INCOME SHOCKS, EDUCATIONAL INVESTMENTS AND CHILD WORK: EVIDENCE FROM RURAL INDIA

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Abstract: We examine 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 a counter-cyclical effect, such that there is a decline in educational expenditures in years characterized by higher than average rainfall, pointing towards 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. Heterogeneity analyses indicate that some of these effects are stronger for girls, as well as low caste households.

Keywords: rainfall shocks, education expenditures, work status, India

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1. Introduction

Households in low-income and developing countries are routinely exposed to income and price shocks. As large shares of populations in these countries depend on rain-fed agriculture for their livelihood, rainfall shocks constitute critical sources of income volatility and uncertainty. Key markets are either missing or incomplete. In the absence of well-functioning credit or insurance markets, households are unable to easily borrow or save money to tide over periods of income uncertainty. Similarly, labour markets offer inadequate alternative earning opportunities to households in the event of income volatility. In such cases, to smooth consumption, households are often compelled to make decisions that affect productive investments in the well-being of their children, thereby having important consequences for current and future human capital formation.

Aggregate shocks, such as transitory rainfall shocks, have both income and substitution effects on households. In the event of a good rainfall year (one where rainfall has been better than the usual trend), there is an income effect, i.e., an increase in earnings expands the total pool of resources available to the household for consumption and investments in children. However, there is also a productivity or substitution effect. Higher earnings possibility also increases the opportunity cost of children's time spent in attending school or time spent away from income-generating activities. Which of these two effects dominates is theoretically ambiguous and an open empirical question.

The literature on the impacts of transitory weather and commodity price shocks provides evidence of both pro-cyclical and counter-cyclical effects. In a recent review article examining the effects of aggregate shocks, Ferreira and Schady (2009) summarize that, in richer countries, child health and education are largely counter-cyclical in that they tend to improve during recessions as the substitution effect outweighs the income effect. But in low-income and middle-income, the evidence is more nuanced. For instance, using data on changes in the value of coffee production in coffee-growing areas in Brazil, Kruger (2007) finds that enrollment probability decreases as the value of coffee production increases, with stronger effects on low and middle income children. Duryea and Arends-Kuenning (2003) exploit state-level variations in the extent of the Brazilian macroeconomic crises, and find an increase in likelihood of child employment (and decline in schooling) that in states that experienced an increase in unskilled wages. Shah and Steinberg (2017) find a counter-cyclical effect of rainfall shocks on school attendance and test scores in rural India in periods of higher rainfall. In contrast, Jensen (2000) finds that droughts in Cote d'Ivoire reduce school enrolment and increase malnutrition. Beegle, Dehejia and Gatti (2006) find that a transitory income shock in the form of accidental crop loss in Tanzania increases child labour and decreases school attendance.

In this paper, we examine the effect of income shocks, as proxied by exogenous variations in rainfall, on educational investments in children (as measured by child-specific education expenditures), as well as children's contribution to work in rural India. While previous literature has focused on enrolment status and test scores as outcomes, we examine child-specific education expenditures, a critical input into the learning process that is determined by parents. Further, as income volatility is likely to affect children and households depending on factors such as their gender, age, and caste, we investigate these avenues of heterogeneity.

We use a rich, nationally representative, household-level panel data for India that measures child-specific expenditures on different types of education-related categories as well as child-specific work status, and combine it with finely gridded data on rainfall. Our results show that an increase in deviation of rainfall from the long-term average 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 average rainfall. This is accompanied by an increase in likelihood of children working in household farm, non-farm, and animal care activities. Therefore, our results show that the substitution effect is stronger than the income effect.

This paper is organized as follows. Section 2 describes the data sources and the empirical framework employed. Section 3 presents descriptive statistics, regression results, heterogeneity analyses, and robustness checks. Section 4 concludes.

2. Data and Empirical Specification

2.1 Data

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.[1] 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. In both rounds, the respondents included a person who was knowledgeable about the household 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.

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 household sample.

Since our primary interest is in understanding the allocation of educational expenditures and work among school-aged children, we restrict the analysis to households where there is at least one member aged 5-19 at the time of the survey. One of the unique features of this data is the availability of education-related spending for each enrolled child, as compared to other datasets which usually report total expenditures at the level of the household. Child-specific educational expenditures are available for the following three categories: (i) school fees; (ii) books, uniforms and other materials, and transportation; and (iii) private tuition. We calculate the total education expenditure 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, as well as in wage work.

Rainfall shocks are computed based on monthly rainfall data available from the University of Delaware. 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.

We combine the district-level rainfall data with the IHDS data using district identifiers and month and year of interview provided 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

[1] 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.

long-term rainfall is constructed as average monthly rainfall between 1980 and 2005 or 2012 (corresponding to the IHDS data wave), leaving out the twelve months preceding the interview. This definition has been used by Maccini and Yang (2009) and Björkman-Nyqvist (2013), 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:

$$Y_{ijdkl} = \beta_0 + \beta_1 RainfallShock_{dkl} + \beta_2 Sex_{ijkl} + \mu_t + \delta_j + \theta_{kl} + \varepsilon_{ijkl} \qquad (1)$$

Where *Y* is the outcome variable for individual *i* in household *j* in district *d*, interviewed in month *k* and year *l*. Our main outcomes of interest are logarithm of educational expenditures as well as binary variables for participation in the household farm, household non-farm businesses, and animal care, as described in Section 2.1 above. β_1 is the key coefficient of interest that measures the effect of a rainfall shock in district *d*, in month *k* and year *l* on the outcomes of interest. We control for sex (takes value 1 if female, 0 if male), and include age fixed effects (μ_t), household fixed effects (δ_j) and survey month-year fixed effects (θ_{kl}). Standard errors are clustered at the district level.

3. Results

3.1 Descriptive Statistics

In Table 1, we present descriptive statistics. Eight six percent of the sample is currently enrolled in school. Of this, 69 percent are enrolled in public schools, that are highly subsidized compared to their private counterparts. The average yearly expenditure on education is about INR 1954. The average amount spent on school fees and on books, uniforms, and transport is approximately INR 900 respectively. About INR 200 is spent on private tutoring. The average rainfall deviation is approximately 7 percent below the long-term mean. Thirteen percent of children work on the household farm, and about 15 percent in tending to animals. Less than 2 percent work in the non-farm household enterprises. Around 6 percent are engaged in external paid work. As expected, most children in wage work are those over age 15. 45 percent of the sample comprises females. As mentioned before, this sample comprises those aged 5-19, and the average age is 11.8 years.

3.2 Regression Results

Previous studies have convincingly shown that rainfall variations have implications for agricultural productivity in India such that in periods of low (high) rainfall, yields of important crops such as rice, wheat and jowar are significantly lower (higher), thereby affecting incomes of rural farming households (e.g., Jayachandran, 2006; Shah and Steinberg, 2017). Therefore, rainfall shocks are a plausible proxy for income shocks in rural India.[2]

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 significant impact. In column 2, we examine impacts on the total education expenditures. The results provide evidence of a counter-cyclical effect such that an increase in transitory rainfall as compared to the long-term mean leads to a decline in education spending. This is consistent with counter-cyclical 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 as well as 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 better rainfall. We find that girls are less likely to be enrolled and significantly lesser is spent on them. This is consistent with other evidence from India (e.g., Azam and Kingdon, 2013; Maitra, Pal and Sharma, 2016). In results not reported in Table 2, we find that older children are less likely to be enrolled. Among those enrolled, more is spent on older children. This is intuitive as education costs tend to increase for higher grades.

In Table 3, we examine effects of rainfall deviations on children's participation status in different types of work. In better rainfall years, children are 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 no significant effect on participation in wage work. [3]

[2] In future analyses, we will present empirical estimates using district-level agricultural yield data for a period close to our study period.

[3] The IHDS data do not have information on children's involvement in domestic chores related to cooking, cleaning, and caring for elders or younger siblings.

Results from Tables 2 and 3 show that while transitory rainfall shocks do not increase drop-outs from school, there is lower school attendance as attested to by lower expenditures on education. This reduced school attendance is accompanied by a greater likelihood of children being engaged in various household activities.[4]

In Table 4, we examine the effects of rainfall shocks on the work status of adults within the same households for which we observe the children. We find that adults are likely to work more on the household farm, in animal care, and in wage work during positive rainfall years. This suggests that adult and child labour are complements.

3.3 Heterogeneity analyses

We now examine some avenues of heterogeneity. In each of the tables that follows, we report results for the following four outcomes: total education spending, farm work, non-farm household enterprise, and animal care.

The first one is gender. Existing evidence generally documents a significant female disadvantage 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. Björkman-Nyqvist (2013), using panel data from Uganda, finds that negative rainfall shocks have detrimental effects on the enrolment and academic performance of girls, with no effects on 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 5, upon interacting rainfall shock with child gender, we find that girls are less likely to engage in farm work in periods of better rainfall. We do not find rainfall shocks to differentially affects boys and girls in terms of educational expenditures or work in household business or animal care. However, it is possible that girls are more likely to engage in domestic chores that we cannot identify.

In Table 6, 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 were historically subjected to practices of untouchability and large-scale exclusion from

[4] That we do not observe an effect on the margin of enrolment as there is a significant increase in children's probability of work is consistent with previous evidence (e.g., Beegle et al., 2006; Ravallion and Wodon, 2000).

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, Lahiri and Paul, 2012), lower castes continue to fare systematically worse than upper castes on a variety of socioeconomic indicators. In our data, 32 percent of the sample are SCSTs. Using caste as a proxy for socioeconomic status as it is determined exogenously at birth, and interacting that with the rainfall shock, we find that a transitory increase in rainfall induces SCST households to scale back more on the amount spent on their children's education. This is potentially explained by a greater shortage of capital/credit faced by these households on account of which they are unable to hire labour to maximize the productivity gains accruing from higher than usual rainfall. We also find that SCST children are less likely to be working in the non-farm business.

Finally, in Table 7, we examine heterogeneity by age. Substitution effects in this context are likely to be higher for older children as they are more capable of working in various household activities. We use a binary variable for age group that takes a value 1 if the child is aged 5-14, and 0 if the age is 15-19. Our results show that educational spending on 5-14 year old children is more detrimentally affected during higher rainfall years than that of older children. Additionally, they are also less likely to engage in farm work in higher rainfall years.

In future analyses, we will explore this at the intensive margin, i.e., in terms of hours worked. We are in the process of examining other sources of heterogeneity such as credit access (measured by the availability of banks in the district), and availability of local labour markets (proxied by the length of exposure of the district to the National Rural Employment Guarantee Scheme enacted in 2006).

3.4 Robustness checks

To be completed. This will include: alternative definitions of rainfall shocks; instrumenting rainfall at district centre with the rainfall at the five closest rainfall stations as in Maccini and Yang (2009); conducting the analysis at the district level to reduce possible measurement error; and checking for effects of rainfall shocks on: child health, local migration, and availability of local infrastructure such as roads that may be correlated with the ability to attend school.

4. Conclusion

We examine the effect of aggregate 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 a decline in educational expenditures in years characterized by higher than average rainfall. Combined with no significant effect on enrolment status, this points towards reduced school attendance. This indicates a counter-cyclical 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 the household farm, non-farm business, and animal care activities. Heterogeneity analyses indicate that some of these effects are stronger for girls and for low caste households.

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Table 1: Descriptive Statistics

	(1) Mean	(2) Standard deviation
Education related:		
Currently enrolled	0.86	0.34
Total education expenditure	1953.73	3215.28
Expenditures on school fees	919.88	2457.38
Expenditures on books, uniforms, transport	916.13	1171.46
Expenditures on private tuitions	216.92	710.54
Public School	0.693	0.461
Work related:		
Farm work	0.129	0.336
Non-farm household enterprise	0.017	0.128
Animal care	0.153	0.36
Wage work	0.056	0.23
Right-hand side:		
Rainfall shock	-0.069	0.22
Female	0.445	0.496
Age	11.804	4.109
Observations	61,522	

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 enrollment and education expenditures

	(1) Enrolment	(2) Total education expenditures	(3) School fees	(4) Books, uniforms and transport	(5) Tuitions
Rainfall shock	0.018	-0.40**	-1.41***	-0.45**	0.18
	(0.017)	(0.20)	(0.31)	(0.23)	(0.29)
Female	-0.025***	-0.18***	-0.38***	-0.13***	-0.21***
	(0.0034)	(0.021)	(0.033)	(0.020)	(0.030)
Observations	61522	53135	50329	51785	46434
R-squared	0.29	0.18	0.20	0.16	0.066

Notes: These regressions include age fixed effects, survey month-year fixed effects, and household fixed effects. Standard errors clustered at the district level, reported in parentheses. *** sig at 1%, ** sig at 5%, *sig at 10%. 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 status

	(1) Farm work	(2) Non-farm household enterprise	(3) Animal care	(4) Wage work
Rainfall shock	0.20***	0.022***	0.27***	-0.0069
	(0.031)	(0.0079)	(0.033)	(0.012)
Female	-0.031***	-0.011***	-0.0080*	-0.033***
	(0.0035)	(0.0014)	(0.0042)	(0.0023)
Observations	61507	61522	61522	61517
R-squared	0.22	0.024	0.18	0.14

Notes: These regressions include age fixed effects, survey month-year fixed effects, and household fixed effects. Standard errors clustered at the district level, reported in parentheses. *** sig at 1%, ** sig at 5%, *sig at 10%. 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: Effects on adults' work status

	(1) Farm work	(2) Non-farm household enterprise	(3) Animal care	(4) Wage work
Rainfall shock	0.24***	0.016	0.16***	0.11***
	(0.025)	(0.012)	(0.028)	(0.018)
Female	-0.16***	-0.079***	0.023**	-0.30***
	(0.0087)	(0.0032)	(0.012)	(0.0098)
Observations	81346	82025	81974	82003
R-squared	0.12	0.043	0.062	0.20

Notes: This sample consists of adults in the same households for which children are observed. These regressions include age fixed effects, survey month-year fixed effects, and household fixed effects. Standard errors clustered at the district level, reported in parentheses. *** sig at 1%, ** sig at 5%, *sig at 10%. 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 5: Heterogeneity by gender

	(1) Total education expenditure	(2) Farm work	(3) Non-farm household enterprise	(4) Animal care
Rainfall shock	-0.38*	0.22***	0.026***	0.26***
	(0.20)	(0.033)	(0.0087)	(0.034)
Female	-0.19***	-0.033***	-0.011***	-0.0066
	(0.022)	(0.0040)	(0.0014)	(0.0045)
Female x Rainfall shock	-0.046	-0.034**	-0.0084	0.022
	(0.073)	(0.017)	(0.0060)	(0.017)
Observations	53135	61507	61522	61522
R-squared	0.18	0.22	0.024	0.18

Notes: These regressions include age fixed effects, survey month-year fixed effects, and household fixed effects. Standard errors clustered at the district level, reported in parentheses. *** sig at 1%, ** sig at 5%, *sig at 10%. 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 6: Heterogeneity by caste

	(1) Total education expenditure	(2) Farm work	(3) Non-farm household enterprise	(4) Animal care
Rainfall shock	-0.28	0.21***	0.031***	0.26***
	(0.20)	(0.029)	(0.0092)	(0.034)
SCST x Rainfall shock	-0.39***	-0.029	-0.029***	0.045
	(0.15)	(0.035)	(0.0085)	(0.034)
Observations	53126	61496	61511	61511
R-squared	0.18	0.22	0.024	0.18

Notes: These regressions include gender, age fixed effects, survey month-year fixed effects, and household fixed effects. Standard errors clustered at the district level, reported in parentheses. *** sig at 1%, ** sig at 5%, *sig at 10%. 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 age

	(1) Total education expenditure	(2) Farm work	(3) Non-farm household enterprise	(4) Animal care
Rainfall shock	-0.041	0.27***	0.022*	0.30***
	(0.26)	(0.041)	(0.012)	(0.042)
5-14 age x Rainfall shock	-0.43**	-0.090***	-0.00064	-0.036
	(0.21)	(0.032)	(0.0089)	(0.029)
Observations	53135	61507	61522	61522
R-squared	0.18	0.22	0.024	0.18

Notes: These regressions include gender, age fixed effects, survey month-year fixed effects, and household fixed effects. Standard errors clustered at the district level, reported in parentheses. *** sig at 1%, ** sig at 5%, *sig at 10%. 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.