Labour Supply Responses to Rainfall Shocks*

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Abstract

Agricultural production in developing countries is heavily rainfall dependent. Any unexpected variation in rainfall can therefore have considerable impacts on the welfare of households. Using unit record data from India, this paper shows that households respond to agricultural productivity (rainfall) shocks by varying the time allocation of individual members to different activities. There is a gender differentiated aspect to this response. We also examine the heterogeneity of effects across rain–fed and dam–fed districts. Rainfall shocks adversely affect women's opportunities for human capital accumulation and leads to considerable within household re-organization of activities, with women paying disproportionately higher costs, though primarily in rain–fed districts. Our results point to the importance of the National Rural Employment Guarantee Scheme (NREGS) and to the role of adequate infrastructure as *ex post* and *ex ante* mechanisms that will help dampen the impact of shocks.

JEL Codes: J22, O10, Q12

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1 Introduction

Rural households in most developing countries around the world are dependent on agriculture as the main source of income. But this also means that their incomes are susceptible to substantial variability, given that in most of these countries agricultural production is rainfall dependent. In the absence of well functioning local financial institutions, the ability of households to insure against such shocks can be restricted. This has potentially significant effects on poverty and can lead to a range of dire short and long term effects on measures of household welfare. With predictions suggesting that climate change will increase the variability of rainfall and hence the intensity of and uncertainty associated with rainfall shocks, how households respond rainfall shocks becomes crucial.

Observed variation in consumption is, however, less than observed variation in incomes (see, for example, Townsend, 1994, 1995, Jacoby and Skoufias, 1998). This suggests that households are able to, atleast partially, insure against observed variability in incomes. The mechanisms through which this takes place are varied. The existing literature has looked at two broad ways in which households can insure against income volatility: *ex ante* mechanisms, where they directly smooth income through a range of different practices (for example, choice of which crops to cultivate, using low return but low risk seeds, engaging in precautionary savings), and *ex post* where they adjust their behavior *after* the shock has been realized. Examples include borrowing from formal and informal sources, drawing down accumulated savings, and adjusting labour supply (see Morduch, 1995).

Rainfall shocks can be thought of as agricultural productivity shocks. Consider an unanticipated rainfall shock. This reduces the marginal product of on-farm labour. Previous research has documented that in order to smooth consumption in response to weather shocks, they resort to a range of strategies. These include supplying additional labour hours (Kochar, 1999, Maitra, 2001, Rose, 2001, Dercon et al., 2005), reducing human capital investment in children (Jacoby and Skoufias, 1997, Jensen, 2000), marrying daughters to distant households

(Rosenzweig and Stark, 1989), selling productive assets (Rosenzweig and Wolpin, 1993) and borrowing from microfinance institutions (Islam and Maitra, 2012). They may also engage in non-farm activities with low risks even if these activities have low returns (Ito and Kurosaki, 2009); alternatively labour may be reallocated to public works programs (Azam, 2012). This literature also points to gender differences in labour force participation and allocation of time to different activities in response to shocks. For example, in the face of a drought episode, women could adjust their time working in the labour market, whereas males could potentially migrate in search of work.

How vulnerable households deal with such shocks has gained importance in the context of climate change, which is likely to be associated with increased rainfall variability, with rainfall shocks becoming more intense. This is likely to result in increased variations in agricultural production.[1] As Dell et al. (2012) find, changing temperatures and precipitation ultimately affect economic growth via political outcomes, particularly in poor and agriculture-dependent countries. Apart from significant impacts on agricultural productivity for the poor, they document a range of other effects on political economy indicators. For example, a meta-analysis by Hsiang et al. (2013) finds strong causal evidence of climate on conflicts. They find that globally, a one standard deviation change in climate (towards more extreme rainfall or increased temperatures) leads to a 14% increase in inter-group conflicts. Thus, climatic variations are likely to significantly impact the lives of the poor in developing countries. What households can do in response and what safety nets, policies or institutions that governments can design to enable households respond effectively has become crucially important for welfare, growth and distribution.

This paper uses unit record data from India to investigate changes in labour force participation by activity and gender in response to rainfall shocks. Specifically, we investigate how individuals allocate their time between different activities (self-employment, farm labour, off-farm

[1] Auffhammer et al. (2006) show, using a statistical model of historical rice harvests in India, coupled with regional climate scenarios from a parallel climate model, that adverse climate changes due to brown clouds and greenhouse gases contributed to the slowdown in rice harvesting growth over the past two decades.

labour, working in public works programs, domestic work and attending educational institutions) when facing positive or negative agricultural productivity shocks. We match individual level data on time allocation to different activities, to data on rainfall shocks. This allows us to obtain the effects of agricultural productivity shocks on time allocation into different activities. We also use the heterogeneity of the effect of rainfall on agriculture to better understand the channels through which agricultural productivity (rainfall) shocks affect labour supply. To do this we take advantage of the large scale investment that India has made in irrigation since independence. This has primarily taken the form of dams (Duflo and Pande, 2007, Pande, 2008, Sarsons, 2015). Dams allow the so-called dam–fed districts to receive water during periods of rainfall shortage and they also provide protection against excess rain by storing water in the reservoirs. By controlling the flow of water, dams then insure agricultural production in these dam–fed districts against variations resulting from rainfall shocks. Agricultural production in the dam–fed districts is less volatile and incomes of households should be more stable. Labour supply responses to rainfall shocks should therefore also vary by whether or not the district is dam–fed or rain-fed.

Two results stand out. First, both men and women increase their participation in India's national employment guarantee scheme (NREGS) when faced with rainfall shocks.[2] Our results emphasize the importance of NREGS as the *employer of last resort* and the role it plays in insuring against agricultural income shocks. Second, women tend to withdraw from attending educational institutions and also increase the time they allocate to domestic duties in response to agricultural productivity shocks. These results are consistent with the patterns observed by

[2]The NREGS is India's main welfare program for the rural poor and the largest workfare program in the world, covering 11% of the world's population (Muralidharan et al., 2016). The NREGS makes it a statutory obligation for the government to provide at least 100 days of employment on demand to each rural household (with at least one able-bodied and willing adult member) in India at the prevailing minimum wage rate, failing which they will be provided with unemployment allowance. One-third of its beneficiaries are to be women. There are no eligibility requirements, since the manual nature of the work involved is expected to encourage the poor to participate (Dey and Sen, 2016). Participating households obtain job cards, which are issued by the local village council. Once issued with a job card, workers can apply for work. Officials are legally obligated to provide work on projects within five kilometres of a worker's home. The projects vary greatly, though road construction and irrigation earthworks predominate (Niehaus and Sukhtanker, 2013). Administration of the projects under NREGS is the responsibility of the local village council. The program came into operation in February 2006 in the 200 most backward districts (administrative units lower than the State) of India. In the second phase of the program (in 2007), NREGS was scaled up to another 130 districts. Finally, in its third and final phase, the program was extended to the remaining 285 districts of the country.

Jacoby and Skoufias (1997), Cameron and Worswick (2001), Björkman-Nyqvist (2013) across a number of different developing countries. Rainfall shocks therefore adversely affect women's opportunities for human capital accumulation and leads to considerable within household re-organization of activities, with women paying disproportionately higher costs. Importantly, these negative impacts on human capital accumulation of women is concentrated in rain–fed districts, suggesting that infrastructure has a significant role to play in helping households insure against income shocks.

The literature on how agricultural productivity shocks (measured by rainfall shocks) affects outcomes in different spheres of life in South Asia, general and India, in particular, has also grown in recent years. Shah and Steinberg (2017) estimate the impacts of early-life rainfall shocks on test scores and schooling outcomes of children aged 5–16 and find that more early life rainfall is associated with higher test scores. However, they also find that more rainfall during school years lowers total years of schooling. Brey and Hertweck (2018) examine the effects of monsoon rainfall shocks on output, wages, and prices in India and find that negative regional rainfall shocks exert long term adverse effects on prices. Negative local shocks however, affect only wages, but not prices. Interestingly, they find that the labour market does not have a strong role to play in this respect. Chuang (2019) finds that farmers in India respond to rainfall shocks by diversifying their income: they work more in the non-farm sector. Bandopadhyay and Skoufias (2015) and Skoufias et al. (2015), using data from Bangladesh and India, respectively, show that households in South Asia engage in occupational diversification as an adaptation strategy against risks arising from local level variability in rainfall. Kurosaki (2015), using data from Pakistan, shows that ability of households to share risk (when faced with natural disasters) is heterogeneous in both risk aversion and credit access.[3]

Our paper contributes to the understanding of how climatic variations can impact labour force participation and human capital accumulation in rural India. To the best of our knowledge,

[3] Our research is also related to the literature on response to natural disasters by firms, households and individuals (Sawada, 2007, Coffman and Noy, 2012, Cameron and Shah, 2015, Islam and Nguyen, 2018, Elliott et al., 2019).

ours is one of the first papers to exploit variations in the month of the survey to test the impact of rainfall shocks on household labour supply. In doing so, we are able to link changes in household insurance behaviour to participation in a range of labour activities. Taking into account monthly variations in rainfall shocks also allows us to examine whether and how specific months of the year are crucial in terms of their contribution to household welfare. If we expect policies to be designed to enable households to insure against such shocks, then having evidence and information on the timing of labour supply adjustments becomes critical. Our paper also contributes to the understanding of how gender dynamics play out in rural households, thus enabling us to better understand intra-household responses to agricultural productivity shocks. Finally, our heterogeneity analysis provides evidence on the role of infrastructure development in providing *ex ante* insurance against such shocks.

The rest of the paper is organized as follows. Section 2 contains a description of the data and summarizes key variables used in the estimation. Section 3 describes the empirical framework that we use to investigate the impact of positive and negative rainfall shocks on labour allocation to different activities. The key results are discussed in section 4. Section 5 examines the heterogeneity of the effect of rainfall shocks and the role of infra-structure. Finally, Section 6 concludes.

2 Data and Descriptive Statistics

We use data from a number of different surveys for our analysis. These include (*i*) data from multiple rounds of the employment schedule of India's national sample surveys (NSS); (*ii*) monthly historical rainfall data at the district level; (*iii*) the Village Dynamics in South Asia (VDSA) Meso-level dataset collected by ICRISAT, which provides information on crop production at the district level; and (*iv*) the Duflo and Pande (2007) data on dams in India, which we use to examine the heterogeneous effects of a rainfall shock.

2.1 National Sample Survey Data

Data on allocation of labour to different activities is obtained from the National Sample Survey (NSS) data from India. The NSS data was collected through surveys conducted across the country by the Ministry of Statistics and Programme Implementation (MOSPI), Government of India. We use the Employment Schedule of the NSS, which provides data on employment status and more importantly on time allocation to different activities at the individual level. The survey collects data on household members time disposition for a week. For each of the previous 7 days, which is termed the *reference week*, household members report the intensity of activity in a number of different activities: full intensity (coded as 1.0) or half intensity (coded as 0.5). The activities include own account work (i.e., self-employment), unpaid family work, regular (salaried) wage work, casual wage work in public works, in NREGS, in other types of work, attending educational institution and attending domestic duties and any other work (including begging and prostitution). Aggregating, over activities, over the reference week gives us a measure of the number of days allocated to the different activities. This is our measure of time allocation (and consequently of occupational choice).

While the data on time allocation is collected from 1983 (38^{th} round of the NSS) onwards, the date of the survey, and, hence the date of the reference week is publicly available only from the 62^{nd} round of the survey, conducted in 2005–2006. This information is important because we need to match time allocation to different activities to productivity (rainfall) shocks by month. Therefore, for our analysis in this paper, we restrict ourselves to the 62^{nd} (survey conducted in 2005–2006), 64^{th} (2007–2008), 66^{th} (2009–2010) and 68^{th} (2011–2012) rounds of the NSS data. The data also contains information on a range of other individual and household characteristics: gender, age, marital status, rural urban residence, religion, social group (caste), household size and monthly per capita household expenditure. We restrict ourselves to males and females aged 15–60, the working age group, residing in rural areas of the 21 major states of India.[4] Each round of the survey was conducted over the period July to the following June

[4]These are Himachal Pradesh, Punjab, Uttaranchal, Haryana, Rajasthan, Uttar Pradesh, Bihar, Assam,

and Figure 1 shows that for all four rounds there is considerable variation in the number of households that were surveyed in each month. This is important for identification purposes. The data contains information on the district of residence of the household and this enables us to match the households with the corresponding rainfall shock, which is defined at the district level (see Section 2.2, below).

We use this data on time allocation to calculate the total number of days each individual spent in the different activities during the past week. We begin by categorizing these into three broad groups: *total days worked* (which is the sum of own account work, unpaid family work, regular wage work, casual wage work in public works, in NREGS, in other types of work and any other work); *domestic duties* (days worked in attending domestic duties); and total days *attending educational institutions*. The top panel of Table 1 presents the average (by gender) of the number of days spent in the different activities in the reference week. Men spend significantly more time in outside work (5.3 vs 2.1), in attending educational institutions (0.84 vs 0.52) while women spend more time in domestic duties (0.05 vs 2.26). The bottom panel of Table 1 disaggregates the total days worked into its different components. Men allocate more time on average to own account work, regular wage work, casual wage work (public works and other works). Women work more in unpaid family work and NREGS. The descriptive statistics in Table 1 are indicative of significant gender differences in time allocation to different activities.

There is also considerable variation in time allocation to the different activities over the different months of the year. Figure 2 presents the average number of days worked by men and women in the different activities by month. For own account work, regular wage work, casual wage work (other works) and domestic duties, the average number of days worked by men and women is fairly stable through the year. Irrespective of the month of the year, men spend more time in outside work, regular wage work, casual wage work (other works) and attending educational institutions, while women allocate more time to domestic duties. There is, however,

West Bengal, Jharkhand, Odisha, Chhattisgarh, Madhya Pradesh, Gujarat, Maharashtra, Andhra Pradesh, Karnataka, Goa, Kerala and Tamil Nadu.

considerable variation in time allocated to unpaid family work, casual wage work (public works) and NREGS works. Women allocate more time to NREGS work during the peak summer months of May and June. Conversely, in these months, women spend less time in unpaid family work than men, while the opposite is true for the other months of the year.

Table 2 presents the means and standard deviations of a key set of individual and household characteristics for the full sample (columns 1 and 2) and separately for males (columns 3 and 4) and females (columns 5 and 6). The average age of those included in the estimating sample is 33.5 years; 21% of individuals belong to Scheduled Castes, 11% belong to Scheduled Tribes; 43.5% belong to Other Backward Castes and 24.5% belong to General (Upper) Castes, A large majority of the sample (85.5%) are Hindus, with Muslims making up almost 11%. The rest belong to an assortment of religions including Sikhs and Christians. Close to 72% of the sample are married, slightly higher for the female sample at 76%, compared to the male sample at 66%. The average household size is 5.5, with a monthly per capita expenditure of Rs. 2136. We use these individual and household level variables as additional controls in our regressions.

2.2 Rainfall Data and Defining Rainfall Shocks

We use monthly rainfall data collected by the University of Delaware to determine monthly rainfall shock within districts.[5] The data cover all of India over the period 1900—2016. For the purposes of this paper we use data for the period 1975—2012. The data are gridded by latitudes and longitudes. To match these to the districts where the households reside, we use the closest point on the grid to the center of the district and assign that level of rainfall to the district in the given month and year.[6] This way we are able to match rainfall data to 482 districts across the country over a 40 year period.

[5]The data is available for download from `http://climate/geog.udel.edu/~climate/html_pages/download.html#P2009`.

[6]There were cases where districts were either renamed or separated to form new districts. In such cases, new districts carved out of older ones were matched with the coordinates for the older districts to maintain consistency in matching.

All households residing in a district are assigned the district level rainfall. One could argue that aggregating rainfall in this manner implies that shocks in any one part of the district can affect outcomes in a different part of the same district. Given that the district is the smallest administrative unit at which weather shocks and agricultural productivity shocks can be analyzed, we have little recourse. However, it is worth noting that most districts in India are fairly small (on average 3500 km^2) and thus aggregation of rainfall to the district level should not be a major concern.

Figure 3 shows that there is large variation in median rainfall (median defined over the period 1975–2016) over months: pooling all districts together, the highest monthly median rainfall is more than 300 mm in July and around 15 mm in December. In Figure 3, the line in the centre of the box denotes the median, while the box itself denotes the interquartile ($75^{th} - 25^{th}$) range.

For each district and each month we define the rainfall shock as follows. First, we calculate the average (μ_{dm}) and the standard deviation (σ_{dm}) in rainfall for each district (d) and each month (m) over the 30 years prior to the date of the survey. We then compute a standardized measure of rainfall $z_{dmy} = \frac{R_{dmy} - \mu_{dm}}{\sigma_{dm}}$, where R_{dmy} is the rainfall in district d in month m in year y. Following GOI (2016), we define district d in month m in year y to face a rainfall shock if $z_{dmy} < -1$ or $z_{dmy} > 1$. The rainfall shock is defined to be a positive shock if $z_{dmy} > 1$ and a negative shock if $z_{dmy} < -1$. Note that these rainfall shocks should not be taken in an absolute sense in that we are not comparing districts that are prone to higher average rainfall to those that are prone to lower average rainfall: rather they are high or low-rainfall for each district for each month, relative to the historical average for that district in that month. Figure A1 shows the percentage of districts in each month and each year that experience a rainfall shortage (or drought/negative rainfall shock) or excess rainfall (floods/positive rainfall shock). As the figure shows, in any given month, up to 60% of districts might be affected by positive or negative shocks. Figure A2 present the histograms of the distribution of deviations (z) from average historical rainfall in the sample, by year. There are more positive shocks than negative shocks.

For our empirical analysis, we define a dummy variable $\xi_{dmy} = 1$ if district d in month m in year y experienced any rainfall shock ($z_{dmy} < -1$ or $z_{dmy} > 1$). Similarly, we define $\xi^{+}_{dmy} = 1$ if district d in month m in year y experienced a positive rainfall shock or excess rain ($z_{dmy} > 1$) and $\xi^{-}_{dmy} = 1$ if district d in month m in year y experienced a negative rainfall shock or rainfall shortage ($z_{dmy} < -1$). In additional specifications we disaggregate rainfall shocks into different categories to examine whether severity of shocks play a role.

2.3 Rainfall Shocks and Agricultural Production

In India, more than 70% of total net area under cultivation is rain fed. Nearly two-third of all adult males and four-fifth of all adult females report agriculture as their principal economic activity. Rainfall could therefore explain variations in agricultural productivity in India. To investigate this relationship, we construct a panel comprising of monthly crop production data from 310 Indian districts over the periods 2005–2012. This is a subset of the 482 districts for which we have monthly rainfall data. The data on crop production comes from the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) Village Dynamics in South Asia (VDSA) Meso-level dataset (Rao et al., 2012).[7] We use data on total production (quantity in thousands of tons) and area (in thousands of hectares) under cultivation for rice and wheat, the two major crops cultivated in India.

$$y_{dy} = \alpha_0 + \alpha_1 \xi_{dy} + \delta_d + \psi_y + \varepsilon_{dy} \tag{1}$$

where y_{dt} is the outcome of interest in district d in year y. We first examine the effects of rainfall shock in district d in year y (ξ_{dy}) on area cultivated and on total production of rice and wheat. In this case, we repeat the analysis described in Section 2.2 at the year level so that $\xi_{dy} = 1$ if district d experienced *any* rainfall shock in year y ($z_{dy} < -1$ or $z_{dy} > 1$).

[7] The data can be accessed from http://vdsa.icrisat.ac.in/vdsa-mesodoc.aspx.

The estimated value of α_1 gives the effect of the rainfall shock (ξ_{dy}) in district d in year y. The regressions also condition for a set of district and year fixed effects. The district fixed effects (δ_d) condition for time-invariant characteristics such as cropping patters, soil types and socio-economic characteristics that vary considerably across districts. The time fixed effects (ψ_y) allow us to examine whether the relationships have changed over time. The regression results are presented in columns 1–4 of Table 3.

Surprisingly *any* rainfall shock has no effect on the production of rice: the effect of the rainfall shock variable is never statistically significant on either total area cultivated or total production of rice (see columns 1 and 2). *Any* rainfall shock, on the other hand, is associated with a statistically significant increase in the area cultivated and total production of wheat.

We also disaggregate rainfall shocks into positive and negative rainfall shocks and estimate an extended version of equation (1) as follows:

$$y_{dy} = \alpha_0 + \alpha_1 \xi^{+}_{dy} + \alpha_2 \xi^{-}_{dy} + \delta_d + \psi_y + \varepsilon_{dy} \tag{2}$$

Here ξ^{+}_{dy} and ξ^{-}_{dy} are dummy variables that take a value of 1 if district d in year y experienced a positive rainfall shock (excess rain or flood) and experienced a negative rainfall shock (rainfall shortage or drought) respectively. This allows us to separate out the effect of positive and negative rainfall shocks. The corresponding regression results, presented in columns 5–8 in Table 3 show that positive and negative rainfall shocks have different effects on area cultivated and production of both rice and wheat. A rainfall shortage is associated with a statistically significant decline in both area cultivated and total production of rice and wheat. An excess rainfall, on the other hand, is associated with a statistically significant increase in the both area cultivated and total production of rice and wheat.[8] Therefore, positive and negative rainfall shocks have very different impacts on agricultural production. Therefore in our empirical analysis, we distinguish between positive and negative rainfall shocks. These results

[8] Rosenzweig and Binswanger (1993) show that droughts lead to significant reduction in farm profits in India. Shah and Steinberg (2017) argue that irrespective of the type of crop, crop yields are significantly lower in drought years. However, they do not specify the impacts of excess rainfall on crop yields.

are therefore consistent with the fairly large literature that shows that rainfall shocks affect productivity and wages in rural economies (see, for example, Jensen, 2000, Maccini and Yang, 2009, Jayachandran, 2006, Shah and Steinberg, 2017, Kaur, 2018).

2.4 Dams

We can use the heterogeneity of the effect of rainfall on agriculture to better understand the channels through which agricultural productivity (rainfall) shocks affect labour supply. To do this we take advantage of the large scale investment that India has made in irrigation since independence. This has primarily taken the form of dams (Duflo and Pande, 2007, Pande, 2008, Sarsons, 2015). Almost all of the dams constructed during the post-independence period have been for irrigation purpose and these dams form the core of the country's irrigation infrastructure (World Commission on Dams, 2000). These dams are typically constructed as embankment dams, with a wall across the river valley. The water is then channeled to districts downstream of the dam through a series of irrigation canals. These downstream districts (and the district where the dam is located) are categorised as *dam–fed* districts: they receive water during periods of rainfall shortage and these dams also provide protection against excess rain by storing water in the reservoirs. By controlling the flow of water, dams then insure agricultural production in these dam–fed districts against variations resulting from rainfall shocks. Agricultural production in the dam–fed districts should then be less volatile and incomes of households should be more stable. Typically the area upstream of the dam receives little or no irrigation benefits and farmers and households in these upstream areas of *rain–fed* districts are likely to be vulnerable to adverse effects arising from rainfall variations (Thakkar, 2000). Labour supply responses to rainfall shocks should therefore also vary by whether or not the district is dam–fed or rain-fed.

To categorize households as dam–fed or rain–fed we follow the approach adopted by Sarsons (2015). We use the data on dam construction as reported in Duflo and Pande (2007). Panel A of Figure 7 presents the districts with (dark shade) and without (light shade) dams. This data also identifies the downstream (dam–fed) and upstream (rain–fed) districts. There are two potential concerns in using the data on dams. First, whether one can categorize the entire district as being rain–fed or dam–fed is open to debate. Further, even if the entire district is categorized as dam–fed, it is not clear whether the entire district benefits from irrigation. However, as we mention in Section 2.2 the district is the lowest administrative level at which we can conduct this analysis. The second issue arises from the potential endogeneity of placement of dams. Duflo and Pande (2007) show that dam construction is correlated with state wealth as construction of dams is largely a state responsibility. However, in this paper we are essentially exploiting differences in dam construction across districts and this should reduce the bias arising from the correlation between state wealth and dam construction (see Sarsons, 2015).

However, the possibility that factors other than state wealth (for example the area under agricultural production) affecting dam construction cannot be ignored. We therefore follow Duflo and Pande (2007) and Sarsons (2015) to use geographical characteristics to predict the number of dams in a district. There are three main geographic characteristics that determines the likelihood of dam constriction in an area. These are river length, elevation of the district and gradient of the river. For example, Duflo and Pande (2007) show that gentle or steep river gradients (between 1.5–3% or more than 6%) are conducive for dam construction; while gradients less than 1.5% or between 3–6% are not. So we can estimate the following first stage regression:

$$
\begin{aligned}
\hat{D}_{ist} &= \zeta_1 + \sum_{j=2}^{5} \zeta_{2j}(RG_{ji} \times \bar{D}_{st}) + \sum_{j=2}^{4} \zeta_{3j}(E_{ji} \times \bar{D}_{st}) \\
&+ \sum_{j=2}^{5} \zeta_{4j}(G_{ji} \times \bar{D}_{st}) + \zeta_5(X_i \times \bar{D}_{st}) + \lambda_i + \mu_{st} + \varepsilon_{ist} \qquad (3)
\end{aligned}
$$

Districts are divided into five gradient areas and four elevation categories, indexed by j. RG_{ji} is the fraction of river area within a district i that has gradient j; E_{ji} is the fraction of a district that has elevation level j; $\bar{D}_{st}$ is the number of dams that have been built in the state

s upto and including year t. Finally X_i is a set of controls, which include district area and river length, and district and state-year fixed effects. Using equation (3) we can compute the predicted number of dams $\hat{D}_{ist}$, and use this to create a dummy variable *Dam–fed*, which takes a value of 1 if the downstream district contains at least one dam ($\hat{D}_{ist} > 0$). All districts with *Dam–fed* $= 0$ are categorized as rain–fed. We then conduct our estimation separately for the dam–fed and rain–fed districts.

3 Empirical Specification

Consider the agricultural production problem. There is a planting stage and a harvesting stage (these are the two most crucial stages in the agricultural production cycle) and there is a time gap between planting and harvesting.[9] For simplicity, agricultural production can be thought of as a two-period problem. The household makes production and labour supply decisions in both periods. The structure is illustrated in Figure 4.[10] The first period decisions are made before the value of rainfall is realized and the second period decisions are made after rainfall is revealed.[11] Here R denotes the random variable (like rainfall) that affects agricultural production and hence household income. In period 1, the household does not know what value of R will be realized (it only knows the long term average and the variability). In the second period, the household knows the realized value of R and can adjust labour supply decisions accordingly. Contingent on how the realization of rainfall affects labour supply decisions in the second period (when rainfall is too low or too high relative to the long run average), incomes are affected (see Table 3). To the extent households use labour market engagement to insure against such shocks, we expect to observe an effect on time allocation to different activities.

[9] Figure A3, which presents the crop cycle for the major crops grown in the country, shows that there is *always* a gap between the planting stage and the harvesting stage.

[10] See Rose (2001) for more details on this framework.

[11] Note that this is distinct from the theoretical framework in Rosenzweig and Udry (2014), who also explore the impacts of accuracy of rain forecasts in *ex-ante* and *ex-post* migration and labour allocation decisions. We do not consider here the possibility that rainfall forecasts influence *ex-ante* labour allocation decisions.

To determine the impact of productivity (rainfall) shocks on labour supply decisions of household members, we estimate the following regression

$$L_{ihdmy} = \beta_0 + \beta_1 \xi_{dmy} + \gamma \mathbf{X}_{ihdmy} + \delta_d + \phi_m + \psi_y + \varepsilon_{ihdmy} \tag{4}$$

Here L_{ihdmy} denotes the labour supply decision of individual i, in household h, in district d, in month m and in year y. As measures of L_{ihdmy}, we use time allocation (number of days of engagement) in the reference week, by the individual in different activities (own account work, unpaid family work, regular wage work, casual wage work in public works, in NREGS, in other types of work, domestic duties and attending educational institutions). ξ_{dmy} is as defined in Section 2.2. So β_1 captures the effect of contemporaneous rainfall shocks on labour allocation decision. As before, δ_d, ϕ_m and ψ_y denote a set of district, month and (survey) year fixed effects respectively. Finally, $\mathbf{X}_{ihdmy}$ includes a vector of individual and household characteristics (as listed in Table 2) and ε_{idmy} denotes idiosyncratic errors. Note that our regressions contain district fixed effects δ_d, and therefore our estimated coefficients will not be biased by the presence of systematic differences across districts. Standard errors are clustered at the district level.

Our first specification (given by equation (4)) ignores the difference between positive and negative rainfall shocks. So ξ_{dmy} is a dummy variable, which takes the value of 1 if the district is categorized as experiencing either excess rain or rainfall shortage in that month (i.e., between a positive and a negative rainfall shock), as defined above. In our second specification we explicitly differentiate between a positive and a negative rainfall shock (ξ^+_{dmy} and ξ^-_{dmy}, respectively). This specification, therefore, allows us to examine whether positive and negative shocks have symmetric impacts on time allocation to the different activities.[12] In this case the estimated equation is given by

$$L_{ihdmy} = \beta_0 + \beta_1 \xi^+_{dmy} + \beta_2 \xi^-_{dmy} + \gamma \mathbf{X}_{ihdmy} + \delta_d + \phi_m + \psi_y + \varepsilon_{ihdmy} \tag{5}$$

[12] In a third specification, we define *Rain Shock* as equal to –1 if the district experiences a negative shock, 1 if the district experiences a positive shock and 0 otherwise in line with the measure of Shah and Steinberg (2017). These results are available on request.

The remaining variables are as defined previously.

The specifications given by equations (4) and (5) consider only contemporaneous rainfall (productivity) shocks. However, given the nature of agricultural production and the time gap between planting and harvesting, it is feasible that the households adjust their time allocation in month m in response to rainfall shocks in previous months. For example, consider the case of Kharif rice (see Figure A3). Planting of Kharif rice is during the months March–May and harvesting is during the period October–January. Thus, a rainfall shock in July is as likely to affect output, as is a rainfall shock in September. To account for this potential lagged effect, we consider extended versions of equations (4) and (5) and estimate the following regressions:

$$L_{ihdmy} = \beta_0 + \sum_{j=0}^{k} \beta_{1j} \xi_{m-j,dy} + \gamma \mathbf{X}_{ihdmy} + \delta_d + \phi_m + \psi_y + \varepsilon_{ihdmy} \tag{6}$$

and

$$L_{ihdmy} = \beta_0 + \sum_{j=0}^{k} \beta_{1j} \xi^{+}_{m-j,dy} + \sum_{j=0}^{k} \beta_{2j} \xi^{-}_{m-j,dy} + \gamma \mathbf{X}_{ihdmy} + \delta_d + \phi_m + \psi_y + \varepsilon_{ihdmy} \tag{7}$$

where k is the number of lags. So in equation (6), $\hat{\beta}_{1j}$ captures the impact of rainfall shock j months prior to the month of survey. Note that $\xi_{m,dy}$, i.e., ($j = 0$ in equation (7)) is the contemporaneous effect of rainfall shocks. Equation (4) is a restricted version of equation (6), where we exclude the effect of lagged rainfall shock on current time allocation. In a similar vein, equation (5) is a restricted version of equation (7). We estimate two versions of equations (6) and (7) for two different lag lengths: $k = 2$ and $k = 4$. For $k = 2$ we include upto and including a 2-month lagged rainfall shock and for $k = 4$ we include upto and including a 4-month lagged rainfall shock.

While the regression specifications above include a set of month dummies, they are agnostic of the month in which the rainfall shock occurs. However, information on the month of the shock is important because the cropping patterns vary significantly across the country as does the extent of water required for each crop. Thus, rainfall shocks at different times of the year are likely to have different implications for household incomes. Consequently, household responses to rainfall (productivity) shocks will potentially vary depending on the month in which the shock is realized. As Figure A1 suggests, shocks for each district are dispersed through the year.

To take into account this variation in rainfall shocks over the year, we extend equation (4) to include interactions of the rainfall shock with the month of the survey (and hence the month of the reference week).

$$L_{ihdmy} = \beta_0 + \sum_{m=1}^{12} \beta_{1m}\phi_m + \beta_2\xi_{dmy} + \sum_{m=1}^{12} \beta_{3m}(\xi_{dmy} \times \phi_m) + \gamma\mathbf{X}_{idmy} + \delta_d + \psi_y + \varepsilon_{ihdmy} \quad (8)$$

Here ϕ_m is a dummy variable that takes the value of 1 if month $= m$ and 0 otherwise. So the estimated coefficient $\hat{\beta}_0 + \beta_{1m}$ gives us the time allocation in a "normal" month m; $\hat{\beta}_0 + \hat{\beta}_{1m} + \hat{\beta}_2 + \hat{\beta}_{3m}$ denotes time allocation in a month m that experiences a rainfall shock; $\hat{\beta}_2 + \hat{\beta}_{3m}$ the change in time allocation in month m that experiences a shock relative to a normal month. We do not consider the effect of lagged rainfall in this case.

To separate out the effects of positive and negative rainfall shocks by month, we estimate the following equation:

$$\begin{aligned} L_{ihdmy} =& \beta_0 + \sum_{m=1}^{12} \beta_{1m}\phi_m + \beta_2\xi^+_{dmy} + \sum_{m=1}^{12} \beta_{3m}(\xi^+_{dmy} \times \phi_m) \\ &+ \beta_4\xi^-_{dmy} + \sum_{m=1}^{12} \beta_{3m}(\xi^-_{dmy} \times \phi_m) + \gamma\mathbf{X}_{idmy} + \delta_d + \psi_y + \varepsilon_{ihdmy} \end{aligned} \quad (9)$$

Here, $\hat{\beta}_2 + \hat{\beta}_{3m}$ is the estimated change in time allocation in a month m that experiences a positive rainfall shock relative to a normal month, while $\hat{\beta}_4 + \hat{\beta}_{5m}$ is the estimated change in time allocation in a month m that experiences a negative rainfall shock relative to a normal month.

4 Results

4.1 Rainfall Shocks and Consumption Expenditure

Given that rainfall shocks adversely affect agricultural productivity, then, in the absence of *ex post* insurance, this uncertainty in returns could affect household consumption. To explore this further, we estimate a version of equation (4) but with household monthly per capita expenditure (c_{hdmy}) of household h in district d, reported in month m in year y as the dependent variable. This data is available from the NSS employment schedule. We estimate versions of equations (4)–(7) with c_{hdmy} as the relevant dependent variable. This regression is run at the household level and we include household characteristics such as average age, average years of education, religion, caste, and dependency ratio. We also include district (δ_d), month (ϕ_m) and year (ψ_y) fixed-effects, and standard errors are clustered at the level of the household. The results are presented in Table 4.

We find that contemporaneous rainfall shocks do not have statistically significant impact on monthly per capita consumption expenditure (see column 1). This suggests that households are able to smooth their consumption in the face of potentially adverse shocks to income. When we estimate a model that also includes lagged values of rainfall shocks (see column 2), we find a small negative effect of *any* rainfall shock on consumption expenditure. But even here, the magnitude of the decline in per capita household expenditure is a low Rs.35, which is 1.6% of the mean per capita household expenditure for our estimating sample of households.[13]

In regressions presented in columns 3 and 4 we separate out the effects of positive and negative rainfall shocks. Neither a positive nor a negative rainfall shock has a statistically significant effect on per capita household expenditure. There is some evidence of adjustment in terms of consumption expenditure when we include lagged shocks, but the magnitude of the effects are quite small. The results presented in Table 4 therefore indicate that households are able

[13]There is, however, no effect of lagged rainfall shocks on consumption.

to insure their consumption against rainfall shocks. We hypothesize households are able to do this via adjustments to their labour supply.[14] It is however important to note that at the household level, while such actions result in more income security, it could come, potentially, at the cost of a lower level of welfare and overall growth.

4.2 Basic Regression Results

Table 5 presents the regression results for equations (4) and (5). Separate regression results are presented for Males (Panel A) and Females (Panel B). The bottom row in each panel presents the average number of days in the reference week allocated to the different activities. Males respond to rainfall shocks by reducing the time allocation to casual wage work (public works), but by significantly increasing time allocation to work in NREGS. The effects are large, particularly for the time spent in NREGS work: relative to the average number of days worked in the corresponding activity in a “normal" month, males reduce their time allocation to casual wage work in public works by 27% and increase their time allocation to NREGS work by 80%. Female also increase time allocation to NREGS work by 111% (as a percentage of the number of days worked in a “normal" month) but reduce time attending educational institutions. Remember that these are women aged 15–60, so essentially a rainfall shock reduces the amount of time in secondary school or higher, potentially having an adverse impact on human capital accumulation. It is also worth examining to what extent males and females respond differently to rainfall shocks. For example, both males and females increase their time allocation to NREGS work in response to a rainfall shock and the there is no evidence of any any gender difference (p-value = 0.41).[15] Our results show that time allocated to

[14] As discussed above, potentially households could use a number of different means to insure consumption against income shocks. There are a large number of possibilities: migration/re-organization of the household, remittances, adjusting labour supply including child labour, reducing educational expenditures, sale of non-land non-productive assets like gold and jewelry, increasing borrowing and setting of non-land assets and productive assets like livestock. In this paper we focus on adjustments to labour supply.

[15] We use the test proposed by Clogg et al. (1995) and Paternoster et al. (1998) and used by Fujiwara (2015). Consider regressions on two independent subsamples (in this case males and females) and let β_1 and β_2 denote the estimated coefficients from the two sub-samples for the same explanatory variable (in this case ξ) and SE(β_1) and SE(β_2) the corresponding standard errors. Then the z-test for the difference between the two regression coefficients is given by $z = \frac{\beta_1 - \beta_2}{\sqrt{\mathrm{SE}(\beta_1)^2 + \mathrm{SE}(\beta_2)^2}}$.

attending educational institutions are different by gender (p-value = 0.029): the reduction in time allocated to attending educational institution in response to a rainfall shock is significantly greater for women than for men.

Are the results different depending on whether it is a positive or a negative rainfall shock (i.e., excess rain or rainfall shortage)? Table 5 also presents the impact of excess rain or rainfall shortage (ξ^{+}_{dmy} and ξ^{-}_{dmy} respectively) on time allocation in different labour activities. Both males and females, respond to a positive rainfall shock by increasing their time allocation to NREGS but there is no gender difference in the effect of such a shock on time allocation to NREGS. There is no statistically significant effect on time allocation to NREGS in response to a negative rainfall shock. Additionally, the regression results suggest that males (but not females) respond to a negative rainfall shock by increasing their time in regular wage work and the difference is statistically significant, p-value = 0.022. The effect is however quite small at 11% of the average in a “normal" month. For females any deviation from the normal (i.e., both positive and negative) leads to a reduction in time allocated to attending educational institutions. Therefore, for females but not for males, rainfall shocks adversely affect human capital accumulation. However, the gender difference is statistically significant only in response to a negative shock (p-value of difference = 0.038). For both males and females, the magnitude of increased time allocation to NREGS in response to excess rainfall is large: 100% and 117% for males and female respectively relative to the average number of days in the week spent on NREGS work in a normal year.

4.2.1 Intensity of Shocks

It is unlikely that a rainfall shock defined by z close to 1 has the same effect as a rainfall shock defined by z close to 3. Therefore in order to have a more robust reference group and shocks that are comparable in magnitudes, in Table 6 we consider the effects in bins that are 0.5 standard deviations wide with the bin defined by $z \in (-1, 1)$ (normal rainfall) as the reference category.[16] The bins are defined by the dotted lines in Figure A2. This specification takes into account the intensity (severity) of the rainfall shock. Panel A in Table 6 presents the results on time allocation by males, Panel B those by females. The effects that we observed in Table 5 are driven by the extreme shocks. For men, a very severe rainfall shortage ($z < -2$) reduces the time in own account work, casual wage work in public works and NREGS work, but, surprisingly, increases the time allocated to attending educational institution. For women on the other hand, a very severe rainfall shortage reduces the time spent in unpaid family work, other casual wage work and time spent in attending educational institutions. We find evidence of significant gender differences in time allocated to own account work (significant decline for males relative to female, p-value = 0.00) and in time spent in attending educational institutions (p-value of difference = 0.00). A negative rainfall shock of medium intensity is associated with a significant increase in time allocated to regular salaried work (p-value = 0.056) by males relative to females.

Events of extreme excess rainfall ($z > 3$) on the other hand, lead to men reducing the time spent in regular wage work, casual wage work (public works) and in attending educational institutions. In line with earlier results, a very severe positive rainfall shock increases the time spent in NREGS work by women. While there is no evidence of gender difference in the effect of severe positive shocks on time allocation to different activities, a positive rainfall shock of medium intensity is associated with a significant increase in time allocated to attending educational institutions by males relative to females (p-value = 0.067)

4.3 Effect of Lagged Rainfall

Table 7 presents the regression results corresponding to equation (6) with 2–month lagged monthly rainfall shocks.[17] Panel A presents the results for males while Panel B presents the results for females.

[16] See Sekhri and Storeygard (2014) for a similar specification in the context of rainfall shocks and dowry deaths.

[17] The corresponding results with a 4-month lag are presented in Table A1

For males, a contemporaneous rainfall shock significantly reduces the time allocation to casual wage work in public works, and significantly increases the time allocation to NREGS work. It is worth noting that the two month lagged rainfall shock has a consistent and statistically significant effect on time allocation into different activities by males: reduces unpaid family work, regular salaried work and NREGS work, and increases own account work and casual wage work in public works. For females, a contemporaneous rainfall shock increases time allocated to NREGS work, but significantly reduces the time spent in attending educational institution. The lagged effects are however fairly weak and the only effect is that a 2-month lagged rainfall reduces the time allocated to unpaid family work.[18] We also find evidence of gender differentiated response to rainfall shocks to time allocated to specific activities. First, a two-month lagged rainfall shock is associated with a significantly greater change in time allocated to regular wage work (p-value = 0.025) and other casual wage work (p-value = 0.073) for males, relative to females. Second, and consistent with the results presented in Table 5, a contemporaneous rainfall shock is associated with a significantly higher change in time spent in attending educational institutions by female, relative to males (p-value = 0.026). Finally, a one month lagged rainfall shock is associated with a significantly greater change in time allocated to domestic work for females relative to males (p-value = 0.013).

When we separate out the effects of excess rain and rainfall shortage and their lagged effects (see Table 8), we find that a contemporaneous rainfall shortage significantly increases the time allocation by men to regular wage work and significantly reduces the allocation of time to casual wage work in public works. Again, we observe a strong effect of 2-month lagged rainfall shortage, which significantly increases allocation of time to own account work and casual wage work in public works, but significantly reduces the allocation of time to regular wage work and NREGS work. With the exception of a 1-month lagged negative rainfall shock reducing time allocated to casual wage work in public works, rainfall shortages do not have a statistically significant effect on the time allocation for females.

[18] The regression results with upto and including 4-month lagged rainfall, presented in Table A1, essentially tell the same story as in Table 7.

Consistent with results without the lagged values, a contemporaneous positive rainfall shock significantly increases the allocation to time to NREGS work by males. A 2-month lagged positive rainfall shock significantly reduces the allocation of time to unpaid family work and regular wage work, but significantly increases the allocation of time to casual wage work in public works and other casual wage work by males.

For females, a contemporaneous rainfall shortage and excess rain both significantly increases the time allocation to NREGS work and reduces the allocation of time to attending educational institutions, thereby adversely affecting opportunities for human capital accumulation. A contemporaneous positive rainfall shock increases the time allocation to NREGS work by women. While a 1-month lagged rainfall shortage reduces the time allocated by females to casual wage public works, a 2-month lagged excess rainfall and rainfall shortage both significantly reduce the allocation of time by females to unpaid family work.[19]

Change in time allocated to own account work in response to a two-month lagged negative rainfall shock is significantly greater for males relative to females (p-value = 0.043); a contemporaneous negative rainfall shock is associated with a significantly greater change in time allocated to regular wage work by males relative to females (p-value = 0.06). A two-month lagged positive rainfall shock has a significantly greater effect on time allocated to regular wage work (p-value = 0.075) and other casual wage work (p-value = 0.029) by males relative to females. On the other hand, a contemporaneous positive rainfall shock has a significantly greater effect on time allocation in attending educational institutions by females relative to males (p-value = 0.025), while a one period lagged positive rainfall shock has a significantly greater effect on time allocation on domestic work by females relative to males (p-value = 0.031).

[19] The results are similar when we include upto 4-month lagged rainfall shocks. See Table A2.

4.4 Timing of Shocks

To take into account this variation in rainfall shocks over the year, we estimate equations (8) and (9), which include interactions of the rainfall shock with the month of the survey. The difference estimates $\beta_{1m} + \beta_{3m}$ (which is the change in time allocation in month m that experiences a shock relative to a normal month) from the estimation of equation (8) and the corresponding 90% confidence intervals are presented in Figure 5. The points on the graphs represent the additional effect on time allocation in a particular activity in a month characterized by a rainfall shock, relative to a normal month, i.e., the difference estimates $\beta_{1m} + \beta_{3m}$.[20] We present in Figure 5 the effects for the months of April–September, since this period includes summer, which is the crucial period for agriculture in India.

The largest effect is in adjustment to time allocated to NREGS work. For both men and women, a rainfall shock in May is associated with a significant increase in time allocated to work in NREGS. The effects are quite large at 10 percentage points. The estimated impact on time allocation to NREGS activity is also quite large in June, but the effect is imprecisely estimated. For males, a rainfall shock in May is also associated with a decline in time allocation to own account work, unpaid family work, and casual wage work in public works. For women on the other hand, a rainfall shock in April reduces the time allocated to regular wage work and a rainfall shock in August and September increases the allocation of time to casual wage work in public works and also in domestic duties.

Figure 6 presents the disaggregated effects of positive and negative rainfall shocks on time allocation to the different activities. For both men and women, a positive rainfall shock in May results in a large, positive and statistically significant increase in the allocation of time to NREGS work. For women, a negative rainfall shock in May leads to a large and statistically signficant increase in NREGS work, casual wage work in public works and domestic duties and a significant decline in time allocated to own account work and attending educational

[20] The reference month in all our regressions is July.

institution. For women in particular, a negative rainfall shock in May is associated with considerable re-organization in time spent in the different activities. For men, on the other hand, it appears that a negative rainfall shock in May has very little effect: the only exception being a decline in unpaid family labour when faced with rainfall shortage in May.

Outside of these months that are critical to agricultural production, we find minor effects of rainfall shocks on time allocation to the different activities. When households experience *any* rainfall shock after October, females reduce days allocated to family labour and casual wage labour, and instead spend time in domestic work. If there was a shock before April, males reduced their labour days toward casual and regular wage work, and spent more time in self-employment or family labour. In additional analyses, we re-estimated this model only for major rice-growing districts as defined by their share in total area under cultivation, and find no significant effects of *any* rainfall shock or positive and negative rainfall shocks for men or women outside the summer months. These results are available on request.

These results point to the importance of NREGS in rural India. NREGS is often viewed as an employer of last resort in rural India (Chakraborty and Singh, 2017). May is an important month in the Indian cropping calendar. As Figure A3 shows, May includes the planting season for several of the major crops. May is also the agricultural lean season with few employment opportunities in casual farm labour. Evidence suggests that demand for work under NREGS is the highest in the month of May (see Figures 5.1 and 5.2 in UNDP (2015)). This is consistent with the average time allocation by men and women in NREGS work across months (see Figure 2). What our results show is that that NREGS work is also used for insurance against productivity shocks.

5 Heterogeneity of Effects

This section examines the heterogeneity of the effect of rainfall shocks on time allocation to the different activities. As discussed in Section 2.4, we consider the variable provided by the building of dams. We divide the sample of districts into dam–fed and rain–fed districts and run separate regressions for these two categories of districts.

5.1 Basic Results: Contemporaneous Shocks

Table 9 presents the regression results corresponding to the specification given by equation (4) separately for the dam–fed (columns 1 and 2) and the rain–fed (columns 3 and 4) districts. Each cell in this table presents the estimated coefficient of rainfall shock (ξ) from a different regression. Two results stand out: first, the negative impact of rainfall shock on time allocated to attending educational institutions that we consistently observe and report in Tables 5—7, above, appears to be driven by the response in rain–fed districts: a rainfall shock in a rain–fed district leads to a significant reduction in the time spent attending educational institutions by females, leading to considerable negative effect on human capital accumulation. There is no such effect on either males or females in dam–fed districts and on males in rain–fed districts. Second, an agricultural productivity shock in a rain–fed district leads to women increasing the time spent in domestic duties. A comparison of the coefficient estimates in the relevant cells appears to suggest that the decline in time spent in attending educational institutions is about half of the increase in time spent in domestic duties.

Table 10 presents the regression results corresponding to the regression specification given by equation (5): separately for males and females and in dam–fed versus rain–fed districts. Again, all of the adjustment to time allocation to different activities is concentrated in rain–fed districts. This is true for both males and females. In response to a negative rainfall shock, both males and females in rain–fed districts reduce their time allocation to NREGS work; while in response to a positive rainfall shock, females in rain–fed districts increase their time allocation to NREGS work. Finally in response to both positive and negative rainfall shocks, women in rain–fed districts reduce their time allocation to attending educational institutions resulting in a negative impact on human capital accumulation.

5.2 Effect of Contemporaneous and Lagged Shocks

Table 11 presents the results corresponding to the specification given by equation (5), separately for males (Panel A) and females (Panel B) in rain–fed versus dam–fed districts. Here we take into account the effects of 1 and 2 month lagged rainfall (in addition to the contemporaneous effects). For males, the major adjustment takes the form of allocation of time to casual wage work: in dam–fed districts, a contemporaneous rainfall shock results in a reduction in time allocated to casual wage work in public works; a 1-month lagged rainfall shock, both negative and positive, results in a reduction in time allocated to casual wage work in public works and also NREGS. Importantly in a rain–fed district, a negative rainfall shock (contemporaneous and 1- and 2- month lagged) is associated with a significant reduction in time allocated to NREGS work. Correspondingly, in a dam–fed district, a lagged (but not contemporaneous) rainfall shock, both positive and negative, result in a sharp decline in time allocated to NREGS work.

For females (Panel B) the patterns are quite different. Here the effects are concentrated in rain–fed districts. There is a negative effect of lagged negative rainfall shock on time allocated to casual wage work in public works. Consistent with the earlier results, we find a strong and statistically significant decline in time allocated to educational institutions in response to both positive and negative shocks, and the effect is stronger in response to a negative shock.

5.3 Effect of Severity of Shocks

Table 12 takes into account the severity of the rainfall shocks. The effects for both males (Panel A) and females (Panel B) are strongest when the shocks are most severe $z < -1.5$ or $z > 3$.[21] For males, in a rain–fed district, a severe negative rainfall shock is associated with a reduction in time allocated to own account work, casual wage work in public works, and NREGS work; but an increase in time allocated to attending educational institutions. On the other hand, a severe positive rainfall shock is associated with a reduction in time allocated to both casual wage work in public works and attending educational institutions. In dam–fed districts the effects are considerably muted, with the only noteworthy effect being a reduction in time spent on casual wage work in public works in response to extreme rainfall shocks, both positive and negative.

For females, the patterns are somewhat different. Importantly, for women, the effects are almost entirely concentrated in rain–fed districts. A severe negative shock is associated with a large and statistically significant reduction in time allocated to own account work, unpaid family work, NREGS work, and time spent attending educational institutions, but is associated with a large and statistically significant increase in time spent in domestic duties. There is almost no effect of rainfall shocks (positive or negative) on time allocation to different activities by women who are residents of dam–fed districts. Clearly, extreme weather shocks are more likely to cause variations in rain–fed districts for women's labor activities.

6 Conclusion

Men and women allocate their labour differently in response to exogenous agricultural productivity (rainfall) shocks. Overall, we find that a positive rainfall shock prompts men to reallocate time toward NREGS work, whereas rainfall shortages result in men allocating more

[21] See Section 2.2 for the definition of z. Figure A2 for the distribution and heterogeneity of rainfall shocks.

time toward regular wage work. Women, in contrast, shift time into NREGS activities in response to rainfall shortages and spend less time attending educational institutions. This pattern of response to rainfall shocks (both positive and negative) is potentially intended to insure households against changes in consumption or income. There are several key insights that we highlight. First, that households indeed respond to rainfall shocks by varying their labour allocations across different activities (some productive and some not so productive). Second, monthly variations in rainfall shocks are important since in agricultural households, labour allocation responses appear to vary by the month of the shock. If we ignore these monthly variations, we risk losing out on important contextual underpinnings of labour supply decisions made by households. Finally, infrastructure has significant ameliorating effects of agricultural productivity shocks. The heterogeneous effects of rainfall shocks in rain–fed versus dam–fed districts, and in particular the negative implications on human capital accumulation of women in rain–fed districts have far reaching consequences. Clearly the right infrastructure (in this case dams) can make an important contribution to insuring rural incomes in the face of adverse shocks.

There are several policy implications arising out of this. First, the timing and implementation of NREGS is critical to help ensure that households can cope with adverse effects arising out of rainfall shocks. In particular, rainfall shocks in the summer months (May–August) result in the strongest changes in household labour allocations for men and women. This is not surprising given that Indian agriculture is largely rain fed and production is likely to be affected by adverse weather shocks, ultimately inducing men and women to respond with changes in their labour activities. The availability of work under NREGS during this period is key to enabling household insurance against weather shocks, particularly in predominantly rain–fed districts. Local governments should be able to set aside a roster of works and channel resources into making work available during this period to boost the efficacy of the program in insuring households against shocks.

Second, we find consistent evidence that women withdraw from educational attendance in response to rainfall shocks, potentially affecting their opportunities for human capital accumulation, that could have long-term implications for their well-being. Since changes in labour allocations due to rainfall shocks are typically short-term responses, there could be long-term consequences of withdrawing from educational institutions, particularly for females. One insight for policy here is to perhaps provide other incentives to women currently enrolled in educational institutions to stay in school when facing such shocks. This additional incentive could be in the form of conditional cash transfers to help ensure that education is not significantly affected by the household experiencing a rainfall shock. Such a transfer may serve a dual purpose of providing short-term liquidity to households attempting to smooth their consumption or income flows (which is critical), while also ensuring that women's educational progress is not hampered.

Third, evidence suggests that women (but not men) respond to rainfall shocks by increasing the time allocation to domestic work, which is matched with men increasing their time allocation to own account work and casual wage work. This suggests a pattern of within household reorganization, which is not necessarily favourable to women. However, it is not clear whether this is a demand side effect or a supply side effect and the available data does not necessarily allow us to separate out the channels.

Finally the role of adequate infrastructure should not be underestimated. Dams receive water during periods of rainfall shortage and provide protection against excess rain by storing water in reservoirs. By controlling the flow of water, dams then protect agricultural production in the dam–fed districts against variations resulting from rainfall shocks. Agricultural production in the dam–fed districts should then be less volatile and incomes of households should be more stable.

The sharp variability in rainfall that is increasingly associated with climate change, implies that the prevailing risk mitigation strategies developed after years of exposure and experience with the prior climate regime may become less and less effective. Thus, it is imperative to establish empirically whether auxiliary government interventions can facilitate household adaptation to increased risks due to climatic change faced by households. Importantly, government interventions need to be multifaceted, to take into account the different ways in which households respond to agricultural productivity shocks. On one hand, schemes like the NREGS, which can act as an employer of the last resort are crucial. On the other hand other government policies that encourage women to continue in school/college (this could take the form of conditional cash transfers) or remain in the labour market are of crucial importance. Finally it is crucial to invest in the right infrastructure that can act as an *ex-ante* insurance mechanism. Government policies, adequately defined, can play an important role in protecting household welfare and also enhancing economic growth.

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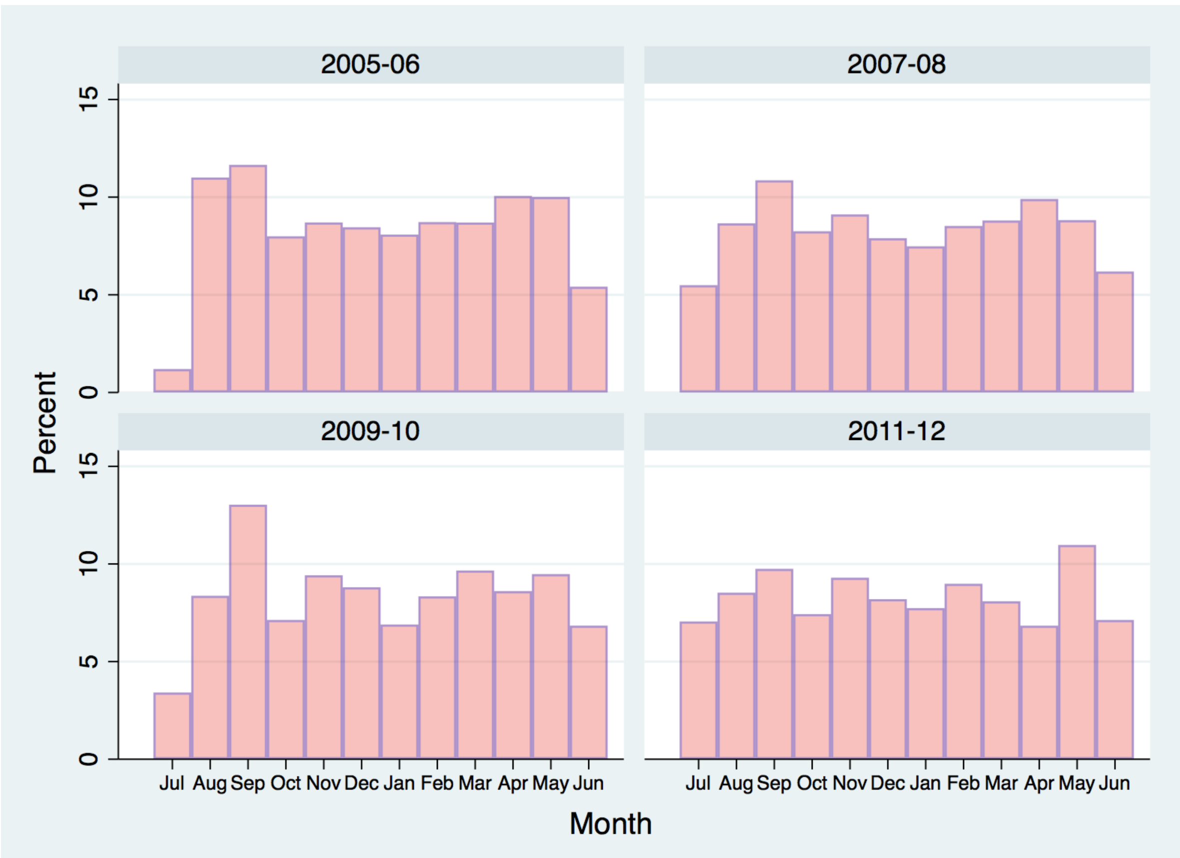
Figure 1: Proportion of Households Surveyed in each Month in each of the Survey Rounds

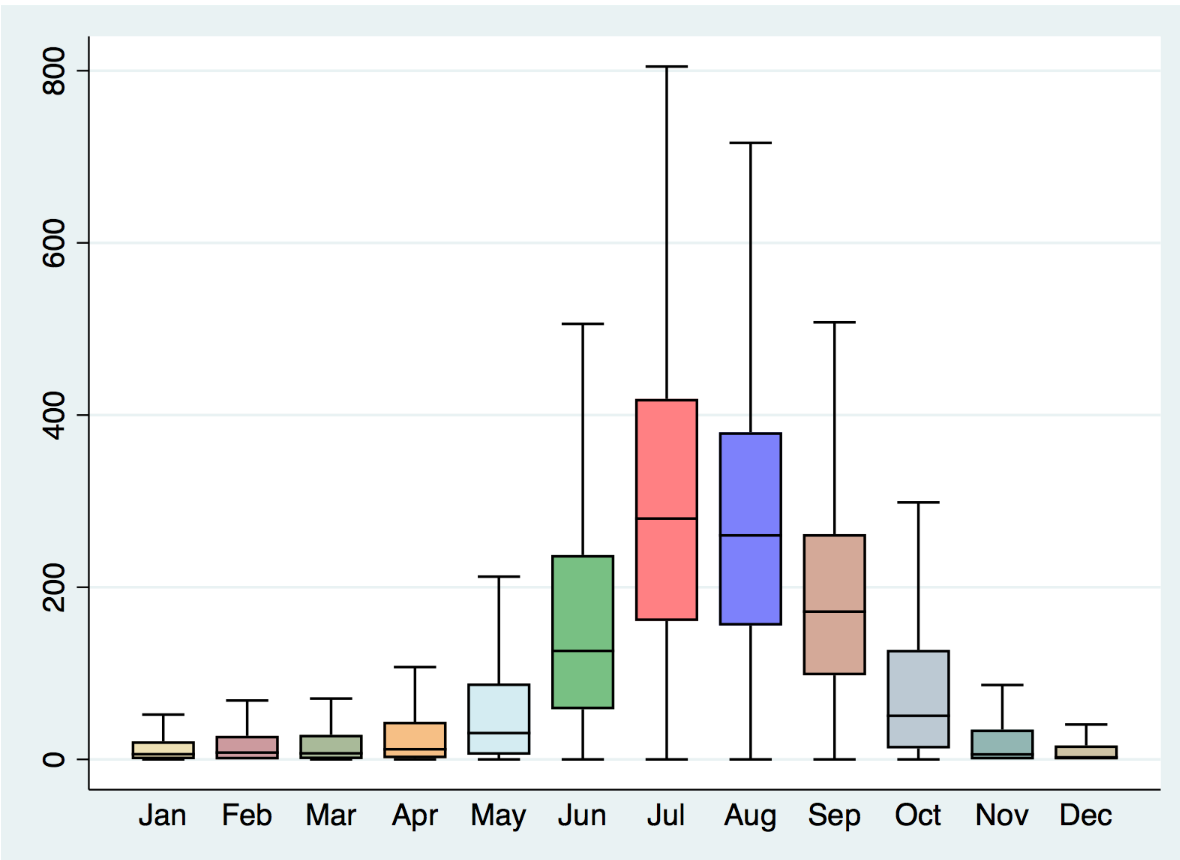


Notes: Authors' computation using the NSS data. See Section 2.1 for more details.

Figure 2: Average Number of Days in Different Activities by Month

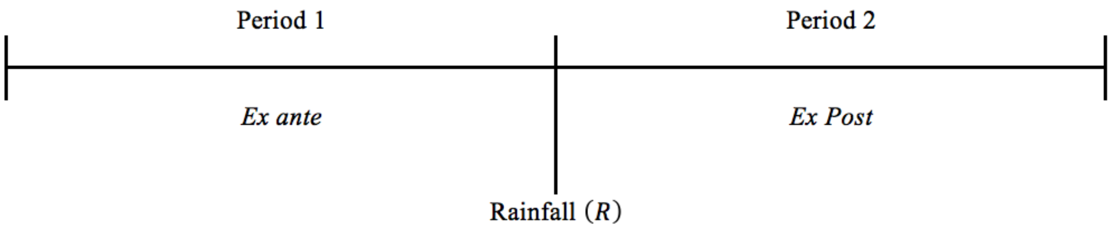
Notes: Averages weighted by the sampling weights provide by NSS.

Figure 3: Rainfall over months of the year. 1975–2016



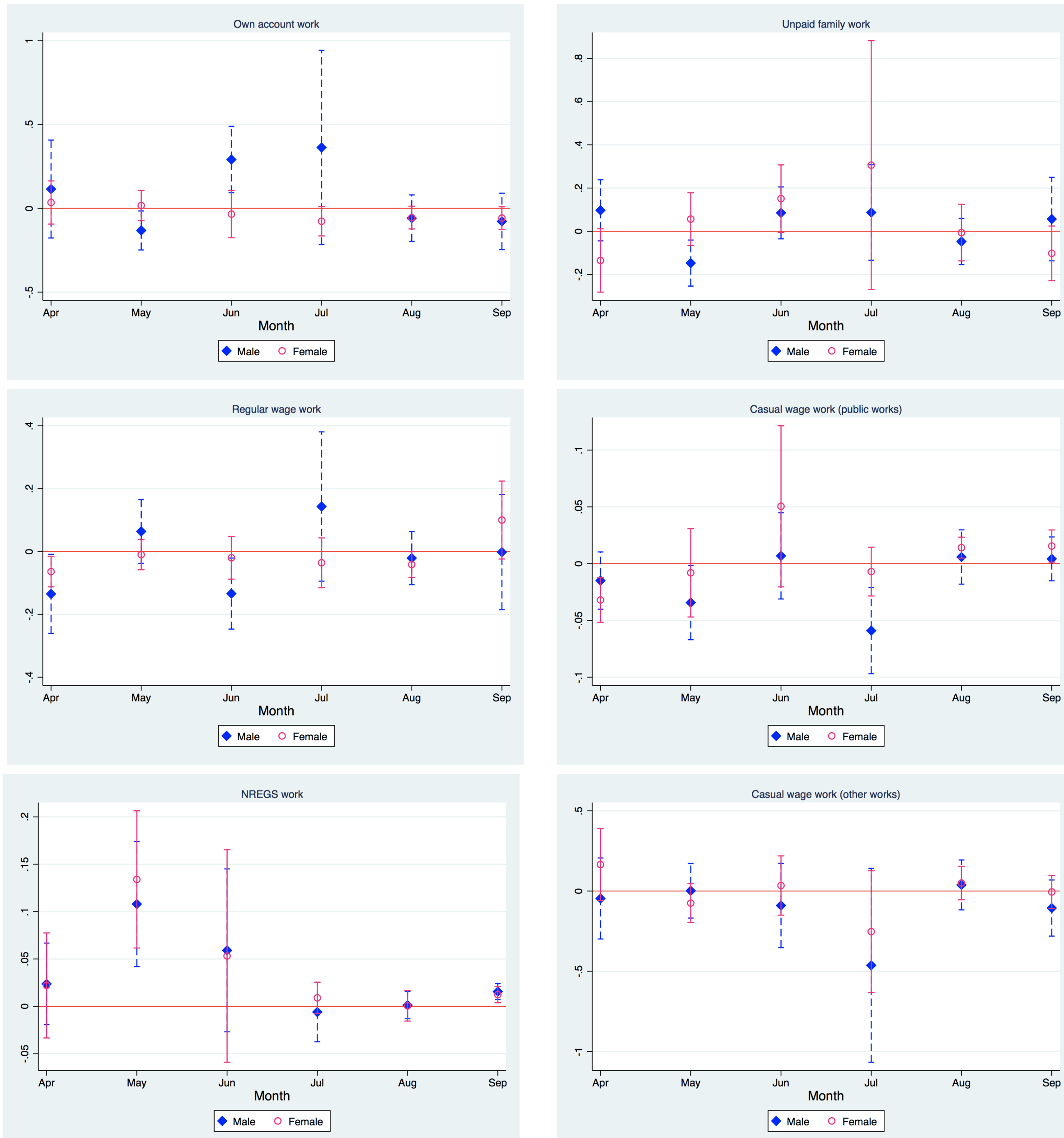
Notes: The line in the centre of the box denotes the median, while the box itself denotes the interquartile ($75^{th} - 25^{th}$) range.

Figure 4: Timing of Rainfall Shocks



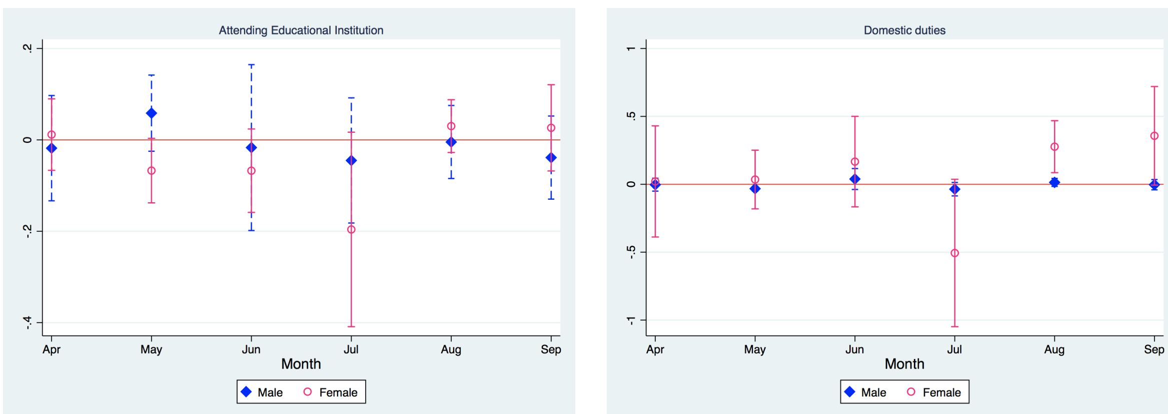
Notes: See Rose (2001), Figure 1.

Figure 5: Effect of any Rainfall Shock by Gender and Occupation



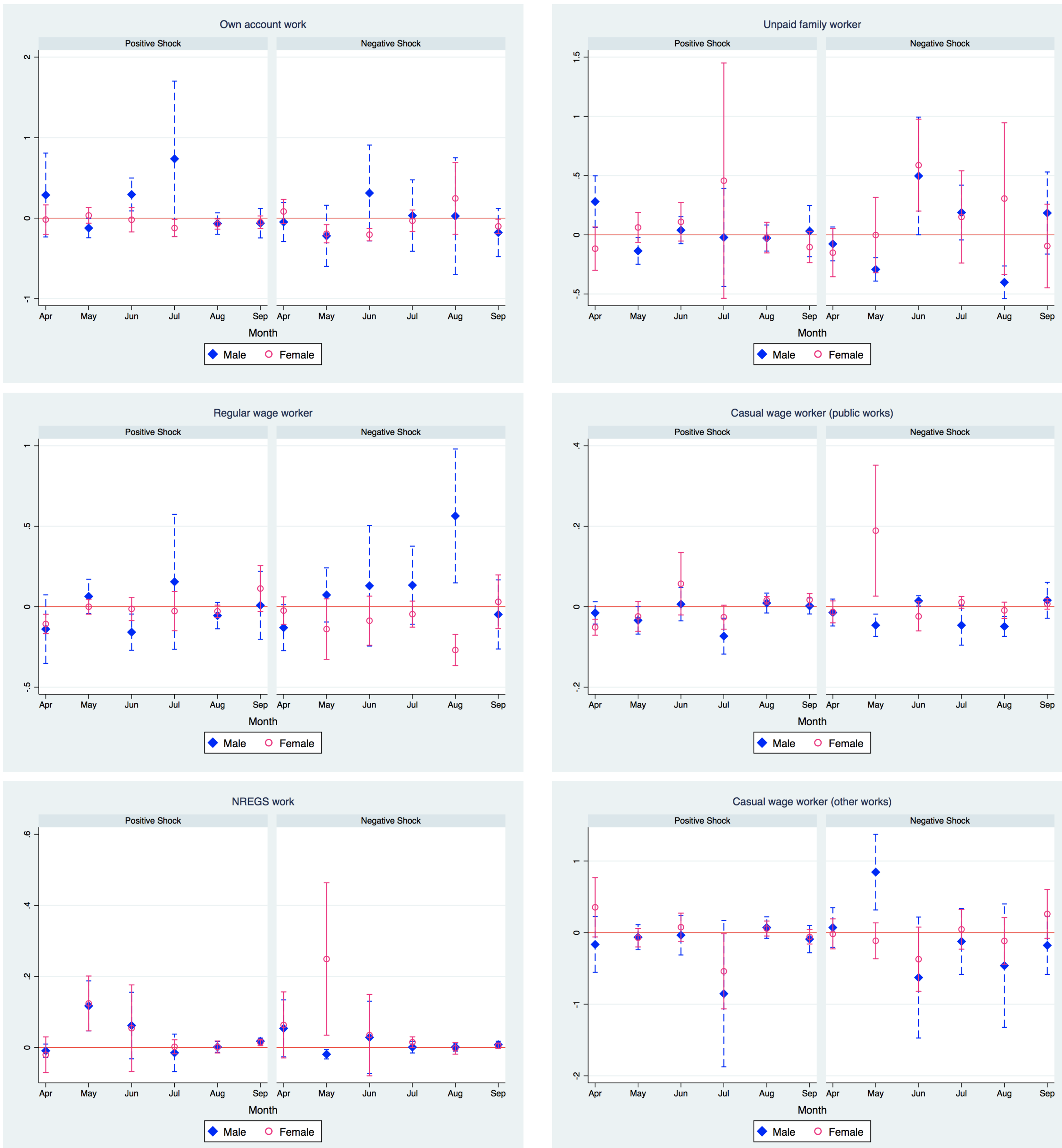
Continued . . .

Effect of any Rainfall Shock by Gender and Occupation (Continued)



Notes: Regression specification given by equation (8). Coefficient estimates and 90% confidence intervals of the difference estimate $\beta_2 + \beta_{3m}$ presented. Regressions control for a set of individual and household characteristics (caste, religion, marital status, household size and monthly per capita household expenditure). Sample restricted to males and females aged 15–60. Regressions also control for a set of district and year dummies. Rainfall shocks as defined in Section 2.2.

Figure 6: Effect of Positive and Negative Rainfall Shock by Gender and Occupation



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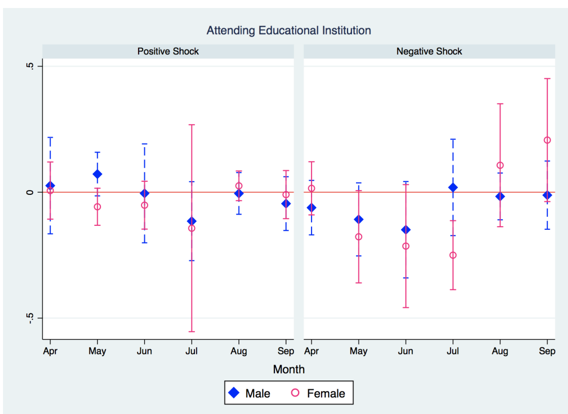
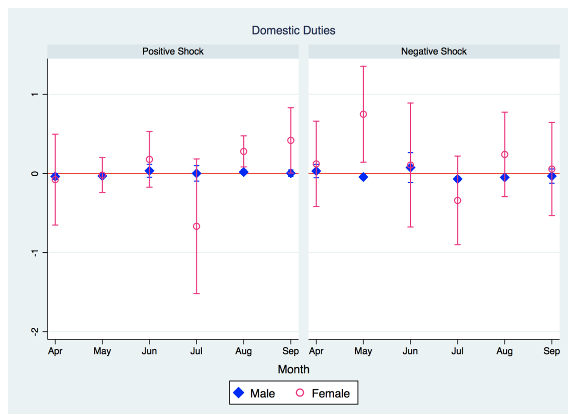
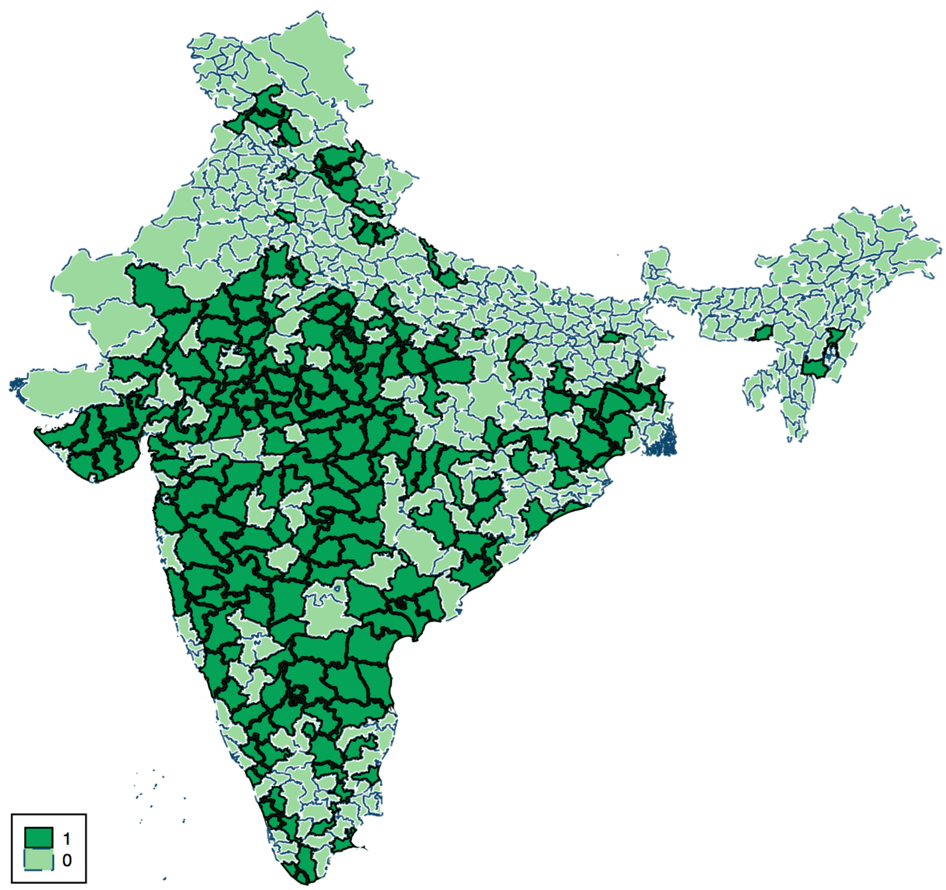
Effect of Positive and Negative Rainfall Shock by Gender Occupation (Continued)





Notes: Regression specification given by equation (9). Coefficient estimates and 90% confidence intervals of the difference estimate $\beta_2 + \beta_{3m}$ presented. Regressions control for a set of individual and household characteristics (caste, religion, marital status, household size and monthly per capita household expenditure). Sample restricted to males and females aged 15–60. Regressions also control for a set of district and year dummies. Positive shocks as defined in Section 2.2.

Figure 7: Dams in India: Districts with and without Dams (2004)



Notes: The darker shaded districts denote districts with a dam.

Table 1: Occupational Choice: Average Number of Days in Different Activities

	Male		*Female*		*Difference*
	Mean	SD	Mean	SD	
	(1)	(2)	(3)	(4)	(5)
Total Days Worked (excluding domestic work)	5.296	2.736	2.093	2.930	3.202***
Domestic Duties	0.055	0.529	2.260	3.184	-2.205***
Attended Educational Institution	0.844	2.271	0.520	1.831	0.324***
Own Account Work	2.138	3.137	0.343	1.372	1.794***
Unpaid Family Work	0.767	2.125	0.822	2.079	-0.055***
Regular Wage Work	0.564	1.898	0.131	0.943	0.433***
Casual Wage Work (Public Works)	0.040	0.505	0.025	0.394	0.015***
NREGS Work	0.019	0.338	0.021	0.351	-0.002***
Casual Wage Work (Other Works)	1.709	2.794	0.672	1.871	1.038***
Sample Size	261095		259077		

Notes: Authors' calculations using NSS data, rounds 62, 64, 66 and 68. Averages weighted by the sampling weights provide by NSS. Total days worked is the sum of days worked in own account work, unpaid family work, regular wage work, casual wage work (public works) NREGS work, casual wage work (other works) and other work including begging and prostitution. Significance of difference by gender computed using a t-test. Significance $^{***}: p < 0.01, ^{**}: p < 0.05, ^{*}: p < 0.1$.

Table 2: Sample Average: Individual and Household Characteristics

	All		*Male*		*Female*	
	Mean	SD	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)
	33.546	12.795	33.343	12.909	33.753	12.675
Scheduled Caste	0.211	0.408	0.211	0.408	0.210	0.407
Scheduled Tribe	0.110	0.313	0.110	0.313	0.109	0.312
Other Backward Caste	0.435	0.496	0.434	0.496	0.437	0.496
General Caste	0.244	0.430	0.245	0.430	0.244	0.429
Hindu	0.855	0.353	0.856	0.351	0.853	0.354
Muslim	0.107	0.309	0.105	0.307	0.108	0.310
Married	0.715	0.451	0.669	0.471	0.762	0.426
Household Size	5.466	2.538	5.473	2.511	5.460	2.565
Monthly Per capita Expenditure	2135.911	2039.433	2149.739	2033.479	2121.856	2045.375
Sample Size	520172		261095		259077	

Notes: Authors' calculations using NSS data, rounds 62, 64, 66 and 68. Averages weighted by the sampling weights provide by NSS.

Table 3: Rainfall Shocks, Area Cultivated and Total Production. Rice and Wheat only

	Any Rainfall Shock				Positive and Negative Rainfall Shock			
	Rice		Wheat		Rice		Wheat	
	Area Cultivated (1)	Total Production (2)	Area Cultivated (3)	Total Production (4)	Area Cultivated (5)	Total Production (6)	Area Cultivated (7)	Total Production (8)
Year = 2006	-1.609*	2.492	5.669***	30.063***	-1.705**	2.108	5.633***	29.824***
	(0.893)	(6.085)	(0.984)	(4.827)	(0.855)	(5.875)	(0.979)	(4.761)
Year = 2007	1.524	20.767***	6.231***	36.859***	1.103	19.088***	6.056***	35.660***
	(1.573)	(6.792)	(1.241)	(5.896)	(1.523)	(6.622)	(1.241)	(5.847)
Year = 2008	5.129***	28.443***	4.019***	41.450***	4.438***	25.682***	3.731***	39.467***
	(1.701)	(7.187)	(0.881)	(6.517)	(1.645)	(6.853)	(0.884)	(6.282)
Year = 2009	-3.070	3.233	6.406***	42.647***	-1.838	8.151	6.920***	46.310***
	(1.986)	(6.206)	(1.084)	(5.387)	(2.039)	(6.435)	(1.124)	(5.658)
Year = 2010	0.545	30.611***	12.023***	79.052***	0.198	29.225***	11.878***	78.269***
	(1.891)	(7.260)	(1.579)	(8.931)	(1.874)	(7.064)	(1.569)	(8.819)
Year = 2011	-0.246	33.482***	10.833***	106.507***	-0.898	30.879***	10.561***	104.697***
	(1.758)	(7.454)	(1.535)	(12.040)	(1.782)	(7.128)	(1.512)	(11.815)
Year = 2012	0.300	16.353***	6.377***	47.075***	0.629	17.670***	6.514***	48.035***
	(0.925)	(3.833)	(0.853)	(5.535)	(0.953)	(3.818)	(0.864)	(5.566)
Any Rainfall Shock (ξ)†	-0.777	-0.663	1.959***	15.708***				
	(1.000)	(3.950)	(0.520)	(3.420)				
Positive Rainfall Shock (ξ^{+})‡					2.183**	11.156***	3.195***	24.110***
					(1.021)	(4.037)	(0.552)	(3.870)
Negative Rainfall Shock (ξ^{-})‡					-11.229***	-42.405***	-2.405**	-14.714***
					(2.856)	(10.544)	(1.046)	(5.015)
Average in a normal year	141.64	312.69	92.58	272.03	141.64	312.69	92.58	272.03
Sample Size	2,269	2,269	2,263	2,239	2,269	2,269	2,263	2,239

Notes: OLS regression results presented. †: Estimating equation is given by equation (1) ‡: Estimating equation is given by equation (2). Regressions also include a set of year and district fixed effects. Area is in thousands of hectares and production quantity is in thousands of tons. Standard errors, clustered at the district level, are in parenthesis. Significance: $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table 4: Rainfall Shocks and Household Monthly Per Capita Consumption Expenditure

	Any Rainfall Shock		Positive and Negative Rainfall Shock	
	(1)	(2)	(3)	(4)
Rainfall Shock (ξ) †	-20.199	-35.039**		
	(16.015)	(16.530)		
Rainfall shock Lag 1 month		31.936		
		(19.535)		
Rainfall shock Lag 2 month		22.543		
		(18.627)		
Negative Rainfall Shock (ξ^{-}) ‡			-25.123	-41.862
			(28.681)	(30.242)
Negative Rainfall Shock Lag 1 month				67.591**
				(31.095)
Negative Rainfall Shock Lag 2 month				15.156
				(27.389)
Positive Rainfall Shock (ξ^{+}) ‡			-16.765	-31.595*
			(17.858)	(18.213)
Positive Rainfall Shock 1 month				19.184
				(24.313)
Positive Rainfall Shock 2 month				25.374
				(22.084)
Average in a normal month			2135.11	
Sample size	520,145	449,538	520,145	449,538

Notes: OLS regression results presented with monthly per capita consumption expenditure (Rs.) as the dependent variable. †: Estimating equation is given by equation (**??**). ‡: Estimating equation is given by equation (**??**). Regressions control for a set of household characteristics (average age, average years of education, religion, social group, and dependency ratio). Regressions also include a set of month, survey year and district fixed effects. Standard errors, clustered at the household level, are in parentheses. Significance: $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.

Table 5: Effect of Contemporaneous Rainfall Shock on Time Allocation to Different Activities

	Own Account Work	**Unpaid Family Work**	**Regular Wage Work**	**Casual Wage Work**			**Attending Educational Institution**	**Domestic Duties**
				Public Works	NREGS	**Other**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Male								
Rainfall Shock (ξ) †	-0.003	-0.017	0.002	-0.010*	0.012**	0.001	0.021	0.004
	(0.030)	(0.023)	(0.020)	(0.006)	(0.006)	(0.034)	(0.021)	(0.007)
Negative Rainfall Shock (ξ^-) ‡	-0.061	-0.031	0.084**	-0.013	0.002	-0.004	-0.019	0.000
	(0.055)	(0.037)	(0.035)	(0.008)	(0.008)	(0.061)	(0.028)	(0.011)
Positive Rainfall Shock (ξ^+) ‡	0.018	-0.012	-0.027	-0.009	0.015**	0.003	0.035	0.005
	(0.035)	(0.028)	(0.024)	(0.007)	(0.007)	(0.040)	(0.027)	(0.007)
Sample Size	261,048	261,048	261,048	261,048	261,048	261,048	261,048	261,048
Average in a Normal Month	2.156	0.829	0.739	0.036	1.414	0.111	0.880	0.056
Panel B: Female								
Rainfall Shock (ξ) †	-0.012	-0.003	-0.004	0.002	0.019***	0.016	-0.034**	0.055
	(0.016)	(0.027)	(0.009)	(0.005)	(0.006)	(0.023)	(0.014)	(0.047)
Negative Rainfall Shock (ξ^-) ‡	-0.033	-0.024	-0.003	0.004	0.016	0.022	-0.047*	0.120
	(0.025)	(0.044)	(0.015)	(0.008)	(0.011)	(0.037)	(0.027)	(0.095)
Positive Rainfall Shock (ξ^+) ‡	-0.005	0.004	-0.004	0.001	0.020***	0.014	-0.030*	0.032
	(0.019)	(0.031)	(0.010)	(0.005)	(0.007)	(0.028)	(0.016)	(0.052)
Sample Size	259,043	259,043	259,043	259,043	259,043	259,043	259,043	259,043
Average in a Normal Month	0.369	0.788	0.173	0.021	0.523	0.073	0.581	2.368

Notes: OLS regression results presented. †: Estimating equation is given by equation (4). ‡: Estimating equation is given by equation (5). Regressions control for a set of individual and household characteristics (age, years of education, marital status, religion, social group, household size and monthly per capita household expenditure). Regressions also include a set of month, survey year and district fixed effects. Standard errors, clustered at the district level, are in parenthesis. Significance: $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table 6: Effect of Rainfall shocks on Time Allocation to Different Activities, by Severity of Shock

	Own Account Work	Unpaid Family Work	Regular Wage Work	Casual Wage Work Public Works	Casual Wage Work NREGS	Other	Attending Educational Institution	Domestic Duties
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Males								
$z < -2$	-1.265***	-0.307	1.778	-0.051***	-0.039**	-0.292	0.385***	-0.039
	(0.219)	(0.218)	(1.119)	(0.011)	(0.019)	(0.769)	(0.116)	(0.029)
$-2 < z < -1.5$	-0.104	-0.251***	0.158	-0.023*	-0.016**	0.313	0.086	0.075
	(0.170)	(0.089)	(0.118)	(0.013)	(0.007)	(0.241)	(0.098)	(0.100)
$-1.5 < z < -1$	-0.050	-0.011	0.068*	-0.012	0.003	-0.030	-0.030	-0.006
	(0.059)	(0.039)	(0.035)	(0.009)	(0.008)	(0.062)	(0.029)	(0.011)
$1 < z < 1.5$	0.010	-0.064*	-0.039	-0.002	0.018*	0.013	0.071*	-0.002
	(0.050)	(0.037)	(0.031)	(0.010)	(0.011)	(0.054)	(0.041)	(0.009)
$1.5 < z < 2$	0.028	0.039	0.018	-0.010	0.003	-0.034	0.005	0.009
	(0.060)	(0.055)	(0.044)	(0.011)	(0.011)	(0.068)	(0.057)	(0.011)
$2 < z < 2.5$	0.118	0.012	-0.082**	-0.012	0.024	-0.076	0.031	0.014
	(0.095)	(0.063)	(0.040)	(0.011)	(0.026)	(0.098)	(0.043)	(0.019)
$2.5 < z < 3$	-0.134	0.050	0.086	-0.027***	-0.004	0.110	0.060	-0.001
	(0.129)	(0.117)	(0.106)	(0.006)	(0.014)	(0.139)	(0.076)	(0.020)
$z > 3$	-0.105	0.036	-0.118**	-0.029***	0.051	0.237	-0.140*	0.026
	(0.123)	(0.106)	(0.050)	(0.011)	(0.040)	(0.176)	(0.072)	(0.029)
Sample Size	261,048	261,048	261,048	261,048	261,048	261,048	261,048	261,048
Average in a Normal Month	2.156	0.829	0.739	0.036	0.015	1.414	0.111	0.880
Panel B: Females								
$z < -2$	-0.203	-0.542***	0.916	0.451	0.232	-0.567***	-0.197*	0.900
	(0.151)	(0.190)	(0.745)	(0.352)	(0.234)	(0.090)	(0.117)	(0.867)
$-2 < z < -1.5$	-0.055	-0.160	-0.037	0.028	-0.009	0.204	-0.062	-0.118
	(0.066)	(0.124)	(0.032)	(0.034)	(0.007)	(0.128)	(0.068)	(0.301)
$-1.5 < z < -1$	-0.030	-0.008	-0.005	-0.001	0.017	0.006	-0.045	0.139
	(0.026)	(0.045)	(0.015)	(0.008)	(0.011)	(0.039)	(0.028)	(0.096)
$1 < z < 1.5$	0.035	-0.019	0.011	-0.001	0.017	-0.051	-0.015	0.105
	(0.034)	(0.039)	(0.014)	(0.007)	(0.011)	(0.035)	(0.023)	(0.071)
$1.5 < z < 2$	-0.032	0.045	-0.012	0.007	0.008	0.011	-0.045	0.006

Continued ...

Effect of Rainfall shocks on Time Allocation to Different Activities, by Severity of Shock (Continued)

	Own Account Work	Unpaid Family Work	Regular Wage Work	Casual Wage Work			Attending Educational Institution	Domestic Duties
				Public Works	NREGS	Other		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0.022)	(0.052)	(0.017)	(0.011)	(0.009)	(0.046)	(0.028)	(0.076)
$2 < z < 2.5$	-0.084**	-0.008	-0.031**	-0.001	-0.008	0.142	-0.028	-0.049
	(0.032)	(0.067)	(0.016)	(0.010)	(0.010)	(0.087)	(0.034)	(0.119)
$2.5 < z < 3$	0.008	0.029	0.017	-0.021***	0.015	0.168	-0.048	-0.138
	(0.068)	(0.127)	(0.063)	(0.006)	(0.027)	(0.107)	(0.075)	(0.175)
$z > 3$	0.022	-0.012	-0.028	0.003	0.191**	0.066	-0.056	-0.047
	(0.088)	(0.134)	(0.023)	(0.030)	(0.089)	(0.129)	(0.059)	(0.204)
Sample Size	259,043	259,043	259,043	259,043	259,043	259,043	259,043	259,043
Average in a Normal Month	0.369	0.788	0.173	0.021	0.017	0.523	0.581	2.368

Notes: OLS regression results presented. Sample restricted to males aged 18–60. Regressions control for a set of individual and household characteristics (age, years of education, marital status, religion, social group, household size and monthly per capita household expenditure). Regressions also include a set of month, survey year and district fixed effects. Severity of Shocks as defined in the text. Standard errors, clustered at the district level, are in parenthesis. Significance: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 7: Effect of Contemporaneous and Lagged Rainfall Shock on Time Allocation to Different Activities

	Own Account Work	Unpaid Family Work	Regular Wage Work	Casual Wage Work Public Works	Casual Wage Work NREGS	Other	Attending Educational Institution	Domestic Duties
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Male								
Rainfall shock	-0.000	-0.015	0.007	-0.010*	0.014**	0.003	0.024	0.003
	(0.033)	(0.026)	(0.022)	(0.006)	(0.007)	(0.037)	(0.024)	(0.007)
Rainfall shock Lag 1 month	0.005	-0.006	-0.023	-0.004	-0.006	-0.009	0.006	0.010*
	(0.030)	(0.023)	(0.020)	(0.007)	(0.006)	(0.034)	(0.017)	(0.006)
Rainfall shock Lag 2 months	0.052*	-0.056**	-0.048**	0.014*	-0.011*	0.054	0.012	0.001
	(0.032)	(0.024)	(0.020)	(0.008)	(0.006)	(0.033)	(0.019)	(0.007)
Sample Size	225,755	225,755	225,755	225,755	225,755	225,755	225,755	225,755
Average in a Normal Month	2.156	0.829	0.739	0.036	0.015	1.414	0.111	0.880
Panel B: Female								
Rainfall shock	-0.006	-0.005	0.003	0.000	0.020***	0.017	-0.039**	0.028
	(0.017)	(0.029)	(0.010)	(0.005)	(0.007)	(0.024)	(0.015)	(0.051)
Rainfall shock Lag 1 month	-0.001	-0.047*	-0.015*	-0.008	0.001	-0.012	0.003	0.123***
	(0.016)	(0.026)	(0.008)	(0.005)	(0.006)	(0.022)	(0.014)	(0.045)
Rainfall shock Lag 2 months	-0.001	-0.064**	-0.005	0.007	-0.003	-0.018	-0.005	0.004
	(0.018)	(0.026)	(0.009)	(0.006)	(0.004)	(0.023)	(0.015)	(0.047)
Sample Size	223,738	223,738	223,738	223,738	223,738	223,738	223,738	223,738
Average in a Normal Month	0.369	0.788	0.173	0.021	0.017	0.523	0.581	2.368

Notes: OLS regression results presented. Regression specification is given by equation (6) with two lags. Regressions control for a set of individual and household characteristics (age, years of education, marital status, religion, social group, household size and monthly per capita household expenditure). Regressions also include a set of month, survey year and district fixed effects. Rainfall shocks are defined in Section 2.2. Standard errors, clustered at the district level, are in parenthesis. Significance: $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table 8: Effect of Contemporaneous and Lagged Positve and Negative Rainfall Shock on Time Allocation to Different Activities: 2-month lags

	Own Account Work	Unpaid Family Work	Regular Wage Work	Casual Wage Work Public Works	Casual Wage Work NREGS	Casual Wage Work Other	Attending Educational Institution	Domestic Duties
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Males								
Negative Rainfall Shock	-0.065	-0.036	0.074**	-0.018**	0.005	0.032	-0.022	0.002
	(0.062)	(0.044)	(0.036)	(0.008)	(0.010)	(0.071)	(0.033)	(0.012)
Negative Rainfall Shock Lag 1 month	-0.042	0.000	-0.001	-0.008	-0.003	0.052	-0.013	-0.000
	(0.059)	(0.046)	(0.043)	(0.010)	(0.005)	(0.072)	(0.033)	(0.013)
Negative Rainfall Shock Lag 2 months	0.101*	-0.012	-0.055*	0.028*	-0.021***	-0.035	0.033	-0.005
	(0.061)	(0.047)	(0.032)	(0.015)	(0.006)	(0.066)	(0.039)	(0.014)
Positive Rainfall Shock	0.028	-0.010	-0.021	-0.013	0.021**	0.036	0.036	0.002
	(0.045)	(0.033)	(0.028)	(0.009)	(0.009)	(0.050)	(0.030)	(0.007)
Positive Rainfall Shock Lag 1 month	-0.010	-0.000	-0.019	0.000	-0.008	-0.023	0.019	0.014*
	(0.040)	(0.031)	(0.025)	(0.009)	(0.009)	(0.044)	(0.023)	(0.008)
Positive Rainfall Shock Lag 2 months	0.036	-0.062*	-0.064**	0.020*	-0.009	0.074*	0.019	0.005
	(0.039)	(0.032)	(0.026)	(0.011)	(0.008)	(0.043)	(0.023)	(0.008)
Sample Size	176,244	176,244	176,244	176,244	176,244	176,244	176,244	176,244
Average in a Normal Month	2.156	0.829	0.739	0.036	0.015	1.414	0.111	0.880
Panel B: Females								
Negative Rainfall Shock	-0.037	-0.039	0.005	0.005	0.017	0.025	-0.046	0.108
	(0.026)	(0.048)	(0.016)	(0.008)	(0.011)	(0.038)	(0.028)	(0.098)
Negative Rainfall Shock Lag 1 month	-0.026	-0.011	-0.014	-0.015**	0.002	0.000	-0.038	0.125
	(0.024)	(0.045)	(0.017)	(0.006)	(0.008)	(0.042)	(0.028)	(0.092)
Negative Rainfall Shock Lag 2 months	-0.010	-0.058	-0.018	-0.005	-0.008	-0.028	0.012	-0.019
	(0.027)	(0.038)	(0.015)	(0.006)	(0.006)	(0.038)	(0.027)	(0.087)
Positive Rainfall Shock	0.007	0.010	0.002	-0.001	0.022***	0.014	-0.038**	-0.004
	(0.021)	(0.032)	(0.012)	(0.006)	(0.008)	(0.030)	(0.017)	(0.056)
Positive Rainfall Shock Lag 1 month	0.009	-0.060**	-0.015*	-0.005	0.000	-0.016	0.017	0.122**
	(0.017)	(0.030)	(0.009)	(0.005)	(0.007)	(0.025)	(0.014)	(0.050)
Positive Rainfall Shock Lag 2 months	0.002	-0.066**	0.001	0.013	-0.001	-0.013	-0.012	0.013
	(0.022)	(0.030)	(0.011)	(0.008)	(0.006)	(0.027)	(0.017)	(0.054)

Continued ...

Effect of Contemporaneous and Lagged Positve and Negative Rainfall Shock on Time Allocation: 2-month lags (Continued)

	Own Account Work	Unpaid Family Work	Regular Wage Work	Casual Wage Work Public Works	Casual Wage Work NREGS	Other	Attending Educational Institution	Domestic Duties
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample Size	223,738	223,738	223,738	223,738	223,738	223,738	223,738	223,738
Average in a Normal Month	0.369	0.788	0.173	0.021	0.017	0.523	0.581	2.368

Notes: OLS regression results presented. Regression specification given by equation (7) with two lags. Sample restricted to males aged 18–60. Regressions control for a set of individual and household characteristics (age, years of education, marital status, religion, social group, household size and monthly per capita household expenditure). Regressions also include a set of month, survey year and district fixed effects. Rainfall shortage (negative rainfall shock) and excess rain (positive rainfall shock) defined in Section 2.2. Standard errors, clustered at the district level, are in parenthesis. Significance: $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table 9: Heterogeneous Impacts: Rainfall Shocks and Time Allocation to Different Activities

	Dam–fed district		**Rain–fed district**	
	Male	Female	Male	Female
	(1)	(2)	(3)	(4)
Own account work	-0.021	-0.034	0.048	0.024
	(0.050)	(0.023)	(0.042)	(0.028)
Unpaid family work	-0.025	-0.012	-0.010	-0.028
	(0.039)	(0.053)	(0.035)	(0.034)
Regular wage work	-0.009	0.006	-0.004	-0.010
	(0.037)	(0.015)	(0.026)	(0.013)
Casual wage work (public works)	-0.006	0.004	-0.011	-0.000
	(0.008)	(0.009)	(0.009)	(0.006)
NREGS work	0.017	0.022*	0.011	0.017
	(0.010)	(0.011)	(0.009)	(0.011)
Casual wage work (other works)	0.060	0.021	-0.057	0.013
	(0.064)	(0.043)	(0.047)	(0.031)
Attending educational institution	0.000	-0.001	0.021	-0.071***
	(0.025)	(0.022)	(0.037)	(0.024)
Domestic duties	0.010	-0.066	0.004	0.150**
	(0.010)	(0.079)	(0.013)	(0.063)
Sample size	88,725	87,056	103,529	103,957

Notes: Coefficient estimate of any rainfall shock (ξ) from OLS regressions presented. Separate regressions for rain–fed and dam–fed districts. Rainfall shock defined in Section 2.2. Sample restricted to males and females aged 15–60. Each row presents the results from a different regression. Regressions control for a set of individual and household characteristics (age, years of education, marital status, religion, social group, household size and monthly per capita household expenditure). Regressions also include a set of month, survey year and district fixed effects. Dam–fed and rain–fed districts are defined in Section 5. Standard errors, clustered at the district level, are in parenthesis. Significance: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 10: Heterogeneous Impacts: Positive and Negative Rainfall Shocks and Time Allocation to Different Activities

	Negative Rainfall shock (ξ^-)				**Positive Rainfall shock (ξ^+)**			
	Dam–fed district		**Rain–fed district**		**Dam–fed district**		**Rain–fed district**	
	Male	Female	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Own account work	-0.064	-0.046	-0.012	-0.020	-0.009	-0.031	0.070	0.041
	(0.110)	(0.038)	(0.077)	(0.041)	(0.052)	(0.027)	(0.051)	(0.037)
Unpaid family work	0.025	0.030	-0.080	-0.013	-0.039	-0.023	0.017	-0.035
	(0.077)	(0.106)	(0.053)	(0.054)	(0.045)	(0.055)	(0.042)	(0.041)
Regular wage work	0.083	0.012	0.085	0.018	-0.035	0.004	-0.038	-0.020
	(0.052)	(0.023)	(0.058)	(0.029)	(0.041)	(0.016)	(0.030)	(0.014)
Casual wage work (public works)	-0.024***	0.010	-0.023	-0.006	-0.000	0.003	-0.006	0.002
	(0.008)	(0.018)	(0.016)	(0.008)	(0.010)	(0.010)	(0.010)	(0.007)
NREGS work	0.024	0.039	-0.013*	-0.015*	0.015	0.017	0.020	0.030*
	(0.022)	(0.025)	(0.007)	(0.008)	(0.010)	(0.012)	(0.012)	(0.015)
Casual wage work (other works)	-0.007	0.046	-0.024	0.028	0.079	0.014	-0.069	0.007
	(0.113)	(0.076)	(0.089)	(0.058)	(0.069)	(0.053)	(0.062)	(0.033)
Attending educational institution	-0.071	-0.012	0.031	-0.121***	0.021	0.002	0.017	-0.052*
	(0.054)	(0.058)	(0.041)	(0.037)	(0.030)	(0.023)	(0.047)	(0.029)
Domestic duties	0.005	-0.160	0.003	0.242*	0.011	-0.039	0.004	0.115
	(0.018)	(0.166)	(0.019)	(0.141)	(0.011)	(0.081)	(0.013)	(0.081)
Sample Size	88725	87056	103529	103957	88725	87056	103529	103957

Notes: Coefficient estimate of rainfall shock (ξ) from OLS regressions presented. Positive and negative rainfall shock defined in Section 2.2. Sample restricted to males and females aged 15–60. Each row presents the results from a different regression. Regressions control for a set of individual and household characteristics (age, years of education, marital status, religion, social group, household size and monthly per capita household expenditure). Regressions also include a set of month, survey year and district fixed effects. Dam–fed and rain–fed districts are defined in Section 5. Standard errors, clustered at the district level, are in parenthesis. Significance: $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table 11: Heterogeneity of Shocks: Effect of Contemporaneous and Lagged Rainfall Shocks on Time Allocation to Different Activities

	Own account work		**Unpaid family work**		**Regular wage work**		**public works**		**Casual wage NREGS**		**other works**		**Attending educational institution**		**Domestic duties**	
	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: Males																
Negative Rainfall Shock	0.007	-0.050	0.065	-0.083	0.088	0.078	-0.017*	-0.028	0.030	-0.015*	-0.153	0.041	-0.050	0.027	0.005	0.009
	(0.110)	(0.080)	(0.082)	(0.057)	(0.057)	(0.060)	(0.009)	(0.018)	(0.023)	(0.008)	(0.123)	(0.090)	(0.057)	(0.043)	(0.020)	(0.017)
Negative Rainfall Shock Lag 1 month	-0.034	-0.123*	0.074	-0.046	0.015	-0.049	-0.031***	-0.007	-0.018**	-0.013**	-0.018	0.172	-0.088	-0.016	0.026	-0.026**
	(0.104)	(0.069)	(0.094)	(0.055)	(0.091)	(0.044)	(0.011)	(0.014)	(0.009)	(0.005)	(0.115)	(0.105)	(0.060)	(0.047)	(0.028)	(0.012)
Negative Rainfall Shock Lag 2 months	0.242**	0.021	-0.140*	-0.061	-0.090	-0.039	0.015	0.009	-0.025***	-0.016**	-0.127	0.072	0.120**	0.049	-0.023	-0.000
	(0.111)	(0.078)	(0.083)	(0.053)	(0.058)	(0.041)	(0.016)	(0.021)	(0.008)	(0.008)	(0.112)	(0.099)	(0.061)	(0.046)	(0.017)	(0.021)
Positive Rainfall Shock	0.006	0.099	0.022	0.022	-0.041	-0.029	-0.006	-0.011	0.016	0.017	0.010	-0.061	0.031	0.009	0.013	-0.002
	(0.064)	(0.062)	(0.053)	(0.049)	(0.047)	(0.034)	(0.012)	(0.011)	(0.011)	(0.014)	(0.076)	(0.066)	(0.036)	(0.059)	(0.012)	(0.012)
Positive Rainfall Shock Lag 1 month	0.065	0.007	0.073	-0.033	0.001	-0.086***	-0.025**	0.007	-0.026**	-0.003	-0.082	0.016	0.003	0.043	0.003	0.014
	(0.059)	(0.052)	(0.051)	(0.036)	(0.038)	(0.031)	(0.011)	(0.012)	(0.012)	(0.012)	(0.065)	(0.060)	(0.036)	(0.032)	(0.008)	(0.013)
Positive Rainfall Shock Lag 2 months	0.095	0.018	-0.062	-0.060	-0.091**	0.008	0.021	0.008	-0.029***	0.012	0.045	0.042	0.007	0.027	-0.006	0.006
	(0.060)	(0.054)	(0.047)	(0.037)	(0.038)	(0.040)	(0.018)	(0.011)	(0.010)	(0.016)	(0.066)	(0.058)	(0.035)	(0.033)	(0.010)	(0.011)
Constant	0.149	-0.234	0.310**	0.219**	-0.068	-0.064	-0.006	-0.028	-0.015	-0.053*	0.651***	0.966***	4.834***	4.742***	0.112***	0.131***
	(0.216)	(0.146)	(0.152)	(0.110)	(0.130)	(0.116)	(0.031)	(0.031)	(0.020)	(0.032)	(0.223)	(0.179)	(0.153)	(0.144)	(0.041)	(0.038)
Sample Size	76,178	89,841	76,178	89,841	76,178	89,841	76,178	89,841	76,178	89,841	76,178	89,841	76,178	89,841	76,178	89,841

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Heterogeneity of Shocks: Effect of Contemporaneous and Lagged Rainfall Shocks on Time Allocation to Different Activities (Continued)

	Own account work		**Unpaid family work**		**Regular wage work**		**public works**		**Casual wage NREGS**		**other works**		**Attending educational institution**		**Domestic duties**	
	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel B: Females																
Negative Rainfall Shock	-0.007	-0.047	0.059	-0.014	0.012	0.032	0.012	-0.005	0.045	-0.012	-0.035	0.041	-0.015	-0.122***	-0.239	0.241
	(0.044)	(0.044)	(0.116)	(0.060)	(0.023)	(0.032)	(0.020)	(0.009)	(0.028)	(0.009)	(0.077)	(0.061)	(0.061)	(0.038)	(0.167)	(0.153)
Negative Rainfall Shock Lag 1 month	-0.060	-0.016	0.080	-0.082	-0.030	-0.015	-0.028***	-0.011*	-0.026	-0.005	0.019	0.041	-0.080	-0.011	0.028	0.092
	(0.042)	(0.037)	(0.102)	(0.052)	(0.032)	(0.021)	(0.010)	(0.006)	(0.015)	(0.007)	(0.084)	(0.066)	(0.056)	(0.040)	(0.181)	(0.134)
Negative Rainfall Shock Lag 2 months	0.008	-0.036	-0.135*	-0.013	-0.032	-0.013	0.007	-0.017***	-0.025**	0.004	-0.030	-0.007	0.012	-0.013	0.006	-0.050
	(0.043)	(0.042)	(0.074)	(0.052)	(0.020)	(0.021)	(0.013)	(0.006)	(0.012)	(0.011)	(0.080)	(0.049)	(0.051)	(0.037)	(0.158)	(0.128)
Positive Rainfall Shock	-0.019	0.040	0.058	-0.006	0.002	-0.007	-0.005	0.001	0.019	0.027	-0.025	0.033	-0.017	-0.066**	-0.093	0.094
	(0.030)	(0.039)	(0.063)	(0.043)	(0.016)	(0.019)	(0.013)	(0.008)	(0.012)	(0.017)	(0.057)	(0.037)	(0.027)	(0.029)	(0.094)	(0.086)
Positive Rainfall Shock Lag 1 month	0.042	-0.017	-0.057	-0.049	-0.030**	-0.017	-0.016	-0.001	-0.014	0.009	-0.052	0.000	0.029	-0.000	0.086	0.189**
	(0.031)	(0.028)	(0.056)	(0.047)	(0.014)	(0.015)	(0.010)	(0.008)	(0.012)	(0.014)	(0.051)	(0.034)	(0.023)	(0.021)	(0.086)	(0.079)
Positive Rainfall Shock Lag 2 months	0.013	0.012	-0.099*	-0.004	0.002	-0.007	0.024	-0.001	-0.009	0.002	-0.003	-0.063	-0.040	0.002	-0.054	0.009
	(0.030)	(0.044)	(0.054)	(0.043)	(0.015)	(0.020)	(0.016)	(0.008)	(0.012)	(0.008)	(0.053)	(0.038)	(0.029)	(0.030)	(0.098)	(0.085)
Constant	0.202**	0.281***	0.541***	0.416***	-0.177***	0.000	-0.029	0.066**	-0.046*	-0.031	1.063***	0.470***	4.018***	4.334***	0.606**	0.206
	(0.089)	(0.091)	(0.203)	(0.102)	(0.052)	(0.048)	(0.025)	(0.028)	(0.025)	(0.022)	(0.170)	(0.100)	(0.162)	(0.149)	(0.266)	(0.217)
Sample Size	74,706	89,969	74,706	89,969	74,706	89,969	74,706	89,969	74,706	89,969	74,706	89,969	74,706	89,969	74,706	89,969

Table 12: Heterogeneity of Shocks: Severity of Shocks and Time Allocation to Different Activities

	Own account work		Unpaid family work		Regular wage work		public works		Casual wage NREGS		other works		Attending educational institution		Domestic duties	
	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: Males																
$z < -2$		-1.274***		-0.338		2.118		-0.059***		-0.036		-0.123		0.472***		-0.045
		(0.239)		(0.258)		(1.282)		(0.022)		(0.025)		(0.908)		(0.067)		(0.035)
$-2 < z < -1.5$	0.197	-0.175	-0.209	-0.125	0.126	-0.022	-0.061**	-0.009	0.001	-0.037**	-0.081	0.439	0.165	0.105	0.002	0.217
	(0.330)	(0.279)	(0.176)	(0.120)	(0.199)	(0.114)	(0.030)	(0.026)	(0.011)	(0.016)	(0.413)	(0.369)	(0.135)	(0.089)	(0.035)	(0.248)
$-1.5 < z < -1$	-0.032	-0.017	0.089	-0.080	0.076	0.084	-0.017*	-0.029*	0.028	-0.013*	-0.148	-0.040	-0.074	0.026	0.006	-0.012
	(0.119)	(0.087)	(0.083)	(0.057)	(0.054)	(0.059)	(0.009)	(0.017)	(0.023)	(0.007)	(0.126)	(0.088)	(0.060)	(0.044)	(0.021)	(0.018)
$1 < z < 1.5$	-0.079	0.112	-0.037	-0.046	-0.039	-0.071*	0.006	-0.005	0.037*	0.016	-0.014	-0.042	0.080*	0.070	0.019	-0.013
	(0.077)	(0.081)	(0.058)	(0.060)	(0.053)	(0.043)	(0.016)	(0.014)	(0.021)	(0.017)	(0.087)	(0.085)	(0.041)	(0.090)	(0.016)	(0.016)
$1.5 < z < 2$	0.115	0.063	0.046	0.123*	-0.006	0.051	-0.008	0.004	-0.012	-0.010	0.066	-0.147*	-0.081	-0.063	-0.003	0.011
	(0.091)	(0.088)	(0.090)	(0.069)	(0.085)	(0.058)	(0.016)	(0.024)	(0.015)	(0.007)	(0.121)	(0.086)	(0.061)	(0.040)	(0.014)	(0.019)
$2 < z < 2.5$	0.195	0.044	-0.023	0.161	-0.136**	-0.142**	-0.009	-0.029***	-0.010	0.027	-0.062	-0.069	0.056	-0.039	-0.006	0.065
	(0.192)	(0.118)	(0.087)	(0.122)	(0.066)	(0.061)	(0.021)	(0.009)	(0.022)	(0.028)	(0.188)	(0.141)	(0.074)	(0.070)	(0.019)	(0.053)
$2.5 < z < 3$	-0.092	-0.034	-0.181	-0.035	0.245	0.050	-0.031***	-0.033***	0.004	0.009	0.193	0.088	0.085	0.152	-0.006	-0.036
	(0.171)	(0.179)	(0.152)	(0.169)	(0.222)	(0.089)	(0.011)	(0.011)	(0.012)	(0.031)	(0.259)	(0.207)	(0.103)	(0.146)	(0.026)	(0.022)
$z > 3$	-0.248	0.176	0.163	-0.126	-0.132**	-0.097	-0.026*	-0.058***	-0.004	0.203	0.351	0.002	-0.124	-0.286**	0.057	-0.009
	(0.173)	(0.179)	(0.163)	(0.105)	(0.066)	(0.119)	(0.013)	(0.022)	(0.016)	(0.132)	(0.261)	(0.272)	(0.100)	(0.125)	(0.038)	(0.067)
Constant	0.123	-0.173	0.395***	0.335***	-0.166	-0.165	0.041	-0.020	0.006	-0.055*	0.753***	0.922***	4.764***	4.756***	0.120***	0.134***
	(0.200)	(0.150)	(0.147)	(0.120)	(0.130)	(0.122)	(0.034)	(0.032)	(0.023)	(0.029)	(0.198)	(0.171)	(0.152)	(0.142)	(0.041)	(0.039)
Sample Size	88,725	103,529	88,725	103,529	88,725	103,529	88,725	103,529	88,725	103,529	88,725	103,529	88,725	103,529	88,725	103,529

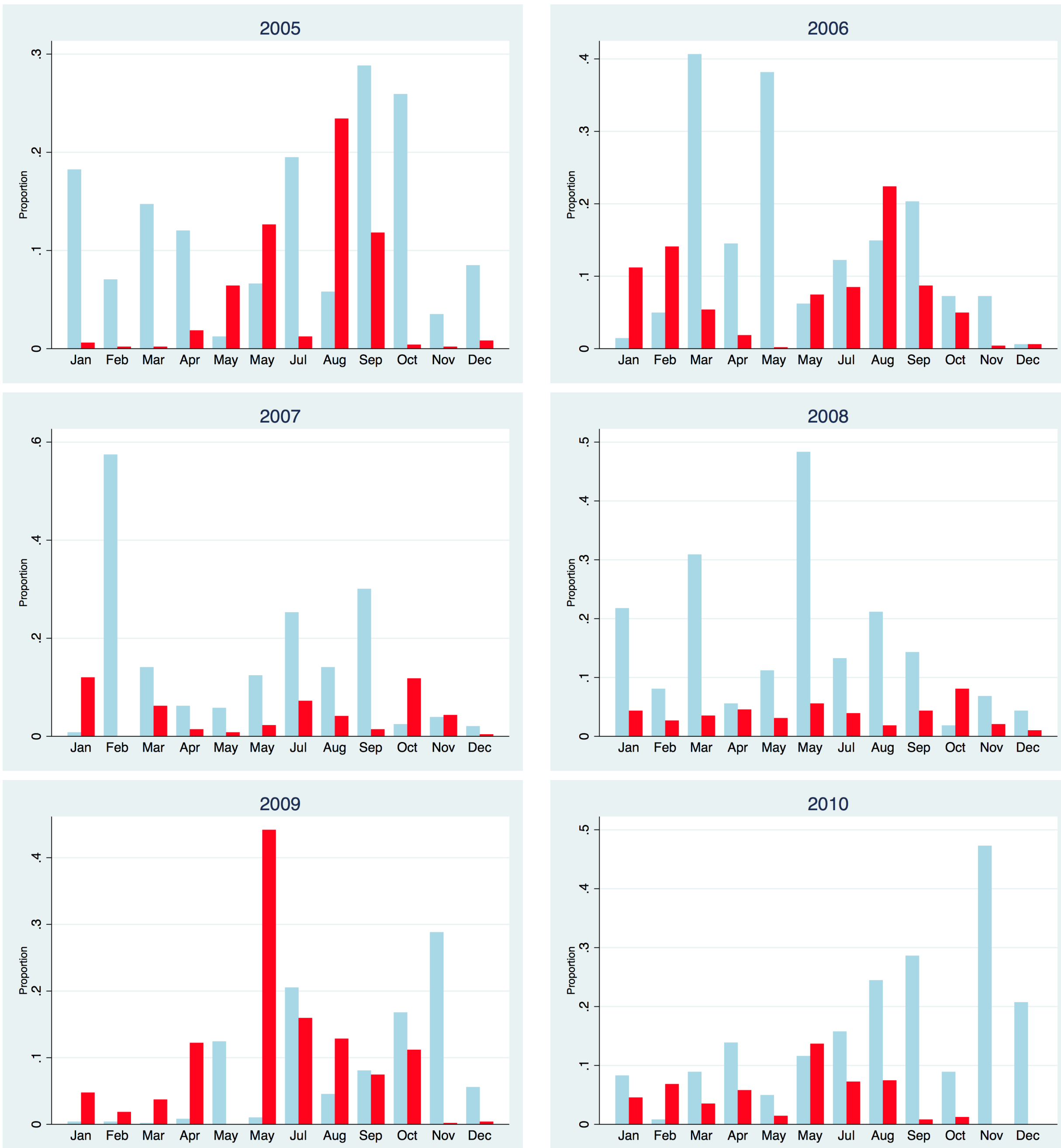
Continued ...

Heterogeneity of Shocks: Severity of Shocks and Time Allocation to Different Activities (Continued)

	Own account work		Unpaid family work		Regular wage work		public works		Casual wage NREGS		other works		Attending educational institution		Domestic duties	
	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed	Dam–fed	Rain–fed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel B: Females																
$z < -2$		-0.291*		-0.659***		1.182		0.108		0.259		-0.461***		-0.141		1.467**
		(0.148)		(0.193)		(0.834)		(0.146)		(0.292)		(0.121)		(0.105)		(0.571)
$-2 < z < -1.5$	0.157	-0.116	-0.290	0.230	-0.034	-0.012	0.101	0.010	-0.015	-0.019***	-0.025	0.455**	0.111	-0.302***	-0.388	-0.475*
	(0.133)	(0.076)	(0.203)	(0.157)	(0.040)	(0.060)	(0.105)	(0.022)	(0.013)	(0.007)	(0.269)	(0.195)	(0.091)	(0.067)	(0.574)	(0.254)
$-1.5 < z < -1$	-0.040	-0.013	0.146	-0.043	0.013	0.007	0.002	-0.008	0.049	-0.012*	-0.005	-0.012	-0.024	-0.112***	-0.216	0.317**
	(0.043)	(0.045)	(0.107)	(0.059)	(0.025)	(0.029)	(0.019)	(0.008)	(0.029)	(0.007)	(0.081)	(0.057)	(0.062)	(0.038)	(0.163)	(0.146)
$1 < z < 1.5$	-0.010	0.081	-0.017	-0.019	0.013	-0.007	-0.018	0.011	0.019	0.024	-0.113*	0.007	-0.005	-0.045	0.088	0.200
	(0.049)	(0.062)	(0.079)	(0.046)	(0.018)	(0.019)	(0.013)	(0.013)	(0.016)	(0.021)	(0.064)	(0.044)	(0.035)	(0.041)	(0.102)	(0.132)
$1.5 < z < 2$	-0.057*	0.017	0.126	0.028	-0.002	-0.018	0.016	0.003	-0.001	-0.003	-0.009	-0.007	0.015	-0.077**	-0.089	0.045
	(0.034)	(0.040)	(0.100)	(0.059)	(0.026)	(0.028)	(0.026)	(0.010)	(0.014)	(0.007)	(0.081)	(0.052)	(0.049)	(0.038)	(0.140)	(0.099)
$2 < z < 2.5$	-0.118**	-0.057	-0.017	-0.092	-0.033	-0.053*	0.010	-0.009	-0.027*	-0.010*	0.275*	0.122	-0.038	0.004	-0.155	-0.085
	(0.056)	(0.051)	(0.106)	(0.107)	(0.026)	(0.028)	(0.022)	(0.007)	(0.015)	(0.006)	(0.159)	(0.110)	(0.055)	(0.056)	(0.203)	(0.198)
$2.5 < z < 3$	0.090	0.006	-0.063	-0.102	0.087	0.018	-0.041***	-0.017	0.007	0.043	0.287	0.041	-0.022	-0.102	-0.427	0.168
	(0.128)	(0.117)	(0.260)	(0.173)	(0.148)	(0.061)	(0.012)	(0.010)	(0.033)	(0.065)	(0.229)	(0.118)	(0.100)	(0.155)	(0.277)	(0.272)
$z > 3$	0.100	-0.089	0.088	-0.280	-0.037	-0.051	0.023	-0.027	0.137	0.431**	0.032	-0.012	-0.018	-0.170	-0.335	0.571*
	(0.144)	(0.101)	(0.190)	(0.190)	(0.028)	(0.053)	(0.048)	(0.023)	(0.118)	(0.199)	(0.201)	(0.142)	(0.084)	(0.107)	(0.279)	(0.311)
Constant	0.302***	0.162*	0.553***	0.445***	-0.175***	0.040	-0.011	0.052*	-0.043*	-0.027	1.050***	0.533***	3.873***	4.392***	0.569**	0.107
	(0.087)	(0.089)	(0.182)	(0.106)	(0.052)	(0.065)	(0.020)	(0.028)	(0.025)	(0.021)	(0.155)	(0.095)	(0.160)	(0.147)	(0.272)	(0.249)
Sample Size	87,056	103,957	87,056	103,957	87,056	103,957	87,056	103,957	87,056	103,957	87,056	103,957	87,056	103,957	87,056	103,957

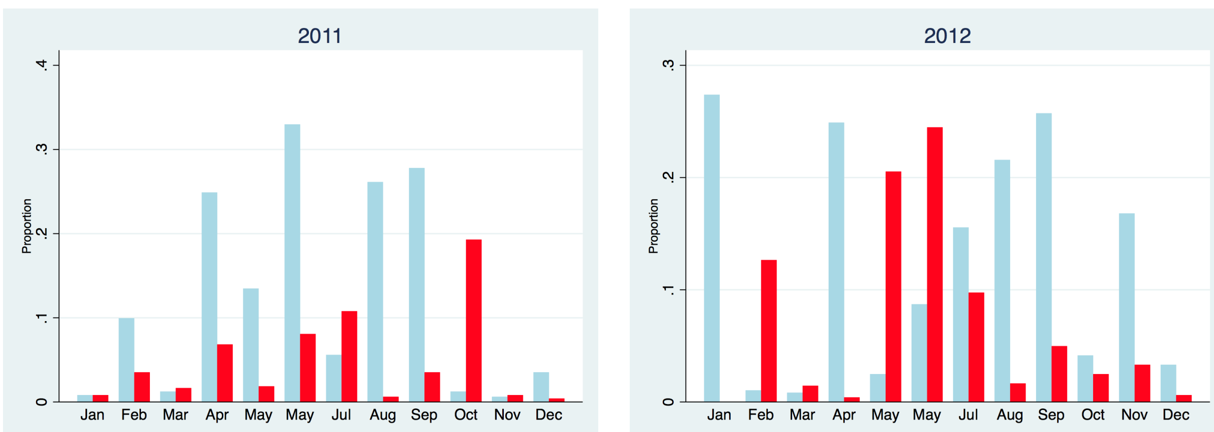
Notes: Coefficient estimates of severity of rainfall shocks from OLS regressions presented. Rainfall shock defined in Section 2.2. Sample restricted to males (Panel A) and females (Panel B) aged 15–60. Regressions control for a set of individual and household characteristics (age, years of education, marital status, religion, social group, household size and monthly per capita household expenditure). Regressions also include a set of month, survey year and district fixed effects. Dam–fed and rain–fed districts are defined in Section 5. Standard errors, clustered at the district level, are in parenthesis. Significance: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Figure A1: Percentage of Districts with Positive and Negative Rainfall Shock in each month, by Survey Year



Continued ...

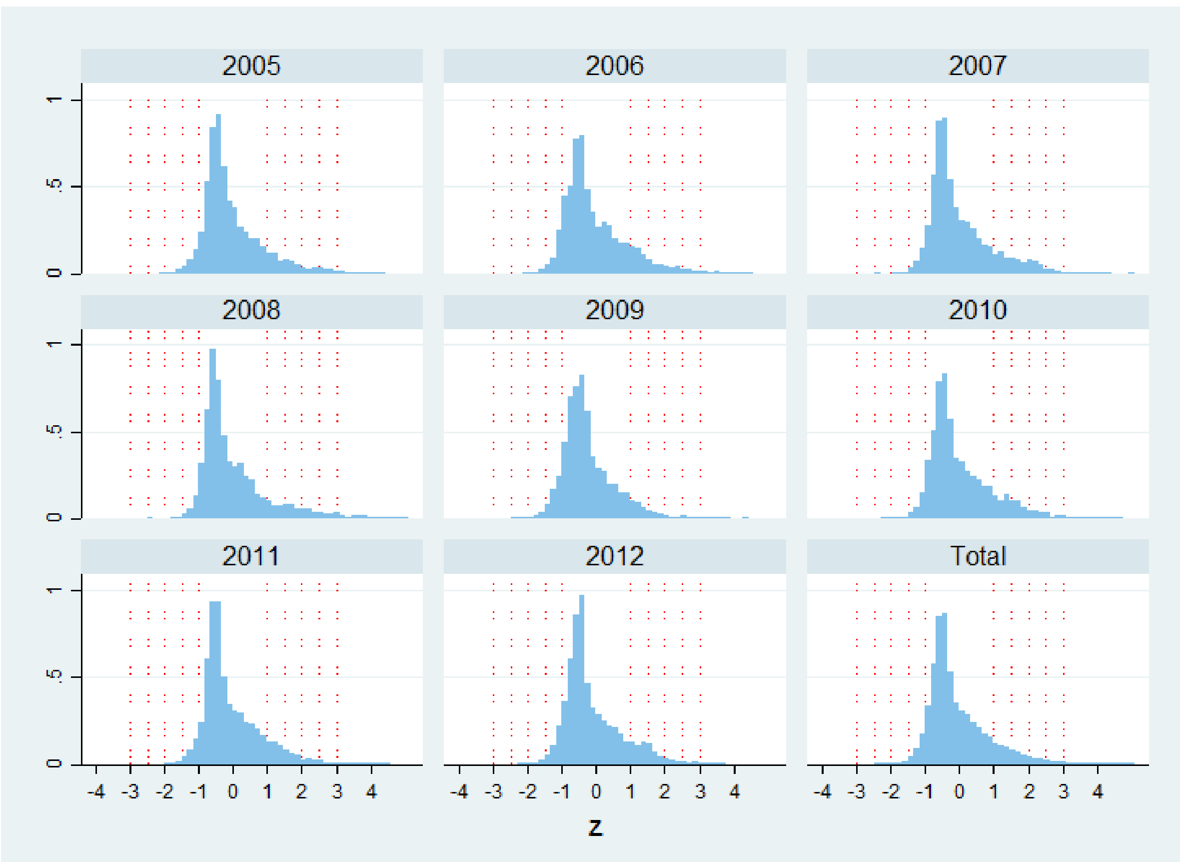
Percentage of Districts with Positive and Negative Rainfall Shock in each month, by Survey Year (Continued)



Notes:

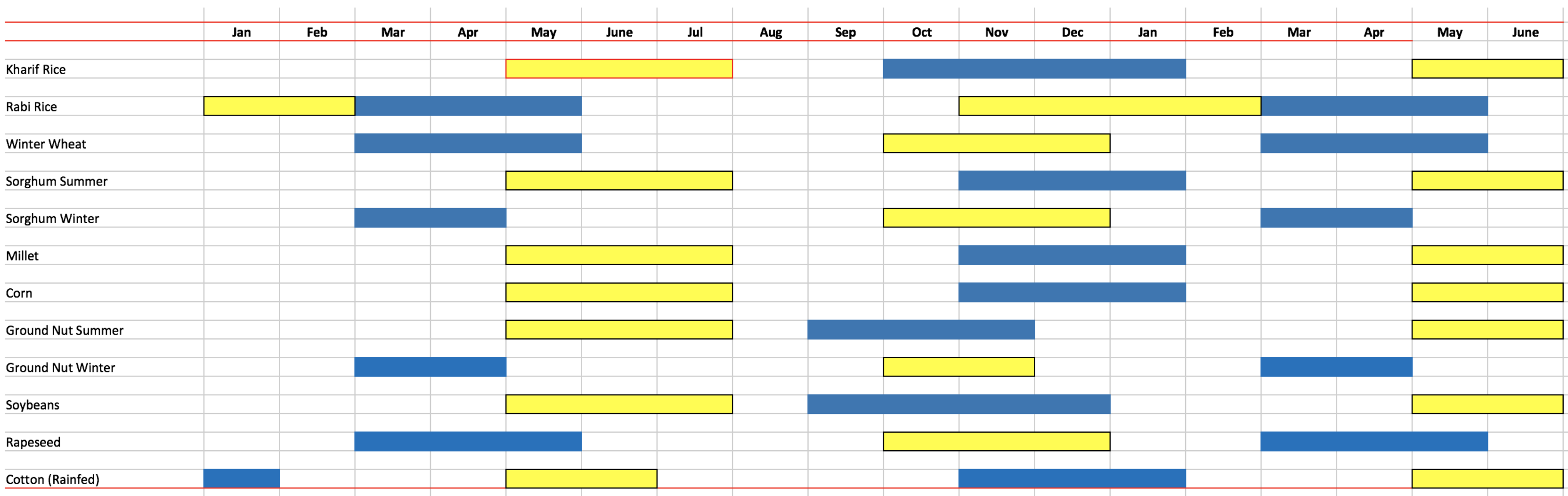
The light blue bars denote the proportion of districts with a positive rainfall shock in the specific month in the specific year. The red bars denote the proportion of districts with a positive rainfall shock in the specific month in the specific year.

Figure A2: Distribution and Heterogeniety of Rainfall Shocks



Notes: The graphs plot histograms of the distribution of deviations from average historical rainfall in the sample by year.

Figure A3: Timing of Planting and Harvesting of major crops



Notes: Timing of Planting (light shade) and Harvesting (dark shade) of major crops in India. Source USDA (1994).

Table A1: Effect of Contemporaneous and Lagged Rainfall Shock on Time Allocation to Different Activities: 4–month lags

	Own Account Work	Unpaid Family Work	Regular Wage Work	Casual Wage Work Public Works	Casual Wage Work NREGS	Other	Attending Educational Institution	Domestic Duties
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Male								
Rainfall shock	0.001	-0.017	0.007	-0.015**	0.017**	0.034	0.019	0.003
	(0.039)	(0.027)	(0.024)	(0.007)	(0.008)	(0.042)	(0.023)	(0.007)
Rainfall shock Lag 1 month	-0.020	-0.002	-0.013	-0.002	-0.007	0.001	0.008	0.010
	(0.035)	(0.026)	(0.023)	(0.008)	(0.007)	(0.040)	(0.019)	(0.007)
Rainfall shock Lag 2 months	0.056	-0.047*	-0.061***	0.022**	-0.013*	0.041	0.023	0.002
	(0.035)	(0.027)	(0.023)	(0.009)	(0.007)	(0.037)	(0.022)	(0.008)
Rainfall shock Lag 3 months	-0.026	-0.017	0.021	-0.007	0.004	0.012	-0.018	0.006
	(0.034)	(0.026)	(0.022)	(0.006)	(0.006)	(0.036)	(0.022)	(0.008)
Rainfall shock Lag 4 months	-0.011	-0.016	-0.007	0.000	0.003	0.043	0.008	-0.012*
	(0.033)	(0.025)	(0.024)	(0.008)	(0.007)	(0.040)	(0.021)	(0.007)
Sample Size	176,244	176,244	176,244	176,244	176,244	176,244	176,244	176,244
Average in a Normal Month	2.156	0.829	0.739	0.036	0.015	1.414	0.111	0.880
Panel B: Female								
Rainfall shock	0.007	0.025	-0.004	-0.000	0.023***	0.021	-0.046***	0.009
	(0.020)	(0.031)	(0.010)	(0.006)	(0.009)	(0.028)	(0.017)	(0.055)
Rainfall shock Lag 1 month	-0.011	-0.041	-0.019*	-0.008	0.001	-0.004	-0.001	0.102*
	(0.018)	(0.030)	(0.010)	(0.006)	(0.007)	(0.025)	(0.015)	(0.053)
Rainfall shock Lag 2 months	-0.001	-0.070**	-0.005	0.007	-0.005	-0.011	-0.015	0.017
	(0.020)	(0.029)	(0.011)	(0.007)	(0.005)	(0.026)	(0.017)	(0.050)
Rainfall shock Lag 3 months	-0.012	-0.000	0.004	0.009	0.005	0.003	0.005	-0.025
	(0.015)	(0.031)	(0.010)	(0.006)	(0.006)	(0.024)	(0.016)	(0.052)
Rainfall shock Lag 4 months	0.038**	0.005	0.006	0.002	0.006	0.054**	0.003	-0.026
	(0.018)	(0.028)	(0.011)	(0.008)	(0.007)	(0.027)	(0.015)	(0.049)
Sample Size	174,479	174,479	174,479	174,479	174,479	174,479	174,479	174,479
Average in a Normal Month	0.369	0.788	0.173	0.021	0.017	0.523	0.581	2.368

Notes: OLS regression results presented. Regression specification is given by equation (6) . Regressions control for a set of individual and household characteristics (age, years of education, marital status, religion, social group, household size and monthly per capita household expenditure). Regressions also include a set of month, survey year and district fixed effects. Rainfall shocks are defined in Section 2.2. Standard errors, clustered at the district level, are in parenthesis. Significance: $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table A2: Effect of Contemporaneous and Lagged Positve and Negative Rainfall Shock on Time Allocation to Different Activities: 4-month lags

	Own Account Work	Unpaid Family Work	Regular Wage Work	Casual Wage Work Public Works	Casual Wage Work NREGS	Casual Wage Work Other	Attending Educational Institution	Domestic Duties
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Males								
Negative Rainfall Shock	-0.065	-0.036	0.074**	-0.018**	0.005	0.032	-0.022	0.002
	(0.062)	(0.044)	(0.036)	(0.008)	(0.010)	(0.071)	(0.033)	(0.012)
Negative Rainfall Shock Lag 1 month	-0.042	0.000	-0.001	-0.008	-0.003	0.052	-0.013	-0.000
	(0.059)	(0.046)	(0.043)	(0.010)	(0.005)	(0.072)	(0.033)	(0.013)
Negative Rainfall Shock Lag 2 months	0.101*	-0.012	-0.055*	0.028*	-0.021***	-0.035	0.033	-0.005
	(0.061)	(0.047)	(0.032)	(0.015)	(0.006)	(0.066)	(0.039)	(0.014)
Negative Rainfall Shock Lag 3 months	-0.027	0.021	0.043	-0.026***	0.003	0.064	-0.032	0.005
	(0.071)	(0.047)	(0.040)	(0.008)	(0.009)	(0.066)	(0.035)	(0.019)
Negative Rainfall Shock Lag 4 months	0.045	-0.089**	-0.032	0.007	-0.008	0.087	0.028	-0.019*
	(0.063)	(0.042)	(0.038)	(0.012)	(0.008)	(0.075)	(0.042)	(0.012)
Positive Rainfall Shock	0.028	-0.010	-0.021	-0.013	0.021**	0.036	0.036	0.002
	(0.045)	(0.033)	(0.028)	(0.009)	(0.009)	(0.050)	(0.030)	(0.007)
Positive Rainfall Shock Lag 1 month	-0.010	-0.000	-0.019	0.000	-0.008	-0.023	0.019	0.014*
	(0.040)	(0.031)	(0.025)	(0.009)	(0.009)	(0.044)	(0.023)	(0.008)
Positive Rainfall Shock Lag 2 months	0.036	-0.062*	-0.064**	0.020*	-0.009	0.074*	0.019	0.005
	(0.039)	(0.032)	(0.026)	(0.011)	(0.008)	(0.043)	(0.023)	(0.008)
Positive Rainfall Shock Lag 3 months	-0.027	-0.031	0.013	-0.000	0.005	-0.008	-0.014	0.006
	(0.039)	(0.030)	(0.024)	(0.008)	(0.008)	(0.042)	(0.026)	(0.007)
Positive Rainfall Shock Lag 4 months	-0.027	0.012	0.001	-0.002	0.006	0.025	0.002	-0.010
	(0.035)	(0.029)	(0.029)	(0.009)	(0.009)	(0.043)	(0.021)	(0.007)
Sample Size	176,244	176,244	176,244	176,244	176,244	176,244	176,244	176,244
Average in a Normal Month	2.156	0.829	0.739	0.036	0.015	1.414	0.111	0.880
Panel B: Females								
Negative Rainfall Shock	-0.018	-0.014	0.005	0.009	0.021	0.013	-0.055*	0.089
	(0.030)	(0.048)	(0.017)	(0.009)	(0.013)	(0.043)	(0.030)	(0.101)
Negative Rainfall Shock Lag 1 month	-0.042	-0.005	-0.020	-0.015**	0.005	0.002	-0.041	0.100
	(0.025)	(0.047)	(0.018)	(0.007)	(0.008)	(0.044)	(0.028)	(0.096)
Negative Rainfall Shock Lag 2 months	-0.007	-0.072*	-0.019	-0.004	-0.008	-0.017	0.006	-0.038

Continued . . .

Effect of Contemporaneous and Lagged Positve and Negative Rainfall Shock on Time Allocation to Different Activities: 4-month lags (Continued)

	Own Account Work	Unpaid Family Work	Regular Wage Work	Casual Wage Work: Public Works	Casual Wage Work: NREGS	Casual Wage Work: Other	Attending Educational Institution	Domestic Duties
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0.028)	(0.043)	(0.017)	(0.007)	(0.007)	(0.040)	(0.028)	(0.092)
Negative Rainfall Shock Lag 3 months	-0.011	0.015	0.000	-0.006	0.008	0.016	0.019	-0.075
	(0.027)	(0.056)	(0.019)	(0.009)	(0.011)	(0.054)	(0.025)	(0.092)
Negative Rainfall Shock Lag 4 months	0.058*	-0.050	0.018	-0.003	0.001	0.071	0.001	-0.069
	(0.032)	(0.046)	(0.024)	(0.010)	(0.009)	(0.044)	(0.028)	(0.093)
Positive Rainfall Shock	0.018	0.040	-0.008	-0.004	0.024**	0.024	-0.042**	-0.025
	(0.024)	(0.036)	(0.011)	(0.007)	(0.010)	(0.034)	(0.019)	(0.061)
Positive Rainfall Shock Lag 1 month	0.003	-0.054	-0.019*	-0.005	-0.001	-0.007	0.017	0.100*
	(0.020)	(0.035)	(0.010)	(0.007)	(0.009)	(0.029)	(0.016)	(0.057)
Positive Rainfall Shock Lag 2 months	0.002	-0.070**	0.001	0.012	-0.004	-0.007	-0.024	0.041
	(0.024)	(0.033)	(0.012)	(0.009)	(0.007)	(0.031)	(0.019)	(0.060)
Positive Rainfall Shock Lag 3 months	-0.013	-0.004	0.006	0.015**	0.005	-0.003	-0.001	-0.004
	(0.018)	(0.038)	(0.013)	(0.008)	(0.008)	(0.027)	(0.018)	(0.055)
Positive Rainfall Shockn Lag 4 months	0.031	0.024	0.001	0.003	0.008	0.049	0.005	-0.017
	(0.021)	(0.032)	(0.011)	(0.009)	(0.008)	(0.030)	(0.017)	(0.054)
Sample Size	174,479	174,479	174,479	174,479	174,479	174,479	174,479	174,479
Average in a Normal Month	0.369	0.788	0.173	0.021	0.017	0.523	0.581	2.368

Notes: OLS regression results presented. Regression specification given by equation (7) with four lags. Sample restricted to males aged 18–60. Regressions control for a set of individual and household characteristics (age, years of education, marital status, religion, social group, household size and monthly per capita household expenditure). Regressions also include a set of month, survey year and district fixed effects. Rainfall shortage (negative rainfall shock) and excess rain (positive rainfall shock) defined in Section 2.2. Standard errors, clustered at the district level, are in parenthesis. Significance: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.