Drought Shocks and School Attendance in Tanzania[1]

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Abstract

In this study, we investigate the effect drought has on school attendance in Tanzania. To do so, we exploit exogenous rainfall variability to explore its effect on the proportion of school attendance after they experienced a drought shock. We resulted in a positive and significant coefficient, indicating that those with a severe-extreme drought shock are likelier to increase school attendance. Notably, this finding holds across different model specifications, demonstrating the robustness and consistency of our results.

Keywords: Drought, SPI, School Attendance, Tanzania, Education, Agriculture, Rainfall, Grid Cell, Severe-Extreme Drought Shock.

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1 Introduction

The increased frequency of severe weather events, such as drought shocks, has profound implications worldwide, especially for those regions facing socioeconomic adversity. Sub-Saharan Africa (SSA) continues to face significant challenges as the world's most food-insecure region, marked by elevated child mortality and poverty rates, limited human and physical capital, and inadequate infrastructure (Arslan et al., 2016). Extreme weather events exacerbate the socioeconomic challenges in the region, particularly affecting countries heavily reliant on smallholder agriculture. This dependency renders them more susceptible to the adverse impacts of climate change. (Barrios et al., 2008; Arslan et al., 2016; Ziervogel et al., 2008). Our study primarily centers on Tanzania, a representative nation within the Sub- Saharan Africa (SSA) region, renowned for its significant reliance on smallholder farmers and the agricultural sector as the primary source of employment and livelihood (Rowhani et al., 2011).

Drought is an insidious natural hazard that results from lower levels of precipitations than what is considered normal (Svoboda et al., 2012). It has affected more people worldwide in the last 40 years than any other natural hazard (FAO, 2020). A growing literature exploits the variability of climate shocks to examine their impact on various economic factors. Some studies have found that severe drought shocks negatively affect children's nutritional status inducing height stunting and malnutrition (Hyland and Russ, 2019; Nsabimana and Mensah, 2020). Additional research has found that exposure to drought shocks during pregnancy at later stages of the first trimester negatively affects children's cognitive and non-cognitive skills in adolescence (Chang et al., 2022). In addition, some findings resulted in women's power reduction and increased transactional sex and sexually transmitted infections (STI) from severe drought exposure. Among women engaged in agriculture, the economic shocks caused by drought compel some to resort to transactional sex as a coping mechanism. Specifically, these women seek relationships with unaffected men, particularly those employed outside the agriculture sector, thereby exposing themselves to the risk of contracting STIs (Treibich et al., 2022; Hyland and Russ, 2019).

A modest focus within this growing literature is establishing associations between drought shocks and school attendance, child labor, and learning stagnation. A study in Uganda, has found that negative rainfall shocks (drought shocks) significantly reduce school attendance, with a particularly pronounced effect observed among children in rural areas and primary schools. Furthermore, exposure to negative rainfall shocks increase children's participation in wage work by approximately 1% (Agamile and Lawson, 2021). Another study in Uganda resulted in a negative enrollment effects in females attending primary schools after a negative deviation in rainfall. This effect grows stronger in older girls, with no effect on boys (Björkman-Nyqvist, 2013). Another research in the Kagera region in Tanzania, has indicated that crop shocks lead to a significant increase in child labor levels, increasing 6.1 hours of work (Beegle et al., 2006). In contrast to these results, another study in rural India found that, during drought years, children reported higher school attendance and achieved higher scores on simple math tests. Whereas, during years of high rainfall, which may result in flooding episodes, children exhibited poorer performance in both math and reading tests and were more likely to report dropout instances (Shah and Steinberg, 2017). The findings from this study provide further evidence of the complex relationship between drought shocks, educational outcomes, and dropout rates.

This study investigates the impact of drought shocks on school attendance in Tanzania. Within this growing literature, there is a notable gap in understanding drought shocks' effects on school attendance in the Tanzanian context. This study contributes to the first estimates of a drought shock's impact on school attendance across all regions in Tanzania. It helps the understanding of a drought shock in the short term and provide insight into how Tanzanian schools and families are affected by drought. In addition, this study differs in two ways from the existing literature that investigates the impact of drought shocks on educational outcomes. First, it uses a georeferenced rainfall dataset that relies on historical weather observations instead of weather models, enhancing accuracy. And second, it exploits drought variability during a crucial time frame within the agricultural rainfall season, focusing on Tanzania's primary crops. This is accomplished by computing the Standardized Precipitation Index (SPI), a reliable measure of drought as per climatology studies. Therefore, we exploit exogenous rainfall variability to explore its effect on the proportion of school attendance after they have experienced a drought shock. The treatment is determined by the spatial area exposed to a drought shock.

The paper is organized as follows. Section 2 provides an insightful overview of the Tanzanian context, incorporating key aspects such as education, rainfall seasons, and agriculture. Section 3 introduces the study's data, descriptive statistics, and the empirical framework for analysis. The estimation results are presented in Section 4, followed by a further results exploration in Section 5 and robustness checks in Section 6. Finally, Section 7 encapsulates the findings and conclusions drawn from the study.

2 Tanzania

The United Republic of Tanzania is situated in East Africa, sharing its borders with the Indian Ocean to the east, and surrounded by Uganda and Kenya to the north, Zambia, Malawi, and Mozambique to the south, and Burundi, Rwanda, and the Democratic Republic of the Congo to the west. (Figure 1) (Commonwealth, 2023). With a population of 59.7 million (2022), administratively, Tanzania is divided into 26 regions. The country achieved its independence from the United Kingdom in 1962 and was ruled until the mid-1980s under a communist, one-party dictatorship. Since 1985, liberalization efforts and democratic reforms helped increase the nation's GDP and food production (Rowhani et al., 2011). Today, Tanzania relies strongly on its agricultural production, representing around 27% of its GDP (2022), the backbone of its economy (Mushi et al., 2022). According to the World Bank (2022), Tanzania has a GDP per cápita (usd) of 1,192.4; it is below average to the SSA region (1,690.4), similar to Uganda (964.2), higher than Malawi (645.2), Democratic Republic of the Congo (586.5) and Mozambique (541.5), and lower than Kenya (2,099.3). Around 12 million of Tanzanian people are below the poverty line, being particularly persuasive in the rural areas, where around 80% of the population lives (WorldBank, 2019).

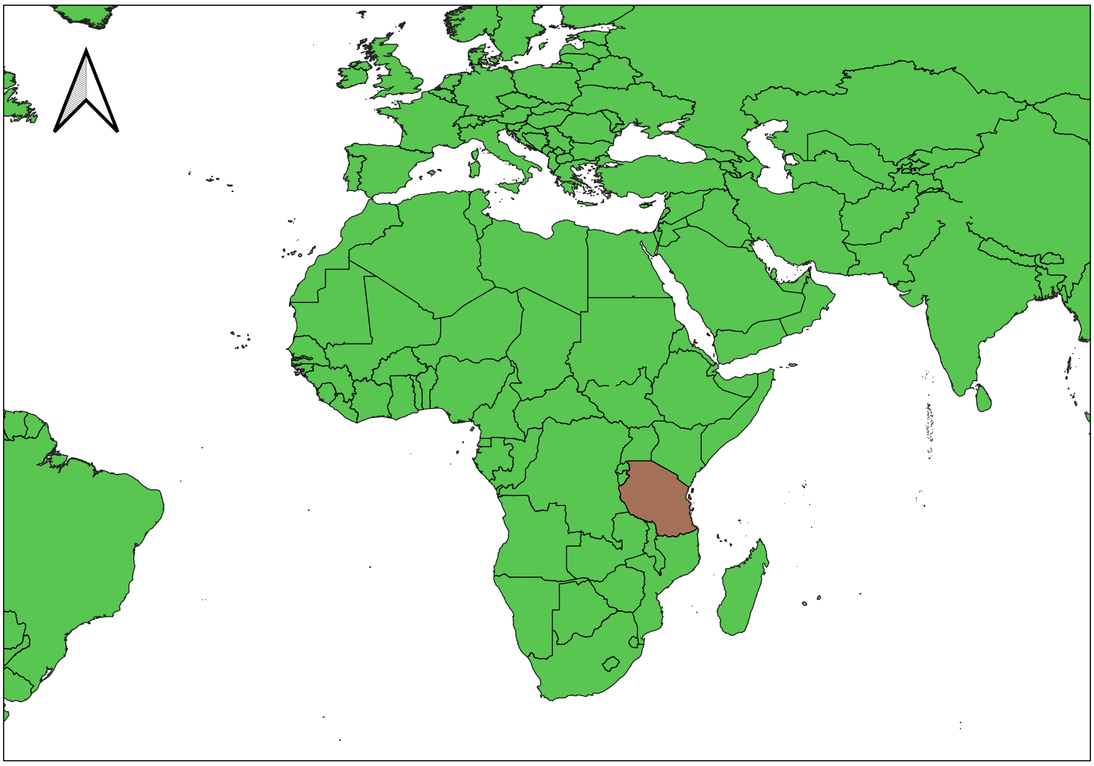


Figure 1. *Tanzania (in brown). Source: Own elaboration using QGIS.*

2.1 Education

Tanzanian education is structured as follows. It is based on a "2-7-4-2-3+" schooling structure: two years of pre-primary school, seven years of primary school, four years of Ordinary level secondary school (O-level), two years of Advanced level secondary school (A-level), and at least three years of higher education (Kyaruzi et al., 2019). Regarding primary school, the Tanzanian Universal Primary Education (UPE) program from the government, implemented between 1974 and 1978, granted universal access to primary education. A study resulted in reduced inequalities of access to schooling from this program, with positive returns to education mainly from the agricultural sector. From 1974 to 1978, the proportion of children aged 7 to 13 years enrolled in schools saw a remarkable surge, rising from 43 to 90 percent. Notably, this positive trend in school enrollment significantly reduced regional disparities in educational access (Delesalle, 2019).

Secondary education in Tanzania encompasses both private and government schools. Over the past two decades, there has been a substantial rise in student enrollment in both government and non-government secondary schools. Nonetheless, the high number of dropouts in secondary schools can be attributed primarily to truancy, accounting for 89% of cases. Pregnancy is the second leading cause at 7%, indiscipline ranks third at 3%, and the least common cause is death, accounting for 1% of the dropouts (Mashala, 2019).

2.2 Rainfall and Agriculture

Tanzania is located within the Sub-Saharan Africa (SSA) region. As most of the countries of the region, it is renowned for its significant reliance on smallholder farmers and the agricultural sector as the primary source of employment and livelihood (Rowhani et al., 2011). The susceptibility of African agriculture to climate change stems from its heavy dependence on rain-fed agricultural practices and a lack of advanced technological interventions. Most farmers in the region operate on small-scale or subsistence levels, facing multiple constraints, including limited financial resources, inadequate infrastructure, and unequal access to crucial information. These challenges collectively impede their ability to adapt effectively to the impacts of climate change, accentuating the overall vulnerability of the agricultural sector in Africa (Pereira, 2017). In most of Africa, agriculture exists without access to irrigation so over 95% of the crop-land is devoted to rain-fed agriculture (Patt and Winkler, 2007). Today in Tanzania, the agricultural sector accounts for more than 25% of the country's GDP, 65% of export earnings, and employs about 80% of the workforce, with over 80% of economically active women employed (Martin and Kahamba, 2017; Jones et al., 2023). The main linkages between weather and incomes go directly through agriculture, having substantial implications for food security and welfare (Arslan et al., 2016).

Tanzania's rainfall areas fall under two broad categories based on: the bi-modal and the uni-modal rainfall areas, as mentioned by Mollet and Barelli (2016) from the Food and Agriculture Organization of the United Nations (FAO). The bi-modal rainfall area is characterized by short rains known as *"Vuli"* from mid-September to January, followed by the long rainy season, called *"Masika"* from March to June. The bi-modal areas extend over the northern and northeastern regions. In the central and southern highland regions, rainfalls are uni-modal, known as *"Msimu"*, which starts in November and finishes around May. Figure 2 shows the crop calendar with the rainy seasons in uni-modal and bimodal rainfall areas.

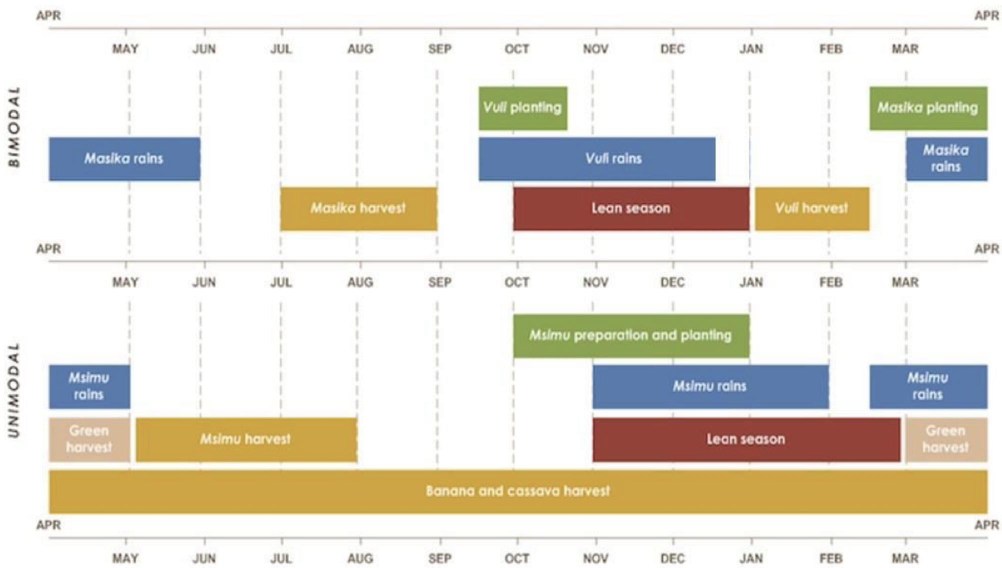


Figure 2. *Generic agricultural production calendar for Unimodal and Bimodal areas in Tanzania*[2].

[2]Retrieved from Tanzania's Ministry of Agriculture: https://www.kilimo.go.tz

In Tanzania, out of a total of 7.1 million hectares of high and medium potential land for agriculture, a mere 6% is currently under cultivation, largely due to forest and pasture extensions. The majority of agricultural activities are carried out by smallholder farmers, operating on plots ranging from 0.9 to 3.0 hectares. These smallholders account for approximately 80-90 percent of the agricultural land use in the country (Mollet and Barelli, 2016). Cereal production from the *"Masika"* and *"Msimu"* seasons accounts for almost 80% of food production. Maize production holds a central position in Tanzania's agricultural activities as it is recognized as the primary driver of the country's economy. Other major cereals are millet, rice, and sorghum (Rowhani et al., 2011). These cereal crops have comparable time-frames for planting, flowering, and harvesting. They are typically planted during the initial rains in November and December, with flowering occurring approximately three months after planting. Harvesting takes place between the end of March to the beginning of June. The first three months after planting are known for their importance for the plant's water demand. During this critical period, abundant and timely rainfall is crucial to achieving optimal crop production, accounting for approximately 70% of the total yield. Conversely, drought conditions during this phase significantly increase the risk of crop failure and yield reduction [3]. This time frame is taken into account when calculating the optimal timescale for the drought index in the following sections.

3 Methodology

This study uses two georeferenced data sets: Tanzania National Panel Survey to obtain educational outcomes and the UDEL precipitation dataset to obtain gridded weather data. These datasets are further described, along with the presentation of descriptive statistics and the empirical framework.

3.1 Tanzania National Panel Survey

The Tanzania National Panel Survey[4] (TNPS) is a nationally representative panel data of household, community, and agriculture surveys collected by Tanzania's National Bureau of Statistics (NBS). It collects data about health, education, labor, crop production, land use, and food consumption, among others. The survey conducts interviews with individuals over a period spanning from October of the initial year to October of the subsequent year, encompassing three waves occurring biennially.

In this study, we use the 2008/2009, 2010/2011, and 2012/2013 waves to obtain the proportion of children aged 5-23 currently enrolled at school. This approach aligns with previous studies in developing countries encompassing individuals up to 23 to account for potential delays or dropouts in educational attainment. By including this age range, we

[3] Stated by two Agronomic Engineers in an interview.

[4] The data is accessible through the World Bank - Living Standards Measurement Study at the following link: https://microdata.worldbank.org/index.php/catalog/lsms/?page=1&ps=15&repo=lsms

aimed to comprehensively and accurately represent Tanzania's school attendance in our analysis.

In 2008/2009, the survey interviewed 3,280 households (a total of 15,987 household members) spanning all regions and all districts of Tanzania, both mainland and Zanzibar. In the second wave, 2010/2011, 93.2% of households were interviewed and tracked in the exact location (attrition of 6.8%). And in the third wave, 2012/2013, 93.4% of household members from the second wave were interviewed and tracked in the exact location (attrition of 6.6%). We erased from the dataset those household members who migrated and moved away from the original household during the waves. The panel is based on a stratified, multi-stage cluster sample design[5]. Figure 3 shows the location of the Enumeration Areas/villages' locations spanning throughout Tanzania's regions.

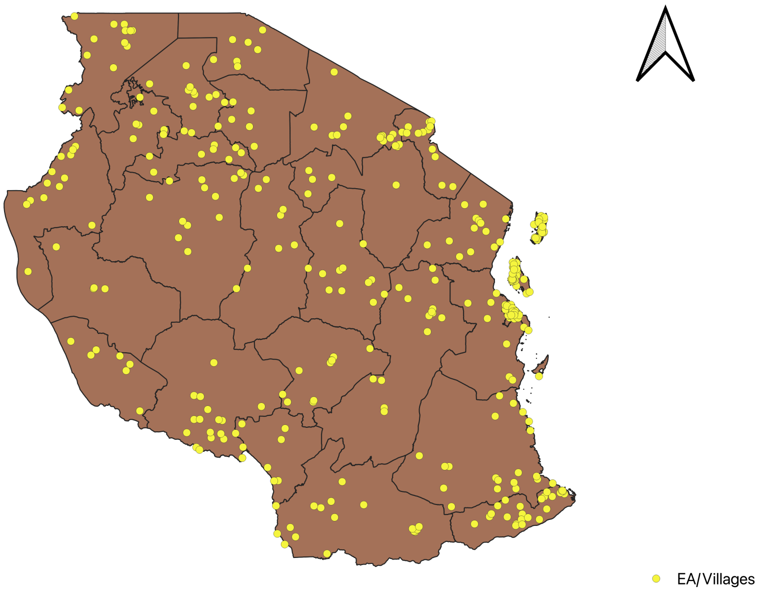


Figure 3. *Map of Tanzania with its 26 regions & the EA/Village locations. Source: Own elaboration using QGIS.*

[5]The survey was stratified into two main regions: Mainland Tanzania and Zanzibar. Each of these regions was further divided into rural and urban areas, with a specific stratum designated for Dar es Salaam. Within each stratum, clusters were selected randomly, with the probability of selection based on their population size. In this context, a cluster refers to a census Enumeration Area (EA) or a village.

3.2 Weather Data and Drought Index

Weather data was obtained from the University of Delaware's Global Land Temperature and Precipitation Data (UDEL)[6]. It provides climate data on monthly precipitation estimates from 1900 to 2017 at a 0.5-degree grid cell level (approximately 50km x 50km at the equator). Gridded weather datasets use interpolation across space and time to combine available weather station data into a balanced panel of observations on a fixed spatial scale or grid (Auffhammer et al., 2013). This dataset has been used in numerous papers that work with climate variability (Hyland and Russ, 2019; Chang et al., 2022; Dell et al., 2012; Jones and Olken, 2010). This dataset was used for several reasons: (1) The data on precipitation is accessible at a fine spatial resolution (0.5-degree grid cell) for the entirety of the 20th century, crucial for calculating the Drought Index (SPI), (2) Data is accurate as the gridded weather data is derived from historical weather observations rather than weather models (Data Assimilation), and (3) uses a highly dense network of weather stations during the years of our study. Tanzania is well covered by weather stations throughout the period of the study, specifically when obtaining historical weather data. Gridded weather data based on historical weather observations address the challenge of missing observations at specific weather stations, making data more accurate in observation-rich regions. However, gridded weather data based on data assimilation combines observational data with physics-based models creating a model prediction, likely to be less accurate in regions abundant with observations but more accurate where observations are more scarce(Auffhammer et al., 2013).

The UDEL dataset has gained prominence as a widely used weather dataset in both regional and global economic studies. It has become a popular choice due to its extensive usage across various studies in the literature, mainly for Africa. Another dataset widely used in the economics literature is the Climatic Research Unit (CRU) at the University of East Anglia.

A refined grid was constructed using the grid cell coordinate points from the UDEL dataset, with each grid cell point positioned at the center of its new corresponding individual grid cell. This tailored grid was explicitly designed to align with the coordinates of Tanzania. Furthermore, a distinct identification number was assigned to each grid cell. Based on the GPS coordinates, each Enumeration Area (EA) or village from the Tanzania National Panel Survey (TNPS) was allocated to its respective grid cell district using the constructed grid. This clustering approach ensured that each EA/village was accurately associated with the corresponding grid cell district based on its georeferenced location.

Figure 4 depicts a map of Tanzania illustrating the spatial distribution of Enumeration Areas (EA) and villages, each assigned to their respective grid cell. The map visually demonstrates the alignment between the EA/villages and their corresponding grid cells, clearly representing the spatial relationship between the two. A total of 149 out of 366 grid cells in Tanzania contain at least one EA/Village.

[6]The data can be accessed at the following link from the University of Delaware, which data was interpolated and documented by Kenji Matsuura (2017) : http://climate.geog.udel.edu/ climate/html_pages/download.html#P2017

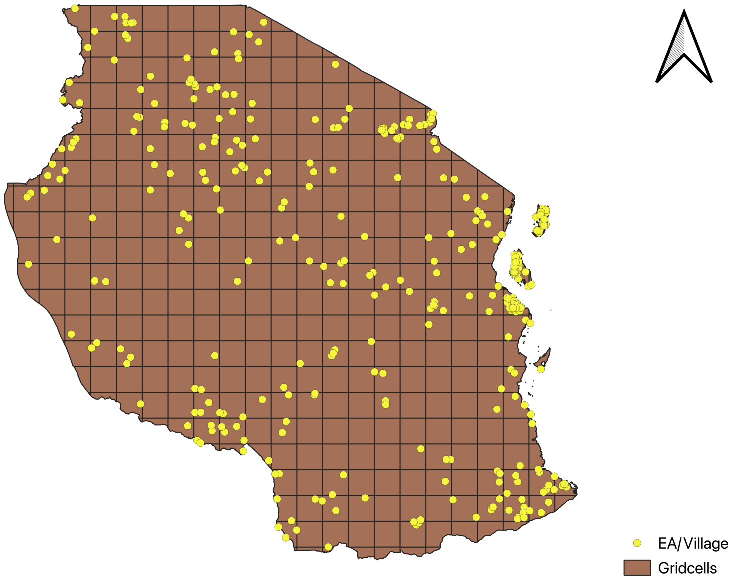


Figure 4. *Map of Tanzania with the gridcells & EA/Village locations. Source: Own elaboration using QGIS.*

The UDEL precipitation dataset is used to calculate the Standardized Precipitation Index (SPI), developed by McKee et al. (1993), for each grid cell. Following the SPI User Guide from the World Meteorological Organization (Svoboda et al., 2012), the SPI serves as a robust and versatile drought index, relying on the probability of precipitation over various time scales. The SPI computation at any location is based on the chosen period's historical precipitation data. It needs at least 50-60 years of monthly historical precipitation data to be calculated accurately. With the long-term precipitation record, the rainfall data is fitted into a gamma distribution to transform it into a normal distribution. Raw precipitation data is not normally distributed; the SPI z-scores allow us to normalize precipitation data making drier and wetter regions to be equally represented. McKee et al. (1993) introduced a classification system to categorize drought and flood intensities based on the Standardized Precipitation Index (SPI) (Table 1). A drought shock occurs when the SPI reaches a value of -1.00 or less.

2.0+	extremely wet
1.5 to 1.99	very wet
1.0 to 1.49	moderately wet
-.99 to .99	near normal
-1.0 to -1.49	moderately dry
-1.5 to -1.99	severely dry
-2 and less	extremely dry

Table 1. *SPI Values.*

The Standardized Precipitation Index (SPI) offers a range of timescales that capture the effects of drought on various water resources. These timescales include 3-, 6-, 12-, 24-, and 48-month intervals. Selecting a specific time scale depends on assessing drought impacts on different water resources. For example, meteorological drought requires a 1- or 2-month SPI, while agricultural drought analysis utilizes SPI ranging from 1 to 6 months. For hydrological drought investigations and applications, longer timescales, such as six months up to 24 months or more, are typically employed (McKee et al., 1993; Svoboda et al., 2012). For this study, a 3-month SPI is calculated for each grid cell to exploit the drought variability during the first three months of planting during the "Msimu" season (December-February). Households interviewed for the survey before February are categorized under the preceding year's potential drought period (December to February). Conversely, households interviewed after February are assigned to the potential drought period of the current year. Table 2 provides an overview of this categorization.

Potential Drought Period	Months Households Interviewed - TNPS	TNPS Wave
Dec 2007 - Feb 2008	Oct 2008 – Feb 2009	2008/2009 - Wave 1
Dec 2008 - Feb 2009	Mar 2009 – Oct 2009	
Dec 2009 – Feb 2010	Oct 2010 – Feb 2011	2010/2011 - Wave 2
Dec 2010 – Feb 2011	Mar 2011 – Oct 2011	
Dec 2011 – Feb 2012	Oct 2012 – Feb 2013	2012/2013 - Wave 3
Dec 2012 – Feb 2013	Mar 2013 – Oct 2013	

Table 2. *Categorization of the Potential Drought Period according to the month the household was interviewed.*

3.3 Descriptive Statistics

To gain insights into the data sets presented, Table 3 shows the frequency of grid cells that had and had not experienced a drought shock at the potential drought period. Drought shocks are categorized as moderate and severe-extreme (severe and extreme drought shocks), including a no-shock column. At first, we can see that December 2010 - February 2011 period experienced more moderate and severe-extreme drought shocks than any other potential drought period listed. This period is followed by the December 2008 - February 2009 period. A number of 68 grid cells experienced more than one moderate drought shock and 33 severe-extreme drought shocks.

Complementing to Table 3, Table A (Appendix) provides supplementary insights into the distribution of drought shocks among the affected grid cells. Specifically, it highlights that 63 grid cells exposed to moderate drought shocks predominantly experienced a single episode, with only a 5 grid cells experiencing two episodes throughout the study period. In contrast, grid cells exposed to severe-extreme drought shocks faced this adverse conditions only once throughout the entire study period, indicating the severity and infrequency of such extreme events. Out of the 149 grid cells, 57 never experienced a drought shock in our study.

	Drought Shock			
Potential Drought Period	No Shock	Moderate	Severe-Extreme	Total
Dec 2007 - Feb 2008	88	5	0	93
Dec 2008 - Feb 2009	93	15	6	114
Dec 2009 – Feb 2010	82	3	0	85
Dec 2010 – Feb 2011	88	26	21	135
Dec 2011 – Feb 2012	92	5	3	100
Dec 2012 – Feb 2013	118	14	3	135

Table 3. *Number of gridcells that had and had not a drought shock during the time categorized to the potential drought period.*

Building upon the insights gained from the distribution of drought shocks among the affected grid cells, Figure 5 presents six distinct maps, each capturing the 3-month Standardized Precipitation Index (SPI) across the potential drought periods in Tanzania. These maps help comprehend the spatial dynamics and intensity of drought shocks on the grid cells.

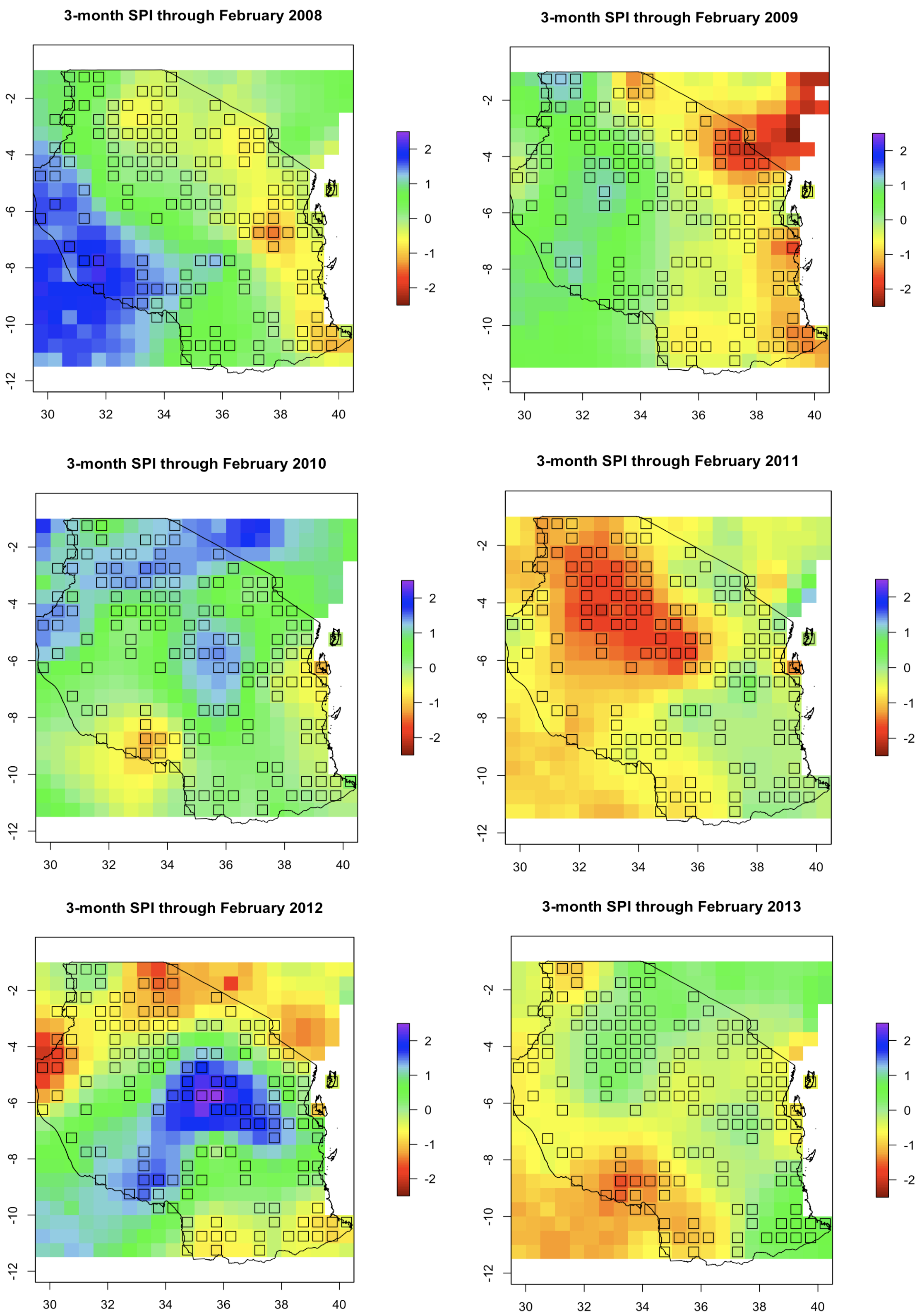


***Figure 5**: 3-month SPI in the potential drought periods in Tanzania. Grid cells in square black correspond to the 149 grid cells from this study. Source: Own elaboration using R-studio.*

Table 4 shows the proportion of school attendance during the TNPS period of those individuals that were categorized to their potential drought period. The proportion is based over the potential exposure of the grid cell to a drought shock. Those grid cells where the individuals are categorized to the potential drought period December 2008 - February 2009, December 2009 - February 2010, and December 2012 - February 2013, the school attendance was higher on those exposed to a drought shock than those who were not. However, on the other periods, school attendance was lower on those grid cells exposed to a drought shock than on those who were not.

		Drought Shock		
Potential Drought Period	No Shock	Moderate	Severe-Extreme	Total
Dec 2007 - Feb 2008	0.76	0.73	-	93
	(0.13)	(0.06)		
Dec 2008 - Feb 2009	0.74	0.80	0.86	114
	(0.14)	(0.10)	(0.08)	
Dec 2009 – Feb 2010	0.71	0.72	-	85
	(0.14)	(0.07)		
Dec 2010 – Feb 2011	0.67	0.62	0.66	135
	(0.21)	(0.23)	(0.15)	
Dec 2011 – Feb 2012	0.61	0.50	0.57	100
	(0.16)	(0.29)	(0.06)	
Dec 2012 – Feb 2013	0.59	0.65	0.67	135
	(0.21)	(0.31)	(0.09)	

SD in parenthesis

Table 4. *Proportion of school attendance during the TNPS period of those individuals that were categorized to their potential drought period. The proportion is based on the grid cell exposure to drought.*

Table 5 examines whether individuals' pre-treatment characteristics are balanced across those who are never exposed to a drought shock (control) and those who are eventually exposed in the following periods (eventually treated). For 13 out of 15 pre-treatment characteristics available there are no statistical significant differences across those never exposed and those eventually exposed to a drought shock.

	Eventually Treated	Control	Difference
Central Government school	0.923	0.931	-0.008
	(0.124)	(0.101)	[0.016]
Age to start school	8.272	8.149	0.123
	(0.653)	(0.538)	[0.085]
Age (5-23 years old)	12.695	12.459	0.237
	(1.306)	(1.323)	[0.192]
Father: did not go to school	0.426	0.403	0.023
	(0.181)	(0.183)	[0.027]
Father: incomplete primary school	0.141	0.172	-0.031*
	(0.094)	(0.140)	[0.018]
Father: complete primary school	0.302	0.311	-0.009
	(0.131)	(0.152)	[0.021]
Father: incomplete secondary school	0.011	0.011	-0.000
	(0.025)	(0.025)	[0.004]
Father: complete secondary school	0.033	0.030	0.003
	(0.053)	(0.044)	[0.007]
Father: higher than secondary school	0.007	0.007	0.000
	(0.017)	(0.025)	[0.003]
Mother: did not go to school	0.586	0.598	-0.011
	(0.179)	(0.172)	[0.025]
Mother: incomplete primary school	0.091	0.106	-0.014
	(0.081)	(0.083)	[0.012]
Mother: complete primary school	0.256	0.233	0.023
	(0.135)	(0.140)	[0.020]
Mother: incomplete secondary school	0.006	0.009	-0.003
	(0.021)	(0.025)	[0.003]
Mother: complete secondary school	0.016	0.008	0.008**
	(0.035)	(0.021)	[0.004]
Mother: higher that secondary school	0.002	0.001	0.001
	(0.009)	(0.008)	[0.001]

Notes: Standard deviations are shown in parenthesis. Standard errors are shown in brackets. * p<0.1, ** p<0.05, *** p<0.01

Table 5. *Pre-treatment characteristics.*

3.4 Empirical Model

In this study, we exploit drought variability of the first three months after the main crops are planted to explore its effect on the proportion of school attendance at the grid cell level of treatment. The effect drought shocks have on school attendance is specified as follows:

$$SchoolAttendance_{jt} = \beta_1 ModerateDS_{jt} + \beta_2 SevereExtremeDS_{jt} + \gamma_j + \alpha_t + \varepsilon_{jt} \quad (1)$$

where *SchoolAttendance* is the proportion of current enrollment to school in the grid cell j at time categorized to the potential drought period t. The variables *ModerateDS*, and *SevereExtremeDShock*, are binary variables that takes the value of one when grid cell j, at time categorized to the potential drought period t, experiences moderate and severe-extreme drought shock, respectively. Otherwise, it takes the value of zero, being β the parameters of interest. γ is a grid cell fixed effect, α is a time fixed effect, and ε is the error term.

The model's identification assumption relies on the variability of exogenous drought shocks. Meaning that, conditional to our fixed effects, the drought shocks are uncorrelated to other variables that may be determinants of school attendance. The control group are those grid cells that were not exposed to a drought shock at the time categorized to the potential drought period. Therefore, our identification assumption sheds light that in the absence of the drought shock, the treated grid cells would have exhibited similar enrollment patterns to the control group. Drought shocks occurring across the grid cells as a result of natural weather variability can be considered exogenous. Concerning inference, the standard errors are clustered at the grid cell level. It is essential to consider the possibility of error within the grid cells to correlate over time. By clustering the standard errors at the level of drought (grid cell level), it considers that the observations within the grid cells are correlated and does not take them as independent. Following the work of (Bertrand et al., 2004), estimations are precise if cluster numbers are equal to or larger than 50. With 149 clusters, we can estimate standard errors following this procedure.

By working with panel data, we can identify the parameter of interest, β, in the presence of unobservable variables that do not change over time (time invariable). Including fixed effects in our model, we control for the omitted variable bias from the unobservable heterogeneity when the heterogeneity is constant over time.

In our analysis, we define the treatment as any grid cell that experiences a drought shock. For our treatment specification, we exclusively consider the initial treated observation, while excluding the subsequent post-treatment periods.

4 Main Results

We estimate equation (1) using Ordinary Least Square (OLS). To draw general conclusions, Table 6 reports the results from estimating equation (1) based on the drought shock classifications from McKee et al. (1993), adopting the specification mentioned in Section 3.4. This study focus only on the impact of severe-extreme drought shocks due of its significant association with school attendance.

	(1) School Attendance
Moderate Drought Shock	0.016
	[0.028]
	(-0.039,0.071)
Severe - Extreme Drought Shock	0.062**
	[0.025]
	(0.012,0.071)
Observations	591
Time Fixed Effect	Yes
Gridcell Fixed Effect	Yes

Notes: Clustered standard errors in brackets. Confidence Intervals in parenthesis. * p<0.1, ** p<0.05, ***p<0.01. Following the specification mentioned in Section 3.4, Column (1) reports the estimates from equation (1) retaining only the first treated observation and excluding the rest of the post-treatment periods.

Table 6. *Estimations.*

As shown in Column (1), the coefficient of Severe-Extreme Drought Shock is positive and statistically significant over its specification, indicating that those grid cells that experience a severe-extreme drought shock are more likely to increase school attendance in the short term. Moreover, school attendance increases by 6.2 percentage points on average when the grid cell is exposed to a severe-extreme drought shock under the specification of including only the initial treated observation, excluding all post-treatment periods.

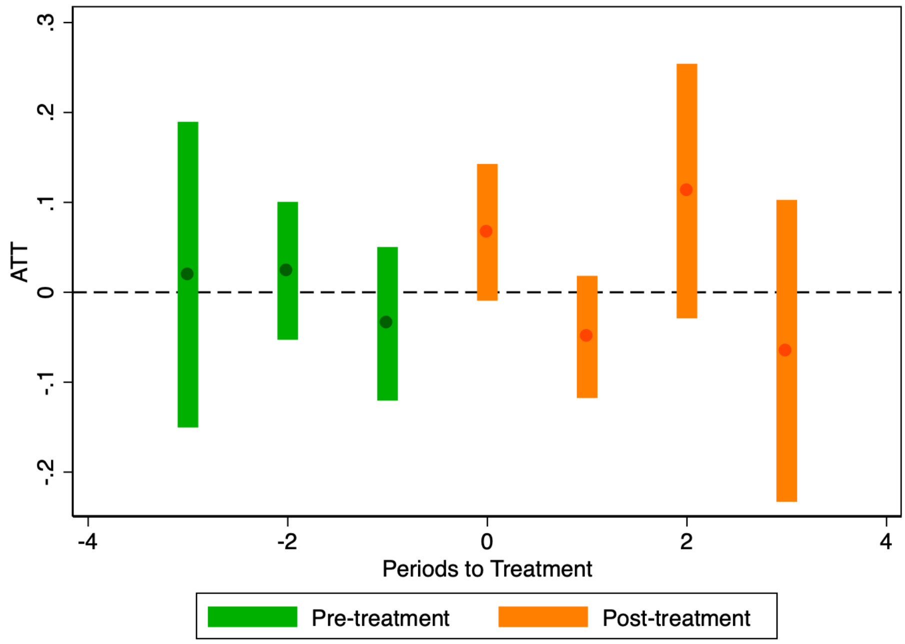
5 Further Results

As further results, we are going to (1) validate our identification strategy by exploring whether the effect of the drought shock is unique to the initial period of treatment and (2) assess whether the observed association between the drought shock and school attendance does not persist in the following periods.

To validate whether the effect of the drought shock is unique to the initial treatment period, we look at the impact of lead and lag periods. Our identification assumption relies on the variability of exogenous drought shocks so that the treated grid cells would have experienced similar enrollment patterns to the control group in the absence of this shock. We consider grid cells treated in period t and its subsequent periods as a difference-in-difference specification to look at the impact of lead and lag periods.

We follow the ATT (Average Treatment Effect on the Treated) estimator proposed by Callaway and Sant'Anna (2021). This estimator allows us to compare the outcomes of observations that receive the treatment in a specific period with those that do not receive the treatment in that period but become treated in the future. Furthermore, it enables a comparison between the treated observations and a group that is never exposed to the treatment. The ATT estimator uses a group-time base as a counterfactual instead of the pre-treatment tendency [7]. This approach allows us to group the ATTs so that we can do a comparison between treatment group, calendar time, or as an aggregated single form, allowing a much clearer notion of the treatment impact.

[7]The *two-way fixed effect*(TWFE) estimator is potentially bias with this staggered adoption of treatment if there are any heterogeneous effects of the treatment over time (if the effect of the treatment differs in the moment it becomes treated).



Graph 1. *Event study ATT. Confidence intervals at 95%.*

Graph 1 depicts the event study analysis based on the previously mentioned model estimation. The graph illustrates the trends observed before and after the treatment period, visually representing the treatment effect. Before the treatment, we follow minimal or no impact on the outcome variable. However, as indicated by the drought shock, the effects become positive and statistically significant once the treatment occurs, as corroborated by the results presented in Table C (appendix).

Following these results, we encounter a specific scenario in our study where the grid cells experiencing a drought shock are only exposed once throughout the study period. We focus on the post-treatment periods to further investigate whether the observed association between drought shock and school attendance remains significant in subsequent periods. This analysis provides additional validation to the assumption that a treated grid cell may transition into the control group if it's unexposed to a drought shock during the subsequent period.

Upon scrutinizing the subsequent post-periods, as depicted in Graph 1, we observe a diminishing statistical significance in the effect. The Average Treatment Effect on the Treated (ATT) begins to exhibit fluctuations, displaying both positive and negative values.

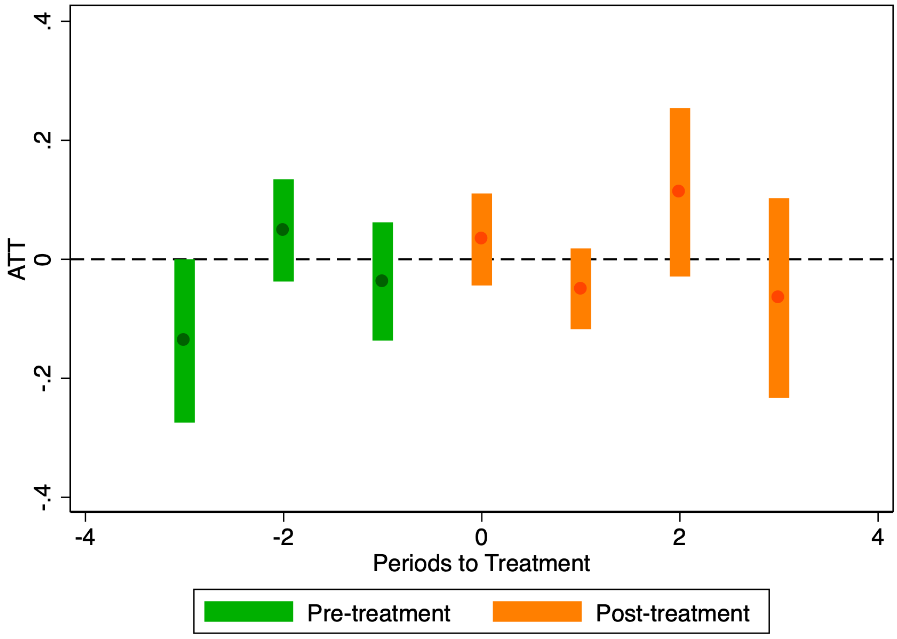
To gain further insights into the behavior of Graph 1, we conducted a group-time study, as presented in Table 7, to identify if there is a specific time period group in which the treated observations predominantly drive the treatment effect. "Group" is defined by the time period when units are first treated. Our findings reveal that the grid cells treated in the last time period (December 2012 - February 2013) carry the primary impact of the treatment.

	(1) School Attendance
GAverage	0.054
	[0.033]
G2: Dec 2008 – Feb 2009	-0.006
	[0.035]
G4: Dec 2010 – Feb 2011	0.047
	[0.057]
G5: Dec 2011 – Feb 2012	-0.017
	[0.077]
G6: Dec 2012 – Feb 2013	0.205***
	[0.058]

Notes: Clustered standard errors in brackets. * p<0.1, ** p<0.05, *** p<0.01

Table 7. *Group study ATT.*

To delve deeper into the analysis, we eliminated these treated grid cells from the dataset and re-ran the event study analysis (Graph 2; Table D in appendix). The coefficient estimate remained similar to the previous analysis without the exclusion, indicating a consistent treatment effect but with reduced statistical power.



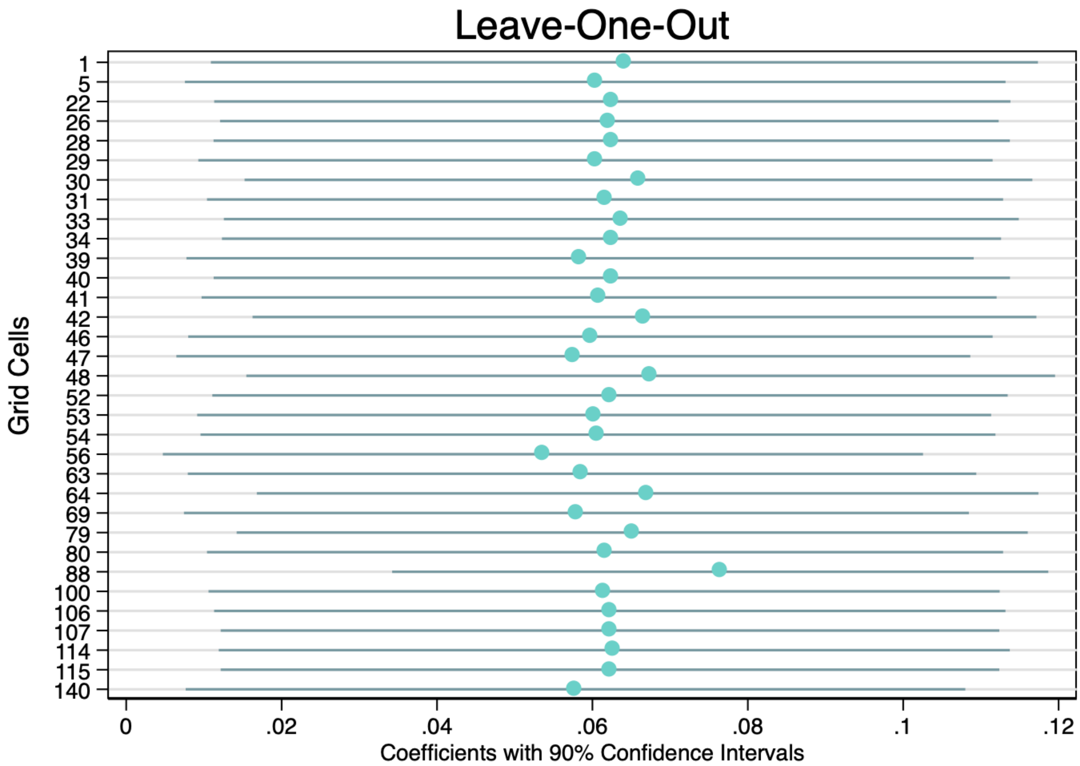
Graph 2. *Event study ATT without G6. Confidence intervals at 95%.*

6 Robustness Check

To ensure the robustness of our findings, we undertake several steps. Firstly, we perform a leave-one-out analysis by excluding each treated grid cell individually to evaluate the sensitivity of our results. Secondly, we examine if there are any heterogeneous effects from the older cohort of children included in our sample. Thirdly, we examine if there are any heterogeneous effects from the individuals interviewed in February. Finally, we assess the impact of drought using a different measurement of the drought index. These comprehensive steps enhance the reliability and credibility of our analysis.

6.1 Leave-one-out

To investigate whether a single treated grid cell primarily drives the treatment effect on the outcome variable, we conducted additional analyses by excluding one treated grid cell at a time and estimating equation (1) without that specific grid cell, following the specification of retaining only the first treated observation excluding all post-treatment periods. The results are presented in Graph 3. The coefficients obtained range from 0.02 to 0.06, consistent with the coefficient estimated in equation (1), where no treated grid cell is excluded. Notably, most of these coefficients are statistically significant at the 10% level, and their confidence intervals overlap, suggesting that our findings are not driven by a single treated grid cell.



Graph 3. *Coefficients excluding one gridcell treated at a time.*

As a result, we can say that the estimated model (1) is robust by excluding one treated gridcell at a time, and is not driven by its effect.

6.2 Age Heterogeneity

To calculate the current proportion of children attending school, we considered individuals aged 5-23, as submitted in Section 3.1. By including individuals up to 23 in our analysis, we acknowledge the potential influence of older individuals returning to school. To assess the impact of this older cohort on our results, we conduct a sensitivity analysis by excluding respondents aged 19 to 23 from the survey. This approach allow us to determine the robustness of our findings and ensure that our results are not driven solely by this specific age group.

Table 8 displays the estimation results obtained by excluding respondents aged 19 to 23 from the survey while employing the model specified in equation (1) through Ordinary Least Squares (OLS). Column (1) presents the estimation after excluding the older cohort of individuals (aged 19 to 23), while Column (2) presents the estimation without any exclusion.

	(1) School Attendance	(2) School Attendance
Severe - Extreme Drought Shock	0.049^{*}	0.067^{**}
	[0.021]	[0.025]
	(-0.003,0.101)	(0.012,0.071)
Observations	577	591
Time Fixed Effect	Yes	Yes
Gridcell Fixed Effect	Yes	Yes

Notes: Clustered standard errors in brackets. Confidence Intervals in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Following the specification mentioned in Section 3.4, both Column (1) & (2) reports the estimates from equation (1) retaining only the first treated observation and excluding the rest of the post-treatment periods.

Table 8. *Coefficients excluding and including the older cohort of individuals.*

Remarkably, the coefficient obtained by excluding the older cohort remains similar to that obtained without any exclusion while maintaining its statistical significance. These findings demonstrate that the presence of the older cohort does not significantly influence our results. Consequently, we can confidently assert that our conclusions are not driven by the inclusion of this specific age group.

6.3 SPEI & Logarithmic Deviation in Rainfall - Drought Indices

As an alternative approach to measuring drought, we consider two commonly used indices in the literature that explores climate variability and drought: the Standardized Precipitation Evapotranspiration Index (SPEI) and the Log Deviation in Rainfall. These indices provide valuable insights into the severity and occurrence of drought events, offering different perspectives on assessing drought conditions.

The Standardized Precipitation Evapotranspiration Index (SPEI) is a widely used index in the study of the impact of global warming on drought severity. It was introduced by Vicente-Serrano et al. (2010) and has gained popularity due to its simplicity and ability to capture drought conditions across different timescales. Like the Standardized Precipitation Index (SPI), SPEI classifies drought based on precipitation data for 3-, 6-,12-, 24-, and 48-month timescales. However, what sets SPEI apart is its consideration of reference evapotranspiration, which represents the amount of water that would evaporate under reference conditions. SPEI considers climatic factors such as temperature, humidity, solar radiation, and wind, providing a more comprehensive measure of the available water (climatic water balance). By incorporating reference evapotranspiration, SPEI offers insights into the combined effects of precipitation and evapotranspiration on drought severity in different locations and time periods (Beguería et al., 2014).

We also employed the Log Deviation in Rainfall as our third drought index, adopting the approach outlined in Hyland and Russ (2019); Maccini and Yang (2009). This index captures the logarithmic deviation of precipitation within each grid cell. Specifically, using the UDEL precipitation database, we computed this deviation by comparing the total rainfall during the three months (December to February) across the three waves of the TNPS with the historical mean total precipitation of each respective grid cell. By examining the logarithmic deviation, we gain insights into the relative variation of rainfall from the long-term average, providing a valuable measure for assessing drought conditions.

We utilized the Climatic Research Unit (CRU) SPEI database to assess drought conditions, which provides global-scale data at a spatial resolution of 0.5×0.5 degrees from 1901 to 2017. Following the methodology outlined in section 3.2, we extracted the 3-month timescale SPEI from this database. For the logarithmic deviation in rainfall, we considered -50% and less deviation from rainfall as indicative of the severe-extreme drought shock, classified in both SPI and SPEI indices.

Table 9 presents the estimation results of the two alternative approaches to measuring drought using the model specified in equation (1) with Ordinary Least Squares (OLS). In Column (1), we report the estimate Severe-Extreme Drought Shock: SPEI, derived from the Standardized Precipitation Evapotranspiration Index (SPEI), while Column (2) presents the estimate derived from the Logarithmic Deviation: Severe-Extreme Drought Shock.

	(1) School Attendance	(2) School Attendance
Severe - Extreme Drought Shock: SPEI	0.055 [0.061] (-0.066,0.177)	
Severe - Extreme Drought Shock: Logarithmic Deviation of Rainfall		0.065** [0.027] (0.011,0.119)
Observations	634	578
Time Fixed Effect	Yes	Yes
Gridcell Fixed Effect	Yes	Yes

Notes: Clustered standard errors in brackets. Confidence Intervals in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Following the specification mentioned in Section 3.4, both Column (1) & (2) reports the estimates from equation (1) retaining only the first treated observation and excluding the rest of the post-treatment periods.

Table 9. *Estimations using alternative drought indices: SPEI and Rainfall Log Deviation.*

Both coefficients exhibit positive values and demonstrate a similar magnitude, aligning with the coefficient estimated using the UDEL database (refer to Table 6). Notably, the Logarithmic Deviation approach estimation is statistically significant, whereas the estimation from SPEI does not reach statistical significance. However, the overlapping confidence intervals between SPEI and SPI indicate that the estimated effect size remains relatively stable across the two approaches, despite the lack of statistical significance in the SPEI coefficient.

Although the statistical power of the SPEI coefficient may be limited due to the exposure of only nine grid cells, the consistency between the different drought measures is evident from the overlapping confidence intervals. Moreover, the Log Deviation approach estimator offers stability and reliability in estimating the effect, bolstering our results' credibility and enhancing our findings' robustness.

6.4 "February" Heterogeneity

In this study, households interviewed for the survey before February are categorized under the preceding year's potential drought period (December to February). Conversely, families interviewed after February are assigned to the potential drought period of the current year. We acknowledge the possible influence of the following potential drought period by including the individuals interviewed in February under the preceding year's potential drought period. To assess the impact of including those interviewed in February on our results, we conducted a sensitivity analysis by excluding them. This approach allows us to ensure that our results are not driven solely by this specific month group.

Table 10 shows the estimation results obtained by excluding those interviewed in February from the survey while employing the model specified in equation (1) through Ordinary Least Squares (OLS). Column (1) displays the estimation after excluding those interviewed in February, while Column (2) presents the estimation without any exclusion.

	(1) School Attendance	(2) School Attendance
Moderate Drought Shock	0.017	0.016
	[0.028]	[0.028]
	(-0.037,0.072)	(-0.039,0.071)
Severe - Extreme Drought Shock	0.059^{**}	0.062^{**}
	[0.026]	[0.025]
	(0.007,0.111)	(0.012,0.071)
Observations	542	591
Time Fixed Effect	Yes	Yes
Gridcell Fixed Effect	Yes	Yes

Notes: Clustered standard errors in brackets. Confidence Intervals in parenthesis. * p<0.1, ** p<0.05, ***p<0.01. Following the specification mentioned in Section 3.4, both Column (1) & (2) reports the estimates from equation (1) retaining only the first treated observation and excluding the rest of the post-treatment periods.

Table 10. *Coefficients excluding and including those interviewed in February.*

Remarkably, the coefficient obtained by excluding those interviewed in February remains nearly identical to that obtained without any exclusion, maintaining its statistical significance. This finding demonstrates that including those interviewed in February does not significantly influence our results and is not driven by the influence of the following potential drought period.

7 Conclusion

Throughout this study, we have explained how Tanzania's school attendance responded to a drought shock. By examining the impact of drought on school attendance, we have provided valuable insights into the educational consequences of climate variability in the Tanzanian context. Be proposed a model that exploits exogenous drought variability in each grid cell to explore its effect on the proportion of school attendance. We resulted in a positive and significant coefficient, indicating that those grid cells that experience a severe-extreme drought shock are more likely to increase school attendance.

Our result is robust to different specifications. We examine its consistency and validity using different drought index measuring, leave-one-out analysis and potential heterogeneity analysis. These ensured the robustness and reliability of our findings and identification assumption, highlighting the consistency and validity of the observed relationship between drought shocks and school attendance in Tanzania.

This study contributes with a first estimate of the effect a drought shock has on school attendance across all regions in Tanzania, providing an insight into how Tanzanian schools and families are affected by drought. It highlights the importance of integrating climate resilience into educational planning, promoting sustainable and adaptive approaches to tackle the challenges posed by climate change in the education sector.

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A Table A

Drought Shock			
Gridcell ID	Moderate	Severe-Extreme	Total
1	0	1	1
3	1	0	1
4	1	0	1
5	0	1	1
9	1	0	1
10	1	0	1
15	1	0	1
16	1	0	1
17	1	0	1
18	1	0	1
20	1	0	1
21	1	0	1
22	0	1	1
23	1	0	1
24	1	0	1
25	2	0	2
26	0	1	1
28	0	1	1
29	0	1	1
30	0	1	1
31	0	1	1
32	1	0	1
33	0	1	1
34	0	1	1
35	1	0	1
36	1	0	1
37	1	0	1
38	2	0	2
39	1	1	2
40	0	1	1
41	0	1	1
42	0	1	1
44	1	0	1
45	1	0	1
46	0	1	1
47	1	1	2
48	1	1	2
49	1	0	1
50	2	0	2
51	1	0	1
52	0	1	1
53	0	1	1
54	0	1	1
55	1	0	1
56	1	1	2
57	1	0	1

58	1	0	1
60	1	0	1
61	1	0	1
62	1	0	1
63	0	1	1
64	0	1	1
66	1	0	1
67	1	0	1
68	1	0	1
69	0	1	1
72	1	0	1
74	1	0	1
78	1	0	1
79	0	1	1
80	0	1	1
83	1	0	1
88	0	1	1
89	1	0	1
91	1	0	1
92	1	0	1
94	1	0	1
95	1	0	1
99	1	0	1
100	0	1	1
101	1	0	1
106	0	1	1
107	0	1	1
113	1	0	1
114	0	1	1
115	0	1	1
118	1	0	1
119	1	0	1
120	1	0	1
127	1	0	1
133	1	0	1
135	1	0	1
136	1	0	1
138	2	0	2
139	1	0	1
140	0	1	1
141	1	0	1
143	1	0	1
144	1	0	1
145	1	0	1
147	1	0	1
148	2	0	2
Total	68	33	101

Table A. *Amount of drought shocks received by the gridcells that where exposed to a shock.*

B Table B

	(1) School Attendance
Pre_avg	0.003
	[0.032]
Post_avg	0.016
	[0.034]
Tm3	0.020
	[0.087]
Tm2	0.024
	[0.039]
Tm1	-0.035
	[0.044]
Tp0	0.067*
	[0.039]
Tp1	-0.050
	[0.035]
Tp2	0.113
	[0.072]
Tp3	-0.065
	[0.086]

Notes: Clustered standard errors in brackets. * p<0.1, ** p<0.05, *** p<0.01

Table B. *Estimations Event Study ATT.*

C Table C

	(1) School Attendance
Pre_avg	-0.042
	[0.031]
Post_avg	0.008
	[0.034]
Tm3	-0.137*
	[0.070]
Tm2	0.048
	[0.044]
Tm1	-0.037
	[0.051]
Tp0	0.033
	[0.039]
Tp1	-0.050
	[0.035]
Tp2	0.113
	[0.072]
Tp3	-0.065
	[0.086]

Notes: Clustered standard errors in brackets. * p<0.1, ** p<0.05, *** p<0.01

Table C. *Estimations Event Study ATT without G6.*