Queen's Economics Department Working Paper No. 1430

Impact of a Severe Drought on Education: More Schooling but Less Learning

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4-2020

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Abstract. From October 2015 to April 2016, Southern Africa experienced one of the severest droughts in history. The drought's intensity varied significantly across locations. This provides a natural experiment to estimate the effect of large, negative agricultural shocks. We consider the impact of this shock on children's educational outcomes using data from rural Zimbabwe. Those who experienced the drought may suffer from decreases in income and food access. This can affect household resource allocation and schooling decisions, while exposing individuals to stress and uncertainty. We find the drought increases the probability that students advance in school, a seemingly positive impact, likely due to lower opportunity costs to education. The drought also led to a significant decline in performance on mathematics assessments and leadership attitudes, suggesting stress or other factors associated with a drought more than offset increases in attendance. This highlights the importance of using multiple indicators in education evaluations.

Date: Current version: May 2020.

Key words and phrases. Education, droughts, agriculture, economic development, natural experiment, impact measurement

JEL: C99, I25, Q56.

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1. Introduction

Perhaps the biggest risk of climate change in the developing world comes from the increase in weather volatility and the frequency of extreme weather events. Throughout Africa, for instance, there has been a rise in both severe flooding and severe droughts in recent years, and scientific predictions indicate that such events will occur with increasing frequency in the future (Masih et al., 2014). This may lead to increased conflict (Couttenier and Soubeyran, 2014), and decreased health and nutrition (Hoddinott and Kinsey, 2001; WHO, 2008), both of which may lead to decreases in educational attainment (Alderman et al., 2006; Maccini and Yang, 2009).

These events can hit agriculturally-dependent populations in developing countries particularly harshly. In rural Zimbabwe, for example, 90.5 percent of employment is in the agricultural sector either as workers on commercial farms or smallholder producers (ZIMSTAT, 2018). Similarly, over 70 percent of Zimbabwe households' food comes from their own agricultural production (Food and Nutrition Council, 2011). Such places may be particularly affected by weather shocks as they will effect the livelihoods of most families.

The current paper studies the impact of a severe drought on education outcomes in rural Zimbabwe. Our analysis relies on a unique dataset from a UKAID/ DFID's Girls' Education Challenge (GEC) project conducted between 2013 and 2016, which tracked education and learning outcomes of nearly 1000 girls. Over the course of this study, during 2015-2016 growing season, parts of Zimbabwe experienced the worst drought in nearly 25 years. During the same period, other areas of the county, which were typically as susceptible to droughts, experienced normal rainfall by historic standards. Of the GEC study population, only 38% lived in locations that suffered a drought that season, providing a natural experiment to assess the impact of droughts on girls' education outcomes.

Whether a drought will lead to improvements or declines in girls education outcomes is not immediately apparent. On one hand, droughts decrease household income and there is a well-established association between poverty and child labor (e.g. Ersado, 2006; Edmonds, 2005; Soares et al., 2012). Furthermore, its been shown that children are more likely to leave school for work when their parents experience a negative income shock (Duryea et al., 2007). There is also substantial anecdotal evidence presented by NGOs and the media, which show examples where economic hardship and hunger caused by droughts lead to children leaving school, either due to the need to work or inability to pay school fees.[1] On the other hand,

[1]Based on a selection of qualitative interviews, Hayati et al. (2010) reports that agriculture-dependent Iranian households who experience a drought are more likely to keep children home from school.

however, is the evidence that children are more likely to leave school for work during times when local wages and demand for low-skilled labor are high. Droughts affect the local labor markets, particularly in primarily-agricultural areas, decreasing the expected returns to child labor and the incentives to leave school (Duryea and Arends-Kuenning, 2003; Kruger, 2007; Soares et al., 2012; Shah and Steinberg, 2017). In other words, a severe drought is likely to increase the potential supply of child labor, while simultaneously decreasing demand for it, which leads to an ambiguous effect on the number of children leaving school for work.[2]

In the context of Zimbabwe, we find that girls in drought-affected locations were 2.8 percentage points *more* likely to be enrolled in school the year following the drought than were those in unaffected areas, controlling for other observable characteristics. Furthermore, girls in drought-affected areas were 7.9 percentage points less likely to repeat a grade during the study period, which, given that children who attend regularly automatically progress, suggests that the drought increased attendance in addition to enrolment. This suggests that the drought's overall impact on school attendance came through there being less demand for children's time outside of school. This hypothesis is supported by the observed changes in household chore burdens in our data, which show that girls in the drought-affected areas spend less time working for the family farm or family business as a result of the drought than their counterparts in unaffected areas.[3]

This suggests that droughts can have a positive impact on education outcomes, at least in the highly-agriculture dependent context of rural Zimbabwe. But, a deeper look at the data illustrates a more-complex story. While the drought led to increases in school enrolment and progression, it simultaneously led to decreases in learning outcomes and leadership skills among the youth. On average, exposure to the drought led to a significant decline in performance on the standardized Early Grade Mathematics Assessment (EGMA), and in CARE International's Youth Leadership Index that measures leadership, agency, and self-confidence.[4] This suggests that as

[2]See also Fafchamps et al. (1998); Beegle et al. (2006); Kazianga and Udry (2006) and Dercon (2004); Dercon and Christiaensen (2011).

[3]It is consistent with Cunguara et al. (2011) who find that poor farmers in Mozambique are more likely to allocate household resources (including household member's time) towards non-farm activities during years with a drought.

[4]We observe no similar decrease in literacy performance due to the drought, suggesting that literacy skills are more resilient to negative shocks in our context. These findings complement past work showing that interventions designed to improve self-confidence or empower girls leads to improvements in mathematics performance but do not have the same effects on literacy (e.g. Cotton et al., 2020), suggesting that literacy performance, whether improvements or declines, is harder to change in the short run compared to mathematics performance. See also Cotton et al. (2013) which explores the impact of reducing time pressure and stress on mathematics and literacy performance.

the amount of schooling increases, the amount of learning does not. This is consistent with the idea that economic hardship can lead to lower student performance due to deterioration of mental health or nutrition (Yoshikawa et al., 2012; Ananat et al., 2017).[5]

Although insights from our analysis likely apply to other contexts, they may not apply to *all* other contexts. We only have data on girls, preventing us from assessing whether boys are impacted by the drought in similar ways. In the context of Ethiopia, for example, Woldehanna et al. (2009) found that households who experience an economic shock from a drought or crop failure were less likely to enroll their children in school, and that the negative impact was larger for boys. It is feasible that the positive impact of the Zimbabwe drought on enrolment and progression will not extend to boys, or that the impact of a drought in simply different between Zimbabwe and Ethiopia.

Similarly, we provide a counterpoint to the several other papers that explore the impact of rainfall on school enrolment. Maccini and Yang (2009) explores the long-term impacts of being exposed to higher rainfall during early life for women born between 1953 and 1974 in Indonesia, showing that exposure to more rainfall when young leads women to be taller, complete 0.22 more grades of schooling, and have more assets as adults. For Côte d'Ivoire in the mid 1980's, Jensen (2000) shows that the enrolment of both boys and girls falls in areas that receive substantially less rainfall than normal. There are several differences between these papers and ours, with perhaps the most-notable being that our study focuses on a much more recent period in which global development efforts have increasingly emphasized the importance of ensuring universal education and keeping kids in school, with an emphasis on girls' education.[6] This includes wide acceptance of the UN Millennium Development Goals (2000-2015) and Sustainable Development Goals (since 2015), which emphasize the importance of universal primary education, gender equality, and female empowerment, all of which may affect household decisions around taking their children out of school.

Perhaps most-closely related to our paper is that of Shah and Steinberg (2017), which considers how variation in India monsoon-season rainfall influences education outcomes. They show how children invest more in schooling during periods of low rainfall. Like us, they show how human capital investments tend to be counter-cyclical. Unlike us, however, they find that test scores move in the same direction as school attendance, increasing when there is low rainfall and students attend more

[5]See also Taras (2005); Stevens and Schaller (2011), and Rege et al. (2011).

[6]Additionally, these other papers only look at enrollment and completion measures and not learning outcomes. In these other papers, variation in rainfall across locations was consistent with the typical annual variation. In our context, on the other hand, variation was caused by the most-severe regional drought in almost 25 years, which directly affected some but not all parts of Zimbabwe.

often. We study a more-extreme weather event, showing that in areas of Zimbabwe that were effected by the severe drought (regionally, the worst in 25 years), school attendance is relatively high, but academic performance relatively low. Even though more people attend school, the harsh economic conditions and hunger lead to lower academic performance overall.

In this way, our results highlight the importance of considering measures of both learning quality and schooling quantity when assessing impact of a program or shock on education outcomes. While the two measures may frequently move in the same direction (e.g. Shah and Steinberg, 2017), this will not always be the case. Focusing only on one type of outcome measure, as many evaluations do, may tell only part of the story, leading to incorrect conclusions about the *overall* impact on education.[7]

Section 2 describes our data, the local context, and our methodology. Section 3 presents the results. Section 4 concludes.

2. Data and Identification Strategy

This analysis exploits the occurrence of a natural experiment to evaluate the impact of a drought on girls' education outcomes. This natural experiment took the form of a severe drought that took place in rural Zimbabwe between 2015 and 2016 affecting different communities with varying degrees of severity.[8] During this time, the Improving Girls' Access through Transforming Education (IGATE) project was also operational in rural Zimbabwe. This project was funded through the UKAid/DFID Girls' Education Challenge (GEC), which was designed to improve access to and quality of education for girls around the world.

IGATE was operational between 2013 and 2016 with data collected at three sampling points: October 2013 - February 2014 ("baseline"), June - August 2015 ("midline"), and November - December 2016 ("endline"). Figure 1 shows the timeline of data collection with respect to the drought period. This clearly shows that the project includes data collected before and after the drought. Since at both intervals the project collected data on girls from both the drought-affected and unaffected areas, and the drought is randomly assigned, this timeline provides an ideal opportunity for a difference-in-differences approach to get a clear estimate of the impact of a severe drought on girls education.

The project followed girls in 85 schools in rural Zimbabwe, as shown in Figure 2 and involved a suite of treatments including interventions designed to inform girls'

[7]For example, typically due to limited data, Stevens and Schaller (2011) looks only at grade repetition, Duflo (2001) looks at total years of education, Jensen (2000) considers progression through school, and Angrist et al. (2012) focuses on standardized test scores but not progression or enrolment.

[8]The most severe period of this drought is concentrated on the 2015-16 growing season (October 2015 - April 2016). Early 2015 also experienced some decrease in rainfall, however, this was not as significant or as widespread.

families about the value of girls' education and to encourage girls to develop a sense of agency in their education by developing their leadership skills, interventions to supply treatment schools with educational materials, teacher training, and bicycles for students. This paper will not focus on the impact of these interventions as the drought has impacted both treatment and control schools randomly. Although slightly more schools in the drought-affected regions were part of the IGATE beneficiary schools (see Table 1), the results to do not change once we have controlled for this.[9]

2.1. **Girls Education Data.** Traditionally, due to data limitations or operational constraints, development economists have focused on either learning (e.g. performance on standardized tests), changes in enrolment, or attendance when measuring education outcomes. The data collected for the IGATE program includes details on not only all of these education-specific measures but also information about girls' leadership skills and household characteristics. By considering all of these dimensions, this paper offers a more comprehensive view of the impact the drought had on girls' education.

The data collected for the IGATE program includes performance on standardized literacy and numeracy assessments, as measured using the widely used Early Grade Reading Assessment (EGRA) and Early Grade Numeracy Assessment (EGMA), respectively. In addition to these outcomes, we will also be able to measure the effect the drought had on girls' self-perceived leadership abilities, as measured using CARE International's Youth Leadership Index, and their sense of "agency", which has been measured through a series of questions that ask girls about their perceived involvement in decisions regarding their education, employment, and life in general.

IGATE follows the same girls over time, which makes it possible to identify if a girl successfully progresses through school (has not skipped a grade or dropped out). Although Zimbabwe technically has automatic grade progression, meaning children are supposed to advance to the next grade even if they did not meet the learning requirements of the previous grade (The Southern and Eastern Africa Consortium for Monitoring Educational Quality, 2018), over 20% of children still repeat at least one grade before they leave school (United National Educational, Scientific, and Cultural Organization, 2012). This is generally because the student fails to attend school consistently, so either the family or the school suggests they repeat a grade.

The IGATE program did not collect data on boys, preventing any conclusion from being made about the impact that this drought had on boys in these areas. However, standardized tests show that boys and girls perform similarly on a national exam taken by students after grade 7, with girls actually performing slightly better (Zimbabwe Schools Examination Council, 2016). Indeed, according to the 2012 progress

[9]See Cotton et al. (2020) for an assessment of the IGATE program's impact on educations overall.

report on Zimbabwe's attainment of the Millennium Development Goals, Zimbabwe was found to have attained gender parity in terms of literacy, enrolment, and attendance at the primary and secondary school levels (United Nations Zimbabwe, 2012). This suggests it may be reasonable to expect that boys have experienced a similar impact, but without evidence, this analysis will not speculate on the effect on boys.

Since tuition is not fully subsidized in Zimbabwe, there is no regularly enforced minimum schooling age. Households are expected to pay both tuition fees, plus levies, which tend to vary between schools. Though reliable statistics on the level of these levies are unavailable given their informal nature, details on tuition show that after grade 7 in Zimbabwe, tuition fees increase from approximately $15/term to $50/term (USD) per child (Higherlife Foundation, 2018). GDP per capita is $1,079.60, making this a significant burden for households, who typically have 4 children per household in the rural areas (reliefweb, 2018).[10] 35% of the baseline sample was also lost to attrition. Although this did not differ significantly across the two regions analyzed here, girls who were not relocated after the baseline data collection period have also been excluded.

The depth of the data collected for the IGATE project, combined with the timing of this natural experiment, allows our analysis to provide the most-comprehensive evidence to date on what impact droughts have on education outcomes. In light of our findings, this analysis will provide policymakers and other development practitioners with the first measure of how significant this relationship is, and how this should be incorporated into future program and evaluation design.

2.2. **2015-16 Drought.** During the 2015-16 growing season, large parts of Southern Africa experienced one of the most severe droughts in history. This drought primarily impacted the October 2015 - April 2016 growing season (Famine Early Warning Systems Network, 2016a). During this time, parts of the region received less than 75% of their normal rainfall levels and experienced severe water shortages. In Zimbabwe, South Africa, Malawi, and Mozambique the drought was so severe that some regions experienced the complete collapse of their usual crops for this growing season, putting significant stress on the financial situation of households in these regions.

Within Zimbabwe, this drought was particularly devastating. According to USAID's Famine Early Warning Systems Network, Zimbabwe had the highest national cereal deficit in the region. 26% of Zimbabwe's population experienced food shortages at some point during the drought, and harvests were on average about 50% lower in the 2015-16 growing season than the previous year (Famine Early Warning Systems Network, 2016b). However, the drought did not affect the entire country

[10]For this reason, girls who were above grade 7 at baseline have been excluded from the analysis since girls who have already progressed into secondary school may be fundamentally different at baseline than the rest of the sample.

equally. This is shown in Figure 2, which highlights the areas that did - or did not - experience an unusually dry growing season. This map has been overlaid with the IGATE school locations,[11] showing there is a good division across the drought-affected and unaffected areas in regions where data collection took place.[12]

In the drought-affected regions, incomes fell as a result of agriculture and livestock collapse, and food shortages were common in the rural areas (Famine Early Warning Systems Network, 2016b). The IGATE project only includes households that reside in rural areas in Zimbabwe. These areas are nearly entirely dependent on subsistence farming and small-scale agricultural production to support households' livelihoods (Famine Early Warning Systems Network, 2014; Food and Agriculture Organization of the United Nations, 2013). According to a report by Zimbabwe's Food and Nutrition Council, 75% of households' food comes from their own crop production in the regions the IGATE schools are in (Food and Nutrition Council, 2011). This means that within this context, households in drought-affected regions are not only less able to earn an income, but are also less able to meet their households' basic nutrition needs, making a drought particularly severe. This reliance on subsistence farming suggests that we can expect the consequences of the drought to be isolated to areas that experienced significantly lower rainfall. Indeed, as shown in table 8, within our data we find that households in drought-affected areas are significantly more likely than households in unaffected areas to have increased reports of hunger after the drought.

The differences in drought severity across the country, combined with the timing of data collection for the IGATE project, make this is an ideal opportunity to use this weather event as a natural experiment to measure the effect of a severe drought on girls' education. It is important to note that the areas more severely hit by the 2015-16 drought are not historically more vulnerable to droughts or poorer weather conditions than the unaffected areas shown in Figure 2. Since the weather is a random event,[13] this drought can be considered a randomly assigned "treatment". Under this framework, the areas that did not experience the drought are a natural "control" group. In the data there are 374 girls in the treatment group and 621 girls in the control group.

Table 1 summarizes the differences of some key characteristics of both the treatment ("drought-affected") and control ("drought-unaffected") groups at baseline.

[11]Both the schools that received IGATE interventions and those who did not are included on this map. Note from Table 1 that IGATE exposure did not significantly vary across drought-affected and unaffected areas.

[12]Note that the term "drought-affected regions" refers to areas that received less than 95% of their usual rainfall levels in the 2015-16 growing season. Referring to Figure 2, this means schools in red, orange, and yellow zones have all experienced a drought in this growing season. In section 3.5 we show that the main results are not sensitive to this threshold.

[13]Note the drought-affected areas do not appear to be correlated with historically dry areas.

Prior to the drought, there was no significant difference between age, disability status, or chore time across the groups. However, girls in the control areas were about 0.37 grades below girls in treatment areas, which is roughly equivalent to being one school term younger. To account for these differences, the analysis includes controls for baseline levels of these characteristics. Girls in the control areas were also more likely to have lower Youth Leadership Index scores, and have lower numeracy and literacy test scores than girls in treatment areas. Almost all girls in both areas are enrolled in school, which is consistent with national statistics, as girls do not tend to drop out of school in Zimbabwe until secondary school.

2.2.1. *Identification Strategy.* This paper considers two classes of education outcomes. The first consists of variables that change over time, and include test scores, attendance, and leadership abilities (as measured using the Youth Leadership Scores). The impact of the drought on these aspects of girls' education will be measured using a difference-in-differences ("DD") approach. This will take the form of the following specification:

$$y_{it} = \beta_0 + \beta_1 drought_i + \beta_2 post_t + \beta_3 drought_i * post_t + \boldsymbol{X_{i0}} \boldsymbol{\beta_4} + \epsilon_{it} \tag{1}$$

where y_{it} can be either the test score, attendance rate, or leadership score of girl i at time t, and β_3 is the coefficient on the interaction term between the indicator variable for whether girl i is in a drought-affected area, $drought_i$ and whether the time of this observation occurred after the drought. β_3 is the coefficient of interest and should be interpreted as the impact that a drought had on test scores, attendance rates, or leadership scores. $\boldsymbol{X_{i0}}$ represents a vector of control variables, which includes measures of age, health, and grade of the girls from the pre-drought period. Post-drought controls have not been included as these may be endogenous. For example, a drought may lead to hunger which may impact girls' performance in school.

Some areas began to experience unusually dry weather towards the end of the 2014-15 growing season (ie. Spring 2015). Since midline data collection took place during this 2014-15 growing season, the baseline data collected between October 2013 and February 2014 is used as the first time period in the DD set up, and endline data as the second time period. The only exception is for youth leadership indicators, for which data was only collected starting at the midline sampling point.

Since the assignment of the treatment here is naturally random, any differences in changes in outcomes found between drought-affected areas and unaffected areas can be interpreted as caused by the drought. The mechanisms that moderate the relationship between the drought and these outcomes will be discussed more thoroughly in Section 3.

The second class of variables involve binary indicators that identify if an outcome has occurred. This includes indicators for whether a girl has repeated a grade[14], dropped out of school, or stayed enrolled. If this evaluation strategy finds that girls are more likely to have successful transition outcomes, this would support the concept that when a drought makes agricultural households less productive, the opportunity cost of education falls leading households to send their children to school more often during the drought. However, if this evaluation finds evidence that progression gets worse, this would support the idea that when households become financially constrained because of the drought they are either unable or unwilling to send their child, in this case their daughters, to school. The specification for this part of the analysis is:

$$Pr(y_i = 1|\boldsymbol{X}) = F(\beta_1 drought_i + \boldsymbol{X_i \beta_2}) \tag{2}$$

where $Pr(y_i = 1|\boldsymbol{X})$ Again, $\boldsymbol{X_i}$ represents the same vector of control variables for characteristics of the girls *at baseline.*

3. Results

3.1. **Progression.** There are several ways to measure progression, including enrolment and grade repetition. Although at baseline nearly 100% of girls were enrolled in school (100% in the control group, 99% in the treatment group), the identification strategy described in section 2.2.1 can estimate the probability that a girl stayed enrolled after their household experienced a drought, compared to households that did not. Columns (1) and (2) in Table 2 show that girls living in a drought-affected region are 2.8 percentage points more likely to be enrolled after the drought, with 93% of girls in the drought-affected areas being enrolled at endline and only 91% of girls being enrolled in unaffected areas.

The other measures of progression considered in Table 2 Columns (3) and (4) are consistent with this. Columns (3) and (4) show the marginal effect of being in a household affected by this exogenous shock on the probability that a girl would repeat a grade by endline. Girls in drought-affected areas are 7.9 percentage points less likely to repeat a grade. This is substantial when we consider that automatic progression is the default policy. This is consistent with the change in chore composition shown in Table 3, which shows that girls are spending less time being

[14]Although it has already been noted that Zimbabwe does have an automatic progression policy to move children to the next grade regardless of their ability to demonstrate that they have met the learning requirements, over 15% of the population sampled in this analysis have repeated a grade between the baseline and endline sample periods so we will look at this outcome specifically. As noted above, over 20% of students in Zimbabwe will repeat a grade at some point during their education, typically because students fail to attend regularly during the year.

economically active on household agricultural works or on the family business as a result of the drought.

3.2. **Learning.** In this section, we exploit the variation created by the drought detailed in section 2.2 to estimate the impact that this had on education outcomes, including literacy and numeracy. Table 4 summarizes these results. Columns (1) and (2) show the relationship between drought exposure and numeracy test scores. Considering this relationship both with and without controls for baseline characteristics, we find that living in a drought-effected area led students to get test scores that were 4 percentage points lower than students living in areas where no shock occurred.

The impact of the drought on literacy, however, is less clear. Columns (3) and (4) show the results of the DID specification to predict literacy test scores, with and without controls. Before adding controls for baseline characteristics there is no statistically significant impact of the drought on literacy test scores.

These findings suggest that literacy and numeracy skills are acquired differently and that, perhaps, factors such as hunger and psychological stress have less of an effect on children's development of literacy skills. If we consider column (4), though, we find that after controlling for baseline characteristics of the girls included in the model it is shown that the drought led to a 1.6 percentage point higher grade on literacy tests. This may also be a symptom of the standardized literacy assessments used by the IGATE program. These tests have automatic stopping rules that lead to many children getting 0 on large components of the reading assessments, and some subtasks are not well calibrated to differences in first languages. This is particularly true within this context as children attend primary school in their local languages until grade 3 when the language of instruction changes to English. As shown in Figure 3, we see that the distribution of the change in scores from baseline to endline does not uniformly change, with a greater number of girls with a slightly improved score.[15] This may be related to the fact that girls in the treatment group were slightly older and in slightly higher grades, so they have had more exposure to English. By comparison, Figure 4 shows that the equivalent change in mathematics scores are systematically lower for the girls in drought-affected areas, except at the most extreme right tail.[16]

3.2.1. *Subgroup Analysis: Secondary School Transition.* As discussed in section 2.1, enrolment fees for Zimbabwean children increase significantly after grade 7. After experiencing a drought, these households would experience have a stronger constraint when making their decision about whether or not to send their daughters

[15]The P-value associated with a Kolmogorov-Smirnov test for equality of distribution functions for these curves was 0.061.

[16]The P-value associated with a Kolmogorov-Smirnov test for equality of distribution functions for these curves was 0.046.

to school. If this constraint becomes strong enough, then we would expect that the results for the whole sample shown in Table 2 may become less pronounced, or even potentially reversed if the higher education cost (as a proportion of household income) dominates the effect of the lower opportunity cost of education.

Table 5 shows that this may, in fact, be the case. There is no longer a significant relationship between the drought and the likelihood that these girls successfully transition through school, stay enrolled, or do not repeat a grade. This suggests that the higher absolute cost of their education is too high for the decrease in the opportunity cost of education to induce their household's decision-maker to choose to send their children to school more often than their counterparts in regions unaffected by the drought, and the extensive margin binds. However, this may be driven by the smaller sample size which may not have sufficient power to measure such an impact.

Table 6 also compares the literacy and numeracy outcomes for these secondary school girls, and shows that girls who transitioned into secondary school when their households experience this drought do even worse in mathematics (compared to the control group) than younger girls. They also now perform significantly worse in literacy tests, with grades on average 5.6 percentage points lower in literacy and 11.7 percentage points lower in mathematics. This may suggest that the physical and mental stress the drought inflicts on children and adolescents is felt more strongly by older girls, who typically have more responsibilities in the household.

3.3. **Leadership Outcomes.** In addition to collecting test score and enrolment data from girls, the IGATE data collects a rich set of details from both the girls and their families. This allows us to consider other dimensions of girls' education. One particularly interesting element is girls' leadership ability. The Youth Leadership Index is a standard measure of attitudes and behaviors, and asks girls questions a series of 21 questions related to leadership-related behavior. This includes questions about how strongly they agree (or disagree) with prompts asking about how likely they are to try new things, participate in class discussions, and lead their peers. The scores have been standardized using baseline scores for ease of interpretation. Table 7 shows the one of the drought's consequences was decreased self-declared leadership behaviors for girls in affected areas. Girls coming from households exposed to the drought had YLI scores about 0.31 SD lower than girls in control regions, which is a substantial decrease and suggests that girls feel less motivated after their household experiences a drought.

3.3.1. *Subgroup Analysis: Remote Households.* Remote households in rural areas are particularly vulnerable during droughts, as these households are more likely to experience malnutrition (Headey et al., 2018, 2019). In this section we consider whether these results differ for girls who live in remote and non-remote households, using the travel time to school at baseline as a proxy for remoteness if a girl travels at least an hour to get to school at baseline. 33% of the sample is considered remote by this definition, with no differences between remoteness prevalence within drought-affected and unaffected areas.

The coefficients from the separated regressions for remote and non-remote households are shown in figures 5 6, and 7. We find that the negative learning results are indeed concentrated amongst the most remote households after the drought. In addition, repetition rates are also significantly lower for girls in the remote households after the drought. However, leadership and progression results do not vary significantly across remote and non-remote households.

3.4. **Other Outcomes.** We have found evidence that girls in drought-affected areas are more likely to have positive progression outcomes, but do worse on assessments of numeracy and leadership. Our findings are generally consistent with the idea that when a household's farm becomes less productive as a result of the drought, the opportunity cost of attending school falls for children in that household. We present additional evidence in Table 3 which shows that girls in the drought areas spent less time on agricultural work and other family business activities after the drought than girls in non-drought areas. No differences exist between the changes in time spent on general housework.

In addition to changes in chore loads, we see increased reports of extreme hunger by children from households that experience the drought. This is shown in table 8, which shows that girls from in drought-affected households are 6 percentage points more likely to report an increase in extreme hunger at endline than girls in the control areas.

These results are intuitive once we consider that the high rates of agriculture-based livelihoods and the high incidence of subsistence farming in the areas these children are from means that these households are more likely to be experiencing more severe hunger after the drought. We know from previous research that children who are malnourished are more likely to under-perform academically. This has been shown in research by Taras (2005), who finds that food and vitamin insufficiency is associated with poorer test performance. We know that this is a risk in our sample, as households in the areas that experienced the drought were more likely to become hungry between baseline and endline evaluation points, leaving 59% of girls reporting either going to school or going to bed hungry on a regular basis.

Table 8 highlights some potential health consequences for girls in households affected by the drought. As we've discussed above, the financial hardship caused by the drought is associated with an increase in reports of hunger. However, girls in drought-affected areas were not more likely to report frequently being ill. This data also allows us to consider the impact of the drought on the girls' families. Table 8 also shows that girls' caregivers (often their mother or grandmother) are less likely to be formally working during the drought period than caregivers of girls in areas unaffected by the drought.

3.5. **Sensitivity to Drought Thresholds.** Tables 9 and 10 compare the results thus far to the same estimations using a more severe drought definition. If we limit the definition of drought to only include areas that received 70% of their usual rainfall or less we find that the results remain relatively unchanged. Under this more strict definition, girls in households experiencing the drought do 6.9 percentage points worse on numeracy tests, which is slightly worse than under the original definition. They are also 6.9% less likely to repeat a grade, though they are no longer significantly more likely to be enrolled in school at endline. Interestingly, under this extreme definition, girls do significantly better on literacy. Specifically, girls in the most severely affected areas do 6.3 percentage points better on literacy assessments. This is further evidence that stress has a different effect on literacy and numeracy acquisition which is consistent with, though more significant than, the results discussed thus far.

4. Conclusion

The severe drought that affected a large part of Zimbabwe in the 2015-16 growing season led to more girls in these areas staying enrolled and progressing through school. We find that these girls are also more likely to spend less time on chores involving economic activity to support the household, which supports the idea that once the opportunity cost of education falls, households are less likely to keep their daughters from school despite the fact that they have less income as a result of decreased agricultural productivity.

This increase in enrolment and progression is not associated with any increase in learning outcomes. Girls living in households affected by the drought performed about 4 percentage points (0.15 SD) worse on numeracy assessments, despite the fact that they are 8% less likely to repeat a grade. They also perform worse on measures of leadership behaviors and attitudes. This may suggest that the negative physical and mental health consequences associated with this shock prohibit students' human capital development despite the fact they are progressing through school.

The depth of information collected by the project allows us to consider multiple dimensions of girls' education. These findings suggest that changes in school participation do not automatically facilitate improvements in learning. We have shown that focusing on only academic progression or attendance may not be a good measure of broader learning outcomes. At the same time, focusing only on test scores may overlook improvements in attendance that can be leveraged by program implementers. For example, if programs were aware of both learning and progression findings in this context, they may find that assistance focusing on nutrition (such as school meal programs) may be beneficial in improving academic performance once they observe that learners are attending more regularly. Collectively, these findings highlight the importance of considering multiple outcomes when evaluating the impacts of education projects. This comprehensive approach has the potential to lead to more informed intervention design.

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Appendix A. Tables and Figures

Figure 1. Drought and Data Collection Timeline

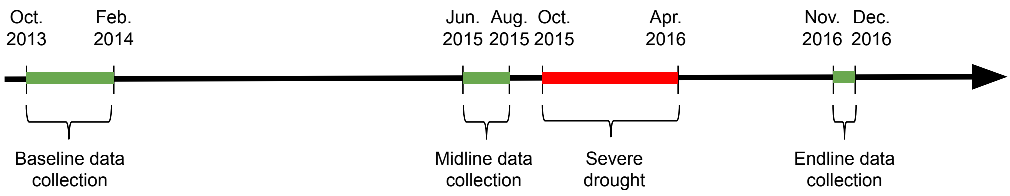
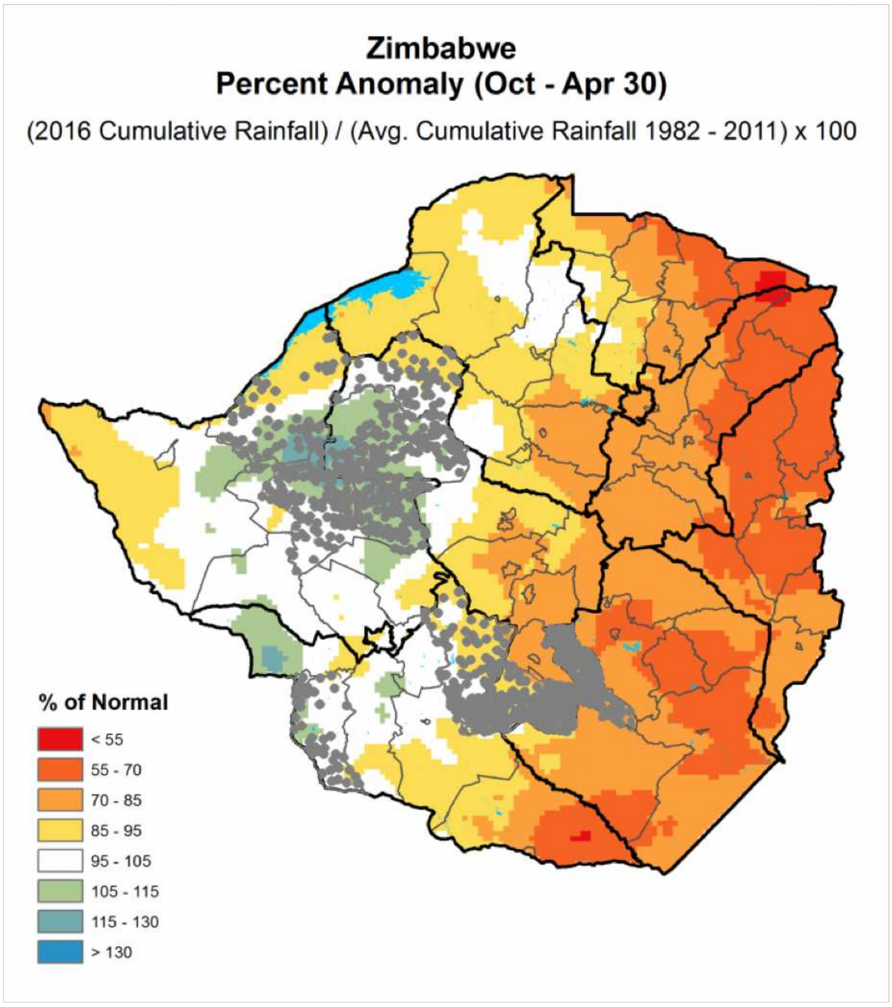


Table 1. Baseline Summary Statistics

	Drought Affected ("Treatment") Schools	Unaffected ("Control") Schools	Difference
Girl Characteristics			
Age	9.365	9.209	−0.156
Grade	3.698	3.312	−0.385***
Disabled	0.172	0.198	0.026
High chore burden	0.583	0.570	−0.013
School Characteristics			
Teacher frequently absent	0.086	0.176	0.090***
IGATE school	0.743	0.605	−0.138***
Travel time to school (minutes)	33.287	34.582	1.296
Household Characteristics			
Difficult to afford school	0.567	0.594	0.027
Experiences hunger	0.214	0.205	−0.009
No water access	0.120	0.132	0.012
Caregiver involved within school	0.123	0.108	−0.015
Education Indicators			
Enrolled at baseline	0.987	1.000	0.013***
Numeracy	0.473	0.435	−0.039**
Literacy	0.087	0.071	−0.016**
Youth leadership index (/84)	57.845	55.532	−2.313*
Attendance	0.937	0.929	−0.008
Numberofgirls	374	621	

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

Figure 2. Rainfall Anomaly and Sample Points



Note: This rainfall map, generated by Famine Early Warning Systems Network (2016a), has been augmented with data from the IGATE program on school locations.

TABLE 2. Progression Outcomes

	Enrolment		Grade Repetition	
	(1)	(2)	(3)	(4)
Drought	0.0168	0.0279*	-0.0715**	-0.0793**
	(0.0210)	(0.0148)	(0.0312)	(0.0326)
Age		-0.0220***		-0.0237**
		(0.00667)		(0.0118)
Grade		-0.00971		0.0403***
		(0.00764)		(0.0155)
Frequently ill		-0.0220		0.0243
		(0.0258)		(0.0405)
Disability		0.00739		0.0564
		(0.0139)		(0.0358)
Orphan		-0.0200		-0.0973***
		(0.0286)		(0.0342)
HH experiences hunger		-0.0423*		0.0182
		(0.0217)		(0.0324)
HH has no access to water		-0.0166		0.0375
		(0.0242)		(0.0343)
IGATE school		-0.00595		0.000746
		(0.0136)		(0.0394)
$Number of girls$	995	877	995	877
pseudo R^2	0.002	0.188	0.011	0.036

Estimates are marginal effects.

Cluster-robust standard errors in parentheses. Standard errors clustered at the school level.

All control variables represent the baseline levels of these characteristics.

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

Table 3. Changes in Chore Time by Chore Category

	Drought Affected Area	Unaffected Area	Difference	
Increased time spent on:				
- Agriculture chores	13.10%	21.74%	-8.64%	**
- Family business chores	2.67%	13.85%	-11.18%	**
- Housework	7.49%	10.47%	-2.98%	
Number of Girls	374	621		

Figure 3. Literacy Score Distributions

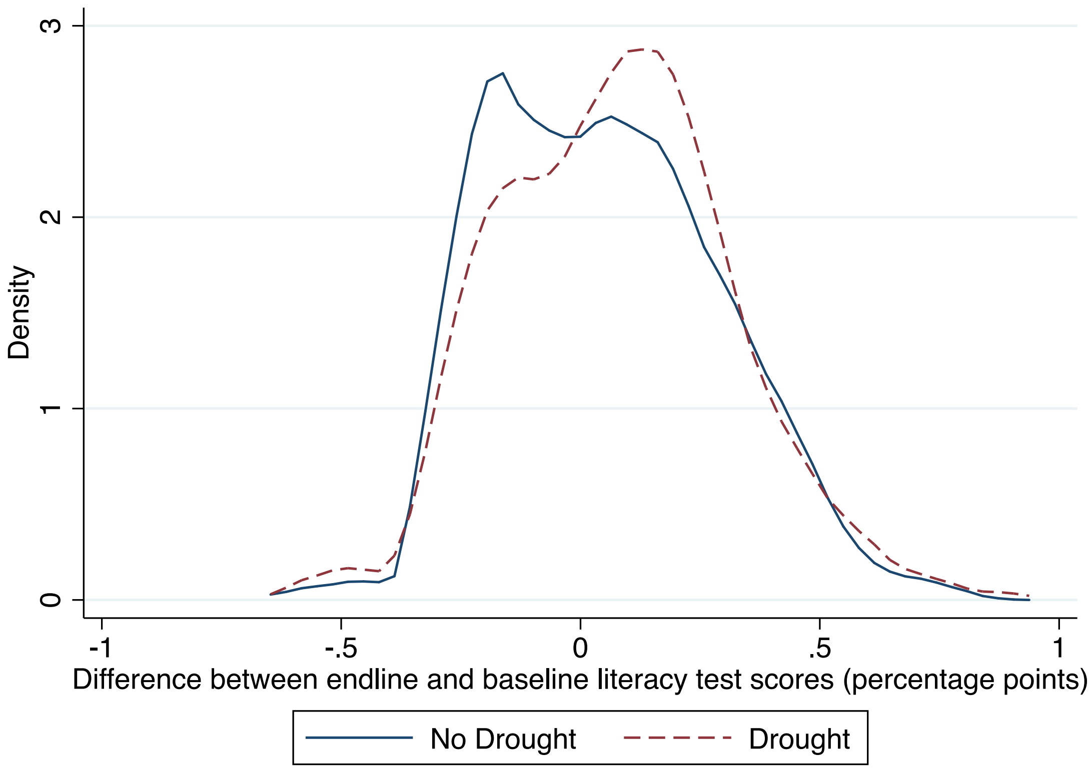


TABLE 4. Learning Outcomes (All Girls)

	Numeracy		Literacy	
	(1)	(2)	(3)	(4)
Drought	0.0386*	0.0177	0.0158*	0.000577
	(0.0231)	(0.0187)	(0.00795)	(0.00808)
Post-drought period	0.276***	0.275***	0.173***	0.175***
	(0.00960)	(0.0104)	(0.00739)	(0.00746)
Drought * Post-drought period	-0.0342**	-0.0404**	0.0141	0.0155
	(0.0154)	(0.0165)	(0.0116)	(0.0120)
Age		-0.00812		-0.00646*
		(0.00538)		(0.00341)
Grade		0.0795***		0.0380***
		(0.00583)		(0.00407)
Frequently ill		-0.00664		0.000282
		(0.0160)		(0.0112)
Disability		-0.0249*		-0.0221**
		(0.0143)		(0.0109)
Orphan		-0.0256		-0.0272
		(0.0246)		(0.0207)
Frequently experiences hunger		-0.0430**		-0.0340***
		(0.0184)		(0.0106)
No access to water		-0.0320*		-0.00867
		(0.0186)		(0.0110)
IGATE school		-0.00351		0.00791
		(0.0159)		(0.0126)
Constant	0.435***	0.269***	0.0710***	0.0139
	(0.0134)	(0.0401)	(0.00497)	(0.0253)
$Number of girls$	995	877	995	877
Adj. R^2	0.252	0.481	0.290	0.409

Cluster-robust standard errors in parentheses. Standard errors clustered at the school level.

All control variables represent the baseline levels of these characteristics.

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

Figure 4. Numeracy Score Distributions

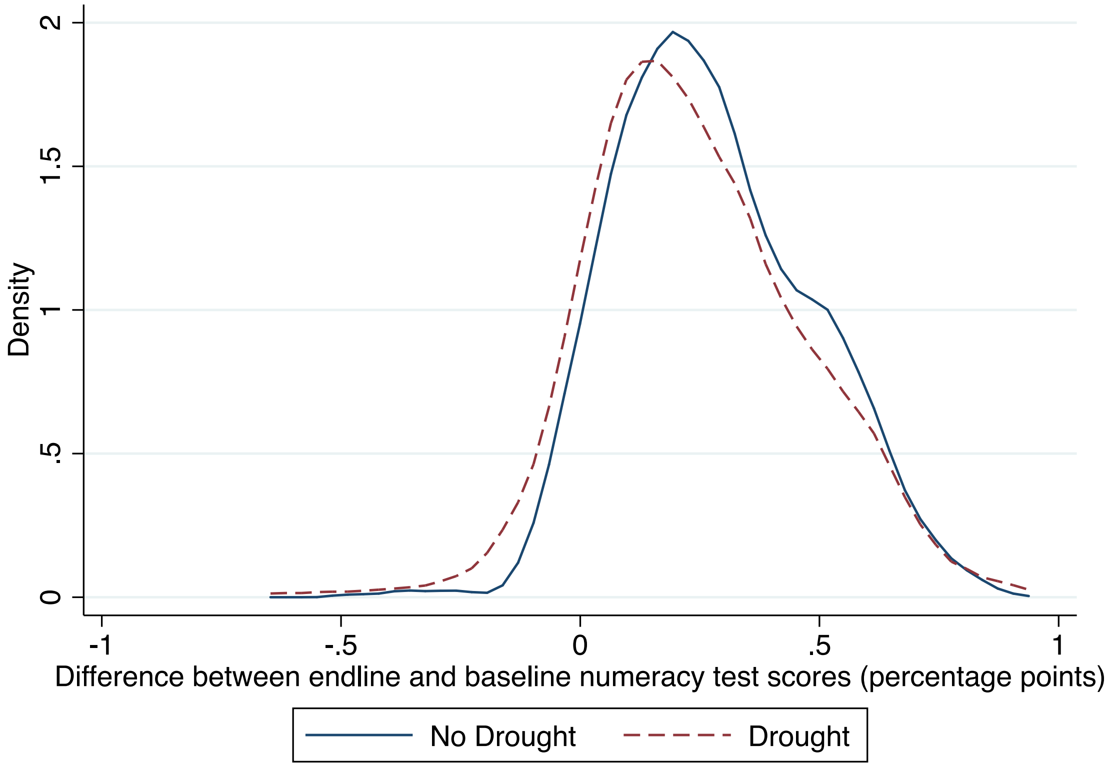


Figure 5. Progression Results by Remoteness

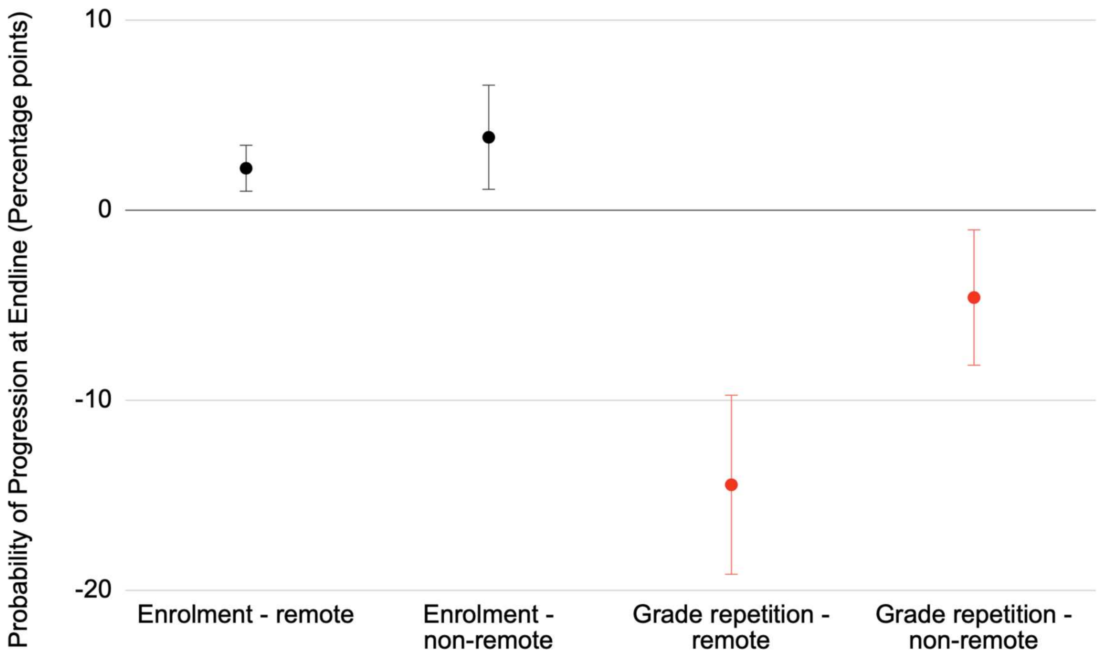


Table 5. Progression Outcomes - Transitioned to Secondary School

	Enrolment		Grade Repetition	
	(1)	(2)	(3)	(4)
Drought	0.0199	0.00606	-0.00725	-0.0139
	(0.0277)	(0.0270)	(0.0425)	(0.0430)
Age		-0.0248*		0.0377**
		(0.0150)		(0.0191)
Grade		0.00357		0.0212
		(0.0141)		(0.0250)
Experiences hunger		0.0150		-0.0225
		(0.0282)		(0.0309)
No access to water		-0.154		0.0468
		(0.119)		(0.0812)
IGATE school		0.0320		0.0562*
		(0.0348)		(0.0291)
Frequently ill				0.0430
				(0.0625)
Disability				0.154*
				(0.0892)
$Number of girls$	188	123	188	164
pseudo R^2	0.012	0.165	0.000	0.227

Coefficients are marginal effects.

Cluster-robust standard errors in parentheses.

Standard errors clustered at the school level.

All control variables represent the baseline levels of these characteristics.

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

TABLE 6. Learning Outcomes (Transitioned to Secondary School)

	Numeracy		Literacy	
	(1)	(2)	(3)	(4)
Drought	0.0890*	0.0904**	0.0544*	0.0676***
	(0.0486)	(0.0442)	(0.0289)	(0.0217)
Post-drought period	0.206***	0.246***	0.264***	0.274***
	(0.0408)	(0.0406)	(0.0275)	(0.0244)
Drought * Post-drought period	-0.0908*	-0.117**	-0.0406	-0.0563*
	(0.0468)	(0.0472)	(0.0318)	(0.0294)
Age		-0.0276***		-0.0166*
		(0.0103)		(0.00920)
Grade		0.0435***		0.00142
		(0.0148)		(0.0140)
Frequently ill		-0.0186		0.0100
		(0.0370)		(0.0270)
Disability		0.00763		-0.0203
		(0.0280)		(0.0305)
Orphan		0.0454**		-0.0431
		(0.0226)		(0.0316)
Frequently experiences hunger		-0.0241		-0.0293
		(0.0345)		(0.0249)
No access to water		0.00830		0.00374
		(0.0362)		(0.0263)
IGATE school		-0.0434*		-0.0445**
		(0.0233)		(0.0211)
Constant	0.610***	0.686***	0.0993***	0.314***
	(0.0420)	(0.111)	(0.0262)	(0.114)
$Number of girls$	154	144	154	144
adj. R^2	0.182	0.225	0.395	0.424

Cluster-robust standard errors in parentheses. Standard errors clustered at the school level.

All control variables represent the baseline levels of these characteristics.

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

Table 7. Youth Leadership Changes

	Youth Leadership Index	Youth Leadership Index
	(1)	(2)
Drought	0.226	0.0859
	(0.140)	(0.151)
Post-drought period	0.128	0.128
	(0.0924)	(0.0965)
Drought * Post-drought period	-0.270*	-0.307*
	(0.149)	(0.170)
Age		-0.108**
		(0.0525)
Grade		0.178***
		(0.0435)
Frequently ill		0.153
		(0.176)
Disability		-0.228*
		(0.120)
Orphan		-0.0297
		(0.141)
Frequently experiences hunger		-0.0533
		(0.146)
No access to water		-0.112
		(0.176)
IGATE school		-0.0156
		(0.138)
Constant	-0.0724	0.361
	(0.104)	(0.549)
$Number of girls$	324	289
Adj. R^2	0.001	0.026

Results are presented in standard deviations. Cluster-robust standard errors in parentheses.

Standard errors clustered at the school level.

All control variables represent the baseline levels of these characteristics.

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

Figure 6. Learning Results by Remoteness

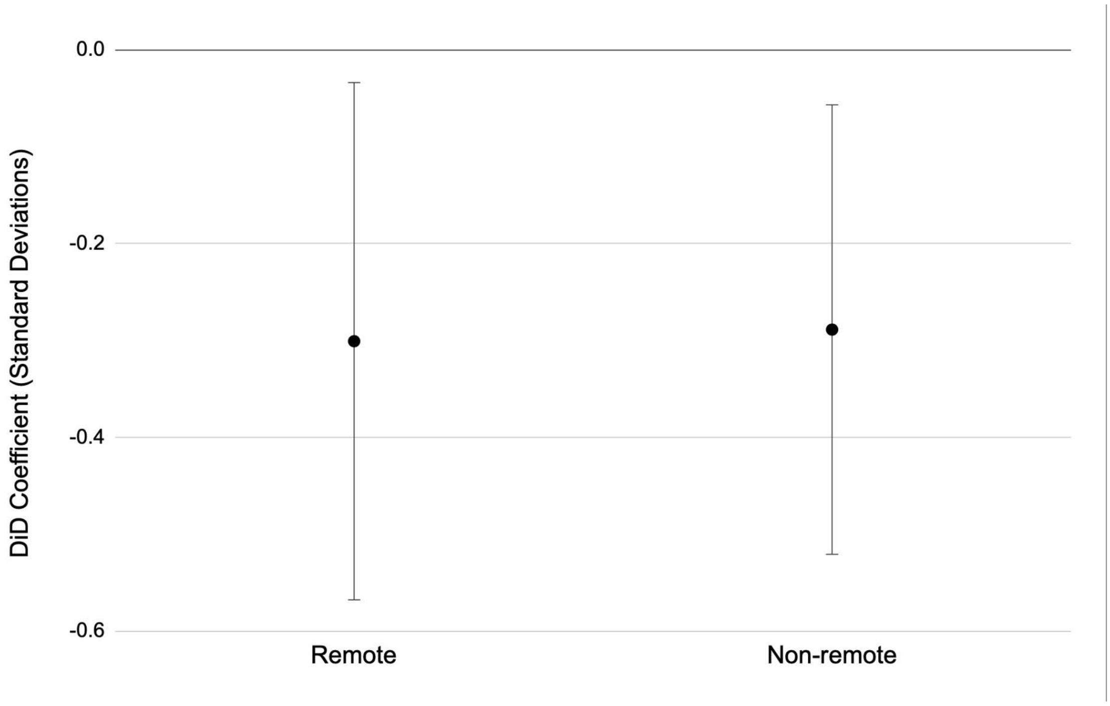


Figure 7. YLI Results by Remoteness

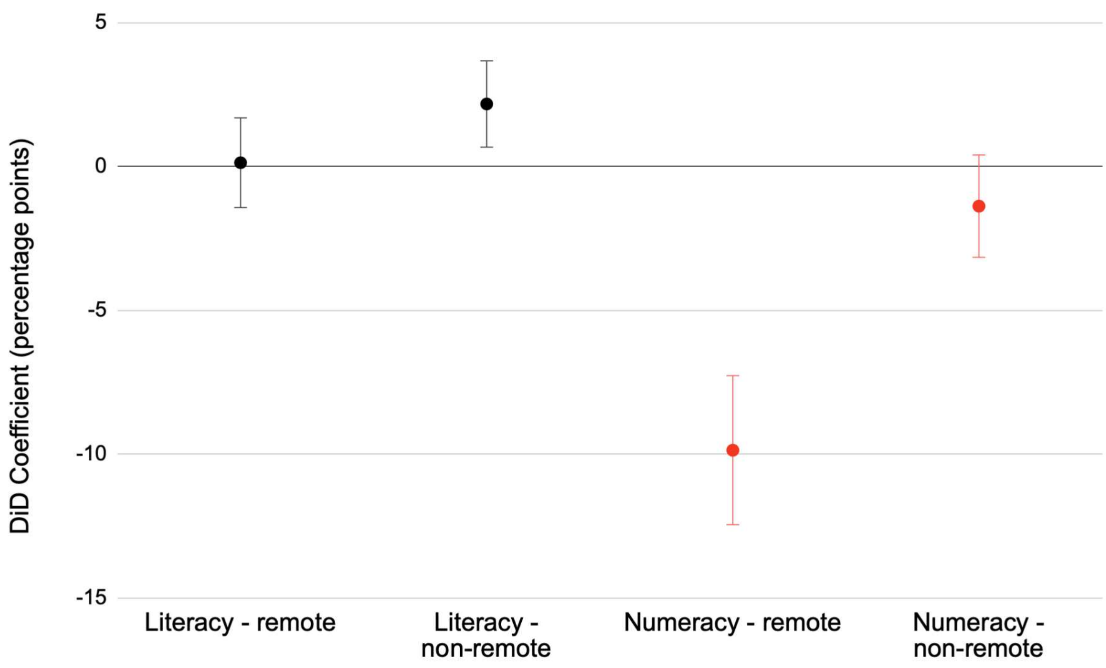


Table 8. Other Outcomes

	Drought Affected Area	Unaffected Area	Difference	
Increased reports of hunger	32.35%	26.57%	5.68%	**
Increased reports of illness	9.36%	8.05%	1.31%	
Caregiver started working	48.93%	59.74%	-10.81%	***
Caregiver started getting involved at girl's school	7.20%	8.51%	-1.31%	
Number of Girls	374	621		

Table 9. Learning Outcomes (Drought = 70% or less than usual rainfall)

	Numeracy		Literacy	
	(1)	(2)	(3)	(4)
Drought	0.177***	0.0625***	0.0563***	-0.0140
	(0.0111)	(0.0135)	(0.00402)	(0.00989)
Post-drought period	0.264***	0.261***	0.178***	0.180***
	(0.00769)	(0.00837)	(0.00580)	(0.00594)
Drought * post-drought period	-0.0830***	-0.0691***	0.0662***	0.0625***
	(0.00769)	(0.00837)	(0.00580)	(0.00594)
Age		-0.00786		-0.00676*
		(0.00526)		(0.00346)
Grade		0.0790***		0.0384***
		(0.00560)		(0.00424)
Frequently ill		-0.00704		0.000542
		(0.0162)		(0.0113)
Disability		-0.0247*		-0.0222**
		(0.0142)		(0.0109)
Orphan		-0.0262		-0.0271
		(0.0245)		(0.0210)
Frequently experiences hunger		-0.0428**		-0.0333***
		(0.0188)		(0.0107)
No access to water		-0.0325*		-0.00927
		(0.0186)		(0.0109)
IGATE school		-0.00440		0.00896
		(0.0162)		(0.0130)
Constant	0.447***	0.275***	0.0763***	0.0145
	(0.0111)	(0.0387)	(0.00402)	(0.0247)
$Numberofgirls$	995	877	995	877
adj. R^2	0.252	0.480	0.289	0.408

Cluster-robust standard errors in parentheses. Standard errors clustered at the school level.

All control variables represent the baseline levels of these characteristics.

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

Table 10. Progression Outcomes (Drought = 70% or less than usual rainfall)

	Enrolment		Grade Repetition	
	(1)	(2)	(3)	(4)
Drought	-0.0228**	0.0134 -0.0523***	-0.0697***	
	(0.0101)	(0.0128)	(0.0175)	(0.0236)
Age		-0.0239***		-0.0212*
		(0.00615)		(0.0119)
Grade		-0.00770		0.0357**
		(0.00752)		(0.0153)
Frequently ill		-0.0191		0.0198
		(0.0255)		(0.0413)
Disability		0.00854		0.0566
		(0.0142)		(0.0353)
Orphan		-0.0175		-0.0982***
		(0.0288)		(0.0358)
Frequently experiences hunger		-0.0405*		0.0128
		(0.0209)		(0.0323)
No access to water		-0.0190		0.0429
		(0.0261)		(0.0365)
IGATE school		0.000714		-0.0126
		(0.0150)		(0.0418)
$Numberofgirls$	995	877	995	877
pseudo R^2	0.000	0.179	0.000	0.023

Estimates are marginal effects.

Cluster-robust standard errors in parentheses. Standard errors clustered at the school level.

All control variables represent the baseline levels of these characteristics.

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