Rainfall shocks and adolescent school-work transition: Evidence from rural South Africa

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Abstract

South Africa, located within a drought belt, has experienced exacerbated drought conditions in recent years. Rural households employ a number of strategies to cope with adverse weather events, including school-work transitions of adolescents and changes in human capital investments. Using rich longitudinal data from South Africa linked with geospatial data on climate indicators, we examine the effect of rainfall variability on the school-work decisions and education expenditures of adolescents and young adults aged 14-22 years in rural South Africa. We employ a fixed effects model which exploits the exogenous temporal variation in exposure to district-level rainfall variability. Our results suggest that current rainfall increases school enrollment and education expenditures and decreases labor market participation on the extensive and intensive margins among females and males. However, lagged rainfall increases work propensity and intensity among male and female adolescents. We do not find statistically different effects for females relative to males. Our results indicate the need to improve access to credit to rural households during times of adverse weather events.

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1 Introduction

Climate change and associated weather variability and extreme events are projected to have adverse effects, particularly in poorer regions such as Sub-Saharan Africa. The economic costs of extreme events, such as droughts and floods, are likely to be exorbitant in economies with high levels of poverty and dependence on rain-fed agriculture. Households employ a number of strategies to cope with adverse weather events, including adjustments in the human capital investments of household members. As rural households in developing countries have limited access to credit and reliance on asset sales, changes in human capital investments of children and their labor supply responses constitute one of the most important coping strategies. Adolescents are particularly vulnerable to such shocks as they may be forced to enter the labor market as a household coping mechanism, thus, resulting in school termination and, consequently, long-lasting adverse effects on human capital accumulation.

South Africa, a country that has experienced exacerbated drought conditions in recent years (Blamey, Kolusu, Mahlalela, Todd, & Reason, 2018), presents a compelling case study. Located within a 'drought belt', South Africa is highly vulnerable to climate shocks due to the high dependence on rain-fed agriculture, high poverty in rural areas, and a low adaptive capacity. Between 1980 and 2013, droughts affected an estimated 15 million South Africans. Moreover, in 2015-2016, South Africa suffered the worst drought in decades which substantially decreased food production. South Africa is predicted to become hotter and drier in the future, with a projected increase in annual precipitation anomaly (World Bank Group, 2021).

In this paper, we investigate the causal effect of agricultural shocks, proxied by rainfall shocks, on school–work decisions of adolescents and young adults in South Africa. We particularly focus on the short-term consequences of exposure to rainfall variability on school–work transition during the key human developmental periods of adolescence. We also assess the effects of these transitory shocks on human capital investment on the intensive margin such as child-specific real education expenditures. Our main interest is whether volatile income resulting from adverse rainfall shocks in an environment of incomplete insurance or capital markets leads to lost opportunities for such investments. If households cannot borrow or save, they must finance a given period's investment and financial losses out of current-period income, and a large negative income shock could lead to a reduction in current-period investment in children (Jensen, 2000). This research question is pertinent in South Africa which has a large number, around 207,714, of out-of-school adolescents with a net secondary school enrollment rate of 70.3 % in 2019 (UNESCO, 2019). In such poorer regions of the world, coping decisions to pull children from school may have long-lasting irreversible effects on human capital formation.

We use rich longitudinal data of adolescents and young adults in South Africa corresponding to five rounds between 2008 and 2017. We match individual level data with geospatial data on precipitation, using information on the district of residence of each individual. We employ an individual fixed effects model which allows us to control of unobserved heterogeneity. Our identification strategy relies on the plausibly exogenous temporal variations in district-level rainfall. We consider both current and one-period lagged rainfall variability. Our results indicate that current positive rainfall deviations from the historical district-level average increases the probability of school enrollment and real child-specific education expenditures for both male and female adolescents. While current rainfall deviations decrease the labor market participation on the extensive and intensive margins, rainfall deviations in the previous growing season increase work propensities, with stronger effects among males. These indicate persistent but opposite impacts of weather shocks on work decisions in the following year. We do not find evidence of gender differential in the household's coping strategies to adverse weather events, in contrast to previous studies which demonstrate that weather shocks have stronger effects on the school–work transition of girls relative to boys (Marchetta, Sahn, & Tiberti, 2019; Zimmermann, 2020).

We also explore the avenue that household wealth, which is associated with increased savings and credit, may mitigate the impacts of weather shocks. We find that the effects of rainfall variability on school enrollment are attenuated for males from wealthier households. This suggests that assets mitigate the effect of transitory shocks and that male adolescents are better shielded from the effects of rainfall variability on school enrollment. However, household wealth attenuates the effects of lagged rainfall on labor market participation of female adolescents.

Our study contributes to the literature in two important ways. First, we contribute to the scarce literature on the impact of weather shocks on school-work transition of adolescents in developing countries. The vast literature on the influence of environmental shocks on human capital accumulation almost exclusively focuses on the early years of childhood. The long-term effects of these shocks in early childhood are well-documented (Maccini & Yang, 2009). However, the period of adolescence (ages 11 to 19) is also marked by important physical and socio-economic transitions. Adolescent males and females begin to increasingly take on adult roles and responsibilities during this growth period, including transitioning from school to the labor market. Consequently, adverse events during adolescence can have long-lasting implications for individuals' adult well-being. While shocks in mid-childhood may result in school discontinuation, adolescents may be at an elevated risk as household shocks may induce school termination. The risks faced by adolescents as they transition to adulthood may be exacerbated by poor infrastructure and lower labor market opportunities, especially in rural areas. Yet, except for a few studies, robust evidence exploring the impact of negative weather events during adolescence in the context of Sub-Saharan Africa is sparse. Our focus here is on adolescents and young adults in rural South Africa.

Second, transitory rainfall shocks affect the school-work decisions in agrarian households through an income effect and a substitution effect. With favorable rainfall conditions, the increase in agricultural income increases resources allocated towards adolescent education, thereby resulting in a positive income effect. However, due to higher agricultural wages, the opportunity cost of schooling increases, which forces households to push children into the labor market. Since, the net effect is, a priori, ambiguous, it is policy relevant to determine whether favorable rainfall hampers or improves human capital accumulation during adolescence. Our results demonstrate that current rainfall shocks induce changes in the school-work decisions of adolescents driven by the credit constraint channel. However, positive rainfall shocks in the previous growing season affect labor decisions through the increase in the opportunity cost (shadow price) of schooling.

Third, we explore the role of household assets in mitigating or reinforcing the effects of weather shocks, similar to Beegle, Dehejia, and Gatti (2006); Dumas (2020); Kazianga (2012). Our results demonstrate gender differences in the role of wealth on the school-work decisions of adolescents.

The rest of the paper is organized as follows. Section 2 provides the conceptual framework for our model. Section 3 describes the data sources and variable descriptions. The empirical model and identification strategy is discussed in section 4. Section 5 describes the results from the empirical analysis, robustness checks and presents the heterogeneity analysis. Finally, we provide concluding remarks and the policy implications in section 6.

2 Conceptual Framework

Negative rainfall conditions represent a substantial shock to human capital attainment during the adolescent school years when children in many developing countries transition from school to work and are deciding whether to terminate or continue schooling. Exogenous rainfall shocks affect school–work decisions not only through the direct income (or production) effect but also through an indirect effect whereby the favorable rainfall conditions affect the shadow wages of labor (Marchetta et al., 2019). As per the theoretical framework in Marchetta et al. (2019), the rainfall induced direct (income) effect is likely to increase the probability of continuing school and decrease the probability of entering the labor market, especially since credit constraints are relieved, children will not be forced to terminate their schooling and, consequently, their labor market entry can be delayed. In contrast, with an increase in the shadow wage or the opportunity cost of labor associated with positive rainfall conditions, the likelihood of schooling decreases, thus, the indirect effect on schooling is negative. The overall effect on school–work decisions, therefore, depends on the relative strengths of the two opposite effects. In this context, they find that negative rainfall shocks increase the probability of young adults entering the labor force and dropping out of school, with larger effects among young women.

Previous studies demonstrate effects of agricultural shocks on children's school-work decisions driven by the credit constraint channel. Rural households adjust human capital investments in children in response to unanticipated agricultural income changes as a form of informal self-insurance (Jacoby & Skoufias, 1997). A large number of studies provide empirical evidence in support of this hypothesis. Negative rainfall shocks decrease school enrollment rates (Jensen, 2000), especially enrollment in primary school for older girls (Björkman-Nyqvist, 2013) and decrease children's school attendance (Agamile & Lawson, 2021; Jacoby & Skoufias, 1997). Similarly, negative transitory agricultural income shocks decrease children's school attendance (Beegle et al., 2006) and increase the probability of school dropout (Gubert & Robilliard, 2008).[2] Instead, adverse rainfall conditions lead to reallocation of time spent on schooling towards farm labor (Colmer, 2021). In one of the early works, Rose (2001) finds that ex post, with unexpected low rainfall, households tend to increase labor force participation. Households substitute adult labor with child labor for household activities such collection of firewood and water (Beegle et al., 2006). Similarly, Bandara, Dehejia, and Lavie-Rouse (2015) find that agricultural shocks such as crop loss increase overall work hours and agricultural work hours, especially among boys, and decrease school attendance, with stronger effects of school termination among girls. Therefore, following a negative shock, child labor may increase if the households are credit-constrained (Alvi & Dendir, 2011).

On the contrary, Shah and Steinberg (2017) show that higher wages induced by positive rainfall conditions increase human capital investment in children from utero to age 2 but lead to a deleterious effect on human capital from age 5 to 16. Favorable rainfall conditions encourage parents to engage children in farm labor, and thus, their school attendance decreases. Consistent with the increase in opportunity cost of education

[2] Beegle et al. (2006) measure agricultural income shocks by accidental crop loss. Gubert and Robilliard (2008) consider 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.

due to better employment opportunities after favorable rainfall conditions, Zimmermann (2020) also finds that negative rainfall shocks in India have a positive impact on school enrollment, with increasingly stronger effects over time. Nordman, Sharma, and Sunder (2020) find that a transitory increase in rainfall decreases education expenditures and increases the likelihood of child labor across multiple work activities in rural India. Baez, Lucchetti, Genoni, and Salazar (2017) find that in rural households hit by large rainfall levels dropped by tropical storm Agatha, children decreased their school attendance and instead increased their engagement in paid and unpaid work. A recent study by Dumas (2020) demonstrate the pro-cyclical responses of child labor to positive rainfall shocks in Tanzania when labor market access is poor and the price effect dominates. However, with an active labor market, the effect becomes statistically insignificant.[3] Favorable rainfall increases not only child labor in agricultural work but also increases time spent on household chores, to substitute for adults who are more likely to engage in agricultural production (Trinh, Posso, & Feeny, 2020).

Pham (2021) finds that excess rainfall during the annual typhoon season decreases school enrollment of children the following year, with pronounced effects for children of ethnic minorities. She also finds that households cope by delaying school entry of primary school aged children. These lagged effects are likely driven by the shock-induced increase in labor in household non-farm work and wage work outside the household.

3 Data Sources

3.1 Individual data

We conduct the analysis using individual-level data from the National Income Dynamic Study (NIDS) implemented by the South African Labor and Development Research Unit (SALDRU). This is a nationally representative face-to-face longitudinal survey of households in South Africa and is available for the periods 2008, 2010-11, 2012, 2014-15

[3] Dumas (2020) also shows that when the labor market access is substantial, child labor does not smooth rainfall variations as the price effect is negligible.

and 2017. 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 use data from all the 5 waves for this study as it enables us to examine the within individual variations in exposure to rainfall shocks over time. As our panel data covers the period 2008–2017, we include adolescents and young adults aged 14-22 years in every survey.

Our outcomes of interest are a dummy variable for school enrollment and labor market participation on the intensive and extensive margins, and education expenditures in the previous year. The NIDS asks respondents aged 15 years and above whether they are enrolled in school[4] during the survey year, whether they are currently working or are engaged in any income-generating activity. In addition, the respondents are asked to provide information on the sectors of occupation and the number of hours per week spent on each job.

While most household surveys collect information on education-related expenditures at the household level, the 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 aggregate the expenditure on these categories to obtain the total education expenditure (in Rands) for each child. We adjust these expenditures for inflation using the Consumer Price Index (CPI) (base December 2012=100) to get the real education expenditure.

Figure 1 present the means of school enrollment and work status at every age in the sample. As expected, we observe that proportion of adolescents enrolled in is high up to age 17 post which children start terminating their education. As adolescents age, the probability of labor market participation increases among both females and males. While labor market participation is higher among males relative to females at every age, school enrollment also follows a similar pattern. In addition to the gender-based inequality

[4]School includes university, technical college as well as school.

in human capital investment in rural South Africa, this is likely driven by the fact that female adolescents engage more in domestic chores and care-giving for siblings. Therefore, they are more likely to delay entry into the labor market.

We include controls for individual, household and geographical characteristics in the models. The individual and household characteristics are age of the adolescent, gender, mother's education; household characteristics such as household wealth,[5] household size, child dependency ratio.[6] The survey also provides information on the districts in which the household is residing in rural South Africa. We use the district council codes for the 52 district councils as per the 2011 Census.[7]

3.2 Climate data

This study employs historical rainfall data from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), a thirty-year rainfall dataset that covers 50°S-50°N (and all longitudes). CHIRPS incorporates 0.05 resolution satellite imagery with in-situ station data to create a gridded rainfall time series for trend analysis and seasonal drought monitoring (Funk et al., 2015). CHIRPS has been primarily developed to support agricultural drought monitoring.[8] We match the weather data based on the geographical coordinates for the 52 district councils in South Africa.

We employ a measure of rainfall variability commonly used in the literature. Following Branco and Féres (2021) and Marchetta et al. (2019), we create a variable measuring the standardized rainfall for each district. We consider the standardized deviations of rainfall during the rainy season ($October_{t-1}$ to $March_t$) by taking the variations between the

[5]Household wealth index is created using Factor Analysis. We consider 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.

[6]Child dependency ratio is defined as the ratio of number of children aged 0-14 to the number of members aged 15-60 years in the household

[7]Between the 2001 and 2011 Census, the district municipal boundaries changed. To ensure comparability, we consider the district municipalities as per the 2011 Census boundaries.

[8]The CHIRPS dataset 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-present (Funk et al., 2015).

total precipitation during this period in year t in district d and the 1987-2017 average, divided by the 1987-2017 standard deviation. This indicator captures the positive and negative deviations in total precipitation relative to the long-term averages. Negative values of standardized rainfall indicate drought conditions whereas positive values indicate favorable rainfall conditions.

Using rainfall variability as a proxy for agricultural shocks rests on the assumption that agricultural productivity is strongly correlated with rainfall deviations. Previous studies in the context of developing countries demonstrate that rainfall shocks affect crop production and the income of rural households substantially (Gubert & Robilliard, 2008; Kazianga, 2012). Rainfall shocks are a relevant measure of a local agricultural shock in South Africa. The country's staple crop, maize, is a rain-fed crop and limited water availability reduces 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.[9] Deficient rainfall can severely affect crop yields. The two consecutive droughts in 2014-15 and 2015-16 that hit South Africa were characterized by large rainfall deficits and led to a huge shortfall in maize production in the major producer of the Southern Africa region (World Food Program, 2017). Appendix Table A.1 shows that negative rainfall deviations decrease annual maize yields per hectare over time. Figure 5 illustrates the strong association between the trends in annual maize production and rainfall during the growing season every year from 1988-2017 in South Africa. These results broadly indicate that transitory rainfall fluctuations serve as a reasonable proxy for productivity shocks in rural South Africa.

We also control for the spatial and temporal variations in the temperature at the district council level. The monthly temperature series is obtained from the ERA5 product of the European Centre for Medium-Range Weather Forecasts (ECMWF). We standardize the annual temperature by considering the deviations of the average annual temperature

[9] Flatø, Muttarak, and Pelser (2017) identify the rainy season as a continuous period with rainfall above average in each month. Our definition of the rainy season complies with this definition as the monthly rainfall during October-March is above average and corresponds with the growing season.

from the average temperature during the period 2008-2017 and dividing by the standard deviation during this period.

3.3 Data Description

Table 1 presents the sample summary statistics of the outcomes, the main explanatory variables and controls over the study period. 73% of our sample adolescents are currently enrolled in school. Around 7.4% of the adolescents participate in the labor market. Of those who are economically active, around 52.08 % of work in wage/salaried jobs, 20 % are involved in casual work, and 17.41 % work on their own garden or plot. Around 5.39 % assist in other's business activities and 4.47 % are self-employed.

The average real annual expenditure on education is about 967.404 Rands. The average rainfall deviation during the growing season is around 6% below the long-term mean. On average, during the study period, districts experienced deficient rainfall relative to their long-term mean rainfall. Approximately 49 percent of our sample comprises female adolescents. In our models, we use an inverse hyperbolic sine transformation of the real education expenditure. The sample consists of those aged 15-22, and the average age of these children is 17.7 years.

Figure 2 presents the distribution of the standardized rainfall deviations for the years 2008-2017. Panel A shows the rainfall deviations for the full sample. Following Marchetta et al. (2019), we show the histogram of the district-specific mean of these deviations in panel B. We observe that the district-specific means are concentrated around 0. This provides support to the assumption that districts do not systematically experience positive or negative rainfall deviations. Therefore, the main variable of interest, standardized precipitation index, is capturing normal rainfall variability.

Figure 3 presents the average monthly rainfall deviations relative to the long-term monthly averages over time. We observe that for a larger proportion of our study period, the average rainfall deviations are negative which means that country experienced drier conditions in comparison to the 30-year long-term rainfall. Rainfall during the growing season varies not just temporally but also spatially. Figure 4 maps the rainfall deviations during the growing season across districts in every study period.

If rainfall deviations of a particular year are correlated with rainfall variability of the previous year, it is difficult to disentangle the effects of rainfall shocks pertaining to a single year or the cumulative effects over multiple years. In our case, precipitation in one year is not systematically related with precipitation in the next year. Figure 4 shows the spatial distribution of rainfall during the growing season varies randomly over time. Additionally, we test for serial correlation in rainfall at the district-level and individual level. The results reported in Table 7 suggest no significant correlation between lagged standardized rainfall and current rainfall across years.

4 Methodology

To identify the effect of rainfall shocks, we employ a linear individual fixed effects model. The empirical strategy exploits the exogenous temporal variation in precipitation within districts. By including individual fixed effects, we compare the same adolescents in periods when they were exposed to relatively high precipitation with periods in which they were exposed to low precipitation resulting in drought conditions.

The decision to discontinue enrollment in school and work in income-generating activities may depend on the rainfall deviations in the current agricultural growing period $October_{t-1} - March_t$ 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 estimate the lagged effect of rainfall shocks on school-work transition by including the lagged standardized rainfall, at time $t-1$ measuring precipitation in the period $October_{t-2} - March_{t-1}$.

We estimate the following linear equation:

$$Y_{idmt} = \beta_0 + \beta_1 Rain_{dt} + \beta_2 Rain_{dt-1} + \beta_3 X_{idmt} + \beta_4 T_{dt} + \lambda_i + \phi_m + \omega_t + u_{idmt} \tag{1}$$

Here, the outcome variable is Y refers to the school attendance, grade attainment, or the labor outcome of adolescent i in district d in survey period t. The main variable of interest is the standardized rainfall, *Rain*. For examining education expenditures which are available for the previous year in every wave, we consider the rainfall deviations in the one year lagged growing season. The coefficient β_1 allows us to estimate the contemporaneous effect of rainfall deviations on school and work decisions and education expenditures. The lagged effect of rainfall variability in the previous agricultural season on school-work transitions is captured by β_2.

X is a vector of individual and household characteristics such as age, household wealth, household size, and child dependency ratio. T is the average annual temperature in district d in year t. Here, λ_i is a vector of individual fixed effects, ϕ_m is a vector of month of interview fixed effects, ω_t is a vector of the survey year dummy variables (time fixed effects), and u_{idmt} is the random error term. We assume correlation among errors within a district, therefore, we cluster standard errors at the district level in all the regressions.

To estimate the gender differential in the effects of rainfall shocks, we include an interaction term between *Rain* and a dichotomous indicator $Female = 1$ in the main specification. Further, we examine the heterogeneity in the school-work decisions across wealth index.[10] We estimate the following regression:

$$\begin{aligned} Y_{idmt} = \beta_0 + \beta_1 Rain_{dt} + \beta_2 Rain_{dt} * W + \beta_3 Rain_{dt-1} + \beta_4 Rain_{dt-1} * W + \\ \beta_5 X_{idmt} + \beta_6 T_{dt} + \lambda_i + \phi_m + \omega_t + u_{idmt} \end{aligned} \tag{2}$$

Here, W refers to the time invariant characteristic, $female$, or the time variant household *wealth*. The coefficients, β_2 and β_4 on the interactions terms capture the differential effect of current and lagged rainfall variability on school-work decisions across

[10] We recognize that using the baseline household wealth index in 2008 would allow us to estimate the differential effects of weather shocks by the wealth status. We use the current household wealth index to conduct heterogeneity analysis as there are missing observations for the baseline wealth index. However, this is unlikely to confound our estimates. First, as shown in Table 6, current and lagged rainfall does not induce changes in household assets. Second, results are similar whether we use the baseline wealth index or the current wealth index. The results with the baseline wealth index are available upon request.

gender and household wealth.

This identification strategy yields unbiased estimates under the assumption that standardized rainfall or drought condition is uncorrelated with unobserved determinants of schooling and labor market outcomes. We acknowledge that a threat to our identification may arise if unobserved individual-level heterogeneity is correlated with rainfall variability. For instance, droughts in the past or in early childhood could have decreased household wealth or increased resilience to shocks. If that is the case, the effect of rainfall variability would capture the effect of the historical long-term rainfall. To mitigate this concern, we use 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, we find that rainfall deviations do not significantly predict any predetermined individual and household-level characteristics. These results are discussed in the section 5.2. The survey year fixed effects in our models capture the unobservable labor market conditions or changes in schooling infrastructure that vary over time. The month fixed effects capture the seasonality in the rural labor markets and any possible seasonal pattern in school enrollment.

It is plausible that differences across districts in terms of the level of local infrastructure and economic development may be systematically related to the rainfall variability. If such differences exist, rainfall shocks may be correlated with unobservables affecting school-work decisions, which would lead to biased estimates. There are three reasons why this concern is unlikely to substantially bias our estimates. First, we employ a measure of rainfall variability relative to district-specific historical levels, so that districts experiencing high rainfall in a particular year is with respect to their long-term trends and not with respect to other districts. Second, we control for individual heterogeneity by using individual fixed effects which capture the effect of residing in a particular district over time. This is because almost the entire sample of adolescents reside in the same district during study period, except for only 1.65% (181) of the sample adolescents who report moving to another district. Third, we run a separate model in which we include province fixed effects and find that our results are unchanged. These results are discussed in section 5.2.

5 Results

5.1 Main results

Table 2 reports the estimates from equation 1 for school-work decisions on the intensive and extensive margins. From columns 1 and 2, we observe that current rainfall variability of one standard deviation increases the probability of school enrollment by 2.65 percentage points and education expenditures by 18.8% among all adolescents. Therefore, expected revenue from agricultural activities is likely to increase human capital investments among adolescents and young adults. In times of adverse rainfall conditions in the current agricultural season, adolescents are less likely to be enrolled in school and instead, are more likely to engage in income-generating activities, although the effect on labor market participation is weakly statistically significant at the 15% level. Column 4 indicates that decrease in rainfall increases the hours spent on working for pay. Transitory increase in rainfall induce adolescents to substitute time allocated for work towards schooling or household chores. Thus, the effects of current rainfall variability is likely driven by the direct income effect whereby in periods of favorable rainfall conditions which increase rural household income, adolescents are likely to be enrolled in school and decrease their labor market participation.

We observe that lagged rainfall does not have a statistically significant effect on human capital investment on the extensive or intensive margins (columns 1 and 2). However, rainfall deviations by one standard deviation in the one-year lagged period increases labor market participation on the intensive and extensive margins by 2.47 percentage points and 9.8 percent, respectively (columns 3 and 4). Transitory lagged rainfall deviations have a pro-cyclical effect on the propensity to work. The lagged effects of rainfall deviations on participation in the labor market can be attributed to the wage (price) effects dominating the income effects.

To estimate the differential effects of rainfall by the gender of the adolescent, we include terms for the interaction of current and lagged rainfall with an indicator $Female$. Table 1 columns 5–8 report the coefficients from estimation of equation 2. The bottom panels report the computed marginal effects of current rainfall and lagged rainfall for females. We observe that standardized current period rainfall deviations increase school enrollment by 2.98 percentage points among males and 2.30 percentage points among females, although the difference in the coefficients is not statistically significant. Similarly, positive rainfall conditions in the current period increase spending on education among both male and female adolescents, with statistically similar marginal effects.

After including the interaction terms, we observe that positive deviations in rainfall decrease the probability of participating in the labor market among both male and female adolescents. However, the effects of current rainfall variability are not statistically significant. We find statistically significant effects of current rainfall on the intensity of participation in the labor market. However, the differential effect of rainfall across gender is not significant at conventional levels of significance.

We observe that lagged rainfall increases the probability of working on the extensive and intensive margins among males and by a lower magnitude among females (columns 7 and 8). However, the coefficients on the interaction terms are not statistically significant. These results indicate that favorable rainfall conditions in rural areas are associated higher shadow wages and therefore, households are likely to push both adolescent males and females into the labor market. Overall, we do not find any evidence of gender bias in the household responses to rainfall shocks.

5.2 Robustness Checks

Notably, our results are robust to alternative definitions of rainfall and other model specifications. First, instead of continuous measure of rainfall variability, we consider a discrete rainfall shock indicator. We construct an indicator for rainfall shock based on the total rainfall during the rainy season. We define $shock = -1$ if the total standardized rainfall during the growing season in a given year is below 1 standard deviation, 1 if it is above 1 standard deviation and 0 otherwise, relative to the district-specific long-term mean. This definition of rainfall has been used to check the robustness of results in studies by Marchetta et al. (2019) and Dumas (2020). Table 3 demonstrates that the estimates, although statistically weak for some coefficients, are qualitatively similar to the main results.

Second, following Björkman-Nyqvist (2013) and Nordman et al. (2020), we consider the deviations of rainfall during the rainy season ($October_{t-1}$ to $March_t$) by taking the logarithm of the total precipitation during this period in year t in district d, minus the logarithm of the 1987-2017 rainy season average, $ln(R_{dt})$ - $ln(\bar{R})$. This indicator captures the positive and negative deviations in total precipitation relative to the long-term averages. We observe from Table 4 that the estimates are qualitatively similar to the main results.

As discussed in section 4, we demonstrate in Table 5 that the our estimates are robust to the inclusion of proxies for geographic variation. Although some estimates are weakly statistically significant, the results are qualitatively similar, Additionally, since only 0.35% (39) of the sample adolescents moves to another province during the study period, the time-invariant province-level variation is captured by the individual fixed effects in the model. Moreover, from Table 6, we observe that rainfall deviations do not significantly predict predetermined individual and household-level characteristics such as adolescent's age, household size, household wealth index, and child dependency ratio, thereby mitigating concerns of any correlation with time-varying individual and household characteristics.

Our data do not allow us to test the effect of rainfall conditions on agricultural yields in the districts. Nevertheless, to check whether these effects operate through the channel of agricultural production, we include rainfall deviations measured outside the primary agricultural growing season which we expect should exert no influence on school-work decisions. As a falsification exercise, we consider district rainfall during other months (April-September) of the year relative to the long-term average during those months.

Table 8 reports the estimates from these regressions. We find no statistically significant effects on school-work decisions, except for a positive effect of lagged rainfall on school enrollment. This is likely if rainfall deviations during other months affect the production of winter crops such as vegetables which are planted in April and May. However, the overall null effects corroborate our assumption that the underlying channel is the change in agricultural productivity in the primary growing season and the subsequent changes in family income.

We also conduct a falsification test where we consider future rainfall variability as the treatment variable. Table 9 reports the estimates when we use standardized total rainfall in the growing season two periods later. We do not consider the next growing season as it coincides with the month of interview of some proportion of our sample or in some cases, occurs before the sample adolescent was surveyed. As rainfall shocks at the district level are not serially correlated over time, using precipitation two-periods after the survey period should not affect the current investments in human capital and labor market participation. If the observed effects of rainfall variability are confounded by omitted trends, we would observe statistically significant coefficients of the same sign. From Table 9, we find evidence that agricultural shocks in the future are uncorrelated with the school-work decisions of our sample adolescents and young adults. This further strengthens our identification strategy.

Another 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 are systematically different in terms of socioeconomic baseline characteristics. In our case, this is of minor concern. Baseline characteristics across sub-samples are reported in Appendix Table A.3. We report 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 child dependency ratio (column 4) and household wealth index (column 5). There are only 26 adolescents from the original baseline survey who exited the sample after wave 2. Most importantly, we find 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 and in the lagged period 2007. Additionally, we demonstrate in Table A.4 that the results are similar if we consider only adolescents who were observed in at least 3 out of the 5 waves.

Relatedly, there was high attrition of white, Indian/Asian, and high-income individuals in waves 2-4. Therefore, a top-up sample was added in the last wave 5. But this is not likely to affect our estimates as our working sample does not comprise the top-up sample.[11] However, our working sample comprises continuing sample members who were members of the original sample of households selected in Wave 1 and temporary sample members who are 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 shocks. We conduct a check by estimating our models on the original baseline sample of continuing sample members. Table A.5 reports the results from this exercise. We observe that the results are similar to our main models. This alleviates any concerns associated with addition of individuals in the subsequent round.

5.3 Heterogeneity Analysis

In this section, we examine the heterogeneity in the effects of rainfall variability on the school-work decisions and human capital investments across household wealth. Assets can mitigate the impact of adverse transitory shocks, as they can serve as buffer stocks or can be used by households as collateral for credit facilities. Therefore, the coping strategies of households involving the school-work transition or vice-versa depends on the

[11] Most of the top-up sample of wave 5 resides in urban areas. The very small proportion of the sample in rural areas does not include adolescents in the our relevant age group.

household's ability to take credit or draw down assets.

Table A.2 reports the coefficients from estimation of equation 2 separately for the sample of females and males. Figures 6–9 present the corresponding marginal effects of rainfall variability on each of the school and work outcomes across household wealth. From Figure 6, we observe that the effect of current rainfall on the decision to be enrolled in school is attenuated for male adolescents belonging to wealthier households. Specifically, the marginal effects become small and statistically insignificant for values of the wealth index higher than -1 among males. The marginal effects of lagged rainfall on male school enrollment are also significant for the extremely poor households. Moreover, the coefficient of the interaction term between *Rain* and household wealth is statistically significant (Table A.2). This finding corroborates our expectations regarding operation of the credit constraint channel. It indicates that greater access to savings and credit can offset the impacts of adverse weather shocks. This result is consistent with the findings of Beegle et al. (2006) and Marchetta et al. (2019), who find that assets mitigate the impacts of transitory agricultural income shocks. However, among female adolescents, we do not find evidence of a buffering effect of household assets. The marginal effects of rainfall variability on the school enrollment of female adolescents are statistically significant only for those in the middle of the wealth distribution (Figure 6 panel c). Therefore, female school enrollment is not sensitive to rainfall deviations in the extremely poor and wealthy households.

While assets may mitigate the effect of adverse rainfall shocks on school enrollment among males, we do not find strong evidence of assets serving as buffers for education expenditures (Figure 7). The only exception is that current rainfall has a positive effect on male education expenditures for those from households with wealth index between -0.4 and 0.6, that is, households neither too poor nor too wealthy. On the contrary, female adolescents from poorer households experience a decrease in education expenditure with favorable rainfall conditions in the previous growing season. This is consistent with an increase in the probability of participating in the labor market and the increase in work intensity of females with lower wealth status. We find evidence from 8 and 9 panel (c) that rainfall deviations increase the probability of working on the extensive and intensive margins for females from very poor households. Wealthier households respond to lagged higher rainfall deviations by pulling female adolescents from the labor market. Table A.2 shows that the differential effect of lagged rainfall by wealth on working propensities of females is statistically significant (column 5). While the sign of the coefficient on the interaction term of lagged rainfall and wealth is negative, we cannot interpret this as rainfall shocks reinforcing the negative effect on female labor. This is because we see that for asset index values which are negative, the marginal effects of lagged rainfall are positive which decrease across the wealth distribution and then become negative. Therefore, the increase in the probability of labor market participation on the extensive and intensive margins is attenuated for females from wealthier households. However, this does not translate into increased education expenditures in the current period for females. Overall, we observe that higher than average rainfall and therefore, higher opportunity costs of schooling increases labor market participation and decreases education expenditure for female adolescents from poorer households. As the survey does not provide us information on school attendance and we find null lagged effects on female school enrollment, we can infer that in response to higher agricultural revenues in the previous period, poorer female adolescents are attending school less frequently.

From Figures 8 panel (d), we observe that the marginal effects of lagged rainfall on labor market participation for male adolescents increase across the wealth distribution. The marginal effects of lagged rainfall on work intensity of males decreases across wealth (Figure 9). However, the differential effect of household wealth is not statistically significant (Table A.2 columns 6 and 8). In other words, the marginal effects of lagged rainfall variability does not differ by the household wealth for male adolescents. Therefore, household wealth does not serve as a buffer to mitigate the effects of rainfall conditions on adolescent male labor.

6 Conclusion

The results from this study help identify the possible channels through which rainfall shocks can affect the human capital and labor outcomes of adolescents. Our results indicate that higher current rainfall increases human capital investment on the extensive and intensive margins (real education expenditures) of both male and female adolescents. Instead, favorable rainfall conditions in the current agricultural season decreases the probability of labor market participation on the extensive and intensive margins. However, higher than average rainfall in the previous period increases the probability of labor market participation and work intensity in the following year. Overall, we do not observe significant gender differences in the effect of rainfall shocks on school-work decisions.

We also find that household assets may mitigate the effect of adverse current rainfall shocks on school enrollment among males. However, we do not find strong evidence of assets serving as buffer stocks for education expenditures. We also find that the increase in the probability of labor market participation on the extensive and intensive margins in response to lagged favorable rainfall conditions is attenuated for females from wealthier households. Therefore, while school enrollment of male adolescents is less affected by current rainfall conditions if they belong to wealthier households, lagged rainfall had opposite effects on the labor outcomes of female adolescents from poorer households relative to wealthier households.

Our results highlight that in credit-constrained agrarian households, transitory agricultural shocks can substantially affect the human capital investments in adolescents. 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 paper 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 rainfall variability on human capital accumulation and work propensity and enable households to cope with unexpected weather shocks.

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Figures

Figure 1: School-work status of adolescents and young adults

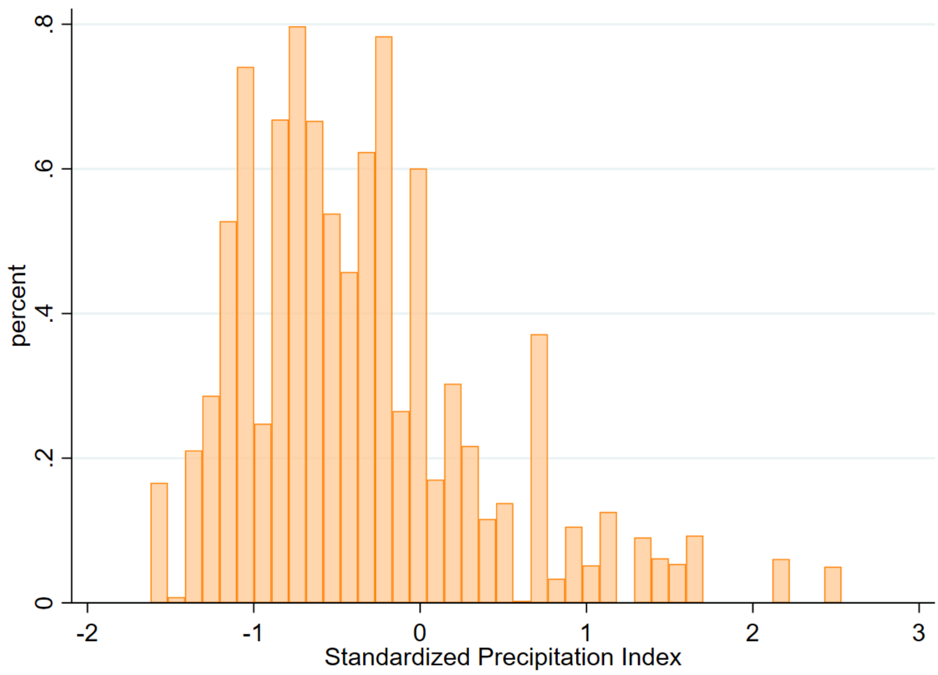
(a) Females

(b) Males

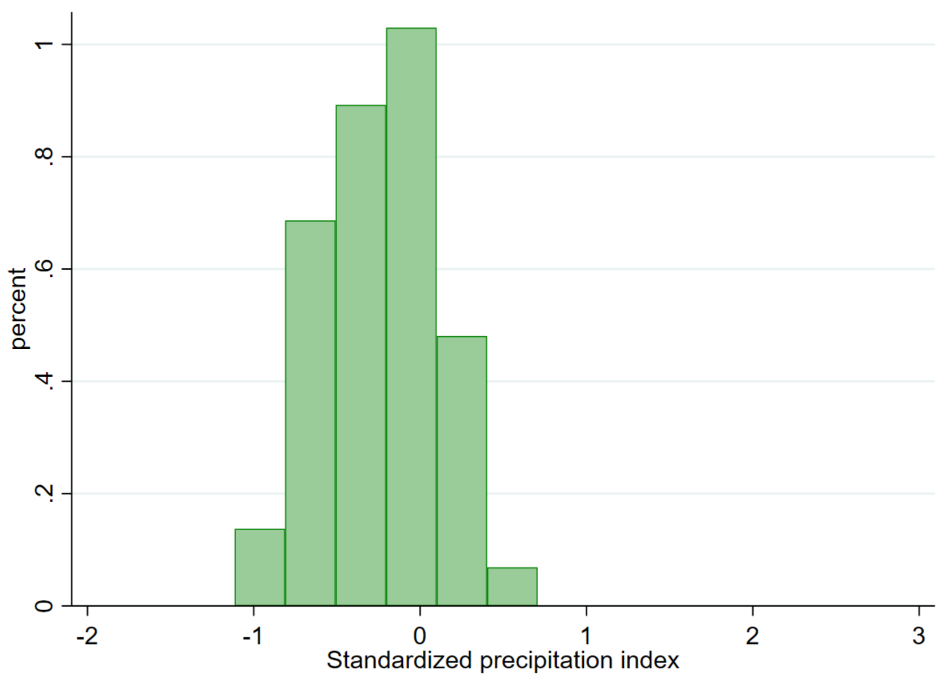
Note: Age in completed years on the x-axis.

Figure 2: Distribution of rainfall variability

(a) Standardized Precipitation Index

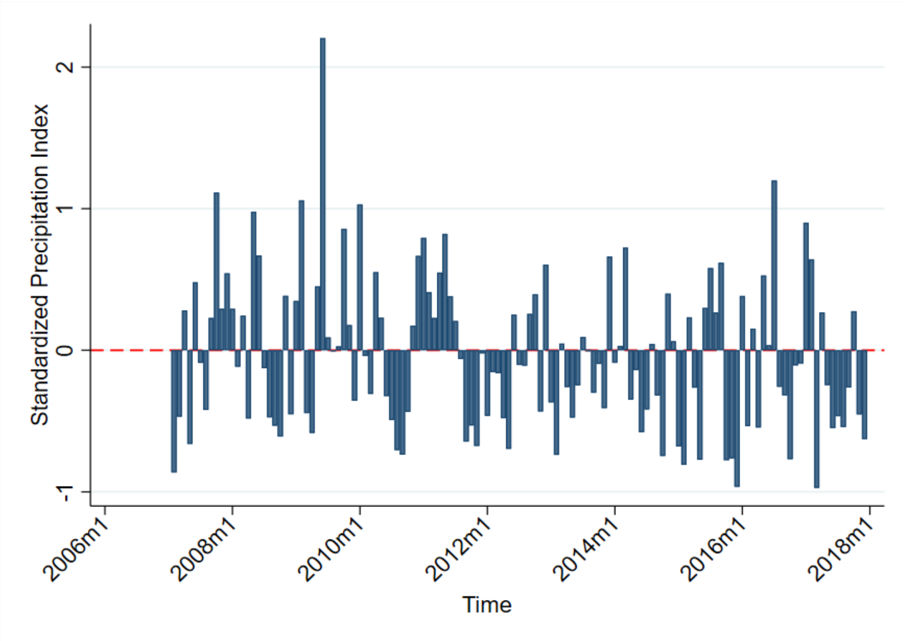


(b) Mean of Standardized Precipitation Index



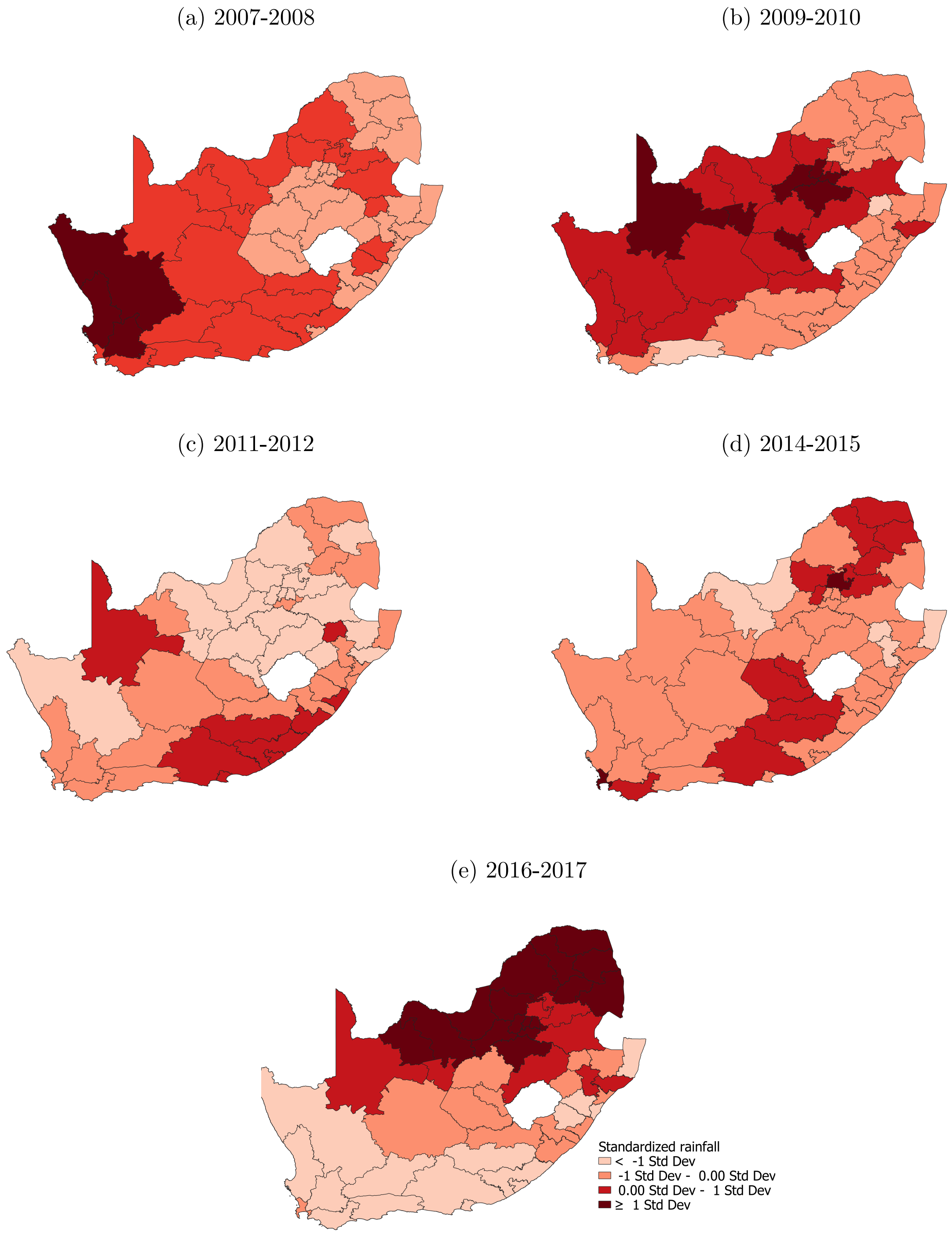
Note: a) Distribution of SPI from 2008-2017 relative to the long-term average. b) Distribution of the district-specific mean of the SPI over 2008-2017.

Figure 3: Monthly Standardized Precipitation Index



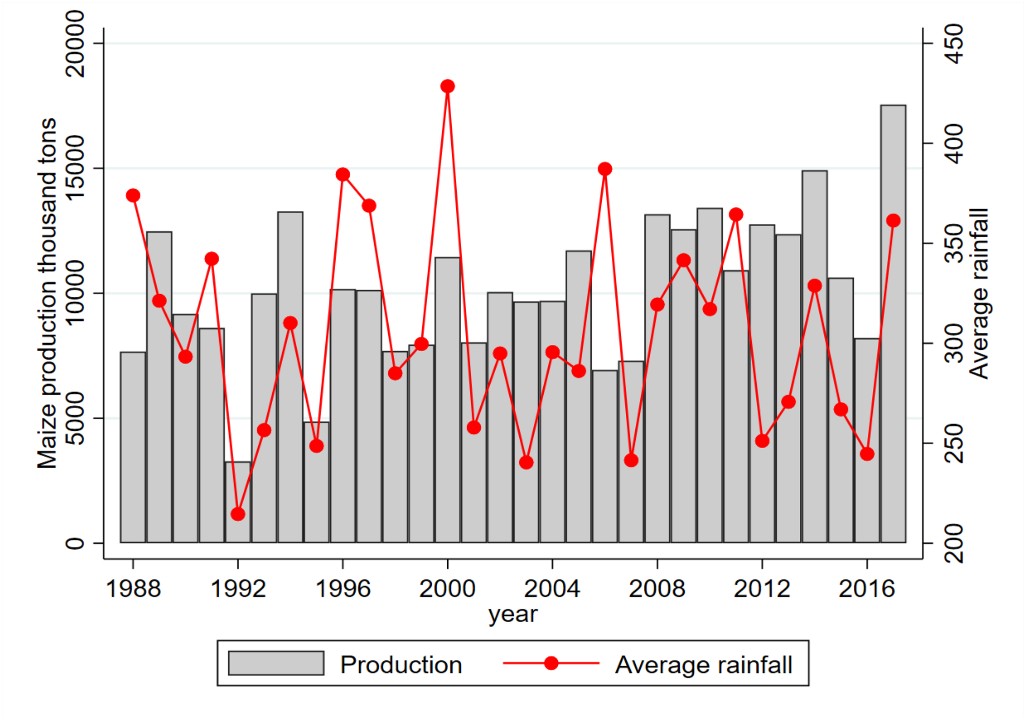
Note: District averages of standardized precipitation index using the average monthly precipitation and standard deviation of monthly total precipitation over 1988-2017.

Figure 4: 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.

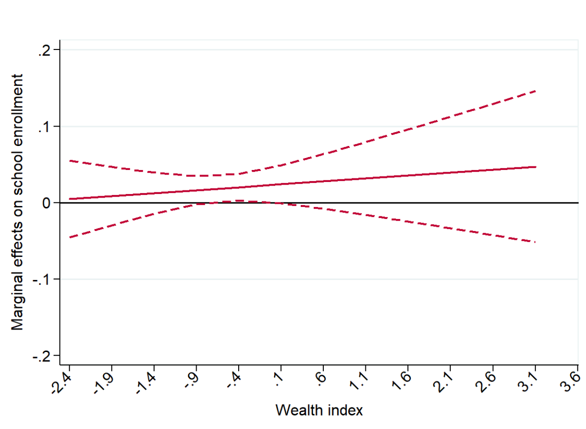
Figure 5: Annual maize production and rainfall



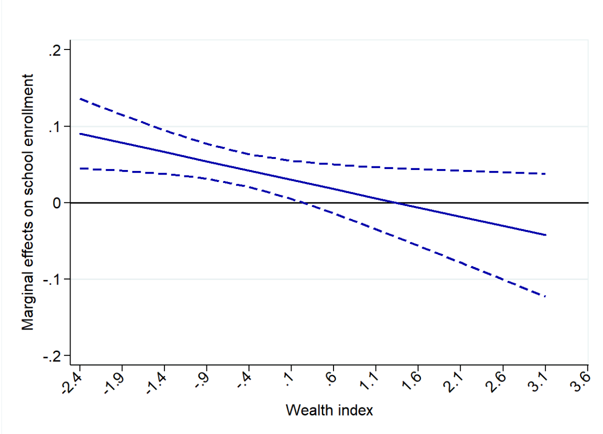
Note: This figure demonstrates the association between average rainfall (inches) during the growing season (October-March) and the annual maize production ('000 metric tons) over 1988-2017.

Figure 6: Marginal effects of rainfall variability on enrollment across wealth

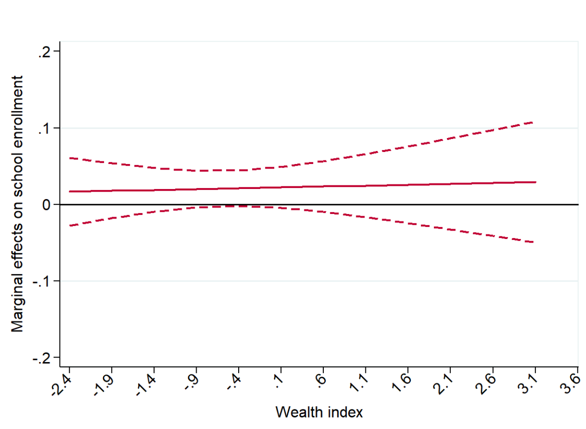
(a) Contemporaneous effect on female school enrollment



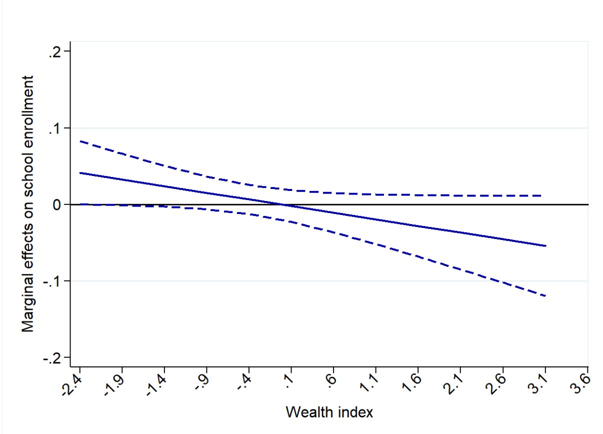
(b) Contemporaneous effect on male school enrollment



(c) Lagged effect on female school enrollment



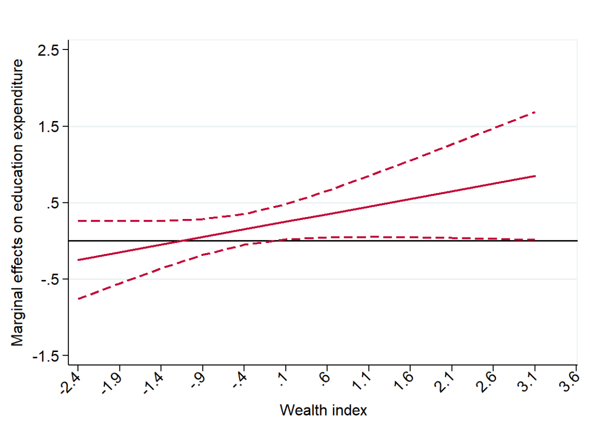
(d) Lagged effect on male school enrollment



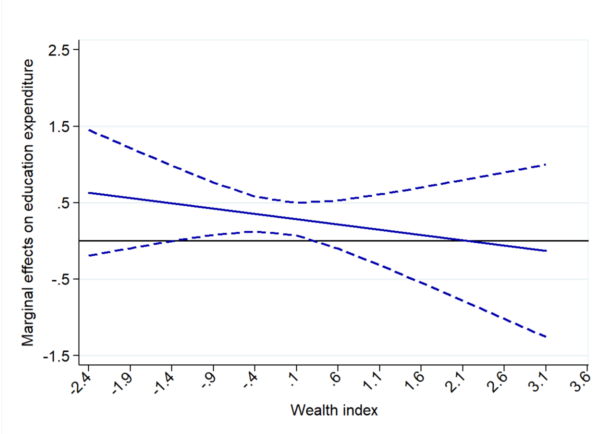
Note: This figure presents the marginal effects of current (panels a-b) and lagged rainfall deviations (panels c-d) on the probability of school enrollment among females and males across household wealth estimated from equation 2. The dashed lines indicate the 90% confidence interval.

Figure 7: Marginal effects of rainfall variability on education expenditure across wealth

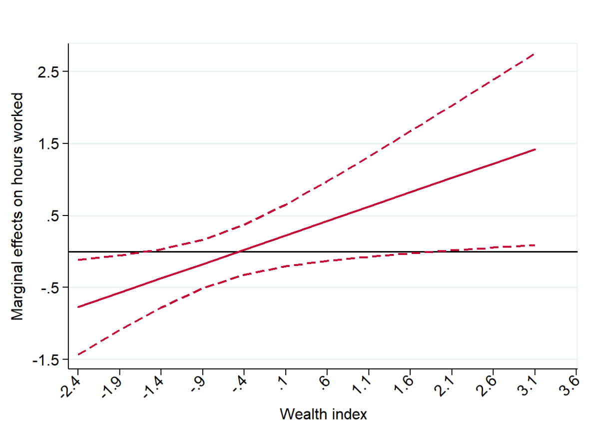
(a) Contemporaneous effect on female education expenditure



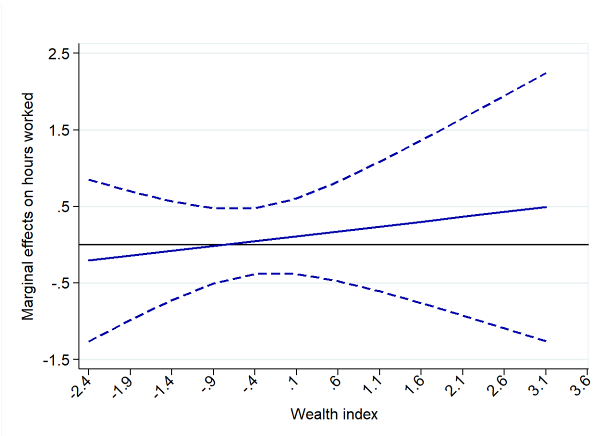
(b) Contemporaneous effect on male education expenditure



(c) Lagged effect on female education expenditure



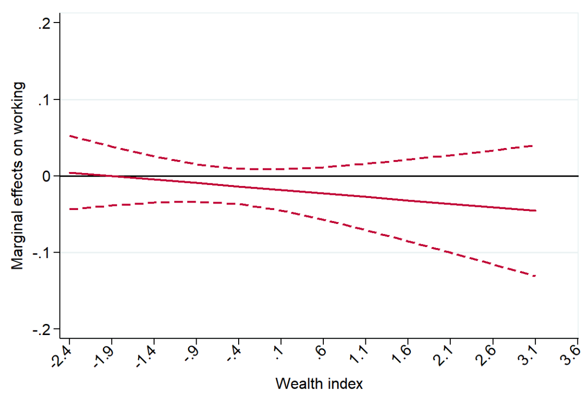
(d) Lagged effect on male education expenditure



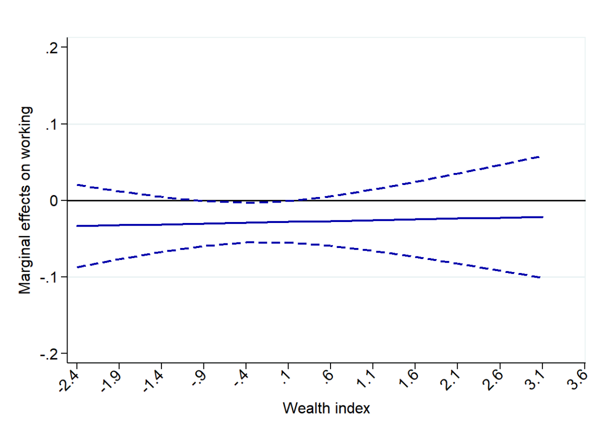
Note: This figure presents the marginal effects of current (panels a-b) and lagged rainfall deviations (panels c-d) on the inverse hyperbolic sine transformation of real education expenditure among females and males across household wealth estimated from equation 2. The dashed lines indicate the 90% confidence interval.

Figure 8: Marginal effect of rainfall variability on labor market participation across wealth

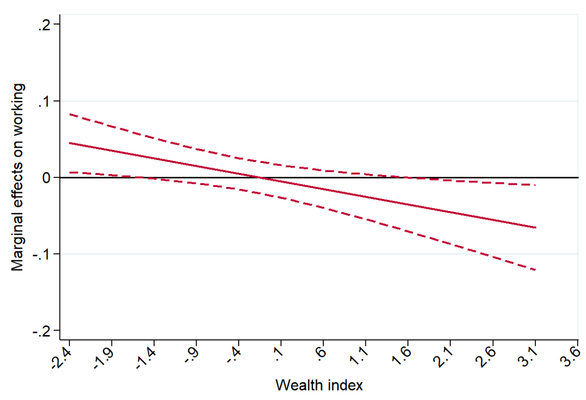
(a) Contemporaneous effect on female employment



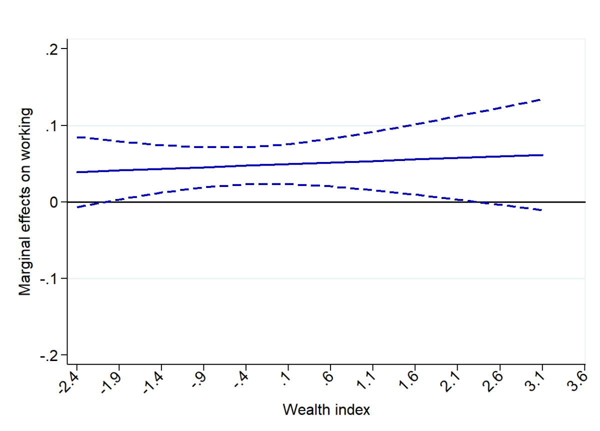
(b) Contemporaneous effect on male employment



(c) Lagged effects on female employment



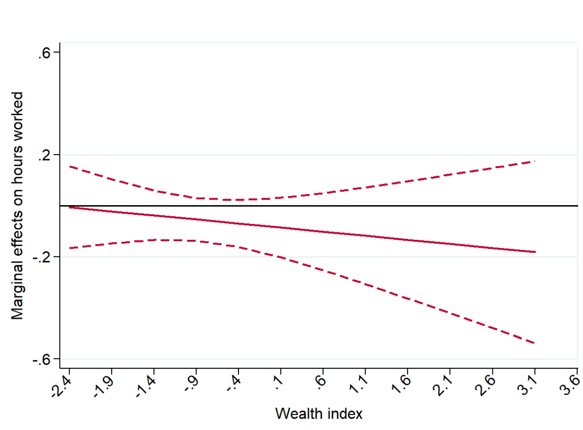
(d) Lagged effect on male employment



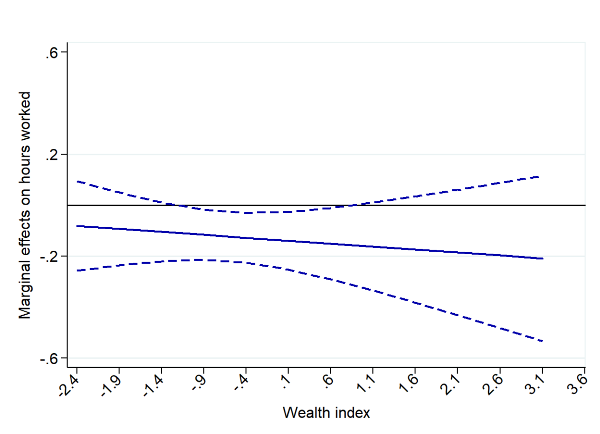
Note: This figure presents the marginal effects of current (panels a-b) and lagged rainfall deviations (panels c-d) on the probability of labor market participation among females and males across household wealth estimated from equation 2. The dashed lines indicate the 90% confidence interval.

Figure 9: Marginal effect of rainfall variability on hours worked across wealth

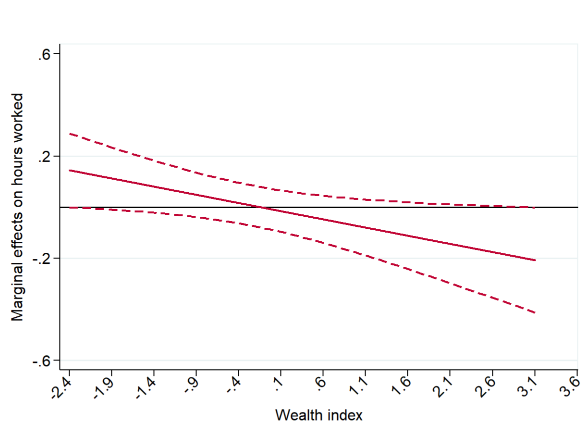
(a) Contemporaneous effect on female hours worked



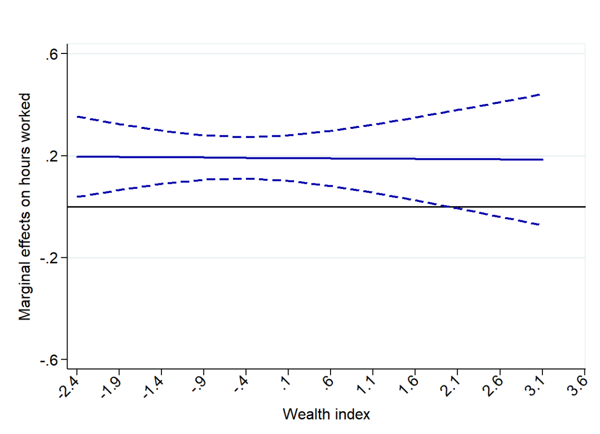
(b) Contemporaneous effect on male hours worked



(c) Lagged effects on female hours worked



(d) Lagged effects on male hours worked



Note: This figure presents the marginal effects of current (panels a-b) and lagged rainfall deviations (panels c-d) on the inverse hyperbolic sine transformation of hours worked per week among females and males across household wealth estimated from equation 2. The dashed lines indicate the 90% confidence interval.

Tables

Table 1: Summary Statistics

		(1) Mean	
Dependent Variables			
Currently enrolled in school	0.680	0.467	9527
Currently working	0.076	0.265	9461
Average weekly hours working	2.318	10.626	9344
Real education expenditure (rands)	928.052	3153.659	7070
Weather Characteristics			
Standardized rainfall	-0.375	0.726	9527
Lagged standardized rainfall	-0.146	0.774	9527
Annual temperature deviation (z-score)	-0.283	0.921	9527
Control Variables			
Age	18.770	2.195	9527
Female = 1	0.507	0.500	9527
Child dependency ratio	0.635	0.568	9527
Household size	7.042	3.844	9527
Household wealth index	-0.530	0.813	9527

Notes: Descriptive statistics of the current province/district dummy variables are omitted from the table. Hours worked is 0 for those not participating in the labor market.

Table 2: Effects of lagged and contemporaneous rainfall variability on school-work transition

	(1) Enrolled=1	(2) Education exp	(3) Working=1	(4) Hours	(5) Enrolled=1	(6) Education exp	(7) Working=1	(8) Hours
Standardized rainfall	0.0278***	0.217**	-0.0187+	-0.0889*	0.0301***	0.267**	-0.0208	-0.0985*
	(0.00811)	(0.0955)	(0.0120)	(0.0455)	(0.0109)	(0.121)	(0.0145)	(0.0566)
Lagged rainfall	0.0106	0.0793	0.0258**	0.0994***	0.0118	0.000353	0.0316**	0.127***
	(0.00914)	(0.198)	(0.0105)	(0.0355)	(0.0123)	(0.256)	(0.0134)	(0.0442)
Female=1 × Standardized rainfall					-0.00458	-0.0936	0.00435	0.0197
					(0.0124)	(0.125)	(0.0144)	(0.0576)
Female=1 × Lagged rainfall					-0.00229	0.152	-0.0116	-0.0539
					(0.0159)	(0.201)	(0.0129)	(0.0472)
Marginal effect of current rainfall for female=1					0.0255***	0.174+	-0.0165	-0.0788+
					(0.00949)	(0.107)	(0.0134)	(0.0508)
Marginal effect of lagged rainfall for female=1					0.00951	0.153	0.0200*	0.0728*
					(0.0119)	(0.181)	(0.0111)	(0.0408)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9527	6063	9429	9263	9527	6063	9429	9263

Notes: This table presents the coefficients and computed marginal effects of lagged and contemporaneous rainfall deviations estimated from equation 1. Standard errors clustered at the district council level in parenthesis. + p<0.15 * p<0.1, ** p< 0.05, *** p< 0.01. We use the inverse hyperbolic sine transformation of hours worked. Hours worked is 0 for those not participating in the labor market. Controls include temperature, age, child dependency ratio, household wealth, and household size.

Table 3: Robustness Check: Using discrete measure of rainfall shocks

	(1) Enrolled=1	(2) Education exp	(3) Working=1	(4) Hours	(5) Enrolled=1	(6) Education exp	(7) Working=1	(8) Hours
Rainfall shock	0.0381***	0.317**	-0.0159	-0.0955+	0.0415**	0.376**	-0.0232	-0.138*
	(0.0123)	(0.130)	(0.0144)	(0.0594)	(0.0188)	(0.160)	(0.0173)	(0.0734)
Lagged rainfall	0.00900	0.322+	0.0290**	0.0992*	0.0234	0.392	0.0269+	0.0920*
	(0.0155)	(0.194)	(0.0129)	(0.0498)	(0.0223)	(0.287)	(0.0166)	(0.0539)
Female=1 × Rainfall shock					-0.00613	-0.109	0.0139	0.0818
					(0.0202)	(0.165)	(0.0179)	(0.0715)
Female=1 × Lagged rainfall					-0.0280	-0.128	0.00414	0.0140
					(0.0222)	(0.383)	(0.0169)	(0.0648)
Marginal effect of current rainfall for female=1					0.0354***	0.267*	-0.00927	-0.0564
					(0.0127)	(0.148)	(0.0165)	(0.0650)
Marginal effect of lagged rainfall for female=1					-0.00458	0.264	0.0310**	0.106+
					(0.0154)	(0.258)	(0.0142)	(0.0641)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9527	6063	9429	9263	9527	6063	9429	9263

Notes: This table presents the coefficients and computed marginal effects of lagged and contemporaneous rainfall shocks estimated from equation 1. Rainfall shock=-1 if the total rainfall deviation during the growing season is below standard deviation of the district-level historical mean, 0 if the rainfall is between -1 and 1 standard deviations, and 1 if the rainfall is 1 standard deviations above the district-level historical mean. Standard errors clustered at the district council level in parenthesis. + $p<0.15$ * $p<0.1$, ** $p< 0.05$, *** $p< 0.01$. We use the inverse hyperbolic sine transformation of hours worked. Hours worked is 0 for those not participating in the labor market. Controls include temperature, age, child dependency ratio, household wealth, and household size.

Table 4: Robustness Check: Effect of rainfall deviation on school-work decisions

	(1) Enrolled=1	(2) Education exp	(3) Working=1	(4) Hours	(5) Enrolled=1	(6) Education exp	(7) Working=1	(8) Hours
Rainfall deviation	0.132***	0.694+	-0.0721+	-0.362*	0.138***	0.765	-0.0736	-0.368+
	(0.0371)	(0.445)	(0.0485)	(0.195)	(0.0505)	(0.539)	(0.0588)	(0.248)
Lagged rainfall deviation	0.0573+	0.516	0.105**	0.400**	0.0513	0.295	0.129*	0.512**
	(0.0362)	(0.801)	(0.0505)	(0.173)	(0.0466)	(1.104)	(0.0647)	(0.218)
Female=1 × Rainfall deviation					-0.0125	-0.136	0.00362	0.0147
					(0.0543)	(0.514)	(0.0640)	(0.268)
Female=1 × Lagged rainfall deviation					0.0123	0.426	-0.0500	-0.227
					(0.0603)	(0.956)	(0.0616)	(0.225)
Marginal effect of current rainfall for female=1					0.126***	0.629	-0.0700	-0.353+
					(0.0413)	(0.487)	(0.0573)	(0.223)
Marginal effect of lagged rainfall for female=1					0.0636	0.722	0.0792+	0.285+
					(0.0475)	(0.730)	(0.0528)	(0.193)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9527	6063	9429	9263	9527	6063	9429	9263

Notes: This table presents the coefficients and computed marginal effects of lagged and contemporaneous rainfall deviation estimated from equation 1. 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 of the total rainfall during the growing season. Standard errors clustered at the district council level in parenthesis. + $p<0.15$ * $p<0.1$, ** $p< 0.05$, *** $p< 0.01$. We use the inverse hyperbolic sine transformation of hours worked. Hours worked is 0 for those not participating in the labor market. Controls include temperature, age, child dependency ratio, household wealth, and household size.

Table 5: Effect of rainfall variability on school-work decisions adding province fixed effects

	(1) Enrolled=1	(2) Education exp	(3) Working=1	(4) Hours	(5) Enrolled=1	(6) Education exp	(7) Working=1	(8) Hours
Standardized rainfall	0.0294***	0.224**	-0.0196*	-0.0925**	0.0317***	0.261**	-0.0217+	-0.102*
	(0.00811)	(0.0990)	(0.0116)	(0.0450)	(0.0114)	(0.126)	(0.0139)	(0.0557)
Lagged rainfall	0.0138+	0.0832	0.0231**	0.0873**	0.0151	0.0278	0.0286**	0.113**
	(0.00893)	(0.196)	(0.0105)	(0.0353)	(0.0116)	(0.256)	(0.0134)	(0.0448)
Female=1 × Standardized rainfall					-0.00450	-0.0687	0.00421	0.0193
					(0.0130)	(0.127)	(0.0146)	(0.0593)
Female=1 × Lagged rainfall					-0.00260	0.106	-0.0110	-0.0517
					(0.0145)	(0.210)	(0.0136)	(0.0519)
Marginal effect of current rainfall for female=1					0.0272***	0.192*	-0.0175	-0.0826+
					(0.00935)	(0.109)	(0.0135)	(0.0518)
Marginal effect of lagged rainfall for female=1					0.0125	0.134	0.0176+	0.0618
					(0.0114)	(0.183)	(0.0115)	(0.0426)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9527	6063	9429	9263	9527	6063	9429	9263

Notes: This table presents the coefficients and computed marginal effects of lagged and contemporaneous rainfall deviation estimated from equation 1 including province fixed effects. Standard errors clustered at the district council level in parenthesis. + p<0.15 * p<0.1, ** p< 0.05, *** p< 0.01. We use the inverse hyperbolic sine transformation of hours worked. Hours worked is 0 for those not participating in the labor market. Controls include temperature, age, child dependency ratio, household wealth, and household size.

Table 6: Effect of rainfall variability on individual and household characteristics

	(1) Age	(2) HH size	(3) Wealth	(4) Child dependency
Standardized rainfall	0.00399	0.0235	-0.0261	-0.000182
	(0.0160)	(0.0800)	(0.0223)	(0.0128)
Lagged SPI	-0.0112	-0.00463	0.00981	0.0161
	(0.0221)	(0.0934)	(0.0187)	(0.0111)
Individual Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	9223	9223	9223	9223

Notes: This table reports the estimates from a linear fixed effects regression of individual and household characteristics on current standardized precipitation index (SPI) and lagged standardized precipitation index controlling for individual and year fixed effects. Standard errors clustered at the district council level in parenthesis. * p<0.1, ** p< 0.05, *** p< 0.01.

Table 7: Serial correlation in rainfall variability

	(1) Current SPI	(2) Current SPI	(3) Current SPI	(4) Current SPI	(5) Current SPI
Lagged SPI	0.00597	-0.0145	-0.0216	0.00446	-0.104
	(0.0221)	(0.0249)	(0.0362)	(0.0497)	(0.101)
District Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	Yes	No	Yes	Yes
Observations	1392	1392	480	480	11013

Notes: SPI refers to the Standardized Precipitation Index. The unit of observation is district-year for regressions in Columns (1)-(4), and individual-year in Column (5). The sample is the period 1988-2017 for Columns (1)-(2) and the study period 2008-2017 for Columns (2) - (5). Standard errors clustered at the district council level in parenthesis. * p<0.1, ** p< 0.05, *** p< 0.01.

Table 8: Effects of lagged and contemporaneous standardized rainfall during other months

	(1)	(2)	(3)	(4)
	Enrolled=1	Education expenditure	Working=1	Hours worked
SPI	-0.00171	0.142	0.000665	0.00206
	(0.00998)	(0.144)	(0.00702)	(0.0304)
Female=1 × SPI	-0.00952	0.0251	-0.00172	-0.00880
	(0.00964)	(0.125)	(0.00982)	(0.0338)
Lagged SPI	0.0133**	0.0608	0.00230	-0.00510
	(0.00540)	(0.0935)	(0.00863)	(0.0254)
Female=1 × Lagged SPI	0.0109*	-0.103	-0.00152	0.00229
	(0.00625)	(0.0871)	(0.00631)	(0.0232)
Controls	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	9527	6063	9429	9263

Notes: This table reports the coefficients from estimation of equation 1. We consider standardized rainfall deviations during the season other than the primary growing season, $April_{t-1}$-$September_{t-1}$ in the previous year. Standard errors clustered at the district council level in parenthesis. + p<0.15 * p<0.1, ** p< 0.05, *** p< 0.01. Controls include temperature, age, ln total household income, child dependency ratio, household wealth, and household size.

Table 9: Falsification test: Rainfall deviations in the future

	(1)	(2)	(3)	(4)
	Enrolled=1	Working=1	Hours worked	Education expenditure
Future SPI	-0.00908	-0.00247	-0.00222	0.149
	(0.00634)	(0.00655)	(0.0247)	(0.149)
Individual Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	9527	9429	9263	6063

Notes: This table reports the coefficients from estimation of equation 1 using standardized rainfall deviations in the year following the survey year. Standard errors clustered at the district council level in parenthesis. + $p<0.15$ * $p<0.1$, ** $p< 0.05$, *** $p< 0.01$. Controls include temperature, age, ln total household income, child dependency ratio, household wealth, and household size.

Appendix

Table A.1: Effect on crop yields at the national level

	(1) Maize production	(2) Ln yield per hectare
Standardized rainfall	1205.6***	0.150***
	(355.2)	(0.0534)
Observations	30	30

Notes: This table reports the estimates of the effect of standardized rainfall on maize production (in thousand metric tons) and the logarithm of yield per hectare (metric tons per hectare) at the national level for the years 1988-2017. Robust standard errors in parenthesis. + p<0.15 * p<0.1, ** p< 0.05, *** p< 0.01. These linear models includes year trends. Source: U.S. Department of Agriculture

Table A.2: Effect on rainfall variability by wealth

	Enrolled=1		Education expenditure		Working=1		Hours	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Females	Males	Females	Males	Females	Males	Females	Males
Standardized rainfall	0.0223*	0.0324**	0.159	0.298**	-0.0166	-0.0282*	-0.0792	-0.137**
	(0.0132)	(0.0145)	(0.132)	(0.124)	(0.0151)	(0.0161)	(0.0651)	(0.0663)
Standardized rainfall × Household wealth index	0.00933	-0.0242*	0.116	-0.138	-0.00998	0.00219	-0.0336	-0.0231
	(0.0157)	(0.0130)	(0.150)	(0.211)	(0.0131)	(0.0135)	(0.0512)	(0.0506)
Lagged rainfall	0.0193	-0.000386	0.243	0.0982	-0.00207	0.0490***	-0.00637	0.191***
	(0.0147)	(0.0122)	(0.256)	(0.287)	(0.0132)	(0.0154)	(0.0523)	(0.0526)
Lagged rainfall × Household wealth index	0.000432	-0.0173+	0.296	0.127	-0.0185**	0.00412	-0.0527+	-0.00214
	(0.0126)	(0.0110)	(0.220)	(0.295)	(0.00862)	(0.0119)	(0.0342)	(0.0420)
Observations	4832	4695	3200	2863	4791	4638	4736	4527

Notes: This table reports the estimates of the effect of standardized rainfall on school-work decisions estimated from equation 2. 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 district level in parenthesis. + p<0.15 * p<0.1, ** p< 0.05, *** p< 0.01. All regressions include individual fixed effects, month fixed effects, year fixed effects, and other controls. Controls include temperature, age, ln total household income, child dependency ratio, household wealth, and household size.

Table A.3: 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	0.48	0.48	0.48	-0.00	0.01
	(0.50)	(0.50)	(0.50)		
Standardized rainfall	-0.10	-0.10	-0.14	0.05	-0.04
	(0.53)	(0.54)	(0.49)		
Lagged rainfall	-0.39	-0.40	-0.32	-0.09	0.08
	(0.73)	(0.73)	(0.74)		
Age	16.88	16.86	16.99	-0.13	0.13
	(1.83)	(1.83)	(1.80)		
Average temperature $^{\circ}C$	15.58	15.61	15.36	0.26	-0.25
	(2.43)	(2.44)	(2.37)		
Household size	6.71	6.74	6.45	0.22	-0.31
	(3.34)	(3.36)	(3.10)		
Child dependency ratio	0.82	0.81	0.90	-0.12**	0.09
	(0.76)	(0.74)	(0.82)		
Household wealth index	-0.58	-0.57	-0.66	0.09*	-0.09*
	(0.69)	(0.69)	(0.67)		
Total household income	3345.86	3384.00	3127.86	296.14	-247.98
	(5018.13)	(5129.32)	(4279.08)		
Observations	1654	1441	200	1654	1654

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 parenthesis. * p<0.1, ** p< 0.05, *** p< 0.01.

Table A.4: Effect on rainfall variability on school work decisions using the sample observed in at least three waves

	(1) Enrolled=1	(2) Education exp	(3) Working=1	(4) Hours	(5) Enrolled=1	(6) Education exp	(7) Working=1	(8) Hours
Standardized rainfall	0.0307***	0.224**	-0.0194+	-0.0928**	0.0342***	0.253**	-0.0212+	-0.0982*
	(0.00838)	(0.0982)	(0.0120)	(0.0458)	(0.0116)	(0.116)	(0.0144)	(0.0568)
Lagged rainfall	0.0114	0.0481	0.0246**	0.0977**	0.0129	-0.00264	0.0307**	0.124***
	(0.00945)	(0.206)	(0.0108)	(0.0374)	(0.0122)	(0.266)	(0.0137)	(0.0457)
Female=1 $\times$ Standardized rainfall					-0.00681	-0.0535	0.00374	0.0114
					(0.0143)	(0.114)	(0.0148)	(0.0589)
Female=1 $\times$ Lagged rainfall					-0.00287	0.0976	-0.0122	-0.0522
					(0.0148)	(0.209)	(0.0136)	(0.0508)
Marginal effect of current rainfall for female=1					0.0274**	0.200*	-0.0175	-0.0868+
					(0.0104)	(0.111)	(0.0138)	(0.0519)
Marginal effect of lagged rainfall for female=1					0.0100	0.0950	0.0185+	0.0720+
					(0.0118)	(0.190)	(0.0118)	(0.0445)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9037	5763	8943	8787	9037	5763	8943	8787

Notes: This table presents the coefficients and computed marginal effects of lagged and contemporaneous rainfall deviation estimated from equation 1 for the sample observed in at least 3 of the 5 waves. Standard errors clustered at the district council level in parenthesis. + p<0.15 * p<0.1, ** p< 0.05, *** p< 0.01. We use the inverse hyperbolic sine transformation of hours worked. Hours worked is 0 for those not participating in the labor market. Controls include temperature, age, child dependency ratio, household wealth, and household size.

Table A.5: Effect on rainfall variability on school work decisions using the baseline sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Enrolled=1	Education exp	Working=1	Hours	Enrolled=1	Education exp	Working=1	Hours
Standardized rainfall	0.0315***	0.212**	-0.0211+	-0.0982*	0.0340***	0.209*	-0.0232+	-0.105*
	(0.00891)	(0.0958)	(0.0131)	(0.0492)	(0.0116)	(0.108)	(0.0154)	(0.0596)
Lagged rainfall	0.0132	0.000875	0.0252**	0.103**	0.0151	-0.0272	0.0308**	0.129**
	(0.00969)	(0.215)	(0.0115)	(0.0406)	(0.0124)	(0.277)	(0.0143)	(0.0483)
Female=1 × Standardized rainfall					-0.00483	0.00594	0.00430	0.0152
					(0.0136)	(0.126)	(0.0156)	(0.0627)
Female=1 × Lagged rainfall					-0.00373	0.0542	-0.0111	-0.0524
					(0.0148)	(0.217)	(0.0142)	(0.0536)
Marginal effect of current rainfall for female=1					0.0291**	0.215*	-0.0189	-0.0902+
					(0.0108)	(0.120)	(0.0150)	(0.0568)
Marginal effect of lagged rainfall for female=1					0.0114	0.0270	0.0197+	0.0767+
					(0.0120)	(0.200)	(0.0127)	(0.0487)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8315	5250	8220	8078	8315	5250	8220	8078

Notes: This table presents the coefficients and computed marginal effects of lagged and contemporaneous rainfall deviation estimated from equation 1 for the original baseline sample of continuing sample members. Standard errors clustered at the district council level in parenthesis. + p<0.15 * p<0.1, ** p< 0.05, *** p< 0.01. We use the inverse hyperbolic sine transformation of hours worked. Hours worked is 0 for those not participating in the labor market. Controls include temperature, age, child dependency ratio, household wealth, and household size.