Remember When It Rained - Schooling Responses to Shocks in India

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Abstract

While most of the existing literature focuses on the school enrollment effects of weather shocks in developing countries, children's education can also be affected through changes in educational expenditures and school quality. This paper uses detailed household and administrative data from India to analyze how the education impacts of rainfall shocks have changed over time. School enrollment effects have switched signs over the past 30 years, consistent with a decreased role for credit constraints and an increased importance of the opportunity costs of the child's time. Households also increasingly re-optimize educational expenditures and school type. One potential explanation for this effect is a change in the quality of government schools relative to private schools after rainfall shocks, which suggests that in developing countries like

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India government efforts to provide high-quality education in government schools remain important despite an increased availability of private schools.

Keywords: Education, school enrollment, educational expenditures, household decision-making, response to shocks, India

JEL Codes: D10, H52, I25

1 Introduction

Over 60 percent of the population in South Asia and Sub-Saharan Africa lives in rural areas (World Bank 2015). This means that many children continue to grow up in rural households that are dependent on agriculture and vulnerable to weather shocks such as droughts. To cope with these shocks, households have to re-optimize their behavior, and this can affect children's education on two dimensions: the extensive and the intensive margin.

At the extensive margin, children may have to drop out of school after a negative shock because it has become too expensive or because they have to work to contribute to household income. Alternatively, school enrollment may actually increase if there are fewer employment opportunities available during a drought. At the intensive margin, the recent expansion of private schools in rural areas gives parents in developing countries more options to adjust expenditures without taking their children out of school (Kingdon, 2007, 2017; Muralidharan and Kremer, 2009).[1] After a negative shock, parents may have to lower educational spending or to re-allocate it across different categories. One potential consequence of this is a change in schools, which may affect learning outcomes. Such a step may become even more necessary if school quality is directly affected by rainfall shocks, for example through changes in school amenities, qualified teachers or school accessibility.

The existing empirical literature on the impact of weather shocks on education in developing countries focuses almost exclusively on the extensive margin with an analysis of school enrollment and opportunity costs (Björkman-Nyqvist, 2013; Duryea and Arends-Kuenning, 2003; Jacoby and Skoufias, 1997; Jensen, 2000; Maccini and Yang, 2009; Shah and Steinberg, 2017; Thomas et al., 2004).[2] If the intensive margin is important, this may substantially underestimate how much children are affected by rainfall shocks, for example if children are sent to worse schools during a drought. Additionally, there is no overall consensus on

[1] Das et al. (2013) find, for example, that households seem to offset their own spending on school inputs in anticipation of grants for schools.

[2] An exception is Thomas et al. (2004) who look at the budget share household spend on education. I analyze child-wise education expenditures, and also observe spending on detailed categories of education.

the direction of the impact of rainfall shocks on school enrollment in the existing literature: While many papers find that adverse shocks negatively affect school enrollment, others find a positive enrollment effect.

In this paper, I use household survey data from India to provide the first detailed analysis of how rainfall shocks affect schooling at the intensive margin: The analysis dataset consists of three large representative cross-sectional household surveys that span three decades (1986, 1995, 2007). The surveys explicitly focus on education, and therefore contain a much richer set of variables than is otherwise common, including detailed information on education expenditures separately reported for every enrolled child in the household. Additionally, the timing of the surveys allows for the rare opportunity to analyze how the impact of rainfall shocks on education has changed in the same context over time at both extensive and intensive margins.

The results show that household re-optimization at the extensive margin has fundamentally changed over time: School enrollment for boys between 6 and 18 years increases by 6 percentage points after a positive rainfall shock, while the effect is small and not statistically significant in 1995. By contrast, school enrollment decreases by 3 percentage points in 2007. A disaggregated analysis separately for positive and negative rainfall shocks shows that the overall effect is symmetric, although children are more heavily affected by negative than by positive rainfall shocks. Credit constraints seem to contribute to the enrollment effect in the 1980s but lose in importance over time, whereas high opportunity costs of a child's time during good rainfall shocks help explain the negative enrollment effect in 2007.

Household re-optimization at the intensive margin has become important in recent years: While there is no big change in education expenditures in 1986, education expenditures in 1995 decrease overall in times of good rainfall, which is driven by a decrease in expenditures on school uniforms. In 2007, households re-allocate their expenditures between multiple categories to keep their sons enrolled in school: less money is spent on school fees and private coaching, whereas expenditures on uniforms increase. Children are also more likely to attend a government school. The impact of rainfall shocks on girls' education at the extensive and intensive margins are qualitatively similar.

The expenditure adjustments and school switching in the most recent survey are consistent with a number of potential explanations, including an increase in the quality of government schools relative to private schools after a positive rainfall shock, or a higher feasibility of combining school and work commitments in government schools. To supplement the household analysis for 2007, I use district-level panel data on Indian schools from 2004 to 2015. I find that the number of schools decreases during better rainfall shocks, but that some proxies for the physical quality of schools increase. The number of teachers is unchanged, but some evidence suggests that there is a slight increase in the educational qualification of regular teachers. These patterns are broadly consistent with an increase of school quality in government schools after a positive shock, leading parents to switch schools. But not all alternative stories can be ruled out. Overall, the results document a big shift in parents' views on education over time and in their willingness to insulate their children from weather shocks.

To the best of my knowledge, my paper provides the first evidence that households in developing countries re-optimize educational expenditures and school type in response to weather shocks in more recent times, and that school quality may be directly affected by rainfall, plausibly contributing to the school switching. A focus on the extensive margin of schooling therefore misses parts of the story.

These results have direct policy implications in two ways. First, existing research has shown that despite the large increase in the availability of private schools, they continue to be less accessible for the poorest households (Alderman et al., 2001; Singh and Bangay, 2014). Additionally, while in general Indian private schools are of higher quality than government schools, this does not seem to hold for low-fee private schools (Chudgar and Quin, 2012; Muralidharan and Sundararaman, 2015). This implies that poor children are much more heavily affected by rainfall shocks than children from richer households, not just because household income is likely to be more affected by the shock, but also because parents are unable to re-optimize their child's quality of education by sending him to a private school. As rainfall variability is projected to increase dramatically in India and other developing countries due to climate change, the importance of this effect will only increase in the future (Thornton et al., 2014).

Second, Shah and Steinberg (2017) find an improvement in the test scores of Indian children during times of low rainfall for roughly the same time period as studied by the latest household survey round and the district-level panel data in this paper. My results imply that the test score effects are plausibly in part driven by a school switching, since parents are willing and able to re-optimize school type, and not entirely due to changes in effort or time devoted to schooling after a rainfall shock. The test score effects are therefore likely to be a lower bound of potential improvements in learning outcomes during times of low opportunity costs of school enrollment if school quality could be improved.

Overall, there is an important role for government policy to improve the quality of government schools in general and to ensure that educational quality remains constant after weather shocks. This would improve learning outcomes and help reduce inequalities in schooling that are created by exposure to rainfall shocks, with potentially large long-run labor-market consequences (Chakraborty and Bakshi, 2016; Government of India, 2013; Self and Grabowski, 2004; Shah and Steinberg, 2017).[3]

The results in this paper also show that parents do not have a general preference for private schools over government schools, since children are actually more likely to attend government schools during times of high rainfall, when credit constraints, if anything, are presumably less binding. While it is well-documented that many parents are willing to pay for high-quality private schools (Drèze and Kingdon, 2003; Goyal, 2009; Kingdon, 1996; Tooley et al., 2010), this suggests that parents pay close attention to the best value for money among schools and are well informed about factors that affect school quality.

[3] Das and Zajonc (2010) find that India's school quality is very low by international standards. Only three countries perform worse than India on an international education test.

Lastly, my paper also suggests a possible explanation for the mix of positive and negative enrollment effects seen in the literature. In India, the flip from a positive to a negative enrollment effect after a positive shock occurs at the same time as a large increase in economic development due to economic liberalization. Similar to my analysis, papers finding a negative enrollment effect in the existing literature tend to use more recent data or to be from Latin America, which is more developed on average than other developing countries, whereas papers finding positive enrollment effects tend to use older data or to use data from less economically developed areas.

The remainder of this paper is structured as follows: Section 2 provides some background information on schooling in India. Section 3 discusses the data and empirical strategy. Section 4 presents the main results, while section 5 looks at a number of extensions and robustness checks. Section 6 concludes.

2 Schooling in India

Education in India is split into primary school (grades 1-5), upper primary school (grades 6-8) as well as secondary and higher secondary school (grades 9-12). According to article 43 of the Indian Constitution, school enrollment is compulsory from age 6 to 14, but in practice, school enrollment is not universal in most Indian states. Nevertheless, school enrollment rates have increased dramatically over time. Table 1 shows that 34 percent of boys between 6 and 18 years were enrolled in school in 1986, which increased to 73 percent in 1995 and 76 percent in 2007.[4]

In addition to economic liberalization reforms in the late 1980s, which set India on a higher economic growth path, the Indian government has also implemented a number of

[4] Enrollment for children of primary school age (6-10 years) increased steadily from 35 percent to 86 percent over the survey period, whereas enrollment at the upper primary age level (11-14 years) jumped from 21 percent in 1986 to about 85 percent in the two more recent survey periods. Enrollment rates for the oldest children in the sample, age 15-18, are more uneven, with 47 percent of children in this age group enrolled in 1986, which increased by about 10 percentage points in 1995, but slightly fell to 51 percent in 2007.

education programs and policies to increase access to education, reduce dropouts and improve learning outcomes.[5] Initiatives have included a number of different programs, including scholarships for low-caste students (scheduled castes and scheduled tribes) or free lunch through the mid-day meal schemes in various Indian states (Government of India, 2005). The number of schools has increased substantially over the time period: In 1981, there were 664,700 schools, whereas there were 1,396,331 schools in India in 2011 (Government of India, 2011). Almost all Indian villages today have a primary school, whereas the proportion of villages with a primary school was only 73 percent in 1991 (Banerjee and Somanathan, 2007).

The number of private schools has expanded especially rapidly over the last 10-15 years. As Table 1 shows, the proportion of boys aged 6 to 18 years who attend government schools in rural areas was 83 percent in 1986 and declined by only one percentage point by 1995. By 2007, however, only 78 percent of boys went to public schools. This trend of increased private school enrollment even in rural areas is consistent with other studies. Kingdon (2017) discusses evidence from a variety of available schooling datasets for India for the time period of 2010-2014: During those four years, 71,000 new private schools opened as compared to only 16,000 new government schools. Government schools on average had fewer students than private schools, and lost students, whereas the number of students in private schools increased. With a median school fee of 275 rupees per month in rural areas, back-of-the-envelope calculations show that annual school fees are around 10 percent of the yearly minimum wage of daily wage laborers, and that 26 percent of students attend private schools with monthly fees below the daily minimum wage in their respective state. This implies that private schools offer a potential alternative to government schools to many households in rural India, except for very poor families (Singh and Bangay, 2014). Parents seem to be especially taking to private schools in states with lower quality government schools (Drèze and Kingdon, 2003; Kingdon, 1996; Tooley et al., 2010).

When controlling for the socio-economic status of children, a number of existing studies

[5] Two important early programs were the New National Policy of Education (1986) and the Programme of Action (1992).

find that private schools are of better quality as measured by learning outcomes, but that this may not be true for low-fee private schools (Chudgar and Quin, 2012; Goyal, 2009; Singh, 2015). While public primary and upper primary schooling is supposed to be free, this is also not completely true. In my analysis dataset, virtually all households with boys of school-going age reported paying fees of some kind, including for children attending government schools.[6]

Government school teachers fall into two categories: regular teachers, who are paid a high minimum wage and are backed by a powerful teacher union, and contract teachers, also referred to as 'para teachers', who are only paid a fraction of that wage. Teacher compensation in private schools roughly corresponds to the market-clearing wage for educated workers. Due to high unemployment rates for that group, Kingdon (2017) finds that private school teachers are paid about 12 to 30 times less than regular government teachers.

3 Data and Empirical Strategy

3.1 Data

Information on education variables for the analysis comes from two sources: household survey data and administrative data. The National Sample Survey (NSS) Organization conducts large representative surveys of the Indian population. The 42nd round (July 1986-June 1987), the 52nd round (July 1995-June 1996) and the 64th round (July 2007-June 2008) have an explicit education focus. These surveys contain a much larger set of questions on education outputs and inputs than is available in other rounds of the survey. Crucial for the analysis, households are asked about the school enrollment of each child and the amount of money households spend for the education of every child. This includes fees, books and stationery, uniforms, transport and other expenditures. The datasets also contain information about

[6]Fees here can include examination fees or tuition fees. This is consistent with Tilak (1996), who finds that less than half of the students in rural India receive free primary school education in government schools.

a child's work status and mode of transportation to school. I restrict the main analysis to children aged 6-18 years living in rural households.

The NSS data allows me to analyze how rainfall shocks affect education inputs and outcomes, and how that relationship has changed over time. I supplement this information with administrative data from the National University of Educational Planning and Administration captured in the DISE database. This dataset contains district-wise information on enrollment, schools and teachers from 2004 to 2015. I focus on variables that are consistently recorded over most of the time period. This includes the number of government and private schools of different school types in the rural areas of the district, and enrollment in these schools.[7] The school types overlap widely in terms of the expected age of enrolled students, which does not allow me to cleanly estimate the impact of rainfall shocks by age in this dataset.[8] For the analysis, I therefore aggregate information from all school types. In addition to the absolute number of schools and school enrollment, I create a variable for the percent of students attending government schools.

The DISE data also allows me to construct a few variables on school characteristics that may be correlated with school quality. These include the proportion of single-classroom schools, single-teacher schools, schools with girl toilets, and schools with fewer than 50 students.[9] Additionally, the dataset contains information on the number of regular and contract teachers (referred to as 'para teachers') as well as their education level.

The education datasets are merged to gridded rainfall data using the closest longitude and latitude coordinates to the center of a district. Weather in India varies widely by region and often also at the sub-regional level. India has six different climatic regions, ranging from humid tropical areas to desert-like dry regions. While there are local differences, India in general experiences four seasons: winter (January to February), summer (March to May), the

[7] School types depend on the grades offered at a particular school, for example 'primary school only', 'primary and upper primary school', or 'upper primary school only'.

[8] Primary school children, for example, can attend schools in three categories: primary only, primary and upper primary, and primary and upper primary and secondary.

[9] Unfortunately, the dataset does not consistently record information for any toilet facility or other, more direct indicators of the physical quality of schools, for example number and material of buildings.

monsoon season (June to September) and the post-monsoon season (October to December) (De et al., 2005; Ribot et al., 1996). About 80 percent of annual rainfall occurs during the monsoon months (Government of India, 2006). As about 60 percent of the agricultural sector depends on rain as the only source of water, agricultural output is heavily influenced by precipitation levels and timing (Government of India, 2010). This relationship has also been documented for India and Indonesia in other papers (Levine and Yang, 2006; Shah and Steinberg, 2017).

For the NSS data, rainfall data comes from the University of Delaware. I aggregate the monthly rainfall data to annual rainfall using the time period of 1955 to 2008. Rainfall shocks are defined in a way that is commonly used in the literature[10]: A negative rainfall shock or drought is defined as an indicator variable equal to one if annual rainfall in a given year is below the 20th percentile in the district, and zero otherwise. A positive rainfall shock indicator variable is equal to one if annual rainfall is above the 80th percentile in the district, and zero otherwise. For the DISE data, analogous rainfall shocks are created using monthly rainfall information from NASA, which are available from 1998 to 2016. The analysis first focuses on an overall rainfall shock variable, which is set to -1 for a negative shock, to 1 for a positive shock, and to 0 for all remaining observations. As an extension, the results are then also estimated separately for negative and positive shocks.

Since district boundaries in the NSS datasets change across surveys, I map districts to the district boundaries from 1981 using administrative boundary change crosswalks from Kumar and Somanathan (2009). This allows me to include district fixed effects in the analysis.

3.2 Empirical Strategy

For the NSS data, I estimate the results using the following regression equation:

$$s_{ijkly} = \beta_0 + \beta_1 shock_{ky} + \beta_2 shock_{ky} year1995 + \beta_3 shock_{ky} year2007 + \eta_j + \theta_k + \gamma_l + \delta_l + \epsilon_{ijkly}$$

[10] See e.g. Jayachandran (2006), Kaur (Forthcoming), and Shah and Steinberg (2017) for similar definitions.

s_{ijkly} is an outcome variable of interest for child i of age j in district k, season l, and year y. $shock_{ky}$ corresponds to the used rainfall shock variable. β_1 estimates the impact of the shock for the reference year, 1986, whereas β_2 and β_3 estimate the interaction effects of the shock variable with the later survey rounds. The regression also includes age, district, season and year fixed effects. Standard errors are clustered at the district level.

This regression equation tests whether the impact of rainfall shocks on education variables has changed over time. The empirical estimation strategy exploits random spatial and temporal variation in rainfall. District fixed effects control for any systematic differences in rainfall or other characteristics across districts. Season fixed effects ensure that the analysis is not driven by the time of the year when households were interviewed, whereas year fixed effects control for any aggregate year-specific factors, such as the aggregate Indian weather conditions: As Table 1 shows, 1986 was much more of a general drought year across India than the later years, for example. Given that the surveys are about 10 years apart, the year-fixed effects will capture general time trends like the increase in school enrollment in Table 1.

For the main results, the regression restricts the sample to boys between 6 and 18 years old, and controls for age using age fixed effects. As an extension, I also report the analogous results for girls. Additionally, I estimate the results separately for boys aged 6-10 years, 11-14 years, and 15-18 years. The results for girls are more difficult to interpret since ultrasound technology for sex-selective abortions became increasingly available over the covered time period. This has led to a heavily skewed sex ratio in favor of boys in India. The number, age and level of wantedness of girls is therefore likely to have changed substantially over time, which could bias the results.

To analyze the impact of rainfall shocks in the DISE data, I use a similar regression format:

$$s_{ky}= \beta_0 + \beta_1 shock_{ky} + \eta_j + \theta_k + \gamma_l + \delta_l + \epsilon_{ijkly}$$

s_{ky} is an outcome variable of interest for district k and year y. $shock_{ky}$ corresponds to the used rainfall shock variable, and β_1 is the coefficient of interest. The regression also includes district and year fixed effects, with standard errors clustered at the district level according to the 2001 Census boundaries.

4 Results

Table 2 uses the NSS household survey data to explore how a rainfall shock affects the school enrollment, household expenditures and work status of boys aged 6 to 18 years. For each regression, the table reports the main effect of a rainfall shock in the reference year, 1986, as well as the interaction effects with later years. The table also shows the sum of main and interaction effect coefficients as well as the F-test statistic for the test that each combined effect is zero.

The first column of Table 2 shows that the impact of a rainfall shock on school enrollment has changed substantially over time: The first row shows that a boy between 6 and 18 years in 1986 was about 6 percentage points more likely to be enrolled in school at higher levels of rainfall. In 1995, the interaction effect is large and negative with a 6 percentage point decrease in school enrollment. The sum of main and interaction effect is therefore a small and statistically insignificant change in school enrollment. In 2007, the interaction effect shows a 9 percentage point decrease in enrollment, which implies an overall decrease in school enrollment of 3 percentage points after the shock. Indian households were therefore either affected very differently by rainfall shocks in 1986 than in 2007, or chose to re-optimize household resources differently in response to the shock.

To explore potential mechanisms, columns 2 to 6 of Table 2 estimate the impact of rainfall shocks on household expenditures, the child's work status, and mode of transportation to school. A simple credit constraints explanation predicts that a positive rainfall shock leads to an increase in household expenditures. Parents are better able to afford sending their child to school, leading to higher school enrollment. A simple opportunity costs explanation for higher school enrollment, on the other hand, implies that the likelihood of working should decrease after a positive rainfall shock since the child's contribution to household income through work is less needed. Both channels are of course not mutually exclusive and are tested in Table 2. A negative enrollment effect as in 2007 could be due to high opportunity costs of the child's time, on the other hand: In periods of high rainfall, employment opportunities may be better than during a drought and thereby raise the opportunity cost of attending school.

Column 2 shows that monthly household per-capita expenditures increase by about 3 percent for boys in 1986, an effect that is marginally significant at the 10 percent level. The next three columns are indicator variables equal to one if a child uses a given mode of transport to get to school.[11] After the shock, boys are less likely to walk to school, and more likely to use the school bus or public transport. Column 6 focuses on the child's work status. The household survey question asks about the usual activity of a child, which includes various categories of employment in and outside the household, including domestic work, self-employment, and work for pay. The indicator variable in column 6 is equal to 1 if a boy works in any capacity, and zero otherwise. The estimated coefficient for 1986 shows that the probability that a boy works increases by 1 percentage point. The patterns are therefore consistent with a credit constraints story, but do not support a simple explanation of low opportunity costs during periods of better rainfall.

In 1995, there is little evidence that the rainfall shock importantly affects household expenditures, although the coefficient is positive. The estimated effects for mode of transportation are all very small and statistically insignificant, and there is no change in the likelihood of working. In 2007, there is again no large change in household per-capita expenditures, but the probability of walking to school declines by 2 percentage points. By contrast, the probability of working increases by 2 percentage points.

[11] The fourth category not reported here is 'other transport'.

Overall, Table 2 suggests that credit constraints help explain the positive enrollment effect for 1986, but it is less clear that they contribute to school enrollment in later years. Children in 1995 appear to be unaffected by the shock, whereas high opportunity costs of a child's time plausibly contribute to the decrease in school enrollment in 2007.

But parents also have less extreme options than changing their children's school enrollment. They could adjust education expenditures, for example by spending more money on less necessary items in times of good rainfall or by sending their children to a more expensive school. Table 3 explores how educational expenditures by parents after a shock have evolved over time.

Column 1 looks at the total log education expenditures on a given child for the academic year, whereas columns 2 to 7 focus on different categories of expenditures: The indicator variables are equal to one if a household spends any money on a given category of expenditures for that particular child, and zero otherwise.[12] Column 8 of Table 3 is an indicator variable equal to 1 if a child attends a government school, and zero if the child attends a private school.

As the results show, the budget allocated to educational expenditures for a particular child, conditional on going to school, does not statistically significantly increase for children in 1986 despite the increase in household per-capita expenditures in the same year, and the estimated coefficient is even negative, although imprecisely estimated. Educational expenditures decrease by 7 percentage points for children in 1995, whereas the estimated coefficient for 2007 is small and statistically insignificant.

With respect to spending across different categories of educational expenditures, parents in 1986 are about 1 percentage point more likely to spend any money on school fees, and are also 7 percentage points more likely to spend money on private coaching. This is consistent with spending more money on less essential categories when household income is higher,

[12] As Table 1 shows, annual education expenditures for a child on average are low relative to monthly per-capita expenditures. In results not reported here, although qualitatively similar, there is less re-optimization based on the amount of money spent on different categories of education expenditures, and the coefficients are less precisely estimated.

since the likelihood of having any expenditures on categories like books and uniforms is not affected. The lower educational budget for children in 1995 to a large extent seems to be due to a large decrease in the probability of spending money on school uniforms, whereas more households spend money on private coaching. The reverse happens in 2007: Households are less likely to spend money on private coaching, other educational expenditures and school fees, while being substantially more likely to spend any money on school uniforms. As the last column shows, the likelihood of attending a government school is only affected in 2007: Children in 2007 are 10 percentage points more likely to attend a government school after a positive rainfall shock, partially explaining the large increase in expenditures on uniforms, whereas the estimated coefficients for earlier years are small and statistically insignificant.

Overall, Table 3 suggests that parents increasingly re-optimize expenditures on monetary educational inputs over time. By 2007, parents seem to take their children out of private schools and to send them to government schools instead, which leads to less money being spent on fees and private coaching. While such a re-optimization at the intensive margin has become much more feasible recently with a larger availability of private schools even in rural areas, it also suggests that parents are willing to carefully evaluate the best value for money for their sons' education after a rainfall shock.

At the same time, one may have expected the probability of attending a government school to decrease after a good rainfall shock. Private schools on average provide a comparable or better-quality instruction than government schools, and the payment of school fees and other costs could be more feasible than during a drought. But since monthly household expenditures and education expenditures in 2007 do not significantly increase, households have the same resources available as during times of lower rainfall. The move from private to government schools could be explained by a number of reasons, including an increased availability of government schools during times of better rainfall if teacher absenteeism is lower than during a drought, or a decrease in the quality of private schools. Since school enrollment drops while the probability of working increases, even children that remain enrolled may do some work while attending school, which may make private schools less cost effective than government schools.

To test the robustness of the school switching effect and to further analyze potential explanations for the behavior of parents, I use the DISE data for the years 2004-2015, which provides information on schools and teachers that is not available in the household survey data. Panel A of Table 4 focuses on the impact of a rainfall shock on enrollment and exam results. Columns 1 and 2 test the results for school enrollment and probability of attending a government school from Tables 2 and 3 using this dataset. The outcome variable in column 1 focuses on the number of children (boys and girls) enrolled in a district in rural areas, and shows that school enrollment decreases by about 4300 children after a positive rainfall shock. This is consistent with the results for 2007 from Table 2.

Column 2 confirms the result from Table 3 that the percentage of children enrolled in government schools in the 2000s increases after a positive rainfall shock. In the administrative data, the percent of children enrolled in government schools increases by 0.87 percentage points. This is likely to substantially underestimate the magnitude of the switching effect, since Kingdon (2017) notes that many private schools are not captured in the DISE dataset.

Columns 3 and 4 focus on the percent of children that pass grade 5 and grade 8 exams, which correspond to the final grades of primary and upper primary schools, respectively. After a shock, there is a decline in the pass rates at both levels in a typical district, with the more pronounced decrease for upper primary school where the pass rate drops by 1.2 percentage points. These empirical patterns are consistent with Shah and Steinberg (2017), who find similar results using test score information from a different dataset for roughly the same time period. Enrollment and educational attainment therefore both suffer after a positive shock, while the probability of attending a government school increases.

To better understand why children could be more likely to enroll in government schools after good rainfall shocks, Panel B analyzes how rainfall shocks affect the characteristics of schools that are reported in the administrative data. Columns 1 and 2 look at the number of government and private schools that operate in a given district. After a positive shock, the number of schools in rural areas decreases by 18 government schools and 7 private schools. The remaining columns show that the probability of a school being a single classroom school or having just one teacher decreases slightly, whereas the probability of a school having a girl toilet increases by about 1 percentage point. There is no change in the likelihood of a school having fewer than 50 students.

These results suggest that some schools close during periods of better rainfall, potentially as a reaction to lower demand for schooling. The slight decrease in single-classroom and single-teacher schools and the increase in the availability of girl toilets suggest that the remaining schools are of better physical quality.

Table 5 explores proxies for the instructional quality at schools by focusing on the number of teachers and their education level. In the dataset, this information is reported separately for regular teachers and para teachers. Since the dataset does not accurately capture many private schools, these are mainly government teachers (Kingdon, 2017). Panel A reveals that the estimated coefficient for the number of regular teachers is positive but not statistically significant after a positive shock. At the intensive margin, there is a slight change in the qualifications of teachers: Teachers are about 0.6 percentage points less likely to have below secondary schooling after the shock, which is mostly driven by more teachers with secondary schooling. The qualification of teachers in government schools therefore slightly improves even though fewer children are enrolled in school. As Panel B shows, the number of para teachers also remains unchanged, and there is a slight increase in the probability that para teachers have secondary schooling.

Overall, the education background changes of teachers are small, but together with the improvement in physical quality of schools they are consistent with an increase in the instructional quality of government schools. One explanation that is consistent with all of these empirical patterns is that some parents take their children out of private schools and enroll them in government schools because the quality of government schools increases after a positive rainfall shock. With the available data it is impossible to rule out all alternative explanations, however, for example that government schools offer more flexibility for children who are working while also attending school, which make them a more attractive option for parents at this time relative to times with lower opportunity costs.

5 Extensions

The results from Tables 2 to 5 suggest that the vulnerability of children's education to rainfall shocks has changed dramatically at both the extensive and intensive margins over the last 30 years. While boys used to be enrolled in school after a positive shock, plausibly because of an increase in household expenditures, they are now less likely to enroll due to high opportunity costs of the child's time during high rainfall periods. This change has also led to an increased re-optimization of educational expenditures and to school switching from private to government schools, potentially due to a quality improvement of government schools. An interpretation consistent with the results is that parents are increasingly willing to spend money on private schools and related expenditures if that means ensuring a higher quality of education, but do not have a general preference for private over government schools if government schools provide the better value for money. For the 2000s, the qualitative patterns of the main results are robust across two different sources of education data (NSS and DISE) as well as across two different sources of rainfall data (University of Delaware and NASA).

The results so far use an overall rainfall shock variable that is equal to 1 for a positive rainfall shock, equal to -1 for a negative rainfall shock, and 0 otherwise. This makes it difficult to know whether the empirical patterns are symmetric across droughts and periods of good rainfall, or whether they are driven by a specific type of shock. Appendix Tables A.1 to A.4 therefore report analogous results for Tables 2 to 5 for two alternative rainfall shock measures: In each table, the results are re-estimated using a negative rainfall shock measure that is equal to 1 for a negative rainfall shock, and 0 otherwise, as well as an analogous positive rainfall shock variable.

The tables show that the impacts for positive and negative rainfall shocks are usually symmetric, although the positive rainfall shock effects tend to be weaker than the impacts of negative shocks. School enrollment after a negative shock declines in 1986, whereas it increases in 1995 and 2007, whereas the opposite pattern occurs after a positive shock. At the intensive margin, many of the empirical patterns are similar to Table 3: After a positive rainfall shock in 2007, for example, parents are less likely to spend any money on school fees, much more likely to spend money on school uniforms, and increasingly send their children to government schools, whereas the reverse is true after a negative shock. The results for the administrative data on enrollment, school characteristics and teachers also show similar patterns for negative and positive rainfall shocks. These results suggest that the overall effects of rainfall shocks are not just driven by a specific type of shock.

Since the main NSS results restrict the sample to boys, Tables 6 and 7 explore the impact of rainfall shocks for girls, whereas Appendix Tables A.5 and A.6 show the analogous results for the negative and positive rainfall shocks.

The tables show that the qualitative results are similar to the impact for boys, although not always as precisely estimated. The change in the impact of negative rainfall shocks on school enrollment is less pronounced than for boys, but there is a similar increase in re-optimization in education expenditures at the intensive margin in later years: As for boys, households are less likely to spend any money on school fees after a positive shock, and are more likely to send their daughter to a government school.

Appendix Table A.7 explores the heterogeneity in the estimated impacts of negative rainfall shocks on boys of different age groups. The overall impact on children aged 6 to 18 years in column 1 is driven by children of compulsory schooling age, 6-14 years. 6-10 year olds are the most affected age group in 1986 and 1995, with a decline in school enrollment of 16 percentage points in 1986, and an increase by 8 percentage points in 1995. In 2007, enrollment for both 6-10 and 11-14 year old children increases by 8 percentage points. The oldest children in the sample are more likely to be enrolled in school even in 1986, suggesting that older children in 1986 were insulated from the negative household shock at the expense of younger children.

6 Conclusion

This paper analyzed the impact of rainfall shocks on the education of Indian children in rural areas at both the extensive and intensive margins. At the extensive margin, school enrollment has moved from being positively affected by higher rainfall to being negatively affected over the last 30 years, plausibly because the importance of credit constraints has been declining while the opportunity costs of the child's time have been increasing. More recently, households increasingly take advantage of their ability to re-optimize education at the intensive margin with respect to school type and category-wise educational expenditures. Some evidence suggests that changes in school type are at least partially driven by changes in the quality of government relative to private schools. The effects are largely symmetric after good and bad rainfall shocks, although absolute magnitudes tend to be larger for negative rainfall shocks.

The analysis is limited by the unavailability of higher-frequency comprehensive data on school quality and the systematic undercounting of private schools in the administrative datasets. Changes in the annual number of schools and school teachers, for example, cannot account for temporary school closures or teacher absenteeism as a reaction to the temporary rainfall shocks. This suggests that the changes in school quality due to rainfall shocks estimated in this paper are likely to be a lower bound for broader changes in school quality.

With the mushrooming of private schools in developing countries in recent years, which are typically able to provide better learning outcomes in more cost-effective ways than government schools, it is tempting for governments to increasingly leave the responsibility for education to parents and the private sector. But the results suggest that reforms of the public education sector remain worthwhile: At least in India, government schools continue to play an important role, and a high school quality that is unaffected by weather shocks would help reduce inequality and improve learning outcomes.

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Table 1: Summary Statistics (Boys 6-18 Years)

	1986	1995	2007
enrollment	0.3382	0.7274	0.7573
N	55,703	42,135	41,521
per-capita expenditures	113.30	326.37	620.82
N	55,703	42,135	41,521
education expenditures	253.34	667.18	1718.47
N	36,496	30,359	30,937
government school	0.8307	0.8232	0.7759
N	36,600	30,615	30,960
negative rainfall shock	0.3830	0.1206	0.0223
N	55,780	42,164	41,534
positive rainfall shock	0.1093	0.2438	0.4087
N	55,780	42,164	41,534

Note: NSS data. Sample restricted to boys of 6-18 years in rural areas. Per-capita expenditures are monthly expenditures in rupees, education expenditures are annual expenditures. Government school refers to the proportion of enrolled children going to government rather than private schools. Negative rainfall shock indicator variable is equal to 1 if rainfall is below the 20th percentile in the district and 0 otherwise. Positive rainfall shock indicator variable is equal to 1 if rainfall is above the 80th percentile in the district, and 0 otherwise.

Table 2: Impact of Rainfall Shock on Household Expenditures, Work and Transportation (Boys 6-18 Years)

	enroll-ment	log per-cap exp	foot	school bus	public transport	work
rainfall shock	0.0598***	0.0316*	-0.0150**	0.0069***	0.0110***	0.0113*
	(0.0125)	(0.0166)	(0.0067)	(0.0022)	(0.0037)	(0.0064)
rainfall shock x 1995	-0.0631***	-0.0161	0.0148	-0.0099***	-0.0138**	-0.0184*
	(0.0157)	(0.0228)	(0.0093)	(0.0029)	(0.0061)	(0.0096)
rainfall shock x 2007	-0.0889***	-0.0203	-0.0067	-0.0132***	-0.0044	0.0054
	(0.0169)	(0.0246)	(0.0117)	(0.0042)	(0.0061)	(0.0112)
rainfall shock 1995	-0.0034	0.0155	-0.0002	-0.0030	-0.0027	-0.0071
F-statistic 1995	0.7508	0.2901	0.9825	0.1805	0.5669	0.3481
rainfall shock 2007	-0.0291***	0.0113	-0.0216**	-0.0063	0.0067	0.0167**
F-statistic 2007	0.0072	0.5590	0.0358	0.1211	0.2176	0.0447
N	139,359	139,359	98,054	98,054	98,054	139,359
R-squared	0.1824	0.7453	0.1979	0.0338	0.1244	0.1333
outcome mean	0.5808	5.4557	0.8369	0.0132	0.0515	0.2655

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$ An observation is a child (boy 6-18 years) living in rural areas. Foot, school bus and public transport are indicator variables equal to 1 if a child uses a given mode of transport, and 0 otherwise. The omitted variable not reported here is other transport. Work is equal to 1 if a child works, whether doing domestic work, work for pay or self-employment, and 0 otherwise. Rainfall shock variable is equal to 1 for a positive rainfall shock (above 80th percentile in the district), -1 for a negative rainfall shock (below 20th percentile in the district), and 0 otherwise. Table first reports the main effect for 1986 and the interaction effects for the shock in 1995 and 2007. It then reports the sum of main and interaction effects for 1995 and 2007 and the F statistic from the test that this combined effect is 0.

Table 3: Impact of Rainfall Shock on Education Expenditures (Boys 6-18 Years)

	log educ exp	any fees	any books	any uniforms	any transport	any coaching	any other	gov school
rainfall shock	-0.0355	0.0107*	0.0039	-0.0081	-0.0035	0.0686***	-0.0036	-0.0073
	(0.0373)	(0.0055)	(0.0030)	(0.0285)	(0.0094)	(0.0158)	(0.0213)	(0.0132)
rainfall shock x 1995	-0.0315	-0.0103*	-0.0041	-0.0787***	0.0074	-0.0306	0.0224	-0.0052
	(0.0477)	(0.0053)	(0.0034)	(0.0301)	(0.0110)	(0.0196)	(0.0265)	(0.0171)
rainfall shock x 2007	0.0421	-0.0412**	-0.0011	0.1631***	0.0014	-0.1104***	-0.0296	0.1120***
	(0.0605)	(0.0175)	(0.0041)	(0.0381)	(0.0220)	(0.0269)	(0.0310)	(0.0236)
rainfall shock 1995	-0.0669**	0.0005	-0.0001	-0.0867***	0.0040	0.0380***	0.0188	-0.0125
F-statistic 1995	0.0212	0.6310	0.9431	0.0000	0.5946	0.0028	0.3348	0.3108
rainfall shock 2007	0.0066	-0.0305**	0.0028	0.1550***	-0.0021	-0.0418**	-0.0332*	0.1047***
F-statistic 2007	0.8802	0.0175	0.1634	0.0000	0.9076	0.0401	0.0780	0.0000
N	97,792	43,906	79,536	73,534	43,698	46,944	68,612	98,175
R-squared	0.5841	0.1057	0.1003	0.5334	0.6794	0.6219	0.4561	0.1752
outcome mean	5.7925	0.9987	0.9881	0.7232	0.2186	0.3212	0.7031	0.8111

Note: *** p<0.01, ** p<0.05, * p<0.1 An observation is a child (boy 6-18 years) living in rural areas. Log educ exp refers to log annual educational expenditures. Outcome variables starting with ‘any’ are indicator variables equal to 1 if a household spends any money on the child’s education in that specific category, and 0 otherwise. Gov school is an indicator variable equal to 1 if an enrolled child goes to a government school rather than a private school. Rainfall shock variable is equal to 1 for a positive rainfall shock (above 80th percentile in the district), -1 for a negative rainfall shock (below 20th percentile in the district), and 0 otherwise. Table first reports the main effect for 1986 and the interaction effects for the shock in 1995 and 2007. It then reports the sum of main and interaction effects for 1995 and 2007 and the F statistic from the test that this combined effect is 0.

Table 4: Impact of Rainfall Shock on Enrollment and School Outcomes (DISE data)

	Panel A: Enrollment and Exam Results			
	rural enrollment	percent gov enrollment	grade 5 passed	grade 8 passed
rainfall shock	-4303.89**	0.0087***	-0.5464*	-1.2385***
	(2082.30)	(0.0030)	(0.3127)	(0.3548)
N	7,938	7,857	3,686	3,686
R-squared	0.6312	0.7178	0.3935	0.5981
outcome mean	225528.8	0.7571	93.7732	88.1179

	Panel B: School Characteristics					
	rural gov. school	rural priv. school	single classroom	single teacher	girl toilet	below 50 students
rainfall shock	-18.09**	-6.72***	-0.0027**	-0.0032***	0.0105***	-0.0004
	(8.96)	(2.01)	(0.0012)	(0.0012)	(0.0038)	(0.0016)
N	8,032	7,962	7,970	7,970	7,970	7,650
R-squared	0.9067	0.8312	0.7641	0.7446	0.8192	0.9110
outcome mean	1495.534	259.67	0.0622	0.0951	0.6698	0.2960

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$ An observation is a district in a given year (2004-2015). Rural enrollment refers to the number of enrolled children (boys and girls), percent gov enrollment to the percent of children enrolled in government schools. Grade 5 passed and grade 8 passed are the percent of children who pass grade 5 (last year of primary school) and grade 8 (last year of upper primary school, respectively). Rural gov. school and rural priv. school refer to the number of government and private schools in rural areas. The remaining outcome variables are indicator variables equal to 1 for a school that has the given characteristic, and 0 otherwise. Rainfall shock variable is equal to 1 for a positive rainfall shock (above 80th percentile in the district), -1 for a negative rainfall shock (below 20th percentile in the district), and 0 otherwise.

Table 5: Impact of Rainfall Shock on Teacher Qualification

	Panel A: Regular Teachers							
	number	below secondary	secondary	higher secondary	graduate	postgraduate	M.Phil	other
rainfall shock	49.25	-0.0055***	0.0069***	-0.0023	-0.0007	0.0007	0.0001	0.0007***
	(81.77)	(0.0009)	(0.0014)	(0.0016)	(0.0014)	(0.0015)	(0.0002)	(0.0001)
N	7,651	7,650	7,650	7,650	7,650	7,650	7,650	7,650
R-squared	0.7257	0.5240	0.7580	0.6465	0.6982	0.7653	0.5737	0.3278
outcome mean	8715.435	0.0276	0.1487	0.2356	0.3630	0.2145	0.0080	0.0025
	Panel B: Para Teachers							
	number	below secondary	secondary	higher secondary	graduate	postgraduate	M.Phil	other
rainfall shock	-8.60	-0.0009	0.0064**	-0.0004	-0.0044	-0.0016	0.0003	0.0007
	(28.74)	(0.0019)	(0.0028)	(0.0031)	(0.0033)	(0.0028)	(0.0005)	(0.0004)
N	7,650	7,156	7,156	7,156	7,156	7,156	7,156	7,156
R-squared	0.4200	0.3717	0.3479	0.4676	0.3605	0.5590	0.2750	0.1831
outcome mean	1023.992	0.0321	0.1073	0.2810	0.3895	0.1787	0.0080	0.0034

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$ An observation is a district in a given year (2004-2015). In each panel, number refers to the number of teachers, and the remaining outcome variables give the proportion of teachers who have a given level of education. Regular teachers have long-term contracts, earn a higher wage and are backed by teacher unions, whereas para teachers are contract teachers with substantially lower wages. Rainfall shock variable is equal to 1 for a positive rainfall shock (above 80th percentile in the district), -1 for a negative rainfall shock (below 20th percentile in the district), and 0 otherwise.

Table 6: Impact of Rainfall Shock on Household Expenditures, Work and Transportation (Girls 6-18 Years)

	enroll-ment	log per-cap exp	foot	school bus	public transport	work
rainfall shock	0.0420*	0.0312*	-0.0259***	0.0101***	0.0214***	-0.0006
	(0.0244)	(0.0167)	(0.0071)	(0.0030)	(0.0045)	(0.0085)
rainfall shock x 1995	-0.1279***	-0.0273	0.0234***	-0.0142***	-0.0232***	0.0079
	(0.0305)	(0.0223)	(0.0089)	(0.0034)	(0.0065)	(0.0123)
rainfall shock x 2007	-0.0435	-0.0212	0.0066	-0.0135***	-0.0166**	0.0381**
	(0.0292)	(0.0260)	(0.0108)	(0.0041)	(0.0065)	(0.0148)
rainfall shock 1995	-0.0858***	0.0039	-0.0025	-0.0041	-0.0018	0.0073
F-statistic 1995	0.0001	0.7776	0.7144	0.1572	0.7069	0.3964
rainfall shock 2007	-0.0014	0.0099	-0.0193*	-0.0034	0.0049	0.0375***
F-statistic 2007	0.9248	0.6165	0.0539	0.4385	0.3625	0.0043
N	114,228	114,228	61,926	61,926	61,926	114,228
R-squared	0.0461	0.7475	0.1729	0.0405	0.1533	0.2578
outcome mean	0.6113	5.4613	0.8853	0.0141	0.0523	0.4345

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$ An observation is a child (girl 6-18 years) living in rural areas. Foot, school bus and public transport are indicator variables equal to 1 if a child uses a given mode of transport, and 0 otherwise. The omitted variable not reported here is other transport. Work is equal to 1 if a child works, whether doing domestic work, work for pay or self-employment, and 0 otherwise. Rainfall shock variable is equal to 1 for a positive rainfall shock (above 80th percentile in the district), -1 for a negative rainfall shock (below 20th percentile in the district), and 0 otherwise. Table first reports the main effect for 1986 and the interaction effects for the shock in 1995 and 2007. It then reports the sum of main and interaction effects for 1995 and 2007 and the F statistic from the test that this combined effect is 0.

Table 7: Impact of Rainfall Shock on Education Expenditures (Girls 6-18 Years)

	log educ exp	any fees	any books	any uniforms	any transport	any coaching	any other	gov school
rainfall shock	-0.0587	0.0147*	-0.0009	0.0020	0.0004	0.0513**	0.0065	-0.0142
	(0.0425)	(0.0076)	(0.0040)	(0.0312)	(0.0131)	(0.0200)	(0.0222)	(0.0137)
rainfall shock x 1995	-0.0113	-0.0129*	-0.0003	-0.0585*	0.0169	-0.0118	0.0124	0.0073
	(0.0506)	(0.0071)	(0.0041)	(0.0325)	(0.0154)	(0.0246)	(0.0276)	(0.0177)
rainfall shock x 2007	0.1416**	-0.0407**	0.0055	0.1313***	-0.0078	-0.0877***	-0.0266	0.1165***
	(0.0663)	(0.0164)	(0.0054)	(0.0396)	(0.0243)	(0.0322)	(0.0319)	(0.0234)
rainfall shock 1995	-0.0699**	0.0017	-0.0012	-0.0565***	0.0174	0.0396**	0.0189	-0.0069
F-statistic 1995	0.0169	0.4439	0.6047	0.0011	0.1027	0.0211	0.3034	0.5425
rainfall shock 2007	0.0829*	-0.0260**	0.0046**	0.1333***	-0.0074	-0.0363	-0.0201	0.1022***
F-statistic 2007	0.0779	0.0153	0.0465	0.0000	0.7125	0.1114	0.2744	0.0000
N	61,696	22,593	45,962	44,739	22,613	25,666	40,530	61,996
R-squared	0.5920	0.0147	0.1246	0.5195	0.7531	0.6948	0.5085	0.1703
outcome mean	5.7433	0.9983	0.9884	0.7781	0.2219	0.3423	0.7304	0.8243

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$ An observation is a child (girl 6-18 years) living in rural areas. Log educ exp refers to log annual educational expenditures. Outcome variables starting with 'any' are indicator variables equal to 1 if a household spends any money on the child's education in that specific category, and 0 otherwise. Gov school is an indicator variable equal to 1 if an enrolled child goes to a government school rather than a private school. Rainfall shock variable is equal to 1 for a positive rainfall shock (above 80th percentile in the district), -1 for a negative rainfall shock (below 20th percentile in the district), and 0 otherwise. Table first reports the main effect for 1986 and the interaction effects for the shock in 1995 and 2007. It then reports the sum of main and interaction effects for 1995 and 2007 and the F statistic from the test that this combined effect is 0.

AppendixA Additional Tables

Table A.1: Impact of Rainfall Shock on Household Expenditures, Work and Transportation (Boys 6-18 Years)

	Panel A: Negative Rainfall Shock (6-18 Years)					
	enroll-ment	log per-cap exp	foot	school bus	public transport	work
rainfall shock	-0.0696***	-0.0476**	0.0197*	-0.0094***	-0.0192***	-0.0161**
	(0.0168)	(0.0218)	(0.0100)	(0.0034)	(0.0051)	(0.0082)
rainfall shock x 1995	0.1076***	0.0642*	0.0020	0.0012	0.0259***	0.0136
	(0.0247)	(0.0345)	(0.0137)	(0.0041)	(0.0097)	(0.0147)
rainfall shock x 2007	0.1476***	0.0169	-0.0029	0.0262**	0.0029	0.0115
	(0.0326)	(0.0493)	(0.0220)	(0.0122)	(0.0146)	(0.0237)
rainfall shock 1995	0.0380*	0.0166	0.0217*	-0.0082*	0.0067	-0.0025
F-statistic 1995	0.0741	0.5534	0.0769	0.0528	0.4349	0.8486
rainfall shock 2007	0.0780***	-0.0307	0.0168	0.0168	-0.0163	-0.0047
F-statistic 2007	0.0021	0.4560	0.3651	0.1444	0.2167	0.8269
N	139,359	139,359	98,054	98,054	98,054	139,359
R-squared	0.1822	0.7454	0.1978	0.0338	0.1246	0.1333
outcome mean	0.5808	5.4557	0.8369	0.0132	0.0515	0.2655
	Panel B: Positive Shock (6-18 Years)					
	enroll-ment	log per-cap exp	foot	school bus	public transport	work
rainfall shock	0.0784***	0.0123	-0.0220**	0.0062**	-0.0032	0.0122
	(0.0266)	(0.0362)	(0.0107)	(0.0026)	(0.0060)	(0.0143)
rainfall shock x 1995	-0.0650**	0.0285	0.0324**	-0.0177***	0.0029	-0.0253
	(0.0303)	(0.0415)	(0.0145)	(0.0043)	(0.0088)	(0.0182)
rainfall shock x 2007	-0.1020***	-0.0010	-0.0038	-0.0112**	0.0094	0.0075
	(0.0292)	(0.0423)	(0.0145)	(0.0051)	(0.0080)	(0.0178)
rainfall shock 1995	0.0134	0.0408**	0.0103	-0.0115***	-0.0002	-0.0131
F-statistic 1995	0.3099	0.0400	0.3253	0.0003	0.9683	0.1977
rainfall shock 2007	-0.0236*	0.0113	-0.0259**	-0.0050	0.0062	0.0197**
F-statistic 2007	0.0539	0.6087	0.0302	0.2894	0.3181	0.0333
N	139,359	139,359	98,054	98,054	98,054	139,359
R-squared	0.1815	0.7453	0.1979	0.0338	0.1241	0.1333
outcome mean	0.5808	5.4557	0.8369	0.0132	0.0515	0.2655

Note: *** p<0.01, ** p<0.05, * p<0.1 An observation is a child (boy 6-18 years) living in rural areas. Foot, school bus and public transport are indicator variables equal to 1 if a child uses a given mode of transport, and 0 otherwise. The omitted variable not reported here is other transport. Work is equal to 1 if a child works, whether doing domestic work, work for pay or self-employment, and 0 otherwise. Table first reports the main effect for 1986 and the interaction effects for the shock in 1995 and 2007. It then reports the sum of main and interaction effects for 1995 and 2007 and the F statistic from the test that this combined effect is 0.

Table A.2: Impact of Rainfall Shock on Education Expenditures (Boys 6-18 Years)

	Panel A: Negative Rainfall Shock (6-18 Years)							
	log educ exp	any fees	any books	any uniforms	any transport	any coaching	any other	gov school
rainfall shock	0.0145	-0.0083	-0.0064	0.0110	-0.0026	-0.1024***	-0.0008	-0.0004
	(0.0475)	(0.0057)	(0.0042)	(0.0334)	(0.0136)	(0.0227)	(0.0281)	(0.0175)
rainfall shock x 1995	0.1273**	0.0066	0.0047	0.0797**	-0.0109	0.0597*	0.0601	-0.0008
	(0.0646)	(0.0046)	(0.0050)	(0.0379)	(0.0163)	(0.0328)	(0.0386)	(0.0266)
rainfall shock x 2007	-0.0487	0.0229**	0.0009	-0.2713***	0.0713**	0.2251***	0.0893	-0.0635**
	(0.0946)	(0.0117)	(0.0056)	(0.0509)	(0.0276)	(0.0532)	(0.0573)	(0.0320)
rainfall shock 1995	0.1418***	-0.0017	-0.0018	0.0908***	-0.0135	-0.0427*	0.0594*	-0.0012
F-statistic 1995	0.0051	0.3284	0.6228	0.0010	0.2820	0.0585	0.0588	0.9589
rainfall shock 2007	-0.0342	0.0147**	-0.0055*	-0.2603***	0.0687***	0.1227***	0.0885**	-0.0639***
F-statistic 2007	0.6609	0.0189	0.0983	0.0000	0.0002	0.0061	0.0497	0.0045
N	97,792	43,906	79,536	73,534	43,698	46,944	68,612	98,175
R-squared	0.5841	0.0891	0.1003	0.5286	0.6795	0.6218	0.4563	0.1712
outcome mean	5.7925	0.9987	0.9881	0.7232	0.2186	0.3212	0.7031	0.8111

	Panel B: Positive Rainfall Shock (6-18 Years)							
	log educ exp	any fees	any books	any uniforms	any transport	any coaching	any other	gov school
rainfall shock	-0.1403*	0.0103	0.0006	0.0541	-0.0223	0.0686*	-0.0325	-0.0093
	(0.0747)	(0.0120)	(0.0046)	(0.0744)	(0.0158)	(0.0369)	(0.0433)	(0.0292)
rainfall shock x 1995	0.0975	-0.0105	-0.0016	-0.1511**	-0.0078	-0.0079	0.1059**	-0.0043
	(0.0875)	(0.0122)	(0.0052)	(0.0737)	(0.0184)	(0.0438)	(0.0516)	(0.0347)
rainfall shock x 2007	0.1319	-0.0442**	0.0023	0.0944	0.0256	-0.1032**	0.0009	0.1251***
	(0.0907)	(0.0185)	(0.0051)	(0.0778)	(0.0252)	(0.0414)	(0.0469)	(0.0385)
rainfall shock 1995	-0.0428	-0.0002	-0.0010	-0.0970***	0.0005	0.0609**	0.0734***	-0.0136
F-statistic 1995	0.2955	0.8321	0.7285	0.0001	0.9647	0.0102	0.0055	0.4296
rainfall shock 2007	-0.0084	-0.0339**	0.0029	0.1485***	0.0033	-0.0345	-0.0316	0.1158***
F-statistic 2007	0.8656	0.0190	0.1883	0.0000	0.8718	0.1754	0.1308	0.0000
N	97,792	43,906	79,536	73,534	43,698	46,944	68,612	98,175
R-squared	0.5841	0.1045	0.1002	0.5318	0.6795	0.6210	0.4568	0.1754
outcome mean	5.7925	0.9987	0.9881	0.7232	0.2186	0.3212	0.7031	0.8111

Note: *** p<0.01, ** p<0.05, * p<0.1 An observation is a child (boy 6-18 years) living in rural areas. Table first reports the main effect for 1986 and the interaction effects for the shock in 1995 and 2007. It then reports the sum of main and interaction effects for 1995 and 2007 and the F statistic from the test that this combined effect is 0.

Table A.3: Impact of Rainfall Shock on Enrollment and School Outcomes (Overall Shock, DISE data)

	Panel A: Enrollment and Exam Results					
	rural enrollment	percent gov enrollment	grade V passed	grade VIII passed		
neg. rainfall shock	7376.15**	-0.0075*	0.5854	1.5868***		
	(3312.53)	(0.0039)	(0.4943)	(0.5827)		
N	7,938	7,857	3,686	3,686		
R-squared	0.7178	0.6321	0.3932	0.5978		
outcome mean	225528.8	0.7571	93.7732	88.1179		
pos. rainfall shock	-2162.46	0.0138**	-0.7208	-1.3169**		
	(3083.71)	(0.0055)	(0.4873)	(0.5441)		
N	7,938	7,857	3,686	3,686		
R-squared	0.7176	0.6323	0.3933	0.5973		
outcome mean	225528.8	0.7571	93.7732	88.1179		
	Panel B: School Characteristics					
	rural gov. school	rural priv. school	single classroom	single teacher	girl toilet	below 50 students
neg. rainfall shock	35.21***	15.7935***	0.0059***	0.0027	-0.0127**	0.0017
	(11.2804)	(3.5037)	(0.0021)	(0.0020)	(0.0054)	(0.0022)
N	8,032	7,962	7,970	7,970	7,970	7,650
R-squared	0.9069	0.8313	0.7643	0.7444	0.8191	0.9111
outcome mean	1495.534	259.67	0.0622	0.0951	0.6698	0.2960
pos. rainfall shock	-3.8699	1.6898	0.0002	-0.0051***	0.0118**	0.0010
	(16.9640)	(3.1921)	(0.0018)	(0.0017)	(0.0058)	(0.0023)
N	8,032	7,962	7,970	7,970	7,970	7,650
R-squared	0.9067	0.8310	0.7640	0.7446	0.8191	0.9111
outcome mean	1495.534	259.67	0.0622	0.0951	0.6698	0.2960

Note: *** p<0.01, ** p<0.05, * p<0.1 An observation is a district in a given year (2004-2015). Rural enrollment refers to the number of enrolled children (boys and girls), percent gov enrollment to the percent of children enrolled in government schools. Grade 5 passed and grade 8 passed are the percent of children who pass grade 5 (last year of primary school) and grade 8 (last year of upper primary school, respectively). Rural gov. school and rural priv. school refer to the number of government and private schools in rural areas. The remaining outcome variables are indicator variables equal to 1 for a school that has the given characteristic, and 0 otherwise.

Table A.4: Impact of Rainfall Shock on Teacher Qualification (Overall Shock)

	Panel A: Regular Teachers							
	number	below secondary	secondary	higher secondary	graduate	postgraduate	M.Phil	other
neg. rainfall shock	-192.22	0.0064***	-0.0062***	0.0025	-0.0009	-0.0006	-0.0002	-0.0010***
	(140.58)	(0.0014)	(0.0021)	(0.0030)	(0.0023)	(0.0025)	(0.0003)	(0.0002)
N	7,651	7,650	7,650	7,650	7,650	7,650	7,650	7,650
R-squared	0.7259	0.5222	0.7575	0.6465	0.6982	0.7653	0.5756	0.3277
outcome mean	8715.435	0.0276	0.1487	0.2356	0.3630	0.2145	0.0080	0.0025
pos. rainfall shock	-98.60	-0.0065***	0.0104***	-0.0029	-0.0029	0.0012	0.0000	0.0007
	(104.15)	(0.0010)	(0.0024)	(0.0019)	(0.0019)	(0.0019)	(0.0003)	(0.0002)
N	7,651	7,650	7,650	7,650	7,650	7,650	7,650	7,650
R-squared	0.7258	0.5219	0.7578	0.6465	0.6983	0.7653	0.5755	0.3260
outcome mean	8715.435	0.0276	0.1487	0.2356	0.3630	0.2145	0.0080	0.0025
	Panel B: Para Teachers							
	number	below secondary	secondary	higher secondary	graduate	postgraduate	M.Phil	other
neg. rainfall shock	60.60	0.0017	-0.0075*	0.0001	0.0039	0.0031	-0.0005	-0.0008
	(44.94)	(0.0027)	(0.0044)	(0.0051)	(0.0049)	(0.0041)	(0.0006)	(0.0006)
N	7,650	7,156	7,156	7,156	7,156	7,156	7,156	7,156
R-squared	0.4203	0.3717	0.3477	0.4676	0.3602	0.5587	0.2747	0.1823
outcome mean	1023.992	0.0321	0.1073	0.2810	0.3895	0.1787	0.0080	0.0034
pos. rainfall shock	49.48	-0.0003	0.0076*	-0.0009	-0.0068	-0.0004	0.0000	0.0008
	(39.71)	(0.0029)	(0.0044)	(0.0052)	(0.0055)	(0.0042)	(0.0009)	(0.0007)
N	7,650	7,156	7,156	7,156	7,156	7,156	7,156	7,156
R-squared	0.4202	0.3716	0.3476	0.4676	0.3603	0.5587	0.2746	0.1822
outcome mean	1023.992	0.0321	0.1073	0.2810	0.3895	0.1787	0.0080	0.0034

Note: *** p<0.01, ** p<0.05, * p<0.1 An observation is a district in a given year (2004-2015). In each panel, number refers to the number of teachers, and the remaining outcome variables give the proportion of teachers who have a given level of education. Regular teachers have long-term contracts, earn a higher wage and are backed by teacher unions, whereas para teachers are contract teachers with substantially lower wages.

Table A.5: Impact of Rainfall Shock on Household Expenditures, Work and Transportation (Girls 6-18 Years)

	Panel A: Negative Rainfall Shock (6-18 Years)					
	enroll-ment	log per-cap exp	foot	school bus	public transport	work
rainfall shock	-0.0372	-0.0536**	0.0306***	-0.0132***	-0.0292***	0.0047
	(0.0327)	(0.0220)	(0.0111)	(0.0047)	(0.0062)	(0.0124)
rainfall shock x 1995	0.3141***	0.0859**	-0.0100	0.0058	0.0303***	-0.0398**
	(0.0467)	(0.0333)	(0.0133)	(0.0049)	(0.0100)	(0.0177)
rainfall shock x 2007	0.0692	0.0392	-0.0125	0.0267**	0.0248	-0.0820**
	(0.0573)	(0.0540)	(0.0236)	(0.0122)	(0.0162)	(0.0409)
rainfall shock 1995	0.1646***	0.0323	0.0206*	-0.0074	0.0011	-0.0350***
F-statistic 1995	0.0000	0.1996	0.0.0902	0.1629	0.9009	0.0067
rainfall shock 2007	0.0319	-0.0144	0.0181	0.0135	-0.0045	-0.0773**
F-statistic 2007	0.4323	0.7597	0.3695	0.2289	0.7565	0.0423
N	114,228	114,228	61,926	61,926	61,926	114,228
R-squared	0.0461	0.7477	0.1726	0.0404	0.1534	0.2577
outcome mean	0.6113	5.4613	0.8853	0.0141	0.0523	0.4345
	Panel B: Positive Shock (6-18 Years)					
	enroll-ment	log per-cap exp	foot	school bus	public transport	work
rainfall shock	0.0846*	-0.0060	-0.0456***	0.0127***	0.0194**	0.0195
	(0.0508)	(0.0339)	(0.0098)	(0.0039)	(0.0086)	(0.0165)
rainfall shock x 1995	-0.1510***	0.0348	0.0534***	-0.0275***	-0.0219**	-0.0224
	(0.0543)	(0.0392)	(0.0143)	(0.0057)	(0.0110)	(0.0207)
rainfall shock x 2007	-0.0862	0.0166	0.0207	-0.0141**	-0.0123	0.0188
	(0.0532)	(0.0412)	(0.0133)	(0.0056)	(0.0099)	(0.0216)
rainfall shock 1995	-0.0664**	0.0287	0.0077	-0.0147***	-0.0025	-0.0030
F-statistic 1995	0.0168	0.1163	0.4568	0.0003	0.6838	0.8113
rainfall shock 2007	-0.0016	0.0106	-0.0249**	-0.0014	0.0071	0.0383***
F-statistic 2007	0.9187	0.6393	0.0381	0.7976	0.2650	0.0096
N	114,228	114,228	61,926	61,926	61,926	114,228
R-squared	0.0444	0.7475	0.1727	0.0338	0.1527	0.2578
outcome mean	0.6113	5.4613	0.8853	0.0141	0.0523	0.4345

Note: *** p<0.01, ** p<0.05, * p<0.1 An observation is a child (girl 6-18 years) living in rural areas. Foot, school bus and public transport are indicator variables equal to 1 if a child uses a given mode of transport, and 0 otherwise. The omitted variable not reported here is other transport. Work is equal to 1 if a child works, whether doing domestic work, work for pay or self-employment, and 0 otherwise. Table first reports the main effect for 1986 and the interaction effects for the shock in 1995 and 2007. It then reports the sum of main and interaction effects for 1995 and 2007 and the F statistic from the test that this combined effect is 0.

Table A.6: Impact of Rainfall Shock on Education Expenditures (Girls 6-18 Years)

	log educ exp	any fees	any books	any uniforms	any transport	any coaching	any other	gov school
	Panel A: Negative Rainfall Shock (6-18 Years)							
rainfall shock	0.0574	-0.0070	-0.0018	0.0063	-0.0071	-0.0719**	-0.0295	-0.0062
	(0.0584)	(0.0063)	(0.0056)	(0.0359)	(0.0200)	(0.0289)	(0.0290)	(0.0174)
rainfall shock x 1995	0.0570	0.0098	0.0005	0.0691*	-0.0296	0.0164	0.0615	0.0172
	(0.0702)	(0.0072)	(0.0053)	(0.0406)	(0.0250)	(0.0413)	(0.0390)	(0.0278)
rainfall shock x 2007	-0.1972*	0.0229**	-0.0080	-0.2536***	0.0892**	0.1723***	0.1546**	-0.0735*
	(0.1159)	(0.0107)	(0.0074)	(0.0559)	(0.0397)	(0.0505)	(0.0600)	(0.0378)
rainfall shock 1995	0.1144**	0.0028	-0.0013	0.0755***	-0.0367**	-0.0556**	0.0320	0.0110
F-statistic 1995	0.0339	0.5008	0.7824	0.0092	0.0366	0.0294	0.2836	0.5991
rainfall shock 2007	-0.1398	0.0159***	-0.0098***	-0.2473***	0.0821***	0.1003***	0.1250***	-0.0797***
F-statistic 2007	0.1421	0.0037	0.0026	0.0000	0.0009	0.0033	0.0078	0.0084
N	61,696	22,593	45,962	44,739	22,613	25,014	40,530	61,996
R-squared	0.5919	0.1119	0.1246	0.5161	0.7532	0.6945	0.5091	0.1660
outcome mean	5.7433	0.9983	0.9884	0.7781	0.2219	0.3423	0.7304	0.8243
	Panel B: Positive Rainfall Shock (6-18 Years)							
	log educ exp	any fees	any books	any uniforms	any transport	any coaching	any other	gov school
rainfall shock	-0.0969	0.0252	-0.0073	0.0874	-0.0181	0.0582	-0.0647	-0.0510*
	(0.0733)	(0.0214)	(0.0066)	(0.0797)	(0.0230)	(0.0428)	(0.0452)	(0.0302)
rainfall shock x 1995	0.0475	-0.0237	0.0045	-0.1314*	0.0283	-0.0077	0.1337***	0.0607*
	(0.0888)	(0.0220)	(0.0073)	(0.0802)	(0.0307)	(0.0504)	(0.0510)	(0.0356)
rainfall shock x 2007	0.1668*	-0.0507*	0.0114	0.0387	0.0185	-0.0869*	0.0541	0.1605***
	(0.0880)	(0.0265)	(0.0072)	(0.0826)	(0.0343)	(0.0507)	(0.0509)	(0.0387)
rainfall shock 1995	-0.0494	0.0015	-0.0029	-0.0469**	0.0102	0.0505	0.0690***	0.0096
F-statistic 1995	0.2647	0.7187	0.3366	0.0465	0.5846	0.1025	0.0053	0.5503
rainfall shock 2007	0.0699	-0.0255**	0.0040*	0.1261***	0.0004	-0.0287	-0.0106	0.1095***
F-statistic 2007	0.1885	0.0314	0.0990	0.0000	0.9868	0.3258	0.5946	0.0000
N	61,696	22,593	45,962	44,739	22,613	25,666	40,530	61,996
R-squared	0.5919	0.1208	0.1247	0.5180	0.7530	0.6957	0.5093	0.1706
outcome mean	5.7433	0.9983	0.9884	0.7781	0.2219	0.3423	0.7304	0.8243

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$ An observation is a child (girl 6-18 years) living in rural areas. Table first reports the main effect for 1986 and the interaction effects for the shock in 1995 and 2007. It then reports the sum of main and interaction effects for 1995 and 2007 and the F statistic from the test that this combined effect is 0.

Table A.7: Impact of Rainfall Shock on School Enrollment (Boys 6-18 Years)

	Negative Rainfall Shock			
	enrollment (6-18 years)	enrollment (6-10 years)	enrollment (11-14 years)	enrollment (15-18 years)
rainfall shock	-0.0696***	-0.1605***	-0.0662***	0.0483**
	(0.0168)	(0.0299)	(0.0161)	(0.0221)
rainfall shock x 1995	0.1076***	0.2361***	0.0934***	-0.0404
	(0.0247)	(0.0427)	(0.0238)	(0.0330)
rainfall shock x 2007	0.1476***	0.2405***	0.1445***	0.0535
	(0.0326)	(0.0514)	(0.0416)	(0.0443)
rainfall shock 1995	0.0380*	0.0756**	0.0272	0.0080
F-statistic 1995	0.0741	0.0464	0.1410	0.7801
rainfall shock 2007	0.0780***	0.0800**	0.0783**	0.1019***
F-statistic 2007	0.0021	0.0249	0.0312	0.0048
N	139,359	54,069	45,161	40,129
R-squared	0.1822	0.2452	0.4135	0.0324
outcome mean	0.5808	0.6324	0.5810	0.5110

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$ An observation is a child (boy 6-18 years) living in rural areas. Table first reports the main effect for 1986 and the interaction effects for the shock in 1995 and 2007. It then reports the sum of main and interaction effects for 1995 and 2007 and the F statistic from the test that this combined effect is 0. Negative rainfall shock is equal to 1 if rainfall is below 20th percentile in the district, and zero otherwise.