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

[LATEST]

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Abstract

Weather shocks pose significant income risks. Using a large household panel survey in India and geo-coded climate data, I find that rainfall shocks reduce household income by 7%. It lowers consumption and asset-holding but increases household debt. Rainfall shocks predominantly affect the asset-poor and the rural households by reducing agricultural and non-agricultural wage income. Moreover, its impact exhibits significant geographical variations. I then analyse if the roll-out of a major workfare program affected earnings in districts exposed to rainfall shocks. Using a difference-in-difference strategy and the phased roll-out of the program, I find that it primarily benefits female-headed households. Thus, intensifying workfare programs could increase climate resilience for the most vulnerable population.

1 Introduction

Increasing variability in the weather poses major economic and non-economic risks (see IPCC 2014, Fischer and Knutti 2015, Morton 2007, Mani et al. 2018, etc.). However, it mainly affects the rural areas of developing countries (Loayza et al. 2012, Skoufias

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2012). There are three reasons for this: first, households in rural areas mainly depend on agriculture for their livelihood. Second, absent or incomplete financial markets constrain farmers from insuring against crop failures, leaving them vulnerable to weather shocks (Rose 2001, Dercon 2002, Cole et al. 2013). Third, negative weather shocks might reinforce existing socioeconomic disadvantages that lower adaptive capacity and exacerbate impact (Flatø et al. 2017). With multiple socioeconomic stressors facing the rural poor, adverse weather events might reduce earnings, lower consumption and assets, and raise the debt-burden, sometimes with fatal consequences (Mani et al. 2018, Carleton 2017, Burke et al. 2018). Hence, to increase climate resilience, it is important that micro-level studies of the impact of weather shocks complement macro-level evidence to inform policy debates.

Yet, our understanding of the heterogeneous impact of weather shocks on households, the different coping measures these households adopt, and the role of public safety nets in moderating its impact, is far from complete. To fill this knowledge gap, I use a large Indian household panel survey conducted in 2005 and 2012 and geo-coded climate data to examine the causal effect of weather shocks on household income, consumption, asset-holding and debt-burden. Identification comes from within-household variations in unanticipated weather shocks that are orthogonal to time-invariant determinants of household-level outcomes. In this study, I concentrate on a specific source of weather shocks – unanticipated variation in rainfall. 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 exposed to unanticipated rainfall shocks.[1] To measure impact, I compare the average change in income for households that received income from NREGS work with the average change in income for households that were eligible, but did not receive NREGS income.[2] Further, in estimating impact, I control for biases arising from self-selection of participants and non-random selection of districts into NREGS phases.

To preview the main results, I find that rainfall shocks reduce household income by 7%, which roughly amounts to one month's foregone earnings for the average-income household. This result is robust to a placebo treatment of randomly drawn shocks, including higher order lags of rainfall shocks, sample selection, alternative measures of rainfall shocks, winsorising data to guard against outliers, controlling for elapsed time

[1] The seasonality of NREGS work might be a concern. However, NREGS 'guarantees' 100 days of unskilled manual work within fifteen days of receiving an application to work, failing which the applicant is entitled to an unemployment allowance. Hence, this is less of a concern for this study.

[2] One concern here is that the decision to work might be endogenous even after obtaining a NREGS job-card. However, I find that, as high as 74% of the eligible non-participants cite 'no work' as the main reason for non-participation, which implies that NREGS income is exogenous to households. In fact, only 9.8% of the eligible non-participants cite 'not interested' as the reason for non-participation.

between the shock and the interview as well as controlling for districtwise variations in temperature. Rainfall shocks predominantly affect the asset-poor and the rural households by reducing agricultural and non-agricultural wage income. However, there is no evidence to suggest that rainfall shocks reinforce existing socioeconomic barriers that exacerbate the financial burden on households. Moreover, while rainfall shocks reduce consumption and asset-holding, it increases household debt. With regard to the impact of NREGS on household income, I find that the workfare program raises the income of female-headed households in districts exposed to rainfall shocks by around 37%. While the overall impact of NREGS is positive, it is not statistically significant. To ensure that the estimates are representative of all the states and union territories in India, I use appropriate sampling weights in all the regressions.

In general, negative weather shocks lower household living standards (Mani et al. 2018). The shock-income gradient might however differ by household characteristics. 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. I engage with the kinds of trade-offs that households make when faced with weather shocks in section 4.2. Moreover, in informal economies with incomplete risk-pooling (Townsend 1994, Ligon et al. 2002), public safety nets can insure households against weather-induced income volatility (Dercon 2002). Against the backdrop of a nationwide roll-out of a public workfare program in India, I analyse if the program has been effective in alleviating weather-induced distress in section 4.3.

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 population vulnerable to climate change in developing countries, which makes this study extremely relevant.

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 critical. Second, I study the impact of an aggregate shock – variation in rainfall at the district level – on households' financial behaviour. 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 districts exposed to rainfall shocks, 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. Not only that, 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 a shock as an event when a district's monsoon rainfall in a year is either below the 20^{th} percentile or exceeds the 80^{th} percentile of its rainfall distribution over past 30 years.[3] As this captures location-specific unanticipated variations in rainfall, it is exogenous by design and orthogonal to time-invariant determinants of household-level outcomes, which allow for clear identification. The results from this study contribute to the literature on the relationship between weather shocks and household finance and the role of public workfare programs as a safety net within a developing country context.

The rest of the paper is organised as follows: In section 2, I outline the framework that connects rainfall shocks to household finance and introduce the dataset. In section 3, I discuss the empirical strategy. In section 4, I present results from the benchmark model, illustrate the effectiveness of NREGS as a safety net, discuss the results and present extensions of the benchmark model to gain additional insight. Section 5 presents several robustness checks. Section 6 concludes.

[3] In section 4.5.3, I examine the impact of floods and droughts separately on a range of dependent variables and find their impact to be symmetric.

2 Climate Change and Household Finance

The weather strongly affects household decisions by increasing income risks (see discussion in Dell et al. 2014). 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 rather optimistically that with adequate development planning the number of climate-migrants can be reduced by 80%. Achieving this target, however, will require adaptation policies informed by micro-level evidence of the impact of weather shocks on financial behaviour of households.

Figure 1 illustrates how, for a negative weather event, households might experience varying degrees of financial burden. In this study, a weather shock constitutes unanticipated variations in rainfall during the preceding monsoon season (more on this in section 2.2). Households face different 'mitigating' and 'intensifying' factors that affect weather-induced impact. In general, weather adversities pose significant income risks. For instance, erratic rainfall might lead to crop failures that shrink agricultural income. The shock-income gradient, however, might 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, as Townsend (1994) finds in India, where rainfall shocks affect landless farmers but not the landed.

Households adjust their saving, consumption and debt in response to fluctuations in income (Wolpin 1982). They 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.

With incomplete risk-pooling, as is often the case in informal economies (Townsend 1994, Ligon et al. 2002), public safety nets can insure households against weather-induced income volatility (Dercon 2002). Thus, it is a combination of the intensifying factors and the mitigating factors that determine the actual weather-induced financial burden at the household-level. To what extent are these factors salient in India? To address this question, I combine household-level panel data in India with high-resolution gridded climate data.

[Figure 1 about here.]

I am guided by economic theory in selecting the household-level economic variables – the dependent variables in the empirical model. Since income accords purchasing power, it is instrumental in gaining access to a wide array of resources. This has first order impact on household finance and is therefore a natural choice. But, as Deaton (2005) argues, consumption better approximates direct living standards of households. I therefore explore the link between weather shocks and household consumption expenditure. To cope with weather-induced income variability, households might take-up debt or draw down assets, which push them deeper into poverty. Hence, I also examine the impact of rainfall shocks on debt-burden and asset-holding.

Next, I introduce the data and discuss the construction of variables.

2.1 Household Level Data

I obtained data on household income, consumption, debt, assets 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 1,503 villages and 971 urban blocks. The follow-up survey in 2012 (IHDS-II) re-interviewed 83% of the households from 2005, and covered 1,420 villages and 1,042 urban blocks.[4] IHDS-II provides information on 42,152 households, which includes an additional replacement sample of 2,134 households.[5]

[4] One concern is the bias arising from sample attrition due to permanent out-migration of households to cope with 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

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.

[Table 1 about here.]

IHDS provides data on income, consumption, and debt 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 expenditure 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, except asset-index, 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 variations in log(MPCE). Not surprisingly, the maps reveal the familiar pattern in regional differences in income and consumption in India. 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.

[Figure 2 about here.]

[Figure 3 about here.]

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 on a household's asset holding. The average asset-index, measured on a 0-33 points scale,

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.

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.

Besides the economic variables facing households, I gathered information on several household characteristics. On average, a household had 5 members. About one-fourth of its members were children. I also obtained 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 households in the sample received payment for NREGS work in 2012.[6]

In addition, I gathered data on variables that might systematically disadvantage households: the fraction of households depending on agriculture, the share of Muslim households and those that belong to lower castes – the Scheduled Castes and Scheduled Tribes. Nearly 40% of the households were dependent on agriculture 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. Nearly 30% of the households were either SCs or STs and around 11% of the households were Muslims.

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.

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

[Figure 4 about here.]

However, rainfall is location-dependent and therefore endogenous to a model that determines variation in household-level 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 rainfall shock as a dummy variable that takes a value of one if a district's monsoon rainfall is either below its 20$^{\text{th}}$ percentile (a drought) or exceeds its 80$^{\text{th}}$ percentile (a flood) during past 30 years, and is zero otherwise (normal rainfall).[7] 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 finance. 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.[8]

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 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 match 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

[7]The 20$^{\text{th}}$ percentile and 80$^{\text{th}}$ 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 15$^{\text{th}}$ percentile as a rainfall shock in sub-Saharan Africa and focus on the number of shocks in the last 10 years.

[8]In sections 4.5.5 and 5.4.4, I show that the main results are robust to alternative definitions of rainfall shocks.

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, while the blue-shaded districts experienced a positive rainfall shock (or floods), the yellow-shaded districts experienced a negative rainfall shock (or droughts).

[Figure 5 about here.]

[Figure 6 about here.]

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 finance. 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 asset-index), for household i in district d at time t. $Rainshock_{dt}$ is a dummy variable that takes a value of 1 if district d received an unanticipated rainfall shock at time t, with β its coefficient. Thus, $Rainshock_{dt}$ is a covariate shock that applies to all households within a district. X_{idt} is a vector of household-head and household composition controls. It includes information on the household head's gender, age and literacy along with controls for the number of household members and the fraction of members that are children with corresponding coefficient vector, γ. Including X_{idt} in the regression model reduces omitted variables bias in estimating β arising from potentially time-varying household-specific features.

I include household fixed effect, α_i, to control for unobservable time-invariant household-specific factors.[9] Year fixed effects, ϕ_t, absorbs year-specific shocks. u_{idt} is an error term clustered at the district level. The clustering takes into account possible serial correlations arising from district-level rainfall shocks. IHDS provides sampling weights that specify the probability that a household is included in the sample based on its sampling design. To obtain coefficient estimates that are representative of the population, I use the sampling

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

weights in 2005 supplied by IHDS.[10] In equation (1), the main coefficient of interest is β. It measures the impact on the dependent variable, y_{idt}, if household i experiences a rainfall shock, $Rainshock_{dt}$, relative to households that do not receive a rainfall shock i.e. experiences a normal monsoon season. 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.

In the next section, I present results from 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 asset-holding. I then assess the effectiveness of NREGS, a public workfare program, in moderating the impact of weather-induced income variability of households.

4.1 Effect on Income: Benchmark Results

A reasonable starting hypothesis is that negative weather shocks adversely affect household income. The impact is likely to be concentrated on households that depend on agriculture as their primary income source. This is because any unanticipated variation in rainfall can ruin harvest, which shrinks agricultural income. Furthermore, 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, asset-holding 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 rainfall shocks reduce 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 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

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

magnitude presents a significant financial shock that affects consumption, asset-holding and debt-burden, as will be discussed in section 4.2.

[Table 2 about here.]

Household-head features and composition of the household affect income. Column 2 presents results after controlling for such differences. After accounting for household-head characteristics and composition effects, the point estimates in column 2 increases to 7.3%. Including the set of controls results in a significant gain in the model fit as the adjusted R-squared increases from 0.03 in column 1 to 0.13 in column 2.

Additionally, households face several socioeconomic barriers that might affect earnings. I consider four such disadvantages: whether agriculture is the main source of income for the household, if the household is female-headed, whether the household belongs to a lower caste or if the household head identifies herself as a Muslim. Columns 3 to 6 present results where I interact $Rainshock_t$ with each of the four disadvantages in separate columns and include the variable itself to capture its direct effect. For instance, in column 3, I interact $Rainshock_t$ with *Agriculture Dependent* – a dummy variable for whether the household is agriculture-dependent – and control for its direct impact on income along with household-head characteristics and composition effects as well as 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. This, suggests that although socioeconomic barriers lower household earnings (not presented in the table), they do not exacerbate the impact of rainfall shocks once their direct impacts are factored into the model.

4.2 Effect on Consumption, Debt and Assets

In this section, I consider the impact of rainfall shocks on household consumption, debt-burden and assets. 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 after controlling for household-head and household composition and including household fixed effects and year fixed effects. In the second specification, I include lagged rainfall shock, $Rainshock_{t-1}$, as an additional covariate.

[Table 3 about here.]

Table 3 shows that rainfall shocks reduce consumption by around 4% (column 1) while it negatively affects asset holdings. The average value of the asset-index is lower by about 0.29 units when households experience an unanticipated rainfall shock than when they do not experience the shock (column 5). Household debt, on the other hand, rises by 52% in response to rainfall shocks (column 3).

To examine the persistence of the impact of rainfall shocks, I additionally include one-period lagged consumption and re-estimate the regressions. I find that both the decline in consumption and assets are quite persistent whereas, the impact on debt is short-lived and do not persist beyond the initial year when the household experiences the shock. For consumption and assets, however, the coefficient on lagged shock is in fact larger than the contemporaneous shock, which suggests limited adaptive capacity of households in the face of negative weather shocks. One explanation why consumption and assets decline beyond the first period but not debt might be due to the presence of credit constraints. If households are constrained in taking-up additional debt, it will result in a more aggressive decline in consumption and assets as the shock is passed through, which columns 2 and 6, respectively suggest in Table 3, without an increase in debt.

If loans do not provide adequate income-buffer to credit-constrained households, as observed in Table 3, a related policy question is the extent to which public safety nets can fill the gap. In the next section, I examine this question in the context of the introduction of NREGS.

4.3 Impact of NREGS on Income

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? In this section, I address these questions by exploiting the phasewise roll-out of NREGS.

[Figure 7 about here.]

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 additional 130 districts in April 2007, while Phase 3 covered the remaining 296 districts in April 2008. Figure 10 in Appendix B maps the phasewise implementation of NREGS for districts covered in the IHDS survey.

In addition, Figure 7 illustrates the key milestones in the implementation of NREGS and the IHDS survey rounds. IHDS-I was conducted in 2005 i.e. before the roll-out of NREGS whereas, IHDS-II was conducted 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 income. To understand how NREGS performs in the face of adverse rainfall shocks, I focus on a sub-sample of households living in districts that received rainfall shocks at least once during the study period. I use a difference-in-difference (DD) strategy to estimate the impact of NREGS on household income. I compare the average change in income for the treatment group – households without NREGS income in 2005 that have NREGS income in 2012 – relative to the average change in income for the control group – households without NREGS income in both 2005 and 2012. One concern, however, is that people self-select into the program. This might arise because NREGS provides work that requires manual labour, which is likely to attract the less educated and the poor that are willing and able to do manual labour. To reduce self-selection bias, I compare treated households with eligible but untreated counterpart. The latter consists of households that have a NREGS jobcard, but do not receive NREGS income. As already mentioned, unavailability of work is reported as the main reason why people who have NREGS card, do not receive income from NREGS. Thus endogenous participation is less of a concern in this study.

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.

[Table 4 about here.]

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 and finds that NREGS increased agricultural wages by 4.3%.

While the increase in wages was gender-neutral, it predominantly affected unskilled work.[11] 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 threshold in a regression discontinuity framework and finds a significant increase in private sector wages for women. Thus, past studies have documented 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, while also exploring the gendered dimension of its impact.

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

$$y_{idt} = \delta T_{idt} + \eta(T_{idt} * Early_d) + \gamma X_{idt} + \alpha_d + \phi_t + v_{idt} \tag{2}$$

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. $Early_d$ is a district-specific dummy variable that takes a value of 1 if NREGS was implemented in district d during either Phase 1 or 2 and is zero otherwise. The parameter η captures the interaction of $Early_d$ with treatment, $(T_{idt} * Early_d)$.[12] The vector X_{idt} is a list of controls that include household-head features and the composition of the household 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

[11] 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).

[12] Imbert and Papp (2015) follow a similar classification of districts into early and late based on the phase under which NREGS was implemented.

year-specific factors. v_{idt} is an error term, which might be correlated within households over time.

[Table 5 about here.]

Table 12 presents results from estimating equation (2). Columns 1 and 2 relate to the impact of the treatment i.e. receiving NREGS income, on log of income of households that are eligible for NREGS work across all districts in the sample. On the other hand, columns 3 and 4 focus on households that are eligible for NREGS work in districts that were exposed to unanticipated rainfall shocks at least once during the study period. 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 the respective sub-samples. Table 12 shows that receiving income from NREGS (Treated) raises log household income by around 11% (column 1). For female-headed households, the corresponding rise is about 33% (column 2). In rainfall affected districts, however, the overall impact is positive but not statistically significant (column 3). In contrast, for female-headed households, receiving income from NREGS raises household income by 37% (column 4). Moreover, the impact of treatment in 'early' districts were notably lower than districts where NREGS was implemented later on.

As already mentioned, I include district fixed effects to rule out selection of districts into one of the three NREGS phases. Additionally, to ensure proper identification, 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 13 in Appendix A presents results from re-estimating equation (2) on a sub-sample of households that satisfy the following criteria: they have an asset-index that exceeds the median value of asset-index in a district-year, they are eligible for NREGS work, and they live in districts that were exposed to unanticipated rainfall shocks at least once during the study period. The premise is that NREGS will have negligible impact on households that are non-poor in terms of asset holdings in the face of negative income shocks. The results in Table 13, 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 on a further restricted subset of female-headed households within this sub-sample.[13]

[13] I consider another estimation strategy where I conduct a phasewise analysis, similar to that in Berg et al. (2018). Table 5 in Appendix A presents results from the phasewise analysis. Table 11 presents corresponding placebo checks on high asset-index households. The results are qualitatively similar to those in Tables 12 and 13, respectively.

4.4 Discussion

Overall, the results suggest that rainfall shocks reduce log household income by about 6.6%-7.8% (see Table 2). This translates to a loss of earnings between Rs.2,397 (=exp(10.5)*0.066 from Tables 1 and 2, respectively) and Rs.2,833 (=exp(10.5)*0.078) 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, there is no evidence to suggest that rainfall shocks reinforce existing socioeconomic disadvantages, once their direct impact is accounted for.

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 contemporaneous rainfall shocks reduce household consumption by around 4%. With average household consumption per capita at Rs.781 (=exp(6.66) from Table 1), a reduction of 4% shrinks it by Rs.30.5 (=exp(6.66)*0.039) per month or annually by Rs.365. A little algebra show that for an average sized household, this represents a reduction of Rs. 1,957. 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 almost 4 foregone medical treatments a year for an average-sized household. The loss is actually much greater since untreated ailments erode human capital that affect 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 attempt to smooth consumption by taking-up debt and drawing down assets in response to negative income shocks.

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 5 shows that while additional income from NREGS do not improve total household income in districts exposed to unanticipated rainfall shocks, it increases income for female-headed households by around 37%, which is indeed an encouraging result. Thus, by providing income-buffer in times of weather-induced shocks, workfare programs act as public safety nets that increase climate resilience for the most vulnerable.

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

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 rainfall shocks differs by household's wealth and location. To investigate the role of wealth, I divide the sample into two groups: households that lie above the median value of asset-index in a district-year, and households with asset-index below the cut-off. Columns 1 and 2 in Table 6 present results corresponding to these two groups. I find that the impact of rainfall shocks is more pronounced for the low asset-index group. While rainfall shocks lower household income by 8% in the low-asset group (column 1), it reduces income by 5% in the high-asset group (column 2). This result is hardly surprising. Assets play an important role in smoothing fluctuations in income. Whereas, households in the high asset-index group are better placed to draw down their assets in times of hardship, which reinstates lost income, it might be less feasible for low asset-index households. Hence, unanticipated weather shocks differentially affect households based on their asset ownership.

[Table 6 about here.]

Rural households depend are more dependent on agriculture than their urban counterpart. Hence, rainfall shocks are much more likely to affect rural households than urban households. This is precisely what columns 3 and 4 in Table 6 indicate. While rainfall shocks reduce household income in rural areas by 9% (column 3), its is much lower and is not statistically significant in urban areas (column 4).

4.5.2 Heterogeneous Impact by State

India encompasses a range of climatic features, as already mentioned. Hence, the impact of rainfall shocks are likely to differ amongst its sub-national regions. Here, I look at the variation in impact across Indian states. 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 11 in Appendix B plots the coefficients of rainfall shocks on log of consumption. The figures indicate that the rainfall shocks indeed exhibit significant heterogeneity in its impact across states.

[Figure 8 about here.]

4.5.3 Impact by Shock Type

Thus far, the constructed rainfall shock series treats floods and droughts in the same way, even though they capture two opposite extremes of the rainfall distribution. While floods capture the upper tail – instances when rainfall exceeds the 80^{th} percentile of a district's 30 year historical rainfall distribution – droughts capture the lower tail – when rainfall lies below the 20^{th} percentile. But, are the impacts of floods and droughts on household income symmetric?

To understand this, Figure 9 plots the result from regressing total household income, agricultural wage income and non-agricultural wage income respectively, on floods and droughts separately. The panel on the left plots the impact of floods whereas, the panel on the right plots the impact of droughts. I find that: first, the impact is indeed symmetric. Both floods and droughts reduce income. However, floods and droughts differ in their intensities and the types of income sources they affect. While both floods and droughts negatively impact agricultural income, the coefficient on drought loses statistical significance in explaining variations in total and non-agricultural wage income. In a similar way, Figure 12 in Appendix B examines how floods and droughts respectively, affect alternative sources of income. A notable distinction is the differential impact of floods and droughts on remittance income, wherein I observe a drop when exposed to floods, but no corresponding decline in the case of droughts. This points towards floods being a more potent covariate shock than droughts, especially when there is low out-migration. In addition to analysing income, Figure 13 in Appendix B examines the impact of floods and droughts on household consumption, debt and asset holding, where again, the effects are symmetric across shock types.

[Figure 9 about here.]

4.5.4 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. The point estimates in Table 7 in columns 1 and 2, show that while rainfall shocks reduce agricultural income by 20%, it lowers non-agricultural wage income by 14%. The negative impact on agricultural income is expected as unanticipated rainfall shocks ruin harvests that shrink agricultural income. 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 resulting increase in labour supply is likely to depress non-agricultural wage rates, which reduces income from non-agriculture wages.

[Table 7 about here.]

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 meaningfully associated with rainfall shocks. In addition, Table 14 in Appendix A, provides pairwise cross-correlations coefficients between different sources of income. The low cross-correlations, 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 location-specific adaptation capacity that permanently lowers a household's earning potential. I examine this next.

4.5.5 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 income (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 22%. The estimate is significant at the 5% level of significance. The standard errors are clustered at the district level. In column 2, I regress the change in log income between 2005 and 2012, that is, the growth rate of income, and find that an additional shock, on average, reduces the growth rate of household income by 23%. Thus, accumulated shocks impact not only the level of income, but also reduces its rate of growth.

[Table 8 about here.]

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, 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[14], household-head and composition controls 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 14 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

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

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 and assets, but not debt. But do higher order lags (of rainfall shocks) affect household income? 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 additionally introduce the second order lag of rainfall shocks to the model in column 1. In both cases, I find that only contemporaneous rainfall shocks turn out to be statistically significant with a negative sign whereas, its lags have no discernible impact.

[Table 9 about here.]

5.3 Sample Selection

Rainfall shocks might force 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 results, I bound the impact of weather shocks following Lee (2009) and applied in Burke et al. (2015). The literature suggests that rural to urban migration in India is typically quite low and is in the region of 2%-6%.[15] 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, or around 17% of the households from IHDS-I could not be re-interviewed in IHDS-II. To address attrition, an additional 2,134 households – the replacement sample – was added in IHDS-II. These additional

[15] 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. A significant share of such migration is driven by females marrying into a different household (Munshi and Rosenzweig 2016).

households were randomly selected from the same neighbourhood where re-interviews failed.[16]

Column 1 in Table 16 in Appendix A shows the impact of rainfall shocks on income using the 'full sample', which includes the attrition sample, the replacement sample and households interviewed in both IHDS-I and IHDS-II. The point estimate of rainfall shocks shows a negative 7.9%. I use within-district variation in rainfall shocks after controlling for household characteristics and year fixed effects to obtain these results. Column 2, on the other hand, presents results from only a subset of households that were interviewed in both IHDS-I and IHDS-II. Column 3 presents results that relate to the 'full sample', except the additional sample from IHDS-II. It regresses log income on a constructed shock, *False Rainshock*$_t$, which assumes that none of the households predisposed to weather-induced out-migration (i.e. households reporting either agriculture or non-agricultural wage income as the primary income source) in the attrition sample receive a rainfall shock. Thus, it makes it difficult to detect the impact of rainfall shocks. However, as column 3 shows, the impact of this constructed shock is still negative and similar to the results in columns 1 and 2. Column 4 is a slight variation of column 3 Here, I consider the 'full sample' and construct a false rainshock to be one where none of the households predisposed to rainfall shocks in the additional sample receive a rainfall shock. Here again, the impact of rainfall shocks remains statistically significant and is in fact higher than the results in columns 1 to 3. Thus, selective sampling do not affect our estimates in any meaningful way.

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 match rainfall shocks to households based on the month of the household interview. As mentioned earlier, if the household was 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 was interviewed before the onset of the monsoon season, I attribute the rainfall shock corresponding to the previous year's monsoon rainfall. This, however, leads to differences in the time-span between when the shock is experienced by the household and the interview, which might systematically affect

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

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, debt or assets) from households receiving a weather shock at a more proximate time. Hence, in this section, I include a variable, 'Time Since Rainshock', to control for the duration (in months) between the rainfall shock and the interview month. Tables 17 and 18 in Appendix A present results after controlling for elapsed time since the rainfall shock. The results are quite similar to the corresponding main results in Tables 2 and 3, respectively. Hence, the benchamark results are robust to controlling for elapsed time since rainfall shock.

5.4.2 Districtwise Temperature Variations

The relationship between rainfall shocks and income might be affected by district-specific time-varying surface temperature. Tables 19 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 20 in Appendix A present additional results that relate to consumption, debt and asset holdings. 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.[17] 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 is 5%/95% winsorised. It shows that rainfall shocks reduce household income by about 7% and is significant at the 1% level even after controlling for outliers.

[Table 10 about here.]

5.4.4 Alternative Measure of Rainfall Variation

Column 2 in Table 10 presents result using an alternative definition of rainfall shock. Instead of a binary measure of rainfall shock like before, I use the probability that a district realises a specific level of rainfall given its 30 years historical distribution i.e. the

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

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 have detrimental effects on income (as shown in section 4.5.3), I account for this non-linear relationship by including a quadratic of the CDF variable. The estimated marginal impact obtained by holding the covariates at their respective average values is about 9.6%. A negative and statistically significant quadratic term of CDF of rainfall suggests that the relationship is indeed non-linear.

6 Conclusion

In this paper, I examine the impact of rainfall shocks on household finance – income, consumption, asset-holding and debt-burden. Variation in rainfall, however, is endogenous to determining household-level outcome variables of interest. For instance, farmers might adopt less-risky strategies and invest less in agricultural innovation in places that experience large fluctuations in the weather, which affect future income streams. I overcome this inference problem by fitting a gamma distribution to district-specific rainfall data during 1980-2012 and define a rainfall shock to be one when the cumulative probability of rainfall in a district-year either falls below the 20$^{\text{th}}$ percentile of its past rainfall distribution or if it exceeds the 80$^{\text{th}}$ percentile. This ensures that the constructed series of rainfall shocks is exogenous in determining the household-level outcome variables, allowing for clear identification.

Utilising IHDS data, a nationally representative panel dataset of more than 40,000 households across two rounds in 2005 and 2012, I find that rainfall shocks reduce household income by about 7%, on average. This is after controlling for several observable potentially time-varying household-head and household composition features as well as unobservable time-invariant factors through household and year fixed effects. Furthermore, I cluster the standard errors at the district level to account for the covariate nature of rainfall shocks.

An important question is whether rainfall shocks reinforce differences along the lines of gender, caste, religion or occupation, that exacerbate impact. I investigate this and find no evidence to suggest that rainfall shocks reinforce pre-existing societal disadvantages, after controlling for the direct effect that such barriers impose on income, and including the full set of controls. I then consider the effect of rainfall shocks on consumption, debt, and asset holding. The results show that rainfall shocks lead to a 4% reduction in consumption, a decline in assets owned, and a 52% increase in household debt. To examine the persistence of shocks on these variables, I introduce lagged rainfall shocks and find that the decline in consumption and assets are more aggressive after the initial period, but not so for debt, which might indicate higher pass-through of the shock as households reach their credit constraints.

A related question is whether public workfare programs act as safety nets that moderate the intensity of weather-related shocks. I examine this question in the context of the phased roll-out of a major workfare program in India – the Mahatma Gandhi Rural Employment Guarantee Scheme (NREGS). NREGS guarantees 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. Using a difference-indifference approach that controls for the self-selection of participants and the non-random selection of districts into NREGS phases, I find that additional income through NREGS has a positive impact on female-headed households in districts that experienced a rainfall shock. The overall impact, however, although positive, does not turn out to be statistically significant. Placebo checks on households with higher asset-index reveal no such gains, which is as expected.

I then consider several extensions of the benchmark model to shed more light on the relationship between rainfall shocks and income. First, I find that rainfall shocks exhibit significant heterogeneity. The impact of rainfall shocks is more pronounced for the asset-poor, highlighting the importance of assets as income-buffer. In addition, rainfall shocks differ by location: it affects households in rural areas, but not those in urban areas, which might be due to the concentration of farming in the rural locations. With different climatic conditions spread across the country, it is hardly surprising that rainfall shocks exhibit significant geographical variations.

Secondly, droughts and floods have symmetric impact. I find that unanticipated variations in rainfall – either in excess or in low amounts – reduce income, consumption and assets, but increase household debt. However, the impact is more pronounced for floods than droughts and to some extent differentially affects few of the income sources, especially remittance income, which is lower during floods but not affected during droughts.

This leads to an investigation of the pathways through which rainfall shocks affect household income. It reveals, rather unsurprisingly, that rainfall shocks affect agricultural income and non-agricultural wage income. There is hardly any impact on the different alternative income sources I consider – business, salary, others, benefits or remittances. This, along with the low cross-correlations between income sources, suggest income diversification as an effective *ex-ante* adaptaion strategy.

Another important question is the extent to which accumulated shocks, measured by the number of shocks that a district is exposed to in the last 5 years, affect income. Controlling for initial household characteristics, I find that an additional episode of rainfall shock reduces income by 22%. More importantly, growth effects are equally large. This shows that the impact of recurring shocks accumulate over time, which affects not only the level of income but also its rate of growth.

I then 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 a regression with income as the dependent variable along with several controls, and detect no significant impact. This shows that the results are not an artefact of the data. Secondly, I use higher order lags of rainfall shocks to explain variations in income and find no significant impact. Since people might permanently out-migrate as a coping measure, it might lead to a spurious relationship. I therefore attempt to bound the impact of rainfall shocks. The results confirm the benchmark estimates. Finally, I conduct additional checks such as controlling for the elapsed time between the shock and interview, controlling for districtwise variations in temperature, winsorising the dependent variables to guard against outliers and using alternative measures of rainfall variation. The results from robustness checks reinforce the benchmark estimates.

Tackling 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 play in moderating the intensity of impact. The results from this study shed light on these critical issues and find that intensifying workfare programs could increase climate resilience for the most vulnerable population.

Appendix

A Tables

[Table 11 about here.]

[Table 12 about here.]

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B Figure

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[Figure 11 about here.]

[Figure 12 about here.]

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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
Asset-Index	11.79	6.046	15.19	6.601	13.49	6.553
Main covariates:						
Rainshock_t	0.31	0.462	0.35	0.476	0.33	0.469
NREGS_{2012}	-	-	0.16	0.362	-	-
Household composition:						
No. of Members	5.85	3.029	4.87	2.341	5.36	2.751
Dependency ratio	0.29	0.216	0.24	0.220	0.26	0.219
Household-head controls:						
Female Headed	0.09	0.292	0.14	0.352	0.12	0.324
Age of Household Head:						
$\text{Age}\leq 25$	0.03	0.162	0.02	0.142	0.02	0.152
$25<\text{Age}\leq 40$	0.31	0.463	0.26	0.440	0.29	0.452
$40<\text{Age}\leq 60$	0.49	0.500	0.50	0.500	0.49	0.500
$\text{Age}\geq 60$	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
Other household controls:						
Agriculture Dependent	0.43	0.495	0.37	0.483	0.40	0.490
Lower 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

Notes: Table shows descriptive statistics. MPCE = monthly per capita consumption expenditure. Income, consumption and debt are deflated by price index provided by IHDS to reflect real values in constant 2005 prices before taking logs. Asset-index is an index measure of household assets that ranges from 0 to 33, where a larger value indicates higher asset ownership. NREGS = National Rural Employment Guarantee Scheme. The row, NREGS_{2012}, shows the fraction of households in the sample receiving positive income from NREGS work. Since NREGS was implemented after IHDS-I, the values appear only for IHDS-II (i.e. in 2012). Dependency ratio is the number of children divided by the total number of household members. Rainshock_t is the fraction of households receiving unanticipated rainfall shocks, where rainfall shock is a dummy variable that takes a value of 1 if the total rainfall during the preceding monsoon season for a particular district either falls below the 20^{th} percentile or exceeds the 80^{th} percentile of its rainfall distribution during the last 30 years. Lower caste households belong to either the Scheduled Castes or the Scheduled Tribes.

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

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Rainshock_t	-0.066**	-0.073**	-0.069**	-0.071**	-0.078**	-0.067**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Rainshock_t x Agriculture			-0.006			
			(0.03)			
Rainshock_t x Female Headed				-0.019		
				(0.04)		
Rainshock_t x Muslim					0.040	
					(0.04)	
Rainshock_t x Lower Caste						-0.019
						(0.03)
Household-head controls	No	Yes	Yes	Yes	Yes	Yes
Household composition	No	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-Sq	0.027	0.125	0.130	0.125	0.125	0.125
Households	39681	39680	39680	39680	39680	39680
Observations	78062	78014	78014	78014	78014	78014

Notes: Dependent variable is log of household income. $Rainshock_t$ is a dummy variable that takes a value of 1 if the district received an unanticipated rainfall shock during the last monsoon season and is zero otherwise. Household-head controls include if the household is female-headed, the age of the head classified into four categories ($\leq$25 years, 26-40 years, 41-60 years and >60 years) and whether the head is literate. Household composition includes the number of household members and the fraction of members that are children. All regressions include a constant term along with household and year fixed effects. Column 3 additionally controls for agriculture dependence, column 5 for whether it is a Muslim household, while column 6 controls for whether it is a SC/ST household. Estimates are weighted to be representative of 33 states and union territories in India. Standard errors clustered at the district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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

	log(MPCE)		log(1+Debt)		Asset-Index	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Rainshock_{t}	-0.038*	-0.039*	0.517***	0.511**	-0.281**	-0.292**
	(0.02)	(0.02)	(0.20)	(0.20)	(0.14)	(0.14)
$\text{Rainshock}_{t\text{-}1}$		-0.053**		-0.208		-0.456***
		(0.02)		(0.19)		(0.12)
Household-head controls	Yes	Yes	Yes	Yes	Yes	Yes
Household composition	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	0.267	0.269	0.015	0.015	0.445	0.449
Households	39714	39714	38990	38990	39714	39714
Observations	79198	79198	68616	68616	79244	79244

Notes: Dependent variables are log monthly per capita consumption expenditure (columns 1 and 2), log (1+total household debt) (columns 3 and 4) and asset-index (columns 5 and 6). $Rainshock_t$ takes a value of 1 if the district received an unanticipated rainfall shock during the last monsoon season and is zero otherwise. Even numbered columns introduce a one-period lagged rainfall shock, $\text{Rainshock}_{t\text{-}1}$. All regressions include a constant term, the full set of controls (see Table 2 for a list of controls) along with household and year fixed effects. Estimates are weighted to be representative of 33 states and union territories in India. Standard errors clustered at the district level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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-head controls:			
Female headed	0.06	0.09	-0.026***
Age of household head:			
Age$\leq$25	0.03	0.04	-0.011*
25<Age$\leq$40	0.32	0.35	-0.034**
40<Age$\leq$60	0.48	0.47	0.013
Age$\geq$60	0.17	0.13	0.033**
Literate	0.56	0.42	0.140***
Household composition:			
No. of members	6.19	6.07	0.112
Dependency ratio	0.31	0.33	-0.021***

Notes: Table shows baseline summary statistics of households in districts receiving rainfall shock at least once (i.e. either in 2005 or 2012 or both). To control for selection on participant characteristics, I include only households that are eligible for NREGS work indicated by having a NREGS job-card. Treatment group = Households without NREGS income in 2005 that received NREGS income in 2012. Control group = Households without NREGS income in 2005 and 2012. $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Impact of NREGS on log of Household Income (Early/Late)

	All Districts		Rainshock Affected Districts	
	All	Female-headed	All	Female-headed
Variables	(1)	(2)	(3)	(4)
Treated	0.112***	0.331***	0.027	0.369**
	(0.04)	(0.10)	(0.06)	(0.17)
Treated x Early	-0.236***	-0.371***	-0.154**	-0.636***
	(0.04)	(0.11)	(0.07)	(0.21)
Household-head controls	Yes	Yes	Yes	Yes
Household composition	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj R-Sq	0.255	0.370	0.293	0.414
Districts	292	245	188	134
Observations	23228	2337	7078	717

Notes: Table shows the impact of receiving NREGS income (Treated) on log of total household income. Columns 1 and 2 consider households that are eligible for NREGS work across all districts in the sample whereas, columns 3 and 4 focus on households that are eligible for NREGS work, but only in districts that received unanticipated rainfall shocks at least once during 2005 or 2012 (rainfall affected districts). 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 received NREGS income in 2012. Early is a district-specific dummy variable that indicates whether NREGS was rolled-out in either Phase 1 or Phase 2. All regressions include a constant term, the full set of controls (see Table 2 for a list of controls) along with district and year fixed effects. Estimates are weighted to be representative of 33 states and union territories in India. Standard errors clustered at the household level. $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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	-0.079**	-0.052*	-0.085**	-0.025
	(0.04)	(0.03)	(0.04)	(0.03)
Household-head controls	Yes	Yes	Yes	Yes
Household composition	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. Columns 1 and 2 show results for households with asset-index below and above the median value of asset-index in a district-year, respectively. Columns 3 and 4 relate to rural and urban residents, respectively. $Rainshock_t$ is a dummy variable that takes a value of 1 if the district received an unanticipated 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 controls) along with household and year fixed effects. Estimates are weighted to be representative of 33 states and union territories in India. Standard errors clustered at the district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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)
Rainshock_t	-0.203***	-0.137**	-0.032	-0.065	-0.096	0.054	-0.145
	(0.07)	(0.07)	(0.05)	(0.05)	(0.07)	(0.06)	(0.09)
Household-head controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household composition	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	0.060	0.031	0.019	0.097	0.087	0.125	0.148
Households	21289	19742	12185	16146	6722	16440	6685
Observations	32834	26897	16504	22724	8595	19454	7486

Notes: Dependent variables are log household income classified by its primary source as in column headings. Column 1 presents result that relates to agricultural income; column 2 on non-agricultural wage income; columns 3-5 on business, salary and other income, respectively; columns 6 and 7 relate to income from benefits (government benefits such as pensions, allowances etc.) and remittances, respectively. $Rainshock_t$ is a dummy variable that takes a value of 1 if the district received an unanticipated 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 controls) along with household and year fixed effects. Estimates are weighted to be representative of 33 states and union territories in India. Standard errors clustered at the district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Impact of Accumulated Rainfall Shocks on Income

	$\log(\text{Income})_{2012}$	$\Delta\log(\text{Income})$
	(1)	(2)
Num. of Rainshocks in the last 5 years	-0.221**	-0.231**
	(0.10)	(0.10)
Initial Household Controls	Yes	Yes
District FE	Yes	Yes
Adj R-Sq	0.241	0.122
Districts	371	371
Observations	39265	38645

Notes: Dependent variables in column headings. Column 1 regresses log household income in 2012 on the number of rainfall shocks experienced by a district in the last 5 years. Column 2 presents long differenced regression result, which regresses the change in log household income between 2005 and 2012 on the number of unanticipated rainfall 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 includes district fixed effects. Estimates are weighted to be representative of 33 states and union territories in India. Standard errors clustered at the district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Impact of Lagged Rainfall Shock on Income

Variable	(1)	(2)
$Rainshock_t$	-0.074**	-0.076**
	(0.03)	(0.03)
$Rainshock_{t-1}$	-0.022	-0.021
	(0.03)	(0.03)
$Rainshock_{t-2}$		-0.014
		(0.03)
Household-head controls	Yes	Yes
Household composition	Yes	Yes
Household FE	Yes	Yes
Year FE	Yes	Yes
Adj R-Sq	0.125	0.125
Households	39680	39680
Observations	78014	78014

Notes: Dependent variable is log of total household income. $Rainshock_t$ is a dummy variable that takes a value of 1 if the district received an unanticipated rainfall shock during the last monsoon season and is zero otherwise. Column 1 introduces one-period lagged rainfall shock, $Rainshock_{t-1}$, whereas column 2 additionally includes two-period lagged rainfall shock, $Rainshock_{t-2}$. All regressions include a constant term, the full set of controls (see Table 2 for a list of controls), household and year fixed effects. Estimates are weighted to be representative of 33 states and union territories in India. Standard errors clustered at the district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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

	Winsorised log(Income)	log(Income)
	(1)	(2)
$\text{Rainshock}_{\text{t}}$	-0.070***	
	(0.02)	
CDF, Rainfall		0.602***
		(0.22)
CDF Squared, Rainfall		-0.720***
		(0.23)
Household-head controls	Yes	Yes
Household composition	Yes	Yes
Household FE	Yes	Yes
Year FE	Yes	Yes
Adj R-Sq	0.127	0.127
Households	39714	39680
Observations	79260	78014

Notes: Dependent variables in column headings. Column 1 presents result where log of income is 5%/ 95% winsorised. $Rainshock_t$ is a dummy variable that takes a value of 1 if the district received unanticipated rainfall shocks during the last monsoon season and is zero otherwise. Column 2 shows result obtained by regressing 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. All regressions include the full set of controls (see Table 2 for a list of controls), household and year fixed effects. Estimates are weighted to be representative of 33 states and union territories in India. Standard errors clustered at the district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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

Variables	All (1)	Female-headed (2)
Treated	-0.107	0.113
	(0.11)	(0.31)
NREGS x Early	0.012	-0.725
	(0.13)	(0.47)
Household-head controls	Yes	Yes
Household composition	Yes	Yes
District FE	Yes	Yes
Year FE	Yes	Yes
Adj R-Sq	0.295	0.478
Districts	161	86
Observations	2281	207

Notes: Table shows results from placebo checks that estimate the impact of receiving NREGS income (Treated) on log of total household income for high asset-index households i.e. households with assets exceeding the median value for a district-year. The analysis is restricted to households that are eligible for NREGS work and live in districts that received an unanticipated rainfall shock at least once during the study period. 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 the household received NREGS income in 2012. Early is a dummy variable that equals 1 if NREGS was rolled-out 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 controls) along with district and year fixed effects. Estimates are weighted to be representative of 33 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 Households Income: Phasewise Analysis

	All Districts		Rainfall Affected	
	All	Female-headed	All	Female-headed
Variables	(1)	(2)	(3)	(4)
Treated	0.112***	0.330***	0.038	0.389**
	(0.04)	(0.10)	(0.06)	(0.17)
Treated x Phase 1	-0.193***	-0.283**	-0.023	-0.398*
	(0.04)	(0.11)	(0.09)	(0.24)
Treated x Phase 2	-0.310***	-0.525***	-0.296***	-0.919***
	(0.05)	(0.13)	(0.09)	(0.27)
Household-head controls	Yes	Yes	Yes	Yes
Household composition	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj R-Sq	0.256	0.371	0.295	0.419
Districts	292	245	188	134
Observations	23228	2337	7078	717

Notes: Table shows the impact of receiving NREGS income (Treated) on log of total household income. Columns 1 and 2 consider households that are eligible for NREGS work across all districts in the sample whereas, columns 3 and 4 focus on households that are eligible for NREGS work, but only in districts that received unanticipated rainfall shocks at least once during 2005 or 2012 (rainfall affected districts). 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 the household received NREGS income in 2012. All regressions include a constant term, the full set of controls (see Table 2 for a list of controls) along with district and year fixed effects. Estimates are weighted to be representative of 33 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 (Phasewise)

Variables	All (1)	Female-headed (2)
Treated	-0.092	0.126
	(0.11)	(0.32)
Treated x Phase 1	0.237*	-0.531
	(0.14)	(0.63)
Treated x Phase 2	-0.290*	-1.097**
	(0.18)	(0.55)
Household-head controls	Yes	Yes
Household composition	Yes	Yes
District FE	Yes	Yes
Year FE	Yes	Yes
Adj R-Sq	0.301	0.478
Districts	161	86
Observations	2281	207

Notes: Table shows results from placebo checks that estimate the impact of receiving NREGS income (Treated) on log of total household income for high asset-index households i.e. households with assets exceeding the median value for a district-year. The analysis is restricted to households that are eligible for NREGS work and live in districts that received an unanticipated rainfall shock at least once during the study period. 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 the household received NREGS income in 2012. All regressions include a constant term, the full set of controls (see Table 2 for a list of controls) along with district and year fixed effects. Estimates are weighted to be representative of 33 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 primary sources of income.

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

Variables	log(Income)
Placebo Rainshock_t	0.014
	(0.01)
True Rainshock_t	Yes
Household-head controls	Yes
Household composition	Yes
Household FE	Yes
Year FE	Yes
Adj R-Sq	0.125
Households	39680
Observations	78014

Notes: Dependent variable is log household income. The result shows 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 controls) along with household and year fixed effects and a constant term. Estimates are weighted to be representative of 33 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)	(4)
Rainshock_t	-0.079***	-0.077***		
	(0.010)	(0.011)		
False Rainshock_t			-0.073***	-0.082***
			(0.011)	(0.010)
Household-head controls	Yes	Yes	Yes	Yes
Household composition	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj R-Sq	0.307	0.301	0.301	0.307
Districts	371	370	372	372
Observations	86847	78014	84771	86849

Notes: Table shows the impact of rainfall shocks on log of household income for different sub-samples. Column 1 presents result that relates to the 'full sample', which includes the attrition sample from IHDS-I, the additional sample from IHDS-II, and households that were interviewed in both IHDS-I and IHDS-II. Column 2 presents result for households that were surveyed in both IHDS-I and IHDS-II, and excludes both IHDS-I attrition sample and IHDS-II additional sample. Column 3 includes the 'full sample', except the additional sample from IHDS-II, and regresses log income on a constructed shock, 'False Rainshock_t', which assumes that none of the households predisposed to weather-induced out-migration in the attrition sample (those reporting positive agricultural and non-agricultural income) received a rainfall shock. Column 4 includes the 'full sample' and constructs a 'False Rainshock_t' wherein none of the households predisposed to weather-induced out-migration in the additional sample received a rainfall shock. $Rainshock_t$ is a dummy variable that takes a value of 1 if the district received an unanticipated 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 controls) along with district and year fixed effects. Estimates are weighted to be representative of 33 states and union territories in India. Standard errors clustered at the district level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Impact of Rainfall Shock on Income After Controlling for Time Since Rainshock

Variables	(1)	(2)	(3)	(4)	(5)
Rainshock_t	-0.071*	-0.070*	-0.068*	-0.076*	-0.064*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Rainshock_t x Agriculture Dep.		0.002			
		(0.03)			
Rainshock_t x Female Headed			-0.026		
			(0.04)		
Rainshock_t x Muslim				0.041	
				(0.04)	
Rainshock_t x Lower Caste					-0.022
					(0.03)
Time Since Rainshock	Yes	Yes	Yes	Yes	Yes
Household-head controls	Yes	Yes	Yes	Yes	Yes
Household composition	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Adj R-Sq	0.128	0.133	0.128	0.129	0.128
Households	39679	39679	39679	39679	39679
Observations	77978	77978	77978	77978	77978

Notes: Dependent variable is log of total household income. Table shows impact of rainfall shocks on income after controlling for the duration (in months) between the rainfall shock and the interview month. $Rainshock_T$ is a dummy variable that takes a value of 1 if the district received an unanticipated rainfall shock during the last monsoon season and is zero otherwise. Household-head controls include if the household is female-headed, the age of the head classified into four categories (≤25 years, 26-40 years, 41-60 years and >60 years) and whether the head is literate. Household composition includes the number of household members and the fraction of members that are children. All regressions include a constant term along with household and year fixed effects. Column 3 additionally controls for agriculture dependence, column 5 for whether it is a Muslim household, while column 6 controls for whether it is a SC/ST household. All regressions include a constant term along with household and year fixed effects. Estimates are weighted to be representative of 33 states and union territories in India. Standard errors clustered at the district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 18: Impact of Rainfall Shock on Consumption, Debt and Assets After Controlling for Time Since Rainshock

Variables	log(MPCE) (1)	log(1+Debt) (2)	Asset-index (3)
$\text{Rainshock}_\text{T}$	-0.038*	0.498***	-0.273**
	(0.02)	(0.18)	(0.13)
Time Since Rainshock	Yes	Yes	Yes
Household-head controls	Yes	Yes	Yes
Household composition	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj R-Sq	0.267	0.018	0.446
Households	39714	38988	39714
Observations	79162	68590	79208

Notes: Dependent variables are log monthly per capita consumption expenditure in column 1, log total household debt in column 2, and asset-index in column 3. Results control for the duration (in months) between the rainfall shock and the interview month along with the full set of controls (see Table 2 for a list of controls), household and year fixed effects. $Rainshock_t$ is a dummy variable that takes a value of 1 if the district received an unanticipated rainfall shock during the last monsoon season and is zero otherwise. Estimates are weighted to be representative of 33 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 Income After Controlling for Temperature

Variables	(1)	(2)	(3)	(4)	(5)
$Rainshock_t$	-0.073**	-0.069**	-0.071**	-0.078**	-0.067**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
$Rainshock_t$ x Agriculture Dep.		-0.006			
		(0.03)			
$Rainshock_t$ x Female Headed			-0.019		
			(0.04)		
$Rainshock_t$ x Muslim				0.040	
				(0.04)	
$Rainshock_t$ x Lower Caste					-0.019
					(0.04)
Temperature	Yes	Yes	Yes	Yes	Yes
Household-head controls	Yes	Yes	Yes	Yes	Yes
Household composition	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Adj R-Sq	0.125	0.130	0.125	0.125	0.125
Households	39680	39680	39680	39680	39680
Observations	78014	78014	78014	78014	78014

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 33 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 Consumption, Debt and Poverty After Controlling for Temperature

Variables	log(MPCE) (1)	log(1+Debt) (2)	Asset-index (3)
$\text{Rainshock}_\text{T}$	-0.037*	0.516***	-0.274**
	(0.02)	(0.20)	(0.13)
Temperature	Yes	Yes	Yes
Household-head controls	Yes	Yes	Yes
Household composition	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj R-Sq	0.269	0.015	0.447
Households	39714	38990	39714
Observations	79198	68616	79244

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 33 states and union territories in India. Standard errors clustered at the district level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

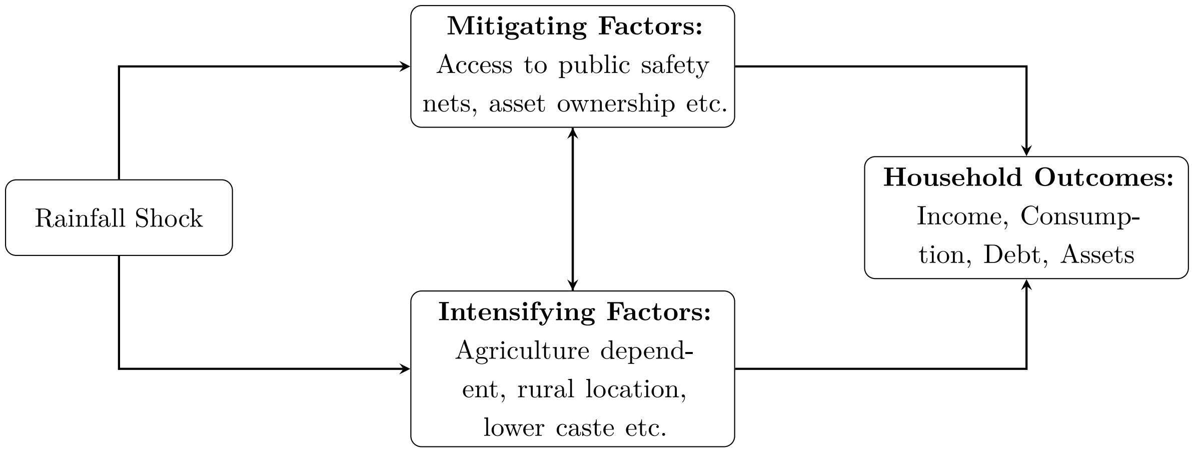

Figure 1: Conceptual framework of the relationship between rainfall shocks and its financial burden on households.

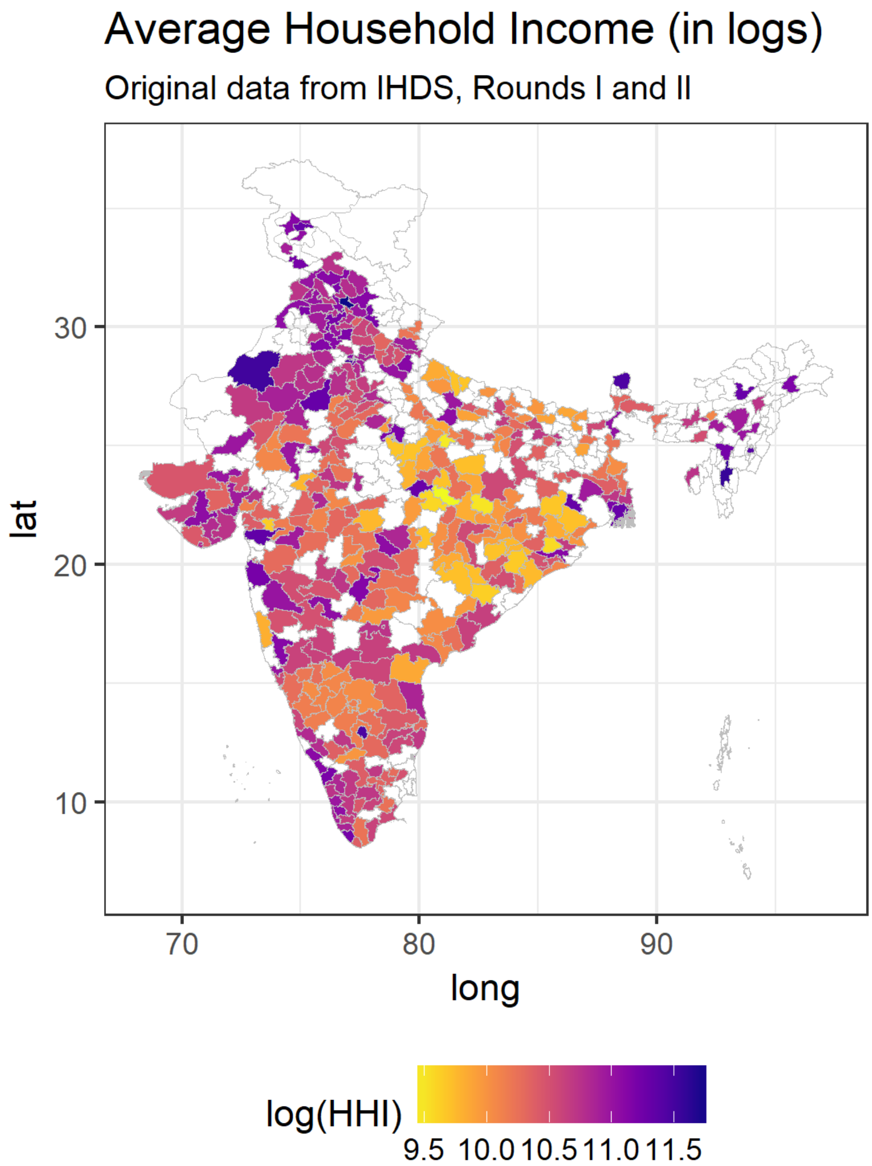

Figure 2: Districtwise average household income in logs (log(HHI)).
Notes: Figure illustrates districtwise log(HHI) averaged over IHDS survey rounds I and II. The scale ranges from low to high where districts shaded yellow report low log(HHI) whereas, districts shaded dark blue report higher values.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

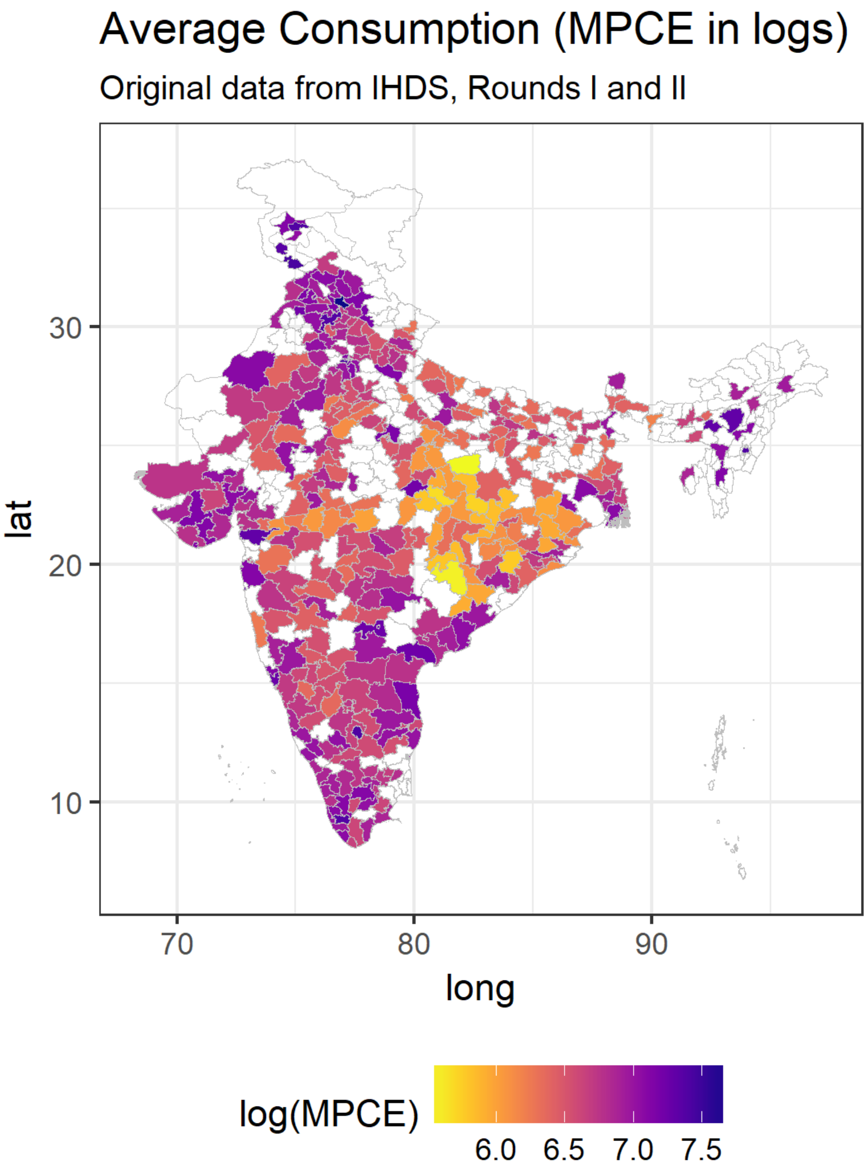

Figure 3: Districtwise monthly per capita consumption expenditure in logs (log(MPCE)). Notes: Figure illustrates districtwise log(MPCE) averaged over IHDS survey rounds I and II. The scale ranges from low to high where districts shaded yellow report low log(MPCE) whereas, districts shaded dark blue report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

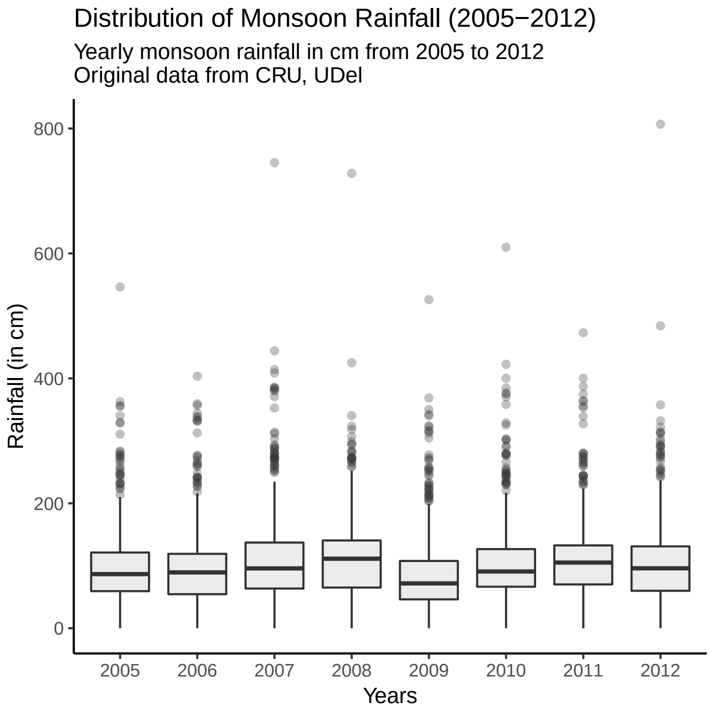

Figure 4: Distribution of Annual Monsoon Rainfall in India During 2005-2012.
Notes: Figure shows annual distribution of rainfall during the months of June to September in a calendar year during 2005-2012.

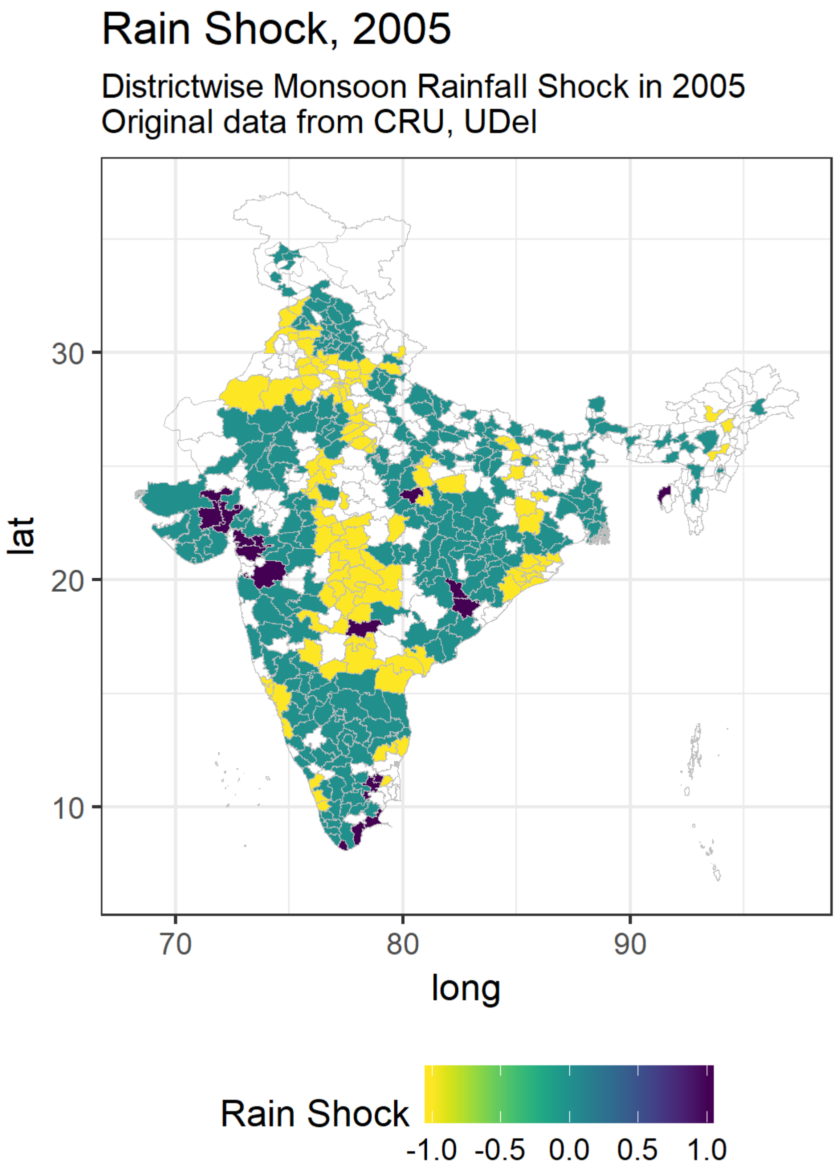

Figure 5: Districtwise monsoon rainfall shocks in 2005.
Notes: Monsoon rainfall is the total rainfall during the months of June-September in a year. Districts shaded yellow experience a negative rainfall shock (or, drought), those in dark blue experience a positive rainfall shock (or, flood), whereas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

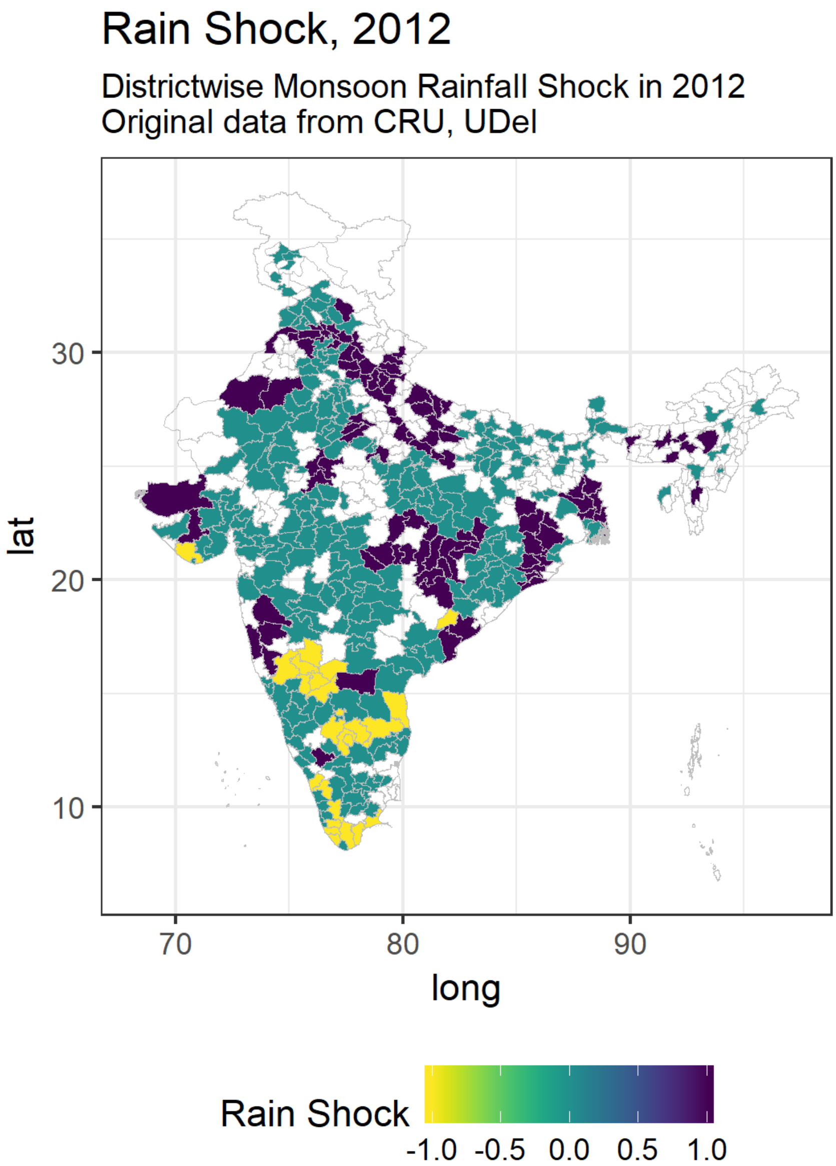

Figure 6: Districtwise monsoon rainfall shocks in 2012.
Notes: Monsoon rainfall is the total rainfall during the months of June-September in a year. Districts shaded yellow experience a negative rainfall shock (or, drought), those in dark blue experience a positive rainfall shock (or, flood), whereas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

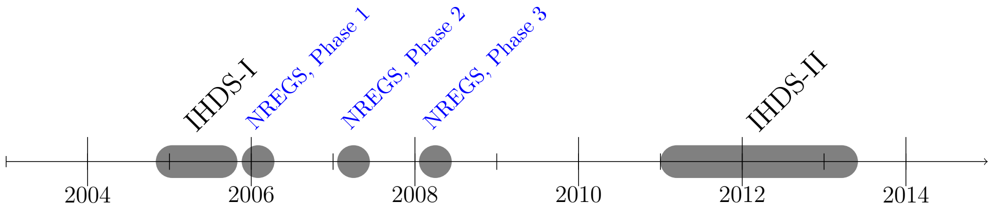

Figure 7: Timeline for NREGS and IHDS implementation.

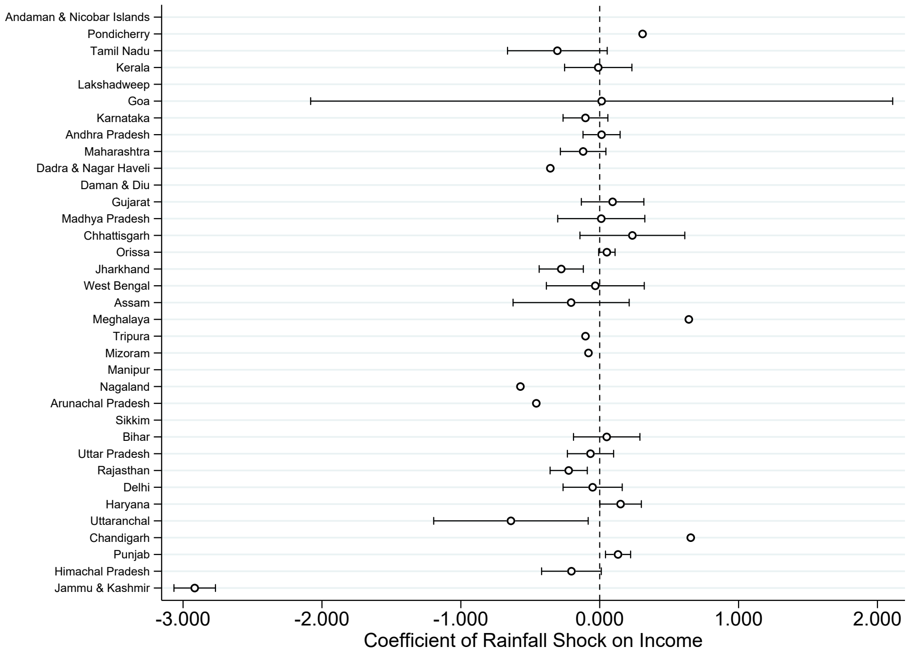

Figure 8: Statewise Impact of Rainfall Shocks on Income.
Notes: Figure plots the coefficient of rainfall shocks on log income by state along with its 95% confidence intervals. The estimates are obtained after including the full set of controls, household and year fixed effects. There are no plots for some states due to missing data.

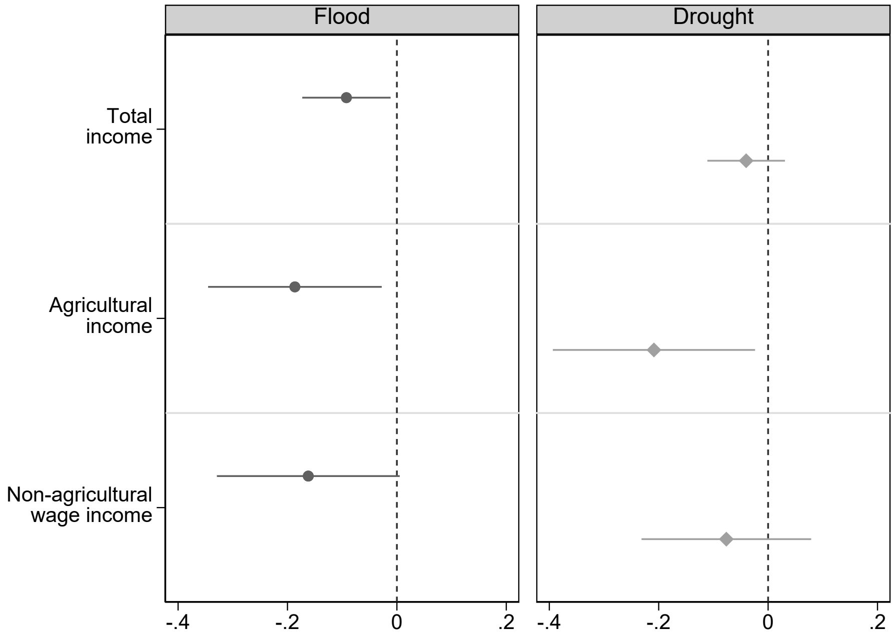

Figure 9: Heterogeneous Impact by Shock Type: Total, Agricultura and Non-agricultural Wage Income.

Notes: Figure plots the impact of unanticipated floods on total, agricultural and non-agricultural wage income in the left panel whereas, the panel on the right shows the impact of unanticipated droughts on the respective variables. A district is affected by a flood if its preceding monsoon rainfall exceeds the 80^{th} percentile of its rainfall distribution during the past 30 years, while it is affected by a drought if it falls below the 20^{th} percentile. The coefficients are obtained after including the full set of controls, household fixed effects and year effects.

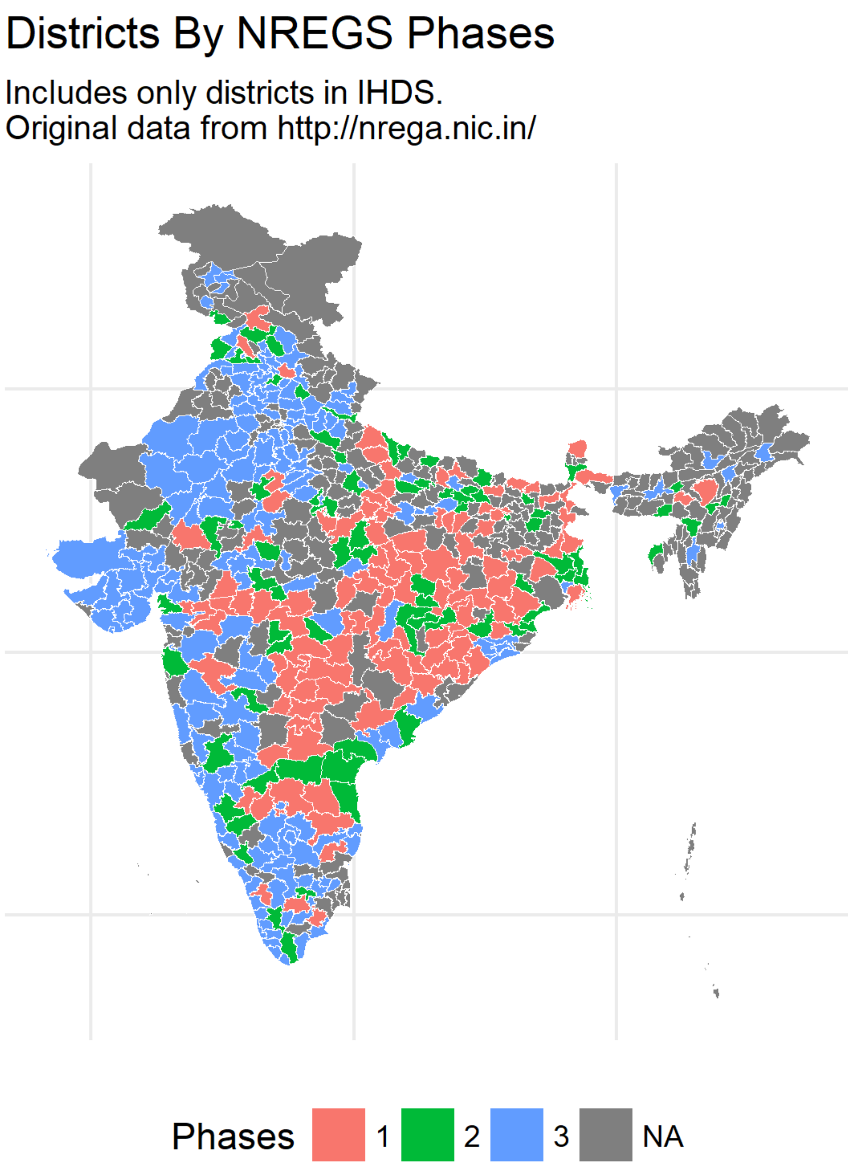

Figure 10: Districts By NREGS Phases.
Notes: Figure maps the NREGS phase corresponding to a district in the IHDS sample. NA=districts not included in the IHDS sample.

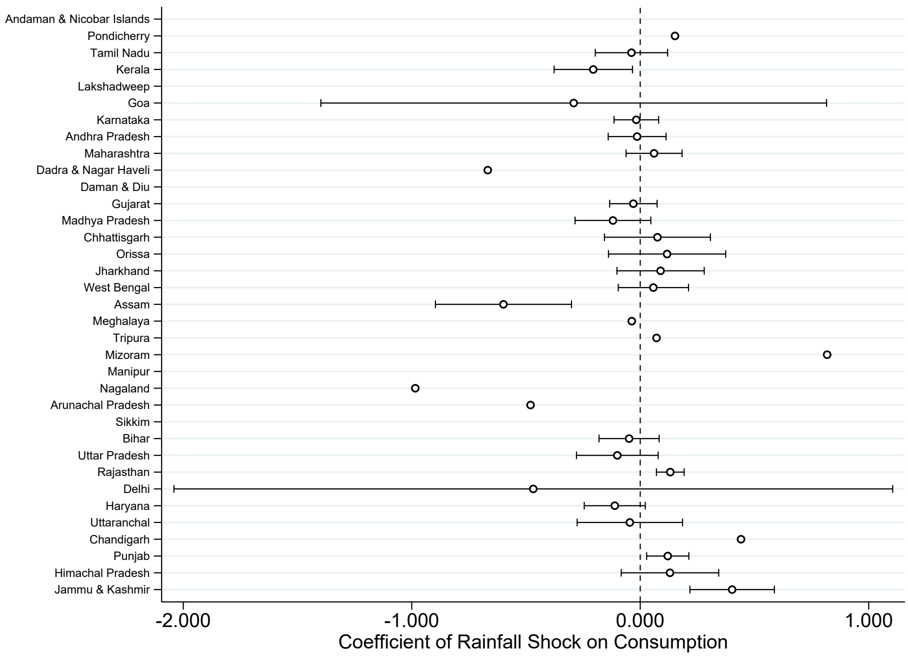

Figure 11: Statewise Impact of Rainfall Shocks on Consumption.
Notes: Figure plots the coefficient of rainfall shocks on log MPCE by state along with its 95% confidence intervals. The estimates are obtained after including the full set of controls, household and year fixed effects. There are no plots for some states due to missing data.

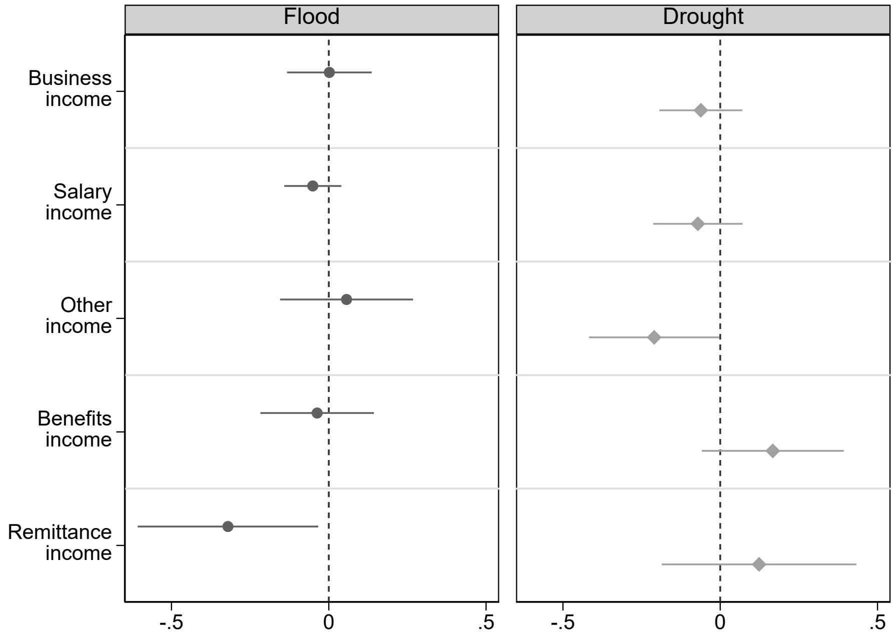

Figure 12: Heterogeneous Impact by Shock Type: Alternative Income Sources.
Notes: Figure plots the impact of unanticipated floods on income from different primary sources – business, salary, other, benefits and remittances – in the left panel whereas, the panel on the right, shows the impact of unanticipated droughts on the respective variables. A district is affected by a flood if its preceding monsoon rainfall exceeds the 80^{th} percentile of its rainfall distribution during the past 30 years, while it is affected by a drought if it falls below the 20^{th} percentile. The coefficients are obtained after including the full set of controls, household fixed effects and year effects.

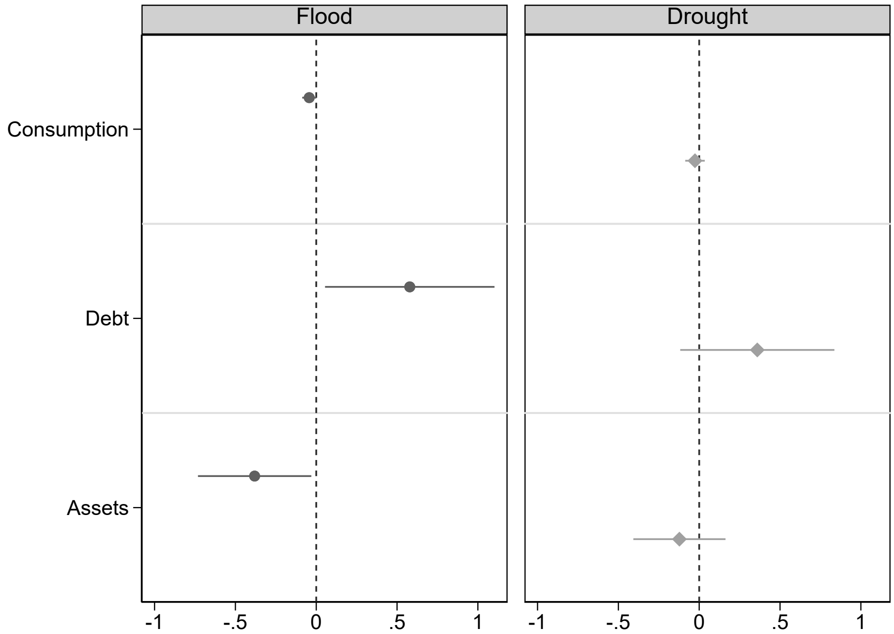

Figure 13: Heterogeneous Impact by Shock Type: Consumption, Debt and Assets.
Notes: Figure plots the impact of an unanticipated floods on consumption, debt and asset-index in the left panel whereas, the panel on the right, shows the impact of an unanticipated droughts on the respective variables. A district is affected by a flood if its preceding monsoon rainfall exceeds the 80$^{\text{th}}$ percentile of its rainfall distribution during the past 30 years, while it is affected by a drought if it falls below the 20$^{\text{th}}$ percentile. The coefficients are obtained after including the full set of controls, household fixed effects and year effects.

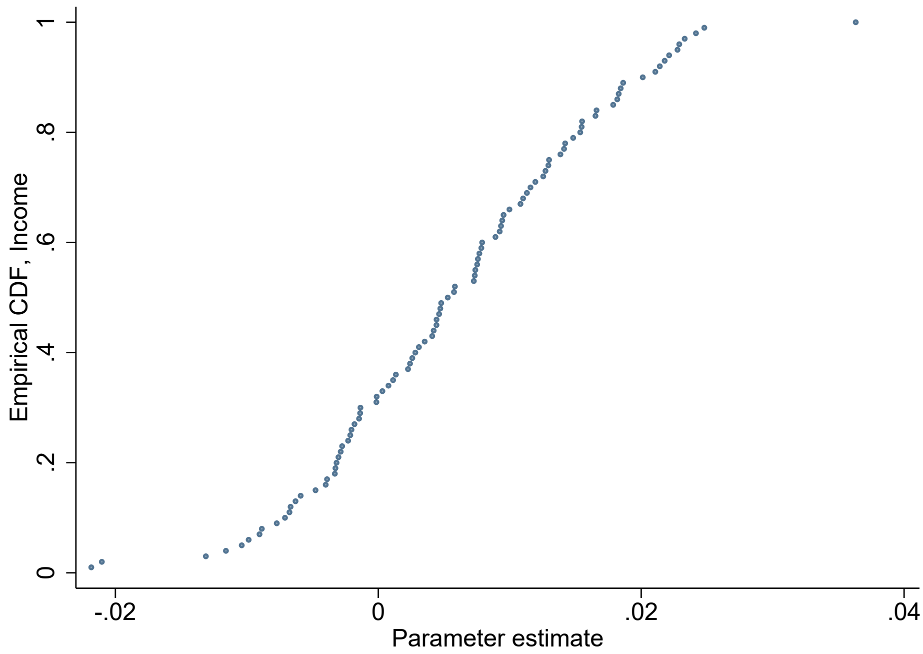

Figure 14: Figure plots Empirical Cumulative Distribution Functions (CDFs) of the coefficients obtained by iteratively regressing log household income on a random draw of rainfall shock from a uniform distribution for each district, the placebo shock, the true shock and full set of controls, 100 times.