}_{\text{T-1}}$	0.007	0.006
	(0.03)	(0.03)
$\text{Rainshock}_{\text{T-2}}$		0.014
		(0.02)
Household Controls	Yes	Yes
Household FE	Yes	Yes
Year FE	Yes	Yes
Adj R-Sq	0.160	0.160
Households	39680	39680
Observations	77999	77999

Notes: Dependent variable is log of total household income. $Rainshock_T$ is a dummy variable that is 1 if the district is exposed to a rainfall shock during the last monsoon season and is zero otherwise. All regressions include a constant term, the full set of controls (see Table 2 for a list of conditioning variables), household and year fixed effects. Estimates are weighted to be representative of 35 states and union territories in India. Standard errors clustered at the district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

results, I follow Lee (2009) in bounding the impact of weather shocks. The literature suggests that rural to urban migration in India is typically quite low and is in the region of 2%-6%.[17] A significant share of such migration is driven by females marrying into a different household (Munshi and Rosenzweig 2016). In examining weather-induced out-migration in Indian districts, Viswanathan and Kumar (2015) find no significant impact of rainfall or temperature on out-migration. Thus, a-priori, migration poses less of a problem in this study. But, to the extent that it does, and assuming that the worst affected migrate-out first, it will downward bias the estimates.

I utilise the attrition sample from IHDS-I and the replacement sample in IHDS-II to bound the effect of selective sampling. About 6,911 households from IHDS-I could not be contacted in IHDS-II. To address attrition, an additional 2,134 households – the replacement sample – were interviewed in IHDS-II. These households were randomly selected from the same neighbourhood.[18] Column 1 in Table 16 in Appendix A shows the impact of rainfall shocks after including the attrition sample from IHDS-I. For identification, it uses within-district variation in rainfall shocks after controlling for household characteristics and year fixed effects. The results are, in fact, quite similar to the benchmark results in Table 2. Column 2, on the other hand, shows results from

[17] Assuming that a household has in-migrated if it has been staying at the location for less than 10 years, I estimate that around 3.9% in the sample in 2005 had in-migrated.

[18] See https://ihds.umd.edu/sample-size

the 'remainers' sample i.e. only households that were interviewed in both 2005 and 2012. Again, the results are very similar to the benchmark estimate. I then identify households predisposed to weather-induced out-migration as those who are agriculture dependents or report non-agricultural wages as their primary source of income. For these 631 households, representing 9% of the attrition sample, I assume that none of them received a weather shock. This extreme assumption theoretically makes it difficult to find impact. The results in column 3, shows that the impact of rainfall shocks remain statistically significant.

In addition, Column 1 in Table 17 presents results from a bounding exercise which trims the distribution of either the treatment (those affected by rainfall shocks) or the control group to account for sample selection. The implicit assumption is that the likelihood of out-migration increases for households that experience a rainfall shock. I further assume that agriculture dependents, younger household-heads and Muslims are more likely to migrate and hence affects sample selection. Using this assumption to tighten the bounds, I find that the impact of rainfall shocks to be between 3.4% and 5.5%, which is quite close to the main results in Table 2. Standard errors obtained by resampling 100 times reinforce the results.

5.4 Additional Checks

Here, I conduct additional robustness checks to ensure the reliability of the benchmark estimates.

5.4.1 Elapsed Time Since Rainfall Shock

In this study, I compute rainfall shock based on the month of the household interview. As mentioned earlier, if the household is interviewed after the onset of the monsoon i.e. on or after the month of June, I attribute the rainfall shock corresponding to the interview-year. However, if the household is interviewed during January to May, I attribute the rainfall shock that corresponds to the previous monsoon season. Thus, the duration of exposure to rainfall shocks varies across households, which might systematically affect results. For instance, households affected earlier would have had more time to cope with the after-effects of the weather shock, and therefore differ (in terms of income, consumption or debt) from households receiving a weather shock at a more recent time. Hence, in this section, I include a variable, 'Time Since Rainshock', to control for the elapsed time (in months) between the rainfall shock and the interview month. Tables 18 and 19 in Appendix A present results after controlling for elapsed time since the rainfall shock. The results are extremely similar to the corresponding main results in Tables 2 and 3, respectively. This shows that the results are robust to controlling for elapsed time since rainfall shock.

5.4.2 Temperature variations

The relationship between rainfall shocks and income might also be affected by time-varying factors like surface temperature. Tables 20 in Appendix A present results on the impact of rainfall shocks on income after controlling for surface temperature during the months of June to September. Table 21 in Appendix A, on the other hand, present similar results for consumption, debt and poverty status. The estimates in both these tables are again quite similar to the benchmark results, which increases its reliability.

5.4.3 Winsorised Data

Another concern is whether outliers are driving the results. To guard against outliers, I conservatively winsorise the top 5% and the bottom 5% of the distribution of log household income, the primary dependent variable in this study.[19] I then estimate equation (1) in the same way as in Table 2 in section 4.1 above. Table 10, column 1 presents estimates from this regression where the dependent variable 5%/95% winsorised. It shows that rainfall shocks reduce household income by about 6% and is significant at the 5% level even after controlling for outliers.

5.4.4 Alternative Measure of Rainfall Variation

In column 2, Table 10, I present results using an alternative definition of rainfall shock. Instead of a binary measure of rainfall shock like before, I include the probability that a district obtains a given level of rainfall, given its 30 years historical distribution i.e. the cumulative probability distribution (CDF) obtained by fitting a gamma distribution to rainfall data from 1980-2012 for each district. Because both deficient and excess rainfall has detrimental effects on income, I account for this non-linear relationship by including a quadratic of the CDF variable.[20] The estimated marginal impact obtained by holding the covariates at their respective average values is about 7%. A negative and statistically significant quadratic of CDF of rainfall suggests non-linearities in impact. Thus, as Figure 12 in Appendix B illustrates, it indicates the presence of a threshold value of rainfall

[19] I get similar results with a 1%/99% winsorisation, but do not present the results to conserve space.

[20] This method is used in Flatø et al. (2017), although their model specification is different and does not consider non-linearities.

Table 10: Additional Robustness Checks: Effect of Rainfall Shock on Income

	Winsorised log(Income)	log(Income)
	(1)	(2)
$\text{Rainshock}_{\text{T}}$	-0.057**	
	(0.02)	
CDF, Rainfall		0.586***
		(0.22)
CDF Squared, Rainfall		-0.651***
		(0.21)
Household Controls	Yes	Yes
Household FE	Yes	Yes
Year FE	Yes	Yes
Adj R-Sq	0.158	0.162
Households	39714	39680
Observations	79244	77999

Notes: Dependent variables in column headings. Col.(1) shows results where we winsorise the top 5% and the bottom 5% of log household income. $Rainshock_T$ is a dummy variable that is 1 if the district is exposed to a rainfall shock during the last monsoon season and is zero otherwise. Col.(2) shows results where we regress log household income on the cumulative distribution of rainfall probability in a district obtained by fitting a gamma distribution to historical rainfall data for each district from 1980-2012 and its squared term to capture non-linearity. Both regressions include the full set of controls (see Table 2 for a list of conditioning variables), household and year fixed effects. Estimates are weighted to be representative of 35 states and union territories in India. Standard errors clustered at the district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

probability, below which its effect is positive (i.e. income increase with rainfall), but becomes negative as it exceeds the cut-off (income declines with excessive rains).

6 Conclusion

In this paper, I examine the impact of rainfall shocks on household living standards. Rural areas in developing countries are most vulnerable to adverse weather events since much of the population depend on agriculture for their livelihood. Furthermore, absent or incomplete financial markets imply that farmers in developing countries are unable to insure against weather-induced income volatility. For the already poor households that depend on agriculture as their primary source of income, an adverse weather shock can lower income with follow-on impact on debt-burden and consumption.

Variation in rainfall, however, is endogenous to determining income. For instance, farmers adopt safer strategies and invest less in agricultural innovation in places that experience large fluctuations in the weather thereby affecting future income streams. I overcome this inference problem by fitting a gamma distribution to rainfall data during 1980-2012 by district and define a rainfall shock to be a dummy variable that takes a value of 1 if the cumulative probability of rainfall in a district-year either falls below the 20^{th} percentile or exceeds the 80^{th} percentile, and is zero otherwise. This method ensures that the variable, rainfall shock, is exogenous to the model, allowing for clear identification.

Utilising panel data from multiple rounds of the IHDS survey conducted in India covering more than 40,000 households in each round during 2005 and 2012, I find that a rainfall shock reduced household income by about 6%, on average. I consider this as my benchmark model which I estimate after controlling for several observable household-specific socioeconomic disadvantages together with household and year fixed effects. I also cluster the standard errors at the district level to account for the covariate nature of rainfall shocks.

While the average impact of rainfall shocks on household income is insightful, does it mask differences in the impact along the lines of gender, caste, religion or occupation? I investigate this and find no evidence to suggest that rainfall shocks reinforce pre-existing societal barriers after controlling for the direct effect that such barriers impose on income. Nonetheless, the factors that are salient are a household's asset-holding and location. I find that the impact of a rainfall shock is only felt by the asset-poor, which highlight the importance of asset as income-buffer. In addition, rainfall shocks affect rural households, but not urban households, since farming is mainly concentrated in rural areas.

I then consider the effect of rainfall shocks on consumption, debt, and poverty. The results show that: contemporaneous rainfall shocks i.e. rainfall shocks during the last monsoon season increase the debt-burden but do not affect consumption. However, closer inspection reveals that rainfall shocks reduce consumption with a lag, but lagged shocks do not affect household debt. This shows, albeit indirectly, that households attempt to smooth consumption by taking up debt. It also shows the limitation of credit as a consumption-smoothing instrument as households hit their credit constraints after one period (as implied by the insignificant effect of lagged rainfall on debt). Moreover, I find that rainfall shocks lower agricultural-income and non-agricultural wage income, but not other sources of income such as from business (shops, trading, etc.), salary, etc. Given the low cross-correlations between income sources, *ex-ante* income diversification seems to be an effective coping strategy. I also find the impact of rainfall shocks to vary across states which is important from a policy perspective.

A related question is whether public workfare programs can work as safety nets to improve household welfare in the face of weather-related shocks. I examine this question by analysing the phased roll-out of a major workfare program in India – the Mahatma Gandhi Rural Employment Guarantee Scheme (NREGS) – that guaranteed 100 days of employment in rural areas to anyone registering her intent to work. The phased implementation of NREGS and the timing of the IHDS survey rounds, provide a unique opportunity to identify the impact of the workfare program on household-level economic variables. The results suggest that workfare programs increased household income and consumption by 16% and 7% respectively. The gains were more pronounced for female-headed households where income increased by 30% and consumption by 20% along with a 12% lower probability of falling below the poverty line. Placebo checks on households with higher asset-index reveals no such gains, which is expected.

I conduct several robustness checks to ensure the validity of the results. First, I conduct 100 placebo runs, whereby in each test I randomly draw a weather shock and use it as a covariate in the regression with income as the dependent variable, but find no significant impact. This shows that the results are not an artefact of the data. Secondly, I use higher order rainfall lags to explain variations in income and find no significant impact. Finally, I conduct additional checks such as winsorising the dependent variables to guard against outliers and using alternative measures of rainfall variation. The results from these robustness checks reinforce the credibility of the benchmark estimates.

To tackle the detrimental effects of climate change requires targeted strategies informed by micro-level evidence on how weather-induced shocks affect households. Policymakers must be aware of the nature of the impact, the existing coping measures that households adopt, and the role that public safety nets can play in improving hosuehold welfare. The results from this study shed light on these critical issues and might be helpful to policymakers grappling with the challenges of adapting to climate change.

Appendix

A Tables

Table 11: Placebo Check: Impact of NREGS on log of Households Income with Assets$\geq$ Median in Districts Experiencing Rainfall Shocks (Phasewise)

Variables	All (1)	Female-headed (2)
Treated	0.028	0.222
	(0.11)	(0.32)
Treated x Phase 1	0.191	-0.658
	(0.14)	(0.60)
Treated x Phase 2	-0.225	-0.960*
	(0.17)	(0.50)
Household Controls	Yes	Yes
District FE	Yes	Yes
Year FE	Yes	Yes
Adj R-Sq	0.352	0.503
Districts	161	86
Observations	2281	207

Notes: Table shows placebo checks by estimating the impact of participating in NREGS (Treated) on households with asset-index exceeding the median value for a district-year, having NREGS job cards and living in districts affected by rainfall shocks during the last monsoon season. Column(1) looks at the entire sub-sample whereas, column (2) focuses on female-headed households within the sub-sample. Treated is a dummy variable that takes a value of 1 if households did not received NREGS income in 2012. All regressions include a constant term, the full set of controls (see Table 2 for a list of conditioning variables) along with district and year fixed effects. Estimates are weighted to be representative of 35 states and union territories in India. Standard errors clustered at the household level. $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Impact of NREGS on log of Household Income (Early/Late)

	All Districts		Rainfall Affected	
	All	Female-headed	All	Female-headed
Variables	(1)	(2)	(3)	(4)
Treated	0.136***	0.379***	0.092*	0.465***
	(0.03)	(0.08)	(0.05)	(0.14)
Treated x Early	-0.188***	-0.306***	-0.108	-0.490***
	(0.04)	(0.10)	(0.07)	(0.18)
Household Controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj R-Sq	0.327	0.426	0.350	0.482
Districts	292	245	188	134
Observations	23225	2336	7078	717

Notes: Table shows the impact of participating in NREGS (Treated) on household income. Columns (1) and (2) consider households with NREGS jobcards in all districts in the sample whereas, columns (3) and (4) consider households with NREGS jobcards in districts affected by rainfall shocks. Even numbered columns focus on 'female-headed' households within the respective sub-samples whereas, odd-numbered columns consider all observations within the respective sub-samples. Treated is a dummy variable that takes a value of 1 if households did not received NREGS income in 2012. Early is a dummy variable that is 1 if NREGS was implemented in the district either in Phase 1 or Phase 2. All regressions include a constant term, the full set of controls (see Table 2 for a list of conditioning variables) along with district and year fixed effects. Estimates are weighted to be representative of 35 states and union territories in India. Standard errors clustered at the household level. $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Placebo Check: Impact of NREGS on log of Households Income with Assets$\geq$ Median in Districts Experiencing Rainfall Shocks(Early/Late)

	All	Female-headed
Variables	(1)	(2)
Treated	0.017	0.217
	(0.11)	(0.31)
NREGS x Early	0.016	-0.764*
	(0.13)	(0.45)
Household Controls	Yes	Yes
District FE	Yes	Yes
Year FE	Yes	Yes
Adj R-Sq	0.349	0.507
Districts	161	86
Observations	2281	207

Notes: Table shows placebo checks by estimating the impact of participating in NREGS (Treated) on households with asset-index exceeding the median value for a district-year, having NREGS job cards and living in districts affected by rainfall shocks during the last monsoon season. Column(1) looks at the entire sub-sample whereas, column (2) focuses on female-headed households within the sub-sample. Treated is a dummy variable that takes a value of 1 if households did not received NREGS income in 2012. Early is a dummy variable that is 1 if NREGS was implemented in the district either in Phase 1 or Phase 2. All regressions include a constant term, the full set of controls (see Table 2 for a list of conditioning variables) along with district and year fixed effects. Estimates are weighted to be representative of 35 states and union territories in India. Standard errors clustered at the household level. $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Cross-Correlation Table: Primary Income Sources

Variables	Agriculture	Non-agri Wage	Business	Salary	Other	Benefits	Remittance
Agriculture	1.000						
Non-agri Wage	-0.045	1.000					
Business	0.216	0.151	1.000				
Salary	0.131	0.132	0.370	1.000			
Other	0.009	0.061	0.140	0.138	1.000		
Benefits	0.083	0.120	0.146	0.156	0.151	1.000	
Remittance	0.175	0.089	0.272	0.207	0.222	0.082	1.000

Notes: Cross-correlation table between different sources of income.

Table 15: Placebo Treatment: Impact of Placebo Shock on Income

Variables	log(Income)
Placebo $\text{Rainshock}_{\text{T}}$	0.011
	(0.01)
True $\text{Rainshock}_{\text{T}}$	Yes
Household Controls	Yes
Household FE	Yes
Year FE	Yes
Adj R-Sq	0.160
Households	39680
Observations	77999

Notes: Dependent variable is log household income. Results show a single instance of a placebo run. In each placebo run I randomly draw a weather shock from a uniform distribution, the placebo, for each district in our sample and repeat the process 100 times. I iteratively regress the placebo shock on log income after controlling for the true shock, the full set of controls (see Table 2 for a list of conditioning variables) along with household and year fixed effects and a constant term. Estimates are weighted to be representative of 35 states and union territories in India. Standard errors clustered at district level. $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 16: Bound Treatment Effect: Impact of Rainfall Shock

Variables	(1)	(2)	(3)
$\text{Rainshock}_\text{T}$	-0.0585***	-0.0579***	
	(0.010)	(0.011)	
False $\text{Rainshock}_\text{T}$			-0.0614***
			(0.010)
Household Controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj R-Sq	0.444	0.431	0.444
Districts	371	370	372
Observations	86830	77999	86832

Notes: Table shows impact of rainfall shocks on log of household income for different samples. Column (1) shows results for a sample that includes attriters from IHDS-I, the additional sample in IHDS-II, and households interviewed in both IHDS-I and IHDS-II. Coumn (2) shows results for always remainers i.e. households that were surveyed in both IHDS-I and IHDS-II and excludes IHDS-I attriters or IHDS-II additional sample. Column (3) shows results which includes households interviewed in IHDS-I (including attriters) plus a replacement sample of households predisposed to out-migration (a subset of the additional sample), which includes households engaged in agriculture or deriving income from non-agriculture wages. Moreover, in column (3), it is assumed that all such replacement households receive no rainfall shocks, 'False $\text{Rainshock}_\text{T}$'. $Rainshock_T$ is a dummy variable that is 1 if the district is exposed to a rainfall shock during the last monsoon season and is zero otherwise. All regressions include a constant term, the full set of controls (see Table 2 for a list of conditioning variables) along with district and year fixed effects. Estimates are weighted to be representative of 35 states and union territories in India. Standard errors clustered at the district level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Bound Treatment Effect (Lee 2009): Impact of Rainfall Shock

	(1)	(2)
Lower bound	0.0063	0.0341*
	(0.010)	(0.018)
		[0.010]
Upper bound	0.0491***	0.0554***
	(0.010)	(0.019)
		[0.010]
Fraction Trimmed	0.006	0.006
Selected	78831	78831
Observations	84913	84913

Notes: Table obtains bounds for $Rainshock_T$ following Lee (2009). Column (2) tightens the bounds using covariates that are *ex-ante* correlated with out-migration – an indicator for whether the household is agriculture dependent, whether the household-head is aged less than 40 years, or if it is a Muslim household. Bootstrapped standard errors in square brackets based on 100 replications. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Impact of Rainfall Shock on Income After Controlling for the Time Since Rainshock

Variables	(1)	(2)	(3)	(4)	(5)
$\text{Rainshock}_\text{T}$	-0.056**	-0.066**	-0.053*	-0.060**	-0.053*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
$\text{Rainshock}_\text{T}$ x Agriculture Dep.		0.022			
		(0.03)			
$\text{Rainshock}_\text{T}$ x Female Headed			-0.027		
			(0.04)		
$\text{Rainshock}_\text{T}$ x Muslim				0.034	
				(0.04)	
$\text{Rainshock}_\text{T}$ x Lower Caste					-0.009
					(0.03)
Time Since Rainshock	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Adj R-Sq	0.162	0.162	0.162	0.162	0.162
Households	39679	39679	39679	39679	39679
Observations	77963	77963	77963	77963	77963

Notes: Dependent variable is log of total household income. Table shows impact of rainfall shocks on income after controlling for the time (in months) between the rainfall shock and the interview month. $Rainshock_T$ is a dummy variable that is 1 if the district is exposed to a rainfall shock during the last monsoon season and is zero otherwise. Household controls include dummies for agriculture dependence, if the household is female headed, four age groups ($\leq$25, 26-40, 41-60 and >60), if the household head is literate, the number of household members, its assets index, whether the household belongs to a lower caste (i.e. scheduled caste or scheduled tribe), if the household head is Muslim and whether the household is located in an urban area. All regressions include a constant term along with household and year fixed effects. Estimates are weighted to be representative of 35 states and union territories in India. Standard errors clustered at the district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 19: Impact of Rainfall Shock on Consumption, Debt and Poverty After Controlling for Time Since Rainshock

Variables	log(MPCE) (1)	log(1+Debt) (2)	BPL (3)
$\text{Rainshock}_\text{T}$	-0.030	0.494***	-0.009
	(0.02)	(0.18)	(0.01)
Time Since Rainshock	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj R-Sq	0.289	0.019	0.069
Households	39714	38985	39714
Observations	79151	68579	79151

Notes: Dependent variables are log monthly per capita consumption expenditure, log total household debt and BPL status on income after controlling for the time (in months) between the rainfall shock and the interview month in columns 1, 2 and 3, respectively. $Rainshock_T$ is a dummy variable that is 1 if the district is exposed to a rainfall shock during the last monsoon season and is zero otherwise. All regressions include a constant term, the full set of controls (see Table 2 for a list of conditioning variables) along with household and year fixed effects. Estimates are weighted to be representative of 35 states and union territories in India. Standard errors clustered at the district level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 20: Impact of Rainfall Shock on Income After Controlling for the Time Since Rainshock

Variables	(1)	(2)	(3)	(4)	(5)
$\text{Rainshock}_\text{T}$	-0.059**	-0.066**	-0.056**	-0.063**	-0.056*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
$\text{Rainshock}_\text{T}$ x Agriculture Dep.		0.016			
		(0.03)			
$\text{Rainshock}_\text{T}$ x Female Headed			-0.023		
			(0.04)		
$\text{Rainshock}_\text{T}$ x Muslim				0.032	
				(0.04)	
$\text{Rainshock}_\text{T}$ x Lower Caste					-0.008
					(0.03)
Temperature	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
AAdj R-Sq	0.160	0.160	0.160	0.160	0.160
Households	39680	39680	39680	39680	39680
Observations	77999	77999	77999	77999	77999

Notes: Dependent variable is log of total household income. Table shows impact of rainfall shocks on income after controlling for surface air temperature. $Rainshock_T$ is a dummy variable that is 1 if the district is exposed to a rainfall shock during the last monsoon season and is zero otherwise. Household controls include dummies for agriculture dependence, if the household is female headed, four age groups ($\leq$25, 26-40, 41-60 and >60), if the household head is literate, the number of household members, its assets index, whether the household belongs to a lower caste (i.e. scheduled caste or scheduled tribe), if the household head is Muslim and whether the household is located in an urban area. All regressions include a constant term along with household and year fixed effects. Estimates are weighted to be representative of 35 states and union territories in India. Standard errors clustered at the district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 21: Impact of Rainfall Shock on Consumption, Debt and Poverty After Controlling for Time Since Rainshock

Variables	log(MPCE) (1)	log(1+Debt) (2)	BPL (3)
$\mathrm{Rainshock_T}$	-0.029	0.513***	-0.009
	(0.02)	(0.20)	(0.01)
Temperature	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj R-Sq	0.289	0.019	0.069
Households	39714	38985	39714
Observations	79151	68579	79151

Notes: Dependent variables are log monthly per capita consumption expenditure, log total household debt and BPL status on income after controlling for surface air temperature in columns 1, 2 and 3, respectively. $Rainshock_T$ is a dummy variable that is 1 if the district is exposed to a rainfall shock during the last monsoon season and is zero otherwise. All regressions include a constant term, the full set of controls (see Table 2 for a list of conditioning variables) along with household and year fixed effects. Estimates are weighted to be representative of 35 states and union territories in India. Standard errors clustered at the district level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B Figure

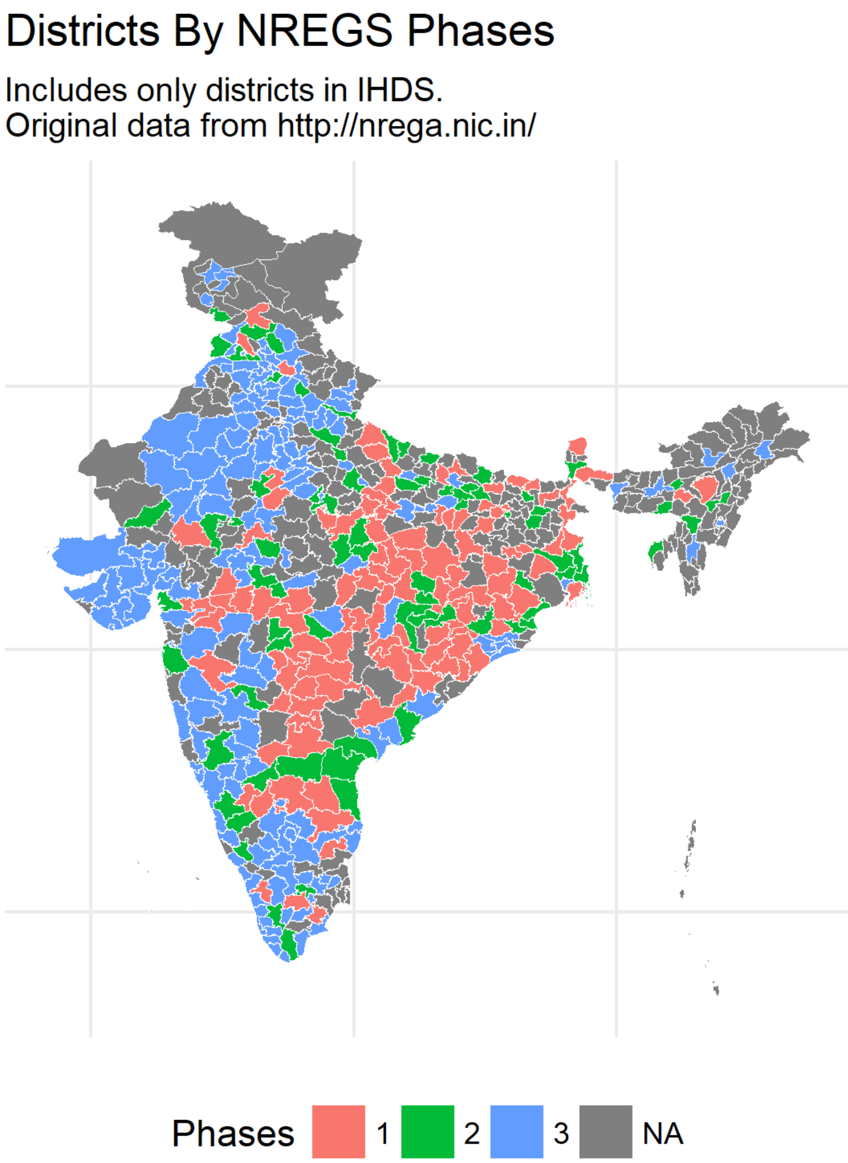

Figure 9: Districts By NREGS Phases.
Notes: Figure maps the NREGS phase corresponding to a district in the IHDS sample. NA=districts not included in the IHDS sample.

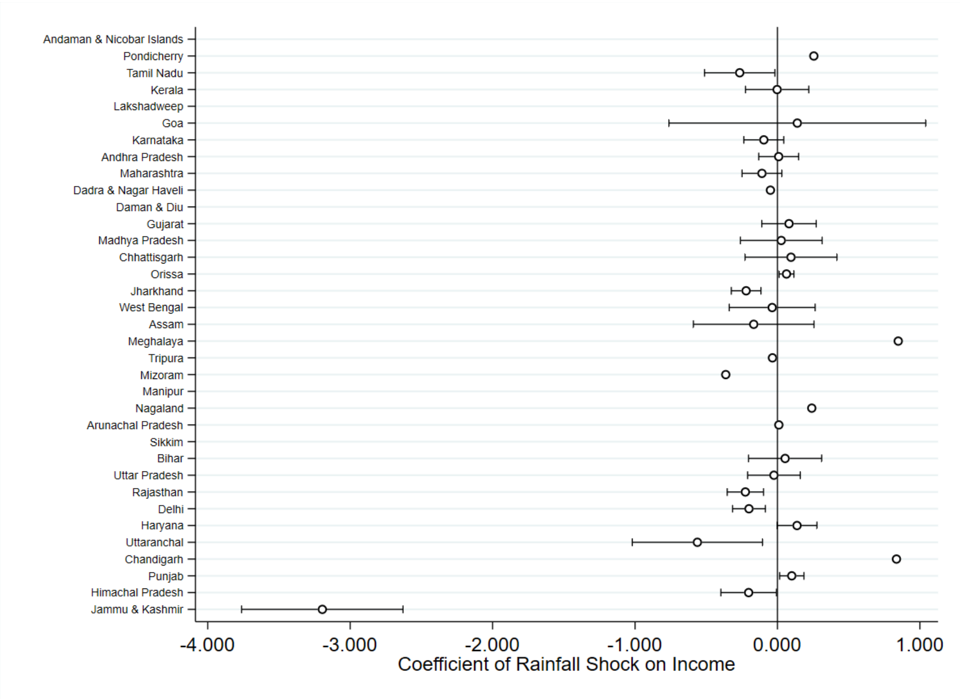

Figure 10: Heterogeneous Impact of Rainfall Shocks on Consumption.
Figure plots the coefficient on rainfall shocks by estimating equation (1) with log MPCE as the dependent variable separately for each of the states in the sample. There are no plots for some states due to missing data.

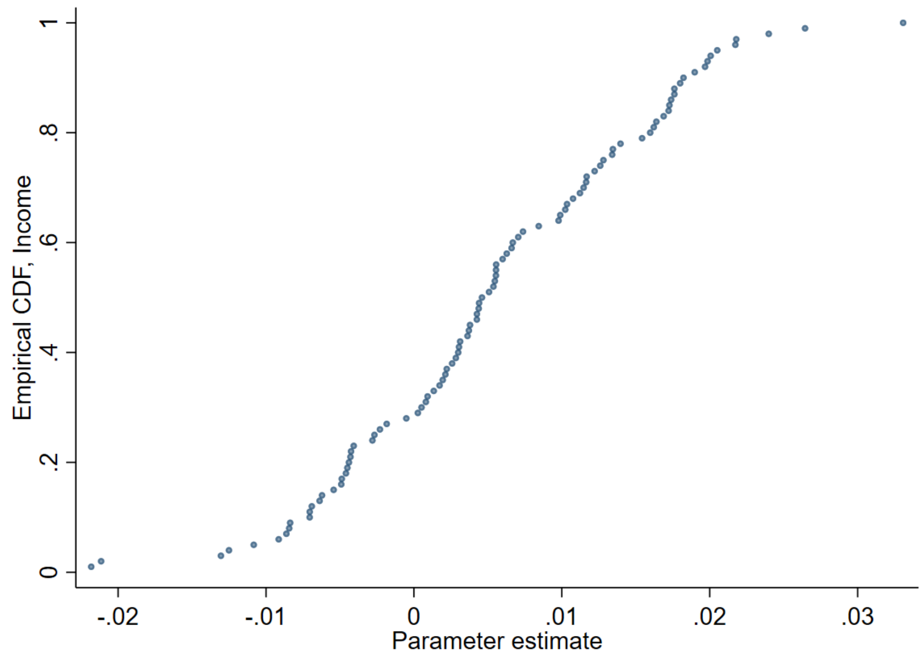

Figure 11: Figure plots Empirical Cumulative Distribution Functions (CDFs) of the coefficients obtained by iteratively regressing log household income on a random draw of rainfall shock from a uniform distribution for each district, the placebo shock, the true shock and full set of controls, 100 times.

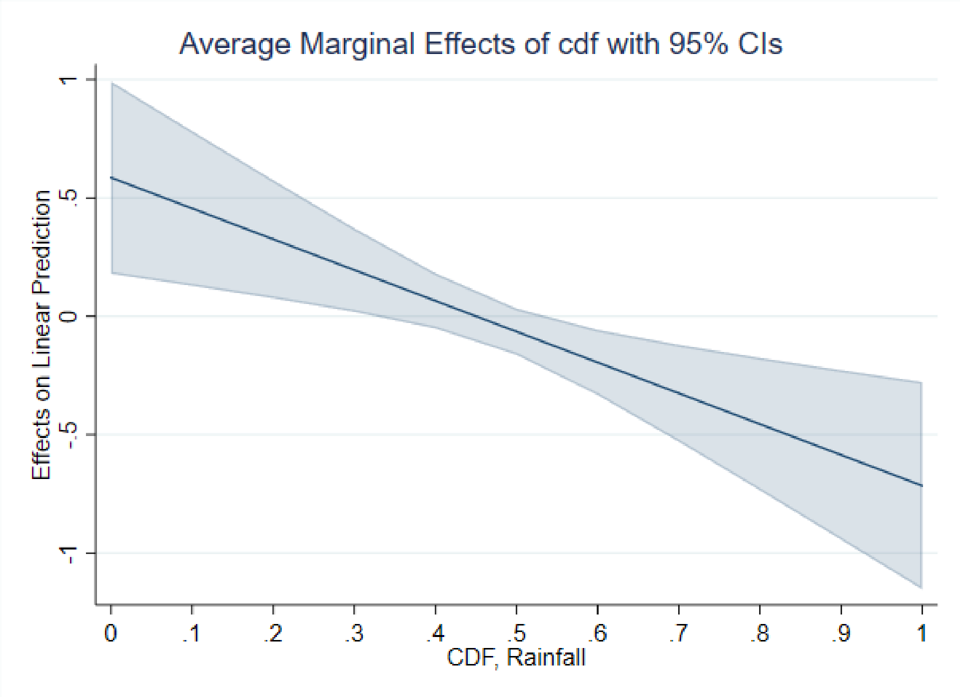

Figure 12: Figure shows average marginal effect of CDF of rainfall.
Notes: Figure plots the average marginal effect of CDF of rainfall as it goes from zero to 1 in steps of 0.10. The shaded area is the 95% confidence interval.

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