# INCOME SHOCKS, EDUCATIONAL INVESTMENTS AND CHILD WORK[*]

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**Abstract:** In predominantly agrarian economies with limited irrigation, rainfall plays a critical role in shaping households' spending decisions. We estimate the effect of income shocks, as proxied by exogenous rainfall deviations in annual rainfall from long-term trends, on children's education and work status in rural Indian households. Using household-level panel data from the nationally representative India Human Development Survey, we find that the substitution effect outweighs the income effect, such that there is a decline in educational expenditures in years characterized by higher than average rainfall, indicating reduced school attendance. This is accompanied by an increase in likelihood of children working in household farm, non-farm household enterprise, and animal care activities. We also document important heterogeneity in impacts based on the household's caste affiliation and landownership status.

**Keywords:** Rainfall shocks, Education expenditures, Child work, India

**JEL classification:** D13, I21, J16, O12

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## 1. Introduction

Households in low-income and developing countries are routinely exposed to a variety of aggregate income and price shocks. As large shares of populations in these countries rely on rain-dependent agriculture for their livelihood, rainfall and other climatic shocks constitute critical sources of income volatility (Dell et al., 2014 provides an overview of the literature on climatic shocks). In the absence of well-functioning formal credit or insurance markets, households are unable to easily borrow or save money to tide over periods of income uncertainty. Similarly, imperfect labour markets do not offer opportunities to households to either hire labour or find alternative employment in the event of income volatility. These constraints impact the households' ability to smooth consumption and have consequences for basic investments in their children, not just through scaling back on consumption but also via asset liquidation and labour reallocation (e.g., Rosenzweig and Wolpin, 1993; Dercon, 2002; Jacoby and Skoufias, 1997; Rose, 1999).

Aggregate shocks, such as transitory or short-term rainfall shocks, have both income and substitution effects on agrarian households. In the event of favourable rainfall (i.e., when rainfall is better than the usual trend), due to higher agricultural productivity, there is an income effect, through which there is an increase in earnings which expands the pool of resources available to the household for consumption and investments in children. However, there is also a substitution effect. A possibility of higher earnings also increases the opportunity cost of children's time spent in school or time spent away from income-generating activities.[1] Which of these two effects dominates is theoretically ambiguous.

In this paper, using data from rural India, we examine the contemporaneous impacts of income shocks, as *proxied* by exogenous variations in rainfall, on educational investments in children, as measured by education expenditures, as well as children's contribution to work. While the previous literature studying educational outcomes has focused on metrics such as enrolment status and test scores, we examine *child-specific* education expenditures, an important parental input into the learning process. Moreover, we find countercyclical impacts of rainfall shocks on educational spending. This makes us among the first to document that transitory positive income shocks can adversely affect investment decisions by parents, potentially translating into long-term consequences for their children's human capital. Further, we use a large-scale nationally representative household-level panel data from India, making our analysis richer than most other studies that rely on repeated cross-sectional data.

[1] Positive rainfall shocks also result in increased wages (Jayachandran, 2006; Kaur, 2018; Shah and Steinberg, 2017).

To date, existing work on aggregate weather and commodity price shocks provides empirical evidence of both procyclical and countercyclical effects. In a review article, Ferreira and Schady (2009) summarize that, in richer countries, child health and education are largely countercyclical in that they tend to improve during recessions as the substitution effect outweighs the income effect. But in low-income and middle-income countries, the evidence is more nuanced. Cogneau and Jedwab (2012) find a procyclical effect of the cocoa crisis in Cote d'Ivoire on school enrolment, labour, height stature, and morbidity. Björkman-Nyqvist (2013) finds that negative rainfall shocks in Uganda have detrimental effects on the enrolment and academic performance, particularly for girls. Jensen (2000) finds that droughts in Cote d'Ivoire reduce school enrolment and increase malnutrition. Beegle et al. (2006) find that a transitory idiosyncratic income shock in the form of accidental crop loss in Tanzania decreases school attendance and increases child labour. In contrast, using data from Brazil, Kruger (2007) finds a countercyclical effect in that probability of school enrolment decreases as the value of coffee production increases, with stronger effects on low- and middle-income children. Duryea and Arends-Kuenning (2003) document an increase in the likelihood of child employment (and decline in schooling) in states that experienced an increase in unskilled wages due to the Brazilian macroeconomic crises. Using Tanzanian data on child labour, Dumas (2018) shows that the importance of the income effect vis-à-vis the substitution effect depends crucially on the labour market quality. Shah and Steinberg (2017) also find a countercyclical effect of rainfall shocks on school attendance and test scores in rural India.

Using a panel data based on two rounds of the India Human Development Survey that measures detailed child-specific education expenditures as well as child-specific engagement in a variety of work categories, and combining it with geo-spatial rainfall data, we find that a positive rainfall shock significantly reduces total educational expenditures with no change in the probability of enrolment. This indicates that children are less likely to be attending school in years characterized by higher than long-term average rainfall. Therefore, our results provide evidence of a countercyclical effect on educational spending. This is accompanied by an increase in likelihood of children working in on-farm and off-farm activities. In contrast to most existing literature, our paper documents important heterogeneity in impacts based on the household's caste affiliation and landownership status. First, low caste children's education spending is more adversely affected, and they are more likely to engage in wage work in the event of positive rainfall shocks. Second, we find that children in landed households are more likely to engage in farm work and animal care than children in landless households in case of positive rainfall deviations. Further, the negative impact of rainfall deviations on education expenditures is mitigated for children from landed families.

This paper is organized as follows. Section 2 describes the data sources and the empirical framework employed. Section 3 presents descriptive statistics, regression results, robustness checks. Section 4 examines heterogeneity in impacts of the rainfall shock. Section 5 concludes.

## 2. Data and Empirical Specification

### 2.1 Data Sources

Our primary data of interest come from the two rounds of the India Human Development Survey (IHDS). The IHDS is a nationally representative panel survey conducted by the University of Maryland in collaboration with the National Council of Applied Economic Research, New Delhi. The first round, IHDS-I, was conducted between November 2004 and October 2005 covering 41,554 households across 1,504 villages and 971 urban areas from 33 states and union territories of India (Desai et al., 2005).[2] The second wave of the survey (IHDS-II), took place between November 2011 and October 2012, covering 42,152 households across 1,420 villages and 1,042 urban areas, and could track 83 percent of households from IHDS-I (Desai et al., 2012). In both rounds, the respondents included a person who was knowledgeable about the household's economic situation (usually the male head of the household) and an ever-married woman aged 15-49. The various modules of the survey collect data on a wide range of topics including economic activity, income and consumption expenditure, asset ownership, social capital, education, health, marriage and fertility etc.

While most other datasets usually report total education expenditures at the level of the household, one of the strengths of this data is the availability of education-related spending for each enrolled child. Child-specific educational expenditures for the year preceding the survey date are available for the following three categories: (i) school fees; (ii) books, uniforms, other materials, and transportation; and (iii) private tuition. We calculate the real total education expenditure per child as the sum of the abovementioned categories. Further, for each child, the survey also provides information on their engagement in household farm-related activities, household non-farm businesses, animal care and external wage work.

As rainfall shocks matter for household income and welfare predominantly in rural areas due to their reliance on rain-fed agriculture, we limit our sample to observations in rural areas, which constitutes 71 percent of the IHDS households sample.[3] However, as a placebo check, we also present results using the sample of urban households. Since our primary interest is in understanding the allocation of

[2] Andaman and Nicobar and Lakshadweep were not included in the sample. These Union Territories account for less than 0.05 percent of India's population.

[3] The following twenty states are in our sample: Jammu and Kashmir, Himachal Pradesh, Punjab, Uttarakhand, Haryana, Rajasthan, Uttar Pradesh, Bihar, Assam, West Bengal, Jharkhand, Orissa, Chhattisgarh, Madhya Pradesh, Gujarat, Maharashtra, Andhra Pradesh, Karnataka, Kerala and Tamil Nadu.

educational expenditures and work among school-aged children, we restrict the analysis to households where there is at least one member aged 5-16 at the time of the survey.

Rainfall shocks are computed based on monthly rainfall data available from the Centre for Climatic Research at the University of Delaware.[4] The first year of data availability is 1900 and we use data beginning 1980. As the monthly rainfall data are gridded at 0.5 intervals of longitude and latitude, we match the station closest to the centroid of the district and assign the value of the rainfall at that station as being the district-level rainfall in a certain month. As a robustness check, following Maccini and Yang (2009), we also instrument rainfall with the rainfall at the second to fifth closest stations.

We combine the district-level rainfall data with the IHDS data using district identifiers and month and year of interview available in the latter. We calculate district-month-specific rainfall shocks as the logarithm of the rainfall in the district in the twelve months preceding the interview minus the logarithm of the long-term average monthly district rainfall. The long-term rainfall is constructed as average monthly rainfall between 1980 and 2005 (corresponding to IHDS-I) and 1980 and 2012 (for IHDS-II), leaving out the twelve months preceding the interview. This definition has been used in other work (Maccini and Yang, 2009; Björkman-Nyqvist, 2013; Levine and Yang, 2014) and has a simple interpretation as a percentage deviation from the long-term mean. A positive (negative) value of the rainfall shock implies higher (lower) than average rainfall within the district.

### 2.2 Empirical Specification

We estimate the following equation:

$$Y_{ijdt} = \beta_0 + \beta_1\, RainShock_{dt} + \beta_2 Sex_{ijt} + \gamma_{ijt} + \delta_j + \theta_t + \varepsilon_{ijdt} \qquad (1)$$

where $Y$ is the outcome variable for individual $i$ in household $j$ in district $d$, interviewed in month-year $t$. Our main outcomes under consideration are logarithm of real educational expenditures as well as binary variables for working in the household farm, household non-farm business, animal care and wage work. $\beta_1$ is the key coefficient of interest and measures the effect of a rainfall shock in district $d$ in month-year $t$. Among individual-level covariates, we control for sex that takes value 1 if female and 0 if male, and year of birth fixed effects ($\gamma_{ijt}$). We include survey month-year fixed effects ($\theta_t$) as well as household fixed effects ($\delta_j$) to purge the estimates of any influence of time-invariant household characteristics that are jointly related to outcomes and to the likelihood of experiencing the rainfall shock. $\varepsilon_{ijdt}$ is the individual-specific error term. Errors are assumed to be correlated within districts, therefore, we cluster standard errors at the district level.

[4] Data available at: https://www.esrl.noaa.gov/psd/data/gridded/data.UDel_AirT_Precip.html#tools.

## 3. Results

### 3.1 Descriptive Statistics

In Table 1, we present descriptive statistics. Ninety four percent of the sample is currently enrolled in school. The average yearly expenditure on education is about INR 1435. The average amounts spent on school fees and on books, uniforms, and transport are approximately INR 580 and INR 757 respectively. About INR 162 is spent on private tutoring annually. The average rainfall deviation is approximately 9 percent below the long-term mean.

[Table 1 here]

Twelve percent of children work on the household farm, and about 13.5 percent in tending to animals. Just over 1 percent work in the non-farm household enterprises. Around 2.5 percent are engaged in external paid work. This is consistent with other evidence that shows that majority of children in developing countries are engaged as agricultural and related labour on their family-operated farms. As expected, most children in wage work are those aged 14-16 years old.

Forty six percent of the sample comprises females. As mentioned before, the sample consists of those aged 5-16, and the average age is just below 11 years. The average household size is 7.5. 32 percent belong to the historically marginalized Scheduled Caste and Scheduled Tribes (SCST) categories. 80 percent are Hindus, the dominant religion in India. Over two-thirds of households report owning any land.

### 3.2 Regression Results

Using rainfall shocks as proxies of income shocks hinges on the assumption that agricultural productivity is systematically correlated with rainfall shocks. Previous studies from several developing country contexts have convincingly shown that rainfall variations have implications for agricultural productivity such that in periods of low (high) rainfall, yields of important crops are significantly lower (higher), thereby affecting rural incomes.[5] For India, Jayachandran (2006) and Shah and Steinberg (2017) show that yields of key crops such as rice, wheat and jowar are sensitive to rainfall variations. Therefore, rainfall shocks can serve as a plausible proxy for income shocks in rural India.

In Table 2, we present regression estimates of equation (1). In column 1, we estimate the effect of rainfall shocks on enrolment status and find that there is no statistically or economically significant impact. In column 2, we examine impacts on total education expenditures. The results point towards a

[5] For example, see Levine and Yang (2014) for Indonesia, Hidalgo et al. (2010) for Brazil, Yang and Choi (2007) for Philippines, and Björkman-Nyqvist (2013) for Uganda. Dell et al. (2014) provide an overview.

countercyclical effect such that a transitory increase in rainfall over the long-term mean leads to a decline in education spending. This is consistent with countercyclical effects observed in Shah and Steinberg (2017) using recent data on test scores from India. Upon disaggregating the educational expenditures into its three sub-components in columns 3-5, we find negative effects of rainfall on school fees and also on associated costs of schooling in the form of spending on books, uniforms, and transportation. While the survey does not canvass information on school attendance, the lack of a significant effect on enrolment combined with decreased spending on essential costs of schooling, provides a strong indication that children are attending school less frequently in periods characterized by higher than usual rainfall. In terms of other controls, we find that girls are less likely to be enrolled and significantly lower amounts are spent on them on all categories of education expenditures. This is in accordance with other evidence from India (e.g., Azam and Kingdon, 2013; Maitra et al., 2016).

[Table 2 here]

In Table 3, we proceed to examine effects of rainfall deviations on children's participation in different types of work. In higher rainfall years, children are significantly more likely to work on the household farm, engage in the household's non-farm enterprise, as well as spend time on tending to livestock. There is a negligible and insignificant effect on participation in wage work. As the IHDS data do not contain information on children's involvement in domestic chores such as cooking, cleaning and caring for elders or younger siblings, we are unable to examine effects on outcomes related to household chores. Results from Tables 2 and 3 show that while transitory rainfall shocks do not reduce enrolment in schools, there are lower expenditures on education, indicating reduced attendance at school. This reduced school attendance is accompanied by a greater likelihood of children being engaged in various household activities. That we do not observe an effect on the margin of enrolment along with a significant increase in children's probability of work is has also been previously observed (e.g., Beegle et al., 2006; Ravallion and Wodon, 2000). However, existing literature documents unfavourable effects of child work on learning outcomes (e.g., Heady, 2003; Gunnarson et al., 2006; Emerson et al., 2017). Our results may also be the channel explaining the countercyclical effects on test scores in Shah and Steinberg (2017).

[Table 3 here]

### 3.3 Robustness Checks

The first robustness check is concerned with measurement error in the rainfall variable, which can lead to attenuated impact estimates. As rainfall recorded at the weather station closest to the district centroid may be an imperfect measure of the actual rainfall faced by a household, as in Maccini and Yang (2009), we estimate an instrumental variables (IV) regression. Here, rainfall at the weather station closest to the district centroid is instrumented by average rainfall in the second, third, fourth and fifth closest stations. In Table 4, we find that our results are qualitatively similar when using this IV. We find that an increase in rainfall is associated with lower educational spending and a greater likelihood of engagement in farm work, non-farm business, and animal care by children.

[Table 4 here]

In Table 5, we conduct a placebo test by limiting the sample only to urban areas. A priori we would not expect any impacts of rainfall shocks on spending decisions for urban households as (rain-dependent) agriculture is primarily a rural activity. The results show that none of the educational expenditures in urban areas are significantly associated with rainfall deviations. We find that the female disadvantage in educational spending also prevails in urban India.

[Table 5 here]

## 4. Heterogeneity Analyses

We now examine some avenues of heterogeneity. In this section, we report results for the following outcomes: enrolment, total educational spending, farm work, non-farm household enterprise, animal care, and wage work.

The first avenue we explore is gender. Existing evidence generally documents a significant gender gap in the health and education domains, with females' being more vulnerable to income shocks. For instance, Rose (1999) finds that favourable rainfall shocks increase the ratio of survival probability of girls vis-à-vis that of boys. Focusing on education-related outcomes, Björkman-Nyqvist (2013), using panel data from Uganda, finds that negative rainfall shocks adversely affect the enrolment and academic performance of girls, with no effects on boys. Zimmermann (2012) finds that girls' school enrolment is more sensitive to rainfall variations than that of boys. On the other hand, Shah and Steinberg (2017) do not find significant gender differences in the effects of rainfall shocks on test scores in India. In Table 6, upon interacting rainfall shocks with child gender, we find that transitory rainfall shocks have different effects on the work status of boys and girls. Specifically, our results show that girls are less likely to engage in farm work and wage work in periods of better rainfall. However, in such times, it is possible that girls are more likely to substitute for adult women in domestic chores that we cannot identify in the data.

[Table 6 here]

In Table 7, we examine heterogeneity by caste. Caste is a deeply embedded institution in India that is highly correlated with one's social status and economic well-being in India. The Scheduled Castes and Scheduled Tribes (SCSTs) are the marginalized groups that have been historically subjected to practices of untouchability and large-scale exclusion from mainstream society. While affirmative action was enacted in 1950 after the country gained independence, and there have been some improvements in terms of educational attainment and incomes (e.g., Hnatkovska et al., 2012), lower castes continue to fare systematically worse than upper castes on a variety of socioeconomic indicators (Deshpande, 2011 provides an overview). Using caste as a proxy for socioeconomic status as it is determined exogenously at birth (and is therefore time invariant), and interacting that with the rainfall shock, we find that a transitory increase in rainfall induces SCST households to scale back more than non-SCST households on the amount spent on their children's education, thereby worsening the impact of the shock. Further, SCST children are more likely to engage in paid work during such periods. This is potentially explained by a greater credit constraint faced by these households because of which they are unable to hire labour to maximize the productivity gains accruing from higher than usual rainfall. Adults are potentially spending more time on the farm while children engage in wage work. That SCST children are less likely to work in non-farm household enterprise is explained by the fact that SCSTs tend to perform significantly worse than other higher caste groups in terms of enterprise ownership and performance (Deshpande and Sharma, 2013 and 2016).

[Table 7 here]

The third aspect we examine is related to land wealth. On the one hand, wealthier or land-rich households are in a better position to buffer against shocks, implying that the outcomes of children are less sensitive to weather variability (Beegle et al., 2006). However, in the presence of labour market imperfections, households owning land may not be able to hire appropriate outside labour to take advantage of the productivity shock, leading them to rely on family labour (Bhalotra and Heady, 2003; Dumas, 2007; Dumas, 2018). Further, concerns of moral hazard with hired labour may lead to a preference for household labour. To examine this, we create a binary variable *any land* that takes a value 1 if the household owns any land, and 0 otherwise.[6] Results in Table 8 show that children in landed households are more likely to engage in farm work and animal care than children in landless households in case of positive rainfall deviations. This is in line with evidence presented in Bhalotra and Heady (2003), who using data from rural Pakistan and Ghana, find that the likelihood of child work is positively related to the size of landholding. Further, the negative impact of rainfall shocks on education expenditures is smaller for children from landed families. We also find that children from land-owning households are less likely to engage in external wage work in periods of better rainfall.

[Table 8 here]

[6] In this analysis, we do not examine the intensive margin of landownership (i.e., land size).

Finally, we examine heterogeneous impacts based on exposure to a large-scale public works program. The reason we examine this policy is because it is one of the world's largest workfare programs that was introduced between the two rounds of the data we use for this study. India's National Rural Employment Guarantee Act (NREGA) announced in 2005, legally guarantees 100 days of unskilled wage employment in a year to a rural household whose adult members are willing to undertake unskilled manual work at state-level statutory minimum wages. The program was rolled out in three phases in 2006, 2007 and 2008 with the 200 poorest districts being the earliest program recipients. Several studies find that the program increased rural private sector wages (e.g., Azam, 2012; Berg et al., 2018; Imbert and Papp, 2015). We examine if exposure to the program has differential effects on the relationship between rainfall shocks and child education and work. As the first IHDS wave in 2004-05 is entirely pre-NREGA and the second wave in 2011-12 is post-NREGA rollout, we operationalize this by interacting the rainfall shock with the length of program exposure at the district level (measured as number of months elapsed between the NREGA rollout and the median interview month for a district in IHDS-II). Our results (Table A1 in the online appendix) show that the duration of a district's exposure to the NREGA has no differential impact on the relationship between rainfall shocks and allocation of child-specific educational expenditures and work.

## 5. Conclusion

Increased rainfall can have both income and substitution effects – income effect dictates a higher investment in children via enhanced earnings. Simultaneously, there is a rise in the opportunity cost of child labour which in turn leads to increased participation in children's work inside and outside the household. We examine which of these effects is stronger by the estimating the effect of income shocks, as proxied by exogenous rainfall shocks, on children's education and work status in rural Indian households. Using household-level panel data from the nationally representative India Human Development Survey, we find that there is a decline in educational expenditures in years characterized by higher than average rainfall. Combined with no significant effect on school enrolment, this points towards reduced school attendance. This indicates a countercyclical effect such that the substitution/productivity effect of rainfall exceeds the income effect. This is accompanied by an increase in likelihood of children working in household farm, non-farm household enterprise, and animal care activities. These results have implications for the learning outcomes. In contrast to most existing literature, our paper documents important heterogeneity in impacts based on the household's caste affiliation and landownership status. Low caste children's education spending is more adversely affected, and they are more likely to engage in wage work in the event of positive rainfall shocks. Children in landed households are more likely to engage in farm work and animal care than children in landless households in case of positive rainfall deviations. Further, the negative impact of rainfall deviations on education expenditures is mitigated for children from landed families.

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## Table 1: Descriptive Statistics

| | (1) Mean | (2) Standard deviation |
|---|---|---|
| *Education related:* | | |
| Currently enrolled | 0.936 | 0.245 |
| Total education expenditure | 1435.659 | 2345.968 |
| Expenditures on school fees | 580.595 | 1625.227 |
| Expenditures on books, uniforms, transport | 757.603 | 993.476 |
| Expenditures on private tuitions | 161.826 | 565.621 |
| *Work related:* | | |
| Farm work | 0.122 | 0.328 |
| Non-farm household enterprise | 0.012 | 0.111 |
| Animal care | 0.135 | 0.341 |
| Wage work | 0.026 | 0.159 |
| *Right-hand side:* | | |
| Rainfall shock | -0.092 | 0.227 |
| Female | 0.462 | 0.499 |
| Age | 10.856 | 3.201 |
| Household size | 7.497 | 3.291 |
| Scheduled Caste/Tribe (SCST) | 0.322 | 0.467 |
| Any land owned (binary variable) | 0.672 | 0.469 |
| Observations | 27,719 | |

**Notes:** Authors' calculations using India Human Development Surveys, 2004-05 and 2011-12. Rainfall shock is computed as log of rainfall in the district in the twelve months preceding the interview date minus the log of long-term average monthly district rainfall.

**Table 2: Effects on Enrolment and Education Expenditures**

| | | | Total education expenditures | | |
|---|---|---|---|---|---|
| | (1) Enrolment | (2) Total education expenditures | (3) School fees | (4) Books, uniforms and transport | (5) Private tuition |
| Rainfall Shock | 0.023 | -0.380* | -1.341*** | -0.457* | 0.114 |
| | (0.015) | (0.217) | (0.340) | (0.247) | (0.265) |
| Female | -0.011*** | -0.217*** | -0.407*** | -0.160*** | -0.228*** |
| | (0.003) | (0.023) | (0.040) | (0.022) | (0.031) |
| Constant | 0.796*** | 6.364*** | 4.751*** | 5.569*** | 1.728** |
| | (0.064) | (0.857) | (0.764) | (0.880) | (0.667) |
| Observations | 27,719 | 25,885 | 24,623 | 25,457 | 22,121 |
| R-squared | 0.114 | 0.111 | 0.123 | 0.104 | 0.056 |

**Notes:** These regressions include household fixed effects, year of birth fixed effects and month-year of survey fixed effects. Standard errors clustered at the district level, reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Rainfall shock is computed as log of rainfall in the district in the twelve months preceding the interview date minus the log of long-term average monthly district rainfall.

**Table 3: Effects on Children's Work**

| | (1)<br>Farm work | (2)<br>Non-farm household enterprise | (3)<br>Animal care | (4)<br>Wage work |
|---|---|---|---|---|
| Rainfall Shock | 0.206*** | 0.016** | 0.262*** | 0.003 |
| | (0.033) | (0.008) | (0.036) | (0.015) |
| Female | -0.026*** | -0.006*** | -0.008* | -0.010*** |
| | (0.004) | (0.001) | (0.005) | (0.002) |
| Constant | 0.221** | 0.031 | 0.253** | 0.022 |
| | (0.088) | (0.035) | (0.114) | (0.045) |
| Observations | 27,719 | 27,719 | 27,719 | 27,718 |
| R-squared | 0.181 | 0.020 | 0.175 | 0.068 |

**Notes:** These regressions include household fixed effects, year of birth fixed effects and month-year of survey fixed effects. Standard errors clustered at the district level, reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Rainfall shock is computed as log of rainfall in the district in the twelve months preceding the interview date minus the log of long-term average monthly district rainfall.

**Table 4: Instrumental Variables Regressions**

| | (1) Total education expenditures | (2) Farm work | (3) Non-farm household enterprise | (4) Animal care | (5) Wage work |
|---|---|---|---|---|---|
| Rainfall Shock | -0.882*** | 0.124*** | 0.0185* | 0.228*** | -0.0271 |
| | (0.259) | (0.0419) | (0.0102) | (0.0489) | (0.0216) |
| Female | -0.228*** | -0.0265*** | -0.00582*** | -0.00830* | -0.0102*** |
| | (0.0229) | (0.00460) | (0.00153) | (0.00503) | (0.00214) |
| Constant | 6.326*** | 0.217** | 0.0316 | 0.255** | 0.0201 |
| | (0.855) | (0.0887) | (0.0347) | (0.114) | (0.0449) |
| Observations | 24,793 | 26,550 | 26,550 | 26,550 | 26,549 |

**Notes:** These regressions include household fixed effects, year of birth fixed effects and month-year of survey fixed effects. Standard errors clustered at the district level, reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Rainfall shock is computed as log of rainfall in the district in the twelve months preceding the interview date minus the log of long-term average monthly district rainfall. Rainfall instrumented with rainfall in the second through fifth closest rainfall stations following Maccini and Yang (2009).

**Table 5: Effects on Enrolment and Education Expenditures in Urban Areas**

| | | | Total education expenditures | | |
|---|---|---|---|---|---|
| | (1) Enrolment | (2) Total education expenditures | (3) School fees | (4) Books, uniforms and transport | (5) Private tuition |
| Rainfall Shock | -0.013 | 0.079 | -0.390 | 0.068 | -0.168 |
| | (0.015) | (0.170) | (0.247) | (0.174) | (0.363) |
| Female | 0.004 | -0.090** | -0.307*** | -0.050 | -0.129** |
| | (0.005) | (0.040) | (0.056) | (0.036) | (0.058) |
| Constant | 0.690*** | 6.692*** | 9.112*** | 5.538*** | -0.191 |
| | (0.087) | (0.732) | (1.799) | (0.710) | (3.109) |
| Observations | 9,828 | 9,172 | 8,857 | 8,953 | 8,007 |
| R-squared | 0.109 | 0.058 | 0.057 | 0.060 | 0.048 |

**Notes:** These regressions include household fixed effects, year of birth fixed effects and month-year of survey fixed effects. Standard errors clustered at the district level, reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Rainfall shock is computed as log of rainfall in the district in the twelve months preceding the interview date minus the log of long-term average monthly district rainfall. Sample is restricted to households in urban areas.

**Table 6: Heterogeneity by Gender**

| | (1) Enrolment | (2) Total education expenditures | (3) Farm work | (4) Non-farm household enterprise | (5) Animal care | (6) Wage work |
|---|---|---|---|---|---|---|
| Rainfall shock | 0.032** | -0.430** | 0.226*** | 0.018** | 0.257*** | 0.014 |
| | (0.016) | (0.216) | (0.035) | (0.008) | (0.040) | (0.017) |
| Female | -0.013*** | -0.207*** | -0.030*** | -0.006*** | -0.007 | -0.012*** |
| | (0.004) | (0.025) | (0.005) | (0.002) | (0.006) | (0.003) |
| Female x Rainfall shock | -0.020 | 0.108 | -0.042** | -0.006 | 0.011 | -0.025*** |
| | (0.014) | (0.081) | (0.018) | (0.006) | (0.021) | (0.009) |
| Observations | 27,719 | 25,885 | 27,719 | 27,719 | 27,719 | 27,718 |
| R-squared | 0.114 | 0.111 | 0.182 | 0.021 | 0.175 | 0.069 |

**Notes:** These regressions include household fixed effects, year of birth fixed effects and month-year of survey fixed effects. Standard errors clustered at the district level, reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Rainfall shock is computed as log of rainfall in the district in the twelve months preceding the interview date minus the log of long-term average monthly district rainfall.

## Table 7: Heterogeneity by Caste

| | (1) Enrolment | (2) Total education expenditures | (3) Farm work | (4) Non-farm household enterprise | (5) Animal care | (6) Wage work |
|---|---|---|---|---|---|---|
| Rainfall shock | 0.029* | -0.276 | 0.206*** | 0.026*** | 0.254*** | -0.019 |
| | (0.017) | (0.217) | (0.033) | (0.009) | (0.039) | (0.013) |
| SCST x Rainfall shock | -0.020 | -0.317** | -0.000 | -0.030*** | 0.023 | 0.066*** |
| | (0.025) | (0.159) | (0.039) | (0.010) | (0.038) | (0.017) |
| Observations | 27,716 | 25,882 | 27,716 | 27,716 | 27,716 | 27,715 |
| R-squared | 0.114 | 0.111 | 0.181 | 0.021 | 0.175 | 0.070 |

**Notes:** These regressions include household fixed effects, year of birth fixed effects and month-year of survey fixed effects. Standard errors clustered at the district level, reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Rainfall shock is computed as log of rainfall in the district in the twelve months preceding the interview date minus the log of long-term average monthly district rainfall.

**Table 8: Heterogeneity by Land Ownership**

| | (1) Enrolment | (2) Total education expenditures | (3) Farm work | (4) Non-farm household enterprise | (5) Animal care | (6) Wage work |
|---|---|---|---|---|---|---|
| Rainfall shock | 0.010 | -0.807*** | -0.097*** | 0.027** | 0.199*** | 0.040 |
| | (0.021) | (0.255) | (0.031) | (0.011) | (0.036) | (0.026) |
| Any land | 0.005 | 0.119 | 0.200*** | -0.003 | 0.057*** | -0.004 |
| | (0.009) | (0.079) | (0.013) | (0.004) | (0.015) | (0.006) |
| Rainfall shock * Any Land | 0.020 | 0.645*** | 0.447*** | -0.017 | 0.091*** | -0.057** |
| | (0.020) | (0.210) | (0.040) | (0.012) | (0.032) | (0.022) |
| Observations | 27,719 | 25,885 | 27,719 | 27,719 | 27,719 | 27,718 |
| R-squared | 0.114 | 0.112 | 0.209 | 0.021 | 0.177 | 0.069 |

**Notes:** These regressions include household fixed effects, year of birth fixed effects and month-year of survey fixed effects. Standard errors clustered at the district level, reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Rainfall shock is computed as log of rainfall in the district in the twelve months preceding the interview date minus the log of long-term average monthly district rainfall.

## Online Appendix

### Table A1: Heterogeneity by NREGA Exposure

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Enrolment | Total education expenditures | Farm work | Non-farm household enterprise | Animal care | Wage work |
| Rainfall shock | 0.025 | -0.541** | 0.167*** | 0.021** | 0.243*** | 0.007 |
| | (0.019) | (0.248) | (0.045) | (0.009) | (0.044) | (0.018) |
| NREGA Exposure | -0.000 | 0.010** | 0.003*** | -0.000 | 0.001* | 0.001*** |
| | (0.000) | (0.004) | (0.001) | (0.000) | (0.001) | (0.000) |
| NREGA x Rainfall shock | -0.000 | 0.011 | 0.002 | -0.000 | 0.001 | -0.000 |
| | (0.001) | (0.008) | (0.001) | (0.000) | (0.001) | (0.000) |
| Observations | 27,519 | 25,698 | 27,519 | 27,519 | 27,519 | 27,518 |
| R-squared | 0.114 | 0.113 | 0.184 | 0.021 | 0.176 | 0.069 |

**Notes:** These regressions include household fixed effects, year of birth fixed effects and month-year of survey fixed effects. Standard errors clustered at the district level, reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Rainfall shock is computed as log of rainfall in the district in the twelve months preceding the interview date minus the log of long-term average monthly district rainfall. NREGA exposure is the number of months in the second wave that the district has been included under NREGA.