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No rain no gain – how reduced rainfall impacts on children's school attendance in Uganda

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Abstract

The increasing frequency of negative rainfall shocks presents households with a challenge of whether to send their children to school or withdraw them, in order to provide shock-coping support in the household. We use high-resolution spatial rainfall data matched with geo-referenced Uganda National Panel Survey data to estimate the effect of negative rainfall shocks on children's school attendance. We find that exposure to negative rainfall shocks reduces children's school attendance by almost 10%. These results have important policy implications for improving children's schooling in Uganda, particularly in geographical areas that receive highly erratic levels of rainfall.

Keywords

Rainfall shocks, children's school attendance, Uganda

JEL Codes

H52, H75, I21

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1. Introduction

Over the past three decades global efforts to promote children's education in developing countries has increased, as manifested initially through, for example, Millennium Development Goal Two (MDG 2) and, more recently, Sustainable Development Goal Four (SDG 4). These goals seek to promote children's school enrolment and attendance by addressing challenges such as the lack of suitable school infrastructure, a shortage of teachers and teaching materials and high school fees – which some parents cannot afford (DeJaeghere et al, 2006; Boissiere, 2004; Verspoor, 2008). While some commendable progress has been made in the 'rolling out' of free universal education over the past two decades, the increasing frequency of climate change-induced weather shocks, especially droughts, in Sub-Saharan Africa (SSA) (Masih et al, 2014) now poses serious challenges to children's education.

Therefore, understanding the impact of weather shocks on children's education by examining household coping strategy behaviour is vital. One of the most prevalent coping strategies, used by SSA households when exposed to shocks in general, is to increase off-farm labour supply to earn income to assure their consumption (Ito & Kurosaki, 2009; Dimova et al, 2014). An increase in the off-farm labour supply of adult household members may result in children being withdrawn from school, either to provide substitute household labour or to supply additional off-farm labour (Gubert & Robilliard, 2007; Beegle et al, 2009; Beck et al, 2016). Other coping mechanisms include a reduction in household consumption – including reductions in expenses on children's health and education – possibly to allow limited household stocks to last longer (Kazianga & Udry, 2006; Skoufias et al, 2012; Björkman-Nyqvist, 2013, Lawson & Kasirye 2013).[1] If the majority of educational costs are paid directly by the household then, as found by Jensen (2000), household expenditure on children's education directly affects their schooling. Thus households are confronted with the choice between children attending, relatively free, education or contributing to the shock coping strategies of a household. This paper therefore examines the impact of exogenous negative rainfall shocks on children's school attendance.

[1] Household coping mechanisms may vary significantly across wealth profiles – poorer households typically reduce consumption and asset smooth, at least in the first instance, while wealthier households deplete savings in the immediate term. The reduction in household consumption is usually to smoothen the utilisation of the limited household resources and assets available so that they last longer. See Lawson and Kasirye (2013) for a full literature review on SSA and coping mechanisms and shocks.

Our hypothesis is that negative rainfall shocks negatively affect children's school attendance.[2] This is advanced on the basis that negative rainfall shocks affect household income for the vast majority of rural households, by lowering their agricultural production, which then trends to recovery in the aftermath of the shock. Such a hypothesis has significant policy implications for efforts aimed at achieving universal education, especially considering the projected increase in the frequency of weather shocks in future climate scenarios (Müller et al, 2014).

Our study differs in two ways from the existing literature that has examined shocks and children's education. First, we used high-resolution geo-referenced spatial rainfall data from the US National Oceanic and Atmospheric Administration's (NOAA) Climate and Prediction Center rainfall estimates RFE database to define our negative rainfall shocks. Most previous studies examining rainfall deficits have tended to use rainfall data from local weather stations, which contain both considerable missing data points and a higher geographical aggregation. Second, we provide a comparative analysis of children's school attendance in rural and urban areas and across different school levels – from primary to post-secondary levels. This is in contrast to existent studies, which have tended to examine children's schooling in *either* rural (Thai & Falaris, 2016; Jacoby & Skoufias, 1997; Gubert & Robilliard, 2007) *or* urban (Akampumuza & Matsuda, 2017) areas. Changes in the socioeconomic status of individuals in rural and urban areas in the context of negative rainfall shocks may have complicated and different effects on children's school attendance. A comparative rural–urban focus is therefore necessary. Although most earlier studies indicate a higher prevalence of poverty in rural than urban areas (Bird et al, 2002), we need to consider these findings in the context of rapid levels of urbanisation of about 4% annually in SSA compared to a global average of just 2% in 2019 (World Bank, 2020), coupled with an increasing proportion of urban households living in poverty (Haddad et al, 1999).

Additionally, existing studies, such as Gubert and Robilliard (2007) and Zamand and Hyder (2016), have mainly focused on the school enrolment, up to the age of 15 and 16 years, respectively, of young children in primary and lower secondary levels . Excluding older children, especially those in secondary and post-secondary education, may underestimate the true effect of shocks on children's school attendance (Vella, 1998). Further, older children are commonly the first group that households turn to for provision of labour when exposed to shocks (Kruger, 2007; Björkman-Nyqvist, 2013).

Our results show that exposure to negative rainfall shocks significantly reduces children's school attendance. This trend is particularly pronounced for children in rural areas and in primary schools. These results have important policy implications for improving the school attendance of children in rural areas with endemic erratic rainfall levels. The rest of the paper is organised as follows. In section 2, we describe our data, elaborate upon

[2] Studies have shown that school attendance is directly linked to children's higher educational attainment, thus making it a good indicator for measuring children's schooling. See, for example, Berlinski et al (2009) and Ready (2010).

the definition of our shock variable and present some statistics. In section 3 we present our empirical model. Our estimation results are discussed in section 4 and our conclusion is presented in section 5.

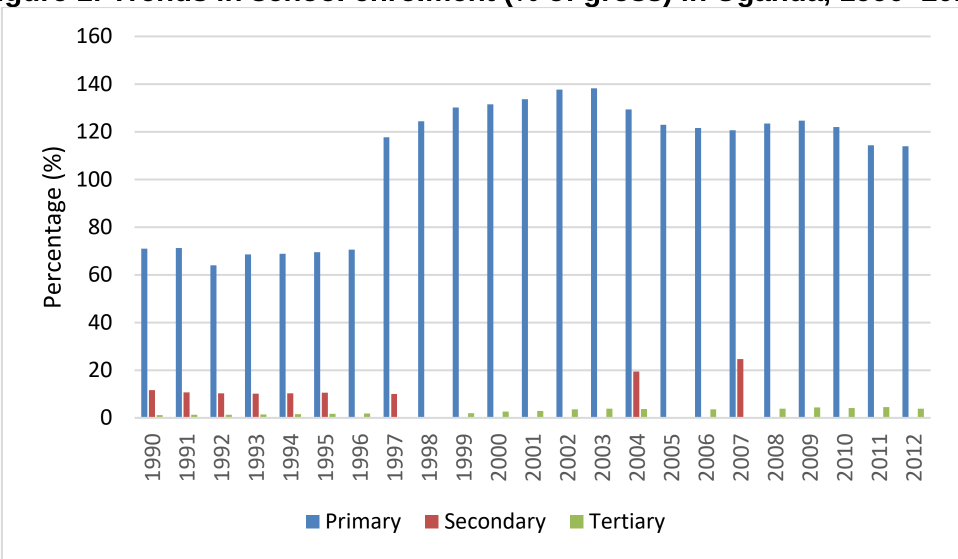
2. Data

2.1 Children's education in Uganda

The Ugandan school system is broadly divided into three levels: primary, secondary and tertiary (university or other tertiary institution). Pre-primary nursery schools are not mandatory and are often not available for the vast majority of children, with attendance as low as 3.7% in some rural areas such as Karamoja (Uganda Bureau of Statistics, 2017). Children usually start school at the age of five and normally take seven years to complete primary, four to six years to complete secondary (depending on the level at which a candidate chooses to exit) and then two to five years to complete tertiary (depending on qualifications sought). For example, a medical student would take 18 years – primary (7), secondary (6) and medical school (5) – to complete their education, while another student training to be a primary school teacher would take 13 years – primary (7), secondary (4) and tertiary (2). On average for the different educational pathways, it takes 15.5 years for a child to complete their education in Uganda. If the child starts school at the expected age of five, they would be 21 years old on completion.

Uganda provides an interesting context for our study because, in line with global development goals, it introduced free universal primary education (UPE) in 1997 (Ministry of Education and Sports, 1999) and ten years later, in 2007, free universal secondary education (USE). Primary school enrolment more than doubled within the first six years of commencing the UPE programme, according to World Bank (2020) World Development Indicators data (Figure 1). Empirical evidence in Deininger (2003), Grogan (2008), Lincove (2012) and Sakaue (2018) shows that the provision of free UPE in Uganda improved the school attendance of children from poor households who would otherwise not have gone to school. Similar increases in children's school enrolment have been documented by Al-Samarrai and Zaman (2007) in Malawi following the introduction of free UPE education.

Figure 1: Trends in school enrolment (% of gross) in Uganda, 1990–2012



Source: World Bank (2020)

2.2. Description of data

We used the 2009–10 and 2011–12 waves of the Uganda National Panel Survey (UNPS) data, which are part of the Living Standards Measurement Study–Integrated Surveys on Agriculture (LSMS-ISA) project of the World Bank. The UNPS data have sections that cover households, women, agriculture and the community. We merged the household and agriculture sections of the data in one wave and then across the two waves (2009–10 and 2011–12) to create a panel dataset for individual children in surveyed households.[3] Our main variable of interest was children's school attendance. While school-age children in Uganda are now required by law to enrol and register in school at the start of every academic year, parents often withdraw them thereafter for work purposes. Fortunately, the UNPS also questions parents or guardians on whether their children were, at the time of the data collection, regularly attending school and we used this to measure children's schooling. Table 1 summarises the characteristics of our sample. In total it comprised 13,263 children (7,016 boys and 6,247 girls) from 4,210 households. The sample was roughly equally distributed across the different regions of the country.

[3] We constructed an individual-level panel of household children up to the age of 21 years, testing for attrition.

Table 1: Sample characteristics

Variable	2009–10	2011–12	Total
Number of households	2154	2056	4210
Number of children	6803	6460	13263
Male	3606	3410	7016
Female	3197	3050	6247
Regional distribution			
Central	0.29	0.26	0.27
Eastern	0.25	0.26	0.25
Northern	0.24	0.26	0.25
Western	0.22	0.23	0.22

Source: Authors' calculations using UNPS Panel 2009–10 and 2011–12.

2.3 Negative rainfall shock definition

We used high-resolution geo-referenced spatial rainfall data from the NOAA Climate and Prediction Center RFE database to define our shocks. First, we extracted the daily rainfall data from the RFE 2.0 database, summed to monthly and then seasonal data. The seasonal rainfall data were then matched to the geo-referenced UNPS data at enumeration area (EA) level. As there is a wide variation in the start and end of the first agricultural season across the country,[4] for uniformity we summed rainfall from January to June to make our first agricultural season. Summing rainfall over a uniform window of months to compute seasonal rainfall where there is variation in the start and end of an agricultural season has been adopted in earlier studies such as Ahmed et al (2011) and Kubik and Maurel (2016). The data observation point of our key variable – children's school attendance – fell within the first agricultural season.

To define our rainfall shocks, we constructed two rainfall measures – current seasonal rainfall in the periods of our data (2009 and 2012) and long-term average seasonal rainfall from 2001 to 2008 (the last year preceding the year of our data, 2009). Normally, long-term average rainfall is computed using longer years of rainfall but the RFE 2.0 database only has rainfall data available from 2001 to the present. Earlier studies, such as Paxson (1992), Skoufias et al (2012) and Skoufias and Vinha (2013), which used longer years of rainfall data to compute their long-term average rainfall, took rainfall data from local weather stations. These had a significant amount of data missing and higher geographical aggregation which, in turn, necessitated the use of longer time series data. In contrast, we used very rich and reliable spatial rainfall data with no gaps over the period of observation, and which were recorded at a lower geographical aggregation. Recently some studies have tried to use the Africa Rainfall Climatology (ARC) 2.0

[4] Uganda has a bimodal agricultural season, with the first season running from January/February to May/June and the second running from July/August to October/November.

database, which has a longer range of rainfall data (1983–present), but the inputs for this database come from only two sources, compared to four for RFE 2.0. Technically, RFE 2.0 rainfall estimates have been shown to be of superior quality to the ARC 2.0 (Novella & Thiaw, 2013).

We defined three shock variables in our analysis. Our first shock measure was a dummy taking the value of one if there is negative deviation of current seasonal rainfall from the long-term average seasonal rainfall in an EA.[5] This is represented as

$$x_b = ar_e < lr_e \qquad (1)$$

where x_b is the rainfall shock in an EA, *e ar* and *lr* are actual rainfall and long-term average seasonal rainfall, respectively, received in an EA.

Second, we defined a continuous shock variable along the lines of the poverty gap index, showing the depth of negative deviation of current rainfall from the long-term average seasonal rainfall in an EA, as written in the equation below:

$$x_c = \frac{\left|\sum_{january}^{june} ar_e - lr_e\right| \cdot I\left(\sum_{january}^{june} ar_e < lr_e\right)}{lr_e} \qquad (2)$$

where x_c is the continuous rainfall shock variable and *ar* and *lr* are as defined above.

Third, we defined three categories of rainfall as dummy shock variables. Normal rainfall takes the value of one if current seasonal rainfall falls within the 50th percentile of either positive or negative deviation from the long-term average seasonal rainfall. Extreme positive rainfall takes the value of one if current seasonal rainfall falls within the 50th to 100th percentile of positive deviation of current seasonal rainfall from the long-term average seasonal rainfall. Extreme negative rainfall takes the value of one if current seasonal rainfall falls within the 50th to 100th percentile of negative deviation of current seasonal rainfall from the long-term average seasonal rainfall. The distributions of negative rainfall shocks across the country in 2009–10 and 2011–12 are presented in Figures 2a and 2b, respectively.

[5] We defined our shock measure along the lines of Paxson (1992). We also tested the sensitivity of our rainfall data by running correlation tests between the rains in wave one (2009–10) and wave two (2011–12) and found a statistically significant positive correlation between the two.

Figure 2a: Map showing distribution of rainfall shocks across Uganda 2009/2010

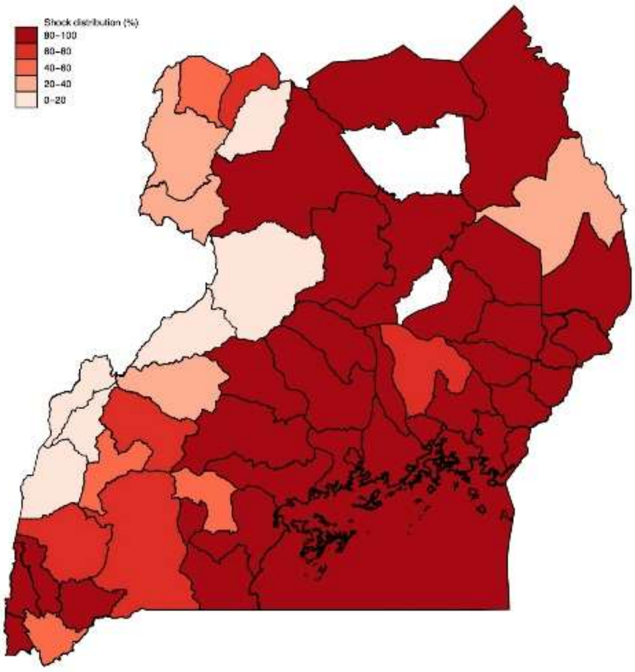
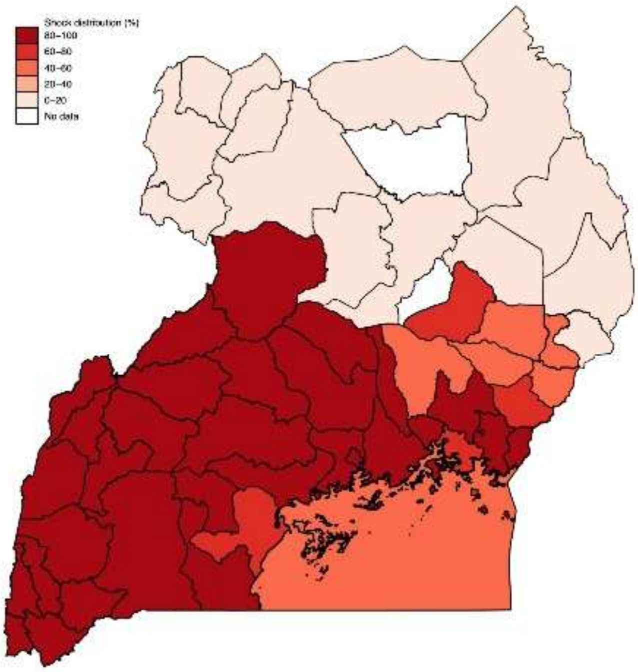


Figure 2b: Map showing distribution of rainfall shocks across Uganda 2011/2012



Source: Authors' calculations using UNPS Panel 2009–10 and 2011–12.

2.4 Descriptive statistics

Table 2 summarise children's school attendance status,[6] current educational levels and other school attributes, comparing the mean value dependent on exposure to negative rainfall shocks. The descriptive results show that there is no statistically significant difference in the means of children's attributes dependent on exposure to negative rainfall shocks. In general, over 79% of the children in our sample were reported as currently attending school, with over 65% of them in primary school. With most primary schools offering free UPE, this could explain why over 59% of the children are in receipt of a scholarship.

Table 2: Descriptive statistics of children's school attendance

	Total	No shock	Shock	Difference	SE
School attendance					
Never enrolled	0.127	0.129	0.126	0.003	(0.007)
Past enrolment	0.080	0.082	0.079	0.002	(0.006)
Current enrolment	0.791	0.786	0.793	-0.006	(0.008)
Current education level					
Primary	0.654	0.650	0.655	-0.005	(0.010)
Secondary	0.129	0.132	0.128	0.004	(0.007)
Tertiary	0.010	0.007	0.011	-0.003	(0.002)
Scholarship	0.592	0.579	0.597	-0.018	(0.011)
School meal	0.369	0.354	0.373	-0.019	(0.012)
Distance to school	1.923	2.016	1.895	0.121	(0.287)
Observations	13261				

Source: Authors' calculations using UNPS Panel 2009-10 and 2011-12.

Table 3 summarises the key descriptive statistics of children's and household characteristics. The average age of the children in our sample was around 11 in the first and 13 in the second wave, respectively. As the age of our target sample went up to 21 years, to avoid erroneous classification of older girl children as women, we used the 'relationship' variable in the household roster, which consists of a range of mutually exclusive dummy variables, including household head, spouse and child, among others. Therefore, in addition to meeting the age requirement, all the children in the sample were identified as children in their respective households. The average household size and number of children per household in our sample was eight persons and five children.

The prevalence of poverty in our sample ranged from 27% to 38% for the two waves. Household poverty status in our data was based on the national poverty threshold, which ranges from US$1.36 to $1.55, depending on the cost of living and consumption patterns

[6] Children's school attendance was taken as 'regular registration' and going to school at the time of the survey.

in the different regions of the country. National poverty thresholds in Uganda are some three-quarters of the international extreme poverty threshold of $1.90, which is broadly used to define poverty status in developing countries (Ferreira et al, 2015).

Given the age restriction imposed on our sample, inevitably some children aged 21 in the first wave dropped out in the second wave. We implemented the Becketti, Gould, Lillard and Welch (BGLW) (1988) test of attrition to check whether this attrition biased our results. The F-test of the attrition dummy and the interaction between the attrition dummy and other variables all equal to zero, indicating no attrition bias in our results. The results of this test are presented in Appendix Table 1.

Table 3: Summary statistics of household demographic and physical characteristics

	2009–10			2011–12			Attrited		
Variable	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD
Child characteristics									
Female	4807	0.46	0.50	4807	0.46	0.50	2011	0.49	0.50
Age	4807	10.95	4.01	4807	12.89	3.99	2011	13.56	5.06
Sick	4802	0.35	0.48	4798	0.18	0.39	1993	0.29	0.46
Child wage work	4770	0.02	0.15	4722	0.02	0.15	1970	0.06	0.23
Child farm work	4769	0.33	0.47	4722	0.38	0.48	1970	0.35	0.48
Household head characteristics									
Age	4799	46.83	12.40	4789	48.48	12.22	2010	51.03	14.21
Female	4807	0.25	0.43	4807	0.28	0.45	2011	0.33	0.47
Married	4794	0.82	0.39	4807	0.81	0.40	2010	0.70	0.46
Household characteristics									
Household size	4807	8.00	2.98	4807	7.70	2.82	2011	8.42	3.81
Poor household	4800	0.27	0.44	4793	0.38	0.48	2001	0.25	0.44
Food shortage	4784	0.51	0.50	4801	0.24	0.43	1990	0.46	0.50
Rural	4807	0.80	0.40	4807	0.81	0.39	2011	0.76	0.43
Number of children	4807	5.72	2.60	4807	5.51	2.45	2011	6.09	3.31
<5 yrs	4807	1.40	1.17	4807	1.20	1.11	2011	1.27	1.29
5–12 yrs	4807	2.10	1.22	4807	1.98	1.25	2011	1.99	1.48
13–18 yrs	4807	1.52	1.24	4807	1.59	1.20	2011	1.73	1.34
19–21 yrs	4807	0.36	0.62	4807	0.57	0.83	2011	0.59	0.78
Household assets									
Land	4785	0.83	0.38	4743	0.88	0.33	1997	0.76	0.43
Transport means	4785	0.57	0.50	4743	0.56	0.50	1997	0.55	0.50
School meal	3613	0.41	0.49	3094	0.30	0.46	1241	0.48	0.50

Source: Authors' calculations using UNPS Panel 2009–10 and 2011–12.

3. Empirical model

We estimated the effect of rainfall shocks on children's school attendance using Ordinary Least Squared (OLS) fixed effects. The regression model is written as

$$y_{ijt} = \beta_0 + \beta_1 x_{et} + \beta_2 c_{ijt} + \beta_3 h_{jt} + \beta_4 g_{it} + \eta_i + \gamma_t + \mu_{ijt} \quad (3)$$

where *y* is the school attendance of child *i* in household *j* and time *t* (t=2009–10 and 2011–12). School attendance is a dummy that takes the value of one if the child is attending school and zero otherwise.[7] The school attendance dummy was also used in Gubert and Robilliard's (2007) study, which examined the impact of shocks on children's schooling. *x* is a rainfall shock variable which is measured at the enumeration area *e,* level. The measure takes the value of one if there is a negative deviation of the current rainfall from its long-term average in the enumeration area and zero otherwise. Alternative definitions of *x* we used in the estimations include continuous and three-category rainfall shock variables (see description in section 2.3)

c is a vector of child characteristics and includes variables such as age and gender. Age is the number, in years, of the child, and gender is a dummy which takes the value of one if the child is female and zero if male. ***h*** is a vector of household characteristics including age, gender, marital status and highest education attainment level of the household head. Age and gender variable of the household head are as defined for the child. Marital status is a dummy variable which takes the value of one if the household head is married and zero otherwise. We also included the highest level of education attained by the household head; this consists of a range of mutually exclusive dummy variables which include primary, secondary and post-secondary education. Additional characteristics covered were household size, number of children, incidence of food shortages, and household poverty status.

g is a vector of school-level controls, such as school feeding and free tuition scholarship. School feeding is a dummy variable which takes the value of one if it is provided to the children and zero otherwise. Similarly, tuition scholarship is a dummy variable which takes the value of one if the child gets a scholarship at school and zero otherwise. In Uganda, children who go to government-aided schools receive a tuition scholarship. However, this does not provide other necessary school items such as books, pens and school uniforms. The β are parameter estimates measuring the effect of the different variables on children's school attendance. η_i is child fixed effects and allows us to control for time-invariant child characteristics such as ability, motivation, child personality and background. The fixed-effect estimator uses the individual child variation to estimate the

[7] The UNPS specifically asks for children's current school attendance at data collection. Since the introduction of UPE in Uganda in 1997, children's enrolment in school, as in many other countries, is now mandatory; however, some may still fail to attend. Nevertheless, our measure of school attendance could still be considered similar to the simple school enrolment used in studies such as Jensen (2000), Ferreira and Schady (2009) and Björkman-Nyqvist (2013).

effect of the parameters on school attendance. γ_t is a set of wave dummy variables and μ is the idiosyncratic error.

We are aware of potential endogeneity problems in our estimation strategy as a result of omitted variables.[8] Authors such as Angrist and Krueger (1991), Card (1999) and Flabbi (1999) have suggested the use of instrumental variables (IV) to resolve this challenge. However, there are considerable practical challenges in finding good IVs that are strongly correlated with the endogenous variable and uncorrelated with the error term (Bound et al, 1995). In addition, using IVs that are weakly correlated with the endogenous variable or correlated with the error term, or both, usually produces large inconsistencies in results (Bound et al, 1995; Crown et al, 2011).

4. Regression results and discussion

Table 4 summarises the results of the fixed-effect estimation using our first binary negative rainfall shock variable. The results show that exposure to negative rainfall shocks reduces children's school attendance by 2.3%. This is particularly pronounced in rural areas. This reduction can be explained by the fact that the vast majority of households in rural settings practise rainfed smallholder agriculture,[9] and thus any exposure to negative rainfall shocks leads directly to a loss of income. Consequently, such households are likely to reduce consumption by cutting expenses on children's education. However, in general, as mentioned at the outset of this paper, another possible explanation for this reduction is the likelihood of parents choosing to keep children at home to provide shock-coping support. Although in many instances this may just involve providing substitute labour at home, children have also been shown to engage in wage work, thus keeping them away from school. The results from our control variable on children's engagement in wage work support this logic, because exposure to negative rainfall shocks reduced children's school attendance by 12.5%. This result is consistent with the earlier findings of Gubert and Robilliard (2007) and Beegle et al (2009), who showed that children tend to engage in wage work when their households are exposed to negative shocks. The results for the other explanatory variables are also consistent with our expectations. Household poverty significantly reduces children's school attendance. Provision of free school meals significantly increases children's school attendance. This is in line with previous empirical findings such as Jomaa et al (2011), Acham et al (2012) and Alderman et al (2012).

[8] The challenge of omitted variables in empirical studies on education is not new and has been widely reported in the estimation of returns to education (Griliches, 1977; Blackburn & Neumark, 1995).

[9] Essentially these farmers rely on rains for all their agricultural production, with limited or no use of irrigation technologies. Because of this reliance on rainfall, their agricultural production is particularly vulnerable to losses if the rains fail.

Table 4: Fixed-effect estimation – dummy shock variable

		Location		Age group		
Variables	All	Rural	Urban	5–12 yrs	13–18 yrs	19–21 yrs
Shock	-0.023**	-0.023**	-0.003	-0.017	-0.025	-0.096
	(0.010)	(0.011)	(0.041)	(0.014)	(0.020)	(0.081)
Female child	-0.118	-0.131	0.010	-0.025	-0.057**	0.000
	(0.085)	(0.092)	(0.026)	(0.024)	(0.023)	(0.000)
Sick child	-0.014	-0.016	-0.006	-0.018	0.013	-0.119
	(0.010)	(0.011)	(0.014)	(0.013)	(0.020)	(0.098)
Child wage work	-0.125**	-0.092*	-0.366*	0.107	-0.132	-0.015
	(0.050)	(0.050)	(0.193)	(0.081)	(0.081)	(0.133)
Child farm work	0.002	-0.000	0.001	0.031***	-0.024	-0.135*
	(0.008)	(0.009)	(0.022)	(0.011)	(0.018)	(0.081)
Household head – Age	0.006***	0.006***	0.004	0.008***	-0.005	0.013
	(0.002)	(0.002)	(0.004)	(0.002)	(0.004)	(0.038)
Female	0.016	0.012	0.018	0.038	-0.048	0.000
	(0.024)	(0.031)	(0.022)	(0.036)	(0.032)	(0.000)
Married	-0.016	-0.020	-0.000	-0.016	-0.107*	-0.040
	(0.032)	(0.042)	(0.021)	(0.054)	(0.059)	(0.186)
Number of children	0.005	0.006	0.004	0.006	-0.005	0.015
	(0.003)	(0.004)	(0.009)	(0.005)	(0.007)	(0.045)
Food shortage	-0.012	-0.017*	-0.001	-0.029**	0.050***	0.125
	(0.009)	(0.010)	(0.022)	(0.012)	(0.019)	(0.090)
Assets – Land	0.031**	0.040**	-0.003	0.020	0.023	-0.068
	(0.013)	(0.018)	(0.016)	(0.018)	(0.026)	(0.069)
Transport	0.009	0.007	0.013	0.005	0.067***	-0.050
	(0.013)	(0.014)	(0.023)	(0.018)	(0.023)	(0.110)
School meal	0.059***	0.064***	0.043***	0.039***	0.043***	0.117
	(0.009)	(0.010)	(0.016)	(0.011)	(0.016)	(0.115)
Poor household	-0.028***	-0.025**	-0.017	0.000	-0.046**	-0.144
	(0.010)	(0.011)	(0.025)	(0.014)	(0.020)	(0.092)
Observations	10223	8425	1798	5506	3417	665
R-squared	0.026	0.025	0.071	0.036	0.054	0.274

*Notes: The dependent variable in all regressions is children's school attendance in the different categories, as listed in the column head. Robust standard errors are in parenthesis. *p<0.10, ** p<0.05, *** p<0.01.*

Source: Authors' calculations using UNPS Panel 2009–10 and 2011–12.

To further examine the mechanism of children's engagement in wage work as a key factor in reducing their school attendance when exposed to shocks, we re-estimated the regression in Table 4, using children's engagement in wage work as the dependent variable. Table 5 summarises the results of that re-estimation. Consistent with prior expectations, exposure to negative rainfall shocks significantly increases children's participation in wage work by 1%. This is particularly the case in rural areas, where exposure to negative rainfall shocks is significantly associated with increases children's participation in wage work by 0.9%. In the face of loss of household income, children's engagement in wage work can be seen as a source of income to assure household consumption even at the detriment of missing school. In other results, land ownership significantly increases children's school attendance by 3.1%. While this may appear counterintuitive, here we treat ownership of land as a measure of wealth; therefore households that have more land can be considered to be wealthier. It is conceivable that wealthier households can afford to keep their children in school and possibly use hired farm labour when exposed to shocks. This is consistent with a series of papers that have looked at shocks and coping mechanisms in Uganda over the period 1992–2012 (Lawson et al, 2006; Lawson & Kasirye, 2013).

Table 5: Fixed-effect estimation – dummy shock variable (mechanism)

		Location		Age group		
Variables	All	Rural	Urban	5–12 yrs	13–18 yrs	19–21 yrs
Shock	0.010**	0.009*	0.022	0.002	0.022	0.043
	(0.005)	(0.005)	(0.017)	(0.003)	(0.014)	(0.085)
Female child	-0.088	-0.096	-0.026	0.005	0.010	0.000
	(0.088)	(0.096)	(0.017)	(0.006)	(0.015)	(0.000)
Sick child	-0.001	-0.000	-0.008	0.006	-0.011	0.118
	(0.006)	(0.007)	(0.010)	(0.005)	(0.018)	(0.101)
Household head – Age	0.001	0.001	0.002	-0.000	0.001	-0.017
	(0.000)	(0.000)	(0.002)	(0.000)	(0.001)	(0.023)
Female	0.007	0.008	-0.006	0.004	0.005	0.000
	(0.005)	(0.005)	(0.015)	(0.003)	(0.018)	(0.000)
Married	0.001	0.000	-0.012	0.002	0.043	0.046
	(0.014)	(0.019)	(0.011)	(0.002)	(0.041)	(0.307)
Number of children	-0.002	-0.001	-0.006	-0.000	-0.008	0.006
	(0.002)	(0.002)	(0.004)	(0.002)	(0.007)	(0.047)
Food shortage	0.010**	0.016***	-0.024	0.007	0.014	-0.049
	(0.005)	(0.006)	(0.015)	(0.005)	(0.014)	(0.086)
Assets – Land	-0.003	-0.001	-0.010	0.005	-0.026	0.071
	(0.007)	(0.008)	(0.014)	(0.008)	(0.019)	(0.085)
Transport	0.004	0.003	0.016	0.003	0.020	-0.005
	(0.006)	(0.006)	(0.021)	(0.003)	(0.019)	(0.036)
School meal	-0.002	-0.002	0.002	0.005	0.006	-0.113
	(0.006)	(0.007)	(0.014)	(0.006)	(0.015)	(0.093)
Poor household	-0.015**	-0.016**	0.007	-0.009**	-0.039**	0.068
	(0.006)	(0.007)	(0.017)	(0.004)	(0.018)	(0.141)
Observations	10224	8426	1798	5506	3418	665
R-squared	0.007	0.010	0.024	0.011	0.020	0.099

Notes: The dependent variable in all regressions is children's participation in wage work in the different categories, as listed in the column head. Robust standard errors are in parenthesis. *p<0.10, ** p<0.05, *** p<0.01.

Source: Authors' calculations using UNPS Panel 2009–10 and 2011–12.

Table 6 summarises the results of the fixed-effect estimation using our second continuous negative rainfall shock variable. The results show that there was a significant overall reduction of 9.8% in children's school attendance on exposure to negative rainfall shocks. The significantly larger 10.5% and 9.4% respective reduction in school attendance of children in rural areas and attending primary schools on exposure to negative rainfall shocks than that shown in Table 4 could be attributed to the difference in our measure of the shocks variable in the respective estimations. Most importantly, the two estimation results still show that exposure to negative rainfall shocks reduces children's school attendance. The results for the other explanatory variables are similar to those in Table 4, which are consistent with our expectations. For example, children's engagement in wage work, and household poverty all significantly reduced children's school attendance. Similarly, the provision of school meals significantly increased their attendance.

Table 6: Fixed–effect estimation – continuous negative rainfall shock variable

		Location		Age group		
Variables	All	Rural	Urban	5–12 yrs	13–18 yrs	19–21 yrs
Shock	-0.098**	-0.105**	-0.040	-0.094*	0.087	-0.354
	(0.042)	(0.048)	(0.079)	(0.056)	(0.082)	(0.372)
Female child	-0.115	-0.128	0.013	-0.025	-0.039**	0.000
	(0.086)	(0.093)	(0.029)	(0.025)	(0.016)	(.)
Sick child	-0.013	-0.015	-0.006	-0.018	0.007	-0.122
	(0.010)	(0.011)	(0.014)	(0.013)	(0.020)	(0.093)
Child wage work	-0.126**	-0.092*	-0.368*	0.106	-0.136*	0.038
	(0.050)	(0.050)	(0.192)	(0.080)	(0.082)	(0.140)
Child farm work	0.001	-0.000	0.001	0.030***	-0.027	-0.148*
	(0.008)	(0.009)	(0.023)	(0.011)	(0.018)	(0.085)
Household head – Age	0.006***	0.006***	0.004	0.007***	-0.004	0.006
	(0.002)	(0.002)	(0.004)	(0.002)	(0.004)	(0.039)
Female	0.015	0.011	0.017	0.038	-0.045	0.000
	(0.024)	(0.030)	(0.021)	(0.036)	(0.032)	(.)
Married	-0.015	-0.019	0.001	-0.015	-0.112*	-0.047
	(0.032)	(0.042)	(0.021)	(0.053)	(0.059)	(0.144)
Number of children	0.005	0.006*	0.004	0.006	-0.004	0.013
	(0.003)	(0.004)	(0.009)	(0.005)	(0.007)	(0.047)
Food shortage	-0.010	-0.015	0.000	-0.027**	0.044**	0.130
	(0.009)	(0.010)	(0.022)	(0.012)	(0.019)	(0.091)
Assets – Land	0.029**	0.039**	-0.003	0.018	0.022	-0.093
	(0.013)	(0.018)	(0.016)	(0.018)	(0.026)	(0.085)
Transport	0.009	0.007	0.014	0.005	0.071***	-0.048
	(0.013)	(0.014)	(0.022)	(0.018)	(0.023)	(0.093)
School meal	0.060***	0.064***	0.043***	0.039***	0.045***	0.110
	(0.009)	(0.010)	(0.015)	(0.011)	(0.016)	(0.109)
Poor household	-0.031***	-0.028**	-0.019	-0.003	-0.043**	-0.141
	(0.010)	(0.011)	(0.026)	(0.014)	(0.020)	(0.102)
Observations	10223	8425	1798	5506	3417	665
R-squared	0.026	0.026	0.071	0.037	0.053	0.272

Notes: The dependent variable in all regressions is children's school attendance in the different categories, as listed in the column head. Robust standard errors are in parenthesis. *p<0.10, ** p<0.05, *** p<0.01.
Source: Authors' calculations using UNPS Panel 2009–10 and 2011–12.

Since over 80% of the children in our sample come from rural areas (Table 3), we also re-estimated the regression results in Table 6 by restricting the sample to households that were engaged in agricultural production, ie either a food or cash crop,[10] something which is prevalent in rural areas. Table 7 summarises the results from that re-estimation. Once again, the trends in the results in the preceding estimations still hold in the sense that exposure to negative rainfall shocks reduced children's school attendance in general, and did so particularly in rural areas and among children attending primary schools. Unlike in the previous estimations, here we observed that sickness reduced children's school attendance by 2.9% and 21.2%, respectively for those attending primary and post-secondary schools. The reduction in attendance because of sickness has been documented in previous studies such as Forrest et al (2013) and Burke and Beegle (2004). Essentially these authors showed that children suffering from sickness tend to miss school, with negative implications for their educational outcomes. It is likely that a sick child will engage less in learning and score poorly in school examinations.

Table 7: Fixed-effect estimation – agricultural households

		Location		Age group		
Variables	All	Rural	Urban	5–12 yrs	13–18 yrs	19–21 yrs
Shock	-0.094*	-0.092*	-0.171	-0.128**	0.141	-0.059
	(0.049)	(0.052)	(0.165)	(0.063)	(0.098)	(0.320)
Sick child	-0.014	-0.018	0.010	-0.029*	0.015	-0.212*
	(0.012)	(0.012)	(0.028)	(0.015)	(0.024)	(0.125)
Child wage work	-0.112**	-0.095*	-0.282	0.121	-0.103	-0.103
	(0.056)	(0.057)	(0.263)	(0.085)	(0.102)	(0.142)
Child farm work	-0.003	-0.001	0.002	0.032***	-0.038*	-0.095
	(0.009)	(0.009)	(0.027)	(0.012)	(0.020)	(0.085)
School meal	0.067***	0.069***	0.048*	0.048***	0.037**	0.161
	(0.010)	(0.011)	(0.028)	(0.013)	(0.018)	(0.127)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8554	7638	916	4576	2918	546
R-squared	0.023	0.024	0.076	0.041	0.050	0.408

*Notes: The dependent variable in all regressions is children's school attendance in the different categories, as listed in the column head. Robust standard errors are in parenthesis. *p<0.10, ** p<0.05, *** p<0.01.*

Source: Authors' calculations using UNPS Panel 2009–10 and 2011–12.

[10] Although we do not include animal production in our definition, crop cultivation is an adequate indicator of whether a household is agricultural or not, since it is the primary production undertaken by rural dwellers in Uganda. Exceptions to this maybe areas where cattle rearing is predominant, but people in these regions still produce some crops.

4.1 Robustness check

In order to test the robustness of our results, we used our alternative categorical rainfall measure variables to estimate their effect on children's school attendance. Table 8 summarises the results. While neither extreme positive nor normal rainfall appear to have a significant impact on children's school attendance, extreme negative rainfall, on the other hand, significantly reduces it. This result is consistent with those from the preceding sections, which show that negative rainfall shocks reduce children's school attendance.

Table 8: Fixed-effect estimation – dependent on amount of rainfall

	Normal rainfall						Extreme positive rainfall					
		Location		Age group				Location		Age group		
Variables	All	Rural	Urban	5–12 yrs	13–18 yrs	19–21 yrs	All	Rural	Urban	5–12 yrs	13–18 yrs	19–21 yrs
Shock	0.008	0.006	0.027	-0.011	0.019	0.004	0.020	0.020	-0.006	0.038**	-0.030	0.064
	(0.009)	(0.010)	(0.020)	(0.012)	(0.018)	(0.056)	(0.013)	(0.013)	(0.012)	(0.018)	(0.022)	(0.079)
Sick child	-0.015	-0.017	-0.005	-0.020	0.012	-0.136	-0.015	-0.017	-0.006	-0.019	0.009	-0.122
	(0.010)	(0.011)	(0.014)	(0.013)	(0.020)	(0.097)	(0.010)	(0.011)	(0.014)	(0.013)	(0.021)	(0.094)
Child wage work	-0.128**	-0.095*	-0.367*	0.105	-0.135*	-0.019	-0.126**	-0.093*	-0.367*	0.109	-0.138*	-0.006
	(0.050)	(0.050)	(0.192)	(0.081)	(0.081)	(0.137)	(0.050)	(0.050)	(0.193)	(0.081)	(0.082)	(0.139)
Child farm work	0.000	-0.001	-0.001	0.030***	-0.026	-0.146*	0.001	-0.001	0.001	0.031***	-0.027	-0.144*
	(0.008)	(0.009)	(0.023)	(0.011)	(0.018)	(0.085)	(0.008)	(0.009)	(0.023)	(0.011)	(0.018)	(0.084)
School meal	0.059***	0.064***	0.041***	0.041***	0.045***	0.091	0.060***	0.065***	0.043***	0.041***	0.046***	0.100
	(0.009)	(0.010)	(0.015)	(0.011)	(0.016)	(0.106)	(0.009)	(0.010)	(0.015)	(0.011)	(0.016)	(0.112)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10223	8425	1798	5506	3417	665	10223	8425	1798	5506	3417	665
R-squared	0.024	0.024	0.073	0.035	0.053	0.258	0.025	0.024	0.071	0.038	0.053	0.264

Extreme negative rain

		Location		Age group		
Variables	All	Rural	Urban	5–12 yrs	13–18 yrs	19–21 yrs
Shock	-0.020*	-0.019	-0.022	-0.010	-0.005	-0.054
	(0.010)	(0.012)	(0.018)	(0.014)	(0.020)	(0.072)
Sick child	-0.013	-0.015	-0.005	-0.018	0.012	-0.136
	(0.010)	(0.011)	(0.015)	(0.013)	(0.020)	(0.097)
Child wage work	-0.125**	-0.092*	-0.366*	0.107	-0.135*	-0.013
	(0.050)	(0.050)	(0.192)	(0.081)	(0.082)	(0.130)
Child farm work	0.000	-0.001	-0.001	0.030***	-0.026	-0.143*
	(0.008)	(0.009)	(0.023)	(0.011)	(0.018)	(0.085)
School meal	0.059***	0.064***	0.041***	0.039***	0.045***	0.102
	(0.009)	(0.010)	(0.015)	(0.011)	(0.016)	(0.104)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10223	8425	1798	5506	3417	665
R-squared	0.025	0.025	0.073	0.035	0.052	0.263

*Notes: The dependent variable in all regressions is children's school attendance in the different categories, as listed in the column head. Robust standard errors are in parenthesis. *p<0.10, ** p<0.05, *** p<0.01.*

5. Conclusion

In this paper we have examined the effects of exposure to negative rainfall shocks on children's school attendance. Our results show that exposure to negative rainfall shocks significantly reduces children's school attendance. These results have potentially significant implications for policies aimed at promoting children's education in the context of increased climate change-induced rainfall shocks, and are consistent with a series of specialised papers from two specific streams of the literature.

The first of these literature streams has typically analysed shocks and coping mechanisms across time – an area where the Ugandan literature, perhaps more than that for any other African country, is particularly well advanced. For example, research spanning more than two decades, adopting quantitative and qualitative methodological approaches, at national and local level, and using panel data commencing in 1992 has found higher educational attainment to be negatively and significantly associated with a reduction in consumption, which in turn is strongly correlated with negative rainfall shocks (see, for example, Lawson & Kasirye, 2013). The second stream of literature considers the direct relationship between rainfall and educational outcomes (see, for example, Randall & Gray, 2019).

In this paper we have connected both the aforementioned strands of literature by combining panel data with far more advanced and accurate rainfall data measurements, enabling us to provide policy suggestions. We found the educational effects of negative rainfall shocks to be particularly pronounced for children in primary school. Policy suggestions that commonly arise from the aforementioned second strand of literature usually suggest programmes and policies that can disproportionately benefit rural households – for example, crop insurance programmes or elimination of school fees. However, it would seem more sensible to take a blended policy approach. For example, rainfall effects differ by the level of education analysed, geographical location and welfare levels of a household. It is therefore perhaps more appropriate to embed policy responses within adaptive social protection frameworks for countries, frameworks that are increasingly based on national social assistance registries (Lawson et al, 2017, 2020). Such an approach is perhaps further to be advocated when we consider that households facing negative rainfall shocks also face a combination of other types of exogenous shock – such as Covid-19. Adaptive assistance frameworks need to be incorporated to cover a variety of shocks that affect households over time. Future research is required to further understand how negative rainfall shocks affect children's school attendance over longer time periods, and how such effects are accentuated by other shocks. Using the most reliable rainfall data and panel data, as in this research, is one such step forward in measuring the longer-term sequential impacts and provides a juncture for the designing of appropriate policy responses.

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Appendix

Table 1: BGLW attrition test

Attrition	= 0
Attrition*Child – female	= 0
Attrition*Household head – age	= 0
Attrition*Household head – female	= 0
Attrition*Household head – married	= 0
Attrition*Number of children in household	= 0
Attrition*Food shortage	= 0
Attrition*Household asset – land	= 0
Attrition*Household asset – transport	= 0
Attrition*Child wage work	= 0
Attrition*Child farm work	= 0
Attrition*School meal	= 0
Observations	10249

Notes: Generated using STATA's testparm command.
Source: Authors' calculations using UNPS Panel 2009–10 and 2011–12.