Rainfall, Human Capital and Labour Market Outcomes: Evidence from Rural South Africa

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Contents

List of tables

List of figures

Abstract

Rural households rely on several strategies to cope with weather variability, including school-work transitions of adolescents and changes in human capital investments. Using rich longitudinal data from rural South Africa linked with geospatial data on climate indicators, we examined the effect of rainfall realizations on the schooling and work decisions and education expenditures of adolescents and young adults. We exploited the exogenous within-individual variation in exposure to district-level rainfall realizations over age. Our results suggest that current and lagged growing-season rainfall increases adolescent human capital investments on the intensive margin among both female and male adolescents. While current rainfall decreased labour market participation among adolescents in non-agricultural households, current rainfall increased female labour supply in agricultural households. We also found that previous-period rainfall positively affected work propensity among all male adolescents. Our results documented schooling and labour supply adjustments among adolescents in agricultural and non-agricultural households, in response to rainfall fluctuations.

JEL Classification: I38, H53, I12

Keywords: rainfall, schooling, labor, education expenditure

1. Introduction

Life in rural areas of developing countries is typically characterized by high dependence on rainfed agriculture and low access to financial markets, such as credit and insurance. Consequently, rural households (both agricultural and non-agricultural) are particularly vulnerable to weather variability and environmental shocks. With little to no access to credit and insurance markets, rural households sometimes cope with income fluctuations by adjusting human capital investments and the labour supply of children as a form of informal self-insurance (Jacoby and Skoufias, 1997). However, whether households respond to unanticipated income changes by increasing or decreasing child human capital investments and labour supply is theoretically ambiguous (Rose, 2001; Marchetta et al., 2019). Favourable rainfall conditions increase rural household earnings, which can either increase or decrease the labour supply of household members (Rose, 2001). Additionally, as they age, adolescents face increasingly stark trade-offs between the returns to schooling and the opportunity cost of delayed entry into the labour market. Consequently, the education and labour outcomes of adolescents may be particularly vulnerable to income variability associated with weather variability.

Accordingly, evidence is mixed on the impact of rainfall and the associated agricultural productivity on child education and labour supply. Negative agricultural income shocks or rainfall shocks have been found to decrease school enrolment and attendance and increase work propensity (Jacoby and Skoufias, 1997; Jensen, 2000; Gubert and Robilliard, 2008; Björkman-Nyqvist, 2013; Dillon, 2013; Bandara et al., 2015; Marchetta et al., 2019; Agamile and Lawson, 2021;). However, higher wages induced by positive rainfall conditions have also been found to reduce school attendance and education expenditures (Shah and Steinberg, 2017; Zimmermann, 2020; Nordman et al., 2022) and increase the likelihood of child labour (Dumas, 2020; Trinh et al., 2020; Nordman et al., 2022).

This study investigated the effect of rainfall on the school–work decisions of adolescents and young adults living in both agricultural and non-agricultural households in rural South Africa. Specifically, we combined rich individual-level longitudinal data with geospatial precipitation data to estimate the causal effect of district-specific standardized growing season rainfall on school enrolment, educational expenditures, labour force participation and employment for South African adolescents and young adults aged 15–22 years. We examined the effects of rainfall in both the most recent growing season and in that of the previous year's growing season. By examining both enrolment and expenditures, we assessed the effect of rainfall realizations on human capital investment on both the extensive and intensive margins. We also allowed for heterogeneity in these relationships across relevant dimensions, including agricultural versus non-agricultural households, sex and household wealth.

We obtained plausible exogenous variation in rainfall by standardizing our precipitation measures using district-specific means and standard deviations. We further controlled for individual-level fixed effects, seasonal fixed effects and month-year fixed effects to account for individual, seasonal and temporal heterogeneity. Moreover, our findings were robust to multiple robustness checks, including alternative measures of rainfall, alternatively clustered standard errors, falsification tests and testing for attrition bias.

We found that positive rainfall realizations generally increase human capital investments on the intensive margin among the adolescents in our sample, but that the labour market effects differ across sex and agricultural and non-agricultural households. Specifically, our findings indicated that current and lagged rainfall is generally positively related to educational expenditures among both females and males, in both agricultural and non-agricultural households. However, current rainfall was a stronger predictor of educational spending for males in non-agricultural households but lagged rainfall was a more important predictor for males in agricultural households. For females, lagged rainfall was a more important predictor of educational investment in females in both non-agricultural and agricultural households.

The relationship between growing season rainfall and our labour market outcomes of interest was much more nuanced and differed across sex and agricultural and non-agricultural households. Current season rainfall reduced the labour market participation of non-agricultural males whereas lagged rainfall increased their labour market participation. For males in agricultural households, we found that both current and lagged rainfall increased their labour market activities. However, the estimated effect of current rainfall for agricultural males was noisy and not statistically significant at conventional levels of significance. Females in non-agricultural household exhibited no labour response to either lagged or current rainfall, whereas females in agricultural households increased their labour market activities in response to current rainfall but exhibited no response to lagged rainfall.

Therefore, we found that in agricultural households the education and labour decisions of males appear to respond more strongly to lagged rainfall while that of females respond more strongly to current rainfall. Interestingly, neither response indicated that the labour supply of adolescents in agricultural households influences their educational investment decisions, implying that they likely adjust their time allocation from non-school activities to accommodate their labour market response. This is in contrast to the results of two studies most closely related to ours which provide evidence from India that adolescents reduce schooling in order to increase their labour supply in response to positive rainfall shocks (Shah and Steinberg, 2017; Nordman et al., 2022). Non-agricultural males, however, do appear to draw down on their labour supply while increasing investment in schooling in response to increased current rainfall. However, the labour decisions of non-agricultural males more resembles that of agricultural males in response to lagged rainfall, although, agricultural males exhibit a statistically significantly stronger labour response that males.

This study contributes to the literature on the relationship between environmental conditions and child education and labour outcomes in two key ways. First, it adds to the scarce evidence on the impact of weather on the school–work decisions of adolescents. While a large and growing body of literature documents the effects of weather and environmental shocks on child labour supply and human capital accumulation, most of this work focuses on early or mid-childhood (Jensen, 2000; Beegle et al., 2006; Maccini and Yang, 2009; Tiwari et al., 2017). Only a handful of studies have examined these relationships for younger adolescents (Shah and Steinberg, 2017; Dumas, 2020; Nordman et al., 2022) or both younger and older adolescents (Marchetta et al., 2019; Pham, 2022). Second, this is among the only studies that we are aware of to shed light on how rainfall variability affects these outcomes for non-agricultural households in addition to agricultural households. Most studies have focussed on the effects of weather variability or shocks on agricultural or farm households (e.g., Marchetta et al., 2019; Dumas, 2020; Colmer, 2021; Pham, 2022) or in some cases, demonstrated average effects of covariate shocks, without accounting for heterogeneity across agricultural and non-agricultural households (e.g., Björkman-Nyqvist, 2013; Zimmermann, 2020). While occupations in the agriculture sector are more sensitive to weather shocks, agricultural productivity shocks can also impact the non-agriculture sector through farm and non-farm linkages (Haggblade et al., 1989).

2. Conceptual Framework

Rainfall variability substantially affects rural household income and human capital accumulation as its influence on agricultural productivity can be an important determinant of rural wages (Jayachandran, 2006; Shah and Steinberg, 2017). The impact of rainfall on educational and labour decisions can be particularly salient during adolescence when many children undergo the transition from school to work and/or marriage.

However, the relationship between rainfall and schooling and labour market decisions is theoretically ambiguous due to the competing influences of the income and substitution effects of an income change. Favourable rainfall conditions exert an *income effect* by increasing household income in rural settings, which in turn increases demand of normal goods, including time allocated to non-work activities (e.g., home time) and education. Conversely, rainfall can also exert a *substitution effect* through its impact on the returns to time allocated to both farm and non-farm labour (Marchetta et al., 2019; Shah and Steinberg, 2017), whereby higher agricultural productivity and the associated higher rural wages increase the opportunity cost of time allocated to non-work activities, such as schooling.

Theoretically, the income and substitution effects are both at work simultaneously, however, the household's response to an environmentally induced change in income depends on which of these two effects dominates. Consequently, whether a rainfall shock increases or decreases child labour supply and/or human capital investment depends on whether the income effect or the substitution effect of this shock dominates. Indeed, across multiple countries and contexts, a wide body of evidence demonstrates that it is not only theoretically ambiguous but it is also empirically ambiguous as to whether the income or substitution effect dominates in determining rural household behaviour in developing countries.

First, a large body of literature from developing countries finds behaviour consistent with the dominance of the income effect, in which case we would expect households to increase human capital investment and reduce time allocated to labour in response to weather-induced positive income shocks—and the opposite in the face of negative income shocks. In other words, shocks that improve household income would reduce time allocated from labour towards non-labour activities that can be considered normal goods, such as education or home time. For example, evidence shows that negative agricultural income and/or rainfall shocks decrease school enrolment and attendance (Jacoby and Skoufias, 1997; Jensen, 2000; Gubert and Robilliard, 2008; Björkman-Nyqvist, 2013; Dillon, 2013; Bandara et al., 2015; Baez et al., 2017; Marchetta et al., 2019; Agamile and Lawson, 2021; Pham, 2022).[3] Additionally, studies have shown that negative rainfall shocks increase work propensity (Rose, 2001; Baez et al., 2017; Marchetta et al., 2019), reallocate time away from schooling and towards farm labour (Dillon, 2013; Bandara et al., 2015; Colmer, 2021), and increase child labour in credit-constrained households (Alvi and Dendir, 2011).[4]. Finally, in response to negative income shocks, Beegle et al. (2006) found that households substitute adult labour with child labour for household activities such collection of firewood and water.

Conversely, there is also evidence consistent with the substitution effect being dominant over the income effect. If the substitution effect is dominant, then we would expect the opposite behaviour as an income effect response—that is, households decreasing (increasing) human capital investment and increasing (reducing) time allocated to labour in response to positive (negative) income shocks. In other words, environmental factors that improve labour productivity also raise the opportunity cost of non-labour activities and thus prompt households to substitute their time away from non-labour activities and towards labour activities. Evidence from India, Vietnam and Tanzania indicates that higher wages induced by positive rainfall conditions reduce educational investments, such as school attendance and enrolment, and education expenditures (Shah and Steinberg, 2017; Zimmermann, 2020; Nordman et al., 2022) and increases child time devoted to labour (Dumas, 2020; Trinh et al., 2020; Nordman et al., 2022) across multiple activities, including farm, non-farm and domestic work (Trinh et al., 2020; Nordman et al., 2022).

Which of the opposing forces of the income and substitution effects dominates household response to a weather-induced income change will depend on how the weather event affects the returns to labour relative to the returns to education and time devoted to other activities. These relative returns may vary according the completeness of local labour and financial (i.e., credit, savings and insurance) markets as well as individual and household characteristics, such as gender, primary occupational activities (e.g., agricultural versus non-agricultural) and household socio-economic status.

For example, in the face of imperfect financial and labour markets, households (especially poorer households) may face borrowing constraints and have limited savings to smooth educational investments against transitory income shocks. They may also rely on household labour (including child labour) during rain-induced productivity gains when incomplete labour markets limit their ability to hire non-household labour. In fact, much of the evidence demonstrating the dominance of the substitution effect after a weather-induced income change occurs in contexts where important markets are incomplete or missing, such as land, labour and financial markets (Dumas, 2020; Nordman et al., 2022). Nordman et al. (2022) found further that behaviour consistent with the substitution effect is stronger for more marginalized households.

Additionally, if gender differences exist in the opportunity cost of schooling and/or parental preferences for human capital investment, then there may also be gender differences in whether the income or substitution effect dominates after a weather shock. Some evidence exists for gender differences in the labour and schooling effects of an agricultural shock, which generally indicates stronger labour responses for males (in line with a substitution effect) and stronger educational responses for females (often in line with an income effect) (e.g., Bandara et al.; 2015; Falaris, 2022).[5]

Finally, in rural areas largely dependent on rainfed agriculture, precipitation affects household income and labour activities for both agricultural and non-agricultural households. However, the influence of rainfall on the relative returns of time devoted to labour versus education may differ across agricultural and non-agricultural households. In rural areas, non-farm enterprises are sensitive to rainfall due to forward and backward farm/non-farm linkages (Grabrucker and Grimm, 2021).[6] Rainfall can affect non-agricultural firms through consumption linkages (Haggblade et al., 1989; Grabrucker and Grimm, 2021) and local demand effects driving the growth of non-tradable sectors during years with favourable rainfall (Emerick, 2018). The link between weather and non-agricultural household income can manifest through non-farm employment and wages (Mueller and Osgood, 2009; Jessoe et al., 2018).[7] However, although rainfall influences the income of both agricultural and non-agricultural households, its influence on the relative returns to labour and non-labour activities (including education) likely differs across these groups given differing returns to skill within their occupation types.

3. Theoretical Model

To illustrate the channels through which rainfall can affect school–work decisions in agricultural and non-agricultural households, we developed a two period model following Dumas (2020) and Edmonds (2007). Households maximize utility which is a function of consumption in the two periods and the future welfare of the adolescent, V, which is a function of cumulative non-work time, E, across periods 1 and 2.

$$\max U_1(c_1) + \beta U_2(c_2) + V(E)$$

$$\text{subject to } c_1 = M_1 - e(s_1) \qquad c_2 = M_2 - e(s_2)$$

$$L_1 = 1 + \delta_1 l_1 \qquad L_2 = 1 + \delta_2 l_2$$

$$s_1 + l_1 = T_1 \qquad s_2 + l_2 = T_2$$

$$V = V(s_1 + s_2)$$

For agricultural household : $M_1 = RF(L_1) M_2 = F(L_2)$

For non-agricultural household : $M_1 = w_1 L_1 M_2 = w_2 L_2$

In this model, household income, M, is allocated across consumption, c, and the adolescent's education, whereby the direct cost of schooling is denoted by e. We assumed that the adolescent's non-leisure time, T, in every period is allocated between schooling, s, and work, l. Total labour allocation is denoted by L where adult labour is assumed to be 1 and δ refers to the labour productivity ratio between adolescents and adults, and $0 \leq \delta \leq 1$.

We assumed that the primary source of income in an agricultural household is the production revenue. F is the agricultural production function and R is the productivity factor which is assumed to change exogenously.[8] For simplicity, we assumed away land from the production function. For non-agricultural households, income depends on wages which are likely affected by rainfall fluctuations acting as aggregate productivity shifters (Shah and Steinberg, 2017). Additionally, for non-agricultural households, we assumed that $w_2 = w^2(s^1)$. In other words, wages in period 2 are a function of schooling in period 1 where $\frac{\partial w_2}{\partial s_1} > 0$ refers to the returns from an additional year of schooling.

Similar to Rosenzweig and Evenson (1977), schooling among members of agricultural households was assumed to generate negligible perceived monetary returns.

For ease of exposition, we assumed that the rainfall shock, R, occurs in the first period and there are no shocks in the second period. This simplification allowed us to disentangle the effect of current versus lagged effects of rainfall realizations, which can capture the persistence of productivity shocks. This assumption is reasonable as we later demonstrated that there is no evidence of serial correlation in rainfall variability.

The standard assumptions for the first-order and second-order partial derivatives are:

$\frac{\partial U}{\partial c} > 0$, $\frac{\partial^2 U}{\partial c^2} < 0$, $\frac{\partial F}{\partial L} > 0$, $\frac{\partial^2 F}{\partial L^2} < 0$, $\frac{\partial V}{\partial E} > 0$, $\frac{\partial^2 V}{\partial E^2} < 0$, $\frac{\partial w}{\partial s_1} > 0$, and $\frac{\partial^2 w_2}{\partial s_1^2} < 0$.

The first-order conditions (FOCs) for agricultural (*a*) and non-agricultural (*na*) households

can be solved to obtain the following:

$$\frac{\partial U_1}{\partial c_1} = \frac{\partial U_2}{\partial c_2} \qquad (1)$$

$$\frac{\partial U_1}{\partial c_1}\left(R\frac{\partial F_1}{\partial L_1}\delta_1 + e\right) - \frac{\partial V}{\partial E} = 0$$

or (2)

$$\frac{\partial U_1}{\partial c_1}(w_1\delta_1 + e) - \beta\frac{\partial U_2}{\partial c_2}\frac{\partial w_2}{\partial s_1}(1 + \delta_2 l_2) - \frac{\partial V}{\partial E} = 0$$

$$\beta\frac{\partial U_2}{\partial c_2}\left(\delta_2\frac{\partial F_2}{\partial L_2} + e\right) - \frac{\partial V}{\partial E} = 0$$

or (3)

$$\beta\frac{\partial U_2}{\partial c_2}(w_2\delta_2 + e) - \frac{\partial V}{\partial E} = 0$$

Details for the derivation of all the following results can be found in Appendix A. From the first-order conditions, we get that optimal labor is a function of income and consumption such that $l_1^* = f(M, c_1^*, c_2^*)$, and $l_2^* = f(M, c_1^*, c_2^*)$. As we are interested in understanding the effect of rainfall on schooling and work decisions, comparative statics are a useful exercise. To examine the effect of rainfall on the optimal time allocated to work participation, we take the derivative of the FOCs with respect to R, and rearrange terms to disentangle the income effect (IE) and substitution effect (SE) and obtain the following relationships.

For agricultural households we get:

$$\frac{\partial l_1^a}{\partial R} = -\frac{\overbrace{\frac{\partial U_1}{\partial c_1}\frac{\partial F_1}{\partial L_1}\delta_1}^{SE} + \overbrace{\frac{\partial U_1^2}{\partial c_1^2}F_1\left(R\frac{\partial F_1}{\partial L_1}\delta_1+e\right)+\frac{\frac{\partial F_1}{\partial L_1}\frac{\partial^2 V}{\partial E^2}}{\beta\delta_2\frac{\partial^2 F_2}{\partial L_2^2}}}^{IE}}{D} \tag{4}$$

$$\frac{\partial l_2^a}{\partial R} = \frac{1}{\beta\frac{\partial^2 F_2}{\partial L_2^2}\delta_2^2}\left(R\frac{\partial^2 F_1}{\partial L_1^2}\delta_1^2\frac{\partial l_1}{\partial R}+\delta_1\frac{\partial F_1}{\partial L_1}\right) \tag{5}$$

where the term in the denominator D is negative[9] and for non-agricultural households we get:

$$D = \Bigg[\overbrace{\frac{\partial U_1}{\partial c_1}\left(R\frac{\partial^2 F_1}{\partial L_1^2}\delta_1^2\right)}^{SE} + \overbrace{\frac{\partial^2 U_1}{\partial c_1^2}\left(\frac{R\partial F_1}{\partial L_1}\delta_1+e\right)^2}^{IE} + \frac{\partial^2 V}{\partial E^2}\left(1+R\frac{\frac{\partial^2 F_1}{\partial L_1^2}\delta_1^2}{\frac{\partial^2 F_2}{\partial L_2^2}\delta_2^2}\right)\Bigg] < 0$$

$$\frac{\partial l_1^*}{\partial w_1} = \frac{-\overbrace{\frac{\partial U_1}{\partial c_1}\left(\delta_1+\beta\delta_2\frac{\partial w_2}{\partial s_1}+\beta(1+\delta_2 l_2)\frac{\partial^2 w_2}{\partial s_1^2}\right)} - \overbrace{\frac{\partial U_1^2}{\partial c_1^2}\left(w_1\delta_1+e-\beta\frac{\partial w_2}{\partial s_1}(1+\delta_2 l_2)\right)}}{J} \tag{6}$$

$$\frac{\partial l_2}{\partial w_1} = \frac{\left(-\delta_2\frac{\partial w_2}{\partial s_1}-\beta(1+\delta_2 l_2)\frac{\partial^2 w_2}{\partial s_1^2}\frac{\partial l_1}{\partial w_1}\right)-\delta_1}{-\beta\frac{\partial w_2}{\partial s_1}\delta_2} \tag{7}$$

where the term J is negative.[10]

Assuming that $\frac{\partial w_1}{\partial R} > 0$, for non-agricultural households,

$$\frac{\partial l}{\partial R} = \frac{\partial l}{\partial w_1}\frac{\partial w_1}{\partial R} \tag{8}$$

Higher rainfall, then, in the current growing season has two effects on the optimal level of labor supply. First, the second term in the numerators of results 4 and 6 represents the *income effect* in that higher rainfall increases agricultural production (or wages) and increases consumption which decreases the marginal utility of consumption, such that

$$\frac{-\frac{\partial U_1^2}{\partial c_1^2}F_1\left(R\frac{\partial F_1}{\partial L_1}\delta_1+e\right)+\frac{\frac{\partial F_1}{\partial L_1}\frac{\partial^2 V}{\partial E^2}}{\beta\delta_2\frac{\partial^2 F_2}{\partial L_2^2}}}{D} < 0$$ and $$\frac{-\frac{\partial U_1^2}{\partial c_1^2}\left(w_1\delta_1+e-\beta\frac{\partial w_2}{\partial s_1}(1+\delta_2 l_2)\right)}{J} < 0$$—thus,

encouraging a decrease in the labour supply of adolescents in the face of favorable rainfall conditions.

Second, the first term in the numerators of results 4 and 6 represents the *substitution effect* in that higher rainfall increases the opportunity cost of schooling and leisure (forgone consumption), such that $\frac{\frac{-\partial U_1}{\partial c_1}\frac{\partial F_1}{\partial L_1}\delta_1}{D} > 0$ and $\frac{-\frac{\partial U_1}{\partial c_1}\left(\delta_1+\beta\delta_2\frac{\partial w_2}{\partial s_1}+\beta(1+\delta_2 l_2)\frac{\partial^2 w_2}{\partial s_1^2}\right)}{J} > 0$ —thus reducing the demand for non-work hours and encouraging households to increase the labor supply of adolescents. The net impact of rainfall on optimal labour supply depends on the relative strength of the two opposing effects.

If $\partial T/\partial R = 0$ (no change in non-leisure time), then taking the derivative of the time constraint, we obtained the following:

$$\frac{\partial l^*}{\partial R} + \frac{\partial s^*}{\partial R} = 0 \tag{9}$$

If we assumed the complete time constraint where time is allocated across schooling (s), labour market activity (l), leisure (h) and $\partial T/\partial R \gtreqless 0$, then we obtain the following:

$$\frac{\partial l^*}{\partial R} = -\frac{\partial s^*}{\partial R} - \frac{\partial h^*}{\partial R} \tag{10}$$

Equation 9 shows that the increase or decrease in the optimal labour supply in response to rainfall can be allocated out of a change in the time allocated for schooling or leisure. This is plausible because both schooling and leisure are normal goods and income changes affect them in the same direction. Therefore, if favourable rainfall conditions encourage or discourage the labour market participation of adolescents, school participation could be unimpeded if adolescents substitute between work and leisure instead of work and schooling.

4. Data Sources and Description

4.1 Individual-level data

We conducted our analysis using individual level data from the National Income Dynamics Study (NIDS). This is a nationally representative longitudinal survey of households in South Africa available for the periods 2008, 2010–2011, 2012, 2014–2015 and 2017 (SALDRU, 2018a, 2018b, 2018c, 2018d, 2018e). The survey started in 2008 and since then, the households and their members have been followed to examine the changes in livelihood, occupations, fertility, household composition, health and education etc. We used data from all five waves of this study as it enabled us to examine the within individual variations in exposure to rainfall variability over age. We restricted our sample to rural areas comprising traditional and farm geography types.[11] We included adolescents and young adults aged 15–22 years in every survey.

Our outcomes of interest were school enrolment, education expenditures in the previous year, labour force participation and employment. The NIDS asks respondents aged 15 years and above whether they are enrolled in school[12] during the survey year, whether they are in the labour force, are currently working or are engaged in any income-generating activity. Adolescents in the labour force are defined as those who are economically active, and include employed and unemployed individuals.

While most household surveys in developing countries collect information on education-related expenditures at the household level, NIDS collects information on child-specific expenditure on education in the previous calendar year. Education expenditure for the children enrolled in the year preceding the survey year is collected for five categories: school fees, uniform, books and stationery, school transportation, and allowances and other school expenses. We aggregated the expenditure on these categories to obtain the total education expenditure (in rand) for each child.[13] We obtained the real education expenditure by adjusting these expenditures for inflation using the consumer price index (CPI) (base December 2012 = 100).

We characterized an agricultural household as one where any member of the household participated in growing crops or raising livestock, other than as part of paid employment, over the past 12 months. In an alternative definition, we also incorporate landless agricultural workers in our definition of agricultural households by defining a household as agricultural if any member of the household participated in growing crops or raising livestock other than as part of paid employment or if a majority of working-aged adults are engaged in agriculture as their primary occupation. This check is discussed in section 6. We also constructed an index of household wealth using information on asset ownership.[14] We used the household wealth and agricultural household status observed at baseline (2008) or the earliest of the subsequent waves for those not interviewed at baseline. The survey provides information on the districts in which the household is residing in rural South Africa. We used the district council codes for the 52 district councils as per the 2011 census.[15] After excluding missing and singleton observations, the working sample comprised 46 district councils.[16]

4.2 Climate data

We used historical rainfall data from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), a 30-year rainfall data set that covers 50°S-50°N (and all longitudes) and is available at 6-hourly to 3-monthly aggregates. CHIRPS incorporates 0.05° (approximately 5 × 5 km) spatial resolution satellite imagery with *in situ* station data to create a gridded rainfall time series for trend analysis and agricultural drought monitoring (Funk et al., 2015).[17] We matched the monthly-aggregated weather data based on the geographical coordinates for the district councils in South Africa.

We measured rainfall as the standardized district-specific precipitation, which is computed as the deviation in total growing season precipitation in year t in district d from its 1987-2017 district-specific average divided by its 1987-2017 district-specific standard deviation. This measure is commonly used in the literature (e.g., Marchetta et al., 2019; Branco and Féres, 2021). As South Africa has considerable differences in the timing of rainfall seasons between the east and west, we defined the growing season as a continuous period of above average district rainfall. This period roughly corresponds to $October_{t-1}$ to $March_t$ for most of the country, especially in the east, where most of the rainfall occurs during the summer season. In these regions, maize is the crop with the highest output. For provinces in the west, such as Western Cape, that supply the largest quantity of wheat, the monsoon season occurs during $April_t$ to $September_t$. The standardized rainfall captures the positive and negative deviations in total precipitation relative to the long-term averages. Negative values of standardized rainfall indicate drier conditions whereas positive values indicate wetter conditions.

Using rainfall realizations as a proxy for agricultural productivity fluctuations rests on the assumption that agricultural productivity is one of the most likely mechanisms through which rainfall variability affects school–work decisions. In the context of South Africa, rainfall realizations are a relevant measure of a local agricultural shock. The country's staple crop is maize, and reduced water availability adversely affects maize output by interrupting growth at several points in the growing season (Le Roux et al., 2009). Most of South Africa's rainfall occurs during the warmer months, October-March. The planting season for maize starts from late October and by mid-December, the sowing is completed. Deficient rainfall can severely affect crop yields, evidenced from the two consecutive droughts in 2014–2015 and 2015–2016 that led to a huge shortfall in maize production in the country, which is the major producer of maize in the Southern Africa region (WFP, 2017). Figure 1 illustrates the strong association between annual maize production trends and rainfall during the growing season from 1988 to 2017 in South Africa. Further, Appendix Table B1 demonstrates that standardized rainfall deviations increase maize and wheat yields. These results broadly indicate that transitory rainfall fluctuations serve as a reasonable proxy for productivity fluctuations in rural South Africa.

In our analysis, we also included the spatial and temporal variations in the temperature at the district council level. The monthly temperature series was obtained from the ERA5 product of the European Centre for Medium-Range Weather Forecasts (ECMWF). We standardized the average temperature during the growing season by dividing the deviations of the district level temperature from the district level mean temperature during 1987–2017 by the district-specific standard deviation during this period.

4.3 Data Description

Table 1 presents the sample summary statistics of the outcomes, weather indicators and individual and household characteristics over the study period. The summary statistics for the pooled sample can be found in Table B2. Around 56–81% of our sample adolescents were enrolled in school at the time of the survey. The average real annual expenditure on education ranged from ZAR722–1 566. Around 18–26% of the adolescents were in the labour force and 5–11% were employed.[18] In our models, we used an inverse hyperbolic sine transformation of the real education expenditure to account for 0 education expenditures among those enrolled in school in the previous year.[19]The average rainfall deviation during the growing season showed considerable variation over the study period. On average, during the study period, districts experienced deficient rainfall relative to their long-term mean rainfall. Approximately 50% of our sample comprised female adolescents with an average age of 17.5–20 years.

Table 2 presents the summary statistics of the characteristics of agricultural (column 1) and non-agricultural households (column 2). The average differences between agricultural and non-agricultural households are reported in column 3. We observed that adolescents in agricultural households had a 3.7 percentage point higher school enrolment than those in non-agricultural households and the difference was statistically significant at the 1% level of significance. Education expenditures, conditional on enrolment, and labour market outcomes were not starkly different. A total of 19.6% (20.1%) of the adolescents in agricultural (non-agricultural) households participated in the labour force, however, only 7.3% (7.7%) were employed. There also exists a, possibly spurious, difference in standardized rainfall realizations and temperature between agricultural and non-agricultural households. Agricultural households had a smaller proportion of female adolescents and lower wealth than non-agricultural households. Adolescents in agricultural and non-agricultural households did not differ in age.

Figure 2 presents the proportion of school enrolment and work participation at every age in the sample. As expected, we observed that the proportion of adolescents enrolled in school was high up to age 17, after which children start terminating their education. As adolescents age, the probability of employment increases among both females and males. Employment is higher among males relative to females at every age and school enrolment follows a similar pattern. The gender-based inequality in human capital investment in rural South Africa is likely driven by the fact that female adolescents engage more in domestic chores and caregiving for siblings. Therefore, they have a lower likelihood of entry into the labour market.

Figure 3 presents the distribution of the standardized rainfall deviations during 2008–2017. Panel A shows the rainfall deviations for the full sample. Following Marchetta et al. (2019), we showed the histogram of the district-specific mean of these deviations in panel B. We observed that the district-specific means are concentrated around 0. This provides support to the assumption that districts do not systematically experience wetter or drier rainfall conditions relative to the long-term average. Therefore, the main variable of interest, standardized rainfall, captures normal rainfall variability.

South Africa, a middle-income country located within a drought belt, has experienced exacerbated drought conditions in recent years (Blamey et al., 2018). Figure 4 presents the average monthly rainfall deviations relative to the long-term monthly averages over time. We observed that for a larger proportion of our study period, the average rainfall deviations were negative, indicating that the country experienced drier conditions than the 30-year long-term rainfall. This is also evident in panel (b) of Figure 3. Figure 5 maps the rainfall deviations during the growing season across districts in every study period. We observed that rainfall during the growing season demonstrates not just temporal variation but also substantial spatial variation.

4.4 Empirical Strategy

To identify the effect of rainfall realizations, we employ a linear fixed effects model that includes individual, year, month and age fixed effects. The empirical strategy exploits the within-individual variation over time while accounting for time, season and age trends in our outcomes and exposure to the exogenous rainfall.

The decision to discontinue enrolment in school and work in income-generating activities may depend on the rainfall deviations in the current growing period which affects the expected revenues. The decision to send the child to school or work during the start of the agricultural cycle may also be affected by the household revenues generated in the previous growing period. Therefore, we estimated both the current and lagged effect of growing season rainfall on school-work decisions.

We estimate the following linear equation:

$$Y_{idmta} = \beta_0 + \beta_1 Rain_{dt} + \beta_2 Rain_{dt-1} + \beta_3 T_{dt} + \lambda_i + \delta_a + \phi_m + \omega_t + u_{idmta} \quad (11)$$

Where the outcome variable Y refers to the education and labour outcome of adolescent *i* in district *d* surveyed at age *a* in month *m* and survey period *t*. The main variable of interest is the standardized rainfall, *Rain*. Because our education expenditure variable measured expenditure in the previous year, we used the 1 and 2-year lags of rainfall as our measures of current and lagged rainfall respectively. The coefficient β_1 represents the contemporaneous linear effect of standardized rainfall on school and work decisions. We also include the standardized rainfall in the previous growing season based on the definition in section 4.2. The marginal effect of lagged rainfall is captured by β_2.

T is the standardized annual temperature in district *d* in year *t*; λ_i is a vector of individual fixed effects; δ_a is a vector of age fixed effects; ϕ_m is a vector of month of interview fixed effects; ω_t is a vector of the survey year fixed effects; and u_{idmta} is the random error term. We excluded time varying household-level control variables such as household size, wealth and agricultural household type to avoid intermediate variable bias.[20] Additionally, individual fixed effects capture the time invariant household-level control variables at baseline (or the first survey wave). We clustered standard errors at the level of the primary sampling unit in all the regressions.[21]

To estimate the differential effects of rainfall shocks across baseline agricultural and non-agricultural households, we added an interaction term between *Rain* and a dichotomous indicator for whether an individual resides in an agricultural household to the main specification. We estimated the following regression:

$$Yidmta = \alpha 0 + \alpha 1 Raindt + \alpha 2 Raindt \times Ag + \alpha 3 Raindt{-}1 + \alpha 4 Raindt{-}1 \times Ag \qquad (12)$$

$$+\alpha 5 Tdt + \lambda i + \delta a + \phi m + \omega t + uidmta$$

Where *Ag* refers to the baseline agricultural household status. The coefficients, α_2 and α_4, on the interaction terms capture the differential effect of current and lagged rainfall on school–work decisions across household type.[22]

The identification strategy to estimate the causal effect of rainfall realizations yields unbiased estimates under the assumption that standardized rainfall is uncorrelated with unobserved determinants of schooling and labour market outcomes. We acknowledged that a threat to our identification may arise if unobserved individual level heterogeneity is correlated with rainfall variability. For example, droughts in the past or in early childhood could have affected household socio-economic conditions. If that is the case and past rainfall patterns are correlated with current patterns, the effect of current rainfall realizations would capture the effect of the historical long-term rainfall. To mitigate this concern, we used an individual fixed effects model which controls for the time invariant individual unobserved heterogeneity correlated with the idiosyncratic error term. Individual fixed effects also control for the time invariant household and district characteristics that may affect school–work decisions and education expenditures. Moreover, in Section 6 we show that rainfall deviations do not significantly predict any predetermined individual and household level characteristics and also do not demonstrate serial correlation. The survey year fixed effects in our models captured the unobservable labour market conditions or changes in schooling infrastructure that vary over time. The month fixed effects captured the seasonality in the rural labour markets and any possible seasonal pattern in school enrolment.

It is plausible that differences across districts in terms of the level of local infrastructure and economic development may be systematically related to rainfall variability. If such differences exist, rainfall realizations may be correlated with unobservables affecting schooling and work decisions, which would lead to biased estimates. There are three reasons why this concern is unlikely to substantially bias our estimates. First, we used a measure of rainfall variability relative to district specific historical levels, so that districts experiencing high rainfall in a particular year relates to their long-term trends and not to other districts. Second, we controlled for individual heterogeneity by using individual fixed effects that capture the effect of residing in a particular district. This is because almost the entire sample of adolescents resided in the same district during the study period, except for 1.78% (189) of the sample adolescents who reported moving to another district. Third, we ran a separate model in which we included province fixed effects in addition to the individual fixed effects and found that our results were unchanged. These results are discussed in Section 6.

5. Results

5.1 Rainfall and school-work decisions

This study was interested in the net impact of rainfall on school and labour decisions in the rural sample and how these decisions may differ for males versus females and agricultural versus non-agricultural households. Therefore, we first estimated Equation 10 with our pooled working sample and then for males and females separately in Table 3. We then allowed our estimates to vary across agricultural and non-agricultural households by estimating Equation 11 for the pooled working sample and then again for males and females separately. These results are reported in Tables 4 and 5 respectively.

As described in Section 2, if the income effect outweighs the substitution effect (opportunity cost channel), then we would expect a negative effect of rainfall on labour market participation and a positive effect on schooling or a null effect if work time is allocated towards leisure. However, if the substitution effect dominates, the expected effect of rainfall on labour market participation is positive.

Columns 1 and 2 of Table 3 report estimates from Equation 10 for educational outcomes. We found that current and lagged rainfall exert a possible weak effect on education at the extensive margin (i.e., enrolment) but a stronger effect at the intensive margin (education expenditure). A 1 standard deviation increase in current (lagged) rainfall results in an average increase in education expenditure of approximately 25% (32%), significant at the 1% level. The point estimate on enrolment was also positive but statistically insignificant. However, the enrolment effects in Table 3 are almost statistically significant at conventional levels.

Columns 3 and 4 (Table 3 panel A) report the estimated rainfall effects on labour outcomes for the pooled sample. Point estimates for the effect of current rainfall on labour market outcomes are small and not statistically different from zero. However, a 1 standard deviation increase in lagged rainfall increases labour market participation by 1.75 percentage points, on average, and employment rates by approximately 2.23 percentage points, on average. Together, these results indicate that, on average, behaviour consistent with the income effect dominates educational investment but that the substitution effect dominates labour supply for the pooled sample, meaning that the increase in labour supply does not come at the cost of school investment.

Next, we estimated Equation 10 separately for males and females, reported in Table 3 (panels B and C). Columns 1–4 report these results for education outcomes and again suggest a stronger impact of rainfall on education expenditure than on school enrolment. When looking at males and females separately, both current and lagged rainfall statistically significantly increased education expenditure. Regarding enrolment, current rainfall was associated weakly with increased male enrolment, but not female enrolment. Conversely, lagged rainfall was associated weakly with increased female enrolment but not male enrolment.

Turning to labour outcomes (columns 5–8, Table 4), different responses across males and females become apparent. Again, we found no effect of current rainfall on the labour market decisions of males or females, with point estimates that are small in magnitude and statistically insignificant. However, males and females respond differently to lagged rainfall. Lagged rainfall increases the probability of labour force participation and working for males, however, it exerts no discernible effect on females. Thus, the substitution dominant behaviour with respect to labour found in Table 3 (panel A) appears to be largely driven by sample males.

Because rainfall may impact the relative returns to education and labour market activities differently for agricultural versus non-agricultural households, Table 4 reports estimates from Equation 11, which allows for differential rainfall responses across these two groups. The estimated coefficient on current and lagged rainfall represents the estimated average effect of rainfall on non-agricultural households whereas the linear combination of that coefficient and the coefficient on the interaction terms represent the marginal effect on agricultural households. The marginal effect on agricultural households is reported in the bottom two rows of Table 4. The coefficients on the interaction terms can be found in Appendix Table B.3.

Similar to the results reported in Table 3, when males and females are pooled we found statistically significant and positive impacts of rainfall on educational expenditures for both agricultural and non-agricultural households. The corresponding impacts on enrolment were again positive but not statistically different from zero (columns 1-2, Table 4). Columns 3–4 report the estimated effects of rainfall on labour market decisions of agricultural and non-agricultural households and present a more nuanced picture than those reported in Table 3. We found that current rainfall is associated with reductions in the labour market activities of non-agricultural households (consistent with the income effect) but increased labour market activities for agricultural households (consistent with the substitution effect). However, lagged rainfall was associated with increased labour market activities for both agricultural and non-agricultural households. Thus, for non-agricultural households the income effect may dominate education and labour decisions related to current rainfall but the substitution effect may dominate their labour decisions with respect to lagged rainfall, possibly due the combined effect of lagged rainfall and added schooling on their wages.

Finally, Table 5 reports the estimated effects from Equation 11 for the sample of males (panel A) and females (panel B), separately. We found even further nuances when we allowed estimated effects to vary by both sex and household type. Starting with agricultural households, we found positive point estimates for the effect of current and lagged rainfall on male educational expenditure, but only the point effect for lagged rainfall was statistically significant at conventional levels. Neither the effect of current or lagged rainfall on agricultural male enrolment was statistically significant and the point estimates had opposite signs. For females in agricultural households, the point estimate for the effects of lagged and current rainfall on school expenditure were also positive and statistically significant. The effect of lagged rainfall on enrolment was also positive and significant (at the 10% level) for agricultural females but the impact of current rainfall on enrolment was small and insignificant. Overall, these results indicate behaviour consistent with the income effect regarding the educational investment for both males and females in agricultural households, particularly on the intensive margin.

For non-agricultural households, we also found behaviour consistent with the income effect regarding educational investment. For males and females in non-agricultural households, we found positive point estimates for the effect of current and lagged rainfall on enrolment and educational expenditures. However, these estimates were only statistically significant for the effect of current rainfall on male enrolment and expenditure and for the effect of lagged rainfall on female educational expenditure.

Turning to labour outcomes (columns 3–4, Table 5), we found that the labour market response depends on the type of household (agricultural or non-agricultural), sex and the timing of the rainfall. For labour market outcomes in agricultural households, we generally found behaviour consistent with the substitution effect where lagged rainfall exerts a highly significant and positive effect on male labour market participation and employment and current rainfall exerts a positive and significant effect on these labour market outcomes for females. For non-agricultural households, we found that current rainfall reduces male labour supply while lagged rainfall increases their supply. Specifically, the point estimates for current rainfall on non-agricultural male labour force participation and the probability of working were negative but only the effect on participation was statistically significant, although the effect on working is almost significant at conventional levels. However, lagged rainfall statistically significantly increased both labour outcomes for non-agricultural males. For females in non-agricultural households, point estimates were highly insignificant and largely small, indicating that neither current or lagged rainfall appears to substantially influence the labour supply of females.

Taking all the results reported in Table 6 together, we found that the income effect largely dominates the educational response of agricultural and non-agricultural adolescents with increased educational investment (particularly on the intensive margin) in response to positive rainfall realizations. For males and females in agricultural households, we also generally found that the substitution effect dominates their labour response as rainfall increases their labour supply. Because rainfall generally increases education and labour for agricultural adolescents, they are likely adjusting time away from non-school activities in order to increase their labour activities. For non-agricultural males, evidence showed the income effect dominates their response to current rainfall with regards to their labour supply in addition to educational investment in that positive current rainfall increases their educational investment while also reducing their labour supply. However, one year after the rainfall realization, the substitution effect appears to dominate their labour response with positive and significant effects of lagged rainfall on labour supply. Conversely, neither current nor lagged rain influenced the labour supply of females in non-agricultural households.

As we did not find statistically significant negative effects of current or lagged rainfall on school enrolment and education expenditures, we may infer that any observed increase in work propensity in response to rainfall realizations does not induce a corresponding decrease in school participation. Households trade off children's time allocation between labour, schooling and home time, which is likely affected by income shocks for households lacking access to complete financial markets (Jacoby and Skoufias, 1997). In our context, in response to lagged rainfall, male adolescents likely allocate time toward the labour market by decreasing home time and to a lesser extent, time spent on household chores or sibling caregiving. Similarly, female adolescents do not experience a decrease in school participation in response to current-period favourable rainfall, but nor do they seem to increase their labour.

Although the survey does not provide information on time use, we tested the possibility that adolescents adjust non-work, non-school activities by estimating Equation 11 with dichotomous indicators for both school enrolment and working, and for engaging in neither the labour market nor an educational institution as the dependent variable. Table 6 presents these results. The point estimates indicate that higher rainfall generally increases the probability of female and male adolescents engaging in both schooling and the labour market and reduces the likelihood that they engage in neither school nor work. However, statistical significance and the magnitude of these point estimates change slightly depending on the timing of the rainfall and household type.

Another reason that the higher work propensity in response to rainfall fluctuations might not hamper human capital investment is that the majority (72.5% conditional on working) of older adolescents and young adults engage in informal employment which may offer work-time flexibility.[23] For this sample, the average time engaged in paid economic activity in the past week was 35 hours. Overall, the results provide suggestive evidence that current period rainfall and lagged rainfall induce allocation of time away from home time, instead of dis-enrolment from school, towards the labour market for females and males respectively.

5.2 Heterogeneity across household wealth

In the context of imperfect financial markets in rural areas, poorer households face borrowing constraints and have limited savings to smooth educational investments against transitory income fluctuations. Some papers demonstrated that in poor households, which may lack savings and formal insurance, unanticipated negative income shocks have an adverse effect on school attendance (Jacoby and Skoufias, 1997) and increase child labour (Beegle et al., 2006; Guarcello et al., 2010). One possible explanation is that wealthier households are better able to draw down assets or other resources in response to unanticipated shocks, whereas poor households are forced to sell their productive assets or pull their children from school into the labour market.

This section examines the heterogeneity in the effects of rainfall on the school–work decisions and human capital investments across household wealth. Assets can mitigate the impact of adverse transitory shocks by serving as buffer stocks or enabling households to use them as collateral for credit. Therefore, the coping strategies of households involving the school–work transition or vice versa depend on the household's ability to access credit or utilize assets. We explored the role of wealth in mitigating the effects of only current rainfall as these are likely driven by the income channel. We estimated the following:

$$Y_{idmta} = \gamma_0 + \gamma_1 Rain_{dt} + \gamma_2 Rain_{dt} \times Ag + \gamma_3 Rain_{dt} \times Wealth + \gamma_4 Rain_{dt} \times Ag \times Wealth$$
$$+ \gamma_5 Rain_{dt-1} + \gamma_6 Rain_{dt-1} \times Ag + \gamma_7 Rain_{dt-1} \times Wealth + \gamma_8 Rain_{dt-1} \times Ag \times Wealth$$
$$+ \gamma 9 Tdt + \lambda i + \delta a + \phi m + \omega t + uidmta \qquad (13)$$

Where *Wealth* refers to the baseline household wealth. *T*, λ, ω, δ and ϕ are as defined in Equation 10.

Table B4 reports the coefficients from the estimation of Equation 12 separately for the sample of females and males. Figures 6 and 7 present the corresponding marginal effects of current rainfall on the education and labour outcomes across household wealth percentiles for male adolescents in agricultural and non-agricultural households. We observed that the effect of current rainfall on the school enrolment is attenuated for male adolescents belonging to wealthier non-agricultural households (Figure 6, panel b). Specifically, the enrolment effects become smaller for higher wealth percentiles. The effect of current rainfall on education expenditures in non-agricultural households appears flat across the wealth distribution (Figure 6, panel d). Male adolescents from poorer non-agricultural households are less likely to participate in the labour market in response to positive rainfall realizations but this effect is attenuated at higher wealth percentiles and ultimately goes to zero (Figure 6, panel f). In other words, the school enrolment and labour supply of males from wealthier non-agricultural households was less responsive to rainfall fluctuations relative to those from poorer households. These results reinforce our expectations regarding operation of the income channel among non-agricultural households. Similarly, the employment effect on agricultural males was stronger for those in poorer households. Our results are consistent with those of Beegle et al. (2006) and Marchetta et al. (2019), who found that higher assets mitigate the impact of transitory agricultural income shocks, with the primary difference that their results mainly pertain to agrarian households.

The mitigating effect of household wealth seemed weak for female adolescents (Figure 7). The marginal effects of current rainfall on the labour force participation of female adolescents from agricultural households are positive and statistically significant towards the higher end of the wealth distribution (panel e). Therefore, household wealth may reinforce the influence of current-period rainfall on labour force participation for agricultural household females. We also observed that female educational outcomes and employment are not sensitive to rainfall deviations irrespective of the wealth status. Overall, we found evidence that household wealth serves as a buffer to mitigate the effects of rainfall conditions on largely adolescent male school–work decisions.

6. Robustness and Sensitivity Checks

Notably, our results were not sensitive to how we defined rainfall and other model specifications. Following Björkman-Nyqvist (2013) and Nordman et al. (2022), we considered the deviations of rainfall defined as the logarithm of the total precipitation during the growing season in year *t* in district *d*, minus the logarithm of the 1987–2017 growing season average, $ln_{(Rdt)} - ln_{(}\bar{\boldsymbol{R}}_{)}$. This indicator captures the positive and negative deviations (%) in total precipitation relative to the long-term averages. Table 7 (columns 1-4) shows that the estimates are qualitatively similar to the results in Table 3. We also considered a discrete measure of rainfall shocks. Similar to definitions followed by Jayachandran (2006) and Shah and Steinberg (2017), we defined a rain shock as equal to 1 if the standardized rainfall is above 1 standard deviation, -1 if the rainfall is below -1 standard deviation, and 0 otherwise. The estimates in columns 5-8 demonstrate similar results, except for the noisy coefficient of lagged rainfall shock on labour force participation.

We also check the sensitivity of our results to using an alternative definition of agricultural household. We define a household as agricultural if any member of the household participated in growing crops or raising livestock, other than as part of paid employment or if a majority of the working-aged adults are engaged in agricultural sector occupations.[24] Consistent with the argument that the wide non-farm income diversification observed in rural areas of Africa requires a distinction between off-farm and non-farm activities (Barrett, Reardon, & Webb, 2001), this definition allows us to capture households with landless agricultural workers as agricultural. Appendix Table B.5 presents results qualitatively similar to those in Table 3.

As temperature variation is correlated with the severity of rainfall conditions (Vicente-Serrano et al., 2010) and can also affect local employment and wages (Jessoe et al., 2018), we checked whether our results were robust to excluding temperature from our estimated model. Excluding temperature as a control did not substantially change our results (Appendix Table B.6). The only exception was that the point estimate for the effect of current-period rainfall on school enrolment was statistically significant, although of similar magnitude to our main results in Table 3.

As discussed in section 4.4, a threat to identification arises if rainfall variability is correlated with unobserved time-varying characteristics of schooling and work decisions. While we could not explicitly test this, the results in Table 8 indicate that rainfall deviations do not significantly predict potentially important predetermined individual and household level characteristics such as adolescent's age, household wealth index and agricultural household indicator. Additionally, we demonstrated in

Table B.7 that the our estimates were robust to the inclusion of province fixed effects which capture the time-invariant geographic variation.

If standardized rainfall in a particular year is correlated with rainfall in the previous year, it would be difficult to disentangle the effects of rainfall shocks pertaining to a single year from the cumulative effects over multiple years. In our case, precipitation in one year was not systematically related with precipitation in the next year. Figure 5 shows that the spatial distribution of rainfall during the growing season varied randomly over time. Additionally, we tested for serial correlation in rainfall at the district and individual levels. The results reported in Table 9 indicate no significant correlation between lagged rainfall and current rainfall over time.

We also conducted a falsification test by estimating our model using standardized rainfall during the non-growing season instead of the growing season as our treatment variable. If growing season rainfall simply proxies for other unobserved confounders correlated with weather conditions, then it is plausible that non-growing season rainfall would similarly capture these confounders. If this is not the case, then we would not expect to find a significant effect of non-growing season rainfall on our school–labour outcomes. Specifically, for this falsification test, we estimated the impact of standardized rainfall during the district-specific non-growing season months. For the eastern maize-producing regions, these months correspond to April–September and for the western regions producing wheat, these correspond to October–March. Table 10 reports the estimates from these regressions. We found no statistically significant effects of current or lagged non-growing season rainfall on school–work decisions. The estimated null effects mitigate concerns of confounding factors not captured by our model that are correlated with local rainfall conditions. Similarly, the null effects support our assumption that the primary channel through which rainfall affects our outcomes is agricultural productivity.

We also conducted a falsification test where we considered standardized future rainfall as the treatment variable. Table 11 reports the estimates when we used standardized total rainfall in the growing season of the following year. As rainfall shocks at the district level are not serially correlated over time, using precipitation in the next season should not affect the current investments in human capital and labour market participation. If the observed effects of rainfall variability are confounded by omitted trends, we should observe statistically significant coefficients of the same sign as our main results. Evidence in Table 11 indicates that rainfall variability in the future is uncorrelated with the current school–work decisions of our sample adolescents and young adults. Finally, we also checked whether rainfall affects these decisions for sample adolescents living in the urban areas, where we expect null effects. Table B.8 confirms that rainfall in the current period and previous period does not exert any significant effects on schooling and work decisions, except for a negative effect of lagged rainfall on school enrolment of females.

A source of bias when using panel data is attrition of sample individuals. Individuals and households present in the baseline wave (2008) may have dropped out in later rounds due to migration, non-response or death. In that case, our results would be biased if the individuals who left the survey or were observed with interruption were systematically different in terms of socio-economic baseline characteristics. In our case, this was of minor concern. Baseline characteristics across sub-samples are reported in Appendix Table B.9. We reported the average characteristics and their differences across the full baseline sample, the balanced sample and the sample observed with interruption. This exercise suggests that these samples do not statistically differ in terms of most of the baseline individual and household characteristics, except for lagged (2007) rainfall and standardized temperature. Additionally, only 26 adolescents from the original baseline survey exited the sample after wave 2. Most importantly, we found no evidence of significant correlation between rainfall variability and these sub-samples. In other words, of the baseline sample, individuals who appear in every wave and individuals observed with interruption were exposed to similar rainfall in 2008. We also demonstrated that the results are similar if we considered adolescents who were observed in all five waves, that is, the balanced sample (Table B.10).

Relatedly, there was higher attrition of white, Indian/Asian and high-income individuals in waves 2 to 4. Therefore, a top-up sample was added in wave 5. But this is not likely to affect our estimates as our working sample did not include the top-up sample. [25] Our working sample comprised continuing sample members who were members of the original sample of households selected in wave 1 and temporary sample members who were co-residents with the continuing sample members but were not followed if they left the household. A bias might arise if the characteristics of temporary sample members are systematically related with rainfall. We checked for the possibility of this by estimating our models on the original baseline sample of continuing sample members. Table B.11 shows that the results are similar to our main models. This alleviates concerns associated with addition of individuals in the subsequent rounds.

As we tested multiple hypotheses, we also reported the Romano–Wolf step-down adjusted p-values in Table B.12. The Romano–Wolf correction controls for the familywise error rate when testing multiple hypotheses. We used the procedure by implementing the routine provided by Clarke et al. (2020) for estimating Equation 11. The statistical inference from the corrected p-values was almost unchanged.

Our working sample had 111 missing observations (1.04%) for labour force participation and employment. We demonstrated in Table B.13 that the results remain unchanged if we restricted the regressions for the enrolment outcome to the sample with non-missing observations on labour market outcomes.

7. Conclusions

Using rich longitudinal individual data from rural South Africa, we explored the impact of rainfall realization on the school and work decisions of adolescents and young adults. Our results indicate that higher current-period and previous-period rainfall increases human capital investment on the intensive margin (real education expenditures) among both male and female adolescents. However, the effects of current-period rainfall on labour market outcomes differed across gender and agricultural versus non-agricultural households. We found strong negative effects of current rainfall on the labour supply of non-agricultural household males likely driven by the income effect dominating the substitution effect. In contrast, the effects on labour market participation of agricultural household females was positive, likely driven by the higher opportunity cost of schooling. We confirmed the operation of the income channel by demonstrating that household wealth mitigates the effect of current rainfall on school enrolment and labour market outcomes of males in non-agricultural households. However, we did not find strong evidence of assets serving as buffer stocks for females.

Favourable rainfall in the previous period had persistent effects driven by the opportunity cost of education channel for male adolescents. Lagged rainfall increased labour force participation and employment of male adolescents. Additionally, lagged rainfall variability did not affect the school enrolment of male adolescents. The higher work propensity of male adolescents in response to rainfall shocks in the previous agricultural season was likely allocated by decreasing home time. Therefore, the substitution effect operates without imposing losses in human capital investment. Our results imply that improved economic conditions may exert persistent effects and encourage labour market participation and employment in rural economies in the following periods. This finding has policy implications for labour markets in rural South Africa, which exhibit extremely high youth unemployment.

Our results highlight that credit-constrained non-agricultural households adjust human capital investments in adolescents to smooth income fluctuations induced by transitory agricultural fluctuations. Since adolescence is characterized by economic transitions that have potentially long-term impacts, investments during adolescence, especially in the face of adverse weather events, may elicit high returns. Our study suggests policy interventions targeting adolescents at sensitive periods of human capital formation, especially in the face of climate-induced uncertainty. Better access to credit facilities may mitigate the impacts of adverse rainfall fluctuations on human capital accumulation and work propensity and enable poorer households to cope with unexpected weather variability.

Notes

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2 +Department of Economics, University of New Mexico, Email address: kmvilla@unm.edu. Kritika Sen Chakraborty acknowledges financial support from the African Economic Research Consortium (AERC) collaborative research project on Building Policy Research Institutions to support Human Capital in Africa country case studies. The authors thank (in alphabetical order) Noam Angrist, Catalina Herrera Almanza, Xiaoxue Li, Adrienne Lucas, Germano Mwabu, Lant Pritchett and participants at the Western Economic Association International (WEAI) Conference, Agricultural and Applied Economics Association (AAEA) annual meeting 2022, and at the Southern Economic Association (SEA) Conference 2022 for their comments.

3 Beegle et al. (2006) and Dillon (2013) measured agricultural income shocks by crop loss. Gubert and Robilliard (2008) considered household-specific shocks, such as crop loss resulting from pests, rodents or locusts, and region-specific shocks, such as rainfall deviations from the long-term average.

4 Alvi and Dendir (2011) examinde the effect of 1998 floods in Bangladesh.

5 In rural Ethiopia, Falaris (2022) found that positive agricultural season rainfall induces an increase in educational investments and a reduction in labour time for girls, indicating the dominance of an income effect (except during harvest season) but found that for boys the opposite is true, indicating the dominance of the substitution effect. Conversely, in Tanzania Bandara et al. (2015) found the dominance for the income effect for both boys and girls but with strong labour effects on boys and stronger educational effects on girls.

6 Regarding forward linkages, Grabrucker and Grimm (2021) found suggestive evidence that excessive rainfall shocks increase input costs for food processing enterprises, whereas backward linkages explain the higher input costs for farms and higher sales revenue for agriculture-related non-farm enterprises.

7 Jessoe et al. (2018) found that the reduction in local employment as a result of extreme heat shocks is driven by a decrease in employment in the non-agriculture sector in rural Mexico. They argue that strong linkages exist between decrease in farm income and lower demand for non-agricultural goods, particularly non-tradable services, leading to lower demand for non-agricultural labour.

8 Here, positive agricultural productivity shocks exclude the extreme case of floods which likely have adverse effects on agricultural production.

9 *D* is negative based on second-order conditions and

10 *J* is negative due to second order conditions and diminishing marginal returns and
$$J = \left[\frac{\partial^2 V}{\partial E^2} - \left(\frac{-\partial^2 V}{\partial E^2} + \frac{\partial U_1}{\partial c_1}\beta\frac{w_2}{s_1}\delta_2\right)\left(\frac{1}{\beta} + \frac{(1+\delta_2 l_2)}{\delta_2}\frac{\partial^2 w_2/\partial s_1^2}{\partial w_2/\partial s_1}\right)\right] < 0$$

11 The geographical type classification is traditional, urban and farms. Traditional is defined as communally owned land, with village settlements. Urban geography is defined as a continuously built up area established through cities, towns, townships etc. Land, and structures built on it, allocated for and used for commercial farming are defined as farms.

12 School includes university, technical college, primary and secondary school.

13 We recoded the missing expenditures on the sub-categories (uniforms, stationery etc.) of education expenditures as 0. Total education expenditure is missing only for those individuals for whom all the sub-categories have missing observations (11.02% of the working sample).

14 Household wealth index is created using factor analysis. We considered ownership of the following assets: radio, stereo, television, satellite dish, DVD player, computer, camera, cell phone, electric stove, gas stove, paraffin stove, microwave, fridge, washing machine, sewing machine, lounge suite, private motor vehicle, motorcycle, bicycle, boat, motorized boat, cart, plough, tractor, wheelbarrow, grinding mill, house, water source, toilet type, fuel type, roof type, wall material and livestock.

15 Between the 2001 and 2011 censuses, the district municipal boundaries changed. To ensure comparability, we considered the district municipalities as per the 2011 census boundaries.

16 District council is the second level administrative division of the territory of South Africa.

17 The CHIRPS data set builds on previous approaches and uses a 'smart interpolation' approach to create a record of high resolution estimates. It incorporates daily, pentadal and monthly 0.05° infrared Cold Cloud Duration (CCD)-based precipitation estimates from 1981 to present (Funk et al., 2015).

18 Of those who were economically active in the pooled sample, around 52.08% worked in wage/salaried jobs, 20 % were involved in casual work and 17.41 % worked on their own garden or plot. Around 5.39% assisted in other's business activities and 4.47% were self-employed. Casual work refers to irregular and short-term work that individuals engage in.

19 In our sample, 12.37% adolescents reported 0 education expenditure. Around 69.5–92.9% adolescents were enrolled in a "no-fee" school. Using an inverse hyperbolic sine transformation allowed us to retain observations with value 0 and is similar to a logarithmic transformation. We found similar results if we added 1 to education expenditures and used a logarithmic transformation. The results are available upon request.

20 Results are similar if we include time varying household level controls.

21 For the working sample, the number of primary sampling unit clusters was 231.

22 We recognized that using the baseline agricultural household status is the appropriate way to estimate the differential effects of weather shocks by type of household. This is because using the time varying agricultural household status may introduce intermediate variable bias. For example, favourable rainfall conditions may induce households to take up agricultural activities at their farm and vice versa. However, this is unlikely to confound our estimates as current and lagged rainfall do not have statistically significant effects on time varying household agricultural status (Table 9). In addition, the results were similar if we used the current time varying household type to estimate the interaction effects. These results are available upon request.

23 Informal employment is defined as an occupation which does not have a written contract of employment and does not involve any deductions for medical aid, pension or unemployment insurance. Following ILO (2018), we classified self-employment as informal if the enterprise was not registered for income tax or value added tax (VAT).

Informal employment also includes casual employment (irregular work), personal agriculture and assisting with others' business.

24 Agricultural sector occupations comprise wage/salaried work in agriculture, hunting, forestry, and fishing, self-employment in the agricultural sector, personal agriculture, casual wage work in the agricultural sector, and assisting others' business in the agricultural sector.

25 Most of the top-up sample of wave 5 resided in urban areas. The very small proportion of the sample in rural areas did not include adolescents in our relevant age group.

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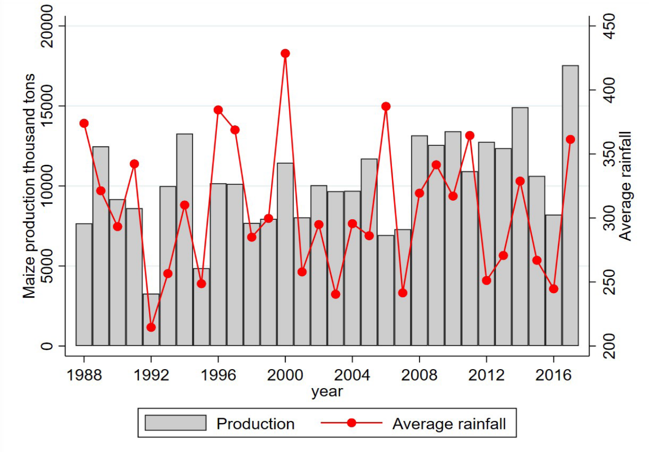
Figures

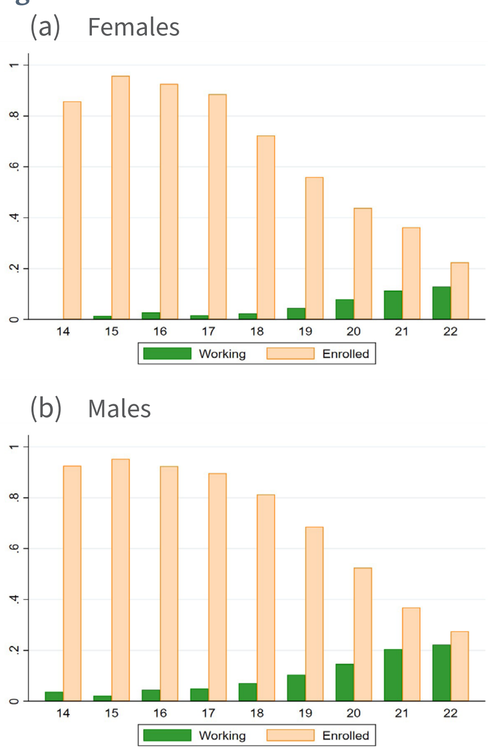
Figure 1: Annual maize production and rainfall



Note: This figure demonstrates the association between average rainfall (inches) during the growing season (October–March) and the annual maize production ('000 metric tons) from 1988 to 2017.

The data are obtained from the U.S. Department of Agriculture.

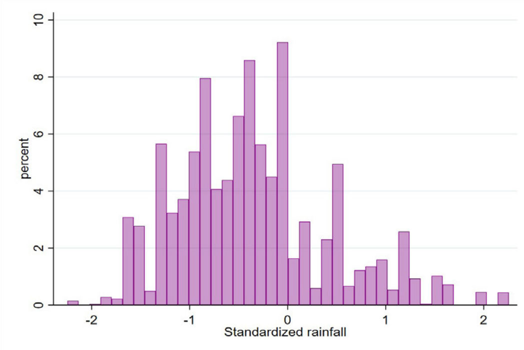
Figure 2: School-work status of adolescents and young adults



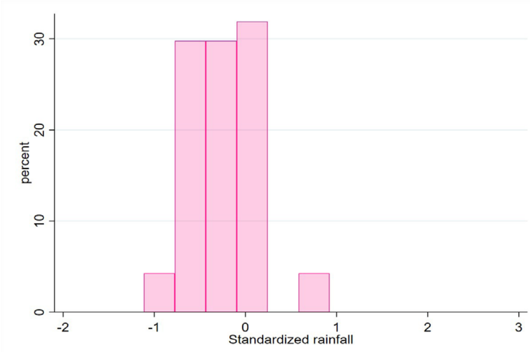
Note: Age in completed years on the x-axis

Figure 3: Distribution of rainfall

(a) Standardized rainfall

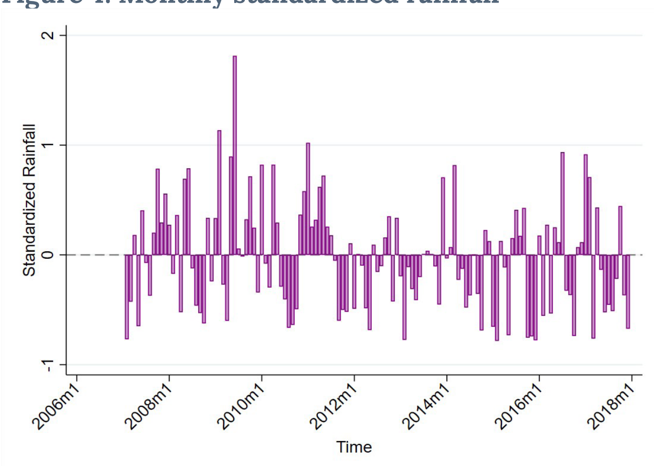


(b) Mean of standardized rainfall



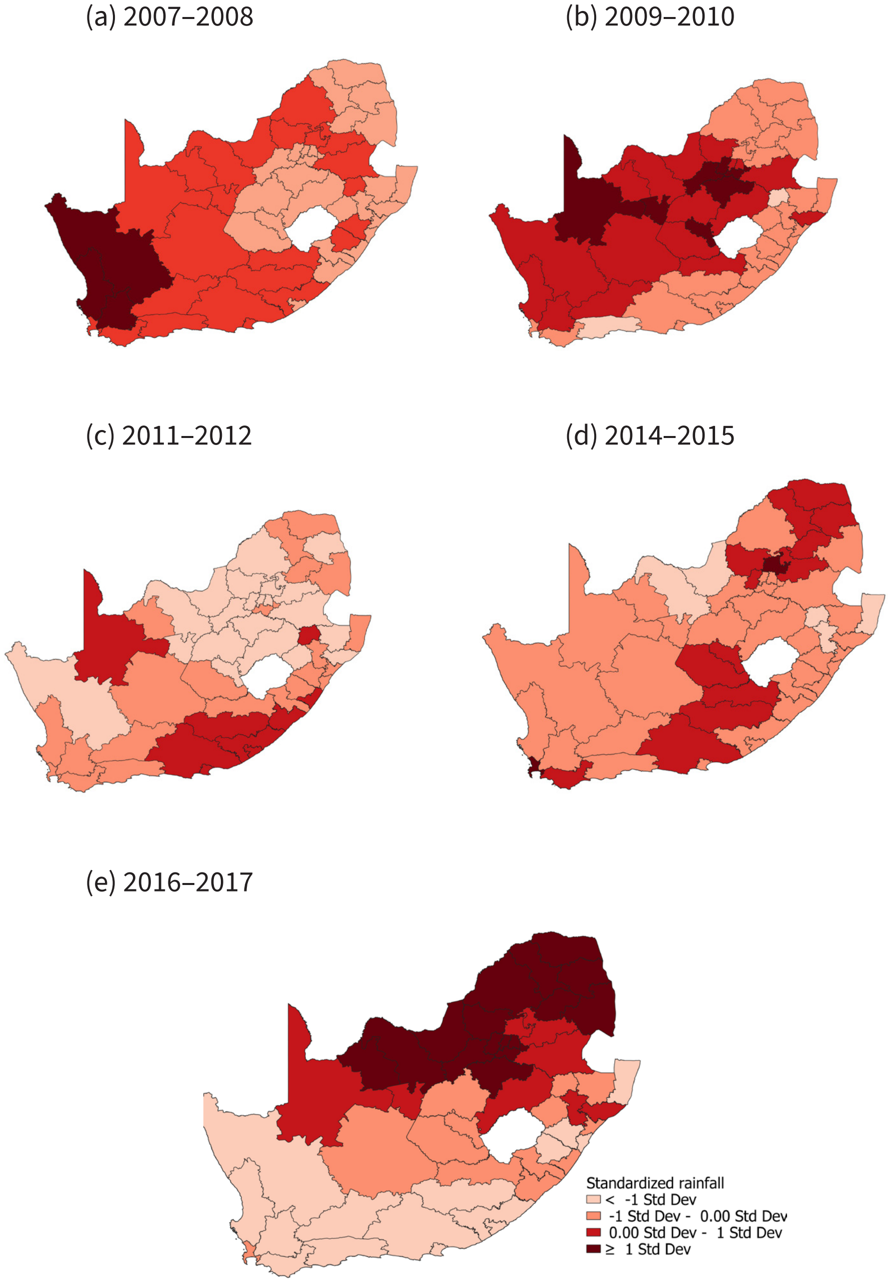
Note: a) Distribution of standardized rainfall from 2008 to 2017 relative to the long-term average. b) Distribution of the district-specific mean of the standardized rainfall from 2008 to 2017.

Figure 4: Monthly standardized rainfall



Note: District monthly standardized rainfall using the average monthly precipitation and standard deviation of monthly precipitation from 1988 to 2017.

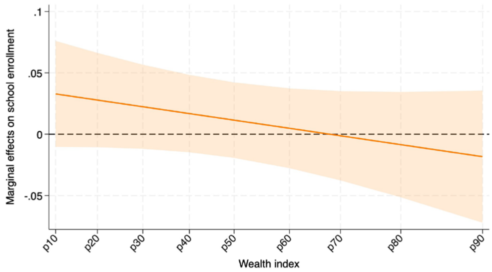
Figure 5: Standardized rainfall across districts over time



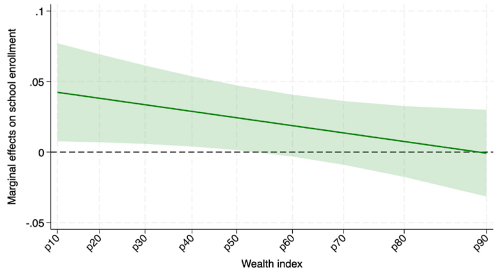
Note: These figures show the spatial and temporal variation in rainfall deviation in South Africa. Rainfall deviations are measured for the growing season October t −1 to March t at the district level.

Figure 6: Marginal effects of current rainfall on male outcomes across wealth

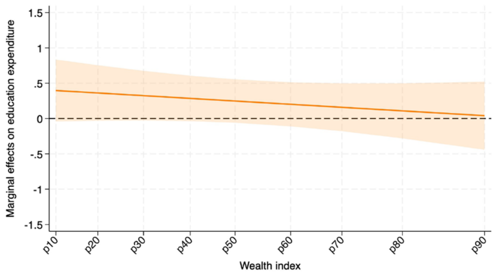
(a) Agricultural hh: enrolment



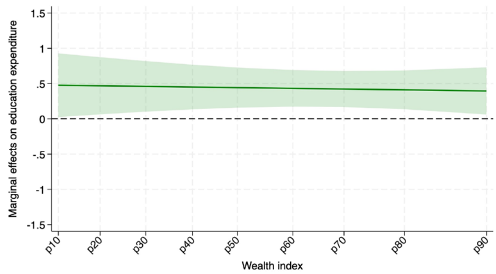
(b) Non-agricultural hh: enrolment



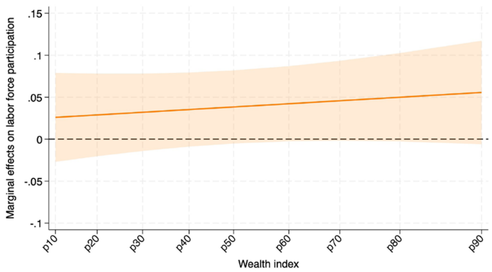
(c) Agricultural hh: education expenditure



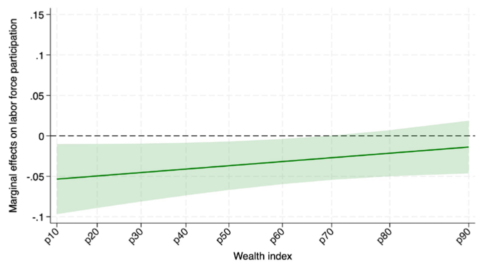
(d) Non-agricultural hh: education expenditure



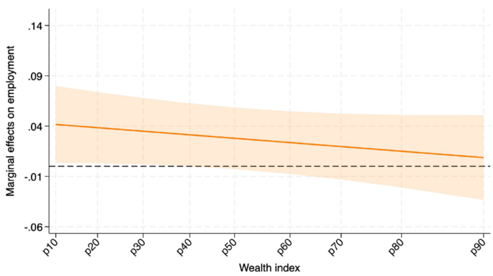
(e) Agricultural hh: labour force



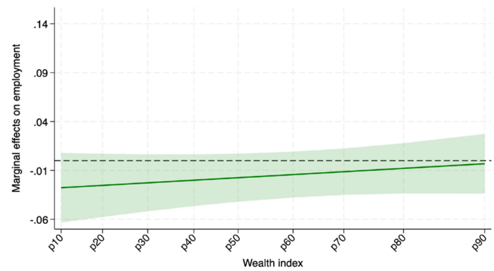
(f) Non-agricultural hh: labour force



(g) Agricultural hh: employed



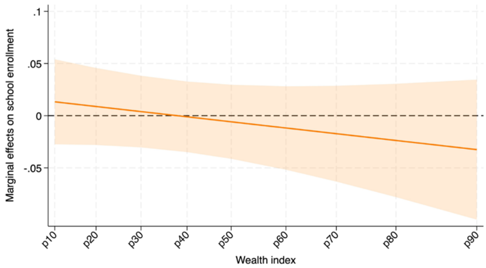
(h) Non-agricultural hh: employed



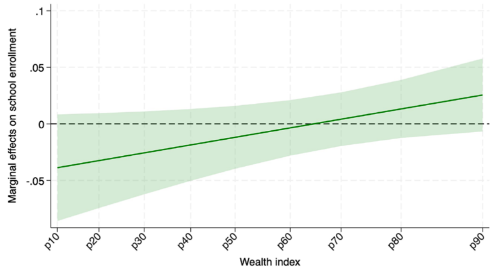
Note: These figures show the marginal effects with 95% confidence intervals of current-period rainfall on schooling and labour market outcomes of male adolescents at wealth percentiles.

Figure 7: Marginal effects of current rainfall on female outcomes across wealth

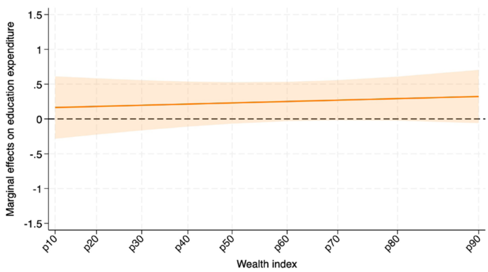
(a) Agricultural hh: enrolment



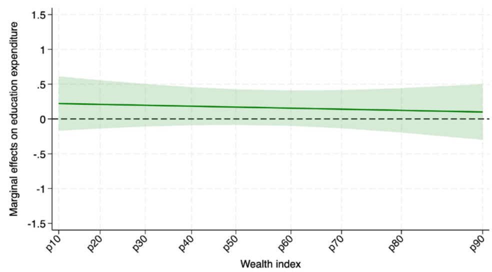
(b) Non-agricultural hh: enrolment



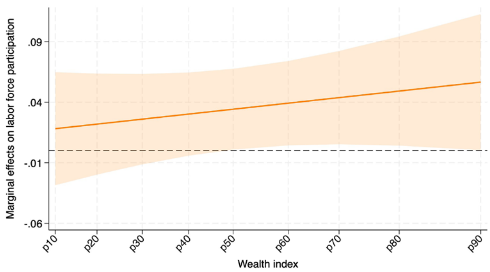
(c) Agricultural hh: education expenditure



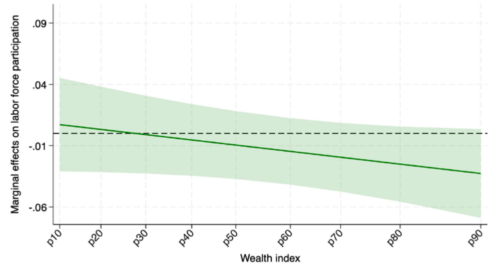
(d) Non-agricultural hh: education expenditure



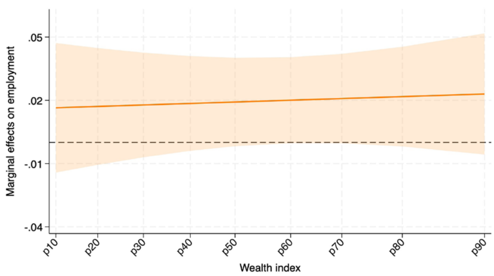
(e) Agricultural hh: labour force



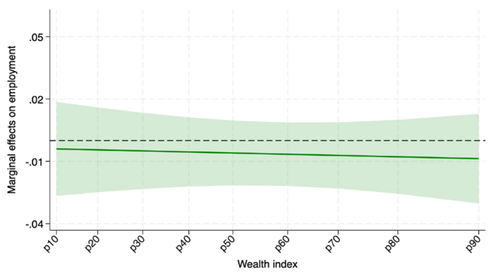
(f) Non-agricultural hh: labour force



(g) Agricultural hh: employment



(h) Non-agricultural hh: employment



Note: These figures show the marginal effects with 95% confidence intervals of current rainfall on schooling and labour market outcomes of female adolescents at wealth percentiles.

Tables

Table 1: Summary statistics

	(1) 2008	(2) 2010–2011	(3) 2012	(4) 2014–2015	(5) 2017
Dependent variables					
Enrolled in school = 1	0.813	0.687	0.679	0.685	0.566
	(0.390)	(0.464)	(0.467)	(0.465)	(0.496)
Real education expenditure (rand)	722.200	1,099.015	1,203.765	1,576.758	1,565.689
	(1,604.326)	(3,193.186)	(3,357.847)	(4,543.272)	(4,560.237)
Labour force = 1	0.177	0.180	0.203	0.183	0.261
	(0.382)	(0.384)	(0.403)	(0.387)	(0.439)
Currently working = 1	0.093	0.050	0.069	0.070	0.114
	(0.291)	(0.218)	(0.253)	(0.256)	(0.318)
Weather characteristics					
Current standardized rainfall (z-score)	0.262	-0.112	-0.659	-0.841	-0.108
	(0.522)	(0.532)	(0.585)	(0.479)	(1.129)
Lagged standardized rainfall (z-score)	-0.219	0.031	0.144	-0.157	-1.223
	(0.745)	(0.610)	(0.657)	(0.577)	(0.455)
Current temperature deviation (z-score)	-1.208	0.327	0.241	-0.177	0.508
	(0.367)	(0.307)	(0.453)	(0.613)	(0.357)
Control variables					
Age	17.475	18.536	18.766	18.854	20.096
	(1.576)	(2.231)	(2.232)	(2.226)	(1.663)
Female = 1	0.501	0.503	0.510	0.504	0.509
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
Wealth at baseline	-0.598	-0.587	-0.594	-0.607	-0.598
	(0.696)	(0.701)	(0.715)	(0.725)	(0.715)
Agricultural household = 1	0.434	0.411	0.395	0.378	0.389
	(0.496)	(0.492)	(0.489)	(0.485)	(0.488)
Observations	1,538	2,524	2,700	2,201	1,669

Notes: Standard deviations in parentheses. Education expenditure is observed only for those enrolled in school in the year preceding the survey year.

Table 2: Summary statistics across agricultural household status

	(1) Agricultural household	(2) Non-agricultural household	(3) Difference (2)-(1)
Dependent Variables			
Enrolled in school = 1	0.706	0.669	-0.037***
	(0.455)	(0.471)	
Real education expenditure (rand)	1,203.237	1,294.290	91.052
	(3,544.368)	(3,750.059)	
Labour force=1	0.196	0.201	0.005
	(0.397)	(0.401)	
Currently working=1	0.073	0.077	0.004
	(0.260)	(0.266)	
Weather characteristics			
Current standardized rainfall (z-score)	-0.384	-0.325	0.059***
	(0.724)	(0.796)	
Lagged standardized rainfall (z-score)	-0.236	-0.198	0.038*
	(0.756)	(0.773)	
Current temperature deviation (z-score)	-0.031	0.032	0.063***
	(0.687)	(0.709)	
Control variables			
Female = 1	0.489	0.516	0.027**
	(0.500)	(0.500)	
Age	18.739	18.759	0.020
	(2.191)	(2.191)	
Wealth at baseline	-0.727	-0.515	0.213***
	(0.696)	(0.708)	
Observations	4,237	6,353	10,590

Notes: This table reports the summary statistics for the sample across agricultural households (column 1) and non-agricultural households (column 2). Column 3 reports the differences in means between columns 2 and 1 and the t-test of the differences. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Education expenditure was observed only for those enrolled in school in the year preceding the survey year.

Table 3: Effect of rainfall on school work decisions

	(1) Enrolled=1	(2) Education expenditure	(3) Labour force=1	(4) Working=1
		PANEL A: Full sample		
Current rainfall	0.0110	0.245***	-0.00141	0.00390
	(0.00731)	(0.0804)	(0.00979)	(0.00635)
Lagged rainfall	0.0112	0.323***	0.0175**	0.0223***
	(0.00716)	(0.110)	(0.00866)	(0.00690)
Observations	10632	6175	10521	10521
		PANEL B:	Males	
Current rainfall	0.0185*	0.301***	-0.00976	0.000107
	(0.0105)	(0.107)	(0.0139)	(0.0103)
Lagged rainfall	0.00258	0.272**	0.0354***	0.0433***
	(0.0104)	(0.131)	(0.0129)	(0.0106)
Observations	5256	3149	5191	5191
		PANEL C: F	emales	
Current rainfall	0.00351	0.179*	0.00302	0.00361
	(0.0111)	(0.104)	(0.0122)	(0.00692)
Lagged rainfall	0.0192*	0.393***	-0.000667	0.00143
	(0.0105)	(0.137)	(0.00936)	(0.00771)
Observations	5376	3026	5330	5330
Individual, age, month, year fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes

Notes: This table presents the coefficients and computed marginal effects of lagged and contemporaneous rainfall deviations estimated from Equation 10. Standard errors clustered at the primary sampling unit (PSU) level in parentheses. * p<0.1, ** p< 0.05, *** p< 0.01. We used the inverse hyperbolic sine transformation of education expenditure. Education expenditure was observed only for those enrolled in school in the year preceding the survey year. Other controls include temperature.

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Table 4: Effects of lagged and contemporaneous rainfall on school work decisions in agricultural and non-agricultural households for the full sample

	(1) Enrolled=1	(2) Education expenditure	(3) Labour force=1	(4) Working=1
		Full sample		
Current rainfall on non-ag hh	0.0102	0.276***	-0.0224**	-0.00932
	(0.00816)	(0.0997)	(0.0101)	(0.00704)
Lagged rainfall on non-ag hh	0.0125	0.244*	0.0144	0.0125*
	(0.00871)	(0.135)	(0.00927)	(0.00735)
Current rainfall on ag hh	0.0122	0.198*	0.0347**	0.0252***
	(0.0116)	(0.106)	(0.0139)	(0.00920)
Lagged rainfall on ag hh	0.00743	0.418***	0.0218*	0.0387***
	(0.0109)	(0.142)	(0.0130)	(0.0102)
Individual, age, month, year fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	10590	6171	10479	10479

Notes: This table presents the coefficients and computed marginal effects of lagged and contemporaneous rainfall deviations estimated from Equation 11. Standard errors clustered at the primary sampling unit (PSU) level in parentheses. * p<0.1, ** p< 0.05, *** p< 0.01. We used the inverse hyperbolic sine transformation of education expenditure. Education expenditure was observed only for those enrolled in school in the year preceding the survey year. Other controls included temperature.

Table 5: Effects of lagged and contemporaneous rainfall on school-work decisions in agricultural and non-agricultural households across gender

	(1) Enrolled=1	(2) Education expenditure	(3) Labor force=1	(4) Working=1
		PANEL A: Males		
Current rainfall on non-ag hh	0.0198*	0.407***	-0.0337**	-0.0170
	(0.0114)	(0.131)	(0.0139)	(0.0116)
Lagged rainfall on non-ag hh	0.0103	0.136	0.0254*	0.0281**
	(0.0118)	(0.168)	(0.0142)	(0.0123)
Current rainfall on ag hh	0.0202	0.162	0.0280	0.0246
	(0.0155)	(0.147)	(0.0211)	(0.0150)
Lagged rainfall on ag hh	-0.0125	0.421**	0.0497***	0.0677***
	(0.0152)	(0.176)	(0.0185)	(0.0149)
Observations	5237	3149	5172	5172
		PANEL B: Females		
Current rainfall on non-ag hh	0.00137	0.138	-0.0161	-0.00718
	(0.0132)	(0.131)	(0.0139)	(0.00743)
Lagged rainfall on non-ag hh	0.0144	0.370**	0.00209	-0.00428
	(0.0131)	(0.161)	(0.0106)	(0.00831)
Current rainfall on ag hh	0.00327	0.236*	0.0389**	0.0229**
	(0.0176)	(0.142)	(0.0161)	(0.0101)
Lagged rainfall on ag hh	0.0272*	0.434**	-0.00577	0.0110
	(0.0150)	(0.182)	(0.0153)	(0.0108)
Individual, age, month, year fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	5353	3022	5307	5307

Notes: This table presents the coefficients and computed marginal effects of lagged and contemporaneous rainfall deviations estimated from Equation 11 separately for the sample of females and males. Standard errors clustered at the primary sampling unit (PSU) level in parentheses. * p<0.1, ** p< 0.05, *** p< 0.01. We used the inverse hyperbolic sine transformation of education expenditure. Education expenditure was observed only for those enrolled in school in the year preceding the survey year. Other controls included temperature.

Table 6: Effect of rainfall shocks on potential activities other than school enrollment and employment

	Neither enrolled nor working		Both enrolled and working	
	(1) Females	(2) Males	(3) Females	(4) Males
Current rainfall	-0.00180	0.00130	0.00417	-0.0000832
	(0.00215)	(0.00482)	(0.0138)	(0.0139)
Lagged rainfall	0.000950	0.0148**	-0.00702	-0.0223*
	(0.00345)	(0.00668)	(0.0140)	(0.0130)
Marginal effect of current rainfall for ag hh	0.0194**	0.0273**	-0.00676	-0.0218
	(0.00834)	(0.0115)	(0.0166)	(0.0175)
Marginal effect of lagged rainfall for ag hh	0.00859	0.0268**	-0.0288*	-0.0303*
	(0.00716)	(0.0110)	(0.0154)	(0.0164)
Individual, age, month, year fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	5307	5172	5307	5172

Notes: This table presents the coefficients and computed marginal effects of lagged and contemporaneous rainfall deviations estimated from Equation 10. Standard errors clustered at the primary sampling unit (PSU) level in parentheses. * p<0.1, ** p< 0.05, *** p< 0.01. Other controls included temperature.

Table 7: Robustness to alternative rainfall definitions

	(1) Enrolled=1	(2) Education expenditure	(3) Labour force=1	(4) Working=1	(5) Enrolled=1	(6) Education expenditure	(7) Labour force=1	(8) Working=1
				PANEL A: Males				
Current rainfall	0.0973**	1.567***	-0.136**	-0.0474	0.0155	0.401*	-0.0359*	-0.00104
	(0.0473)	(0.563)	(0.0602)	(0.0501)	(0.0184)	(0.207)	(0.0196)	(0.0153)
Lagged rainfall	0.0264	0.719	0.143**	0.135**	-0.00119	0.319	0.0353	0.0495**
	(0.0519)	(0.707)	(0.0616)	(0.0538)	(0.0191)	(0.282)	(0.0219)	(0.0202)
Current rainfall on ag hh	0.0909	0.619	0.107	0.107*	0.0372	0.288	0.0298	0.0120
	(0.0667)	(0.598)	(0.0904)	(0.0638)	(0.0231)	(0.287)	(0.0324)	(0.0242)
Lagged rainfall on ag hh	-0.0596	2.171***	0.224***	0.283***	-0.0194	0.607*	0.0441	0.0489**
	(0.0672)	(0.812)	(0.0856)	(0.0687)	(0.0260)	(0.321)	(0.0270)	(0.0201)
Observations	5237	3149	5172	5172	5237	3149	5172	5172
				PANEL B: F	emales			
Current rainfall	0.00234	0.840	-0.0745	-0.0338	-0.00927	0.564**	-0.0142	0.00451
	(0.0576)	(0.582)	(0.0615)	(0.0330)	(0.0185)	(0.231)	(0.0203)	(0.0113)
Lagged rainfall	0.0812	1.766**	0.0224	-0.0126	-0.00363	0.683**	0.0188	0.0131
	(0.0553)	(0.722)	(0.0494)	(0.0379)	(0.0204)	(0.291)	(0.0180)	(0.0134)
Current rainfall on ag hh	0.0317	1.302**	0.159**	0.107**	-0.0266	0.461**	0.0453*	0.0392**
	(0.0816)	(0.610)	(0.0694)	(0.0460)	(0.0265)	(0.216)	(0.0268)	(0.0160)
Lagged rainfall on ag hh	0.121*	1.911**	0.0145	0.0626	0.0296	0.786**	-0.0405*	0.00794
	(0.0657)	(0.868)	(0.0672)	(0.0495)	(0.0223)	(0.311)	(0.0235)	(0.0173)
Individual, age, month, year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5353	3022	5307	5307	5353	3022	5307	5307

Notes: This table presents the coefficients of lagged and contemporaneous rainfall estimated from equation 10. In panel A, rainfall deviation is defined as the logarithm of the total rainfall during the growing season in a particular year minus the logarithm of the district-specific long-term average rainfall during the growing season. In panel B, rainfall shock is defined as -1 if the standardized rainfall -1 standard deviations, +1 if the standardized rainfall > 1 standard deviations, and 0 otherwise. Standard errors clustered at the primary sampling unit (PSU) level in parenthesis. * p 0.1, ** p< 0.05, *** p< 0.01. We use the inverse hyperbolic sine transformation of education expenditures. Education expenditure is observed only for those enrolled in school in the year preceding the survey year. Other controls include temperature.

Table 8: Effect of rainfall on individual and household characteristics

	(1) Age	(2) HH size	(3) Wealth
	PANEL A: Males		
Current rainfall on non-ag hh	-0.00137	0.0879	-0.00299
	(0.00118)	(0.0716)	(0.0215)
Lagged rainfall on non-ag hh	0.00210*	0.0405	0.0331
	(0.00111)	(0.0768)	(0.0202)
Current rainfall on ag hh	0.00231	-0.0317	-0.00718
	(0.00274)	(0.0701)	(0.0237)
Lagged rainfall on ag hh	0.00500**	-0.0481	0.0132
	(0.00242)	(0.0821)	(0.0238)
Observations	5237	5237	4763
	PAN	EL B: Fema	les
Current rainfall on non-ag hh	0.000272	0.0982	-0.0102
	(0.00217)	(0.0870)	(0.0179)
Lagged rainfall on non-ag hh	-0.00159	-0.0816	0.00636
	(0.00244)	(0.0902)	(0.0176)
Current rainfall on ag hh	0.00149	0.0371	-0.0294
	(0.00222)	(0.0945)	(0.0233)
Lagged rainfall on ag hh	-0.000215	-0.0272	-0.00687
	(0.00235)	(0.116)	(0.0235)
Individual, month, year fixed effects	Yes	Yes	Yes
Observations	5353	5353	4893

Notes: This table reports the estimates from a linear fixed effects regression of individual and household time-varying characteristics on current standardized rainfall and lagged standardized rainfall controlling for individual and year fixed effects. Standard errors clustered at the primary sampling unit level in parentheses. * p<0.1, ** p< 0.05, *** p< 0.01.

Table 9: Serial correlation in rainfall

	(1) Current rainfall	(2) Current rainfall	(3) Current rainfall
Lagged rainfall	0.0313	0.0339	0.0697
	(0.0237)	(0.0318)	(0.101)
District Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	No	Yes	Yes
Observations	1,363	1,363	10,632

Notes: The unit of observation is district-year for regressions in columns (1)-(2), and individual-year in column (3). Standard errors clustered at the district council level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Effects of lagged and contemporaneous standardized rainfall during non-growing season

	(1)	(2)	(3)	(4)
	Enrolled=1	Education exp	Labour force=1	Working=1
		PANEL A: Males		
Current rainfall	-0.0115	-0.00370	-0.00401	-0.0169*
	(0.0104)	(0.131)	(0.0120)	(0.00957)
Lagged rainfall	0.00690	0.126	-0.00682	-0.00843
	(0.00896)	(0.128)	(0.0121)	(0.00916)
Current rainfall on ag hh	-0.0218*	0.0957	0.0296*	0.0257**
	(0.0126)	(0.135)	(0.0161)	(0.0129)
Lagged rainfall on ag hh	-0.0161	0.202	0.0198	0.00619
	(0.0117)	(0.123)	(0.0132)	(0.00953)
Observations	5237	3149	5172	5172
		PANEL B:	Females	
Current rainfall	0.00739	0.0140	0.00343	-0.00640
	(0.0109)	(0.110)	(0.0114)	(0.00566)
Lagged rainfall	-0.00366	0.0725	0.00454	0.00668
	(0.00998)	(0.125)	(0.0103)	(0.00596)
Current rainfall on ag hh	0.0134	0.103	-0.0162	0.00756
	(0.0152)	(0.130)	(0.0151)	(0.00926)
Lagged rainfall on ag hh	-0.0139	0.0721	-0.00138	-0.000104
	(0.0121)	(0.150)	(0.0129)	(0.00858)
Individual, age, month, year fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	5353	3022	5307	5307

Notes: This table reports the coefficients from estimation of Equation 11. We consider standardized rainfall deviations during the season other than the primary growing season. This corresponds to $April_{t-1}$-$September_{t-1}$ for major maize producing regions, and from $October_{t-1}$-$March_{t}$ for the major wheat-producing regions. Standard errors clustered at the primary sampling unit (PSU) level in parentheses. * p<0.1, ** p< 0.05, *** p< 0.01. Education expenditure is observed only for those enrolled in school in the year preceding the survey year. Controls include temperature.

Table 11: Falsification test: Rainfall deviations in the future

	(1) Enrolled=1	(2) Education expenditure	(3) Labour force=1	(4) Working=1
		PANEL A: Males		
Future rainfall	0.0116	-0.0294	-0.00436	-0.000609
	(0.00835)	(0.109)	(0.00940)	(0.00728)
Agricultural household=1 × Future rainfall	-0.00668	-0.0130	0.00971	0.000325
	(0.0101)	(0.133)	(0.00980)	(0.00673)
Marginal effect on ag hh	0.00488	-0.0424	0.00536	-0.000284
	(0.00888)	(0.119)	(0.0112)	(0.00702)
		PANEL B: Females		
Future rainfall	0.0116	-0.0294	-0.00436	-0.000609
	(0.00835)	(0.109)	(0.00940)	(0.00728)
Agricultural household=1 × Future rainfall	-0.00668	-0.0130	0.00971	0.000325
	(0.0101)	(0.133)	(0.00980)	(0.00673)
Marginal effect on ag hh	0.00488	-0.0424	0.00536	-0.000284
	(0.00888)	(0.119)	(0.0112)	(0.00702)
Individual, age, month, year fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	10,590	6,171	10,479	10,479

Notes: This table reports the coefficients from estimation of Equation 10 using standardized rainfall deviations in the year following the survey year. Education expenditure is observed only for those enrolled in school in the year preceding the survey year. Standard errors clustered at the primary sampling unit (PSU) level in parenthesis. * p<0.1, ** p< 0.05, *** p< 0.01.

Appendixes

A Theoretical Model

The household maximizes its utility in periods 1 and 2 as per the following:

max $U_1(c_1) + \beta U_2(c_2) + V(E)$

s.t. $c_1 = M_1 - e(s_1) - A \qquad c_2 = M_2 - e(s_2) + \frac{A}{\beta}$

$L_1 = 1 + \delta_1 l_1 \quad L_2 = 1 + \delta_2 l_2$

$s1 + l1 = T1 \qquad s2 + l2 = T2$

$V = V(s_1 + s_2)$

For agricultural household: $M_1 = RF(L_1) \qquad M_2 = F(L_2)$

For non-agricultural household: $M_1 = w_1 L_1 \qquad M_2 = w_2 L_2$

Additionally, for non-agricultural households, we assume that $w_2 = w_2(s_1)$. In other words,

wages in period 2 are a function of schooling in period 1 where $\frac{\partial w_2}{\partial s_1} > 0$ refers to the returns

from an additional year of schooling. The standard assumptions for the first-order and second-

order partial derivatives are: $\frac{\partial U}{\partial c} > 0$, $\frac{\partial^2 U}{\partial c^2} < 0$, $\frac{\partial F}{\partial L} > 0$, $\frac{\partial^2 F}{\partial L^2} < 0$, $\frac{\partial V}{\partial E} > 0$, and $\frac{\partial^2 V}{\partial E^2} < 0$.

Agricultural (a) households:

$$\mathcal{L} = U_1(c_1) + \beta U_2(c_2) + V(1 - l_1 + 1 - l_2) + \lambda_1(RF_1(1 + \delta_1 l_1) - es_1 - A - c_1) + \lambda_2(F_2(1 + \delta_2 l_2) - es_2 + \frac{A}{\beta} - c_2)$$

The first-order conditions are as follows:

$$\frac{\partial \mathcal{L}^a}{\partial c_1} = \frac{\partial U_1}{\partial c_1} - \lambda_1 = 0 \qquad (1)$$

$$\frac{\partial \mathcal{L}^a}{\partial c_2} = \beta \frac{\partial U_2}{\partial c_2} - \lambda_2 = 0 \qquad (2)$$

$$\frac{\partial \mathcal{L}^a}{\partial l_1} = -\frac{\partial V}{\partial E} + \lambda_1 R \frac{\partial F_1}{\partial L_1}\delta_1 + \lambda_1 e = 0 \tag{3}$$

$$\frac{\partial \mathcal{L}^a}{\partial l_2} = -\frac{\partial V}{\partial E} + \lambda_2 \frac{\partial F_2}{\partial L_2}\delta_2 + \lambda_2 e = 0 \tag{4}$$

$$\frac{\partial \mathcal{L}^a}{\partial A} = -\lambda_1 + \frac{\lambda_2}{\beta} = 0 \tag{5}$$

From (1), (2), and (3), we obtain:

$$\frac{\partial U_1}{\partial c_1} = \frac{\partial U_2}{\partial c_2} \tag{6}$$

The above first order conditions (1)-(6) yield the following:

$$\left(R\frac{\partial F_1}{\partial L_1}\delta_1 + e\right) = \beta\left(\delta_2\frac{\partial F_2}{\partial L_2} + e\right) \tag{7}$$

For comparative statistics, we take the derivative of (7) with respect to R:

$$R\frac{\partial^2 F_1}{\partial L_1^2}\delta_1^2\frac{\partial l_1}{\partial R} + \delta_1\frac{\partial F_1}{\partial L_1} = \beta\frac{\partial^2 F_2}{\partial L_2^2}\delta_2^2\frac{\partial l_2}{\partial R} \tag{8}$$

$$\frac{\partial l_2^a}{\partial R} = \frac{1}{\beta\frac{\partial^2 F_2}{\partial L_2^2}\delta_2^2}\left(R\frac{\partial^2 F_1}{\partial L_1^2}\delta_1^2\frac{\partial l_1}{\partial R} + \delta_1\frac{\partial F_1}{\partial L_1}\right) \tag{9}$$

Derivation of (1) and (3) combined with respect to R yields:

$$\frac{\partial U_1}{\partial c_1}\left(R\frac{\partial^2 F_1}{\partial L_1^2}\delta_1^2\frac{\partial l_1}{\partial R} + \frac{\partial F_1}{\partial L_1}\delta_1\right) + \frac{\partial U_1^2}{\partial c_1^2}\left(R\frac{\partial F_1}{\partial L_1}\delta_1 + e\right)\left(R\frac{\partial F_1}{\partial L_1}\delta_1\frac{\partial l_1}{\partial R} + F_1 + e\frac{\partial l_1}{\partial R}\right) - \frac{\partial^2 V}{\partial E^2}\left(-\frac{\partial l_1}{\partial R} - \frac{\partial l_2}{\partial R}\right) = 0 \tag{10}$$

Substituting (9) in (10), we obtain:

$$\frac{\partial l_1^a}{\partial R} = -\frac{\overbrace{\frac{\partial U_1}{\partial c_1}\frac{\partial F_1}{\partial L_1}\delta_1}^{\text{SE}} + \overbrace{\frac{\partial U_1^2}{\partial c_1^2}F_1\left(R\frac{\partial F_1}{\partial L_1}\delta_1 + e\right) + \frac{\frac{\partial F_1}{\partial L_1}\frac{\partial^2 V}{\partial E^2}}{\beta\delta_2\frac{\partial^2 F_2}{\partial L_2^2}}}^{\text{IE}}}{D} \tag{11}$$

where

$$D = \left[\frac{\partial U_1}{\partial c_1} \left(R \frac{\partial^2 F_1}{\partial L_1^2} \delta_1^2 \right) + \frac{\partial^2 U_1}{\partial c_1^2} \left(\frac{R \partial F_1}{\partial L_1} \delta_1 + e \right)^2 + \frac{\partial^2 V}{\partial E^2} \left(1 + R \frac{\frac{\partial^2 F_1}{\partial L_1^2} \delta_1^2}{\frac{\partial^2 F_2}{\partial L_2^2} \delta_2^2} \right) \right] < 0$$

Non-agricultural (na) households:

$$\mathcal{L} = U_1(c_1) + \beta U_2(c_2) + V(1 - l_1 + 1 - l_2) + \lambda_1(w_1(1 + \delta_1 l_1) - es_1 - A - c_1) + \lambda_2(w_2(1 + \delta_2 l_2) - es_2 + \frac{A}{\beta} - c_2)$$

The first-order conditions are as follows:

$$\frac{\partial \mathcal{L}^{na}}{\partial c_1} = \frac{\partial U_1}{\partial c_1} - \lambda_1 = 0 \tag{12}$$

$$\frac{\partial \mathcal{L}^{na}}{\partial c_2} = \beta \frac{\partial U_2}{\partial c_2} - \lambda_2 = 0 \tag{13}$$

$$\frac{\partial \mathcal{L}^{na}}{\partial l_1} = -\frac{\partial V}{\partial E} + \lambda_1 w_1 \delta_1 + \lambda_1 e - \lambda_2 (1 + \delta_2 l_2) \frac{\partial w_2}{\partial s_1} = 0 \tag{14}$$

$$\frac{\partial \mathcal{L}^{na}}{\partial l_2} = -\frac{\partial V}{\partial E} + \lambda_2 w_2 \delta_2 + \lambda_2 e = 0 \tag{15}$$

$$\frac{\partial \mathcal{L}^{na}}{\partial A} = -\lambda_1 + \frac{\lambda_2}{\beta} = 0 \tag{16}$$

From (1), (2), and (3), we obtain:

$$\frac{\partial U_1}{\partial c_1} = \frac{\partial U_2}{\partial c_2} \tag{17}$$

The above first order conditions (12)-(16) yield the following:

$$(w_1 \delta_1 + e) - \beta \frac{\partial w_2}{\partial s_1} (1 + \delta_2 l_2) = \beta \left(\delta_2 w_2 + e \right) \tag{18}$$

For comparative statistics, we take the derivative of the FOCs with respect to w_1 to obtain

the following:

$$\delta_1 + \beta (1 + \delta_2 l_2) \frac{\partial^2 w_2}{\partial s_1^2} \frac{\partial l_1}{\partial w_1} - \beta \frac{\partial w_2}{\partial s_1} \delta_2 \frac{\partial l_2}{\partial w_1} = -\delta_2 \frac{\partial w_2}{\partial s_1} \frac{\partial l_1}{\partial w_1} \tag{19}$$

$$\frac{\partial l_2}{\partial w_1} = \frac{-\delta_2 \frac{\partial w_2}{\partial s_1} \frac{\partial l_1}{\partial w_1} - \beta(1+\delta_2 l_2) \frac{\partial^2 w_2}{\partial s_1^2} \frac{\partial l_1}{\partial w_1} - \delta_1}{-\beta \frac{\partial w_2}{\partial s_1} \delta_2} \tag{20}$$

Derivation of (1) and (3) combined with respect to w_1 yields:

$$\frac{\partial U_1}{\partial c_1}[\delta_1 - \beta \frac{\partial w_2}{\partial s_1} \delta_2 \frac{\partial l_2}{\partial w_1} + \beta(1+\delta_2 l_2) \frac{\partial^2 w_2}{\partial s_1^2}] + [w_1 \delta_1 + e - \beta \frac{\partial w_2}{\partial s_1}(1+\delta_2 l_2)] \frac{\partial U_2^2}{\partial c_2^2} - \frac{\partial^2 V}{\partial E^2}\left(-\frac{\partial l_1}{\partial R} - \frac{\partial l_2}{\partial R}\right) = 0 \tag{21}$$

Solving (20) and (21) simultaneously, we obtain:

$$\frac{\partial l_1^*}{\partial w_1} = \frac{-\overbrace{\frac{\partial U_1}{\partial c_1}\left(\delta_1 + \beta\delta_2 \frac{\partial w_2}{\partial s_1} + \beta(1+\delta_2 l_2) \frac{\partial^2 w_2}{\partial s_1^2}\right)}^{\text{SE}} - \overbrace{\frac{\partial U_1^2}{\partial c_1^2}\left(w_1 \delta_1 + e - \beta \frac{\partial w_2}{\partial s_1}(1+\delta_2 l_2)\right)}^{\text{IE}}}{J} \tag{22}$$

$$\frac{\partial l_2}{\partial w_1} = \frac{\left(-\delta_2 \frac{\partial w_2}{\partial s_1} - \beta(1+\delta_2 l_2) \frac{\partial^2 w_2}{\partial s_1^2} \frac{\partial l_1}{\partial w_1}\right) - \delta_1}{-\beta \frac{\partial w_2}{\partial s_1} \delta_2} \tag{23}$$

where

$$J = \left[\frac{\partial^2 V}{\partial E^2} - \left(\frac{-\partial^2 V}{\partial E^2} + \frac{\partial U_1}{\partial c_1} \beta \frac{w_2}{s_1} \delta_2\right)\left(\frac{1}{\beta} + \frac{(1+\delta_2 l_2)}{\delta_2} \frac{\partial^2 w_2/\partial s_1^2}{\partial w_2/\partial s_1}\right)\right] < 0$$

B Extra Results and Data Description

B.1 *Rainfall and Crop Yields*

Data source: We obtained the data on crop produce estimates from the Spatial Production Allocation Model (SPAM) 2005 and 2010 of the International Food Policy Research Institute (IFPRI). The SPAM model produces gridded maps of agricultural production at the global level at a 5 arc min (approximately 10 × 10 km at the equator) spatial resolution. SPAM2000 provides estimates of global agricultural production for 20 crops. SPAM2005 is an update on SPAM2000, which expands the coverage of crops. SPAM2010 further enhances the crop downscaling modelling, and includes the update of the base year, additional crops, and expanding coverage to sub-national administrative-level (Yu et al., 2020). SPAM2010 uses a cross-entropy method to derive estimates of crop production statistics for 42 crops across disaggregated units.

Variable description: For South Africa, SPAM2005 uses the average of 2002–2003 and SPAM2010 uses the average of 2007 and 2009–2012. The crop yield or the quantity of production per harvested area is measured in kilogrammes per hectare. The total yield of a crop is the weighted average of the four farming systems: irrigated, rainfed high inputs, rainfed low inputs and rainfed subsistence yields.

In Table B.1, standardized rainfall from CHIRPS corresponds to the same time periods for which the crop yields are available.

Table B.1: Effect of rainfall on crop yields

	(1) Maize	(2) Wheat	(3) Rainfed maize	(4) Rainfed wheat
Standardized rainfall	0.513***	0.620***	0.198***	0.0270**
	(0.0665)	(0.0543)	(0.0714)	(0.0116)
Unit fixed effects	Yes	Yes	Yes	Yes
SPAM year fixed effects	Yes	Yes	Yes	Yes
Observations	15,391	15,391	13,949	1,442

Notes: This table reports the estimates of the effect of standardized rainfall on the logarithm of yields of maize (columns 1 and 3) and wheat (columns 2 and 4). Yield is defined as kg/ha. The sample in column 4 comprises the Western Cape Province whereas the sample in column 3 comprises all other provinces. Unit fixed effects refer to fixed effects at the level of the centroid for which the crop production information is available. The year dummy variable is 1 for SPAM2005, 0 for SPAM2010. Robust standard errors clustered at the unit level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.2 *Additional Tables*

Table B.2: Summary statistics for the pooled sample

	Mean	Standard deviation	Observations
Dependent Variables			
Enrolled in school = 1	0.684	0.465	10,632
Real education expenditure (rand)	1,263.209	3,702.188	6,175
Labour force = 1	0.199	0.399	10,521
Currently working = 1	0.075	0.264	10,521
Weather Characteristics			
Current standardized rainfall (z-score)	-0.347	0.770	10,632
Lagged standardized rainfall (z-score)	-0.212	0.766	10,632
Current temperature deviation (z-score)	0.007	0.700	10,632
Control Variables			
Age	18.751	2.191	10,632
Female = 1	0.506	0.500	10,632
Wealth at baseline	-0.596	0.711	9,922
Agricultural household = 1	0.400	0.490	10,590

Notes: This table reports the summary statistics for the sample pooled across 2008, 2010–2011, 2012, 2014–2015 and 2017 waves. Education expenditure is observed only for those enrolled in school in the year preceding the survey year.

Table B.3: Effects of lagged and contemporaneous rainfall on school-work decisions in agricultural and non-agricultural households across gender

	(1)	(2)	(3)	(4)
	Enrolled=1	Education expenditure	Labour force=1	Working=1
		PANEL A: Males		
Current rainfall	0.0198*	0.407***	-0.0337**	-0.0170
	(0.0114)	(0.131)	(0.0139)	(0.0116)
Agricultural hh=1 × Current rainfall	0.000371	-0.245	0.0617***	0.0416**
	(0.0166)	(0.176)	(0.0215)	(0.0172)
Lagged rainfall	0.0103	0.136	0.0254*	0.0281**
	(0.0118)	(0.168)	(0.0142)	(0.0123)
Agricultural hh=1 × Lagged rainfall	-0.0228	0.286	0.0243	0.0396**
	(0.0170)	(0.229)	(0.0196)	(0.0171)
Marginal effect of current rainfall for ag hh	0.0202	0.162	0.0280	0.0246
	(0.0155)	(0.147)	(0.0211)	(0.0150)
Marginal effect of lagged rainfall for ag hh	-0.0125	0.421**	0.0497***	0.0677***
	(0.0152)	(0.176)	(0.0185)	(0.0149)
Individual, age, month, year fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	5237	3149	5172	5172
		PANEL B: Females		
Current rainfall	0.00137	0.138	-0.0161	-0.00718
	(0.0132)	(0.131)	(0.0139)	(0.00743)
Agricultural hh=1 × Current rainfall	0.00191	0.0984	0.0550***	0.0301***
	(0.0207)	(0.176)	(0.0176)	(0.0104)
Lagged rainfall	0.0144	0.370**	0.00209	-0.00428
	(0.0131)	(0.161)	(0.0106)	(0.00831)
Agricultural hh=1 × Lagged rainfall	0.0129	0.0638	-0.00786	0.0153
	(0.0185)	(0.206)	(0.0171)	(0.0110)
Marginal effect of current rainfall for ag hh	0.00327	0.236*	0.0389**	0.0229**
	(0.0176)	(0.142)	(0.0161)	(0.0101)
Marginal effect of lagged rainfall for ag hh	0.0272*	0.434**	-0.00577	0.0110
	(0.0150)	(0.182)	(0.0153)	(0.0108)
Individual, age, month, year fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	5353	3022	5307	5307

Notes: This table presents the coefficients and computed marginal effects of lagged and contemporaneous rainfall deviations estimated from equation 11 separately for the sample of females and males. Standard errors clustered at the primary sampling unit (PSU) level in parenthesis. * p<0.1, ** p< 0.05, *** p< 0.01. We use the inverse hyperbolic sine transformation of education expenditure. Education expenditure is observed only for those enrolled in school in the year preceding the survey year. Other controls include temperature.

Table B.4: Effect of rainfall across wealth

	Enrolled=1		Education expenditure		Labour force = 1		Working = 1	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Females	Males	Females	Males	Females	Males	Females	Males
Current rainfall	0.0133	0.00743	0.123	0.411***	-0.0251	-0.0214	-0.00781	-0.00786
	(0.0131)	(0.0128)	(0.163)	(0.140)	(0.0156)	(0.0145)	(0.00907)	(0.0131)
Current rainfall × Wealth	0.0359**	-0.0241*	-0.0677	-0.0453	-0.0223	0.0221	-0.00263	0.0137
	(0.0178)	(0.0138)	(0.174)	(0.168)	(0.0145)	(0.0146)	(0.00910)	(0.0132)
Agricultural household = 1 × Current rainfall	-0.0371	-0.0160	0.169	-0.303	0.0743***	0.0714***	0.0296**	0.0228
	(0.0304)	(0.0227)	(0.221)	(0.229)	(0.0242)	(0.0267)	(0.0125)	(0.0204)
Agricultural household = 1 × Current rainfall × Wealth	-0.0615**	-0.00445	0.156	-0.154	0.0437*	-0.00556	0.00629	-0.0321
	(0.0302)	(0.0246)	(0.242)	(0.250)	(0.0260)	(0.0258)	(0.0143)	(0.0202)
Lagged rainfall	0.0135	0.0199	0.365*	0.109	-0.00945	0.0266*	-0.0134	0.0321**
	(0.0138)	(0.0126)	(0.191)	(0.214)	(0.0122)	(0.0144)	(0.00996)	(0.0149)
Lagged rainfall × Wealth	0.00121	0.0141	0.187	0.0775	-0.0237	0.0108	-0.0168*	0.0160
	(0.0154)	(0.0155)	(0.183)	(0.266)	(0.0149)	(0.0163)	(0.00934)	(0.0147)
Agricultural household=1 × Lagged rainfall	0.0263	-0.0340	-0.271	0.435	-0.0203	0.0214	0.00793	0.0271
	(0.0236)	(0.0212)	(0.269)	(0.314)	(0.0234)	(0.0235)	(0.0135)	(0.0208)
Agricultural household=1 × Lagged rainfall × Wealth	0.0215	-0.0185	-0.579***	0.187	-0.00895	-0.0197	-0.00745	-0.0274
	(0.0260)	(0.0232)	(0.221)	(0.327)	(0.0238)	(0.0275)	(0.0144)	(0.0225)
Observations	5,016	4,906	2,847	2,941	4,973	4,841	4,973	4,841

Notes: This table reports the estimates of the effect of standardized rainfall on school–work decisions estimated from Equation 11. We include interactions of current and lagged rainfall with household wealth separately for the sample of female and male adolescents. Standard errors clustered at the primary sampling unit level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include individual fixed effects, month fixed effects, year fixed effects and other controls, including temperature.

Table B.5: Effect of rainfall on school-work decisions using an alternative definition of agricultural households

	(1) Enrolled=1	(2) Educationexp	(3) Labour force=1	(4) Working=1
		PANEL A: Males		
Current rainfall	0.0171	0.444***	-0.0278**	-0.00839
	(0.0116)	(0.136)	(0.0139)	(0.0117)
Agricultural hh=1 × Current rainfall	0.00731	-0.317*	0.0451**	0.0204
	(0.0159)	(0.176)	(0.0199)	(0.0170)
Lagged rainfall	0.00992	0.141	0.0325**	0.0386***
	(0.0126)	(0.169)	(0.0151)	(0.0124)
Agricultural hh=1 × Lagged rainfall	-0.0194	0.274	0.00511	0.0115
	(0.0167)	(0.228)	(0.0188)	(0.0164)
Marginal effect of current rainfall for ag hh	0.0244*	0.127	0.0173	0.0120
	(0.0148)	(0.141)	(0.0200)	(0.0150)
Marginal effect of lagged rainfall for ag hh	-0.00947	0.415**	0.0376**	0.0500***
	(0.0141)	(0.174)	(0.0170)	(0.0147)
Individual, age, month, year fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	5237	3149	5172	5172
		PANEL B:	**Females**	
Current rainfall	-0.000419	0.131	-0.0105	0.000470
	(0.0135)	(0.132)	(0.0137)	(0.00780)
Agricultural hh=1 × Current rainfall	0.00660	0.113	0.0391**	0.0102
	(0.0203)	(0.175)	(0.0170)	(0.0115)
Lagged rainfall	0.0143	0.360**	0.00828	0.00361
	(0.0142)	(0.161)	(0.0110)	(0.00820)
Agricultural hh=1 × Lagged rainfall	0.0116	0.0870	-0.0216	-0.00484
	(0.0190)	(0.200)	(0.0166)	(0.0109)
Marginal effect of current rainfall for ag hh	0.00618	0.244*	0.0287*	0.0107
	(0.0170)	(0.140)	(0.0162)	(0.0104)
Marginal effect of lagged rainfall for ag hh	0.0259*	0.447**	-0.0133	-0.00123
	(0.0140)	(0.178)	(0.0143)	(0.0109)
Individual, age, month, year fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	5353	3022	5307	5307

Notes: This table presents the coefficients and computed marginal effects of lagged and contemporaneous rainfall deviation estimated from equation 10. Standard errors clustered at the primary sampling unit (PSU) level in parenthesis. * p<0.1, ** p< 0.05, *** p< 0.01. We use the inverse hyperbolic sine transformation of education expenditures. Other controls include temperature. Agricultural household=1 if any member of the household was engaged in agriculture outside of paid employment or has a majority of adults in primary agricultural occupation.

Table B.6: Effect of rainfall on school-work decisions without controlling for temperature

	(1) Enrolled=1	(2) Education expenditure	(3) Labour force=1	(4) Working=1
		PANEL A: Males		
Current rainfall on non-ag hh	0.0229**	0.432***	-0.0341***	-0.0155
	(0.0104)	(0.133)	(0.0128)	(0.0102)
Lagged rainfall on non-ag hh	0.00991	-0.00990	0.0255*	0.0280**
	(0.0118)	(0.160)	(0.0142)	(0.0123)
Current rainfall on ag hh	0.0225	0.182	0.0277	0.0257*
	(0.0150)	(0.148)	(0.0204)	(0.0146)
Lagged rainfall on ag hh	-0.0133	0.328*	0.0498***	0.0674***
	(0.0152)	(0.177)	(0.0187)	(0.0149)
Observations	5237	3149	5172	5172
		PANEL B: F	emales	
Current rainfall on non-ag hh	0.0147	0.136	-0.0276**	-0.0102
	(0.0124)	(0.132)	(0.0120)	(0.00689)
Lagged rainfall on non-ag hh	0.0141	0.384**	0.00228	-0.00423
	(0.0132)	(0.155)	(0.0105)	(0.00827)
Current rainfall on ag hh	0.0130	0.235*	0.0305**	0.0207**
	(0.0168)	(0.142)	(0.0149)	(0.00978)
Lagged rainfall on ag hh	0.0242	0.443**	-0.00312	0.0117
	(0.0149)	(0.180)	(0.0153)	(0.0108)
Individual, age, month, year fixed effects	Yes	Yes	Yes	Yes
Other controls	5353	3022	5307	5307

Notes: This table presents the coefficients and computed marginal effects of lagged and contemporaneous rainfall deviation estimated from equation 10. Standard errors clustered at the primary sampling unit (PSU) level in parentheses. * p<0.1, ** p< 0.05, *** p< 0.01. We use the inverse hyperbolic sine transformation of education expenditures.

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Table B.7: Effect of rainfall on school-work decisions adding province fixed effects

	(1) Enrolled=1	(2) Education expenditure	(3) Labour force=1	(4) Working=1
		PANEL A: Males		
Current rainfall on non-ag hh	0.0101	0.280***	-0.0224**	-0.00915
	(0.00825)	(0.101)	(0.0101)	(0.00708)
Lagged rainfall on non-ag hh	0.0124	0.242*	0.0141	0.0122*
	(0.00873)	(0.135)	(0.00927)	(0.00736)
Current rainfall on ag hh	0.0126	0.197*	0.0340**	0.0246***
	(0.0116)	(0.106)	(0.0140)	(0.00917)
Lagged rainfall on ag hh	-0.0125	0.197*	0.0497***	0.0677***
	(0.0152)	(0.106)	(0.0185)	(0.0149)
Observations	5237	6171	5172	5172
	PANEL B: Females			
Current rainfall on non-ag hh	0.0101	0.280***	-0.0224**	-0.00915
	(0.00825)	(0.101)	(0.0101)	(0.00708)
Lagged rainfall on non-ag hh	0.0124	0.242*	0.0141	0.0122*
	(0.00873)	(0.135)	(0.00927)	(0.00736)
Current rainfall on ag hh	0.0126	0.197*	0.0340**	0.0246***
	(0.0116)	(0.106)	(0.0140)	(0.00917)
Lagged rainfall on ag hh	0.0272*	0.443**	-0.00577	0.0110
	(0.0150)	(0.180)	(0.0153)	(0.0108)
Individual, age, month, year fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	5353	3022	5307	5307

Notes: This table presents the coefficients and computed marginal effects of lagged and contemporaneous rainfall deviation estimated from equation 10 including province fixed effects. Standard errors clustered at the primary sampling unit (PSU) level in parentheses. * p<0.1, ** p< 0.05, *** p< 0.01. We use the inverse hyperbolic sine transformation of education expenditure. Other controls include temperature and province fixed effects.

Table B.8: Effect of rainfall on school-work decisions in urban areas

	(1) Enrolled=1	(2) Education expenditure	(3) Labour force=1	(4) Working=1
		PANEL A: Males		
Current rainfall	0.0200	-0.147	-0.0160	-0.0151
	(0.0125)	(0.113)	(0.0124)	(0.0100)
Lagged rainfall	0.00786	-0.125	0.00240	0.00222
	(0.00873)	(0.162)	(0.00981)	(0.00860)
Observations	3284	2070	3853	3853
		PANEL B: F	emales	
Current rainfall	0.00190	0.00278	0.0158	-0.00145
	(0.0127)	(0.105)	(0.0112)	(0.00892)
Lagged rainfall	-0.0201**	0.124	0.0158	0.00519
	(0.00962)	(0.148)	(0.00971)	(0.00722)
Individual, age, month, year fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	3462	2048	4022	4022

Notes: This table presents the coefficients and computed marginal effects of lagged and contemporaneous rainfall deviation estimated from equation 10 for the urban sample. Standard errors clustered at the primary sampling unit level in parentheses. * p<0.1, ** p< 0.05, *** p< 0.01. We use the inverse hyperbolic sine transformation of education expenditure. Other controls include temperature.

Table B.9: Baseline characteristics for the baseline sample (2008)

	(1) Baseline sample	(2) Balanced panel	(3) Observed with interruption	(4) Diff: (2) - (1)	(5) Diff: (3) - (1)
Female = 1	0.50	0.50	0.49	0.02	-0.01
	(0.50)	(0.50)	(0.50)		
Standardized rainfall	0.26	0.26	0.28	-0.02	0.02
	(0.52)	(0.53)	(0.49)		
Lagged rainfall	-0.22	-0.24	-0.11	-0.13**	0.12**
	(0.74)	(0.74)	(0.75)		
Age	17.47	17.46	17.55	-0.13	0.09
	(1.58)	(1.58)	(1.51)		
Standardized temperature	-1.21	-1.21	-1.16	-0.05*	0.06**
	(0.37)	(0.37)	(0.33)		
Household size	6.61	6.63	6.49	0.14	-0.14
	(3.32)	(3.34)	(3.22)		
Household wealth index	-0.60	-0.59	-0.67	0.09	-0.08
	(0.70)	(0.70)	(0.67)		
Total household income	3,402.96	3,462.94	3,072.74	458.96	-376.21
	(5,778.23)	(5,985.25)	(4,223.23)		
Observations	1,538	1,337	188	1,538	1,538

Notes: This table reports the average baseline characteristics for the baseline sample (column 1), the balanced panel of adolescents observed in every wave (column 2) and the sample observed with interruption (column 3). The sample observed with interruption is defined as those who were surveyed more than once in later rounds. Columns 4 and 5 report average differences between the baseline sample and the balanced panel and the sample observed with interruption respectively with significance levels. Standard deviation in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.10: Effect of rainfall on school-work decisions using the balanced samples

	(1) Enrolled=1	(2) Education expenditure	(3) Labour force=1	(4) Working=1
		PANEL A: Males		
Current rainfall on non-ag hh	0.0210	0.350**	-0.0297*	-0.0206
	(0.0133)	(0.142)	(0.0159)	(0.0135)
Lagged rainfall on non-ag hh	0.00619	0.202	0.0271*	0.0232*
	(0.0128)	(0.207)	(0.0151)	(0.0125)
Current rainfall on ag hh	0.0131	0.183	0.0347	0.0256
	(0.0177)	(0.156)	(0.0219)	(0.0158)
Lagged rainfall on ag hh	-0.0145	0.446**	0.0574***	0.0697***
	(0.0166)	(0.190)	(0.0192)	(0.0159)
Observations	4222	2591	4169	4169
		PANEL B: Females		
Current rainfall on non-ag hh	0.00445	0.156	-0.0170	-0.00469
	(0.0147)	(0.145)	(0.0147)	(0.00875)
Lagged rainfall on non-ag hh	0.00211	0.286	0.00972	-0.00216
	(0.0142)	(0.196)	(0.0115)	(0.00830)
Current rainfall on ag hh	0.00839	0.104	0.0385**	0.0222**
	(0.0192)	(0.149)	(0.0162)	(0.0104)
Lagged rainfall on ag hh	0.0297*	0.358*	-0.00906	0.00589
	(0.0159)	(0.207)	(0.0169)	(0.0112)
Individual, age, month, year fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	4218	2419	4174	4174

Notes: This table presents the coefficients of lagged and contemporaneous rainfall estimated from equation 10 for the sample observed in all 5 waves. Standard errors clustered at the primary sampling unit (PSU) level in parentheses. * p<0.1, ** p< 0.05, *** p< 0.01. We use the inverse hyperbolic sine transformation of education expenditure. Other controls include temperature.

Table B.11: Effect of rainfall on school-work decisions using the baseline sample

	(1)	(2)	(3)	(4)
	Enrolled=1	Education expenditure	Labour force=1	Working=1
		PANEL A: Males		
Current rainfall on non-ag hh	0.0226*	0.332**	-0.0319**	-0.0186
	(0.0127)	(0.133)	(0.0148)	(0.0128)
Lagged rainfall on non-ag hh	0.0130	0.199	0.0262*	0.0271**
	(0.0127)	(0.193)	(0.0150)	(0.0129)
Current rainfall on ag hh	0.0176	0.182	0.0322	0.0264
	(0.0162)	(0.150)	(0.0220)	(0.0160)
Lagged rainfall on ag hh	-0.0119	0.454**	0.0491***	0.0703***
	(0.0158)	(0.187)	(0.0188)	(0.0154)
Observations	4636	2773	4577	4577
		PANEL B: Females		
Current rainfall on non-ag hh	0.00705	0.140	-0.0135	-0.00579
	(0.0142)	(0.139)	(0.0148)	(0.00812)
Lagged rainfall on non-ag hh	0.00861	0.258	0.00794	-0.00528
	(0.0140)	(0.184)	(0.0115)	(0.00890)
Current rainfall on ag hh	0.00545	0.141	0.0386**	0.0241**
	(0.0180)	(0.143)	(0.0164)	(0.0105)
Lagged rainfall on ag hh	0.0333**	0.344*	-0.00334	0.0113
	(0.0148)	(0.194)	(0.0163)	(0.0114)
Individual, age, month, year fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	4602	2569	4557	4557

Notes: This table presents the coefficients of lagged and contemporaneous rainfall estimated from equation 10 for the original baseline sample of continuing sample members (panel B). Standard errors clustered at the primary sampling unit (PSU) level in parentheses. * p<0.1, ** p< 0.05, *** p< 0.01. We use the inverse hyperbolic sine transformation of education expenditure. Other controls include temperature.

Table B.12: Multiple hypothesis testing

	(1) Enrolled=1	(2) Education exp	(3) Labor force=1	(4) Working=1
		PANEL A: Males		
Current rainfall	0.0198*	0.407***	-0.0337**	-0.0170
	(0.085)	(0.002)	(0.016)	(0.145)
	[0.1782]	[0.0099]	[0.0297]	[0.2970]
Agricultural hh=1 × Current rainfall	0.000371	-0.245	0.0617***	0.0416**
	(0.982)	(0.164)	(0.005)	(0.016)
	[0.9703]	[0.3168]	[0.0198]	[0.0297]
Lagged rainfall	0.0103	0.136	0.0254*	0.0281**
	(0.387)	(0.420)	(0.075)	(0.024)
	[0.5347]	[0.5347]	[0.1485]	[0.0297]
Agricultural hh=1 × Lagged rainfall	-0.0228	0.286	0.0243	0.0396**
	(0.183)	(0.214)	(0.217)	(0.022)
	[0.3267]	[0.3663]	[0.3663]	[0.0297]
Observations	5237	3149	5172	5172
		PANEL B:	Females	
Current rainfall	0.00137	0.138	-0.0161	-0.00718
	(0.918)	(0.293)	(0.248)	(0.335)
	[1.000]	[0.8713]	[0.8020]	[0.8812]
Agricultural hh=1 × Current rainfall	0.00191	0.0984	0.0550***	0.0301***
	(0.927)	(0.576)	(0.002)	(0.004)
	[1.000]	[0.9901]	[0.0198]	[0.0297]
Lagged rainfall	0.0144	0.370**	0.00209	-0.00428
	(0.275)	(0.023)	(0.843)	(0.607)
	[0.8515]	[0.0693]	[1.000]	[1.000]
Agricultural hh=1 × Lagged rainfall	0.0129	0.0638	-0.00786	0.0153
	(0.487)	(0.757)	(0.647)	(0.167)
	[0.9802]	[1.000]	[1.000]	[0.6436]
Observations	5353	3022	5307	5307

Notes: This table presents the coefficients of lagged and contemporaneous rainfall estimated from equation 11 for the sample of males. Standard errors are clustered at the primary sampling unit level. * p<0.1, ** p< 0.05, *** p< 0.01. Conventional p-values are in parenthesis. Romano-Wolf p-values for multiple hypothesis testing are in brackets. We use the inverse hyperbolic sine transformation of education expenditure conditional on enrollment. All regressions control for individual, age, month, and year fixed effects, and temperature.

Table B.13: Effect of rainfall on school-work decisions using the sample of non-missing observations

	(1) Enrolled=1	(2) Education expenditure	(3) Labour force=1	(4) Working=1
		PANEL A: Males		
Current rainfall on non-ag hh	0.0184	0.416***	-0.0337**	-0.0170
	(0.0118)	(0.131)	(0.0139)	(0.0116)
Lagged rainfall on non-ag hh	0.00891	0.121	0.0254*	0.0281**
	(0.0120)	(0.168)	(0.0142)	(0.0123)
Current rainfall on ag hh	0.0244	0.169	0.0280	0.0246
	(0.0157)	(0.149)	(0.0211)	(0.0150)
Lagged rainfall on ag hh	-0.0106	0.419**	0.0497***	0.0677***
	(0.0154)	(0.177)	(0.0185)	(0.0149)
Observations	5172	3126	5172	5172
		PANEL B: F	emales	
Current rainfall on non-ag hh	0.00121	0.147	-0.0161	-0.00718
	(0.0132)	(0.133)	(0.0139)	(0.00743)
Lagged rainfall on non-ag hh	0.0123	0.385**	0.00209	-0.00428
	(0.0131)	(0.160)	(0.0106)	(0.00831)
Current rainfall on ag hh	0.00327	0.258*	0.0389**	0.0229**
	(0.0175)	(0.141)	(0.0161)	(0.0101)
Lagged rainfall on ag hh	0.0263*	0.438**	-0.00577	0.0110
	(0.0151)	(0.180)	(0.0153)	(0.0108)
Individual, age, month, year fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	5307	2991	5307	5307

Notes: This table presents the coefficients and computed marginal effects of lagged and contemporaneous rainfall deviation estimated from Equation 10 for the sample of non-missing observations. Standard errors clustered at the primary sampling unit (PSU) level in parentheses. * p<0.1, ** p< 0.05, *** p< 0.01. We use the inverse hyperbolic sine transformation of education expenditures. Other controls include temperature.

Mission

To strengthen local capacity for conducting independent, rigorous inquiry into the problems facing the management of economies in sub-Saharan Africa.

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