Young Lives
An International Study of Childhood Poverty

From Drought to Distress: Examining the Mental Health Consequences of Water Scarcity in Ethiopia

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Motivation

- Mental disorders represent one of the leading causes of disability worldwide, with **depression and anxiety** being the most common illnesses.
  - In Africa, over 29 million people (9% of the population) suffer from depression (Gbadamosi et al., 2022).
- Climate change is leading to higher temperatures and increasingly erratic weather patterns.
- Climate variability has been well documented to have adverse effects on agricultural production, household consumption, and even mortality (Dell et al., 2012; Skoufias et al., 2011; Deschênes and Moretti, 2009).
- **Climate variability can also exacerbate mental illnesses** (e.g., Berry et al., 2010; Pailler and Tsanever, 2018; Carleton, 2017; Hua et al., 2022).
- No rigorous empirical evidence for these effects in **Africa**, despite the region being particularly vulnerable to climate change.

This paper

- I examine the effects of the **2021 drought in Ethiopia on the anxiety and depression of young adults**.
- Exposure to precipitation below its long-run average leads to a **11.5 percentage point (9.8 percentage point) increase** in the probability of experiencing symptoms consistent with either mild or severe anxiety (depression).
  - **63% (55%) increase** relative to the average prevalence among the sample before the drought.

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  - **63% (55%) increase** relative to the average prevalence among the sample before the drought.
- The impact on depression is driven by those who were **severely exposed** to the drought, while both mild and severe exposure affect anxiety.
- The effects are driven by individuals in **rural areas**, and the effect on depression is significantly higher among those working in **agriculture** and those who **grew up in the poorest households**.

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  - **63% (55%) increase** relative to the average prevalence among the sample before the drought.
- The impact on depression is driven by those who were **severely exposed** to the drought, while both mild and severe exposure affect anxiety.
- The effects are driven by individuals in **rural areas**, and the effect on depression is significantly higher among those working in **agriculture** and those who **grew up in the poorest households**.
- Applying mediation analysis, I find that changes in **perceived poverty, household physical illness, and inflation** explain roughly half of the increase in anxiety and depression.

Country context

- Ethiopia is a country plagued by a history of droughts; between 1980 and 2004, the country experienced 16 severe drought events (World Bank, 2006).
- The population is particularly vulnerable to drought, as **80% lives in rural areas** and relies on rain-fed agriculture (UN DESA, 2019).
- Like many LMICs, mental disorders have not been adequately studied (Yitbarek et al., 2021) and individuals face considerable **social stigma** (Girma et al., 2022).
- In 2021, Ethiopia experienced a **prolonged drought after both rainy seasons failed in the year**, affecting roughly 6.8 million people during the year (UN OCHA, 2022).
- By January 2022, over 260,000 livestock deaths had been reported, and an additional two million were at risk (UN OCHA, 2022).
- UNICEF reported treating over 1.2 million cases of diarrhoea in children between June 2021 and June 2022 (UNICEF, 2022).

Young Lives

- The **Young Lives longitudinal study** has tracked 2,999 children (now adolescents and young adults) in Ethiopia since 2002.
- Two age cohorts: Aged 18-19 (Younger Cohort), and 25-26 (Older Cohort) in 2020.
- Comparison to national statistics data indicate that Young Lives households are generally **poorer** than the average Ethiopian household.
- This paper employs data from a **five-part phone survey**, implemented following the COVID-19 outbreak.
  - Reduced questionnaires given remote nature.
  - Focus on surveys in November-December 2020 (before drought) and November-December 2021 (during drought).
- 1,738 interviews were completed in November-December 2021.
  - Sample excludes participants from the Tigray region.

Mental health outcomes

- Symptoms of anxiety and depression were measured using the **Generalized Anxiety Disorder-7 (GAD-7)** scale and the **Patient Health Questionnaire depression scale-8 (PHQ-8)**, respectively.
- Both scales have previously been validated (Zhong et al., 2015; Nguyen et al., 2016) and used in the Ethiopian context (e.g., Gelaye et al., 2013; Gezie et al., 2018; Mokona et al., 2020).
- Scales were slightly adapted for administration during a phone survey, and were piloted before implementation.
- Construct two **binary dependent variables** where 0 indicates no/minimal anxiety (or depression) and 1 indicates the presence of **symptoms consistent with at least mild anxiety (or depression)** (Spitzer et al., 2006; Kroenke et al., 2009).

Precipitation data

- I match the Nov-Dec 2020 Young Lives woreda GPS information to rainfall data from the **Climate Hazards Group InfraRed Precipitation with Station (CHIRPS)** data set (Funk et al., 2015).
- For each woreda, I calculate monthly rainfall as an **inverse-distance-weighted average** of the rainfall registered at the four closest grid points to that community.
- I then compute the yearly **Standardised Precipitation Index (SPI)**, a relative measure of precipitation that reflects the number of standard deviations that rainfall varies from its long-run average.

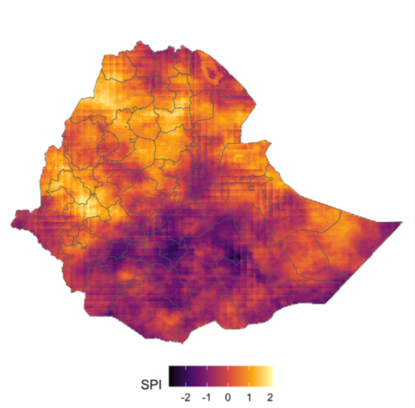


Fig. 12-month SPI for January-December 2021

Summary statistics

- I define drought-affected villages as those with a **2021 12-month SPI less than 0**.

	Drought	Control
Age (in years)	20.74	20.68
Female	0.48	0.43
Urban (Nov-Dec 2020)	0.46	0.36***
Mother has primary schooling (2016)	0.62	0.55**
Wealth index (2016)	0.45	0.38***
Wealth index (2002)	0.24	0.18***
Access to electricity (Aug-Oct 2020)	0.79	0.65***
Has a television (Aug-Oct 2020)	0.61	0.38***
At least mild anxiety (Nov-Dec 2020)	0.13	0.36***
At least mild depression (Nov-Dec 2020)	0.14	0.34***
Observations	1,266	337

Notes: Wealth index takes values between zero and one, such that a larger value reflects a wealthier household. It is the simple average of a housing-quality index, an access-to-services index, and a consumer-durables index * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Empirical Strategy (1)

- I test the effect of the 2021 drought on mental health using the following canonical **difference-in-differences (DiD)** specification:

$$MH_{ihgt} = \alpha + \beta_1 D_{ig} + \beta_2 Post_t + \beta_3 (D_{ig} \times Post_t) + \boldsymbol{\delta X}_{ih} + \mu_{ihgt} \quad (1)$$

- Controls $\boldsymbol{X}$ include: age, education enrolment, highest education, household size, number of rooms, ownership of pit latrine, television, access to electricity, location (urban/rural), migration from pre-drought location, and whether any members of the household have been infected with COVID-19.
- Standard errors are **clustered at the woreda level** (Abadie et al., 2023).
- Also present standard errors following Conley (2008) that allow for **spatial correlations between nearby woredas**.
- The **coefficient of interest** is β_3.

Pre-trends

	At least mild anxiety	At least mild depression
Drought$_{t-1}$ (β_3)	-0.012	0.043
	(0.047)	(0.031)
Controls	No	No
Observations	3,202	3,204

Notes: Estimated using Equation (1) applied to data from August-October 2020 and November-December 2020. Standard errors (in parentheses) are clustered at the woreda level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

- Lagged DiD using data from August-October 2020 and November-December 2020 suggests that we cannot reject that **pre-trends are parallel** just prior to the 2021 drought.

Empirical Strategy (2)

- I extend the DiD framework to estimate whether outcomes are sensitive to **drought intensity**:

$$MH_{ihgt} = \alpha + \beta_1 D^M_{ig} + \beta_2 D^S_{ig} + \beta_3 Post_t + \beta_4 (D^M_{ig} \times Post_t) + \beta_5 (D^S_{ig} \times Post_t) + \boldsymbol{\delta X}_{ih} + \mu_{ihgt} \quad (2)$$

  - D^M reflects **mild exposure** to the drought (SPI >-1 and SPI $<$ 0), while D^S reflects **severe exposure** to the drought (SPI $\leq$ -1) (McKee et al., 1993).

- Lastly, I quantify whether individuals with certain **characteristics (I)** are more or less vulnerable to drought:

$$MH_{ihgt} = \alpha + \beta_1 D_{ig} + \beta_2 Post_t + \beta_3 (D_{ig} \times Post_t) + \beta_4 (I_{ihg} \times Post_t) + \beta_5 (I_{ihg} \times D_{ig}) + \beta_6 (I_{ihg} \times D_{ig} \times Post_t) + \boldsymbol{\delta X}_{ih} + \mu_{ihgt} \quad (3)$$

Effect of 2021 drought on mental health

	At least mild anxiety	At least mild depression
Drought (β_3)	0.115^{***}	0.098^{**}
	(0.040)	(0.044)
p-value: robust SE	0.004	0.033
p-value: spatially adjusted SE	0.002	0.024
Nov-Dec 2020 mean	0.181	0.178
Controls	Yes	Yes
Observations	3,206	3,206

Notes: Regressions control for age, education status, highest education, household size, number of rooms, ownership of a pit latrine, a television, and access to electricity, location (urban/rural), whether the household has migrated, and whether any members of the household have been infected/suspected to be infected with COVID-19. Standard errors (in parentheses) are clustered at the woreda level. Conley (1999, 2008) spatial standard errors are estimated using a 10km cut-off. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

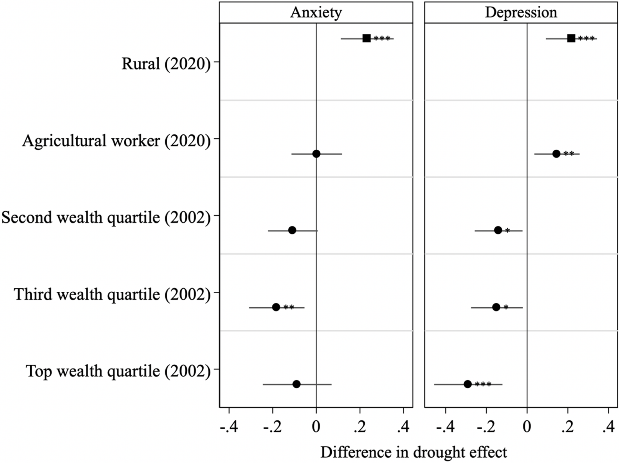
- The effects represent a **63% (55%) increase relative to the average prevalence** among the sample in November-December 2020.

Heterogeneity by drought intensity

	At least mild anxiety	At least mild depression
Mild drought (β_4)	0.110^{**}	0.077
	(0.050)	(0.054)
Severe drought (β_5)	0.128^{***}	0.135^{***}
	(0.028)	(0.031)
Observations	3,206	3,206

Notes: Estimated using Equation (2). Mild exposure to the drought takes the value of one if the SPI $>$-1 and SPI < 0, while severe exposure to the drought takes the value of one if the SPI $\leq$ -1. Regressions control for age, education status, highest education, household size, number of rooms, ownership of a pit latrine, a television, and access to electricity, location (urban/rural), whether the household has migrated, and whether any members of the household have been infected/suspected to be infected with COVID-19. Standard errors are clustered at the level of the woreda. * p < 0.10, ** p < 0.05, *** p < 0.01.

Heterogeneity by socio-demographics



Notes: Figure shows estimated $\hat{\beta}_6$ from Equation (3). Vertical bars indicate a 90% confidence interval around predictions.

Doubly robust DiD

- Incorporating time-varying controls into the DiD assumes homogenous treatment effects in **X** and requires that the evolution of covariates is the same for both treatment and control groups (Sant'Anna and Zhao, 2020).
- As an alternative approach, Sant'Anna and Zhao (2020) propose a **doubly robust DiD estimator** which uses pre-treatment covariates to model a propensity score and combines this with a conditional outcome regression model.
  - The doubly robust estimator is consistent if either (but not necessarily both) the propensity score or outcome regression working model is correctly specified.
- I add additional controls for sex, wealth index score in 2002 and 2016, and the mother's highest schooling grade achieved.

Doubly robust DiD: results

	At least mild anxiety	At least mild depression
Drought	0.133**	0.118**
	(0.053)	(0.046)
Observations	2,962	2,962

Notes: Estimated using the Stata command *drdid*. All regressions control for sex, age, education status, highest education grade, household size, wealth index score in 2002 and 2016, number of rooms in the house, whether the household has a pit latrine, a television, and access to electricity, mother's highest schooling grade, whether the household is in an urban (or rural) area, whether the household has migrated, and whether any members of the household have been infected/suspected to be infected with COVID-19. I use a linear outcome regression model and a logistic propensity score model. Standard errors (in parentheses) are clustered at the woreda level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Mediation analysis

- My results may partly be explained by increases in **poverty**, a deterioration of **physical health**, and a rise in the **cost of living** (e.g., Berry et al., 2010; Vins et al., 2015; Di Tella et al., 2001).
- To investigate the importance of these mechanisms, I present the results of a **mediation analysis**, using three observed mediators:
  - (1) A binary variable of **perceived household poverty** that takes the value of one if the participant describes their household as destitute or poor.
    - Follows increasing body of evidence documenting that the *perception* of poverty itself can enact a psychological toll (e.g, Mani et al., 2013; Kaur et al., 2022; Demakakos et al., 2008)
  - (2) A binary variable of **household illness** that takes the value of one if the household has experienced an illness, injury, or death of an income-earning member of the household.
  - (3) A binary variable of **inflation** that takes the value of one if the household has experienced an increase in the price of major food items and/or farming business inputs.

Mediation analysis: empirical strategy

- The primary estimating equation for the mediation model can be written as follows:

$$MH_{ihgt} = \alpha + \beta_1 D_{ig} + \beta_2 Post_t + \beta_3 (D_{ig} \times Post_t) + \sum_{m \in M} \theta_0^m \pi_{ih}^m + \boldsymbol{\delta X}_{ih} + \mu_{ihgt} \quad (4)$$

  - π_0^m are the set of observed mediator variables.

- I also estimate separate regressions of Equation (1) with each of the observed mediator variables as the outcome:

$$\pi_{ih}^m = \alpha_{0,m} + \mu_{1,m} D_{ig} + \mu_{2,m} Post_t + \mu_{3,m} (D_{ig} \times Post_t) + \boldsymbol{\delta X}_{ih} + \epsilon_{ihgt} \quad (5)$$

- The average treatment effect can then be decomposed as follows:

$$ATT = \underbrace{\beta_3}_{\text{Direct effect}} + \underbrace{\sum_{m \in M} \theta_0^m (\mu_{3,m})}_{\text{Indirect effect}}$$

Mediation analysis: results

	Poverty	Illness	Inflation	Anxiety	Depression
Drought	0.188	0.121	0.354	0.054	0.051
	{0.001}***	{0.025}**	{0.001}***	{0.056}*	{0.075}*
Poverty				0.126	0.058
				{0.004}***	{0.025}**
Physical illness				0.088	0.059
				{0.014}**	{0.052}*
Inflation				0.079	0.075
				{0.008}***	{0.005}***
Nov-Dec 2020 mean	0.155	0.068	0.664		
Observations	3,191	3,191	3,191	3,191	3,191

Notes: Columns (1)-(3) estimated using Equation (1), with mediator as the outcome variable. Columns (4) and (5) estimated using Equation (4). All regressions control for age, education, household size, number of rooms, ownership of a pit latrine, a television, and access to electricity, location, migration, and whether any members of the household have been infected/suspected to be infected with COVID-19. Below each coefficient, I report a q-value in curly braces, obtained using the sharpened procedure of (Benjamini et al., 2006). Standard errors are clustered at the woreda level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Mediation analysis: results

- The indirect effects arising from changes in the observed mediators account for about **54% (47%)** of the average effect of drought exposure on anxiety (depression).
- For both outcomes, **inflation is the most important mediator**, accounting for 45% (60%) of the indirect effect on anxiety (depression).
    - The negative impacts of the drought on mental health may be operating through a general equilibrium effect in rural areas.
- Changes in **perceived poverty** are the next most important mediator, contributing 38% and 25% of the of the indirect effects of the drought on anxiety and depression, respectively.
- Changes in physical illness in the household contribute relatively little.

Conclusion

- Three key findings:
  - **Exposure to precipitation below its long-run average leads** to statistically significant, and economically large, increase in the probability of young adults experiencing symptoms consistent with either **mild or severe anxiety (depression)**.
  - The impact on depression seems to increase with the **severity** of drought exposure, and the effects are driven by individuals in **rural areas** (particularly poorer individuals for depression).
  - **Perceived poverty, physical illness, and inflation** explain roughly half of the increase in anxiety and depression, with increases in inflation being the most important mediator.
- My results suggest that providing **mental health support** to young people is important. In particular, **poverty alleviation programmes** that protect individuals from the negative effects of inflation may be effective in mitigating the adverse mental health effects of rainfall variability.

Thank you

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Any questions?

Young Lives is a collaborative partnership between research institutes, universities and NGOs in the four study countries and the University of Oxford.

Special thanks are owed to the children and families who participate in Young Lives, without whom this study would not exist.

UKaid from the British people

Controlling for potential conflict spillover effects

- In November 2020, a **civil war** broke out in northern Ethiopia, which lasted until the end of 2022.
  - Evidence has documented widespread loss of life, displacement, and disruptions to infrastructure, livelihoods, and food security (Abay et al., 2022).
  - Using Young Lives data, Favara et al. (2022) find that mental health significantly worsened after the outbreak of conflict among individuals living in Tigray.
- To control for possible conflict spillover effects, I match the Young Lives data to information from The **Armed Conflict Location and Event Data Project (ACLED)** (Raleigh et al., 2010) and control for the **cumulative number of reported fatalities in each woreda** since the outbreak of the conflict.
- Additionally, I control for whether, as of November-December 2021, the participant reported having been **internally displaced due to the conflict**.

Controlling for potential conflict spillovers effects

	At least mild anxiety	At least mild depression
Drought (β_3)	0.153^{***}	0.113^{**}
	(0.045)	(0.044)
p-value: robust SE	0.001	0.012
p-value: spatially adjusted SE	0.000	0.008
Observations	3,064	3,064

Notes: Regressions control for the cumulative number of reported fatalities in each participant's woreda and self-reported internal displacement due to the conflict. Regressions also control for age, education status, highest education, household size, number of rooms, ownership of a pit latrine, a television, and access to electricity, location (urban/rural), whether the household has migrated, and whether any members of the household have been infected/suspected to be infected with COVID-19. Conley (1999, 2008) spatial standard errors are estimated using a 10km cut-off. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.