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From Drought to Distress: Unpacking the Mental Health Effects of Water Scarcity

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Abstract

I provide quasi-experimental evidence of the effect of drought exposure on young adults' experiences of anxiety and depression by leveraging a natural experiment: the 2021 drought in Ethiopia. My analysis applies a difference-in-differences strategy and couples 40 years of rainfall data with longitudinal data on mental health. I find that exposure to below long-run average rainfall increases in the probability of experiencing at least mild anxiety and depression by 0.35 and 0.29 standard deviations, respectively. These effects are strongest among those who grew up in the poorest households and those with low childhood reading ability. The impact on depression is also pronounced among those with low self-esteem. Additional evidence on mechanisms suggests the mental health effects may partly be explained by the drought's impact on food insecurity, inflation, and perceived household poverty.

Keywords: Mental Health; Drought; Ethiopia; Climate Change; Depression; Anxiety

JEL Classification: I1; I3; Q51; Q54

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1. Introduction

It is widely recognised that climate change is leading to increasingly erratic weather patterns and a rise in the number of drought events experienced around the world (Masson-Delmotte et al., 2021). For instance, Sub-Saharan Africa experienced nearly three times as many droughts in the period 2010-2019 compared to 1970-1979 (Zeufack et al., 2021). A growing body of international evidence documents that rainfall variability typically has a negative effect on mental health.[1] In Australia, drought exposure has been linked to an increase in anxiety, depression, and suicide rates (e.g., Bourque and Willox, 2014; Carroll et al., 2009; Edwards et al., 2015; Obrien et al., 2014). In Indonesia, Christian et al. (2019) find that higher rainfall significantly reduces incidences of suicide and depression, and, in India, Carleton (2017) conclude that increased rainfall during the growing season is associated with a decline in annual suicide rates.[2]

However, due to micro data limitations, existing studies largely fail to look beyond the average effect, and there is limited information on whether the mental health effects of rainfall variability exacerbate pre-existing inequalities. Understanding this is important for determining whether climate variability might contribute to a 'psychological poverty trap' (de Quidt and Haushofer, 2019; Ridley et al., 2020; Haushofer and Fehr, 2014), as well as for identifying specific target populations which should be targeted during periods of low rainfall to increase mental health most cost-effectively.[3] Additionally, there is insufficient evidence concerning the precise individual-level mechanisms by which water scarcity exacerbates mental health conditions.[4] Understanding these mechanisms is critical for informing which combination of policy interventions is best suited to improve mental health during periods of drought.

In this paper, I take advantage of time and geographic variation to provide quasi-experimental evidence on the impact of drought exposure on symptoms of anxiety and depression in

[1] There is also a large body of literature documenting the negative mental health effects of other forms of climate variability, such as of air pollution (e.g., Chen et al., 2018; Cao et al., 2023; Balakrishnan and Tsaneva, 2023) and high ambient temperatures and heat waves (e.g., Mullins and White, 2019; Burke et al., 2018; Hua et al., 2022; Adhvaryu et al., 2023).
[2] However, Pailler and Tsaneva (2018) find that rainfall has no effect on psychological well-being in India after controlling for changes in temperature, suggesting that the effects of climate on mental health in the country may be largely driven by extreme temperatures and not precipitation.
[3] The economic consequences of increased mental ill-health are substantial, as lost productivity resulting from anxiety and depression is estimated to cost the global economy US$ 1 trillion each year (Lancet, 2020).
[4] Christian et al. (2019) find that cash transfers more strongly reduce suicides in the presence of rainfall shocks, suggesting that income may be one mechanism.

Ethiopia. This study has three features that make it a good complement to existing papers. First, I utilise rich information from a long-standing longitudinal survey that couples mental health experiences in adulthood with early life conditions. I am therefore able to investigate how the mental health effects of drought vary by conditions going back to early childhood.[5] Second, by employing individual-level data from just before and after the drought, I can quantitatively examine several mechanisms proposed in the existing literature that may underlie my estimated treatment effects. Finally, I add to the limited evidence on the causal effects of rainfall variability on mental conditions in Africa.[6] Drought is Africa's foremost natural disaster[7] and we may expect the mental health effects of drought to be larger in Africa due to the population's high reliance on rainfed agriculture[8], its inadequate infrastructure, and low adaptive capacity (World Meteorological Organization, 2022).

I employ three datasets in my analysis: the first two datasets contain monthly precipitation and temperature data in Ethiopia from 1981 to 2021, respectively; the third consists of information collected in the Young Lives longitudinal study. My analysis relies on a difference-in-differences research design, where one of the dimensions of variation is the community of residence, and the other dimension is whether the participant was exposed to the 2021 drought. The timing of the drought was such that it fell between two survey rounds, allowing a before-and-after comparison of the same individuals. Under a parallel trends assumption, the variation generated by drought exposure allows me to obtain causal estimates of water scarcity on young adults' mental health. My empirical strategy allows me to control for various confounding factors: first, community-specific differences fixed in time (e.g., individuals in poorer communities may have worse baseline mental health than their counterparts in wealthier

[5] I also provide novel evidence on the effects of rainfall variability on mental health during young adulthood – a life period also known as 'impressionable years'. Young adulthood is a particularly important time to examine the determinants of mental health, as global evidence suggests that the majority of mental disorders emerge in adolescence and early adulthood (Patel et al., 2018) and are often persistent over time with significant personal and public health consequences (Burcusa and Iacono, 2007).

[6] There are two studies in Africa that are closely related to this one. First, Dinkelman (2017) finds that early childhood drought exposure has a negative impact on later-life mental disability in South Africa. Mental disabilities and mental conditions are closely related but are not the same; disability is produced by mental illness, but it also depends on simultaneously present comorbid diseases or impairments. Indeed, Sartorius (2009) argues that disabilities and mental illnesses are distinct phenomena and should be evaluated independently. Second, Alem and Colmer (2022) find that increases in rainfall variability are associated with reductions in life satisfaction in Ethiopia. While subjective well-being and mental conditions are related, they are not the same. Clark et al. (2017) finds that the correlation between life satisfaction and mental illness ranges from -0.21 in USA to just -0.07 in Indonesia.

[7] In the last three decades, droughts in Africa have affected more people than all other natural disasters combined. (http://www.emdat.be/).

[8] In Africa, 95% of agriculture still relies on rainfall for water (Abrams, 2018).

communities); second, differences across time that affect all individuals in a similar way (e.g., certain macroeconomic fluctuations). I also address recent econometric concerns with two-way fixed-effects research designs by showing robustness to alternative estimators.[9]

I find that exposure to drought worsens young adults' mental health. More specifically, exposure to below-average precipitation leads to a 0.35 and 0.29 standard deviation increase in the probability of experiencing symptoms consistent with either mild or severe anxiety and depression, respectively. As a point of comparison, these magnitudes are around 75-90% of the effect of unemployment on mental health observed in developed countries, as reported in Cygan-Rehm et al. (2017).

Beyond this, I establish several novel facts regarding the relationship between drought and mental health. First, the effect on depression increases with the intensity of drought exposure, while the effect on anxiety is more generalized and is experienced equally among those exposed to below-average rainfall. Second, the negative effects are consistently strongest among those who grew up in the poorest households in early childhood and those who had low childhood reading abilities, while the effect on depression is also pronounced among those with the low self-esteem. This suggests that the mental health effects of rainfall variability may exacerbate existing inequalities. Third, running a mediation analysis, I find that that drought-induced changes in food insecurity, inflation, and perceived household poverty explain roughly 45% of the increase in anxiety, and 42% of the increase in depression, respectively - with changes in food insecurity consistently being the most important mediator.

The rest of the paper is organised as follows: the next section discusses the country context in Ethiopia. Section 3 describes the data, while Section 4 presents the empirical strategy. My main results are reported in Section 5. Section 6 reports heterogenous treatment effects, while Section 7 presents a decomposition of the main results, quantifying the extent to which changes in food insecurity, perceived poverty, physical illness, and inflation play a role in explaining the negative effects of drought on mental health. Section 8 concludes.

[9] See Roth et al. (2023) for a recent overview of the differences-in-differences literature.

2. Country context

The context of my study is Ethiopia. Like many countries in Africa, Ethiopia is a country plagued by a history of droughts, experiencing approximately one drought event per decade between the 1950s and 1980s. Moreover, a number of studies have indicated a drying trend for the long rain season over the past few decades (e.g., Funk et al., 2005; Williams and Funk, 2011), corroborated by an increase in the prevalence of severe droughts. For example, between 1980 and 2004, the country experienced 16 severe drought events - roughly one every 18 months (World Bank, 2006). This increase in frequency is concerning as the country is particularly vulnerable to droughts, given that 80% of its population lives in rural areas and depends on rain-fed agriculture (UN DESA, 2019).

In 2021, Ethiopia experienced a prolonged drought after both rainy seasons failed in the year, affecting roughly 6.8 million people (UN OCHA, 2022a). While the drought in 2021 was relatively mild compared to recent droughts[10], the situation continued to worsen throughout 2022 , resulting in one of the most severe droughts in the country in the last four decades (UN OCHA, 2022b). Descriptive evidence suggests that the event had a significant impact on vulnerable livelihoods, especially those reliant on livestock. By January 2022, over 260,000 livestock deaths had been reported, and two million more were at risk in affected areas. This, combined with widespread crop failures, affected communities' food security. In early 2022, the World Food Programme estimated that 5.7 million people affected by the drought needed food assistance (Khorsandi and Snowdon, 2022).

Like many low- and middle-income countries, Ethiopia is also a country where mental conditions have not been adequately studied (Yitbarek et al., 2021) and those suffering from mental health conditions are often faced with social stigma (Girma et al., 2022). A meta-analysis by Kassa et al. (2018) revealed that the prevalence of common mental illnesses in Ethiopia is higher than most developed countries, with approximately 22% of the population estimated to be suffering from depression. Despite this, the availability of mental health care in the country is extremely low. According to the Ministry of Health, mental health professionals constitute only 0.26% of the national health workforce, and there are only 46 practicing clinical psychologists in the country (0.045 per 100,000 population) (Ministry of

[10] The 2015 drought was estimated to have affected roughly 10 million individuals (Philip et al., 2018).

Health, 2020). Additionally, there is only one dedicated psychiatric hospital (in Addis Ababa) and just 26% of health facilities are reported to have integrated mental health services into their general services. Consequently, despite many individuals wanting to seek help for mental illnesses (Bifftu et al., 2018), few manage to visit appropriate health facilities (Hailemariam et al., 2012).

3. Data and descriptive statistics

My analysis replies on three main data sources. The first data source consists of information collected in the Young Lives longitudinal study, one of the most comprehensive surveys about young people available in the country. The second and third data sources contains monthly precipitation and temperature data, respectively, in Ethiopia from 1981 to 2021.

3.1 Young Lives

I use data from the Young Lives survey, a unique longitudinal study following children in Ethiopia.[11] Prior to the COVID-19 pandemic, the participants had been visited in person on five occasions since 2002, approximately once every three years, and most recently in 2016. The initial sample consisted of 2,999 participants from 20 woredas in the regions of Addis Ababa, Amhara, Oromiya, the Southern Nations, Nationalities, and People's Region, and Tigray. The woredas were picked in an attempt to oversample areas with food-deficit status, capture ethnic and geographic diversity, and find urban/rural and development-level balance.[12] Hence, Young Lives is not a nationally representative survey; comparison to national statistics data indicate that Young Lives households are generally poorer than the average Ethiopian household. Despite this, existing research has found that the Young Lives sample covers the diversity of children in the country in a wide variety of attributes and experiences (Outes-Leon and Sánchez, 2008).

The COVID-19 outbreak began when the Young Lives fieldwork was about to start for the sixth round of (in-person) data collection. In recognition of the health crisis, the fieldwork was

[11] Young Lives also collects information on young people in Vietnam, Peru, and India. Further details can be found at www.younglives.org.uk.

[12] Within each woreda, a village was randomly selected, and households were randomly contacted (moving clockwise from a random initial location) until approximately 100 eligible families were found.

postponed; instead, a five-part phone survey was implemented (Favara et al., 2021). At that time, participants were, on average, 21 years old. An initial contact phone call with the respondents took place in June-July 2020, a few months after the COVID-19 outbreak. The second and third calls took place in August-October and November-December of 2020, while the fourth and fifth calls took place in August 2021 and November-December 2021, respectively. Given their remote nature, the phone surveys consisted of reduced questionnaires compared to an in-person survey round.

Attrition rates observed in the Young Lives sample have been relatively low compared to similar long-running studies; in 2016 (the last in-person survey round), the attrition rate in Ethiopia was 12.4% (Sánchez and Escobal, 2020). However, in November 2020, a long simmering feud between Ethiopia's federal government and Tigray's regional ruling party - the Tigray People's Liberation Front (TPLF) - escalated into a civil war, preventing Young Lives from contacting participants in the Tigray region. Consequently, I have restricted my sample to Young Lives participants not in this region. Among this sample, the annual attrition rate has been just 1.35% since 2002. Analysing attrition, I find that those who have attrited are similar to non-attritors along a host of characteristics measured in 2002, suggesting that attrition is unlikely to be systematically related to baseline characteristics (Table A.1 in the Appendix). While the initial Young Lives sample covered 20 woredas, the study continued to track participants as they moved (Sánchez and Escobal, 2020), and my analytical sample consists of 117 woredas.

In the second, third, and fifth phone survey calls, 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. The GAD-7 assesses the frequency of seven symptoms of anxiety over the past 14 days, while the PHQ-8 gauges the frequency of eight symptoms of depression over the same period.[13] Amharic versions of both scales have previously been validated and used in the Ethiopian context (e.g., Hanlon et al., 2015; Gelaye et al., 2013; Abdisa et al., 2022). The ninth question of the PHQ (relating to suicidal thoughts) was dropped due to ethical concerns about how to provide support, and the scales were slightly

[13] The full list of statements is reported for the GAD-7 and PHQ-8 in Figures A.1 and A.2 in the Appendix, respectively.

adapted for administration during a phone survey.[14] For each item, participants were asked whether the symptom had been experienced (Yes/No), and, if 'Yes', they were then asked about the frequency. The frequency was reported using a 3-item Likert scale ranging from 1 'Less than half the days' to 2 'more than half the days' to 3 'nearly every day'. By summing up the frequency of all symptoms, one can generate a continuous raw score, which has a maximum value of 21 for the GAD-7 and 28 for the PHQ-8. Following previous literature (e.g., Porter et al., 2021), for both anxiety and depression, I construct a binary dependent variable where 0 indicates no/minimal anxiety (or depression) and 1 indicates the presence of symptoms consistent with at least mild anxiety (or depression). For each indicator variable, a cut-off of ≥ 5 was used to represent the presence of "at least mild symptoms" of anxiety (Spitzer et al., 2006) or depression (Kroenke et al., 2009).

3.2 Climate data

3.2.1 Precipitation data

To construct an exogeneous measure of drought exposure, I use high spatial resolution (0.05° or 6x6 kilometre grid) monthly rainfall data from 1981 to 2021 from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data set (Funk et al., 2015). The CHIRPS dataset has previously been validated in Ethiopia (Dinku et al., 2018; Degefu et al., 2022), and used in recent economic studies (Brunckhort, 2020). I merge the Young Lives data to the climate data using the GPS co-ordinate of the centre of each participant's woreda in November-December 2020. For each woreda, monthly rainfall precipitation is calculated as an inverse-distance-weighted average of the monthly rainfall registered at the four closest grid points to that community.

To identify exogenous rainfall shocks and their intensity, for each woreda, I construct a Standardised Precipitation Index (SPI). The SPI was first proposed by McKee et al. (1993) and is recommended by the World Meteorological Organisation for the characterization of droughts (Wu et al., 2007). The SPI derives a value for a month's rainfall in terms of standard deviations

[14] First, participants were asked whether they were alone in the room and if not, whether they could find a quiet space and/or make sure their phone speaker was off. Second, for each item, individuals were first asked whether the symptom had been observed (Yes/No) over the past 14 days, and only if 'Yes' then they were asked about the frequency. The adapted questions were piloted prior to the data collection, and the scales were administered as the last section of the survey.

from the long-term mean of the transformed standardised normal distribution for that month-of-year and community specifically. Deviations from the mean are more relevant than absolute rainfall because individuals and communities typically adapt to local average conditions (e.g., with regard to composition of agricultural products). The SPI is preferred to using raw precipitation data as the non-negative and positively skewed nature of rainfall is accounted for prior to normalisation. Figure 1 displays the estimated SPI in Ethiopia in 2021, showing that the drought was concentrated primarily in the south of the country.

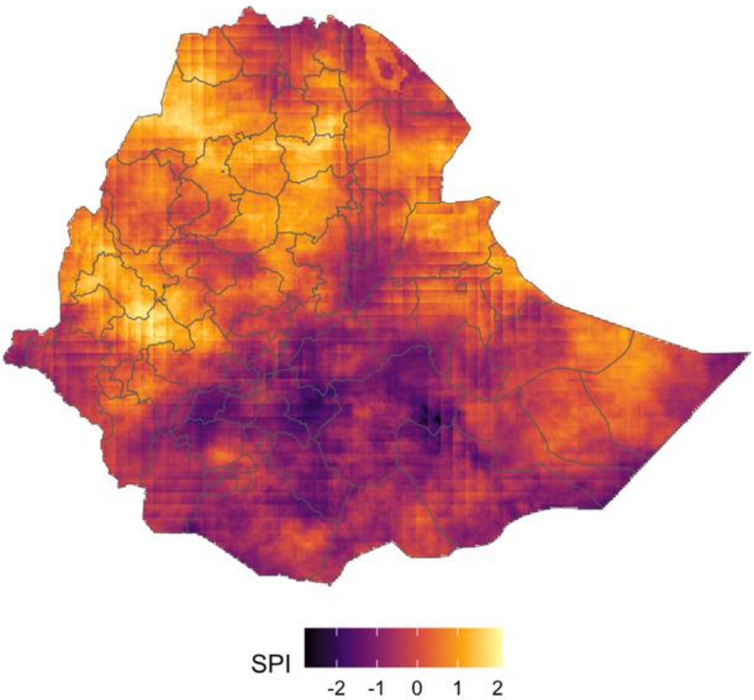

Figure 1. 12-month SPI for January-December 2021.
Source: Author's calculation using precipitation data from the CHIRPS.

3.2.2 Temperature data

Temperature data are drawn from the latest version of the Climatic Research Unit Time Series (CRUTS, version 4.05). The dataset is produced by the University of East Anglia's Climatic Research Unit and covers the period 1901-2021. Each 0.5° grid cell is assigned temperature data according to its covering land-based stations. If a cell is covered by one station, temperature data are taken from that station. If a cell is covered by two or more stations, temperature data are calculated using the angular distance-weight average from those stations.[15] In addition, the numbers and locations of stations contributing to any grid cell will change over time. While these issues have been shown to be problematic for precipitation data, temperature, in particular, has been shown to be largely resilient to these problems, in part due to its long correlation decay distance (Harris et al., 2020).[16]

To ensure comparability of long-term trends with the CHIRPS precipitation data, I use temperature data from 1981 onwards. For each woreda, monthly temperature is calculated as an inverse-distance-weighted average of the temperature registered at the four closest grid points to the GPS co-ordinate of each community. Next, to characterise exogenous temperature shocks and their intensity, I construct a variable capturing temperature deviation. Specifically, I measure the difference in the average temperature in each woreda in 2021 compared to the long-run average temperature in the same area.

3.3 Descriptive statistics

Given the relative nature of the SPI, I define villages affected by drought as those with a 2021 12-month SPI less than 0 (McKee et al., 1993). Table 1 reports descriptive statistics from my analytical sample and presents normalised differences between the two groups (as recommended by Imbens and Rubin, 2015). I find that the majority (79%) of respondents experienced below long-run average precipitation in 2021, with an average SPI among the drought-exposed of -0.68.[17] However, those not exposed to the drought faced significantly higher temperature deviations in 2021, with an average temperature deviation of nearly 0.2°C.[18]

On average, the two groups are well balanced according to age, sex, education enrolment, ownership of pit latrines, and number of rooms. However, there are significant differences across all other variables. In particular, it appears as though drought-affected participants come from relatively wealthier families, as their mothers are more likely to have at least primary

[15] If a cell is not covered by any stations, data are interpolated with the cell's average temperature between 1961–1990. This has the advantage of being a known entity, rather than an estimate, but has the unavoidable side effect of decreasing variance.
[16] The CRUTS also contains information on precipitation. However, Degefu et al. (2022) find that it does not accurately capture the spatial pattern and severity of major drought events in the country.
[17] The full distribution of the SPI among my sample is shown in Figure A.3 in the Appendix.
[18] Some existing studies, such as Christian et al. (2019) and Carleton et al. (2017), do not control for temperature changes when analysing the effects of rainfall variability on mental health. The fact that temperature deviations in 2021 are higher among my control group implies that I would likely underestimate the true effect of the drought on mental health were I not to control for temperature changes during the year.

schooling, and their households had higher average wealth index scores in both 2002 and 2016.[19] In line with this, I also find that individuals exposed to the 2021 drought had higher reading ability in 2013,[20] higher self-esteem in 2016, and lower rates of at least mild anxiety and depression in November-December 2020.

Additionally, individuals in the control group come from communities that have been more affected by recent conflict, as nearly 23% of participants report that they have been internally displaced in 2021 due to the civil war (compared to less than 1% of those in the drought group). Furthermore, control participants experienced an average of 21.6 reported fatalities in their woreda since November 2020, compared to just 2.4 fatalities in drought-exposed woredas.[21] In accordance with this, the majority of participants in the control group come from Amhara, the neighbouring region to the recent Tigray conflict.

The differences between those exposed to the drought and those not exposed may raise questions about their comparability. However, previous research suggests that lower wealth is typically associated with poorer mental health (Ridley et al., 2020), particularly in LMICs (Thomson et al., 2022), and that exposure to conflict significantly worsens mental health (e.g., Favara et al., 2022; Osiichuk and Shepotylo, 2020). Consequently, if drought-exposed participants come from relatively wealthier families that have been less affected by conflict, this would imply that, if anything, I would be likely to *understate* the magnitude of the drought's effect on mental health.

Table 1. Summary statistics

	(1)	(2)	(3)	
Variable	**Total**	**Non drought affected**	**Drought affected**	**Normalized difference**
	Mean	Mean	Mean	(2) - (3)
Individual characteristics				
Age (in years)	20.728	20.740	20.725	0.005
Female	0.471	0.441	0.479	-0.076

[19] The Young Lives 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 (see Briones, 2017 for more details).

[20] Reading ability was measured using a reading comprehension based on extensive piloting of a bank of potential reading items. Given that the participants were different ages in 2013, a straightforward comparison is not appropriate without first equating scores. This equating has been implemented using a 2-parameter item response theory model to generate standard scores which are comparable across time (see Espinoza Revello and Scott, 2022).

[21] Data from The Armed Conflict Location and Event Data Project (ACLED) (Raleigh et al., 2010).

Enrolled in school (Nov-Dec 2020)	0.664	0.700	0.654	0.098
Self-esteem score (2016)	0.026	-0.034	0.042	-0.138***
Reading score (2013)	0.149	-0.134	0.234	-0.362***
At least mild depression (Nov-Dec 2020)	0.182	0.353	0.136	0.522***
At least mild anxiety (Nov-Dec 2020)	0.187	0.373	0.137	0.563***
Household characteristics				
Urban (Nov-Dec 2020)	0.443	0.373	0.462	-0.182***
Household size (Aug-Oct 2020)	5.404	5.136	5.472	-0.154**
Mother has primary schooling (2016)	0.598	0.553	0.610	-0.116*
Skipped a meal in past year (Nov-Dec 2020)	0.141	0.251	0.111	0.371***
Wealth index (2016)	0.432	0.377	0.447	-0.428***
Wealth index (2002)	0.225	0.175	0.239	-0.351***
Number of rooms (Aug-Oct 2020)	2.520	2.596	2.449	0.075
Has pit latrine (Aug-Oct 2020)	0.788	0.794	0.787	0.017
Has a television (Aug-Oct 2020)	0.557	0.376	0.605	-0.472***
Has access to electricity (Aug-Oct 2020)	0.759	0.655	0.786	-0.295***
Household member suspected to be infected with COVID-19 (Nov-Dec 2020)	0.009	0.000	0.011	-0.152**
Community characteristics				
Standardized Precipitation Index (2021)	-0.374	0.776	-0.683	3.837***
Average temperature deviation (2021)	0.165	0.195	0.157	2.201***
Addis Ababa (Nov-Dec 2020)	0.207	0.006	0.261	-0.810***
Amhara (Nov-Dec 2020)	0.153	0.721	0.002	2.249***
Oromiya (Nov-Dec 2020)	0.293	0.271	0.298	-0.061
SNNP (Nov-Dec 2020)	0.191	0.000	0.241	-0.798***
Sidama (Nov-Dec 2020)	0.156	0.003	0.197	-0.683***
Internally displaced due to conflict (Nov-Dec 2021)	0.068	0.229	0.005	0.896***
Cumulative reported fatalities since Nov 2020 (Nov-Dec 2021)	6.249	21.652	2.373	0.793***
Observations	1,633	343	1,290	

Notes: Drought affected refers to individuals living in a woreda with a 2021 12-month SPI < 0, while non-drought-affected reflects individuals living in a woreda with a SPI ≥ 0. Wealth index is based on the Young Lives wealth index (Briones, 2017). Self-esteem is measured using the Rosenberg self-esteem scale (Rosenberg, 1965), and is represented as a z-score. Reading score represents the results of a reading comprehension test that was asked to children who could read Amharic, Oromifa, or Tigrinya. Reading scores have been equated using an item response theory model (Espinoza Revello and Scott, 2022). The normalized difference between treatment and control groups are computed as the difference in means divided by the square root of half of the sum of the variances. * p < 0.10, ** p < 0.05, *** p < 0.01

4. Empirical strategy

The primary goal of this paper is to identify the causal impact of water scarcity on mental health. The timings of the Young Lives phone surveys, and the quasi-experimental variation in exposure to the 2021 drought, allows me to estimate the impact of drought exposure on mental health using a canonical difference-in-differences (DiD) strategy. The strategy compares the before-after differences in outcomes between individuals in communities that were exposed to the drought and individuals in communities that did not experience the drought between the two periods. As documented by Currie et al. (2020), DiD methods have been widely adopted in applied economics over the last few decades, as they can lead to a substantial reduction in selection bias and give us an effect of the "treatment on the treated" (ATT).

I estimate the following DiD model:

$$MH_{it} = \alpha + \beta_1 D_{ig} + \beta_2 Post_t + \beta_3 (D_{ig} \times Post_t) + \boldsymbol{\delta X_{ihg}} + \gamma_r + \varepsilon_{it}, \quad (1)$$

where MH_{it} represents the mental health outcome for individual *i* at time *t*. I standardize both mental health outcome measures by the baseline (2020) means and standard deviations of the control individuals who were not exposed the drought. D_{ig} is a treatment dummy with D_{ig} = 1 if individual *i* in woreda *g* is in the treated (drought-exposed) group. $Post_t$ is a binary variable with *Post* = 1 in November-December 2021, and 0 in November-December 2020 (equivalent to a time fixed effects term). $\boldsymbol{X_{ih}}$ is a vector of time-varying individual, household, and community controls, including the average temperature deviation in 2021, the participant's age (in months), education enrolment status, highest education grade, household size, number of rooms in the house, whether the household has a pit latrine, a television, and access to electricity, whether the household is in an urban (or rural) area, whether the household has migrated from its pre-drought location (Nov-Dec 2020)[22], and whether any members of the household have been infected/suspected to be infected with COVID-19.[23] γ_r represents region fixed effects, included to mitigate the concern that, given regional autonomy, different regions may have responded to the drought differently.

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[22] Just 10% of my analytical sample moved during the 2021 year. However, it is possible that migration is endogenous and is induced by drought exposure. I find that my results are also robust to excluding individuals who migrated during the drought (Table A.3 in the Appendix).

[23] Given the shortened nature of the phone surveys, not all time-varying controls are observed in every call. Information about the participants' highest education grade, household size, number of rooms, whether the household has a pit latrine, a television, and access to electricity was collected in the second and fifth phone survey, but not in the third. Given the relatively short time period between the second and third surveys (Aug-Oct 2020 and Nov-Dec 2020), I assume that they remain constant between the two calls. This could be controversial, however, if, for example, some household sell assets as a response to climate shocks. I find that my results are robust to both excluding the more pliant controls (ownership of TV and household size – Table A.4) and excluding all controls (Section 5.3).

Ethiopia has experienced a number of civil conflicts in recent years that might also affect mental health (Favara et al., 2022). Most notably, in November 2020, a war broke out between Ethiopia's government and the Tigray People's Liberation Front, which lasted until a peace treaty was signed at the end of 2022. To control for possible mental health effects of conflict exposure, I match the Young Lives data to longitudinal conflict 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 participant's woreda since November 2020. Additionally, I control for whether participants report having been internally displaced in 2021 due to conflict. I cluster standard errors at the woreda level, the unit of treatment assignment (Abadie et al., 2023), and also present spatial standard errors following Conley (2008) that allow for spatial correlations between woredas whose centres lie within a certain cut-off distance (Dell et al., 2014).[24]

To the extent that, in the absence of the drought, the mental health outcomes of individuals in communities in different drought-exposed groups would have evolved along parallel trends, the coefficient of interest, β_3, identifies the ATT of the 2021 drought on young adults' mental health. Given the baseline differences observed in Table 1, one may worry about the plausibility of the parallel trends assumption in my setting. To test for pre-drought differences in mental health trends, I use information collected before the drought and apply Equation (1) to data for August-October 2020 and November-December 2020; here, β_3 captures the difference in trends in the pre-period. For both anxiety and depression, the coefficient of interest is not significantly different from zero, suggesting that I cannot reject that pre-trends were parallel prior to the 2021 drought (Table A.2 in the Appendix).[25] A limitation of my data is that symptoms of anxiety and depression were not recorded prior to 2020 and so I am unable to directly test for pre-trends beyond this. However, as a proxy for mental health, I use information collected since 2006 on life satisfaction and test for pre-trends.[26] For all periods

[24] I set the cut-off distance to 10 kilometres. However, my results are insensitive to variations of the cut-off distance.

[25] Given the shortened nature of the third phone survey, not all time-varying controls are observed in this call. Consequently, in the pre-trends analysis, I am only able to control for age, education enrolment, location (urban/rural), migration, and region. I find that the estimated coefficients are not significantly different from zero both with and without time-varying controls.

[26] Information on life satisfaction has been collected since 2006 using the Cantril (1965) self-anchoring scale (also known as Cantril's Ladder). This asks the participants to visualize a ladder of nine steps, with the bottom step representing the worst life for them and the top step representing their best possible life. Respondents were asked to identify which step they presently stood on.

considered, I cannot reject that pre-trends in self-reported life satisfaction were parallel prior to the 2021 drought (Figure A.4 in the Appendix).

Another assumption required for identification is that the drought had no causal effect before its onset (i.e., no anticipation effects). This is unlikely to be an issue in this setting as, although Ethiopia is subject to frequent droughts, Colmer (2021) finds that there is no meaningful effect of rainfall variability on historical or future rainfall realizations, suggesting that individuals would have been unlikely to have been able to anticipate the 2021 drought. Indeed, the last severe drought (in 2015) was concentrated in the north of the country rather than the south.

Lastly, I extend the framework to identify heterogeneous effects and quantify whether individuals with certain characteristics are more or less vulnerable to drought. The estimated specification is as follows:

$$MH_{it} = \alpha + \beta_1 D_g + \beta_2 Post_t + \beta_3 I_{ihg} + \beta_4 (D_g \times Post_t) + \beta_5 (I_{ihg} \times Post_t) + \beta_6 (I_{ihg} \times D_g) + \beta_7 (I_{ihg} \times D_g \times Post_t) + \boldsymbol{\delta X_{ihg}} + \gamma_r + \varepsilon_{ihgt,} \quad (2)$$

where *I* represents a participant's characteristic of interest. In particular, I am interested in whether the effects differ according to pre-drought location (urban/rural), whether the participant was working in agriculture before the drought[27], early childhood household wealth, childhood reading skills, and psychosocial skills (self-esteem).

5. Results

5.1 Main results

Table 2 presents estimates of β_3 in Equation (1) and shows the average effects of water scarcity on mental health. I find that exposure to the 2021 drought significantly increases young adults' experiences of both anxiety and depression. More specifically, exposure to below long-run

[27] In November-December 2020, Young Lives collected information on employment in the week before the survey, defined as working (paid or unpaid) for at least an hour in one's own business, for a household member, or for someone else. I define a participant as working in agriculture if they reported working in one of the following activities: self-employed (food crops), self-employed (non-food, including horticulture, sericulture and floriculture), self-employed (aquaculture), self-employed (livestock), wage employment (agriculture), annual farm servant, or other (allied) agriculture.

average rainfall increases the probability of experiencing symptoms of at least mild anxiety and depression by 0.35 standard deviations and 0.29 standard deviations, respectively.[28]

Table 2. Effect of the 2021 drought on anxiety and depression

	(1) **At least mild anxiety**	**(2)** **At least mild depression**
Drought (β_3)	0.346***	0.291***
	(0.103)	(0.110)
Inference robustness (β_3)		
p-value: robust SE	0.001	0.009
p-value: spatially adjusted SE	0.001	0.006
R^2	0.136	0.120
Observations	3,117	3,117

Notes: This table presents estimates of β_3 in Equation (1). Mental health outcomes are standardized using the baseline (2020) means and standard deviations of the control group. All regressions control for temperature deviations, age, education status, highest education grade, household size, number of rooms in the house, whether the household has a pit latrine, a television, and access to electricity, whether the household is in an urban (or rural) area, whether the household has migrated, the cumulative number of reported fatalities in each participant's woreda since November 2020, whether participants report having been internally displaced due to conflict, region fixed effects, 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 (2008) spatial standard errors are estimated using a 10km cut-off. * p < 0.10, ** p < 0.05, *** p < 0.01.

To facilitate intuition about the size of my effects, I provide a few benchmarks. First, I benchmark the magnitude of my estimates against the effect of unemployment on mental health. Comparing my estimates to that of Cygan-Rehm et al. (2017), I find that the estimated impacts of the drought on anxiety and depression are around 90% and 75% of the estimated effect of unemployment on mental health in developed countries.[29] Second, extrapolating the estimates provided by Romero et al. (2021), the point estimate for depression in Table 2 implies that a cash transfer of roughly $1,155 would be needed to fully offset the negative impact of the drought on depression.[30]

Online Appendix Table A.5 presents the impacts of drought exposure on each symptom in the GAD-7 and PHQ-8 scale separately. The table also provides unadjusted p-values and, to account for multiple hypothesis testing, sharpened false discovery rate-adjusted q-values

[28] To ensure that my results are not driven by specific woredas, I re-estimate Equation (1) dropping one woreda at a time. My findings remain robust to this approach, and point estimates range from 0.280-0.437 for anxiety, and 0.267-0.387 for depression. Figures A.5 plots all estimated treatment effects.

[29] Cygan-Rehm et al. (2017) analyse the effect of unemployment on mental health in Australia, Germany, the UK and the US. Across all four countries, they find, on average, that unemployment impairs mental health by no more than 0.386 standard deviations.

[30] In a recent meta-analysis on the causal impact of cash transfers on mental health, Romero et al. (2021) found that transfers, with an average worth of $540 per person, reduced depression in LMICs by 0.136 standard deviations.

following the procedure of Benjamini et al. (2006). For all but two of the GAD-7 symptoms, the point estimates are positive and statistically significant, indicating heightened anxiety. For the PHQ-8 questions, however, the point estimates are only significant for three of the eight symptoms. The symptoms that appear to be most affected by the drought are “feeling down, depressed or hopeless”, “trouble falling or staying asleep, or sleeping too much” and “feeling bad about yourself – or that you are a failure or have let yourself or your family down”. This negative impact of water scarcity on sleep patterns may have wider economic implications, as a large body of research documents severe negative effects of sleep deprivation on a number of outcomes, including earnings (e.g., Gibson and Shrader, 2018; Giuntella and Mazzonna, 2019) and cognitive functioning (e.g., Banks and Dinges, 2007; Lim and Dinges, 2010).

5.3 Differences by drought intensity

It is straightforward to estimate how sensitive outcomes are to drought intensity (the “dose-response”) by replacing D_{ig} in Equation (1) with the SPI for the treated group. However, in this class of DiD models with continuous treatment, an additional identifying assumption is required - that the “average treatment effect function” does not differ with the treatment dose (Callaway et al., 2021). In other words, we need to assume that high-dose individuals (those exposed to greater drought) would have had the same treatment effects as the low-dose groups, had they been exposed to the same treatment intensity. While we cannot test this empirically, this is unlikely to be true if the dose itself is correlated with observables (Cook et al., 2023). Appendix Figure A.6 shows the results of a balancing test that evaluates the degree to which the SPI is related with covariates (conditional on being in the drought-exposed group). The estimates show that there is little to distinguish between those in mildly- and severely-drought-exposed areas.

Table 3 reports the DiD results. The table suggest that drought intensity seems to matter more for depression, as a one unit increase in the SPI (relatively more rainfall) leads to a 0.21 standard deviation reduction in the probability of experiencing at least mild depression. In contrast, while the coefficient for anxiety is negative, it is not significantly different from zero. This suggests that the negative effect on anxiety is more generalized and likely to be observed even among those who are only mildly exposed to drought. The observation that even minor deviations in rainfall may impact anxiety is in line with international evidence documenting that there is typically a sequential relationship between the emotions such that anxiety comes before depression (Boland and Keller, 2009; Fava et al., 2000).

Table 3. Effect of the 2021 drought on anxiety and depression, by drought intensity

	(1) **At least mild anxiety**	**(2)** **At least mild depression**
SPI (β_3)	-0.139	-0.256**
	(0.111)	(0.117)
Inference robustness (β_3)		
p-value: robust SE	0.213	0.031
p-value: spatially adjusted SE	0.193	0.023
R^2	0.134	0.127
Observations	3,117	3,3117

Notes: This table presents estimates of β_3 in Equation (1), replacing D_{ig} with the SPI for the treated group. Mental health outcomes are standardized using the baseline (2020) means and standard deviations of the control group. All regressions control for temperature deviations, age, education status, highest education grade, household size, number of rooms in the house, whether the household has a pit latrine, a television, and access to electricity, whether the household is in an urban (or rural) area, whether the household has migrated, the cumulative number of reported fatalities in each participant's woreda since November 2020, whether participants report having been internally displaced due to conflict, region fixed effects, 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 (2008) spatial standard errors are estimated using a 10km cut-off. * p < 0.10, ** p < 0.05, *** p < 0.01.

5.3 Robustness: Alternate estimators

Although regressions resembling Equation (1) have been the workhorse models for quasi-experimental DiD research designs[31], they have been shown to deliver consistent ATT estimates only under relatively strong assumptions about homogeneity in treatment effects (Roth et al., 2023). Specifically, incorporating time-varying covariates into the DiD assumes homogenous treatment effects in $\boldsymbol{X}$ (e.g., the ATT cannot vary by age of participants), and it requires that the evolution of control covariates is the same for both treatment and control groups over the period (i.e., it rules out $\boldsymbol{X}$-specific trends in both treated and comparison groups) (Sant'Anna and Zhao, 2020).

I pursue a two-pronged strategy to check the robustness of my results to such concerns: first, I estimate a version of Equation (1) with no time-varying controls. Second, as an alternative

[31] de Chaisemartin and D'Haultfœuille (2020) found that 19 percent of all empirical studies published by the *American Economic Review* between 2010 and 2012 used a two-way fixed-effects regression to estimate the effect of a treatment on an outcome.

approach to allow for covariate-specific trends, I implement Sant'Anna and Zhao's (2020) doubly robust estimator, which uses pre-treatment covariates to model a propensity score (i.e., the conditional probability of belonging to the drought-exposed group) and combines this with a conditional outcome regression model. As this estimator uses time-invariant covariates, I add additional controls for the participants' sex, wealth index score in 2002 and 2016, and mother's highest schooling grade. For both estimations, I find that my results remain statistically significant at the 5% level.[32] Indeed, the point estimates using the doubly robust estimator are larger than those in Table 2 (at 0.498 and 0.307, respectively), confirming that, if my results are biased, I am likely underestimating the true magnitude of the effect of drought on mental health.

6 Heterogeneous effects

To identify populations whose mental health is more susceptible to drought, I next investigate heterogeneous effects of drought exposure across individuals with different pre-drought characteristics. Figure 3 reports the heterogenous impacts using Equation (2).[33]

Four key patterns emerge. First, in accordance with previous literature (e.g., Carroll et al., 2009; Pailler and Tsaneva, 2018), the negative effects of the drought on mental health are driven by individuals in rural locations. Respondents in rural areas are 0.59 and 0.50 standard deviations more likely to experience an increase in anxiety and depression, respectively, than their urban counterparts. Indeed, the increase in anxiety and depression symptoms is only significantly different from zero for those residing in rural areas, and not among those in urban areas. Second, analysing differences by agricultural work, I find that while the interaction is close to zero for anxiety, participants who were working in agriculture just before the onset of the drought are nearly 0.32 standard deviations more likely to experience an increase in depression, compared to those who were not working in agriculture.

Third, the negative effects of drought on mental health are strongest for young adults who grew up in the poorest households. Individuals who grew up in households with below-average early life household wealth are 0.250 and 0.440 standard deviations more likely to experience an

[32] Full results are shown in Appendix tables A.6-A.7.

[33] All interaction coefficients (β_7) are shown in Table A.8 in the Appendix. The table also sharpened q-values to account for multiple hypothesis testing (Benjamini et al., 2006).

increase in anxiety and depression, compared to those who grew up in relatively wealthier households. Fourth, in a similar vein, the effects of the drought are most pronounced among those who had the lowest reading ability in 2013.[34] Those with below-average reading ability in childhood are roughly one third of a standard deviation more likely to experience a rise in both anxiety and depression. Last, the effects on depression are largest among those who had below-average self-esteem in 2016. Taken together, these findings suggest that rainfall variability has the potential to exacerbate existing inequalities and earlier-life deprivations. This may have long-lasting consequences, particularly if enhanced mental illnesses during young adulthood lead to worse labour market and other economic outcomes (Lund et al., 2022). Potential mechanisms will be discussed further in Section 7.

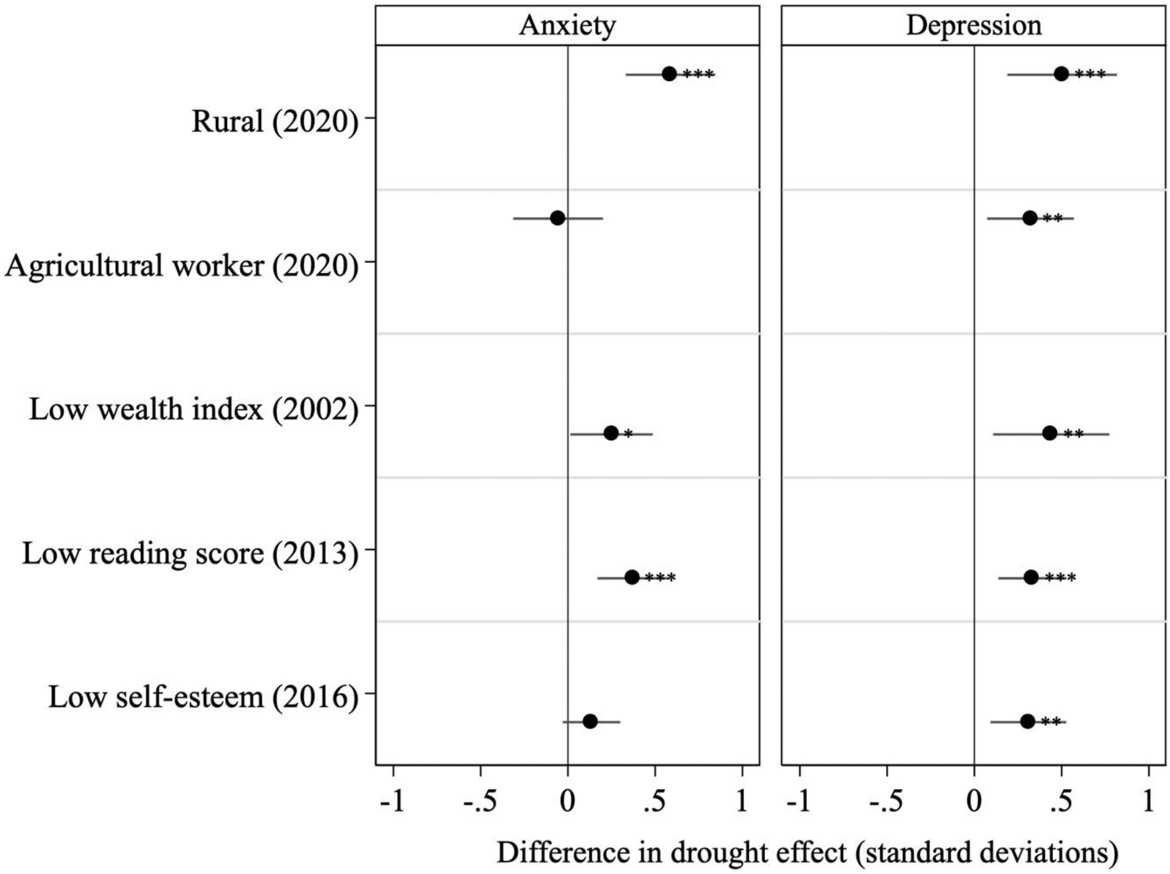


Figure 3. Heterogeneous effects of the 2021 drought on anxiety and depression

Notes: Figure shows estimated $\widehat{\beta_7}$ from Equation (2). Vertical bars indicate a 90% confidence interval around predictions. Wealth index is based on the Young Lives wealth index (Briones, 2017). Self-esteem is measured using the Rosenberg self-esteem scale (Rosenberg, 1965), and reading is measured using a comprehension test that was asked to children who could read Amharic, Oromifa, or Tigrinya. A variable has a 'low' value if it is below the mean value in the sample. All regressions control for temperature deviations, age, education status, highest education grade, household size, number of rooms in the house, whether the household has a pit latrine, a television, and access to electricity, whether the household is in an urban (or rural) area, whether the household

[34] The reading comprehension test was only asked to children who could read Amharic, Oromifa, or Tigrinya. This meant that it was not administered to 34.7% of the drought-exposed group and 19.2% of the control group.

has migrated, the cumulative number of reported fatalities in each participant's woreda since November 2020, whether participants report having been internally displaced due to conflict, region fixed effects, and whether any members of the household have been infected/suspected to be infected with COVID-19. Conley (2008) spatial standard errors are estimated using a 10km cut-off. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7 Mechanisms: the role of changes in perceived poverty, inflation, physical illness, and food insecurity

The previous results suggest that exposure to below long-run average rainfall leads to a significant increase in symptoms of both anxiety and depression among young adults in Ethiopia. To investigate what mechanisms could be at play, I conduct a mediation analysis[35] and estimate the average treatment effects that operate through two separate channels: (*i*) indirect effects resulting from the impact of treatment on measured mediators, and (*ii*) direct effects that operate through channels other than changes in the mediators (including changes in mediators that are not observed) (Heckman et al., 2013).

Existing literature proposes that the effects of droughts on mental conditions can partly be explained by increases in poverty (Berry et al., 2010; Vins et al., 2015). Previous research in Ethiopia has shown that rainfall shocks typically have a negative impact on household consumption and agricultural production (Dercon, 2004; Gao and Mills, 2018), and broader evidence from sub-Saharan Africa suggests that households who experience severe droughts are more vulnerable to poverty (Carter et al., 2007). Unfortunately, given the reduced nature of the phone surveys, Young Lives did not collect objective information on household poverty during the phone surveys. However, in the second and fifth phone surveys, participants were asked a Likert scale question about how they would describe the wealth of their household. Possible answers included 'destitute', 'poor', 'struggle – never have quite enough', 'comfortable – manage to get by', 'rich', and 'very rich'.[36] From this information, I generate a binary variable of perceived household poverty that takes the value of one if the participant described their household as destitute or poor, and zero otherwise.

[35] My mediation analysis closely follows the implementation of Castells-Quintana et al. (2022) and Fagereng (2021), who base their mediation analysis on Heckman et al. (2013) and Heckman and Pinto (2015).

[36] In the last in-person survey round (2016), this subjective measure of household poverty was significantly correlated with a lower wealth index score (Pearson correlation coefficient = -0.176, significant at the 1% level).

This approach follows an increasing body of evidence documenting that the perception of poverty itself, along with its associated uncertainties and worries, can enact a psychological toll and affect cognition (e.g., Mani et al., 2013; Kaur et al., 2022). Thus, whether individuals' subjective assessments of their household wealth are "accurate" in some ex-post sense is perhaps beside the point. As long as young people are reporting their subjective beliefs of poverty without any systematic bias, it is the perceived treatment effects, rather than the actual ones, which are fundamental to informing young people's mental health (Demakakos et al., 2008; Scholten et al., 2017).

Secondly, I include a mediator of household physical health. Prior research suggests that droughts may impair physical health (Stanke et al., 2013), which can lead to a deterioration of mental health conditions (Prince et al. 2007). Research in Ethiopia has found negative impacts of past droughts on health and nutrition outcomes (Dercon and Porter, 2014; Hirvonen et al., 2020). As a proxy for physical health, I use information on illness, death, or injuries in the household. In the second and fifth phone surveys, participants were asked whether, in the past 12 months, their household had experienced an illness, injury, or death of an income-earning member of the household.

Thirdly, as a potential mediator, I include information on inflation. In the past, droughts in Ethiopia have typically been associated with increased inflation due to agricultural supply shocks (Durevall et al., 2013). Although literature on the links between inflation and mental health is scant, research by Di Tella et al. (2001) show, using a panel analysis of nations in Africa, Europe, Latin America, and the US, that reported well-being is strongly (negatively) correlated with the inflation rate. Similarly, Alesina et al. (2004) find that inflation is negatively associated with life satisfaction in 12 European countries. As an indicator of inflation, I use information on whether, in the past year, respondents reported an increase in the price of major food items consumed and/or farming business inputs.

Lastly, I include information related to household food insecurity. Previous literature (e.g., Jones, 2017; Porter et al., 2022) has documented a negative relationship between food insecurity and mental health, and a large body of research has found that droughts can lead to increased food insecurity and malnutrition among those affected (e.g., Dercon and Porter, 2014; Hirvonen, 2020). As an indicator of food insecurity, I use information on whether, in the past year, respondents reported that they, or any household member, had to skip a meal because there was not enough food.

The primary estimating equation for the mediation model can be written as follows.[37]

$$MH_{ihgt} = \alpha + \beta_1 D_{ig} + \beta_2 Post_t + \beta_3 (D_{ig} \times Post_t) + \sum_{m \in M} \theta_0^m \pi_{ih}^m + \boldsymbol{\delta X_{ihg}} + \gamma_r + \varepsilon_{ihgt}. \quad (3)$$

π_{ih}^m are the set of observed mediator variables. The remaining variables on the right-hand side of Equation (3) are defined as in Equation (1). Treatment effects are generated through changes in observed mediators, if the mediators affect the outcomes and the mediators are affected by the treatment. Therefore, estimation of the mediation analysis proceeds in two steps. First, I estimate two models based on Equation (3) with symptoms of anxiety and depression as the outcomes, including both exposure to drought and the set of observed mediators, π_{ih}^m . Second, I estimate separate regressions of Equation (1) with each of the observed mediator variables as the outcome. To deal with the potential issue of multiple hypothesis testing, I also report the sharpened q-values of Benjamini et al. (2006). Results are reported in Table 5.

In Columns (1)-(4) of Table 5, I find that drought exposure leads to a statistically significant, and economically meaningful, increase in food insecurity, perception of household poverty, physical illness, and the experience of inflation. Results in Columns (5) and (6) show that all considered mediators, with the exception of physical illness, are also significant predictors of increased mental conditions. Columns (5) and (6) also indicate that the point estimates of the effect of drought on mental health are markedly lower when controlling for the observed mediators, and the coefficient for depression is no longer statistically significant.

Table 5. The role of perceived poverty, inflation, illness, and food insecurity

	(1) Poverty	**(2) Food insecurity**	**(3) Physical illness**	**(4) Inflation**	**(5) At least mild anxiety**	**(6) At least mild depression**
Drought (β_3)	0.202	0.182	0.124	0.381	0.151	0.109
	(0.045)	(0.081)	(0.058)	(0.096)	(0.092)	(0.092)
	{0.001}	{0.029}	{0.034}	{0.001}	{0.060}	{0.110}
Poverty					0.195	0.077
					(0.064)	(0.048)
					{0.005}	{0.060}

[37] For details, see Appendix B.

Food insecurity					0.343	0.371
					(0.061)	(0.065)
					{0.001}	{0.001}
Physical illness					0.067	0.038
					(0.075)	(0.076)
					{0.165}	{0.174}
Inflation					0.116	0.126
					(0.055)	(0.049)
					{0.034}	{0.016}
Nov-Dec 2020 mean	0.157	0.140	0.069	0.670		
R^2	0.094	0.141	0.078	0.166	0.165	0.130
Observations	3,104	3,104	3,104	3,104	3,104	3,104

Notes: Columns (1)-(4) are estimated using Equation (1), with each mediator as the outcome variable. Columns (5) and (6) are estimated using Equation (3). Poverty takes the value of one if a participant describes their household as destitute or poor, and zero otherwise. Food insecurity takes the value of one if, in the past year, respondents reported that they, or any household member, had to skip a meal because there was not enough food. Physical illness takes the value of one if a respondent reported an illness, injury, or death of an income-earning member of the household, and zero otherwise. Inflation takes the value of one if, in the past year, respondents reported an increase in the price of major food items consumed and/or farming business inputs. Mental health outcomes are standardized using the baseline (2020) means and standard deviations of the control group. All regressions control for temperature deviations, age, education status, highest education grade, household size, number of rooms in the house, whether the household has a pit latrine, a television, and access to electricity, whether the household is in an urban (or rural) area, whether the household has migrated, the cumulative number of reported fatalities in each participant's woreda since November 2020, whether participants report having been internally displaced due to conflict, region fixed effects, and whether any members of the household have been infected/suspected to be infected with COVID-19. Below each coefficient, I report a standard error in parenthesis and a sharpened q-value in curly braces. Standard errors are clustered at the woreda level. q-values are obtained using the sharpened procedure of Benjamini et al. (2006) .

Decomposing the average causal effect of drought, I find that the indirect effects arising from changes in the observed mediators account for 45% and 42% of the average effect of drought exposure on anxiety and depression, respectively.[38] For both mental health outcomes, food insecurity is the most important observed mediator, accounting for 41% and 46% of the indirect effects on anxiety and depression, respectively. Inflation is the next most important mediator, contributing 29% and 38% of the indirect effects of the drought on anxiety and depression, respectively. This suggests that, at least in part, the negative impacts of the drought on mental health may be operating through general equilibrium effects in rural areas. Changes in perceived poverty explain 25% and 12% of the indirect effects of drought on anxiety and depression, while changes in physical illness contributes little.

8 Conclusion

As climate change continues to disrupt water cycles and rainfall patterns, the adverse impacts of drought are likely to intensify. It is therefore increasingly critical to move beyond the average

[38] Detail on the mediation analysis, including calculation of the estimated effects, is included in Appendix B.

mental health effects of drought exposure and identify which individuals are most vulnerable and the underlying mechanisms at play. In this paper, I examine the impacts of drought exposure in Ethiopia on symptoms of anxiety and depression among young adults by matching the Young Lives longitudinal survey to monthly rainfall and temperature data from 1981 to 2021. I find that exposure to low rainfall in 2021 has a significant deleterious effect on mental health. Specifically, exposure to precipitation below its long-run average leads to a 0.35 and 0.29 standard deviation increase in the probability of experiencing symptoms consistent with either mild or severe anxiety and depression, respectively. The effect on depression increases with drought intensity, while the effect on anxiety is more generalized and is experienced equally among those exposed to below-average rainfall.

Heterogenous analyses indicates that the negative effects are consistently driven by individuals living in rural areas, those who grew up in the poorest households in early childhood, and those with low reading abilities in mid-childhood. Additionally, the effect on depression is most pronounced among those who were working in agriculture just before the drought and those with low self-esteem. These findings suggest that the mental health effects of drought have the potential to exacerbate existing inequalities.

Using a simple mediation analysis approach enables me to get a sense of the relative magnitude of the estimated effects that is attributable to changes in food insecurity, perceived poverty, physical illnesses, and inflation. I find that changes these mediators explain close to half of the increase in anxiety and depression, with changes in food insecurity and inflation consistently explaining the most. However, I recognize that there may be many other potential mechanisms, which I am unable to measure in my data, that might explain some of the "direct" relationship between drought and mental health (such as declined agricultural production, household tension, and dietary changes). Future research could attempt to quantify a broader range of potential mechanisms.

My findings hold important policy relevance. Heightened instances of depression may affect productivity and labour supply due to fatigue and disrupted sleep, leading to reduced income. Consequently, the socio-economic effects of droughts may persist even after the period of water scarcity, extending into periods of good harvests. Furthermore, enhanced symptoms of anxiety and depression may induce anhedonia and pessimism, reducing the perceived benefits of taking action, and discouraging individuals with mental disorders from investing in mitigation strategies against future negative shocks (Angelucci and Bennett, 2021). This, coupled with my findings that the observed effects are pronounced among the most historically disadvantaged individuals suggests that, if left unaddressed, droughts possess the potential to perpetuate poverty traps through their adverse effect on mental health (Haushofer, 2019).

Given that nearly half of the population in Sub-Saharan Africa lives in rural areas, and that droughts are occurring more frequently, understanding the effects of water scarcity on mental health is critical for insuring vulnerable populations. My findings suggest that providing mental health and psychosocial support to young people in the wake of droughts is of vital importance. In particular, my mediation results suggest that food rations and poverty alleviation programmes – such as cash transfers – may be an effective policy instrument in mitigating the adverse mental health effects of rainfall variability.

References

Abadie, A., Athey, S., Imbens, G.W. and Wooldridge, J. (2023). When should you adjust standard errors for clustering? The Quarterly Journal of Economics 138(1), 1-35.

Abdisa, L., Letta, S. and Nigussie, K. (2022). Depression and anxiety among people with hypertension on follow-up in Eastern Ethiopia: A multi-center cross-sectional study. Frontiers in Psychiatry 13, 853551.

Abrams, L. (2018). Unlocking the potential of enhanced rainfed agriculture. Report no. 39. SIWI, Stockholm.

Adhvaryu A., Fenske J. and Nyshadham, A. (2019). Early life circumstance and adult mental health. Journal of Political Economy 127(4):1516–1549.

Alem, Y. and Colmer, J. (2022). Blame it on the rain: Rainfall variability, consumption smoothing, and subjective well-being in rural Ethiopia. American Journal of Agricultural Economics 104, 905–920.

Alesina, A., Di Tella, R. and MacCulloch, R. (2004). Inequality and happiness: are Europeans and Americans different? Journal of Public Economics 88, 2009– 2042.

Angelucci, M. and Bennett, D. (2021). The Economic Impact of Depression Treatment in India. IZA Discussion Paper No. 14393.

Balakrishnan, U. and Tsaneva, M. (2023). Impact of Air Pollution on Mental Health in India. The Journal of Development Studies, 59(1), 133-147.

Banks, S., and Dinges, D. (2007). Behavioral and Physiological Consequences of Sleep Restriction. Journal of Clinical Sleep Medicine, 3, 519–528.

Benjamini, Y., Krieger, A.M. and Yekutieli, D. (2006). Adaptive Linear Step-up Procedures that Control the False Discovery Rate. Biometrika, 93(3): 491–507.

Berry, H. L., Bowen, K., & Kjellstrom, T. (2010). Climate change and mental health: A causal pathways framework. International Journal of Public Health, 55(2), 123–132.

Bifftu, B.B., Takele, W.W., Guracho, Y.D. and Yehualashet, F.A. (2018). Depression and Its Help Seeking Behaviors: A Systematic Review and Meta-Analysis of Community Survey in Ethiopia. Depression Research and Treatment.

Boko, M., Niang, I., Nyong, A., Vogel, C., Githeko, A., Medany, M.., Osman-Elasha, B., Tabo, R. and Yanda, P. 2007. Africa. Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson, Eds., Cambridge University Press, Cambridge UK, 433-467.

Boland, R. J., and Keller, M. B. (2009). Course and outcome of depression. In I. H. Gotlib and C. L. Hammen (Eds.), Handbook of depression (2nd ed., pp. 23±43). New York, NY: Guilford.

Bourque, F. and Willox, A. C. (2014). Climate change: The next challenge for public mental health?, International Review of Psychiatry, 26:4, 415-422.

Briones, K. (2017). How many rooms are there in your house? Constructing the young lives wealth index. Young Lives Technical Note, 43, 1–18.

Brunckhorst, B. (2020). Rural Mobility and Climate Vulnerability: Evidence from the 2015 Drought in Ethiopia. CSAE Working Paper Series 2020-17. Centre for the Study of African Economies, University of Oxford.

Burcusa, S.L. and Iacono W.G. (2007). Risk for recurrence in depression. Clinical Psychology Review 27, 959–985.

Burke, M., González, F., Baylis, P., Heft-Neal, S., Baysan, C., Basu, S. and Hsiang, S. (2018). Higher temperatures increase suicide rates in the United States and Mexico. Nature Climate Change 8, 723–729.

Callaway, B., Goodman-Bacon, A., and Sant'Anna, P.H.C. (2021). Difference-in-Differences with a Continuous Treatment. University of Georgia Working Paper.

Cao, Z., Zhou, J., Li, M., Huang, J. and Dou, D. (2023). Urbanites' mental health undermined by air pollution. Nature Sustainability 6, 470–478.

Cantril, H. (1965). The pattern of human concerns. New Brunswick, NJ: Rutgers University Press.

Carleton, T. A. (2017). Crop-damaging temperatures increase suicide rates in India. PNAS, 114(33), 8746–8751.

Carroll, N., Frijters, P., & Shields, M. A. (2009). Quantifying the costs of drought: new evidence from life satisfaction data. Journal of Population Economics, 22(2), 445–461.

Carter, M.R., Little, P.D., Mogues, T., and Negatu, W. (2007). Poverty Traps and Natural Disasters in Ethiopia and Honduras. World Development.

Castells-Quintana, D., Lopez-Uribe, M.d.P. and McDermott, T.K.J. (2022). Population displacement and urban conflict: Global evidence from more than 3300 flood events. Journal of Development Economics 158, 102922.

Chen, S., Oliva, P. and Zhang, P. (2018). Air Pollution and Mental Health: Evidence from China. NBER Working Paper 24686.

Christian, C., Hensel, L. and Roth, C. (2019). Income Shocks and Suicides: Causal Evidence from Indonesia. The Review of Economics and Statistics 101(5): 905-920.

Clark, S.R., Layard, R., Powdthavee, N. and Ward, G. (2017). The Key Determinants of Happiness and Misery. In Helliwell, J., Layard, R. and Sachs, J (Eds.), World Happiness Report 2017. New York: Sustainable Development Solutions Network.

Colmer, J. (2021). Rainfall Variability, Child Labor, and Human Capital Accumulation in Rural Ethiopia. American Journal of Agricultural Economics 103(3): 858–77.

Conley, T.B. (2008). Spatial Econometrics in The New Palgrave Dictionary of Economics (London: Palgrave).

Cook, L.D., Jones, M.E.C., Logan, T.D. and Rosé, D. (2023). The Evolution of Access To Public Accommodations in The United States. The Quarterly Journal of Economics, 37–102.

Currie, Janet, Henrik Kleven, and Esmée Zwiers. (2020). Technology and Big Data Are Changing Economics: Mining Text to Track Methods. AEA Papers and Proceedings 110: 42–48.

Cygan-Rehm, K., Kuehnle, D. and Oberfichtner, M. (2017). Bounding the causal effect of unemployment on mental health: Nonparametric evidence from four countries. Health Economics 26, 1844-1861.

De Chaisemartin, C. and d'Haultfoeuille, X. (2020). Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. American Economic Review 110 (9), 2964–96.

de Quidt, J. and Haushofer, J. (2019). Depression through the Lens of Economics: A Research Agenda. In The Economics of Poverty Traps (pp. 127–152). Cambridge, MA: National Bureau of Economic Research.

Degefu, M.A., Bewket, W. and Amha, Y. (2022). Evaluating performance of 20 global and quasi-global precipitation products in representing drought events in Ethiopia I: Visual and correlation analysis. Weather and Climate Extremes, 35.

Dell, M., Jones, B.F. and Olken, B.A. (2014). What Do We Learn from the Weather? The New Climate–Economy Literature. Journal of Economic Literature 52(3), 740-798

Demakakos, P., Nazroo, J., Breeze, E. and Marmot, M. (2008). Socioeconomic status and health: The role of subjective social status. Social Science & Medicine 67, 330–340.

Dercon, S. and Porter, C. (2014). Live aid revisited: Long-term impacts of the 1984 Ethiopian famine on children. Journal of the European Economic Association, 12 (4): 927–948

Dercon, S. (2004). Growth and shocks: Evidence from rural Ethiopia. Journal of Development Economics.

Dinkelman, T. (2017). Long-Run Health Repercussions of Drought Shocks: Evidence from South African Homelands. The Economic Journal 127(604), 1906–39.

Dinku, T., Funk, C., Peterson, P., Maidment, R., Tadesse, T., Gadain, H. and Ceccato, P. (2018). Validation of the CHIRPS satellite rainfall estimates over eastern Africa. Q J R Meteorol Soc. 2018;144 (Suppl. 1):292–312.

Di Tella, R., MacCulloch, R.J. and Oswald, A.J. (2001). Preferences over Inflation and Unemployment: Evidence from Surveys of Happiness. The American Economic Review 91(1), 335-341.

Durevall, D., Loening, J.L., Birru, Y.A. (2013). Inflation dynamics and food prices in Ethiopia. Journal of Development Economics 104, 89–106.

Edwards, B., Gray, M. and Hunter, B. (2018). The social and economic impacts of drought. *Aust J Soc Issues*; 54: 22–31.

Espinoza Revello, P. and Scott, D. (2022). Cognitive and Achievement Tests in the Young Lives Study. Young Lives Technical Note No. 54.

Fagereng, A., Mogstad, M. Rønning, M. (2021). Why Do Wealthy Parents Have Wealthy Children? Journal of Political Economy 129(3), 703-755.

Fava, M., Rankin, M. A.,Wright, E. C., Alpet, J. E., Nierenberg, A. A., Pava, J., et al. (2000). Anxiety disorders in major depression. Comprehensive Psychiatry, 41, 97±102.

Favara, M., Crivello, G., Penny, M., Porter, C., Revathi, E., Sánchez, A., Scott, D., Duc, L. T., Woldehanna, T and McKay, A. (2021). Cohort profile update: The Young Lives study. International Journal of Epidemiology.

Favara, M., Hittmeyer, A., Porter, C., Singhal, S. and Woldehanna, T. (2022). Young people, mental health, and civil conflict: Preliminary findings from Ethiopia's Tigray region. Psychiatry Research Communications 2(1), 100025.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., and Michaelsen, J (2015). The climate hazards infrared precipitation with stations - A new environmental record for monitoring extremes. Scientific Data. Available from:

Funk, C. et al. (2005). Recent drought tendencies in Ethiopia and equatorial subtropical eastern Africa. U.S. Agency for International Development, 12.

Gao, J. and Mills, B.F. (2018). Weather Shocks, Coping Strategies, and Consumption Dynamics in Rural Ethiopia. World Development.

Gelaye, B., Williams, M.A., Lemma, S., Deyessa, N., Bahretibeb, Y., Shibre, T., et al. (2013). Validity of the Patient Health Questionnaire-9 for depression screening and diagnosis in East Africa. *Psychiatry Res*, 210, 653-661.

Gibson, M. and Shrader, J. (2018). Time Use and Labor Productivity: The Returns to Sleep. Review of Economics and Statistics, 100, 783–798.

Girma, E., Ketema, B., et al. (2022). Mental health stigma and discrimination in Ethiopia: evidence synthesis to inform stigma reduction interventions. International Journal of Mental Health Systems 16:30

Giuntella, O. and Mazzonna, F. (2019). Sunset Time and the Economic Effects of Social Jetlag: Evidence from US Time Zone Borders. Journal of Health Economics, 65, 210–226.

Global Burden of Disease Collaborative Network. (2020). Global Burden of Disease Study 2019. Results.

Hailemariam, S., Tessema, F., Asefa, M., Tadesse, H. and Tenkolu, G. (2012). The prevalence of depression and associated factors in Ethiopia: findings from the National Health Survey. International Journal of Mental Health Systems 6:23.

Hanson, C., Medhin, G., Selamu, M., Breuer, E., Worku, B., Hailemariam, M., Lund, C., Prince, M. and Fekadu, A. (2015). Validity of brief screening questionnaires to detect depression in primary care in Ethiopia. Journal of Affective Disorders 186, 32-39.

Harris, I., Osborn, T.J., Jones, P. and Lister, D. (2021). Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset. Scientific Data 7, 109.

Haushofer, J., and Fehr, E. (2014). On the psychology of poverty. Science, 344, 862–867.

Haushofer, J. (2019). Is there a Psychological Poverty Trap? Mimeo.

Heckman, James J., and Rodrigo Pinto. (2015). Econometric Mediation Analyses: Identifying the Sources of Treatment Effects from Experimentally Estimated Production Technologies with Unmeasured and Mismeasured Inputs. Econometric Reviews 34(1/2), 6–31.

Heckman, James J., Rodrigo Pinto, and Peter Savelyev. (2013). Understanding the Mechanisms through which an Influential Early Childhood Program Boosted Adult Outcomes. American Economic Review 103(6), 2052–86.

Hirvonen, K., Sohnesen, T.P. and Bundervoet, T. (2020). Impact of Ethiopia's 2015 drought on child undernutrition. World Development 131, 104964.

Hua, Y., Qiu, Y. and Tan, X. (2022). The effects of temperature on mental health: evidence from China. Journal of Population Economics. https://doi.org/10.1007/s00148-022-00932-y

Imbens, G.W. and D. B. Rubin (2015). Causal Inference in Statistics, Social, and Biomedical Sciences. Cambridge University Press.

Jones, A.D. (2017). Food Insecurity and Mental Health Status: A Global Analysis of 149 Countries. American Journal of Preventative Medicine 53(2):264–273.

Kassa, G.M. and Abajobir, A.A. (2018). Prevalence of common mental illnesses in Ethiopia: A systematic review and meta-analysis. Neurology, Psychiatry and Brain Research 30, 74–85.

Kaur, S., Mullanaithan, S., Oh, S. and Schilbach, F. (2022). Do Financial Concerns Make Workers Less Productive? Mimeo.

Khorsandi, P. and Snowden, G. (2022). Millions face hunger as drought grips Ethiopia, Kenya and Somalia, warns World Food Programme. World Food Programme, 08 February.

Kroenke, K., Strine, T. W., Spitzer, R. L., Williams, J. B., Berry, J. T., & Mokdad, A. H. (2009). The PHQ-8 as a measure of current depression in the general population. Journal of Affective Disorders, 114(1–3), 163–173.

Lancet. (2020). Mental health matters. Editorial.

Lim, J. and Dinges, D.F. (2010). A Meta-Analysis of the Impact of Short-Term Sleep Deprivation on Cognitive Variables. Psychological Bulletin, 136, 375–389.

Lund, C., Orkin, K., Witte, M., Davies, T., Walker, J., Haushofer, J., Murray, S., Bass, J., Murray, L. and Patel, V. (2022). Treating Mental Health Conditions Improves Labor Market and Other Economic Outcomes in Low and Middle-Income Countries. Mimeo.

Mani, A., Mullanaithan, S., Shafir, E. and Zhao, J. (2013). Poverty Impedes Cognitive Function. Science 341 (976).

Masson-Delmotte, V., Zhai, P…, Caud, N. (2021) IPCC, 2021: climate change 2021: the physical science basis Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (Cambridge University Press)

McKee, T. B., Doesken, N., and Kleist, J. (1993). The relationship of drought frequency and duration to time scales. 8th Conference on Applied Climatology, 179–184.

Ministry of Health. (2020). National Mental Health Strategic Plan: 2020-2025. Diseases Prevention and Control Directorate. Addis Ababa, Ethiopia.

Mullins, J.T. and White, C. (2019). Temperature and mental health: Evidence from the spectrum of mental health outcomes. Journal of Health Economics 68, 102240.

Obrien, L.V., Berry, H.L., Coleman, C. and Hanigan, I.C. (2014). Drought as a mental health exposure. Environmental Research 131, 181–187.

Osiichuk, M. and Shepotylo, O. (2020). Conflict and well-being of civilians: The case of the Russian-Ukrainian hybrid war. Economic Systems, 44(1).

Outes-Leon, I. and Sanchez, A. (2008). An Assessment of the Young Lives Sampling Approach in Ethiopia. Young Lives Technical Note No. 1.

Pailler, S. and Tsaneva, M. (2018). The effects of climate variability on psychological well-being in India. World Development, 106: 15-26.

Patel, V., Saxena, S., Lund, C., et al. (2018). The Lancet Commission on global mental health and sustainable development. The Lancet;392:1553–98.

Philip, S., Kew, S.F., van Oldenborgh, G., Otto, F., O'Keefe, S., Haustein, K., King, A., Zegeye, A., Eshetu, Z., Hailemariam, K., Singh, R., Jjemba, E., Funk, C. and Cullen, H. (2018). The drought in Ethiopia, 2015. Climate and Development Knowledge Network and World Weather Attribution Initiative, Science Summary.

Porter, C., Favara, M., Hittmeyer, A., Scott, D., Sánchez, A., Ellanki, R., Woldehanna, T., Le Thuc, D., Craske, M.G. and Stein, A. (2021). Impact of the COVID-19 pandemic on anxiety and depression symptoms of young people in the global south: evidence from a four-country cohort study. BMJ Open 2021;11:e049653.

Porter, C., Hittmeyer, A., Favara, M., Scott, D. and Sánchez, A. (2022). The evolution of young people's mental health during COVID-19 and the role of food insecurity: Evidence from a four low-and-middle-income-country cohort study. Public Health in Practice 3, 100232.

Prince, M., Patel, V., Saxena, S., Maj, M., Maselko, J., Phillips, M.R., and Rahman, A. (2007) No health without mental health. The Lancet 370(9590):859–877.

Raleigh, C., Linke, A., Hegre, H., & Karlsen, J. (2010). Introducing ACLED: An Armed Conflict Location and Event Dataset. Journal of Peace Research, 47, 651-660.

Ridley, M., Rao, G., Schilbach, F. and Patel, V. (2020). Poverty, depression, and anxiety: Causal evidence and mechanisms. Science, 370, 1±12.

Romero, J., Esopo, K., McGuire, J. and Haushofer, J. (2021). The Effect of Economic Transfers on Psychological Well-Being and Mental Health. Mimeo.
Rosenberg, M. (1965). Society and the adolescent self-image. New Jersey: Princeton University Press.
Roth, J., Sant'Anna, R., Bilinskim A. and Poe, J. (2023). What's Trending in Difference-in-Differences? A Synthesis of the Recent Econometrics Literature. Journal of Econometrics 235(2), 2218-2244.
Sánchez, A. and Escobal, J. (2020). Survey attrition after 15 years of tracking children in four developing countries: The Young Lives study. Review of Development Economics, 24: 1196–1216.
Sant'Anna, P.H.C. and Zhao, J. (2020). Doubly robust difference-in-differences estimators. Journal of Econometrics.
Sartorius, N. 2009. Disability and mental illness are different entities and should be assessed separately. World Psychiatry 8:2.
Scholten, S., Velten, J., Neher, T. and Margraf, J. (2017). Wealth, justice and freedom: Objective and subjective measures predicting poor mental health in a study across eight countries. SSM - Population Health 3, 639–648.
Spitzer, R. L., Kroenke, K., Williams, J. B., & Lowe, B. (2006). A brief measure for assessing generalized anxiety disorder: The GAD-7. Archives of Internal Medicine, 166, 1092–1097.
Stanke, C., Kerac, M., Prudhomme, C., Medlock, J. and Murray, V. (2013). Health effects of drought: a systematic review of the evidence. PLoS Currents.
Thomson, R.M., Igelström, E., Purba, A.K., Shimonovich, M., Thomson, H., McCartney, G., Reeves, A., Leyland, A., Pearce, A. and Katikireddi, S.V. (2022). How do income changes impact on mental health and wellbeing for working-age adults? A systematic review and meta-analysis. Lancet Public Health 7: e515–28
UN DESA. (2019). World Urbanization Prospects: The 2018 Revision. New York: United Nations.
UN OCHA. (2022a). Ethiopia, Drought Update No. 1.
UN OCHA. (2022b). Horn of Africa Drought: Humanitarian Update. June 2022.
Vins, H., Bell, J., Saha, S. and Hess, J.J. (2015). The Mental Health Outcomes of Drought: A Systematic Review and Causal Process Diagram. Int. J. Environ. Res. Public Health 2015, 12, 13251-13275; doi:10.3390/ijerph121013251
Williams, A. P., and C. Funk. (2011). A westward extension of the warm pool leads to a westward extension of the Walker circulation, drying eastern Africa. Climate Dyn., 37, 2417–2435
World Bank. (2006). IDA Countries and Exogenous Shocks, IDA Resource Mobilization. World Bank, Washington, DC.
World Meteorological Organization. (2022). State of the Climate in Africa 2021. Geneva, Switzerland.
Wu, H., Svoboda, M.D., Hayes, M.J., Wilhite, D.A., and Wen, F. (2007). Appropriate application of the Standardized Precipitation Index in arid locations and dry seasons. International Journal of Climatology.
Yitbarek, K., Birhanu, Z., …, Tesfaye, Y. (2021). Barriers and Facilitators for Implementing Mental Health Services into the Ethiopian Health Extension Program: A Qualitative Study. Risk Management and Healthcare Policy 14, 1199–1210.
Zeufack, A.G., Calderon, C., Kubota, M., Korman, V., Cantu Canales, C. Kabundi, A.N. (2021). Africa's Pulse, No. 24. World Bank, Washington, DC. Doi: 10.1596/978-1-4648-1805-9. License: Creative Commons Attribution CC BY 3.0 IG

Appendix A: Additional information

Table A.1 Balance table: attritors vs non-attritors

	Has not attrited	Attrited
Age (in months)	38.75	41.02
Height (cm)	86.50	86.99
Weight (kg)	11.69	11.81
Body Mass Index	15.14	15.00
Mother has at least primary schooling	0.14	0.13
Wealth Index	0.23	0.24*

Notes: The sample is restricted to individuals not located in the Tigray region. All variables are measured in 2002. Stars relate to t-tests of equality of variable means between those who had not attrited by November-December 2021 and those who had attrited. * p < 0.10, ** p < 0.05, *** p < 0.01.

FIGURE A.1. GAD-7 questionnaire in the Young Lives survey

SAY: I am going to read you some questions and I want you to tell me whether these situations have occurred to you or not in t weeks. If this has happened to you, I will also ask you how often this happened

Q.3-Q.4	**FIELDWORKER:** read the table line by line. **Q.3. SAY:** In the last two weeks, have you been…? 00=No, not at all 01=Yes, even if a little bit **CAPI:** Enable Q.4, for those items where Q.3 =01. If the answer is 00=No, move to the next line **ENUMERATOR:** please make sure that the [YL Child] understand that No means never not even for a moment or a day in the past two week.		**Q.4** How often the situation occurred in the last two weeks? 01= Less than half the days 02=More than half the days 03=Nearly everyday 77=NK 79=RTA 88=NA
01	Feeling nervous, anxious or on edge	○ No, not at all ○ Yes, even if a little bit	[__]
02	Not being able to stop or control worrying	○ No, not at all ○ Yes, even if a little bit	[__]
03	Worrying too much about different things	○ No, not at all ○ Yes, even if a little bit	[__]
04	Trouble relaxing/ Can't relax	○ No, not at all ○ Yes, even if a little bit	[__]
05	Being so restless that it's hard to sit still	○ No, not at all ○ Yes, even if a little bit	[__]
06	Becoming easily annoyed or irritable	○ No, not at all ○ Yes, even if a little bit	[__]
07	Feeling afraid as if something awful might happen	○ No, not at all ○ Yes, even if a little bit	[__]

FIGURE A.2. PHQ-8 questionnaire in the Young Lives survey

PHQ-8
Say: I am going to read you some questions and I want you to tell me whether these situations have ocurred to you or not. If t happened to you, I also want to know how often have occurred in the last two weeks

			Q.6 How often the situation occurred in the last two weeks?
Q.5-Q.6	**FIELDWORKER:** read the table line by line. **Q.5. SAY:** In the last two weeks, have you been bothered by any of the following problems…? 00=No, not at all 01=Yes, even if a little bit **CAPI:** Enable Q.6, for those items where Q.5 is 01=Yes. If the answer is 00=No, move to the next line **ENUMERATOR**: please make sure that the [YL Child] understand that No means never not even for a moment or a day in the past two week.		01= Less than half the days 02=More than half the days 03=Nearly everyday 77=NK 79=RTA 88=NA
01	Little interest or pleasure in doing things	O No, not at all O Yes, even if a little bit	[__]
02	Feeling down, depressed or hopeless	O No, not at all O Yes, even if a little bit	[__]
03	Trouble falling or staying asleep, or sleeping too much	O No, not at all O Yes, even if a little bit	[__]
04	Feeling tired or having little energy	O No, not at all O Yes, even if a little bit	[__]
05	Poor appetite or overeating	O No, not at all O Yes, even if a little bit	[__]
06	Feeling bad about yourself - or that you are a failure or have let yourself or your family down	O No, not at all O Yes, even if a little bit	[__]
07	Trouble concentrating on things, such as reading the newspaper or watching television	O No, not at all O Yes, even if a little bit	[__]
08	Moving or speaking so slowly that other people could have noticed. Or the opposite - being so fidgety or restless that you have been moving around a lot more than usual.	O No, not at all O Yes, even if a little bit	[__]

Figure A.3 Distribution of 2021 Standardized Precipitation Index

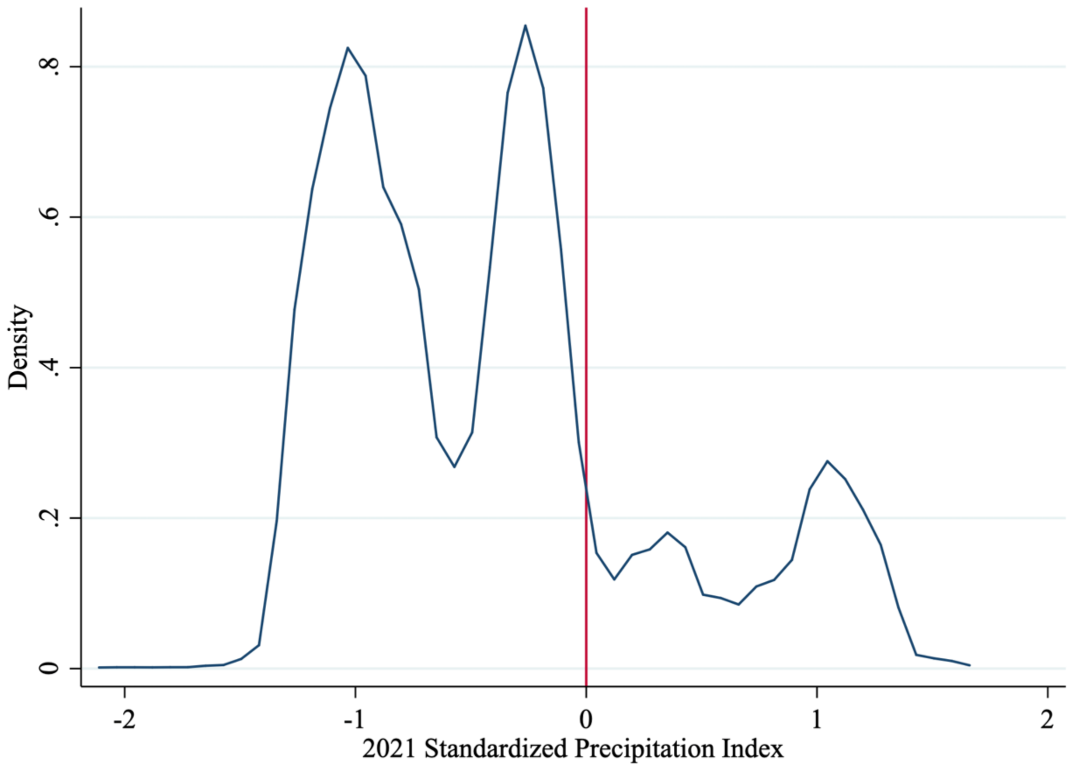
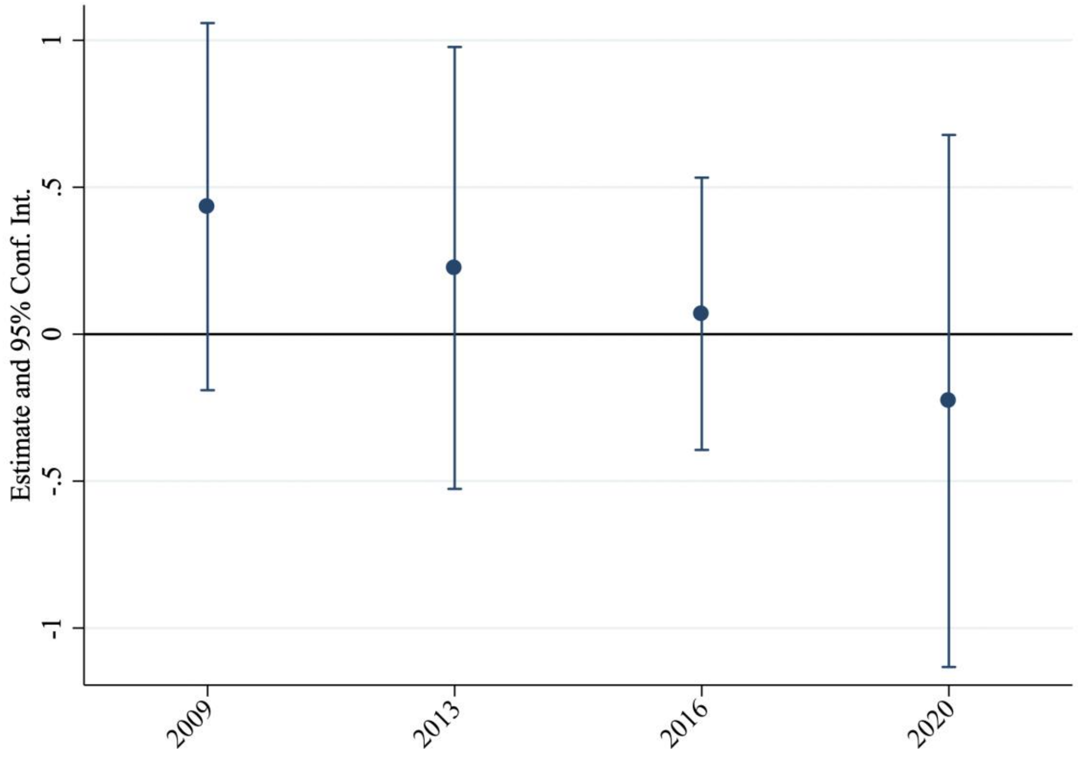


Table A.2. Pre-drought parallel trend checks

	(1) **At least mild anxiety**	(2) **At least mild depression**
Drought$_{t-1}$ (β_3)	-0.025	0.076
	(0.098)	(0.066)
Inference robustness (β_3)		
p-value: robust SE	0.779	0.252
p-value: spatially adjusted SE	0.793	0.236
R^2	0.157	0.060
Observations	3,333	3,335

Notes: Estimated using Equation (1) applied to data from August-October 2020 and November-December 2020 (without time-varying controls). Mental health outcomes are standardized using the baseline means and standard deviations of the control group. Regressions control for age, education enrolment status, location (urban/rural), migration, and region fixed effects. Standard errors (in parentheses) are clustered at the woreda level. Conley (2008) spatial standard errors are estimated using a 10km cut-off. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.4 Trends in life satisfaction over time (2006-2020)



Notes: The figure shows the estimated differences in life satisfaction over time between individuals exposed to the 2021 drought and those in the conrol group. The coefficients are all compared to the original difference in 2006. Life satisfaction is estimated using the Cantril (1965) self-anchoring scale (also known as Cantril's Ladder), which asks the young people to visualize a ladder of nine steps, with the bottom step representing the worst life for them and the top step representing their best possible life. Respondents were asked to identify which step they presently stood on. In 2020, life satisfaction was collected in August-October. Vertical lines represent a 95% confidence interval.

Table A.3. Effect of the 2021 drought on anxiety and depression, excluding migrants

	(1) **At least mild anxiety**	**(2)** **At least mild depression**
Drought (β_3)	0.330***	0.279**
	(0.101)	(0.107)
Inference robustness (β_3)		
p-value: robust SE	0.002	0.010
p-value: spatially adjusted SE	0.001	0.007
R^2	0.135	0.123
Observations	3,072	3,072

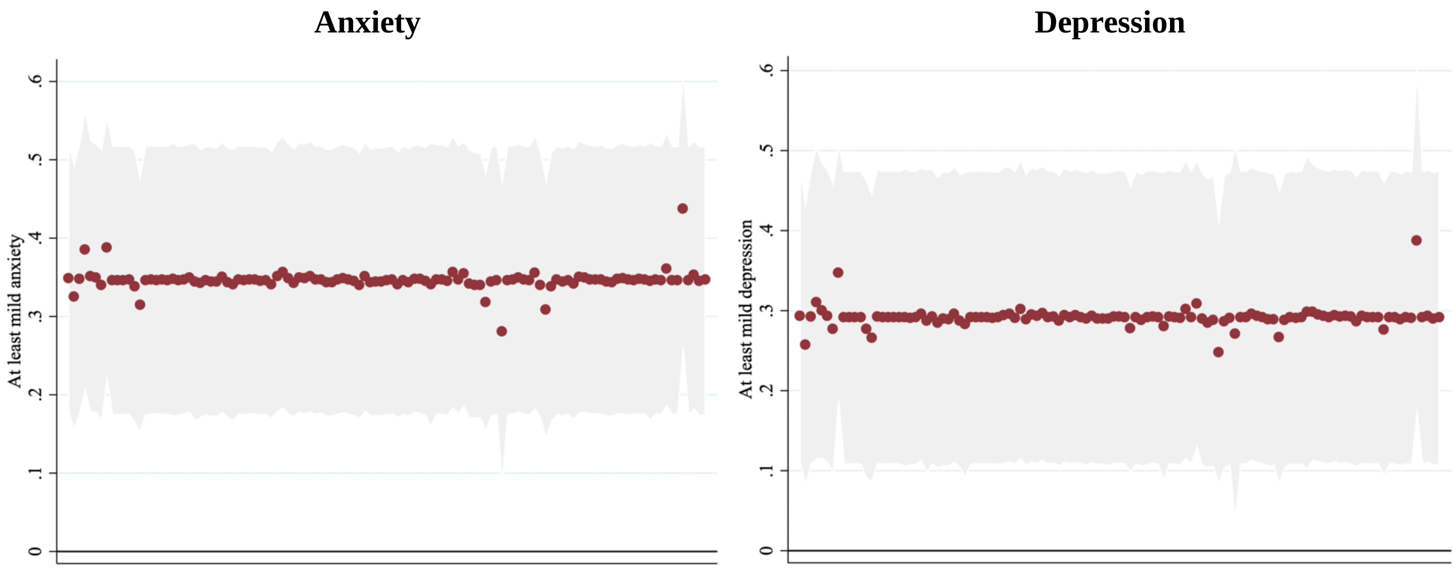
Notes: This table presents estimates of β_3 in Equation (1). Regressions estimated only on individuals who did not migrate during the drought. Mental health outcomes are standardized using the baseline means and standard deviations of the control group. All regressions control for temperature deviations, age, education status, highest education grade, household size, number of rooms in the house, whether the household has a pit latrine, a television, and access to electricity, whether the household is in an urban (or rural) area, the cumulative number of reported fatalities in each participant's woreda since November 2020, whether participants report having been internally displaced due to conflict, region fixed effects, and whether any members of the household have been infected/suspected to be infected with COVID-19. Conley (2008) spatial standard errors are estimated using a 10km cut-off. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4. Effect of the 2021 drought on anxiety and depression, excluding TV ownership and household size

	(1) **At least mild anxiety**	**(2)** **At least mild depression**
Drought (β_3)	0.344	0.306
	(0.104)	(0.114)
Inference robustness (β_3)		
p-value: robust SE	0.001	0.008
p-value: spatially adjusted SE	0.001	0.006
R^2	0.132	0.116
Observations	3,130	3,130

Notes: This table presents estimates of β_3 in Equation (1). Mental health outcomes are standardized using the baseline means and standard deviations of the control group. All regressions control for temperature deviations, age, education status, highest education grade, number of rooms in the house, whether the household has a pit latrine, a television, and access to electricity, whether the household is in an urban (or rural) area, whether the household has migrated, the cumulative number of reported fatalities in each participant's woreda since November 2020, whether participants report having been internally displaced due to conflict, region fixed effects, 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 (2008) spatial standard errors are estimated using a 10km cut-off. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.5 Range of treatment effect coefficients, dropping one woreda at a time



Notes: Each dot represents a separate estimate of β_3 in Equation (1), having dropped one woreda in the analytic sample. Mental health outcomes are standardized using the baseline means and standard deviations of the control group. All regressions control for temperature deviations, age, education status, highest education grade, number of rooms in the house, whether the household has a pit latrine, a television, and access to electricity, whether the household is in an urban (or rural) area, whether the household has migrated, the cumulative number of reported fatalities in each participant's woreda since November 2020, whether participants report having been internally displaced due to conflict, region fixed effects, 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. The grey shaded area indicates the 90% confidence interval.

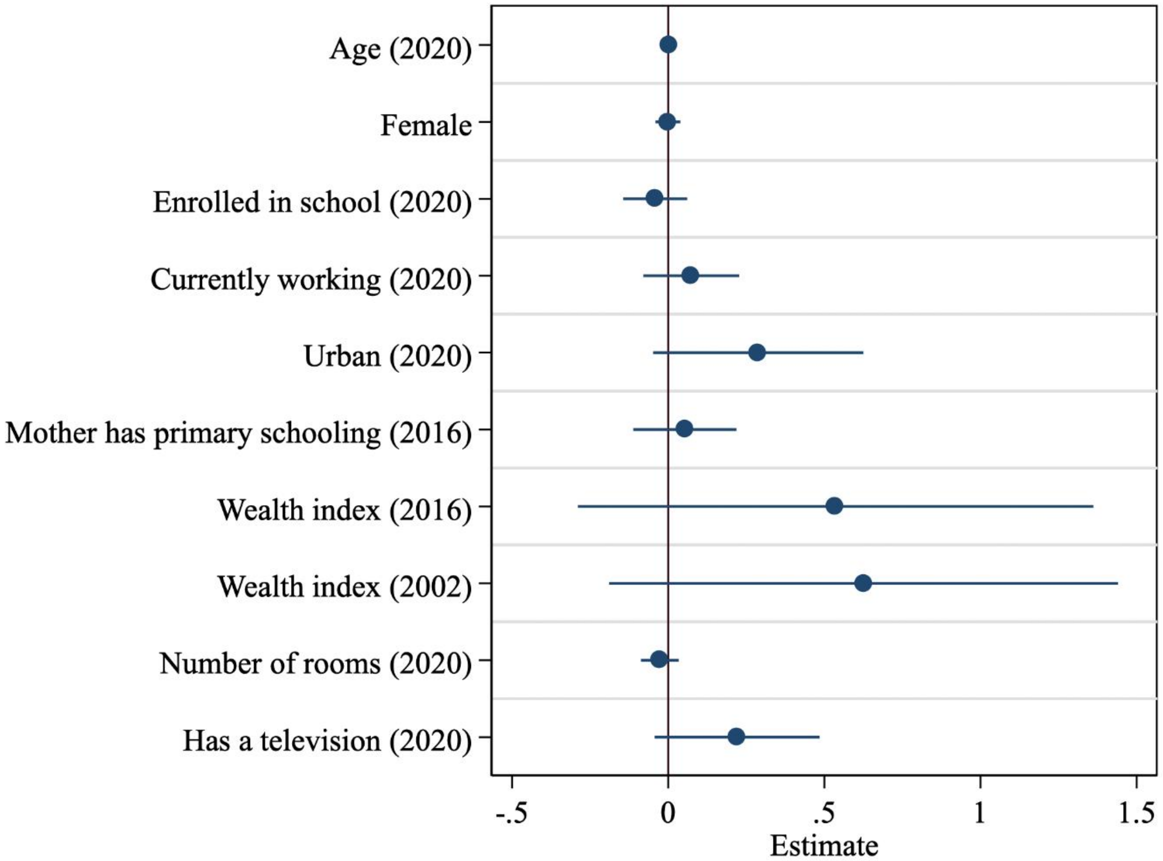
Table A.5 Effect of the 2021 drought on individual symptoms of anxiety and depression

	Treatment effect (SD units)	Standard error	p-value	q-value
Anxiety symptoms				
Feeling nervous, anxious or on edge	0.534	0.241	0.026	0.039
Not being able to stop or control worrying	0.503	0.081	0.000	0.001
Worrying too much about different things	0.018	0.097	0.853	0.744
Trouble relaxing/Can't relax	-0.011	0.111	0.923	0.757
Being so restless that it's hard to sit still	0.272	0.103	0.010	0.026
Becoming easily annoyed or irritable	0.445	0.156	0.005	0.023
Feeling afraid as if something awful might happen	0.260	0.123	0.037	0.044
Depression symptoms				
Little interest or pleasure in doing things	-0.207	0.256	0.435	0.391
Feeling down, depressed or hopeless	0.459	0.186	0.015	0.031
Trouble falling or staying asleep, or sleeping too much	0.246	0.070	0.001	0.008
Feeling tired or having little energy	0.078	0.110	0.481	0.391

Poor appetite or overeating	0.152	0.157	0.333	0.350
Feeling bad about yourself – or that you are a failure or have let yourself or your family down	0.260	0.098	0.009	0.026
Trouble concentrating on things, such as reading the newspaper or watching television	0.183	0.245	0.456	0.391
Moving or speaking so slowly that other people could have noticed. Or the opposite – being so fidgety or restless that you have been moving around a lot more than usual	0.064	0.105	0.545	0.416

Notes: This table presents estimates of coefficient β_3 in Equation (1) using each individual symptoms of anxiety and depression as the outcome. Columns (1) and (2) present effects and standard errors on standardized outcomes, where each outcome has been standardized using the baseline mean and standard deviation of the control group. Columns (3) and (4) present unadjusted p-values and sharpened False Discovery Rate-adjusted q-values, respectively. All regressions control for temperature deviations, age, education status, highest education grade, household size, number of rooms in the house, whether the household has a pit latrine, a television, and access to electricity, whether the household is in an urban (or rural) area, whether the household has migrated, the cumulative number of reported fatalities in each participant's woreda since November 2020, whether participants report having been internally displaced due to conflict, region fixed effects, and whether any members of the household have been infected/suspected to be infected with COVID-19. Standard errors are clustered at the woreda level.

Figure A.6 Correlates of the SPI, conditional on being in the drought-exposed group



Notes: Each point represents the magnitude of the coefficient estimate on the regressor associated with the label on the vertical axis. Estimates are from separate regressions of the SPI on each correlate, conditional on being in the (treated) drought-exposed group. Error bands represent 95% confidence intervals. Standard errors are clustered at the woreda-level.

Table A.6. Effect of the 2021 drought on anxiety and depression, no time-varying controls

	(1) **At least mild anxiety**	**(2)** **At least mild depression**
Drought (β_3)	0.202**	0.183**
	(0.080)	(0.094)
Controls	No	No
R^2	0.046	0.051
Observations	3,344	3,3344

Notes: Mental health outcomes are standardized using the baseline means and standard deviations of the control group. Standard errors are estimated using Conley (2008) spatial standard errors, using a 10km cut-off. * p < 0.10, ** p < 0.05, *** p < 0.01

Table A.7. Effect of drought on anxiety and depression using Sant'Anna and Zhao's (2020) estimator

	(1) **At least mild anxiety**	**(2)** **At least mild depression**
Drought	0.498***	0.307***
	(0.105)	(0.115)
Observations	2,718	2,718

Notes: Mental health outcomes are standardized using the baseline means and standard deviations of the control group. 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, the cumulative number of reported fatalities in each participant's woreda since November 2020, whether participants report having been internally displaced due to conflict, 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. * p < 0.10, ** p < 0.05, *** p < 0.01

Table A.8. Heterogeneous effects of the 2021 drought on anxiety and depression

			(1) **At least mild anxiety**					**(2)** **At least mild depression**		
Interactions (β_7)										
Rural	0.588					0.503				
	(0.156)					(0.191)				
	{0.001}					{0.017}				
Agricultural worker		-0.056					0.322			
		(0.156)					(0.151)			
		{0.168}					{0.030}			
Low wealth index (2002)			0.245					0.440		
			(0.144)					(0.202)		
			{0.050}					{0.030}		
Low reading score (2013)				0.371					0.333	
				(0.123)					(0.119)	
				{0.014}					{0.016}	
Low self-esteem (2016)					0.135					0.309
					(0.100)					(0.132)
					{0.063}					{0.024}
R^2	0.144	0.137	0.138	0.108	0.140	0.129	0.123	0.127	0.086	0.125
Observations	3,117	3,117	3,087	2,141	3,006	3,117	3,117	3,087	2,141	3,006

Notes: The table shows estimated $\widehat{\beta_6}$ from Equation (2). Mental health outcomes are standardized using the baseline means and standard deviations of the control group. Self-esteem is measured using the Rosenberg self-esteem scale (Rosenberg, 1965), and reading is measured using a comprehension test that was asked to children who could read Amharic, Oromifa, or Tigrinya. A variable has a 'low' value if it is below the mean value in the sample. All regressions control for temperature deviations, age, education status, highest education grade, household size, number of rooms in the house, whether the household has a pit latrine, a television, and access to electricity, whether the household is in an urban (or rural) area, whether the household has migrated, the cumulative number of reported fatalities in each participant's woreda since November 2020, whether participants report having been internally displaced due to conflict, region fixed effects, and whether any members of the household have been infected/suspected to be infected with COVID-19. Below each coefficient, I report a standard error in parenthesis and a sharpened q-value in curly braces. Conley (2008) spatial standard errors are estimated using a 10km cut-off. q-values are obtained using the sharpened procedure of Benjamini et al. (2006).

Appendix B: Additional detail on the mediation analysis

Mediation model

The specification of the mediation model that I apply follows Castells-Quintana et al. (2022) and Fagereng et al. (2021), who in turn follow Heckman et al. (2013) and Heckman and Pinto (2015). In order to identify the parameters in the mediation model, two assumptions are required. The first is that the unobserved mediators are uncorrelated with both the measured mediators and any other control variables included in the mediation model. The second assumption is that the treatment (drought exposure) affects the mediator variables but does not affect the impact of these variables (or any of the other control variables) on the outcomes. With these assumptions, I can write the mediation model as follows.

$$MH_{ihgt} = \alpha + \beta_1 D_{ig} + \beta_2 Post_t + \beta_3 (D_{ig} \times Post_t) + \sum_{m \in M} \theta_0^m \pi_{ih}^m + \boldsymbol{\delta X_{ihg}} + \gamma_r + \varepsilon_{ihgt} \tag{B.1}$$

$$= \alpha + \beta_1 D_{ig} + \beta_2 Post_t + \beta_3 (D_{ig} \times Post_t) + \sum_{m \in M} \theta_0^m [\mu_{0,m} + \mu_{1,m} D_{ig} + \mu_{2,m} Post_t + \mu_{3,m} (D_{ig} \times Post_t) + \mu_{4,m} \boldsymbol{X_{ih}} + \eta_{ihgt}] + \boldsymbol{\delta X_{ihg}} + \gamma_r + \varepsilon_{ihgt},$$

where π_{ih}^m are the set of observed mediator variables. The remaining variables on the right-hand side of Equation (4) are defined as in Equation (1). The second equality of Equation (B.1) comes from substituting a linear expression for each observed π_{ih}^m.

Based on the above, I can decompose the average treatment effect into direct and indirect components as follows:

$$E[(\Delta MH_{ight} | D_{ig} = 1) - (\Delta MH_{ight} | D_{ig} = 0)] = \beta_3 + \sum_{m \in M} \theta_0^m (\mu_{3,m}) = \underbrace{\beta_3}_{Direct\ Effect} + \underbrace{\sum_{m \in M} \theta_0^m (\mu_{3,m})}_{Indirect\ Effect} \tag{B.2}$$

Estimation proceeds in two steps. First, I estimate two models based on Equation (B.2) with symptoms of anxiety and depression as the outcomes, including both exposure to drought and the set of observable mediators, π_{ih}^{m} . The second step is to estimate separate linear regressions for each of the observed mediator variables. This involves estimation of Equation (1) with π_{ih}^{m} as the dependent variable. Results of the mediation analysis are presented in Table 5 (in the main text).

Calculation of indirect effects: Illustrative example:

Indirect treatment effects are generated through changes in mediators if mediators affect outcomes and mediators are impacted by treatment. Taking a specific example from my findings, we see in Columns (1)-(4) of Table 5, that perceived household poverty, food insecurity, physical illness, and inflation are all affected by drought exposure, while in Column (5) of Table 5, we see that perceived poverty, food insecurity, and inflation in turn affect symptoms of anxiety. The magnitude of the indirect effect can be calculated based on Equation (B.2).

The indirect effect via perceived poverty is based on multiplying the coefficient for household poverty from Column (5) of Table 5, which is 0.195, by the coefficient on drought exposure in the mediator regression (Column (1) of Table 5) of 0.202. This gives an indirect effect of 0.039. Applying the same method for food insecurity, physical illness and inflation, we get indirect effects of 0.062, 0.008, and 0.044, respectively. Taken together, this implies a combined indirect effect of 0.153. Compared to the ATT of 0.346 (Table 2), this represents roughly 45% of the total average causal effect of drought on anxiety.