The Causal Effect of Drought on Energy Poverty

Evidence from Panel Data

Yonas Alem and Leulseged L. Woldemichael

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Keywords: Income shock; Energy Poverty; Ethiopia
JEL codes: Q40; Q54; O13; I32

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December 30, 2025

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1. Introduction

Weather shocks—especially droughts—are among the most pervasive and damaging risks faced by households in rain-fed agricultural systems across many developing countries (Bank, 2013). In these settings, households generally lack access to formal financial institutions that could help them buffer the impact of such shocks. Instead, they rely on informal coping mechanisms, which are often insufficient and can lead to lower long-run welfare or even trap households in chronic poverty (Bardhan & Udry, 1999). A large body of research has examined the consequences of drought for agricultural production (Huang *et al.*, 2015; Wang *et al.*, 2022; Agamile *et al.*, 2021), household consumption (Dercon *et al.*, 2005; Dercon, 2002), livestock wealth (Carter & Lybbert, 2012; Abebe & Alem, 2025), child development and labor (Hoddinott & Kinsey, 2001; de Janvry *et al.*, 2006), and nutrition (Hirvonen *et al.*, 2020).

In this paper, we focus on a relatively understudied dimension of vulnerability: the impact of drought on energy poverty. Understanding this relationship is important for at least three reasons. First, energy poverty captures deprivations in access to clean lighting, cooking, heating/cooling, and energy for productive use. These deprivations constrain households' ability to cope with shocks, protect health, and maintain their livelihoods, making energy poverty both a direct welfare indicator and a channel through which drought-related harms accumulate (Modi *et al.*, 2005; Barnes *et al.*, 2011; Nussbaumer *et al.*, 2012; Alem & Demeke, 2020). Second, energy poverty interacts with other aspects of well-being—including food security, water access, health outcomes, and gender inequality—thus forming an integral part of multidimensional poverty linked to human capital and long-term development (Nussbaumer *et al.*, 2012; Alkire & Santos, 2014). Third, as climate change intensifies drought frequency and severity, households' ability to adapt becomes increasingly critical (IPCC, 2014, 2021). Limited access to modern energy services undermines climate resilience, making energy poverty a central constraint in climate adaptation.

We analyze two waves of nationally representative panel data from the Ethiopian Socioeconomic Survey (ESS), matched with high-resolution rainfall data from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), to estimate the causal effect of drought on energy poverty among rural and small-town households. Energy poverty is measured using the Multidimensional Energy Poverty Index (MEPI) developed by Nussbaumer *et al.* (2012), which aggregates key dimensions of energy deprivation using weighted indicators. Ethiopia offers a compelling empirical setting: more than 80% of the population depends on rain-fed agriculture, rendering livelihoods highly vulnerable to frequent droughts—15 major events between the mid-1960s and 2010s (Guha-Sapir *et al.*, 2016). Energy poverty is also acute; in 2016, only 45% of Ethiopians had electricity access and just 6% used clean cooking technologies (Benti *et al.*, 2021).

Using the MEPI, we document that 76.6% of rural and small-town households in Ethiopia are energy poor. Fixed-effects estimates indicate that drought in the previous production year raises the energy poverty score by 0.019 points and increases the probability of being multidimensionally energy poor by 3.5%. Our results further show that the primary mechanism through which drought worsens energy poverty is via reduced per capita income, which limits households' ability to acquire cleaner fuels or energy-using appliances. Specifically, drought reduces per capita income by 33.7%—a substantial economic shock. Heterogeneity analyses reveal that households participating in Ethiopia's Productive Safety Net Programme (PSNP) are effectively shielded from the impact of drought: for PSNP beneficiaries, drought has no statistically significant effect on either the energy poverty score or status. These findings, which are robust across multiple checks, underscore the critical role of social protection programs in mitigating climate-induced energy poverty.

This paper makes three key contributions to the literature. First, it advances the emerging body of work linking climatic shocks to energy poverty. While prior studies have focused on fuel price shocks (Alem & Demeke, 2020), temperature extremes (Feeny et al., 2021; Que et al., 2022; Li et al., 2023), and self-reported climatic disruptions such as floods and landslides (Ssennono et al., 2023), we extend this literature by employing objective, fine-resolution rainfall data to identify the causal effect of drought in a highly drought-prone context. Second, we shed light on the central mechanism through which drought intensifies energy poverty—income loss. Although earlier work highlights productivity and expenditure channels, our findings underscore the dominant role of income collapse in shaping energy deprivation in East Africa. Third, we demonstrate that Ethiopia's Productive Safety Net Programme (PSNP) significantly mitigates the energy-poverty consequences of drought, illustrating how well-targeted safety nets can strengthen household resilience to climate shocks.

More broadly, the study contributes to understanding the welfare implications of climate change. With droughts projected to become more frequent and severe across the Global South—particularly in Eastern Africa (IPCC, 2014; Wang et al., 2019; IPCC, 2021)—our findings quantify an important but often overlooked cost of climate change: its adverse impact on household energy access. By identifying both the magnitude and mechanisms of this relationship, the paper highlights the potential gains from adaptive and protective policies that can help buffer vulnerable populations from intensifying climate risks.

The remainder of the paper proceeds as follows. Section 2 provides an overview of Ethiopia's energy landscape and climate vulnerabilities. Section 3 describes the data and presents descriptive statistics. Section 4 outlines the empirical strategy and reports the main results, including mechanisms and heterogeneity analysis. Section 5 concludes.

2. Ethiopia: Energy Landscape and Climate Vulnerabilities

Covering an area of 1.1 million square kilometers and hosting about 132 million people in 2024, 81% of whom reside in rural areas, Ethiopia ranks as the second-most populous country in Africa, next to Nigeria (WorldBank, 2025a). It lies in the northeastern region of the Horn of Africa, sharing borders with Kenya to the south, Djibouti and Somalia to the east, Eritrea to the north, and Sudan and South Sudan to the west. The country's climate is classified as tropical monsoon but exhibits considerable variation due to its diverse topography. Three main climatic zones can be distinguished: the high-altitude cool zone (Dega), located above 2400 meters, with temperatures ranging from near freezing to about 16°C; the temperate zone (Woina Dega), situated between 1500 and 2400 meters, where temperatures range from 16°C to 30°C; and the lowland hot zone (Qola), below 1500 meters, encompassing both tropical and arid areas with temperatures between 27°C and 50°C (USAID, 2016). Rainfall patterns are equally diverse, varying from as high as 2000 mm annually in localized areas of the southwest to less than 100 mm in the arid Afar lowlands of the northeast, with a national average of about 848 mm (FAO, 2016a). Paralleling the climate diversity, Ethiopia is a drought-prone country, experiencing 15 drought events in the decades between the mid 1960's and the mid-2010s alone, which affect every dimension of the vast majority of the Ethiopian population (Abebe & Alem, 2025).

Although Ethiopia remains a low-income economy—with a per capita gross national income of about USD 1,020 in 2024—it has achieved remarkable economic expansion over the past two decades, at times exceeding annual growth rates of 10 percent (WorldBank, 2025b). Guided by a state-led development strategy, the country has invested substantial resources in infrastructure and agriculture. These efforts have yielded notable progress, including a tenfold increase in electricity-generation capacity over the past three decades (Kruger *et al.*, 2019). The national electrification rate has reached roughly 45 percent, with near-universal access in urban areas (97 percent) but only about one-third of rural households connected (IEA, 2020). Hydropower generation alone has expanded dramatically, rising from 850 MW to 2,000 MW within a decade (FDRE-NPC Federal Democratic Republic of Ethiopia, 2016).

Ethiopia has an estimated renewable-energy potential of 45 GW in hydropower, 10 GW in wind, and 5 GW in solar (Gebremeskel *et al.*, 2021; Mengistu *et al.*, 2015). However, the country's energy mix remains dominated by traditional biomass. Around 91 percent of total national energy use still comes from biomass sources (Hailu & Kumsa, 2021; Beyene *et al.*, 2018; Mondal *et al.*, 2018), and about 95 percent of households rely on polluting fuels—primarily firewood, crop residues, and animal dung (Federal Democratic Republic of Ethiopia & Development, 2011; Guta *et al.*, 2015). This dependence imposes substantial socioeconomic and health costs, as rural households—particularly women and

children—spend on average an hour each day collecting fuel (Alem *et al.*, 2023), while facing significant exposure to indoor air pollution (Chowdhury *et al.*, 2019).

Ethiopia's electricity sector stands at a critical juncture. The government's current expansion strategy envisions adding 10 GW of new hydropower capacity—including the 6,000 MW Grand Ethiopian Renaissance Dam (GERD)—and 3 GW from other renewable sources, alongside the construction of over 13,500 km of transmission lines and 114 substations (Kruger *et al.*, 2019). These investments aim to alleviate recurrent load shedding, which has intensified as electricity demand outpaces the country's rapid economic growth (Bank, 2017; FDRE-NPC Federal Democratic Republic of Ethiopia, 2016; Gebremeskel *et al.*, 2021; Bianco *et al.*, 2009). Despite rapid economic growth, the power system remains highly dependent on hydropower, accounting for roughly 90% of the nation's installed capacity of 4.5 GW (Gebremeskel *et al.*, 2021). This concentration exposes the grid to climatic variability, a risk reflected in Ethiopia's low electricity reliability ranking—118th out of 144 countries (Kruger *et al.*, 2019). Efforts to diversify remain modest: the national grid includes only 324 MW of wind and 7.5 MW of geothermal capacity, underscoring the gap between Ethiopia's abundant renewable endowments and their limited exploitation (Khan & Pawan, 2017).

Taken together, these features make Ethiopia an especially compelling context for examining how drought influences energy poverty. The country's heavy reliance on hydropower renders its modern energy system acutely sensitive to rainfall variability. At the same time, widespread dependence on biomass exposes rural households to greater vulnerability during dry spells, which constrain both water and fuelwood availability. With over four-fifths of the population residing in rural areas where electrification remains limited, droughts can amplify existing inequalities in energy access, affordability, and reliability. Moreover, the intersection of rapid economic growth, ambitious energy-sector reforms, and recurrent climate shocks creates a natural experiment for understanding how climatic stress interacts with structural energy constraints in low-income economies. Studying Ethiopia, therefore, provides valuable insights into the broader dynamics of climate-induced energy poverty and the challenges of achieving equitable and climate-resilient energy transitions across developing regions.

3. Data and Descriptive Statistics

3.1. Household Data: Sampling and Collection

This study examines the effect of drought on energy poverty using household-level data from two waves of the Ethiopian Socioeconomic Survey (ESS), a nationally representative longitudinal dataset designed to capture rural household dynamics. The ESS is part of the World Bank's Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) program, implemented jointly with Ethiopia's Central Statistics

Agency (CSA). The survey aims to generate comprehensive evidence on agricultural practices and their relationship to household welfare. The first round, conducted in 2011/12 as the Ethiopian Rural Socioeconomic Survey (ERSS), covered only rural and small-town areas and sampled 3,776 households from 333 enumeration areas (EAs). Subsequent rounds in 2013/14 and 2015/16 expanded the scope to include urban areas, producing nationally representative data covering 5,262 households across 433 EAs.[1]

The ERSS employed a two-stage probability sampling design covering Ethiopia's four largest regions—Amhara, Oromia, Southern Nations, Nationalities and Peoples (SNNP), and Tigray. In the first stage, 290 rural and 43 small-town EAs were selected with probabilities proportional to regional population size. In the second stage, 12 households were randomly chosen from each rural EA and 10 from each small-town EA. The second survey wave added 1,500 households from 100 urban EAs, including Addis Ababa, with 15 households randomly selected per EA. This expansion increased the total sample to 5,469 households across 433 EAs. The third wave, fielded in 2015/16, revisited the same EAs and households, with minimal attrition in the rural sample (below 2%).

Because of missing and inconsistent information in the first-round data—particularly on variables required to construct the energy poverty index—the analysis in this paper uses only the second and third ESS waves. The study further restricts the sample to rural and small-town households primarily dependent on rain-fed agriculture, as these are most directly exposed to drought risk. Data collection in each round began in September to minimize seasonality effects. The ESS remains Ethiopia's most comprehensive and nationally representative household panel survey, collecting detailed information through five instruments: household, community, post-planting, post-harvest, and livestock questionnaires.

3.2. Weather Data

In addition to the household survey data, we compiled rainfall information from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). Earlier analyses of drought impacts on household welfare in Ethiopia predominantly relied on either self-reported drought experiences (Dercon *et al.*, 2005; Porter, 2012) or meteorological records (Dercon, 2004; Yamano *et al.*, 2005; Thiede, 2014) obtained from the Ethiopian Meteorological Agency. Both approaches have essential limitations: self-reported measures are prone to recall and perception biases, while meteorological data often contain substantial gaps and measurement errors due to sparse spatial coverage. The density of weather stations across Africa has also declined markedly over the past few decades—from roughly 3,500 in 1990 to about 500 more recently (Lorenz & Kunstmann, 2012). In Ethiopia, specifically, (Alem & Colmer, 2021) documents an

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[1]See https://microdata.worldbank.org/index.php/catalog/2053 for details

average of only 0.03 reporting stations per woreda (district), disproportionately located in high-productivity agricultural zones, which likely leads to systematic upward bias in estimates derived from such data.

CHIRPS is a quasi-global rainfall dataset that spans more than 35 years, providing daily, pentadal, and monthly precipitation estimates from 1981 to the present at a spatial resolution of 0.05 degrees (approximately 5×5 km). It combines high-resolution satellite imagery with ground-based station observations and long-term climatology to generate consistent gridded time-series data suitable for analyzing rainfall trends and monitoring drought conditions (Funk *et al.*, 2015). In this study, we employ CHIRPS data with a spatial resolution of roughly 5 km (at the equator) and a monthly temporal resolution. The CHIRPS dataset has been widely applied in empirical research assessing the economic and welfare impacts of climatic and weather shocks (Hirvonen *et al.*, 2020; Tambet & Stopnitzky, 2019; Aragón *et al.*, 2018).

3.3. Sample Construction

We linked the CHIRPS satellite precipitation dataset with the Ethiopian Socioeconomic Survey (ESS) using each household's geographic coordinates (latitude and longitude). For each household, we computed rainfall as the inverse-distance-weighted mean of the four closest CHIRPS grid cells. Consistent with the methodology of Shah & Steinberg (2017) and Mahajan (2017), we constructed a binary drought indicator to capture rainfall shocks. This variable equals 1 when rainfall in the previous year falls more than one standard deviation below the 1981–2015 long-term mean, and zero otherwise. As an alternative specification, we defined drought as rainfall in the preceding year being below the 20th percentile of the location-specific long-term rainfall distribution. The use of lagged rainfall allows us to exploit plausibly exogenous weather variation as a proxy for income shocks, in line with prior studies such as Alem *et al.* (2010) and Dercon & Christiaensen (2011).

3.4. Outcome Variable

Existing studies on developing countries employ three main approaches to assess household energy deprivation and access to basic energy services: the Minimum Energy Consumption Threshold (MECT) approach introduced by Modi *et al.* (2005), the Minimum End-Use Energy (MEE) or income-invariant measure proposed by Barnes *et al.* (2011), and the Multidimensional Energy Poverty Index (MEPI) developed by Nussbaumer *et al.* (2012). The MECT method identifies energy-poor households as those whose total energy use falls below the minimum level required to satisfy essential needs such as cooking, heating, and lighting. The MEE framework, in contrast, defines an energy poverty line corresponding to the point where energy consumption begins to rise with income, classifying households below this threshold as energy poor. The MEPI offers a more comprehensive perspective

by capturing multiple dimensions of energy deprivation, incorporating technological access and the availability of modern energy services into its assessment.[2]

To assess energy poverty among households in rural areas and small towns of Ethiopia, we apply the Multidimensional Energy Poverty Index (MEPI) initially developed by Nussbaumer *et al.* (2012) and subsequently employed in various developing-country studies (Zhang *et al.*, 2019; Alem & Demeke, 2020; Koomson & Churchill, 2022). The MEPI aggregates five key dimensions of energy deprivation, each represented by specific indicators with assigned weights (Nussbaumer *et al.*, 2012; Alem & Demeke, 2020; Zhang *et al.*, 2021; Koomson & Churchill, 2022). These dimensions include cooking, lighting, ownership of household appliances, entertainment, and communication (see Table 1 for the complete set of indicators and weights). A household is considered deprived in a given dimension if it lacks access to clean or modern energy sources. For instance, households relying on solid fuels such as firewood, charcoal, or agricultural residues are considered deprived of cooking energy. At the same time, those without access to grid or off-grid electricity are deemed deprived of lighting.

Reliance on traditional cooking fuels and stoves has substantial implications for both time efficiency and household well-being (Malla & Timilsina, 2014; Pratiti *et al.*, 2020). In many least developed regions, cooking accounts for as much as 80% of total household energy consumption (IRENA, 2017). Accordingly, the cooking dimension of the energy poverty index is assigned the highest weight, totaling 0.4. This dimension includes two equally weighted indicators—use of modern cooking fuels and exposure to indoor air pollution—each assigned a weight of 0.2. The lighting dimension carries a weight of 0.2, while the remaining three dimensions—entertainment, communication, and ownership of appliances—each receive a weight of 0.13 (see Table 1). The overall energy deprivation score for each household, representing the weighted sum of deprivations across all five dimensions, is computed as shown in Equation 1.

$$EDS_h = w_1 E_1 + w_2 E_2 + w_3 E_3 + \ldots + w_n E_n \tag{1}$$

where EDS_h denotes the energy deprivation score for household h, E_h takes the value 1 if the household is deprived in indicator h and 0 otherwise, and w_h represents the weight assigned to each indicator such that $\sum_{h=1}^{EP} w_h = 1$. The primary measure of energy poverty in this study is the continuous deprivation score (energy poverty score) derived from Equation (1). To verify the robustness of our findings, we also employ an alternative binary classification of energy poverty—indicating whether a household is energy poor—based on the same underlying indicators.

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[2]It is worth noting that these measures of energy poverty apply to households in developing countries. In developed countries, energy poverty is the inability to heat one's homes or spending more than 10% of income on energy expenditure (Phimister *et al.*, 2015; Roberts *et al.*, 2015).

Table 1: Multidimensional Energy Poverty Index - Construction

Dimension (weight)	Indicator (weight)	Energy deprived if...
Cooking (0.4)	Modern cooking fuel (0.2)	Uses charcoal/firewood/farm products
	Indoor pollution (0.2)	No access to gas/kerosene/electric or electric mitad
Lighting (0.2)	Electric access (0.2)	Not using electricity or solar energy as a main light source
Appliance (0.13)	Ownership of fridge (0.13)	Does not own a fridge
Entertainment (0.13)	Ownership of television and/or radio (0.13)	Does not own television and/or radio
Communication (0.13)	Ownership of mobile phone and/or landline (0.13)	Does own mobile and/or landline telephone

Notes: This table presents different dimensions used to construct a multidimensional energy poverty index. *mitad* is a cooking appliance used to bake Injera, the main staple food in Ethiopia. It can be built to use electricity or biomass as cooking fuel.

3.5. Descriptive Statistics

Table 2 reports the descriptive statistics for the variables used in the analysis. The energy poverty rate was 81% in 2013/14 and declined to 72.1% in 2015/16, resulting in an average of 76.6% across the two survey waves. Likewise, the average energy deprivation score declined from 0.643 in 2013/14 to 0.613 in 2015/16, with an overall mean of 0.628. The data also show that about 7.5% of households experienced drought in the production year preceding 2013/14, rising slightly to 8.2% in the year preceding 2015/16, for an overall average of 7.9% across the two periods.[3]

The sample is predominantly male-headed households, accounting for 74% of the total, while female-headed households account for 26%. The average age of household heads is 46.8 years, and the mean household size is 5.87 members. The highest level of education attained within households averages 5.07 years of schooling. Livestock and land are the leading asset indicators among smallholder rural households, with the sample owning on average 2.51 tropical livestock units (TLU) and 1.19 hectares of land.

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[3]Ethiopia, along with much of the Global South, experienced an El-Niño-induced drought in 2015-16 that affected 51% of rural households (FAO, 2016b). Our analysis doesn't capture this event because we use lagged weather shocks as proxies for agricultural income in the current period. Under this assumption, the El-Nino-induced drought of 2015-16 would influence agricultural income and energy poverty in the subsequent period (i.e., 2016-17).

Table 2: Summary statistics

	1	2	3
	Pooled	Wave 2013/14	Wave 2015/16
MEPI score	0.628 (0.171)	0.643 (0.166)	0.613 (0.175)
MEPI status	0.766 (0.423)	0.810 (0.392)	0.721 (0.448)
Drought (less than -1 SD)	0.079 (0.269)	0.075 (0.263)	0.082 (0.275)
Drought ($<$ 20 percentile)	0.114 (0.318)	0.131 (0.338)	0.0970 (0.296)
Household Head's Age	46.80 (15.17)	45.97 (15.18)	47.64 (15.12)
Household Head's gender	0.740 (0.438)	0.746 (0.435)	0.735 (0.442)
Household size	5.870 (2.585)	5.609 (2.498)	6.131 (2.643)
Household's maximum education	5.072 (3.986)	4.908 (3.949)	5.236 (4.017)
Livestock holding (TLU)	2.512 (3.559)	2.448 (3.562)	2.577 (3.555)
Land holding (ha)	1.193 (1.769)	1.237 (1.833)	1.148 (1.702)
Home Ownership	0.886 (0.318)	0.874 (0.332)	0.897 (0.304)
Number of rooms	1.813 (1.163)	1.799 (1.002)	1.828 (1.305)
Rural	0.885 (0.319)	0.885 (0.319)	0.885 (0.319)
Observations	7274	3635	3639

Notes: Column [1] reports summary statistics of the pooled sample. Column [2]-[3] present summary statistics for the years 2013/14 and 2015/16, respectively.

4. Results

4.1. Empirical Strategy

To explore the impact of weather shocks on household energy poverty, we exploit plausibly exogenous variation in rainfall across survey rounds. Given whether shocks are strictly exogenous, we can identify their causal impact on energy poverty from the following fixed effects specification,

$$EDS_{ivt} = \beta_1 Drought_{vt-1} + \sum \gamma_n X_{ivt} + \mu_i + \vartheta_v + \varphi_t + \varepsilon_{iht} \qquad (2)$$

where EDS_{ivt} represents our outcome variable of interest (the energy deprivation score of household i at village (or enumeration area) v at time t. The key explanatory variable of interest is lagged drought, represented by $Drought_{vt-1}$. X_{ivt} represents a vector of control variables representing household and household-head characteristics presented in Table 2. These control variables include the age and gender of the household head, household size, the highest level of education in the household, land size, livestock holding in TLU, a dummy for household house ownership, and the total number of rooms. μ_i, ϑ_v and φ_t represent household, village, and time fixed effects. ε_{iht} captures an idiosyncratic error

term. β and γ are parameters to be estimated, β_1 specifically capturing the causal effect of drought on energy poverty.

4.2. Rainfall Shocks and Energy Poverty

We begin by presenting the fixed effects regression results in Table 3. Panel A presents fixed-effects regression results on the effect of drought on energy poverty, as measured by the multidimensional energy poverty score. Panel B reports fixed-effects regression results on the impact of drought on multidimensional energy poverty status. Columns 1 and 3 control for drought time and village fixed effects only, while columns 2 and 4 control for drought, time, and village fixed effects and household head and household characteristics reported in Table 2. In all specifications, the standard errors are clustered at the enumeration area level.

Across all specifications, the regression results indicate that drought in the previous period has a positive, statistically significant effect on energy poverty. Column 1 suggests that experiencing drought in the last period increases the energy poverty score by 0.019. The effect remains almost the same in column 2 (0.018), which controls for household and household head characteristics. Similarly, column 3 suggests that experiencing drought in the previous production period increases energy poverty by 3.8%, an effect that persists at 3.5% in column 4, which controls for covariates.

Our results are consistent with previous studies that documented a positive impact of temperature shocks on multidimensional energy poverty across different contexts (Feeny *et al.*, 2021; Que *et al.*, 2022; Li *et al.*, 2023; Churchill *et al.*, 2022).

Table 3: Impact of Income Shock on Energy Poverty

	Panel A		Panel B	
	Multidimensional EP Score		Multidimensional EP Status	
	(1)	(2)	(3)	(4)
$Drought_{t-1}$	0.019***	0.018***	0.038**	0.035**
	(0.007)	(0.007)	(0.017)	(0.017)
Time Fixed Efffects	Yes	Yes	Yes	Yes
Village Fixed Efffects	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	7274	7274	7274	7274

Notes: This table presents fixed-effects results on the impact of drought on energy poverty. Columns [1] and [2] present the impact on the energy poverty score. Columns [3]-[4] present the impact on energy poverty status. Drought is defined as a binary variable that takes 1 if the standardized deviation of the previous year's rainfall is less than -1 from the long-term mean (i.e., 1981- 2015); it takes 0 otherwise. The control variables include the head's age and gender; the highest level of education in the household; household size; landholding, livestock holding, home ownership, and number of rooms. Standard errors (in parentheses) are clustered at the enumeration area level. * p < 0.10, ** p < 0.05, *** p < 0.01.

What are the mechanisms through which weather shocks affect energy poverty? The fundamental premise we use to model energy poverty as a function of rainfall shocks (drought) is the direct impact of weather shocks on income in rain-fed agrarian settings. If that is the case, a drought in the previous production period would lead to a reduction in income per capita in the current period. If income is the primary mediator linking weather shocks to an increase in multidimensional energy poverty, the effect of drought on income should be statistically significant in a regression running per capita income on drought and relevant covariates. We investigate this mechanism using fixed effects regressions.

Table 4 presents fixed effects regression results on the impact of drought on two types of household income. Panel A shows the effect of lagged drought on the log of total per capita income. Panel B displays the impact of lagged drought on the log of per capita farm income. In both panels, the first regressions control only for drought, and the second regressions control for household covariates. In all regressions, we clustered standard errors at the enumeration-area level.

The results suggest that drought in the previous period negatively affects total per capita income this year, and the effect is statistically significant at the 1% level. Column 1 suggests that experiencing drought in the previous production year leads to a 31.6% reduction in total per capita income. Controlling for household covariates increases the drought effect to 33.7% (column 2). However, column 3 suggests that experiencing drought

in the previous year reduces current per capita farm income by 20.2%. However, the effect is statistically insignificant at conventional levels due to relatively large standard errors. When we control for household covariates in column 4, the effect becomes weakly significant (at 10%).

Given that farming in rural Ethiopia is almost entirely rain-fed, why would a drought not affect per capita farm income? The likely reason is the impact of drought on off-farm income. There is extensive literature (e.g., Kochar, 1999; Arndt *et al.*, 2011; Musungu *et al.*, 2024) documenting that off-farm employment opportunities are significantly reduced during droughts because of reduced demand for hired labor. Kochar (1999) uses fixed-effects regressions on household data from rural India and shows that agricultural employment declines after droughts, and that household members have difficulty shifting into off-farm occupations because of the contraction in rural labor markets, which limits off-farm employment growth during droughts. Arndt *et al.* (2011) merge weather data with labor market surveys and documents that droughts reduce overall employment, including off-farm jobs, due to the contraction of rural economies and the decline in non-agricultural activities dependent on farm incomes. More recently, Musungu *et al.* (2024) uses panel data from the same rural Ethiopian setting as ours and finds that drought shocks reduce agricultural productivity, forcing households to cut back on on-farm work.

Table 4: Impact of Income Shock on Energy Poverty-Mechanism

	Panel A		Panel B	
	log(Per Capita Total Income)		log(Per Capita Farm Income)	
	(1)	(2)	(3)	(4))
$Drought_{t-1}$	-0.316***	-0.337***	-0.202	-0.221*
	(0.109)	(0.107)	(0.127)	(0.119)
Time Fixed Effects	Yes	Yes	Yes	Yes
Village Fixed Effects	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	7274	7274	7274	7274

Notes: This table presents fixed-effects results on the impact of drought on per-capita income. Panel A presents results on the impact of drought on total per capita income. Panel B presents the impact of drought on per capita farm income. The first column in each panel controls for drought only. The second column in each panel controls for covariates. Drought is defined as a binary variable that takes 1 if the standardized deviation of the previous year's rainfall is less than -1 from the long-term mean (i.e., 1981-2015), and 0 otherwise. The regression control variables include the head's age and gender; the highest level of education in the household; household size; landholding; livestock holding; home ownership; and number of rooms. Standard errors (in parentheses) are clustered at the enumeration area level. * p < 0.10, ** p < 0.05, *** p < 0.01.

Taken together, the results in Table 4 show that the key mechanism through which drought affects multidimensional energy poverty is its effect on income, including income from off-farm employment. A decline in income increases multidimensional energy poverty because households are likely to shift to polluting solid fuels, such as charcoal and firewood, rather than cleaner fuels. Indeed, several previous studies (e.g., Liu & Hu, 2024; Karymshakov & Azhgaliyeva, 2025) document that households increase their use of polluting fuels in response to income declines.

4.3. Heterogeneous Effects

4.4. Head's Gender and Place of Residence

The main regression results we presented in Table 3 assume that the effect of a weather shock on energy poverty remains constant across variations in the households affected. However, even if the average effect is significant, the impact of a weather shock might vary across subgroups. In view of this, investigating the heterogeneous impact of drought on key socio-economic variables is warranted. In this sub-section, we investigate the heterogeneous effects of drought on multidimensional energy poverty based on four key variables: the household head's gender, the household's place of residence (rural vs. urban), access to safety net programs, and access to credit. These variables are among the most widely used for heterogeneous effects of shocks in low-income settings.

Table 5: Impact of Income Shock on Energy Poverty-Heterogeneous Analysis

	1	2	3	4
	Male	Female	Male	Female
Panel A: By Gender of HH Head				
$Drought_{t-1}$	0.018***	0.017	0.051***	0.003
	(0.007)	(0.014)	(0.019)	(0.027)
Observations	5,384	1,888	5,384	1,888
	Rural	Small Town	Rural	Small Town
Panel B: By Place of Residence				
$Drought_{t-1}$	0.014**	0.060***	0.025	0.168*
	(0.007)	(0.010)	(0.016)	(0.090)
Observations	6,440	834	6,440	834
Time FE	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: This table presents fixed-effects regression results on the heterogeneous effects of drought on multidimensional energy poverty. Panel A presents results by the gender of the head of the household. Panel B presents results by place of residence (rural vs small town). Drought is defined as a binary variable that takes 1 if the standardized deviation of the previous year's rainfall is less than -1 from the long-term mean (i.e., 1981- 2015), and 0 otherwise. The regression control variables include the head's age and gender; the highest level of education in the household; household size; landholding; livestock holding; home ownership; and number of rooms. Standard errors (in parentheses) are clustered at the enumeration area level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A of Table 5 presents fixed-effects regression estimates of the heterogeneous effects of drought on energy poverty by the gender of the household head. Panel B reports heterogeneous effects by place of residence (rural versus small town). All regressions include time fixed effects, village fixed effects, and household covariates, and the standard errors are clustered at the enumeration-area level.

Panel A indicates that the impact of drought on multidimensional energy poverty differs between male-headed and female-headed households. For male-headed households, the effect is positive and statistically significant. For female-headed households, although the effect is also positive, it is not statistically significant at conventional levels. Specifically, drought increases the multidimensional energy poverty score of male-headed households by approximately 0.018 points, and raises their probability of experiencing multidimensional

energy poverty by about 5.1%. One possible explanation is that in low-income settings such as rural Ethiopia, female-headed households often face structural disadvantages—limited access to income, assets, and energy-using appliances—which place them at higher baseline levels of energy poverty. Consequently, their energy access is already severely constrained, leaving less scope for observable deterioration following a weather shock. In contrast, male-headed households typically have lower baseline energy poverty levels, making the drought-induced decline in energy access more detectable.

Panel B of Table 5 shows that the effects of drought also vary by place of residence. For the multidimensional energy poverty score, the estimated impacts are positive and statistically significant for both rural and small-town households. For multidimensional energy poverty status, the impact is positive in both settings, but only weakly statistically significant for small-town households. Specifically, drought increases the likelihood that small-town households are classified as energy poor by about 16.8%. One plausible explanation is that access to electricity is extremely low in rural Ethiopia; therefore, drought-induced income shocks may have limited additional impact on already constrained rural energy consumption. In contrast, small-town households may have greater baseline access to modern energy sources, making drought-related disruptions more visible in measured energy poverty outcomes.

4.5. Access to PSNP and Credit

We next examine how access to social safety nets and credit shapes the heterogeneous impacts of drought on energy poverty. Ethiopia is highly susceptible to drought, having endured more than 15 major drought episodes since the 1960s, each causing substantial losses in lives and household assets (Guha-Sapir *et al.*, 2016). In response, the Government of Ethiopia, with support from international partners, has made considerable investments over the past two decades to strengthen national disaster preparedness and shock-responsive systems. The most prominent initiative is the Productive Safety Net Programme (PSNP), launched in 2005 to transition millions of chronically food-insecure rural households from reliance on emergency food aid to a more predictable, institutionalized form of social protection (Bank, 2013).

Table 6 reports fixed-effects regression estimates of the effects of drought on energy poverty for PSNP beneficiaries versus non-beneficiaries, as well as for households with and without access to credit. Columns 1 and 5 indicate that drought has no statistically significant effect on the energy poverty of PSNP participants, whether measured by the multidimensional energy poverty score or by energy poverty status. This suggests that the program effectively cushions participating households from the adverse energy-related consequences of weather shocks.

By contrast, the effects are both positive and statistically significant for households not enrolled in the PSNP. Among non-participants, drought raises the MEPI score by

roughly 0.017 points and increases the probability of multidimensional energy poverty by approximately 3.4% (significant at the 10% level). This pattern aligns with the intended role of the PSNP—to help vulnerable households maintain consumption and buffer income declines during climatic shocks.

We also find compelling evidence that access to credit reduces the impact of drought on multidimensional energy poverty as measured by the energy poverty score. Column 4 shows that, for households without credit access, drought increases the MEPI score by about 0.02 points. However, we do not observe a similar mitigating effect of credit on multidimensional energy poverty status: for households lacking credit, the estimated impact on poverty status is positive but statistically insignificant.

Table 6: Impact of Income Shock on Energy Poverty-The Role PSNP

	Panel A: MEPI Score				Panel B: MEPI Status			
	1	2	3	4	5	6	7	8
	PSNP	No PSNP	Credit	No Credit	PSNP	No PSNP	Credit	No Creedit
$Drought_{t-1}$	-0.046	0.017**	0.007	0.020**	0.128	0.034*	-0.042	0.037
	(0.028)	(0.007)	(0.014)	(0.009)	(0.085)	(0.018)	(0.039)	(0.025)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,022	6,249	1,833	5,441	1,022	6,249	1,833	5,441

Notes: This table reports fixed-effects results on the heterogenous effects of drought by access to productive safety net program (PSNP) and credit. Panel A presents effects on the multidimensional poverty score. Panel B displays effects on the mutidimensional poverty status. Drought is defined as a binary variable that takes 1 if the standardized deviation of the previous year's rainfall is less than -1 from the long-term mean (i.e., 1981- 2015), and 0 otherwise. The regression control variables include the head's age and gender; the highest level of education in the household; household size; landholding; livestock holding; home ownership; and number of rooms. Standard errors (in parentheses) are clustered at the enumeration area level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.6. Robustness Checks

We assess the robustness of our findings using two complementary approaches.

First, following Shah & Steinberg (2017) and Mahajan (2017), we construct an alternative drought indicator. Under this specification, a household is classified as experiencing drought if lagged village-level rainfall falls below the 20th percentile of its long-term mean. The regression estimates reported in Table 7 indicate that our core results in Table 3 remain qualitatively unchanged under this alternative definition.

Second, we test the sensitivity of our findings to the weighting scheme used in constructing the multidimensional energy poverty index. While the primary analysis assigns distinct weights to each dimension, we re-estimate the results using equal weights of 0.2 across all dimensions. The results in Table 8 reaffirm the robustness of our main conclusions: drought increases energy poverty by approximately 0.0214 points. After controlling for household covariates, the coefficient slightly declines to 0.019 points, yet the effect remains statistically significant at conventional levels.

Table 7: Impact of Income Shock on Energy Poverty-Robustness Checks

	Panel A: Multidimensional EP Score		Panel B: Multidimensional EP Status	
	(1)	(2)	(3)	(4)
$Drought_{t-1}$	0.0163***	0.0161***	0.0357**	0.0344**
	(0.00609)	(0.00599)	(0.0160)	(0.0160)
Time Fixed Effects	Yes	Yes	Yes	Yes
Village Fixed Effects	Yes	Yes	Yes	Yes
Controls	No	Yes	No	yes
Observations	7,274	7,274	7,274	7,274

Notes: This table reports fixed-effects regression results using an alternative definition of drought. Panel A presents estimates for the MDEP score, while Panel B reports results for MDEP status. Drought is defined as a binary variable equal to 1 if the previous year's rainfall falls below the 20$^{\text{th}}$ percentile of the long-term mean (1981–2015), and 0 otherwise. All control variables included in the main specification are retained. Standard errors, shown in parentheses, are clustered at the enumeration-area level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Impact of Income Shock on Energy Poverty-Robustness Check

	1	2
$Drought_{t-1}$	0.0214**	0.0190**
	(0.00858)	(0.00845)
Time Fixed Effects	Yes	Yes
Village Fixed Effects	Yes	Yes
Controls	No	Yes
Observations	7,274	7,274

Notes: Clustered standard errors in parentheses. Columns [1] and [2] describe the impact of drought on energy poverty using a fixed effect model with and without controls, respectively. Drought is defined as a binary variable takes 1 if the standardized deviation of the previous year's rainfall is less than negative one from the long-term mean (i.e., 1981- 2015) it takes zero otherwise. All controls included in the main analysis are included. Standard errors are clustered at the enumeration area level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5. Conclusion

This paper examines the causal impact of drought on multidimensional energy poverty in rural and small-town Ethiopia by combining nationally representative panel data with high-resolution weather information. We document that drought substantially increases both the intensity and likelihood of energy poverty, with effects that are robust across alternative drought definitions and weighting schemes for the multidimensional index. The results highlight the extent to which households' energy deprivation is sensitive to climatic shocks in settings where both agricultural livelihoods and access to modern energy infrastructure remain highly constrained.

Our analysis shows that the primary mechanism through which drought exacerbates energy poverty is a sharp decline in household income—particularly total per capita income—following a rainfall shock. Income losses restrict households' ability to afford cleaner energy sources, driving them toward cheaper, more polluting solid fuels. This mechanism aligns with prior evidence indicating that households substitute toward dirtier fuels when their purchasing power declines. The effects of drought, however, are not uniform: male-headed households and small-town households exhibit stronger increases in energy poverty, reflecting differences in baseline energy access, livelihood diversification, and exposure to income shocks.

Finally, the results underscore the critical role of policy interventions in mitigating climate-induced energy deprivation. Ethiopia's Productive Safety Net Programme (PSNP) effectively shields beneficiary households from drought-related increases in energy

poverty, highlighting the importance of stable, shock-responsive social protection systems in vulnerable agrarian economies. Access to credit also dampens the impact of drought on energy poverty scores, though its effect on poverty status is more limited. Together, these findings reveal that strengthening adaptive capacity—through targeted safety nets, rural credit markets, and broader investments in modern energy access—is essential for protecting households from the escalating welfare risks posed by climate change.

References

Abebe, Meseret, & Alem, Yonas. 2025. Drought, livestock holding and milk production: A difference-in-differences analysis. *European Review of Agricultural Economics.*

Agamile, Peter, Dimova, Ralitza, & Golan, Jennifer. 2021. Crop Choice, Drought and Gender: New Insights from Smallholders' Response to Weather Shocks in Rural Uganda. *Journal of Agricultural Economics*, **27**(3), 829–856.

Alem, Y., & Demeke, E. 2020. The persistence of energy poverty: A dynamic probit analysis. *Energy Economics*, **90**, 104789.

Alem, Y., Bezabih, M., Kassie, M., & Zikhali, P. 2010. Does fertilizer use respond to rainfall variability? Panel data evidence from Ethiopia. *Agricultural Economics*, **41**(2), 165–175.

Alem, Yonas, & Colmer, Jonathan. 2021. Blame it on the rain: Rainfall variability, consumption smoothing, and subjective well-being in rural Ethiopia. *American Journal of Agricultural Economics.*

Alem, Yonas, Hassen, Sied, & Köhlin, Gunnar. 2023. Decision-making within the Household: The Role of Division of Labor and Differences in Preferences. *Journal of Economic Behavior and Organization*, **207**, 511–528.

Alkire, Sabina, & Santos, Maria Emma. 2014. Measuring Acute Poverty in the Developing World: Robustness and Scope of the Multidimensional Poverty Index. *World Development*, **59**, 251–274.

Aragón, Fernando M., Oteiza, Francisco, & Rud, Juan Pablo. 2018. *Climate change and agriculture: farmer adaptation to extreme heat.* Tech. rept. IFS Working Papers.

Arndt, Channing, Davies, Rob, & Thurlow, James. 2011. The impact of weather shocks on employment outcomes: evidence from South Africa. *Environment and Development Economics*, **16**(3), 367–384.

Bank, World. 2013. World development report 2014: Risk and opportunity–managing risk for development.

Bank, World. 2017. Ethiopia - Urban Productive Safety Net Project. World Bank Document. https://projects.worldbank.org/en/projects-operations/project-detail/P163438.

Bardhan, Pranab, & Udry, Christopher. 1999. *Development Microeconomics.* New York: Oxford University Press.

Barnes, Douglas F, Khandker, Shahidur R, & Samad, Hussain A. 2011. Energy poverty in rural Bangladesh. *Energy Policy*, **39**(2), 894–904.

Benti, Natei Ermias, Gurmesa, Gamachis Sakata, Argaw, Tegenu, Aneseyee, Abreham Berta, Gunta, Solomon, Kassahun, Gashaw Beyene, Aga, Genene Shiferaw, & Asfaw, Ashenafi Abebe. 2021. The current status, challenges and prospects of using biomass energy in Ethiopia. *Biotechnol Biofuels*, **14**(1), 209.

Beyene, G. E., Kumie, A., Edwards, R., & Troncoso, K. 2018. Opportunities for transition to clean household energy in Ethiopia: application of the household energy assessment rapid tool (HEART). *In Opportunities for transition to clean household energy in Ethiopia: application of the household energy assessment rapid tool (HEART).*

Bianco, V., Manca, O., & Nardini, S. 2009. Electricity consumption forecasting in Italy using linear regression models. *Energy*, **34**(9), 1413–1421.

Carter, Michael R., & Lybbert, Travis J. 2012. Consumption versus asset smoothing: testing the implications of poverty trap theory in Burkina Faso. *Journal of Development Economics*, **99**(2), 255–264.

Chowdhury, Sourangsu, Dey, Sagnik, Guttikunda, Sarath, Pillarisetti, Ajay, Smith, Kirk R., & Di Girolamo, Larry. 2019. Indian annual ambient air quality standard is achievable by completely mitigating emissions from household sources. *Proceedings of the National Academy of Sciences*, **116**(22), 10711–10716.

Churchill, S. A., Smyth, R., & Trinh, T. A. 2022. Energy poverty, temperature and climate change. *Energy Economics*, **114**, 106306.

de Janvry, Alain, Finan, Frederico, Sadoulet, Elisabeth, & Vakis, Renos. 2006. Can conditional cash transfer programs serve as safety nets in keeping children at school and from working when exposed to shocks? *Journal of Development Economics*, **79**(2), 349–373. Special Issue in honor of Pranab Bardhan.

Dercon, S. 2002. Income risk, coping strategies, and safety nets. *World Bank Research Observer*, **17**(2), 141–166.

Dercon, S., & Christiaensen, L. 2011. Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of development economics*, **96**(2), 159–173.

Dercon, Stefan. 2004. Growth and shocks: evidence from rural Ethiopia. *Journal of Development Economics*, **74**(2), 309–329.

Dercon, Stefan, Hoddinott, John, Woldehanna, Tassew, *et al.* 2005. Shocks and consumption in 15 Ethiopian villages, 1999-2004. *Journal of African economies*, **14**(4), 559.

FAO. 2016a. Food and Agriculture Organizations of the United Nations.

FAO. 2016b. *SITUATION REPORT– May 2016. Ethiopia.*

FDRE-NPC Federal Democratic Republic of Ethiopia, National Planning Commission. 2016. Growth and Transformation Plan – II (GTP-II): 2015/16 – 2019/20, Volume II: Policy Matrix.

Federal Democratic Republic of Ethiopia, Ministry of Agriculture, & Development, Rural. 2011. Ethiopia's agricultural sector policy and investment framework (PIF) 2010-2020: Final report.

Feeny, S., Trinh, T. A., & Zhu, A. 2021. Temperature shocks and energy poverty: Findings from Vietnam. *Energy economics*, **99**, 105310.

Funk, Chris, Peterson, Pete, Landsfeld, Martin, Pedreros, Diego, Verdin, James, Shukla, Shraddhanand, Husak, Gregory, Rowland, James, Harrison, Laura, Hoell, Andrew, *et al.* 2015. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific data*, **2**(1), 1–21.

Gebremeskel, D. H., Ahlgren, E. O., & Beyene, G. B. 2021. Long-term evolution of energy and electricity demand forecasting: The case of Ethiopia. *Energy Strategy Reviews*, **36**, 100671.

Guha-Sapir, D., Below, R., & Hoyois, P. 2016. EM-DAT: the CRED/OFDA international disaster database.

Guta, F., Damte, A., & Ferede, T. 2015. The residential demand for electricity in Ethiopia. EfD Discussion Paper No. 15-07, Environment for Development.

Hailu, A. D., & Kumsa, D. K. 2021. Ethiopia renewable energy potentials and current state. *Aims Energy*, **9**(1).

Hirvonen, Kalle, Sohnesen, Thomas Pave, & Bundervoet, Tom. 2020. Impact of Ethiopia's 2015 drought on child undernutrition. *World Development*, **131**, 104964.

Hoddinott, John, & Kinsey, Bill. 2001. Child Growh in the Time of Drought. *Oxford Bulletin of Economics and Statistics*, **63**(4), 409–436.

Huang, J., Wang, Y., & Wang, J. 2015. Farmers' adaptation to extreme weather events through farm management and its impacts on the mean and risk of rice yield in china. *American Journal of Agricultural Economics*, **97**(2), 602–617.

IEA. 2020. SDG7: Data and Projections. IEA, Paris https://www.iea.org/reports/sdg7-data-and-projections.(accessed on 31 January 2022).

IPCC. 2014. Climate change 2014: Synthesis report. contribution of working groups i, ii and iii to the fifth assessment report of the intergovernmental panel on climate change. Core writing team, R.K. Pachauri and L.A. Meyer (eds.).

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. Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.).

IRENA. 2017. *Accelerating the Energy Transition through Innovation*. Working Paper. International Renewable Energy Agency.

Karymshakov, Kamalbek, & Azhgaliyeva, Dina. 2025. *Assessing the Impact of Income Decline on Household Clean Fuel Choice: Evidence from the Kyrgyz Republic*. Tech. rept. 773. Asian Development Bank. Income decline may result in the use of cheaper and solid fuels.

Khan, B., & Pawan, S. 2017. The current and future states of Ethiopia's energy sector and potential for green energy: A comprehensive study. *Int J Eng Res Africa*, **33**, 115–139.

Kochar, Anjini. 1999. The effect of drought on household occupation choices in rural India. *Environment and Development Economics*, **4**(4), 431–449.

Koomson, I., & Churchill, S. A. 2022. Employment precarity and energy poverty in post-apartheid South Africa: Exploring the racial and ethnic dimensions. *Energy Economics*, **110**, 106026.

Kruger, W., Fezeka, S., & Olakunle, A. 2019. Ethiopia country report.

Li, X., Smyth, R., Xin, G., & Yao, Y. 2023. Warmer temperatures and energy poverty: Evidence from Chinese households. *Energy Economics*, **120**, 106575.

Liu, Huan, & Hu, Tiantian. 2024. Energy poverty alleviation and its implications for household energy consumption and health. *Environment, Development and Sustainability*, **26**, 10063–10083. Shows that poor households rely on cheap but polluting fuels such as wood, coal, and dung.

Lorenz, Christof, & Kunstmann, Harald. 2012. The hydrological cycle in three state-of-the-art reanalyses: Intercomparison and performance analysis. *Journal of Hydrometeorology*, **13**(5), 1397–1420.

Mahajan, K. 2017. Rainfall shocks and the gender wage gap: evidence from Indian agriculture. *World Development*, **91**, 156–172.

Malla, Sunil, & Timilsina, Govinda R. 2014. *Household Cooking Fuel Choice and Adoption of Improved Cookstoves in Developing Countries: A Review.* Policy Research Working Paper 6903. The World Bank.

Mengistu, M. G., Simane, B., & Eshete, G. et al. 2015. A review on biogas technology and its contributions to sustainable rural livelihood in Ethiopia. *Renewable Sustainable Energy Rev*, **48**, 306–316.

Modi, Vijay, McDade, Susan, Lallement, Dominique, Saghir, Jamal, *et al.* 2005. *Energy services for the Millennium Development Goals.* Tech. rept. Energy Sector Management Assistance Programme, United Nations Development Programme, UN Millennium Project, and World Bank.

Mondal, M. A. H., Bryan, E., Ringler, C., Mekonnen, D., & Rosegrant, M. 2018. Ethiopian energy status and demand scenarios: prospects to improve energy efficiency and mitigate GHG emissions. *Energy*, **149**, 161–172.

Musungu, A. L., Kubik, Z., & Qaim, M. 2024. Drought shocks and labour reallocation in rural Africa: evidence from Ethiopia. *European Review of Agricultural Economics*, **51**(2), 345–372.

Nussbaumer, P., Bazilian, M., & Modi, V. 2012. Measuring energy poverty: Focusing on what matters. *Renewable and Sustainable Energy Reviews*, **16**(1), 231–243.

Phimister, Euan, Vera-Toscano, Esperanza, Roberts, Deborah, *et al.* 2015. The dynamics of energy poverty: Evidence from Spain. *Economics of Energy and Environmental Policy*, **4**(1), 153–166.

Porter, Catherine. 2012. Shocks, consumption and income diversification in rural Ethiopia. *Journal of Development Studies*, **48**(9), 1209–1222.

Pratiti, Rebecca, Vadala, David, Kalynych, Zirka, & Sud, Parul. 2020. Health effects of household air pollution related to biomass cook stoves in resource limited countries and its mitigation by improved cookstoves. *Environmental Research*, **186**, 109574.

Que, N. D., Van Song, N., Thuan, T. D., Van Tien, D., Van Ha, T., Phuong, N. T. M., & Phuong, P. T. L. 2022. How temperature shocks impact energy poverty in Vietnam:

mediating role of financial development and environmental consideration. *Environmental Science and Pollution Research*, **29**(37), 56114–56127.

Roberts, Deborah, Vera-Toscano, Esperanza, Phimister, Euan, *et al.* 2015. Energy poverty in the UK: Is there a difference between rural and urban areas. *Pages 13–15 of: 89th Annual Conference, April.*

Shah, M., & Steinberg, B. M. 2017. Drought of opportunities: contemporaneous and long-term impacts of rainfall shocks on human capital. *Journal of Political Economy*, **125**(2), 527–561.

Ssennono, V. F., Ntayi, J. M., Buyinza, F., Wasswa, F., Adaramola, M. S., & Aarakit, S. M. 2023. Climatic shocks and multidimensional energy poverty in Ugandan households: does women empowerment play a moderating role? *International Journal of Sustainable Energy*, **42**(1), 103–127.

Tambet, Heleene, & Stopnitzky, Yaniv. 2019. Climate Adaptation and Conservation Agriculture among Peruvian Farmers. *American Journal of Agricultural Economics.*

Thiede, Brian C. 2014. Rainfall shocks and within-community wealth inequality: Evidence from rural Ethiopia. *World Development*, **64**, 181–193.

USAID. 2016. Climate Change Risk Profile – Ethiopia.

Wang, Bin, Luo, Xiao, Yang, Young-Min, Sun, Weiyi, Cane, Mark A., Cai, Wenju, Yeh, Sang-Wook, & Liu, Jian. 2019. Historical change of El Niño properties sheds light on future changes of extreme El Niño. *Proceedings of the National Academy of Sciences*, **116**(45), 22512–22517.

Wang, Ruixue, Rejesus, Roderick M., Tack, Jesse B., Balagtas, Joseph V., & Nelson, Andy D. 2022. Quantifying the Yield Sensitivity of Modern Rice Varieties to Warming Temperatures: Evidence from the Philippines. *American Journal of Agricultural Economics*, **104**(1), 318–339.

WorldBank. 2025a (July). *Population, total - Ethiopia.*

WorldBank. 2025b. *The World Bank in Ethiopia.*

Yamano, Takashi, Alderman, Harold, & Christiaensen, Luc. 2005. Child growth, shocks, and food aid in rural Ethiopia. *American Journal of Agricultural Economics*, **87**(2), 273–288.

Zhang, D., Li, J., & Han, P. 2019. A multidimensional measure of energy poverty in China and its impacts on health: An empirical study based on the China family panel studies. *Energy Policy*, **131**, 72–81.

Zhang, Q., Appau, S., & Kodom, P. L. 2021. Energy poverty, children's wellbeing, and the mediating role of academic performance: Evidence from China. *Energy Economics*, **97**, 105206.