I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 13405

Here Comes the Rain Again: Productivity Shocks, Educational Investments and Child Work

Christophe J. Nordman
Smriti Sharma
Naveen Sunder

JUNE 2020

DISCUSSION PAPER SERIES

IZA DP No. 13405

Here Comes the Rain Again: Productivity Shocks, Educational Investments and Child Work

Christophe J. Nordman
IRD, LEDa-DIAL, IFP and IZA

Smriti Sharma
Newcastle University Business School and IZA

Naveen Sunder
Bentley University

JUNE 2020

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Here Comes the Rain Again: Productivity Shocks, Educational Investments and Child Work*

This study uses household-level panel data from a nationally representative survey to estimate the effect of agricultural productivity shocks – as proxied by exogenous annual rainfall deviations – on education expenditures and children's work status in rural India. We find that a transitory increase in rainfall significantly reduces education expenditures and increases the likelihood of child labor across multiple work activities. Additionally, households owning land and those with better credit access increase the use of child labor as rainfall increases because labor (and land) markets are incomplete. The effects of productivity shocks are reinforced for marginalized castes and for less educated households, thereby exacerbating inequalities in education.

JEL Classification: D13, I21, J16, O12

Keywords: rainfall shocks, education expenditures, child work, market imperfections, India

Corresponding author:
Christophe Jalil Nordman
DIAL
4 rue d'Enghien
75010 Paris
France
E-mail: nordman@dial.prd.fr

* We thank the editor and two anonymous reviewers, Yasmine Bekkouche, Nils Braakmann, Christelle Dumas, Arya Gaduh, Heidi Kaila, Subha Mani, Saurabh Singhal, John Wildman and participants at the Nordic Conference in Development Economics 2017 for helpful comments. This version supersedes the draft of the earlier working paper. This version corrects errors discovered in the original program files that resulted in an increase in the analysis sample. While there are some small differences in the estimates, the key results remain.

1. Introduction

Households in developing countries are routinely exposed to a variety of risks. As a large share of rural populations in these countries relies on rain-dependent agriculture for their livelihood, rainfall and other climatic shocks constitute critical sources of income volatility.[1] Failures in labor, credit and land markets have an impact on households' ability to smooth consumption during periods of income uncertainty, thereby having important consequences for human capital investments in children.[2]

Aggregate shocks, such as transitory rainfall shocks, have both an income and a substitution effect on agrarian households. When rainfall is favorable (i.e., when it is higher than average), due to higher agricultural productivity, there is an increase in earnings. This income effect might increase the resources allocated towards children's education. However, there is also a substitution effect such that higher earnings – due to higher wages in agriculture and related sectors as well as greater returns to working on family farm – increase the opportunity cost of children being in school.[3] Since which of these two effects dominate is theoretically ambiguous, the net effect is *a priori* unknown.

In this paper, we examine the contemporaneous impacts of productivity shocks – as proxied by exogenous variations in rainfall – on educational investments in children and children's work, using nationally representative panel data from rural India. In doing so, we first empirically test the relative strengths of the income and substitution effects. In that regard, our paper is closest to recent work by Shah and Steinberg (2017) who examine the effects of (contemporaneous and early life) rainfall shocks on test scores in rural India. Our study

[1] Dell, Jones and Olken (2014) provides an overview of the literature on climatic shocks.
[2] Dercon (2002) and Fafchamps (2003) provide critical discussions of poor households' risk coping strategies.
[3] Positive rainfall shocks have been shown to increase wages (e.g., Jayachandran, 2006; Shah and Steinberg, 2017; Kaur, 2019).

contributes to the literature by investigating the importance of factors that could mitigate or exacerbate the effects of shocks on households' decisions about schooling and child labor. The first relates to productive factors that can potentially help households cope with shocks – land ownership and credit access. The second focuses on socioeconomic factors – caste and parental education. While previous work has shown that these factors affect children's outcomes, we specifically examine whether they *differentially* affect the relationship between transitory rainfall variations and households' decisions regarding education and child work. Documenting this heterogeneity in impacts allows us to shed light on the importance of market imperfections.

We combine household-level panel data based on two rounds of the India Human Development Survey, that measures detailed child-specific education expenditures on different categories and engagement in a variety of work activities, with geo-spatial rainfall data. This enables us to include household fixed effects, not previously possible in other studies that used repeated cross-sectional data. More importantly, while previous literature has generally focused on individual-specific measures of educational attainment such as enrollment, attendance, and more recently, test scores, we examine child-specific education expenditures, an important parental input into the learning process. In examining school participation, one can detect effects only at the extensive margin. In contrast, by using expenditure information, we are able to make inferences about the intensive margin of human capital investment decisions made by households. Further, disaggregated data on a variety of avenues of child work represents an extension of previous work that generally uses an aggregated measure of child labor.

Our results show that a transitory increase in rainfall significantly reduces education expenditures with no change in the probability of school enrollment. We show that there is a simultaneous increase in the likelihood of child labor. Together, this suggests that children are less likely to attend school and more likely to work when there is higher than average rainfall. These findings are consistent with Shah and Steinberg (2017). Investigating heterogeneous effects of rainfall variations based on households' land ownership, credit access, caste affiliation and child sex reveals interesting patterns. First, the negative impacts of rainfall deviations on education expenditures are smaller for children from land-owning families. However, children in land-owning households are more likely to engage in work during higher rainfall periods than children in landless households. Second, better access to credit reinforces the countercyclicality of education expenditures and child work. Both these results show that as households demand for labor increases due to higher rainfall, they use more child labor due to labor (and land) market imperfections and leading education spending to be differentially affected. Therefore, land ownership and improved credit access are likely to not be mitigating factors. Third, a transitory increase in rainfall induces significantly greater cuts on educational spending and a greater probability of work for children belonging to lower castes. Fourth, we find smaller effects of rainfall deviations on children from more educated households. In other words, these shocks increase inequality in education between economically vulnerable and non-vulnerable groups. Therefore, our results show that estimating average effects may be masking important heterogeneity based on household and regional characteristics.

We contribute to the body of work on the effects of aggregate weather and commodity price shocks on schooling and child labor. 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. Papers from various contexts have found evidence for a procyclical effect where the income effect dominates the substitution effect. Björkman-Nyqvist (2013) documents that negative rainfall shocks in Uganda have detrimental effects on girls' school enrollment and academic performance. Jensen (2000) finds that droughts in Côte d'Ivoire reduce school enrollment and increase malnutrition. Beegle, Dehejia and Gatti (2006) find that an idiosyncratic income shock in Tanzania decreases school enrollment and increases child labor. Jacoby and Skoufias (1997) show that children were withdrawn from school to go to work in response to adverse rainfall shocks in south India. Studies have also found procyclical effects of commodity price shocks on children's outcomes (e.g., Edmonds and Pavcnik, 2005; Cogneau and Jedwab, 2012; Beck, Singhal and Tarp, 2019).

In contrast, there is literature which finds countercyclical effects as well. Shah and Steinberg (2017) find a countercyclical effect of rainfall shocks on school attendance and test scores in rural India.[4] Kruger (2007) finds a countercyclical effect in that the probability of school enrollment decreases as the value of coffee production in Brazil increases. Duryea and Arends-Kuenning (2003) document an increase in child employment and decline in school attendance in areas that experienced an increase in unskilled wages due to the Brazilian macroeconomic crises.

However, little is known about how the relative strength of the countervailing income and substitution effects can vary depending on the presence of market imperfections and other institutional factors. Using data from Tanzania, Dumas (2020) shows that income and

[4] Zimmermann (2020) shows that the relationship between school enrollment and rainfall shocks has fundamentally changed over time from being procyclical to countercyclical in India.

substitution effects of rainfall shocks on child labor depend crucially on labor market quality. She finds that child labor increases less when agricultural households have access to labor markets but that access to the credit market does little to reduce the impact of rainfall shocks on child labor. In a similar vein, our paper also shows that the countercyclical effects of rainfall deviations on children's outcomes vary based on productive factors (land ownership and credit access) and socioeconomic characteristics (caste and parental education), making it important to consider heterogeneous impacts.

This paper is organized as follows. Section 2 describes the data sources and the empirical framework. Section 3 presents summary statistics and regression analyses. Section 4 examines heterogeneity in impacts of the rainfall deviations. Section 5 concludes.

2. Data and Empirical Specification

2.1 Data Sources

The main data for our analysis is from 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). 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 to 49 years. The survey collects data on a wide range of topics including economic activity, income and consumption expenditure, asset ownership, social capital, education, health, marriage and fertility, etc.[5]

While most other surveys usually collect and report total education expenditures at the level of the household, one of the advantages of these data is the availability of education-related spending for each enrolled child. As explained in Section 1, this allows us to draw inferences about the intensive margin of human capital investment decisions made by households. Child-specific education expenditures for the year preceding the survey date are collected for the following three categories: (i) school fees; (ii) books, uniforms, other materials, and transportation; and (iii) private tuition. We sum the abovementioned categories and calculate the real total education expenditure per child (in 2004-05 Indian Rupees or INR) by using the rural poverty lines specified by the Indian Planning Commission as deflators. 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. We also create a dummy variable 'any work' that takes a value of one if the child engages in any kind of work listed above, and zero otherwise. However, the IHDS does not collect data on children's involvement in household chores and caring for young and old.

Fifty-two percent of agricultural land in India is un-irrigated and rainfall-reliant (Economic Survey, 2018). As rainfall variations matter for household income and welfare predominantly in rural areas, we limit our sample to rural households, which constitutes 71 percent of the IHDS sample. Since our primary interest is in understanding the allocation of education expenditures and work among school-aged children, we restrict the analysis to households

[5] Online Appendix Section A provides details on construction of the panel data using both rounds of the IHDS.

where there is at least one member aged 5-16 in each survey round. This results in a final sample size of 46,225 children.

Rainfall shocks are computed based on monthly rainfall data available from *Terrestrial Precipitation: Gridded Monthly Time Series* from the Centre for Climatic Research at the University of Delaware.[6] The first year of data availability is 1900 and we use data beginning 1980. As the monthly rainfall data are gridded at 0.5-degree 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 available in the latter. We calculate district-month-specific rainfall deviations as the logarithm of average 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 (e.g., 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 deviation implies higher (lower) than average rainfall within the district.

2.2 Empirical Specification

We estimate the following equation:

$$Y_{ihdty} = \beta_0 + \beta_1 RainDeviation_{dt} + \beta_2 Female_{ihdty} + \gamma_y + \delta_h + \theta_t + \varepsilon_{ihdty} \qquad (1)$$

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

where Y is the outcome variable for individual i in household h in district d, interviewed in month-year t and born in year y. Our main outcome variables are logarithm of real education expenditures as well as binary variables for working in the household farm, household non-farm business, animal care and wage work. β_1 is the key coefficient of interest and measures the effect of rainfall deviation in district d in month-year t. We also control for a categorical variable for a female child, year of birth fixed effects (γ_y), survey month-year fixed effects (θ_t), and household fixed effects (δ_h). Household fixed effects enable us to control for any unobserved, time-invariant household and district characteristics that may affect spending. Conditional on household fixed effects, rainfall deviations are likely to be orthogonal to unobserved determinants of educational spending and child work and enable us to identify the causal effects of rainfall deviations. ε_{ihdt} is the individual-specific error term. Errors are assumed to be correlated among observations within a district, therefore, we cluster the standard errors at the district level.

Further, as our interest is in understanding heterogeneous impacts of rainfall variations on educational spending and child work, we estimate regressions of the following type:

$$Y_{ihdty} = \alpha_0 + \alpha_1 RainDeviation_{dt} + \alpha_2 X + \alpha_3 RainDeviation_{dt} * X + \alpha_4 Female_{ihdty} + \gamma_y + \delta_h + \theta_t + \varepsilon_{ihdty} \qquad (2)$$

Where the specification is similar to equation (1) above and now X represents the aspect of heterogeneity we are concerned with (whether the household owns or cultivates land as of 2005, credit access in the district that the household resides in as of 2005, caste affiliation of the household, and education of the mother in 2005). In all cases, X is collinear with respect to household fixed effects and therefore, the level effect of X (α_2) is absorbed. This specification assumes that changes in district-year unobservables are not correlated with X.

3. Results

3.1 Summary Statistics

In Table 1, we present summary statistics. Ninety four percent of the sample is currently enrolled in school. The average real yearly expenditure on education is about INR 1559 (USD 22 in January 2019). The average real amounts spent annually on school fees and on books, uniforms, and transport are approximately INR 614 and INR 834 respectively. About INR 176 is spent on private tutoring annually. The average rainfall deviation is approximately 9 percent below the long-term mean.

[Table 1 here]

Around 12.5 percent of children work on the household farm, and about 13.8 percent tend 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 labor on their family-operated farms. As expected, most children in wage work are those aged 14-16 years old (not reported in Table 1). Twenty one percent are classified as doing any work.

Forty eight 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. Thirty two percent belong to the historically marginalized Scheduled Caste and Scheduled Tribes (SCST) categories.

3.2 Rainfall and agricultural productivity

Using rainfall variations to proxy productivity shocks hinges on the assumption that agricultural productivity is systematically correlated with rainfall deviations. Previous studies from several developing country contexts have shown that rainfall variations have implications for agricultural productivity, thereby affecting rural incomes (Björkman-Nyqvist, 2013; Levine and Yang, 2014; Shah and Steinberg, 2017). We also establish this relationship using district-level agricultural yields from the World Bank India Agriculture and Climate Data. We estimate the following equation:

$$Y_{idt} = \gamma_0 + \gamma_1 RainDeviation_{dt} + \delta_d + \mu_t + \varepsilon_{idt} \qquad (3)$$

Where Y_{idt} is the logarithm of yields of crop i in district d in year t. We consider yields of six major crops (rice, wheat, jowar, bajra, groundnut and sugar). γ_1 is the key coefficient of interest and measures the effect of rainfall deviation in district d in year t. We also control for district fixed effects (δ_d) and year fixed effects (μ_t). Standard errors are clustered at the district level.

Table B1 in the online Appendix presents the results. We find a positive and significant relationship between agricultural yields and rainfall variation in Table B1, with the exception of wheat where the effect is positive but not statistically significant at conventional levels (*p-value* = 0.102). The results broadly indicate that the incomes of agricultural households are affected by fluctuations in precipitation. Therefore, transitory rainfall deviations can serve as a plausible proxy for productivity shocks in rural India.

3.3 Rainfall deviations, education spending and child work

In Table 2, we present regression estimates of equation (1). Before we examine effects on expenditures, we look at enrollment status in column 1. We find that there is no statistically or economically significant impact of rainfall deviations on enrollment status. As enrollment is almost universal during the time period under study (93 percent as reported in Table 1), this result is unsurprising. In column 2, we examine impacts on total education expenditures. A 10 percent increase in rainfall deviation leads to a fall in total expenditures by 2.3 percent. While not statistically significant at conventional levels, this result points towards a countercyclical effect such that a transitory increase in rainfall leads to a decline in education spending. This is consistent with negative effects of rainfall shocks on test scores in rural India in Shah and Steinberg (2017). Upon disaggregating the education expenditures into three sub-components in columns 3-5, we find a highly significant and negative effect of transitory increase in rainfall on school fees (column 3), and insignificant effects on associated costs of schooling in the form of spending on books, uniforms, and transportation and private tuition (columns 4 and 5).

[Table 2 here]

While the survey does not canvass information on school attendance, the lack of an effect on enrollment combined with decreased spending on essential costs of schooling indicates that children are attending school less frequently in periods characterized by higher than usual rainfall. Using attendance data from two other Indian datasets, Shah and Steinberg (2017) also find that children in a positive rainfall shock year are less likely to be attending school.[7] Girls are less likely to be enrolled and significantly lower amounts are spent on them, in line with other evidence from India (e.g., Azam and Kingdon, 2013).

[7] Shah and Steinberg (2017) also do not find current year rainfall shocks to significantly affect enrollment.

In Table 3, we examine effects of rainfall deviations on children's participation in work. As rainfall deviations increase, children are significantly more likely to work on the household farm, in the household's non-farm enterprise, and on tending to livestock (columns 1-3). A 10 percent increase in rainfall leads to a rise in probability of farm work by around 0.021, which translates to about 17 percent increase over the sample mean. There is a negligible and insignificant effect on participation in wage work (column 4). Overall, children are more likely to engage in some sort of work as rainfall increases (column 5). A 10 percent increase in rainfall deviation leads to an increase in any work by 0.03 (14.5 percent over the mean). Girls are less likely to be working. This likely underestimates girls' work because household chores are not recorded as work activities in the IHDS.[8]

Taken together, results from Tables 2 and 3 show that while transitory rainfall variations do not reduce school enrollment, there is lower spending on education, indicating reduced school attendance. This reduced attendance is consistent with a greater likelihood of children being engaged in work activities.

[Table 3 here]

These results are robust to a number of checks. The first check is regarding measurement error in the rainfall variable. Following Maccini and Yang (2009), we estimate an instrumental variable regression, where rainfall recorded at the second to fifth closest stations is an instrument for district-level rainfall. Our results are mostly robust to this (Table B3 in the online Appendix). Second, one might be concerned about the exogeneity of the rainfall shocks. We find that rainfall deviations do not predict predetermined household-level

[8] We do not find transitory rainfall deviations to have any differential gender effects on educational spending (except for private tuition) or the probability of any work (Table B2 in the online Appendix). The education results are in line with Shah and Steinberg (2017) who also do not find any gender-differentiated effects of rainfall shocks on test scores in India.

characteristics such as asset ownership, household size, and parental education. These results are reported in Table B4 in the online Appendix. Third, while our rainfall measure exploits naturally occurring variation in rainfall compared to the long-term mean, we also construct a discrete rainfall shock measure. This variable takes a value 1 if the annual rainfall exceeds 1 Standard Deviation (SD) of the mean district rainfall, -1 if it is below 1 SD of mean district rainfall, and 0 otherwise. Table B5 in the online Appendix shows that our results in Tables 2 and 3 are robust to using this discretized shock measure. Finally, these results are also robust to including district fixed effects instead of household fixed effects (Table B6 in the online Appendix).

4. Heterogeneity

Until now, we have examined the effects of productivity shocks – as proxied by rainfall deviations – on education-related spending and child work. In this section, we go a step further and examine the importance of factors that may result in the effects of such shocks being mitigated or reinforced. Specifically, we examine the role played by land ownership, credit access, caste of the household and parental education. This is a critical point of departure for our paper as compared to existing work.

The first avenue we examine is whether the effects of rainfall variations on education spending and child work are dependent on land ownership. Land plays an important dual role as both a source of wealth and as a productive input. On the one hand, landholdings have the potential of generating higher incomes, which puts land-owning households in a better position to buffer against shocks, implying that children's outcomes may be less sensitive to weather variability. Beegle et al. (2006) find that households with assets are better able to offset agricultural shocks. On the other hand, in the presence of labor market imperfections, land-owning households may not be able to hire appropriate outside labor to take advantage of these transitory productivity shocks, leading them to rely on family labor. Family labor may also be preferred due to concerns of moral hazard by hired labor (Nguyen and Nordman, 2018), as they could resolve some of the information asymmetries characterizing rural labor markets (Bharadwaj, 2015). Foster and Rosenzweig (1994) provide evidence of moral hazard in rural labor markets. This 'wealth paradox', wherein the likelihood of child work is positively related to the size of landholding, has also been noted in a range of developing countries (e.g., Bhalotra and Heady, 2003; Dumas, 2007; 2013; 2020). Edmonds and Turk (2004) find that households that own businesses in Vietnam are more likely to have their children doing work. This negative effect of land ownership on child labor due to labor market imperfections is exacerbated by poorly functioning land markets.[9] Therefore, it is *a priori* unclear whether possessing land would mitigate or reinforce the effects of rainfall variations that we find on children's education and labor outcomes.

To examine the differential effects of land ownership on the relationship between rainfall deviations and children's educational and work outcomes, we create a binary variable 'any land' that takes a value one if the household owns or cultivates any agricultural land in 2005 (the first year in our panel data), and zero otherwise, and interact that with the rainfall deviation. Around two-thirds of households in our sample either owned or cultivated any land in 2005. Results based on estimating equation (2) are reported in Table 4. Column 1 shows that the negative effects of rainfall deviations on education expenditures are mitigated for children from landed households – the coefficient implies that a 10 percent rise in rainfall

[9] If land markets are active but labor markets are not, then households that cannot hire labor can sell or rent out the land. Conversely, if the land market is characterized by imperfections but the labor market is not, then external labor can be hired. Ray (1998) discusses land market imperfections in developing countries.

leads to 6.4 percent smaller drop in total education expenditures in landed households as compared to landless households. These findings imply that they are better shielded from the effects of weather variations on their education. In terms of work, children in landed households are more likely to engage in farm work (10 percent rainfall deviation leads to an effect of 14.4 percent of the mean) than children in landless households as rainfall deviations increase (column 5). We also find that children from land-owning households are less likely to engage in wage work in periods of better rainfall as compared to those from landless households (column 8). Overall, children from landed households are differentially more likely (10 percent rainfall deviation leads to an effect size of 3.4 percent of the mean) to engage in any type of work than children from landless households as rainfall deviations increase (column 9). The work results are consistent with imperfections prevailing in both the labor and land markets.

[Table 4 here]

Second, we examine whether access to credit differentially affects the relationship between rainfall deviations and children's education and work outcomes. The role of credit can be important in shaping child education and labor market outcomes as it allows poor households to borrow against future earnings to smooth consumption. Key theoretical works have shown that, despite parental altruism, child labor occurs when credit markets are imperfect or missing (Ranjan, 1999; Baland and Robinson, 2000). This has also found some empirical support (e.g., Edmonds, 2004; Alvi and Dendir, 2011). On the other hand, Wydick (1999) argues that if access to credit improves the ability of households with family enterprises to undertake investment in working capital which in turn increases the marginal productivity of family labor, then it could have adverse effects on children's well-being. This effect may be due to the aforementioned high potential for moral hazard among hired labor, which makes hired labor a poor substitute for family labor. Such investments, fostered by credit markets, would increase the opportunity cost of schooling for children, leading to an increase in child work and decrease in schooling. It might also be the case that households prefer to make their own children work to gain specific work experience, especially in family enterprises. Hazarika and Sarangi (2008) find that during seasons of peak labor demand, access to microcredit increases the probability of child work in households with land and retail enterprises in rural Malawi. Maldonado and Gonzalez-Vega (2008) also find that access to microcredit increases child labor for landed households in Bolivia. Therefore, it is not obvious whether better access to credit would improve children's educational outcomes (via better avenues for smoothing consumption) or adversely affect them (via increased child labor due to rise in marginal productivity of farms).

Based on the abovementioned literature, we hypothesize that credit access will result in differential effects of rainfall variations on children's outcomes among land-owning households. This is because local rainfall variations generate transitory shocks to labor demand in land-owning households. If moral hazard concerns make hiring of external labor difficult, as suggested by results of heterogeneity by land ownership, then in periods of higher-than-average rainfall, landed households with better credit access are more likely to use child labor. But if households are able to hire external labor easily, then child labor may decline. To that end, we focus on landed households (i.e., those that owned or cultivated any agricultural land in 2005). We construct a proxy for credit access: the number of rural bank branches per capita in a district in 2005 ('rural banks'), using data from the Reserve Bank of India's annual publication *Basic Statistical Returns of Scheduled Commercial Banks in India*. For ease of interpretation, we standardize this using the sample mean and standard deviation and interact that with the rainfall deviation.

[Table 5 here]

Results are reported in Table 5. We find that transitory rainfall deviations are positively correlated with the probability of any work, and the effect is stronger for children in districts with better access to credit (column 9). Looking at separate work activities, this appears to be driven by differential effects on farm work (column 5) and animal care (column 7). Correspondingly, in column 1, we find that transitory rainfall deviations have a greater negative effect on total education expenditures in districts with better credit access as compared to those with poorer credit access. This is consistent with the effect documented by Dumas (2020) for Tanzania where she finds that the presence of credit markets may not mitigate the impact of a productivity shock on child labor when labor markets imperfections exist. In that sense, we are the first – to the best of our knowledge – to document such a finding in the Indian context.

Next, we investigate how socioeconomic factors may mediate the relationship between rainfall variations and children's outcomes. Using an overlapping generations model that allows for inequality of opportunity which results in heterogeneous returns to education, Emerson and Knabb (2006) show that poor households will choose to make their children work as compared to wealthy households if the returns to education for the former are sufficiently low. Poor and wealthy in their model represent low status and high status, broadly speaking, where status represents class, race, ethnicity, etc. The low returns can be due to discrimination, labor market segmentation, lack of information, and differences in school quality. They also show that if there is some social mobility that allows poor households to become wealthy over time, then families may withhold their children from working and send them to school. In this framework, we examine the role of caste and parental education.

Caste is a deeply embedded institution in India and is highly correlated with one's social status and economic well-being.[10] The Scheduled Castes and Scheduled Tribes (SCSTs) are marginalized groups that have been historically subjected to practices of untouchability and large-scale exclusion from mainstream society. While there have been some improvements in terms of educational attainment and incomes since affirmative action was introduced in 1950 (Hnatkovska, Lahiri and Paul, 2012), lower castes continue to fare systematically worse than upper castes in terms of wages, occupations, education, credit access, etc.[11] Discrimination in labor and credit markets play an important role in determining the adverse outcomes of SCSTs (e.g., Deshpande, 2011; Kumar and Venkatchalam, 2019). Further, caste is immutable as it is determined at birth, and intergenerational mobility in India remains generally low.

To examine whether these marginalized groups' outcomes are more susceptible to rainfall variations as they potentially have fewer coping strategies available, we interact caste (which takes a value one if SCST, zero otherwise) with the rainfall deviation. About a third of our sample are SCSTs. In Table 6, we find that a transitory increase in rainfall by 10 percent induces significantly greater cuts on educational spending for SCST children than for non-SCST children by 3.6 percent (column 1). Further, SCST children are more likely than non-SCST children to engage in wage work during such periods (column 8). SCST children are differentially less likely to work in non-farm household enterprises as compared to non-SCST children (column 6). This could be due to lower rates of enterprise ownership and poorer firm

[10] Deshpande (2011) provides an overview of the caste system and caste-based discrimination in India.
[11] One may be concerned that caste is simply picking up variations in wealth. We find that 54 percent of SCSTs are landless as compared to 48 percent of non-SCSTs. This shows that while there is an overlap between caste and a measure of wealth (such as landownership), it is not perfect.

performance among SCSTs than other caste groups (Deshpande and Sharma, 2013; 2016). Overall, SCST children are more likely to engage in any type of work as compared to their non-SCST counterparts when rainfall deviation increases but this result is not statistically significant (column 9).

[Table 6 here]

The final avenue we explore is parental education. Past studies have found that parents' education is positively associated with a wide range of socioeconomic outcomes of children, including education and health (e.g., Black, Devereux and Salvanes, 2005; Holmlund, Lindahl and Plug, 2011). This can be because educated parents have more resources and are able to provide a more conducive environment for their children, have preferences for and place value on their children's human capital, and intergenerational correlations in ability. In the Indian context, Banerji, Berry and Shotland (2017) find that improvement in maternal education enhanced children's learning outcomes. Similarly, Sunder (2020) and Mazumder, Rosales and Triyana (2019) find that mothers who benefitted from a school construction program were able to transfer human capital gains to their children in the form of higher test scores in India and Indonesia, respectively. Andrabi, Das and Khwaja (2012) find that mothers with some education invested more time in their children's education. However, we know little about whether outcomes of children with more educated mothers are more resilient to rainfall variations and other shocks. Andrabi, Daniels and Das (2018) find that the negative effects of the 2005 Pakistan earthquake on human capital accumulation are almost fully mitigated for children of mothers who have completed primary education. Kruger (2007) finds that commodity price shocks have more adverse effects on children's education and work outcomes in less educated households.

In Table 7, we interact rainfall deviation with a categorical variable measuring mother's education – this variable takes a value of one when the mother reports having any education in 2005.[12] Around 62 percent of mothers report some education in 2005. Column 2 shows that a 10 percent increase in transitory rainfall deviation has smaller effects on spending on school fees (8.7 percent) among children with educated mothers as compared to those with uneducated ones. The effects of productivity shocks on children's work are mitigated in more educated households as compared to less educated households (columns 5, 7, 8 and 9). The effect size differences between children of educated and uneducated mothers varies by the type of work – farm work (5 percent of the mean), animal care (3 percent of the mean), wage work (20 percent of the mean) and any work (2.3 percent of the mean). Broadly, these findings are consistent with those of Kruger (2007) and Andrabi et al. (2018), and we are among the first to report such findings in the Indian context. These results also suggest that differences in household responses to shocks based on parental education can exacerbate existing inequalities between more and less educated households.

[Table 7 here]

Overall, the results reported in this section suggest that estimating average effects may mask considerable heterogeneity based on household and regional characteristics. Results in Tables 4 and 5 suggest that in the presence of market imperfections (in labor and land markets), land ownership and improved credit access are likely to not be mitigating factors. Additionally, historically disadvantaged lower castes suffer more than other castes in case of transitory shocks, and children with educated mothers experience smaller adverse effects of rainfall

[12] In 30 percent of households, there is more than one mother with children aged 5-16. In these cases, the variable takes a value of one if at least one of the mothers in the household has some education.

deviations as compared to those with illiterate mothers. This line of investigation is critical and provides domains that policy can target.

5. Conclusion

Using household-level panel data from the nationally representative India Human Development Survey, we estimate the effect of productivity shocks, as proxied by exogenous rainfall deviations, on children's education and work status in rural Indian households. We find that there is a decline in education expenditures in years characterized by higher-than-average rainfall. This is accompanied by an increase in likelihood of children working in a range of activities. This indicates a countercyclical effect such that the substitution effect of rainfall exceeds the income effect.

In contrast to most existing literature, our paper examines heterogeneity in impacts based on the households' land ownership status, credit access, caste affiliation and maternal education. We find that the negative impact of rainfall deviations on education expenditures is mitigated for children from landed families but that children in landed households are more likely to work than children in landless households in higher rainfall periods. Better access to credit reinforces the countercyclical effects on education expenditures and child work, suggesting that some productivity-enhancing investments may have a perverse effect on children's wellbeing. Low caste children's education spending is more adversely affected by rainfall deviations, and they are more likely to engage in work than upper caste children. Finally, maternal education can play a significant role in mitigating the effects of rainfall variations on children's work and education.

Our results shed light on the fact that in agrarian economies that rely on rainfed systems, even transitory rainfall variations can have (unintended) consequences for children's human capital accumulation in the short-term. These can translate into medium- and long-term detrimental impacts in adulthood by affecting children's learning outcomes. In the light of climate change induced variability in rainfall and temperature, there is a crucial need to invest in enhanced irrigation systems in a timely manner to reduce the impact of both positive and negative climatic uncertainty on agricultural households. Another policy prescription would be to provide conditional cash transfers linked to school attendance to households so that they can smoothen their consumption and investment decisions over longer horizons. Improving school quality may also increase the returns to education and incentivize households to reduce child labor.

References

Alvi, Eskander, and Seife Dendir. 2011. "Weathering the storms: Receipt and child labour in the aftermath of the great floods (1998) in Bangladesh." *World Development* 39, no. 8:1398-1409.

Andrabi, Tahir, Jishnu Das, and Asim I. Khwaja. 2012. "What did you do all day? Maternal education and child outcomes." *Journal of Human Resources* 47, no. 4: 873-912.

Andrabi, Tahir, Benjamin Daniels, and Jishnu Das. (2018). "Human capital accumulation and disasters: Evidence from the Pakistan earthquake of 2005." Working Paper.

Azam, Mehtabul, and Geeta G. Kingdon. 2013. "Are girls the fairer sex in India? Revisiting intra-household allocation of education expenditure." *World Development* 42: 143-164.

Baland, Jean-Marie, and James A. Robinson. 2000. "Is child labor inefficient? *Journal of Political Economy* 108, no.4: 663-679.

Banerji, Rukmini, James Berry, and Marc Shotland. 2017. "The impact of maternal literacy and participation programs: Evidence from a randomized evaluation in India." *American Economic Journal: Applied Economics* 9, no. 4: 303-337.

Beck, Ulrick, Saurabh Singhal and Finn Tarp. 2019. "Commodity prices and intra-household labor allocation." *American Journal of Agricultural Economics* 101, no. 2: 436-454.

Beegle, Katherine, Rajeev H. Dehejia, and Roberta Gatti. 2006. "Child labor and agricultural shocks." *Journal of Development Economics* 81: 80-96.

Bhalotra, Sonia, and Christopher Heady. 2003. "Child farm labor: The wealth paradox." *World Bank Economic Review* 17, no. 2: 197-227.

Bharadwaj, Prashant. 2015. "Fertility and rural labor market inefficiencies: Evidence from India." *Journal of Development Economics* 115: 217-232.

Björkman-Nyqvist, Martina. 2013. "Income shocks and gender gaps in education: Evidence from Uganda." *Journal of Development Economics* 105: 237-253.

Black, Sandra. E., Paul J. Devereux, and Kjell G. Salvanes. 2005. "Why the apple doesn't fall far: Understanding intergenerational transmission of human capital." *American Economic Review* 95, no. 1: 437-449.

Cogneau, Denis, and Remi Jedwab. 2012. "Commodity price shocks and child outcomes: The 1990 cocoa crisis in Cote d'Ivoire." *Economic Development and Cultural Change* 60, no. 3: 507-534.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2014. "What do we learn from the weather? The new climate-economy literature." *Journal of Economic Literature* 52, no. 3: 740-798.

Dercon, Stefan. 2002. "Income risk, coping strategies, and safety nets." *World Bank Research Observer* 17, no. 2: 141-166.

Desai, Sonalde, Reeve Vanneman, and National Council of Applied Economic Research, New Delhi. 2005. India Human Development Survey (IHDS). ICPSR22626-v8. Ann

Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2010-06-29.

Desai, Sonalde, Reeve Vanneman, and National Council of Applied Economic Research, New Delhi. 2012. India Human Development Survey-II (IHDS-II). ICPSR36151-v2. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2015-07-31.

Deshpande, Ashwini. 2011. *The Grammar of Caste*. Oxford University Press.

Deshpande, Ashwini, and Smriti Sharma. 2013. "Entrepreneurship or survival? Caste and gender of small business in India." *Economic and Political Weekly* XLVIII, no. 28: 38-49.

Deshpande, Ashwini, and Smriti Sharma. 2016. "Disadvantage and discrimination in self-employment: Caste gaps in earnings in Indian small businesses." *Small Business Economics* 46, no. 2: 325-346.

Dumas, Christelle. 2007. "Why do parents make their children work? A test of the poverty hypothesis in rural areas of Burkina Faso." *Oxford Economic Papers* 59, no. 2: 301-329.

Dumas, Christelle. 2013. "Market imperfections and child labor." *World Development 42*: 127-142.

Dumas, Christelle. 2020. "Productivity shocks and child labor: The role of credit and agricultural labor markets." *Economic Development and Cultural Change*, 68, no. 3: 763-812.

Duryea, Suzanne, and Mary Arends-Kuenning, M. 2003. "School attendance, child labor and local labor market fluctuations in urban Brazil." *World Development* 31, no. 7: 1165-1178.

Economic Survey. 2018. *Climate, Climate Change, and Agriculture*. Ministry of Finance, Government of India.

Edmonds, Eric. V. 2004. "Does illiquidity alter child labor and schooling decisions? Evidence from household responses to anticipated cash transfers in South Africa." NBER Working Paper No. 10265.

Edmonds, Eric. V., and Nina Pavcnik. 2005. "The effect of trade liberalization on child labour." *Journal of International Economics* 65, no. 2: 401-41.

Edmonds, Eric. V., and Carrie Turk. 2004. "Child labor in transition in Vietnam." in *Economic Growth, Poverty and Household Welfare in Vietnam*, ed. Paul Glewwe, Nisha Agrawal and David Dollar. Washington DC: World Bank.

Emerson, Patrick M., and Shawn D. Knabb. 2006. "Opportunity, inequality and the intergenerational transmission of child labour." *Economica* 73: 413-434.

Fafchamps, Marcel. 2003. *Rural poverty, risk, and development*. Cheltenham: Edward Elgar.

Ferreira, Francisco H.G., and Norbert Schady. 2009. "Aggregate economic shocks, child schooling, and child health." *World Bank Research Observer* 24: 147-181.

Foster, Andrew D., and Mark R. Rosenzweig. 1994. "A test for moral hazard in the labor market: Contractual arrangements, effort, and health." *Review of Economics and Statistics* 76, no. 2: 213-27.

Hazarika, Gautam, and Sudipta Sarangi. 2008. "Household access to microcredit and child work in rural Malawi." *World Development* 36: 843-859.

Hnatkovska, Viktoria, Amartya Lahiri, and Sourabh Paul. 2012. "Castes and labor mobility." *American Economic Journal: Applied Economics* 4, no. 2: 274-307.

Holmlund, Helena, Mikael Lindahl, and Erik Plug. 2011. "The causal effect of parents' schooling on children's schooling: A comparison of estimation methods." *Journal of Economic Literature* 49, no. 3: 615-651.

Jacoby, Hanan, and Emmanuel Skoufias. 1997. "Risk, financial markets, and human capital in a developing country." *Review of Economic Studies* 64, no. 3: 311-335.

Jayachandran, Seema. 2006. "Selling labor low: wage responses to productivity shocks in developing countries." *Journal of Political Economy* 114, no. 3: 538-575.

Jensen, Robert. 2000. "Agricultural volatility and investments in children." *American Economic Review: Papers and Proceedings* 90, no. 2: 399-404.

Kaur, Supreet. 2019. "Nominal wage rigidity in village labor markets." *American Economic Review* 109, no.10: 3585-3616.

Kruger, Diana I. 2007. "Coffee production effects on child labor and schooling in rural Brazil." *Journal of Development Economics* 82: 448-463.

Kumar, Sunil M. and Ragupathy Venkatchalam. 2019. "Caste and credit: a woeful tale?" *Journal of Development Studies* 55, no.8: 1816-1833.

Levine, David I., and Dean Yang. 2014. "The impact of rainfall on rice output in Indonesia." NBER Working Paper 20302.

Maccini, Sharon, and Dean Yang. 2009. "Under the weather: Health, schooling, and economic consequences of early-life rainfall." *American Economic Review* 99, no. 3: 1006-1026.

Maldonado, Jorge H., and Claudio Gonazalez-Vega. 2008. "Impact of microfinance on schooling: Evidence from poor rural households in Bolivia." *World Development* 36, no. 11: 2440-2455.

Mazumder, Bhash, Maria F. Rosales, and Margaret Triyana. 2019. "Social interventions, health and well-being: The long-term and intergenerational effects of a school construction program." *Federal Reserve Bank of Chicago, WP 2019-09.*

Nguyen, Chi H. and Christophe J. Nordman. 2018. "Household entrepreneurship and social networks: Panel data evidence from Vietnam." *The Journal of Development Studies* 54(4): 594-618.

Ranjan, Priya. 1999. "An economic analysis of child labor." *Economics Letters* 64: 99-105.

Ray, Debraj. 1998. *Development Economics*. Princeton University Press.

Shah, Manisha, and Bryce M. Steinberg. 2017. "Drought of opportunities: Contemporaneous and long-term impacts of rainfall shocks on human capital." *Journal of Political Economy* 125, no. 2: 527-561.

Sunder, Naveen. 2020. “Parents’ Schooling and Intergenerational Human Capital: Evidence from India.” Working Paper

Wydick, Bruce. 1999. “The effect of microenterprise lending on child schooling in Guatemala.” *Economic Development and Cultural Change* 47: 853–869.

Zimmermann, Laura. 2020. “Remember when it rained – Schooling responses to shocks in India.” *World Development* 126: 104705.

Table 1: Summary Statistics

	(1) Mean	(2) Standard deviation
Education related outcomes:		
Currently enrolled (= 1)	0.927	0.260
Total education expenditure (INR)	1559.282	2561.214
Expenditures on school fees (INR)	613.536	1595.445
Expenditures on books, uniforms, transport (INR)	834.397	1212.311
Expenditures on private tuitions (INR)	175.517	579.046
Work related outcomes:		
Farm work (=1)	0.125	0.330
Non-farm household enterprise (=1)	0.012	0.108
Animal care (=1)	0.138	0.345
Wage work (=1)	0.025	0.155
Any work (=1)	0.207	0.405
Right-hand side variables:		
Rainfall deviation	-0.086	0.227
Female (=1)	0.480	0.500
Age	10.654	3.269
Other characteristics:		
Scheduled Caste/Tribe (SCST) (=1)	0.328	0.469
Any land in 2005 (=1)	0.670	0.470
Observations	46,225	

Notes: Authors' calculations using India Human Development Surveys (IHDS) of 2004-05 and 2011-12. All expenditures are measured in 2004-05 INR. The IHDS sample consists of households with children in the 5-16 age group in both rounds of the survey. Rainfall deviation 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, using data from University of Delaware. Scheduled Castes and Scheduled Tribes (SCST) refers to the low caste groups. Any land takes value 1 if the household owns or cultivates any agricultural land in 2005, 0 otherwise.

Table 2: Effects of Rainfall Deviations on Enrollment and Education Expenditures

			Total education expenditures		
	(1) Enrollment	(2) Total education expenditures	(3) School fees	(4) Books, uniforms and transport	(5) Private tuition
Rainfall deviation	0.009	-0.235	-1.371***	-0.203	0.288
	(0.014)	(0.189)	(0.310)	(0.224)	(0.252)
Female	-0.024***	-0.216***	-0.386***	-0.169***	-0.192***
	(0.003)	(0.020)	(0.036)	(0.019)	(0.027)
Constant	0.658***	6.773***	5.348***	6.103***	1.334**
	(0.038)	(0.893)	(0.716)	(0.881)	(0.526)
Observations	46,225	42,841	40,471	42,560	36,799
R-squared	0.155	0.097	0.119	0.091	0.052

Notes: Enrollment in column 1 is a binary variable. The educational expenditure outcomes in columns 2-5 are the log of the real expenditure in each category (in 2004-05 INR). Enrollment and expenditure data are from India Human Development Surveys (IHDS) of 2004-05 and 2011-12. The IHDS sample consists of households with children in the 5-16 age group in both rounds of the survey. Rainfall deviation 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, using data from University of Delaware. 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 are reported in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 3: Effects of Rainfall Deviations on Children's Work

	(1) Farm work	(2) Non-farm household enterprise	(3) Animal care	(4) Wage work	(5) Any work
Rainfall deviation	0.212***	0.020***	0.272***	-0.002	0.295***
	(0.028)	(0.007)	(0.033)	(0.010)	(0.035)
Female	-0.025***	-0.006***	-0.003	-0.010***	-0.023***
	(0.004)	(0.001)	(0.004)	(0.002)	(0.005)
Constant	0.165**	0.011	0.193***	0.111***	0.394***
	(0.071)	(0.024)	(0.072)	(0.028)	(0.071)
Observations	46,225	46,225	46,225	46,223	46,225
R-squared	0.164	0.016	0.161	0.061	0.238

Notes: The outcomes in all columns are binary variables constructed using the India Human Development Surveys (IHDS) of 2004-05 and 2011-12. The IHDS sample consists of households with children in the 5-16 age group in both rounds of the survey. Rainfall deviation 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, using data from University of Delaware. 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 are reported in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 4: Heterogeneity by Land Ownership

	(1) Total education expenditure	(2) School fees	(3) Books, uniforms and transport	(4) Private tuition
Rainfall deviation	-0.648***	-2.380***	-0.511**	0.224
	(0.218)	(0.316)	(0.244)	(0.279)
Rainfall deviation*Any land	0.639***	1.570***	0.480***	0.100
	(0.155)	(0.266)	(0.173)	(0.252)
Observations	42,841	40,471	42,560	36,799
R-squared	0.099	0.124	0.092	0.052

	(5) Farm work	(6) Non-farm household enterprise	(7) Animal care	(8) Wage work	(9) Any work
Rainfall deviation	0.097***	0.030***	0.237***	0.016	0.250***
	(0.026)	(0.009)	(0.032)	(0.016)	(0.036)
Rainfall deviation*Any land	0.180***	-0.014	0.054**	-0.029**	0.071**
	(0.027)	(0.009)	(0.026)	(0.014)	(0.029)
Observations	46,225	46,225	46,225	46,223	46,225
R-squared	0.167	0.016	0.161	0.061	0.238

Notes: The outcomes in column 1-4 are the log of the real educational expenditures (in 2004-05 INR). The outcomes in columns 5-9 are binary variables. All outcomes are constructed using the India Human Development Surveys (IHDS) of 2004-05 and 2011-12. The IHDS sample consists of households with children in the 5-16 age group in both rounds of the survey. Rainfall deviation 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, using data from University of Delaware. Any land takes value 1 if the household owns or cultivates any agricultural land in 2005, 0 otherwise. These regressions include female dummy, household fixed effects, year of birth fixed effects and month-year of survey fixed effects. Standard errors clustered at the district level are reported in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 5: Heterogeneity by Credit Access

	(1) Total education expenditure	(2) School fees	(3) Books, uniforms and transport	(4) Private tuition	
Rainfall deviation	-0.170	-1.070***	-0.228	0.529*	
	(0.209)	(0.317)	(0.251)	(0.304)	
Rainfall deviation*Rural banks	-0.631***	-0.158	-0.80***	-0.220	
	(0.183)	(0.227)	(0.201)	(0.158)	
Observations	27,853	26,331	27,646	23,761	
R-squared	0.114	0.132	0.108	0.059	
	(5) Farm work	(6) Non-farm household enterprise	(7) Animal care	(8) Wage work	(9) Any work
Rainfall deviation	0.265***	0.011	0.307***	-0.022**	0.302***
	(0.039)	(0.008)	(0.039)	(0.010)	(0.044)
Rainfall deviation*Rural banks	0.080**	-0.001	0.132***	-0.002	0.108***
	(0.031)	(0.005)	(0.028)	(0.006)	(0.032)
Observations	29,923	29,923	29,923	29,922	29,923
R-squared	0.226	0.016	0.189	0.057	0.271

Notes: Sample is limited to households that report owning or cultivating any agricultural land in 2005. The outcomes in column 1-4 are the log of the real educational expenditures (in 2004-05 INR). The outcomes in columns 5-9 are binary variables. All outcomes are constructed using the India Human Development Surveys (IHDS) of 2004-05 and 2011-12. The IHDS sample consists of households with children in the 5-16 age group in both rounds of the survey. Rainfall deviation 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, using data from University of Delaware. 'Rural banks' represents rural bank branches per capita in 2005 from the Reserve Bank of India. These regressions include female dummy, household fixed effects, year of birth fixed effects and month-year of survey fixed effects. Standard errors clustered at the district level are reported in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 6: Heterogeneity by Caste

	(1) Total education expenditure	(2) School fees	(3) Books, uniforms and transport	(4) Private tuition
Rainfall deviation	-0.121	-0.908***	-0.146	0.432
	(0.194)	(0.318)	(0.229)	(0.269)
Rainfall deviation*SCST	-0.362**	-1.495***	-0.177	-0.443**
	(0.158)	(0.228)	(0.178)	(0.179)
Observations	42,841	40,471	42,560	36,799
R-squared	0.098	0.123	0.091	0.052

	(5) Farm work	(6) Non-farm household enterprise	(7) Animal care	(8) Wage work	(9) Any work
Rainfall deviation	0.219***	0.025***	0.262***	-0.011	0.282***
	(0.028)	(0.005)	(0.034)	(0.010)	(0.036)
Rainfall deviation*SCST	-0.020	-0.013**	0.029	0.028**	0.040
	(0.031)	(0.006)	(0.031)	(0.012)	(0.032)
Observations	46,225	46,225	46,225	46,223	46,225
R-squared	0.164	0.016	0.161	0.061	0.238

Notes: The outcomes in column 1-4 are the log of the real educational expenditures (in 2004-05 INR). The outcomes in columns 5-9 are binary variables. All outcomes are constructed using the India Human Development Surveys (IHDS) of 2004-05 and 2011-12. The IHDS sample consists of households with children in the 5-16 age group in both rounds of the survey. Rainfall deviation 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. SCST refers to the Scheduled Castes and Scheduled Tribes (i.e., low castes). These regressions include female dummy, household fixed effects, year of birth fixed effects and month-year of survey fixed effects. Standard errors clustered at the district level are reported in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 7: Heterogeneity by Maternal Education

	(1) Total education expenditure	(2) School fees	(3) Books, uniforms and transport	(4) Private tuition
Rainfall deviation	-0.200	-1.689***	-0.146	0.248
	(0.203)	(0.325)	(0.238)	(0.260)
Rainfall dev*Mother educ	-0.098	0.865***	-0.155	0.106
	(0.144)	(0.191)	(0.161)	(0.197)
Observations	42,743	40,382	42,465	36,709
R-squared	0.097	0.120	0.091	0.052

	(5) Farm work	(6) Non-farm household enterprise	(7) Animal care	(8) Wage work	(9) Any work
Rainfall deviation	0.234***	0.016**	0.287***	0.014	0.312***
	(0.030)	(0.006)	(0.034)	(0.013)	(0.036)
Rainfall dev*Mother educ	-0.063**	0.014*	-0.044*	-0.05***	-0.048*
	(0.025)	(0.008)	(0.026)	(0.012)	(0.028)
Observations	46,120	46,120	46,120	46,118	46,120
R-squared	0.164	0.016	0.161	0.062	0.238

Notes: The outcomes in column 1-4 are the log of the real educational expenditures (in 2004-05 INR). The outcomes in columns 5-9 are binary variables. All outcomes are constructed using the India Human Development Surveys (IHDS) of 2004-05 and 2011-12. The IHDS sample consists of households with children in the 5-16 age group in both rounds of the survey. Rainfall deviation 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. Mother education takes a value 1 if the mother reports any education in 2005, and 0 otherwise. These regressions include female dummy, household fixed effects, year of birth fixed effects and month-year of survey fixed effects. Standard errors clustered at the district level are reported in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Online Appendix (not for publication)

Section A: Construction of panel data using the two rounds of the India Human Development Survey (IHDS)

The “linking dataset” of IHDS – which provides the mapping of households/individuals across the two rounds of the IHDS – contains 204,568 observations. As we need households to have been surveyed in both rounds, we first remove 9,760 individuals belonging to households that were not surveyed in both survey rounds. The remaining individual observations belong to 40,018 households.

The 2012 data (N = 204,569 individuals) has 47,825 individuals in the 5-16 age range (belonging to 24,005 households). The 2005 data (N = 215,574 individuals) has 58,755 individuals in the 5-16 age range (belonging to 26,765 households). Of these 26,765 households in 2005, 22,974 households were surveyed in 2012 as well. These 22,974 households in 2005 correspond to 26,986 households in the 2012 data (as some households split between 2005 and 2012).[13]

Putting the 2005 and 2012 datasets together (at the household level), there are 15,609 households that satisfy our sample condition of having at least one child aged 5-16 in both survey rounds.

Of the 58,755 individuals aged 5-16 in the 2005 round, 38,222 individuals belong to the 15,609 households indicated above. Similarly, out of the 47,825 individuals aged 5-16 in the 2012 data, 36,039 individuals belong to these aforementioned 15,609 households. This yields a total of 74,261 observations aged 5-16 across both rounds. We limit the sample to observations in rural areas of the twenty major states[14] where information on variables to be included in regressions are non-missing. This results in a final analysis sample of 46,225 observations.

[13] We use the household unit in 2005 to define the household fixed effects in our analysis.

[14] These are: 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.

Section B: Additional Results

Table B1: Effects of Rainfall Deviations on Crop Yields

	(1) Rice	(2) Wheat	(3) Jowar	(4) Bajra	(5) Groundnut	(6) Sugar
Rainfall deviation	0.153***	0.035	0.099**	0.070*	0.087**	0.075***
	(0.025)	(0.022)	(0.039)	(0.038)	(0.037)	(0.026)
Observations	6,926	6,493	5,991	5,079	6,163	6,803
R-squared	0.681	0.705	0.607	0.587	0.338	0.674

Notes: The dependent variables are yearly log of the yield of the respective crops. The yield data is from the World Bank India Agriculture and Climate Dataset for the years 1956 to 1987. Rainfall deviation 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, using data from University of Delaware. These regressions include district and year fixed effects. Standard errors clustered at the district level are reported in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table B2: Heterogeneity by Gender

	(1) Total education expenditure	(2) School fees	(3) Books, uniforms and transport	(4) Private tuition	
Rainfall deviation	-0.243	-1.326***	-0.210	0.396	
	(0.193)	(0.309)	(0.227)	(0.264)	
Female	-0.215***	-0.394***	-0.168***	-0.208***	
	(0.022)	(0.038)	(0.020)	(0.029)	
Rainfall deviation*Female	0.015	-0.096	0.016	-0.233**	
	(0.077)	(0.105)	(0.073)	(0.099)	
Observations	42,841	40,471	42,560	36,799	
R-squared	0.097	0.119	0.091	0.052	

	(5) Farm work	(6) Non-farm household enterprise	(7) Animal care	(8) Wage work	(9) Any work
Rainfall deviation	0.226***	0.021***	0.268***	0.006	0.305***
	(0.029)	(0.007)	(0.035)	(0.011)	(0.037)
Female	-0.027***	-0.007***	-0.003	-0.011***	-0.025***
	(0.004)	(0.001)	(0.005)	(0.002)	(0.005)
Rainfall deviation*Female	-0.029**	-0.001	0.007	-0.018**	-0.019
	(0.013)	(0.006)	(0.015)	(0.008)	(0.017)
Observations	46,225	46,225	46,225	46,223	46,225
R-squared	0.164	0.016	0.161	0.061	0.238

Notes: The outcomes in column 1-4 are the log of the real educational expenditures (in 2004-05 INR). The outcomes in columns 5-9 are binary variables. All outcomes are constructed using the India Human Development Surveys (IHDS) of 2004-05 and 2011-12. The IHDS sample consists of households with children in the 5-16 age group in both rounds of the survey. Rainfall deviation 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. 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 are reported in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table B3: Instrumental Variables Regressions

	(1) Total education expenditure	(2) School fees	(3) Books, uniforms and transport	(4) Private tuition
Rainfall deviation	-0.670***	-0.941***	-0.755***	0.408***
	(0.138)	(0.167)	(0.141)	(0.157)
Constant	6.737***	5.384***	6.053***	1.350**
	(0.606)	(0.614)	(0.616)	(0.649)
Observations	42,841	40,471	42,560	36,799

	(5) Farm work	(6) Non-farm household enterprise	(7) Animal care	(8) Wage work	(9) Any work
Rainfall deviation	0.143***	0.0266***	0.228***	-0.0178*	0.145***
	(0.0183)	(0.00636)	(0.0188)	(0.0100)	(0.0201)
Constant	0.162*	0.0122	0.195**	0.110***	0.304***
	(0.0833)	(0.0286)	(0.0770)	(0.0304)	(0.0827)
Observations	46,225	46,225	46,225	46,223	46,225

Notes: The outcomes in column 1-4 are the log of the real educational expenditure (in 2004-05 INR). The outcomes in columns 5-9 are binary variables. All outcomes constructed using the India Human Development Surveys (IHDS) of 2004-05 and 2011-12. The IHDS sample consists of households with children in the 5-16 age group in both rounds of the survey. Rainfall instrumented with rainfall in the second through fifth closest rainfall stations following Maccini and Yang (2009). Rainfall deviation 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, using data from University of Delaware. These regressions include female dummy, household fixed effects, year of birth fixed effects and month-year of survey fixed effects. Standard errors clustered at the district level are reported in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table B4: Effect of Rainfall Deviations on Predetermined Characteristics

	(1)	(2)	(3)	(4)
	Asset index	Household size	Mother education	Father education
Rainfall deviation	-0.102	0.019	0.159	-0.069
	(0.090)	(0.098)	(0.121)	(0.122)
Constant	0.067	6.913***	2.687***	3.249***
	(0.457)	(0.471)	(0.654)	(0.814)
Observations	21,234	21,360	22,417	20,396

Notes: All outcomes constructed using the India Human Development Surveys (IHDS) of 2004-05 and 2011-12. Regressions are estimated at the level of the household. Rainfall deviation 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, using data from University of Delaware. The asset index is constructed based on a principal component analysis of categorical variables on whether the household owns a range of assets. Mother and father any education takes a value one if the mother or father report having any education. 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 are reported in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table B5: Effects of Rainfall Shocks on Educational Expenditures and Child Work

	(1) Total education expenditure	(2) School fees	(3) Books, uniforms and transport	(4) Private tuition	
Rainfall Shock	-0.16	-0.45*	-0.15	0.17	
	(0.13)	(0.23)	(0.14)	(0.13)	
Constant	6.90***	5.77***	6.22***	1.20**	
	(0.89)	(0.71)	(0.88)	(0.55)	
Observations	42,958	40,579	42,676	36,903	
R-squared	0.098	0.113	0.091	0.052	
	(5) Farm work	**(6) Non-farm household enterprise**	**(7) Animal care**	**(8) Wage work**	**(9) Any work**
Rainfall Shock	0.06**	0.01*	0.08***	-0.01	0.08***
	(0.02)	(0.00)	(0.02)	(0.01)	(0.03)
Constant	0.10	0.00	0.12	0.11***	0.31***
	(0.08)	(0.02)	(0.08)	(0.03)	(0.08)
Observations	46,225	46,225	46,225	46,223	46,225
R-squared	0.157	0.016	0.151	0.061	0.23

Notes: The outcomes in column 1-4 are the log of the real educational expenditures (in 2004-05 INR). The outcomes in columns 5-9 are binary variables. Enrolment and expenditure data are from India Human Development Surveys (IHDS) of 2004-05 and 2011-12. The IHDS sample consists of households with children in the 5-16 age group in both rounds of the survey. Rainfall Shock variable is defined as equal to 1 if the annual rainfall is above 1SD of the mean district rainfall, -1 if it is below 1SD of the mean district rainfall, and 0 otherwise, using data from University of Delaware. These regressions include female dummy, household fixed effects, year of birth fixed effects and month-year of survey fixed effects. Standard errors clustered at the district level are reported in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table B6: Effects of Rainfall Deviations on Educational Expenditures and Child Work, with District Fixed Effects

	(1) Total education expenditure	(2) School fees	(3) Books, uniforms and transport	(4) Private tuition	
Rainfall deviation	-0.197	-1.383***	-0.168	0.308	
	(0.187)	(0.283)	(0.221)	(0.222)	
Constant	6.481***	5.412***	6.029***	1.446***	
	(0.280)	(0.290)	(0.364)	(0.452)	
Observations	42,841	40,471	42,560	36,799	
R-squared	0.079	0.092	0.075	0.035	
	(5) Farm work	(6) Non-farm household enterprise	(7) Animal care	(8) Wage work	(9) Any work
Rainfall deviation	0.169***	0.017***	0.234***	-0.004	0.252***
	(0.025)	(0.005)	(0.028)	(0.007)	(0.031)
Constant	0.247***	0.011	0.186***	0.100***	0.374***
	(0.039)	(0.017)	(0.038)	(0.031)	(0.034)
Observations	46,225	46,225	46,225	46,223	46,225
R-squared	0.121	0.012	0.122	0.056	0.188

Notes: The outcomes in column 1-4 are the log of the real educational expenditures (in 2004-05 INR). The outcomes in columns 5-9 are binary variables. All outcomes are constructed using the India Human Development Surveys (IHDS) of 2004-05 and 2011-12. The IHDS sample consists of households with children in the 5-16 age group in both rounds of the survey. Rainfall deviation 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, using data from University of Delaware. These regressions include female dummy, district fixed effects, year of birth fixed effects and month-year of survey fixed effects. Standard errors clustered at the district level are reported in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.