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Rainfall shocks and children's school attendance: evidence from Uganda

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ABSTRACT

The increasing frequency of negative rainfall shocks presents households with the challenging choice of whether to send their children to school or to withdraw them in order for them to provide support in the household. We use high-resolution spatial rainfall data matched with the georeferenced 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 significantly reduces children's school attendance by almost 10%. These results have important policy implications for improving children's schooling, particularly in geographical areas that receive particularly erratic rainfalls, in Uganda.

KEYWORDS

Climate change; shocks; children's education; coping strategy; uganda

1. Introduction[1 2 3]

Over the last three decades, global efforts to promote children's education in developing countries have increased; manifested initially through, for example, Millennium Development Goal Two (MDG 2) and more recently in 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, shortage of teachers and teaching materials, and high school fees, which some parents cannot afford (Boissiere, 2004; DeJaeghere, Chapman, & Mulkeen, 2006;). Whilst some commendable progress has been made in the rolling out of free universal education over the last two decades, increasing frequency of climate change induced weather shocks, especially droughts in sub-Saharan Africa (SSA) (Masih, Maskey, Mussá, & Trambauer, 2014), now pose 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 (Dimova, Gangopadhyay, Michaelowa, & Weber, 2014; Ito & Kurosaki, 2009). An increase in off-farm labour supply of adult household members may result in children being withdrawn from school either to provide substitute household labour or to supply additional off-farm labour (Beck, Singhal, & Tarp, 2016; Beegle, Dehejia, & Gatti, 2009; Gubert & Robilliard, 2007). Other coping mechanisms include a reduction in household consumption[4] including reductions in expenses on children's health and education possibly to allow limited household stocks to last for a longer period of time (Björkman-Nyqvist, 2013; Kazianga & Udry, 2006; Lawson & Kasirye, 2013; Skoufias, Katayama, & Essama-Nssah, 2012). If the majority of educational costs are paid for directly by the household then, and as found by Jensen (2000), household expenditure on children's education directly affects their schooling. Confronted with the

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choice of attending, relatively free, education or contributing to the shock coping strategies of a household, this paper examines the impact of exogenous negative rainfall shocks on children's school attendance.

Our hypothesis is that negative rainfall shocks negatively affect children's school attendance.[5] 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. The outcome of such hypotheses 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, Waha, Bondeau, & Heinke, 2014).

Our study differs in two ways from the existing literature that examines shocks and children's education. First, we use high-resolution georeferenced spatial rainfall data from the National Oceanic and Atmospheric Administration's (NOAA) Climate and Prediction Center (CPC) rainfall estimates (RFE) database to define our negative rainfall shocks. Most prior 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 existing studies which have tended to examine children's schooling in either rural (Gubert & Robilliard, 2007; Jacoby & Skoufias, 1997; Thai & Falaris, 2014) 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 prior studies indicate a higher prevalence of poverty in rural than urban areas (Bird, Moore, Hulme, & Shepherd, 2002), it is important to consider these findings in the context of rapid levels of urbanisation of about 4% annual growth 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 (Mitlin & Satterthwaite, 2013).

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

Our results show that exposure to negative rainfall shocks significantly reduces children's school attendance. This trend is significantly 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 that have endemic erratic rainfalls. The rest of this paper is organised as follows. In Section 2, we present an overview of children's education in Uganda. In section 3, we describe our data, elaborate upon the definition of our shock variable and present some statistics. In Section 4 we present our empirical model. Thereafter, our estimation results are discussed in Section 5 and the conclusion is presented in Section 6.

2. 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 often not available for the vast majority of children, with attendance as low as 3.7% in some rural areas such as in Karamoja (Uganda Bureau of Statistics, 2017). Children usually start school at the age of 5 years and normally take 7 years to complete primary, 4–6 years to complete secondary (depending on the level at which a candidate chooses to exit) and then 2–5 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 5 years, 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 program, according to World Bank (2020) world development indicators data (see Figure 1). Empirical evidence by Deininger (2003), Grogan (2008), Lincove (2012) and Sakaue (2018) shows that the provision of free universal primary education 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 universal primary education.

3. Description of data

We use the 2009/2010 and 2011/2012 waves of the Uganda National Panel Survey (UNPS) data which is 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 household, woman, agriculture and the community. We merge the household and agriculture sections of the data in one wave and then across the two waves (2009/2010 and 2011/2012) to create a panel data set for individual children in the households.[6] Our main variable of interest is children's school attendance. Whilst 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, UNPS data also question parents or guardians on whether their children were, at the time of the data collection, regularly attending school and we use this to measure children's schooling. Table 1 summarises the characteristics of our sample. In total, our sample comprises 13,263 children (7,016 boys and 6,247 girls) from 4,210 households. The sample is roughly equally distributed across the different regions of the country.

Figure 1: Trends in school enrolment (% of Gross) in Uganda, 1990-2012

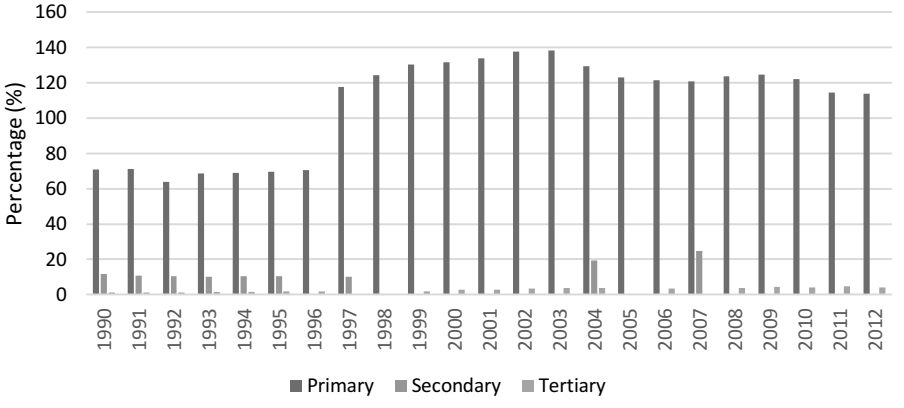

Figure 1. Trends in school enrolment (% of Gross) in Uganda, 1990-2012.

Table 1. Sample characteristics.

	2009/10	2011/12	Total
Number of households	2154	2056	4210
Number of children	6803	6460	13,263
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 – UNPS Panel 2009/2010 and 2011/2012

3.1. Negative rainfall shock definition

We use a high-resolution georeferenced spatial rainfall data from the National Oceanic and Atmospheric Administration's (NOAA) Climate and Prediction Center (CPC) rainfall estimates (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 georeferenced UNPS data at enumeration area (EA) level. As there is a wide variation in the start and end of the first agricultural season,[7] across the country, for uniformity we sum 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 priori studies such as Ahmed et al. (2011) and Kubik and Maurel (2016). Data observation point of our key variable, children's school attendance falls within the first agricultural season.

To define our rainfall shocks, we construct 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, the 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. Prior studies, such as Paxson (1992), Skoufias and Vinha (2013) and Skoufias, Bandyopadhyay, and Olivieri (2017) that used longer years of rainfall data to compute their long-term average rainfall, used rainfall data from local weather stations which contained significant missing data and higher geographical aggregation, which in turn, necessitated the use of longer time series data. In contrast, we use a very rich and reliable spatial rainfall data which has no missing data over the period of observation and is recorded at a lower geographical aggregation. Recently some studies have tried to use the Africa Rainfall Climatology (ARC) 2.0 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 than the ARC 2.0 (Novella & Thiaw, 2013).

We define three shock variables in our analysis. Our first shock measure is a dummy that takes the value of one if there is a negative deviation of current seasonal rainfall from the long-term average seasonal rainfall in an EA.[8] This is represented as:

$$x_b = ar_e < lr_e \tag{1}$$

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.

Secondly, we define 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:

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

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

Thirdly, we define three categories of rainfall as dummy shock variables. Normal rainfall takes the value of one if current seasonal rainfall falls within 50th percentile of either positive or negative deviation of the long-term average seasonal rainfall. Extreme positive rainfall takes the value of one if current seasonal rainfall falls within 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 50th to 100th percentile of negative deviation of current seasonal rainfall from the long-term average seasonal rainfall. The measure of the intensity of the shocks across the country in 2009/2010 and 2011/2012 are presented in Figures 2a and 2b, respectively.

3.2 Descriptive statistics[9]

Table 2 summarises children's school attendance status,[10] 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 are reported as currently attending school with over 65% of them in primary school. With most primary schools offering free UPE education, this could explain why over 59% of the children are in receipt of scholarship.

Table 3 summarises the key descriptive statistics of children's and household characteristics. The average age of the children in our sample is approximately 11 and 13 years in the first and second waves, respectively. As the age of our target sample is up to 21 years, to avoid erroneous classification of older girl children as women, we use 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 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 is approximately eight persons and five children, respectively.

The prevalence of poverty in our sample ranges from 27% to 38% for the two waves. The household poverty status in our data is based on the national poverty threshold which ranges from US$1.36 to US$1.55 depending on the costs of living and consumption patterns in the different regions of the country. National poverty thresholds in Uganda are approximately three-quarters of the international extreme poverty threshold of US$ 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 that are 21 years of age in the first wave, drop out in the second wave. We implement the Becketti, Gould, Lillard, and Welch (1988) test of attrition to check whether this attrition biases our results. The F-test of the attrition dummy and the interaction between the attrition dummy and other variables all equal to zero, thus indicating no attrition bias in our results. The results of this test are presented in Table A2 in the appendix.

4. Empirical model

We estimate the effect of rainfall shocks on children's school attendance using OLS fixed effects. The regression model is written as:

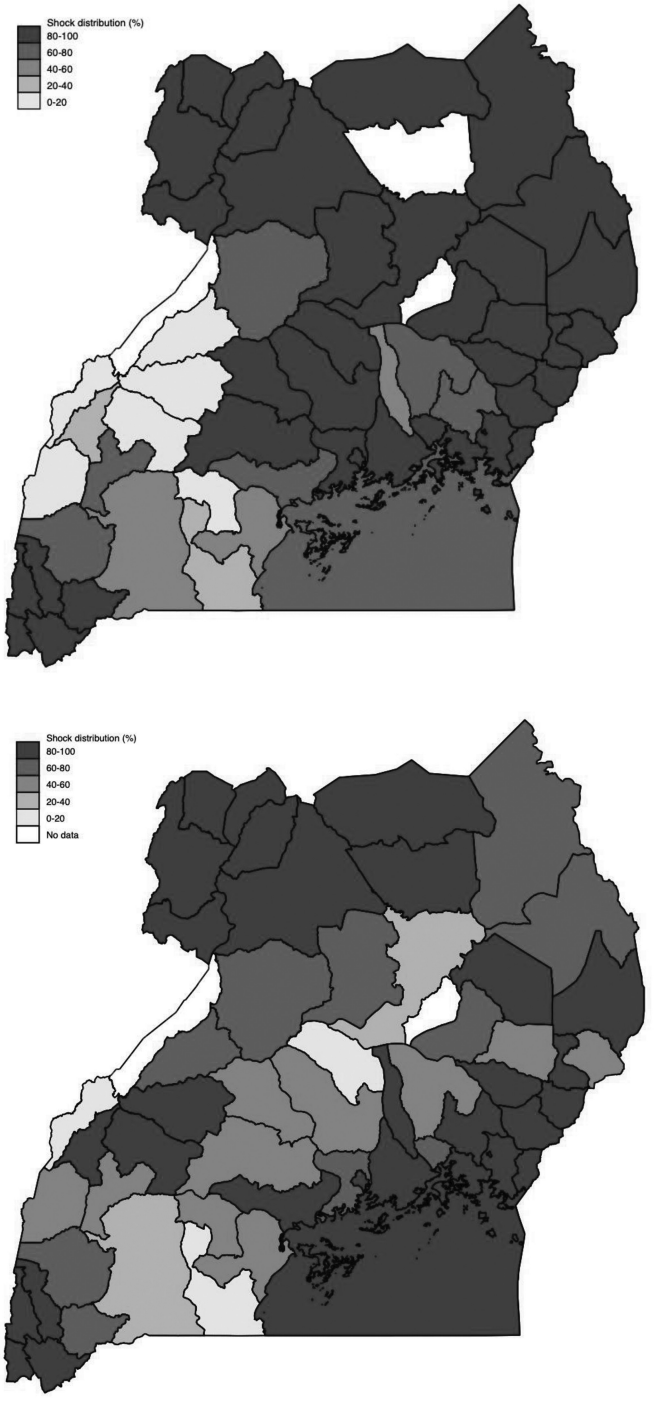
Shock distribution (%)
80-100
60-80
40-60
20-40
0-20
Shock distribution (%)
80-100
60-80
40-60
20-40
0-20
No data

Figure 2. (a)(b)

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	13,261				

Source: Authors calculations – UNPS Panel 2009/2010 and 2011/2012

Table 3. Summary statistics of household demographic and physical characteristics.

		2009/2010		2011/2012			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
Rainfall shocks	4807	0.82	0.39	4807	0.71	0.45	2011	0.80	0.40
Extreme positive rains	4807	0.07	0.25	4807	0.16	0.37	2011	0.08	0.27
Normal rains	4807	0.43	0.50	4807	0.54	0.50	2011	0.52	0.50
Extreme negative rains	4807	0.50	0.50	4807	0.30	0.46	2011	0.40	0.49

Source: Author's calculations – UNPS Panel 2009/2010 and 2011/2012

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

where y is the school attendance of child, i in household, j and time, t (t = 2009/2010 & 2011/2012). The school attendance[11] is a dummy that takes the value of one if the child is attending school and zero otherwise. The school attendance dummy was also used in the study of Gubert and Robilliard (2007) which examined the impact of shocks on children's schooling. x is a rainfall shock variable that 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 use in the estimations include continuous and three category rainfall shock variables (see description in section 2.3)

The vector of child characteristics, $\boldsymbol{c}$ 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. $\boldsymbol{h}$ 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 include the highest level of education attained by the household head and this consists of a range of mutually exclusive dummy variables which include; primary, secondary and post-secondary education. Additional characteristics covered include household size, number of children, incidence of food shortages, and household poverty status.

The vector of school-level controls $\boldsymbol{g}$ includes school feeding and free tuition scholarship. School feeding is a dummy variable that takes the value of one if school feeding is provided to the children and zero otherwise. Similarly, tuition scholarship is a dummy variable that 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 scholarship does not provide other necessary school requirements, such as books, pens and school uniforms. The β are parameters 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, background. The fixed effect estimator uses the individual child variation to estimate the 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 due to omitted variables.[12] 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, Jaeger, & Baker, 1995). In addition, using IVs that are weakly correlated with the endogenous variable or correlated with the error term, or both, usually produce large inconsistencies in results (Bound et al., 1995; Crown, Henk, & Vanness, 2011).

5. Effects of shocks on children's school attendance

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 significantly reduces children's school attendance by 2.3% and this is particularly pronounced in rural areas. This reduction can be explained by the fact that the vast majority of households in rural settings practice rainfed[13] smallholder agriculture and thus any exposure to negative rainfall shocks lead directly to their income loss. Consequently, such households are likely to reduce consumption including cutting expenses on children's education. However, in general as alluded to at the outset of this paper, another possible explanation for this reduction could also be 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 result from our control variable on children's engagement in wage work supports this logic because exposure to negative rainfall shocks reduce children's school attendance by 12.5%. This result is consistent with earlier findings of Gubert and Robilliard (2007) and Beegle et al. (2009) who show 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,

Table 4. Impact of rainfall shocks on children's schooling – fixed effect estimation using 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)
Child- Female	−0.118	−0.131	0.010	−0.025	−0.057**	0.000
	(0.085)	(0.092)	(0.026)	(0.024)	(0.023)	(0.000)
Child- Sick	−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	10,223	8425	1798	5506	3417	665
R-squared	0.026	0.025	0.071	0.036	0.054	0.274

McDonnell, and Probart (2011), Acham, Kikafunda, Malde, Oldewage-Theron, and Egal (2012) and Alderman, Gilligan, and Lehrer (2012).

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.

To further examine the mechanism of children's engagement in wage work as a key factor that reduces their school attendance when exposed to shocks, we re-estimate the regression in Table 4 but 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 significantly 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%. Whilst this may appear counterintuitive, here we treat ownership of land as a measure of wealth and 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 & Kasirye, 2013; Lawson, McKay, & Okidi, 2006).

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.

Table 5. Impact of rainfall shocks on children's participation in wage work – fixed effect estimation using dummy shock variable.

			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)
Child- Female	−0.088	−0.096	−0.026	0.005	0.010	0.000
	(0.088)	(0.096)	(0.017)	(0.006)	(0.015)	(0.000)
Child- Sick	−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	10,224	8426	1798	5506	3418	665
R-squared	0.007	0.010	0.024	0.011	0.020	0.099

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 those 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 reduce 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 their school attendance. Similarly, the provision of school meals significantly increased children's school attendance.

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. *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Since over 80% of the children in our sample come from rural areas (Table 3), we also re-estimate the regression results in Table 6 by restricting the sample to households that were engaged in agricultural production, i.e. either a food or cash crop,[14] 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 reduce children's school attendance in general and in particular in rural areas and among children attending primary schools. Unlike in the previous estimations, here we observe that sickness reduces children's school attendance by 2.9% and 21.2%, respectively, for those attending primary and post-secondary schools. The reduction in children's school attendance due to sickness has been documented in previous studies such

Table 6. Impact of rainfall shocks on children's schooling – fixed effect estimation using continuous 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)
Child- Female	−0.115	−0.128	0.013	−0.025	−0.039**	0.000
	(0.086)	(0.093)	(0.029)	(0.025)	(0.016)	(.)
Child- Sick	−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 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	10,223	8425	1798	5506	3417	665
R-squared	0.026	0.026	0.071	0.037	0.053	0.272

Table 7. Impact of rainfall shocks on children's schooling – sample restricted to 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)
Child- Sick	−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

as Forrest, Bevans, Riley, Crespo, and Louis (2013) and Burke and Beegle (2004). Essentially these authors show that children suffering from sickness tend to miss school with negative implications on their educational outcomes. It is conceivable that a sick child will likely engage less in learning and score poorly in school examinations.

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. *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8. Impact of rainfall shocks on children's schooling – fixed effect estimation using different categories of rainfall.

Variables	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)
Child- Sick	−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	10,223	8425	1798	5506	3417	665	10,223	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

Table 8. (continuation): Extreme negative rain.

Variables	All	Location		Age group		
		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)
Child- Sick	−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	10,223	8425	1798	5506	3417	665
R-squared	0.025	0.025	0.073	0.035	0.052	0.263

The dependent variable in all regressions is children's school attendance in the different categories as listed in the column head of Table 8. Robust standard errors are in parenthesis. *p < 0.10, ** p < 0.05, *** p < 0.01.

5.1. Robustness check

In order to test the robustness of our results, we use our alternative categorical rainfall measure variables to estimate its effect on children's school attendance and Table 8 summarises the results. Whilst extreme positive and normal rainfall appear not to significantly impact 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.

6. Conclusion

In this paper, we examined the effects of exposure to negative rainfall shocks on children's school attendance. Our results show that exposure to negative rainfall shocks significantly reduce 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 – for which the Ugandan literature, perhaps more than 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 levels, and using panel data commencing in 1992 has found higher educational attainment to be negatively and significantly associated with consumption reduction, 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 & Grey, 2019).

In this paper, we connect both the aforementioned strands of literature by combining panel data with far more advanced and accurate rainfall data measurement, enabling us to provide policy suggestions. We find the educational effects of negative rainfall shocks to be particularly pronounced for those children in primary school. Policy suggestions that commonly arise from the aforementioned second strand of literature usually suggest programs and policies that can disproportionately benefit rural households – for example crop insurance programs or elimination of school fees. However, it would seem more sensible for a blended policy approach. For example, rainfall effects differ by the level of education analysed, geographical location and welfare levels of household. It is therefore perhaps more appropriate to embed policy response within adaptive social protection frameworks for countries, that are increasingly based on national social assistance registries. Such an approach is perhaps further advocated when we consider that households facing negative rainfall shock also face a combination of other types of exogenous shocks, e.g.,, such as Covid-19. Adaptive assistance frameworks need to be incorporated to cover a variety of shocks that impact households over time. Future research is required to further understand how negative rainfall shocks impact on 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.

Notes

1. We would like to thank the Editor and two anonymous referees for their comments which enormously improved this paper. We also acknowledge useful comments from Professor David Fielding, GDI, University of Manchester, participants at the 5th Annual Conference of the French Association of Environmental and Resource Economists, 30–31 August 2018, Aix-en-Provence, France and International Workshop on 'Poverty, Inequality Dynamics, and Economic Development: Tensions and Trade-offs in Mixed Methods Research',

Kings College London, 6–7 September 2018 where an earlier version of this paper was presented. An earlier version of this paper was published under a different title as a Global Development Institute Working Paper 2020–050. All remaining errors are our own.

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3. The data used in this study is openly available from the World Bank and can be accessed at https://microdata.worldbank.org/index.php/catalog/lsms
4. Household coping mechanisms can 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 utilization of the limited household resources and assets available to last for longer periods of time (see Lawson & Kasirye, 2013, for a full literature review on SSA and coping mechanisms and shocks).
5. Studies have shown that school attendance is directly linked to higher educational attainment of children thus making it a good indicator to measure children's schooling (see for example, Berlinski, Galiani, & Gertler, 2009; Ready, 2010).
6. We construct an individual level panel of household children up to the age of 21 years, testing for attrition.
7. Uganda has a bimodal agricultural season with the first season starting from January/February to May/June and second season starting from July/August to October/November.
8. We define our shock measure along the lines of Paxson (1992). We also test the sensitivity of our rainfall data by running correlation tests between the rains in wave one (2009/2010) and wave two (2011/2012) and find a statistically significant positive correlation between the two.
9. A full list and definition of variables used in our analysis is presented in Table A1 in the appendix.
10. Children's school attendance is taken as 'regular registration' and going to school at the time of the survey.
11. 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 like in many other countries is now mandatory however they may still fail to attend school. 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).
12. 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 (Blackburn & Neumark, 1995; Griliches, 1977).
13. Essentially these farmers rely on rains for all of their agricultural production with limited or no use of irrigation technologies. Because of this reliance on rains, their agricultural production is particularly vulnerable to losses if the rains fail.
14. Even though 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 may be in areas where cattle rearing is predominant but still people in these regions produce some crops.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix

Table A1: Definition of variables

Variable	Description
Female	Dummy = 1 if child/household head is female and zero otherwise
Age	Age in years of a child or household head
Sick	Dummy = 1 if a child is sick and zero otherwise
Child wage work	Dummy = 1 if a child engaged in wage work and zero otherwise
Child farm work	Dummy = 1 if a child engaged in farm work and zero otherwise
Married	Dummy = 1 if household head is married and zero otherwise
Household size	Number of ordinarily resident household members
Poor household	Dummy = 1 if a household is classified as poor and zero otherwise
Food shortage	Dummy = 1 if a household experienced shortage of food and zero otherwise
Rural	Dummy = 1 if a household is located in a rural area and zero otherwise
Number of children	Number of children in a household
Land	Dummy = 1 if a household owns land and zero otherwise
Transport means	Dummy = 1 if a household owns a means of transport and zero otherwise
Never enrolled	Dummy = 1 if a child has never enrolled in school and zero otherwise
Past enrolled	Dummy = 1 if a child enrolled in school in the past and zero otherwise
Current enrolled	Dummy = 1 if a child is currently enrolled in school and zero otherwise
Primary	Dummy = 1 if a child is in a primary school and zero otherwise
Secondary	Dummy = 1 if a child is in a secondary school and zero otherwise
Tertiary	Dummy = 1 if a child is in a tertiary institution and zero otherwise
School meal	Dummy = 1 if a child receives a meal at school and zero otherwise
Scholarship	Dummy = 1 if a child is in receipt of free tuition fees and zero otherwise
Rainfall shocks	Dummy = 1 if current rainfall in an area is below its long term average and zero otherwise
Extreme positive rains	Dummy = 1 if current seasonal rainfall falls within 50th to 100th percentile of positive deviation of current seasonal rainfall from the long-term average seasonal rainfall and zero otherwise
Normal rains	Dummy = 1 if current seasonal rainfall falls within 50th percentile of either positive or negative deviation of the long-term average seasonal rainfall and zero otherwise
Extreme negative rains	Dummy = 1 if current seasonal rainfall falls within 50th to 100th percentile of negative deviation of current seasonal rainfall from the long-term average seasonal rainfall and zero otherwise

Table A2: 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	10,249

Table generated using STATA's *testparm* command