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# CLIMATE SHOCKS AND RESILIENCE: EVIDENCE FROM RURAL ETHIOPIA

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# ABSTRACT

Climate shock, specifically drought causes serious adverse effects on household welfare in rural Ethiopia. As a direct response to such shocks, resilience and related activities become the country's key development agenda. In this context, we examine the relationship between climate shock and household consumption and then assess how household resilience influences this relationship. By combining historical observations of climate extremes and Ethiopian Socioeconomic survey datasets, we find that both short-term and long-term droughts are significantly associated with reduced consumption, and this relationship is moderated by resilience. We look at the resilience indicators that possibly mediate the effects of drought on either realized or probabilistic measures of consumption to understand what is associated with the ability to withstand or recover quickly from drought. We reframe the resilience as capacity approach and resilience as a normative condition approach that reflect two distinct ways of inferring resilience. In the resilience as capacity approach, we model realized consumption as a dependent variable and interaction terms between drought and hypothesized resilience indicators as joint explanatory variables. From our hypothesized resilience indicators, we find some indicators that are associated with attenuating the adverse effects of drought shock on realized household consumption. These include wealth index, informal transfer, and formal transfer indicators. In the resilience as a normative condition approach, we model probabilistic household consumption as a dependent variable and same interaction terms and find income diversification, livestock diversification, and agricultural asset indicators. This study has important implications for both research and policy. The adverse effects of droughts on consumption inform the investment need and policy design around resilience. The resilience indicators associated with attenuating the adverse effects of drought shock on realized and probabilistic consumption has also important implications. First, the nexus between drought and consumption via specific resilience indicators associated with attenuating the adverse effect of drought on consumption informs policy design around these indicators. Second, our interest variable framing to identify the specific resilience indicators associated with attenuating the adverse effects of drought on both realized and probabilistic household consumption provides insight to bridge the resilience as capacity and resilience as a normative condition approaches classic debate with the question of whether resilience is a right-hand or left-hand side variable.

**Keywords:** Climate shock, consumption, resilience indicators, resilience approach, Ethiopia
**JEL Codes:** Q54, I31, I38, O21

# EXECUTIVE SUMMARY

Climate shock, specifically drought causes serious adverse effects on household welfare in rural Ethiopia. For instance, the 2015 El Niño induced drought in the recent notable drought event that caused the failure of the two main rainy seasons that supply over 80 percent of Ethiopia's agricultural yield and employ 85 percent of the workforce (FDRE, 2016). In search of a strategic response to drought and related shocks, and the government of Ethiopia has put in place various programs focusing on strengthening rural households' resilience. Nevertheless, rigorous studies on the adverse impacts of climate shocks on household wellbeing and the effects of specific programs to strengthen resilience are still limited in Ethiopia.

In this context, we examine the effects of drought on household consumption and look at specific resilience indicators that mediate the adverse effects of drought on consumption in rural Ethiopia using longitudinal survey data combined with climate data and a range of methods—by tying together several threads of the literature. First, we analyze the effects of short-term and long-term droughts on household consumption between 2011-2016 periods. We find the effect of drought on household consumption is substantial. The magnitude of the negative impact is approximately 7%, indicating annual per adult equivalent of the consumption of households in rural Ethiopia with drought decreases approximately by 7%. This adverse impact of drought on household consumption could be explained primarily by the low resilience rural households of Ethiopia developed over time to deal with drought and food shortage.

Second, by reframing the resilience as capacity and resilience as a normative condition approach that reflects two distinct ways of inferring development resilience, we explicitly identify specific resilience indicators that mediate the impacts of drought shock on either realized and probabilistic measures of consumption. These include wealth index, income diversification, livestock diversification, and agricultural asset, informal transfer, and formal transfer indicators. Our goal with reframing resilience approaches was not only to identify the attenuating resilience indicators but to provide relevant settings and insight to speak their functional forms. Specifically, it provides insights to bridge the classic debate of the literature with the question of whether resilience is a right-hand or left-hand side variable. This is a central question that divides these approaches and is also consequential for policy design.

Overall, the study has important policy implications— to make efforts for more policy targeting of drought exposed households and specific effective resilience enhancing interventions. Given the government's resource constraint for drought response humanitarian interventions, our findings imply the necessity to make efforts for more effective policy targeting drought exposed households to address the problem of consumption reduction caused by droughts of different types. The short-term and long-term drought measure provides a sound quantitative synthesis on the relationships between different droughts and household wellbeing outcomes that can help policymakers from the indirect links between the provision of drought shock assistance and the food security impacts that these programs seek to mitigate. This is one of the main ways in which previous work couldn't investigate deeper into the impacts of drought on household wellbeing outcomes in Ethiopia. Therefore, a specific focus on the effects of these droughts on household consumption may help policymakers to choose the appropriate responses to the type of drought.

Furthermore, we identified useful resilience indicators for policy. The study examined a range of resilience indicators that could be employed in the face of climate shocks by rural households, but not all proposed indicators attenuate the adverse impacts of drought on well-being. This leads to the

question of what constitutes attenuating resilience indicators. The nexus between drought and consumption via a few specific attenuating resilience indicators informs policy design around these indicators.

# TABLE OF CONTENTS

# LIST OF TABLES



# LIST OF FIGURES

# ACRONYMS AND ABBREVIATIONS

| | |
|---|---|
| CEDA | Centre for Environmental Data Analysis |
| CPI | Consumer Price Index |
| CSA | Central Statistical Agency of Ethiopia |
| ESS | Ethiopian Socioeconomic Survey |
| FDRE | Federal Democratic Republic of Ethiopia |
| Km | Kilometer |
| SNNP | Southern Nations Nationalities and People |
| SPEI | Standardized Precipitation Evapotranspiration Index |
| SPEI-24 | Standardized Precipitation Evapotranspiration Index at 24 months |
| SPEI-6 | Standardized Precipitation Evapotranspiration Index at 6 months |
| SSA | Sub-Sahara Africa |

# 1. INTRODUCTION

Rural households in Sub-Sahara Africa (SSA) face several types of shocks that threaten their wellbeing. Ethiopia is highly exposed to climate shocks, such as droughts and floods. Since its agriculture is predominantly rain-fed; any shift in the amount or intensity of rainfall affects crops and livestock and therefore is likely to have adverse impacts on wellbeing (e.g., food security) (Di Falco et al., 2011). High dependence on agricultural livelihoods, coupled with pervasive poverty, make households especially vulnerable to climate shocks (Wossen et al., 2018).

In search of insights into appropriate policy responses, many studies examine the impacts of climate shocks on wellbeing outcomes, as well as on households' capacities to mitigate shock impacts. Climate shocks have been shown to adversely affect various wellbeing outcomes in SSA, and Ethiopia in particular. To date, many studies that examine the impact of climate shocks on wellbeing outcomes (Dercon et al., 2005; Hill, R. V. & Porter, C., 2017), as well as on households' capacities to mitigate shock impacts (Gao and Mills, 2018) are conducted in relatively homogenous areas, rather than the country at large. Many of these studies also rely on subjective shock measures, which suffer both from lacking detail on shock intensity and from a recall problem, given typically a one-year time elapse between the shock occurrence and when the survey was conducted (T. Delbiso et al., 2017). Moreover, these studies often mention the potential for heterogeneity in the impacts of climate shocks on wellbeing outcomes due to differences in the capacity of households to deal with shocks, but not clearly point out climate shocks-wellbeing outcomes link, as well as the potential of households' capacity differences for such heterogeneous impacts. This capacity to deal with shocks is analogous to development resilience.

Development resilience has become a key focus of academic and policy research, as a lens through which to assess the adverse and heterogeneous impacts of shocks on wellbeing. This strong interest has generated different definitions and measurement approaches that do not always align with each other. Among the approaches to development resilience, the resilience as capacity (Alinovi et al., 2009) and resilience as a normative condition (Barrett and Constas, 2014; Cissé and Barrett, 2018) offer an explicit conceptualization of resilience and measurement method that follows directly from that conceptualization (Barrett et al., 2021). These approaches have been applied in several contexts (d'Errico et al., 2018; Brück et al., 2019).

Although very encouraging progress in operationalizing the development resilience concept as a policy objective, there are important issues that need further in-depth enquiry. First, the resilience as capacity and resilience as a normative condition approaches struggle in the ways of inferring resilience. They are two distinct development resilience approaches with overlapping identification indicators—wellbeing, climate shocks and observed indicators associated with resilience. One distinction is in writing functional form specification for resilience variable and hence struggle with the question of whether resilience is a right-hand or left-hand side variable. The resilience as capacity approach typically uses realized well-being indicators as left-hand side variables and tries to explain variation in realizations using variation in resilience indicators. By contrast, the resilience as a normative condition approach recognizes that well-being realizations are stochastic and that stochasticity is itself informative about resilience. This is a central question that divides these approaches and is also consequential for policy design.

Second, despite the broad focus on resilience indicators, question of which observed resilience indicators have, to date received little. While indicators are integral to both approaches and included with varying degree of specificity little is known about the indicators that effectively reduce the adverse impact of climate shocks on wellbeing. Studies in both approaches broadly identify set of indicators that have the potential to buffer shock impacts (e.g., d'Errico et al., 2018; Brück et al., 2019; Knippenberg et al., 2019; Phadera et al., 2019; Vaitla et al., 2020), but do not rigorously address the question of which observed resilience indicators effectively buffer against climate shocks and which do not.

This paper uses longitudinal survey data combined with climate data to address its two related objectives—to estimate the effects of climate shocks on household consumption, and to look at the indicators that mediate the impacts of climate shocks on either realized household consumption or probabilistic household consumption in rural Ethiopia. Both objectives are of academic and policy interest, and of topics about which there is little direct evidence in Ethiopia.

To assess the effects of climate shocks on household welfare, we model household-level changes in the wellbeing outcome—the realized consumption measure overtime on a vector of short-term and long-term droughts plus some controls to empirically assess the effects of climate shocks on household consumption. We find the effect of drought on household consumption is substantial. The magnitude of the negative impact is approximately 7%, indicating annual per adult equivalent of the consumption of households in rural Ethiopia with drought decreases approximately by 7%. This adverse impact of drought on household consumption could be explained primarily by the low resilience rural households of Ethiopia developed overtime to deal with drought and food shortage.

Extending our main identification strategy, we model household changes in the two wellbeing outcome variables–realized consumption and probabilistic consumption overtime on a vector of candidate indicators, shocks, and their interactions. We find wealth index, informal transfer and formal transfer, income diversification, livestock diversification, and agricultural asset as important resilience indicators to capture a household's resilience to mediate climate shocks. This identification strategy also allows more nuanced insights. Beyond identifying any specific indicators that are statistically significantly associated with attenuating the adverse impacts of drought shocks on well-being, it provides insight about bridging the classic debates of the resilience as capacity and resilience as a normative condition approaches, especially on the question of whether resilience is a right-hand or left-hand side variable.

This study contributes to the growing literature on the impacts of climate shock and wellbeing outcomes and the potential of resilience in unpacking this link in several ways. First, it capitalizes on the recent availability of gridded climate data sets that combine information from ground stations, satellites, and employ objective shock measures based on climate data to generate more reliable estimates of climate shock impact on household consumption. Second, we incorporate the key aspects of the major climate shock, which is drought in Ethiopia about wellbeing outcomes by accounting both short-term and long-term droughts.[1] This comprehensive approach reveals the extent to which results are influenced by the choice of climate shock metric. Third, we explore the net effects of climate shocks on household consumption. Unlike other studies that explore the overall effects of climate shocks on household consumption in Ethiopia, we consider the nonlinear and asymmetric effects of climate shocks which enable us to empirically explore the net effects of climate shocks on household consumption.

Fourth and perhaps most importantly, we identify the specific resilience indicators that attenuate the adverse impacts of climate shocks on household wellbeing. While several papers explore the overall

[1] There is evidence that crop production—major source of food is affected not only by the intensity and duration of a drought, but also its timing with respect to the growing season.

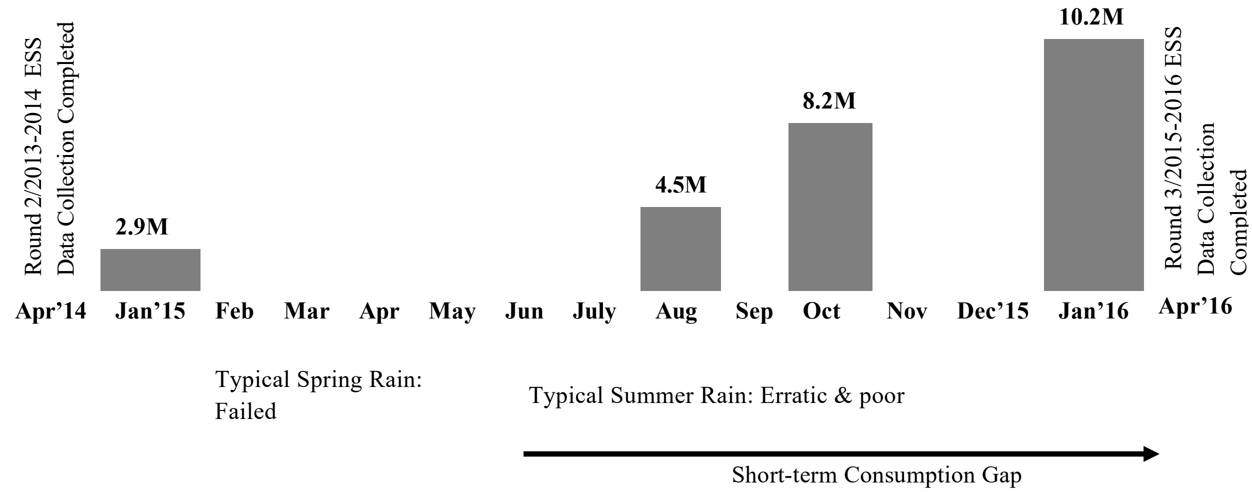
role of resilience indicators to such climate shock in the resilience as capacity and resilience as a normative condition approaches, to our knowledge, this is the first to empirically identify the specific resilience indicators that mediate the impacts of climate shocks on either realized consumption (outcome variable in resilience as capacity approach) or probabilistic consumption (outcome variable in resilience as a normative condition approach) measures of wellbeing using panel method in rural Ethiopia. By reframing the resilience as capacity and resilience as a normative condition approaches, we make progress on understanding the associated ability of such resilience indicators to withstand or recover quickly from climate shocks as well as on bridging these approaches traditions from the well-identified results of the resilience as capacity approach to the resilience as a normative condition approach.

The remainder of this paper is structured as follows. Section 2 reviews the contexts of climate shocks and resilience-building efforts in Ethiopia; Section 3 and 4 present datasets and methods used, respectively; Section 5 presents estimation results; Section 6 presents a discussion and outlines some ways forward for future research, and Section 7 concludes.

# 2. CLIMATE SHOCKS AND RESILIENCE BUILDING IN ETHIOPIA

Climatic shocks, primarily drought and flood, are the most important shocks in Ethiopia that affect many sectors, including agriculture. The frequency and severity of the drought have been increasing since the 1980s (Zeleke et al., 2017); the past fifty years have been touched by thirteen drought episodes of disastrous proportions (Mera, 2018).[1] The increased frequency, and devastating consequences, of the drought, were made manifest by droughts that occurred in three successive years, 2015–2017. The 2015 drought in particular was one of the worst droughts that Ethiopia has ever experienced (FDRE, 2016), with a magnitude at least comparable to historical episodes of droughts that caused dramatic food crisis in the mid-1970s and 1980s. It caused the failure of the two main rainy seasons that supply over 80 percent of Ethiopia's agricultural yield and employ 85 percent of the workforce. Figure 1 shows the crisis timeline with associated humanitarian needs as reported in the official humanitarian document of the country released in 2016. The numbers in the figure represent the total number of people in millions who required food assistance during the period of that drought as estimated in the official Humanitarian Requirement Document (FDRE, 2016).

**Figure 1. Timelines of the 2015 El Niño induced drought and the ESS consumption data collection in Ethiopia**




*Source:* The 2016 Humanitarian Requirement Document for Ethiopia and the 2013-2014 and 2015-2016 ESS

In addition to drought, flood is the other important climate shock that affects the wellbeing of households in Ethiopia. The country had extensive experiences in both flash and riverine flood events.[2] In terms of extent, 1997 was the most catastrophic flood year, with 16.7% area of the country affected by flood events, followed by 2005 and 2013 with 15.7% and 13.9% flood affected area, respectively (Mamo et al., 2019). La Niña episodes are responsible for these events, as they are

[1] These episodes occurred specifically in: 1972-1973, 1975-1976, 1978-1979, 1982-1984, 1987-1988, 1992-1994, 1999-2000, 2002-2003, 2006, 2011, 2015, 2016 and 2017

[2] Notable flood events occurred in 1988, 1996, 1998, 2006, 2010, 2012, and 2016.

associated with heavier than normal rains from June to September (Abtew et al., 2009). Commonly, these La Niña episodes in Ethiopia were preceded by El Niño associated drought events (Mamo et al., 2019). For instance, following the 2015 El Niño induced drought event, many areas in Ethiopia experienced flooding events in the following year.

It is in direct response to these climate shocks that resilience has become a key part of the policy agenda (Béné et al., 2017). The increasing frequency and impacts of climate shocks and increasing cost of humanitarian intervention, as well as the increasing interest of policymakers and international agencies in resilience-building interventions in Ethiopia, motivate us to emphasize our study's contribution to policy. We hence aim to tailor our empirical contribution to inform the design as well as implementation phases of the resilience policy agenda, emphasizing the need to transform the current policy approach from event-based emergency response to resilience-building interventions.

# 3. DATA AND VARIABLES

To address our research agenda demands data on three fronts: (1) climate shocks, ideally from units of measurement associated with the climate event (e.g., rainfall for drought and flood) as well as from subjective reports of shock categories experienced; (2) existing household and community characteristics that account for both exposure and strategies to deal with shocks; and (3) welfare outcomes that crudely speaking results from the interaction of the two, such as food security or consumption.

We draw on data to meet these needs from two sources. First, the rural category of the Ethiopian Socioeconomic Survey (ESS) collected by Ethiopia Central Statistical Agency (CSA) and the World Bank, which includes extensive information on household consumption & various household and community characteristics. The dataset is representative of all of the major regional states of Ethiopia, and includes three survey rounds over five years, from 2011-2016.[1] Second, we use enumeration area level climate data obtained from the Centre for Environmental Data Analysis (CEDA) archive, merged with the ESS dataset using latitude and longitude coordinates collected for all enumeration areas in the sample. Combining these two datasets provides the opportunity to make use of the benefits of panel data to examine the impact of climate shocks on household consumption and assess the contribution of resilience in buffering the impacts of such shocks. Herein we outline our dependent variables— realized household consumption and probability of household consumption exceeding the poverty line measure, as a probabilistic resilience measure, and our interest variables—resilience indicators and climate shocks.

We use the annual ESS consumption data and follow Fuje (2018) and Nakamura et al. (2019) to adjust the consumption aggregates of 2012, 2014, and 2016 in 2016—using the 2016 consumer price index (CPI) and make spatial adjustments using the Fisher spatial price index from the Ethiopian Household Income and Consumption Expenditure survey. We also use Ethiopian Birr 4366 (in 2016 price) poverty line—correspond to 40$^{th}$ percentile of household consumption and used by Fuje (2018) and Nakamura et al. (2019). The realized consumption measure constructed for this study is annual household consumption in adult equivalent in 2016 terms while our probabilistic resilience measure is estimated as the stochastic distribution in wellbeing outcome (poverty) as proposed by Cissé and Barrett (2018), taking annual household consumption in adult equivalent in 2016 terms and Birr 4366 (in 2016 price) poverty line as a proxy measure of poverty.

We identify a range of resilience indicator variables including, variables that are associated with the availability and accessing basic services—household's residence distance to the nearest district town and health post; index variables associated with diversification of households' income sources, diversification of livestock reared by the household, the diversification of crops grown in the households' agricultural land, agricultural asset, wealth; and dummy variables associated with social safety nets—households' status of getting assistance (in the form of transfer of money in Birr) from formal and informal sources in the past twelve months. Indexes of diversification of income sources, crop types grown, and livestock types reared, agricultural assets and wealth are constructed through factor analysis.

[1] Round 1/2011–2012, round 2/2013–2014, and round 3/2015–2016). The 2011-2012, 2013-2014, and 2015-2016 ESS include 3,357, 3,199, and 3,092 rural households, respectively

We use the 6 months and 24 months Standardized Precipitation Evapotranspiration Index (SPEI) from CEDA[2] to construct climate shock variables. Using the 6 months SPEI, we constructed a dummy 6 months SPEI (SPEI-6) variable as a measure of short-term drought as well as a dummy 24 months SPEI (SPEI-24) as a measure of long-term drought. Hence a dummy drought indicator variable is defined as 1 if the standard deviation of rainfall, prior the survey is less than a threshold SPEI (SPEI-6 = -0.5) and 0 otherwise. This threshold was chosen following the non-linear relationship between consumption residuals and rainfall anomalies examined using the local polynomial regressions; the fitted curve in figure 2 shows that the 6-month SPEI scores less than -0.5 were associated with lower consumption than what other household characteristics would otherwise predict (residual <0). We also use the same threshold for SPEI-24 to facilitate comparison and fitted curve in figure 2.

Since the survey periods during which data for our key study variables are collected are in 2012, 2014, and 2016, our SPEI values are calculated for 2011, 2013 and 2015, representing the shock years (a year prior to each of the survey periods). This only attends to realized shocks, not to unrealized ex-ante risk exposure. In addition, using SPEI-6 has the advantage to assess agricultural droughts that occur during critical growing seasons, while SPEI-24 is important to assess beyond just precipitation and soil moisture deficits reflecting hydrological droughts.

[2] CEDA consists of high spatial resolution SPEI dataset covering the whole of the African continent for a 36-year-long period (1981–2016) at a horizontal resolution of 5 km (0.05 deg) and a monthly time resolution. It is calculated based on precipitation estimates from the satellite-based Climate Hazards group InfraRed Precipitation with Station data and potential evaporation estimates by the Global Land Evaporation Amsterdam Model (Peng, J. et al., 2019).

# 4. EMPIRICAL STRATEGIES

The study uses several methods to investigate the impact of climate shocks on household consumption and household resilience in rural Ethiopia.

## 4.1. Climate shocks effect estimation

The recent climate-economy literature outlined a variety of empirical techniques to investigate the effects of climate shocks using standard panel methods (Dell et al., 2014). Our estimation strategy is household fixed effects model, a preferred model our panel data and interest. Our first interest is to estimate the impact of climate shock on household consumption. We begin by estimating the climate shock panel model following (Dell et al., 2014):

$$ln(y_{it}) = \alpha + \beta C_{it} + \gamma Z_{it} + \mu_i + \theta_{rt} + \varepsilon_{it} \quad (1)$$

$y_{it}$ is the consumption of household $i$ in year $t$; $C_{it}$is a vector of dummy climate shock variables: short-term drought variable (SPEI-6) and long-term drought (SPEI-24) variable in year $t$; $Z_{it}$ contains household characteristic that is likely to vary over time: household size, age of household head in years, sex and marital status of household head $i$ in year $t$; $\theta_{rt}$is time indicator; $\mu_i$ are the household fixed effects. The effects of climate shocks on household consumption are captured by$\beta$.

Beyond informing the level of any effects, we can use the panel structure to investigate the magnitude and locus of any effects, which is our another interest. We estimate the climate shock model by interacting our shock dummy variable, $C_{it}$ with a polynomial in the magnitude of the location-normalized shock measure, $W_{it}^2$ :

$$ln(y_{it}) = \alpha + \beta C_{it} + W_{it}^2 \times C_{it} + \gamma Z_{it} + \mu_i + \theta_{rt} + \varepsilon_{it} \quad (2)$$

Our key parameters of interest are $W_{it}^2 \times C_{it}$.[3] These provide estimates of the possibly nonlinear effects of droughts on well-being without conflating variation around the norm with variation in the tail of the distribution. In these spirit, several studies have attempted to estimate the impact of climate shocks (Dell et al., 2012; Deschênes and Greenstone, 2011).

## 4.2. Bridging resilience approaches: attenuating resilience indicators estimation

Our identification strategy is designed to reveal a more nuanced insight. First, by reframing the resilience as capacity and resilience as a normative condition development resilience approaches that reflect two distinct ways of inferring resilience and extending the household fixed effects regression in section 4.1, we explicitly examine and identify the specific indicators that are associated with attenuating the adverse impacts of drought shocks on well-being. In the resilience as capacity approach, we model realized household consumption as a dependent variable and interaction terms between short-term drought shock and key hypothesized resilience indicators as joint explanatory variables. In the resilience as a normative condition approach, we model probabilistic household consumption as a dependent variable and the same interaction terms. Interpretation of the

[3] The implied variables are constructed by interacting a dummy shock variable $C_{it}$ with a polynomial in the magnitude of the location-normalized drought measure variable,$W_{it}^2$.

interaction terms is the objective of the exercise, especially to see if any specific indicators are consistently, statistically significantly associated with attenuating the adverse impacts of drought shocks on well-being (Annan and Schlenker, 2015; Burke and Emerick, 2016; Gao and Mills, 2018).

Second, reframing resilience approaches to identify the specific indicators that are associated with attenuating the adverse impacts of drought shocks on well-being provide an insight about the functional forms these approaches. Specifically, it provides an insight about bridging the classic debates of the resilience as capacity and resilience as a normative condition approaches. Sections 4.2.1 and 4.2.2 below describe the detailed econometric model estimation in the resilience as capacity and resilience as a normative condition approach respectively.

### 4.2.1. Estimation in resilience as capacity approach

Extending our household fixed effects model in equation (1), we examine the mitigating influence of resilience indicators on climate shock through climate shock–indicators interaction.

$$ln(y_{it}) = \alpha + \beta C_{it} + R_{it} \times C_{it} + \gamma Z_{it} + \mu_i + \theta_{rt} + \varepsilon_{it} \quad (3)$$

$y_{it}$ is the realized consumption of household $i$ in year $t$ as used in equation (1); $C_{it}$is a vector of dummy short-term drought variable (SPEI-6) in year $t$; $R_{it}$ is a vector of dummy resilience indicator variables.

From a policy perspective, it is important to know whether households who have better off resilience indicators and/or exposed to drought have benefited from these resilience indicators. Therefore, we transform the continuous index variables associated with diversification—diversification of households' income sources, diversification of livestock reared by the household, the diversification of crops grown in the households' agricultural land, agricultural asset, wealth into binary indicators following Filmer and Pritchett (2001). We first sort sample households by these indicator indices and establish cut-off values for the percentile of the population. We then assign households to a group based on their value on the index. We refer to the bottom 40% as "low", the next 40% as "medium" and the top 20% as high. Finally, we create a binary variable for each indicator–taking the value of 1 if the household in the quintile is in the medium and top category as the better-off, 0 if the household is in the low category as poorest. In the case of two social safety nets indicators, which are expressed by dummy variables (1 if the household received assistance in the form transfer of money in Birr from formal and informal sources in the past twelve months; otherwise, 0). Hence, our implied variables are constructed by interacting drought variable, $C_{it}$ with potentially endogenous resilience indicators variables, $R_{it}$.

### 4.2.2. Estimation in resilience as a normative condition approach

Here, we construct a potentially complementary outcome variable with the resilience as capacity approach above by making two important modifications from the original Cissé and Barrett (2018) method. First, we omit shock and resilience indicators from the right-hand side variable in estimating the conditional mean in equation (4) and variance in equation (5) from which we estimate the probabilistic household consumption measure. Second, we apply the Cissé and Barrett (2018) method in a reduced form, which makes a relatively few identification assumptions and allows unusually strong causative interpretation.[4]

[4] The main advantage of this resilience measure is that it better reflects resilience to broader probabilistic wellbeing outcome (i.e. overall resilience), rather than the condition that reflects one's capacity to avoid adverse wellbeing states

Our probabilistic household consumption using Cissé and Barrett (2018) method in a reduced form in three steps:

First, we estimate the conditional mean of consumption as follows:

$$y_{it} = \beta_{1M_t} y_{i,t} + \beta_{2M_t} y_{i,t}^2 + \beta_{2M_t} y_{i,t}^3 + \delta_{M_i} Z_i + u_{Mit} \quad (4)$$

where $M$ is a subscript to indicate the mean in the stochastic consumption estimation.

Second, we estimate the conditional variance of consumption;

$$u_{Mit}^2 = \beta_{1V_t} y_{i,t} + \beta_{2V_t} y_{i,t}^2 + \beta_{3V_t} y_{i,t}^3 + \delta_{Vt} Z_i + u_{Vit} \quad (5)$$

where $V$ is a subscript to indicate the variance in the consumption estimation.

Third, we estimate resilience score (i.e. probabilistic household consumption), the probability of a household reaching or surpassing a minimum household consumption poverty line (ETB 4366 in 2016 price):

$$\rho_{it} \equiv Pr\left(y_{i,t} \geq \underline{y} | \Omega\right) = \int_{\underline{C}}^{\infty} f y_{it}(y_{it}) \quad (6)$$

where $\hat{\rho}_{it}$ is the estimated resilience score or probability to reach or exceed the poverty line; $\underline{y}$ the poverty line; $\Omega$ is the set of right-hand side polynomial and control variables as included in (5) and (6).

Extending our household fixed effects model in equation (3), we model probabilistic household consumption $\hat{\rho}_{it}$, as a dependent variable and interaction terms between short-term drought shock and key hypothesized resilience indicators as joint explanatory variables using:

$$\hat{\rho}_{it} = \alpha + \beta C_{it} + C_{it} \times R_{it} + \gamma Z_{it} + \mu_i + \theta_{rt} + \varepsilon_{it} \quad (7)$$

the focus of the original normative condition model). As such, this resilience measure is better suited for reconciling with the capacity approach framing of resilience. We therefore consider it our preferred specification for the paper's main analyses.

# 5. RESULTS

## 5.1. Descriptive statistics

Summary statistics for the main outcome and other major variables for each round of the panel are reported in Table 1. The main outcome variable used in this study is household consumption per adult equivalent per year (in 2016 price). Overall, the statistics in table 1 indicate the sample household's variation in consumption, exposure to climate shocks, and resilience indicators.

**Table 1. Descriptive statistics of outcome and key variables, 2012–2016**

| **Variables** | **2012** | **2014** | **2016** |
|---|---|---|---|
| Per adult equivalent annual consumption (2016 Birr) | 7069 | 6502 | 5773 |
| Log of per adult equivalent annual consumption (2016 Birr) | 8.58 | 8.56 | 8.44 |
| Poor (1 if consumption < 4360; otherwise 0) | 0.39 | 0.40 | 0.45 |
| Household size | 4.92 | 5.00 | 5.12 |
| Female headed household | 0.24 | 0.24 | 0.23 |
| Age of household head in years | 44.48 | 46.38 | 48.09 |
| Married household head | 0.79 | 0.79 | 0.80 |
| Exposed to short-term drought (1 if score of SPEI-6 <=-0.5; otherwise 0) | 0.16 | 0.14 | 0.62 |
| Exposed to long-term drought (1 if score of SPEI-24 <=-0.5; otherwise 0) | 0.09 | 0.13 | 0.45 |
| Length of residence distance from district town (km) | 22.12 | 21.38 | 21.37 |
| Length of residence distance from nearest health post (km) | 9.17 | 6.05 | 7.01 |
| Income diversification index | 0.09 | 0.17 | 0.23 |
| Crop diversification index | 0.15 | 0.32 | 0.28 |
| Livestock diversification index | 0.30 | 0.38 | 0.17 |
| Agricultural asset index | 0.07 | 0.17 | 0.13 |
| Wealth index | 0.02 | 0.35 | 0.04 |
| Whether the household received money from informal sources (1 = yes; 0 = no) | 0.10 | 0.09 | 0.10 |
| Whether the household received money from formal sources (1 = yes; 0 = no) | 0.08 | 0.06 | 0.05 |
| Observations (n) | 3,357 | 3,199 | 3,092 |

*Notes*: Data used is the CEDA & ESS 3-wave panel. Per adult equivalent consumption is measured in Birr per year. Poverty line: 4360 ETB. The income diversification index, crop diversification index, livestock diversification index, agricultural asset index, and wealth index are based on a factor analysis.

## 5.2. Effect of climate shocks on consumption

The results from estimating equations (1) and (2) are shown in Table 2. In column 1 of the table, we show results from estimates of equation (1), with the dependent variable as log annual per adult equivalent of household consumption, climate shock variable (using a dummy SPEI-6 drought indicator), household characteristics, and household fixed-effects. Similarly, Table 2, column 2 shows results from the estimates of equation (2) of the same dependent variable on a vector interaction term between dummy drought indicators and a polynomial in the magnitude of the location-normalized drought measures (SPEI-6 & SPEI-24).

We found that drought exposure is associated with reduced household consumption. Compared to those not affected by the drought, consumption declines by 6.5% among households located in areas that experienced negative rainfall anomalies during the growing season in the previous year prior survey periods. When considering rainfall anomalies of two growing seasons, the corresponding consumption reduction associated to drought exposure is slightly higher (7.3%). By including SPEI polynomial and its interaction with dummy drought indicators in our regressions, we considered the importance of rainfall anomaly magnitudes and the expected non-linear relationships with consumption. Previous studies have used a similar approach for modeling the relationship between climate extremes and wellbeing outcomes related with agricultural crop yield (Lobell et al., 2011; Schlenker and Roberts, 2006), household food security (Wineman et al., 2017), and child health outcomes (Cooper et al., 2019; T. D. Delbiso et al., 2017). Our approach in equation (2) therefore, allow for (possibly nonlinear) effects of droughts on well-being without conflating variation around the norm with variation in the tail of the distribution. Several related studies pursue in similar spirit (Dell et al., 2012; Deschênes and Greenstone, 2011).

Our result serves as a check for consistency with the existing literature, which has already established the relationship between wellbeing outcomes and different timescale drought measures. Beyond what can be drawn from observing only drought exposure status, the different timescales of SPEI measures provide a sound quantitative synthesis of rainfall considering historical climate data on the intensity of drought exposure (Bayissa et al., 2018). The SPEI-6 identifies more frequent droughts of shorter duration affecting agricultural practices, whereas the SPEI-24 detects less frequent but longer-lasting droughts associated with water resources (Vicente-Serrano et al., 2010). This adverse impact of drought on household consumption could be explained primarily by the low resilience rural households of Ethiopia developed overtime to deal with droughts. We, therefore, explore the heterogeneity of drought effects by household resilience in the following sections of the paper. We primarily focus on SPEI-6_drought in our subsequent model estimations.

**Table 2.** Effect of short-term and long-term droughts on realized household consumption

| | Realized consumption | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| SPEI-6_drought | -0.065** | -0.058 | | |
| | (0.031) | (0.070) | | |
| SPEI-6_drought x SPEI-6 | | -0.010 | | |
| | | (0.059) | | |
| SPEI-24_drought | | | -0.073** | 0.020 |
| | | | (0.036) | (0.079) |
| SPEI-24_drought x SPEI-24 | | | | -0.015 |
| | | | | (0.070) |
| N | 9,648 | 9,516 | 9,648 | 9,516 |
| R-squared | 0.488 | 0.493 | 0.487 | 0.495 |

*Notes:* All specifications use CEDA & ESS 3-wave panel data and include household fixed effects, and household control variables. Robust standard errors are in parentheses, adjusted for clustering at enumeration area level. SPEI-6_drought is defined as dummy for a household having below -0.5 SPEI-6. SPEI-24_drought is defined as dummy for a household having below -0.5 SPEI-24. *** p<0.01, ** p<0.05, *

## 5.3. Attenuating resilience indicators

The preceding results indicate that both short-term and long-term droughts have adverse effects on the consumption of rural households in Ethiopia. Our next analysis focuses on identifying the specific resilience indicators that have statistically significant influence in attenuating these adverse drought effects. That is, to identify the specific resilience indicators that mediate the impacts of climate shocks on realized consumption—typically used as an indicator of wellbeing in resilience as capacity approach and probabilistic consumption—an indicator of wellbeing in the resilience as a normative condition approach.

Estimation results for equations (3) and (7) that include resilience indicators interacted with dummy drought indicator (SPEI-6) are reported in Table 3. We begin by looking at the interaction terms between drought exposure and key hypothesized resilience indicators as joint explanatory variables in column (1) of table 3 for realized consumption. Among the seven resilience indicators, we found that wealth index, informal transfer and formal transfer indicators effectively mediate the impacts of short-term drought on realized consumption. In column (2) of the same table, the corresponding attenuating effects of resilience indicators on the probabilistic consumption outcome include income diversification, livestock diversification, and agricultural asset indicators. These two different sets of resilience indicators that mediate the effects of drought reflect the importance of considering related outcome variables. While the former sets of indicators contribute to protecting rural households from transitory consumption gaps, the latter sets of indicators would help households to maintain consumption resilience in the face of droughts.

**Table 3.** Resilience indicators associated with attenuating the adverse effects of drought on realized and probabilistic consumption

| | Realized consumption | Probabilistic consumption |
|---|---|---|
| | (1) | (2) |
| SPEI-6_drought | 0.103* | 0.001 |
| | (0.059) | (0.004) |
| Income diversification × SPEI-6_drought | -0.070* | 0.005* |
| | (0.037) | (0.003) |
| Crop diversification × SPEI-6_drought | -0.057 | -0.002 |
| | (0.036) | (0.003) |
| Livestock diversification × SPEI-6_drought | -0.029 | 0.007*** |
| | (0.036) | (0.003) |
| Agricultural asset × SPEI-6_drought | -0.148*** | 0.005* |
| | (0.037) | (0.003) |
| Wealth index × SPEI-6_drought | 0.069* | -0.003 |
| | (0.040) | (0.003) |
| Informal transfer × SPEI-6_drought | 0.081** | -0.005 |
| | (0.039) | (0.005) |
| Formal transfer × SPEI-6_drought | 0.103* | -0.003 |
| | (0.059) | (0.006) |
| N | 9,648 | 6,291 |

| R-squared | 0.100 | 0.883 |
|---|---|---|

*Notes:* All specifications use CEDA & ESS data and include household FE, and household control variables. Robust standard errors are in parentheses, adjusted for clustering at enumeration area level. The variables (labeled "Income diversification × SPEI-6_drought", etc.) refer to interaction term between drought variable and resilience indicators. All resilience indicator variables are binary dummies. *** p<0.01, ** p<0.05, *

Furthermore, we also examined two community level indicators distances to the district town and health post, in mitigating the effects of drought. We split the sample by those households who live nearby or remote[5]to these service centers, and then we estimated separately for those households located in less or greater than 10[6] kilometer (km) from nearest district towns and those located in less or greater than 5[7] km from nearest health posts using the preceding model in equation (1).[8] For realized consumption, table 4 reports estimation results for remoteness beyond the specified kilometer radius from district town and health post.

**Table 4.** Estimates of the impact of drought on realized consumption, by basic service resilience indicators

| | Main impact | District town | | Health post | |
|---|---|---|---|---|---|
| | | Nearby | Remote | Nearby | Remote |
| | (1) | (2) | (3) | (4) | (5) |
| SPEI-6_drought | -0.065** | -0.015 | -0.070*** | 0.054 | -0.070*** |
| | (0.031) | (0.050) | (0.020) | (0.224) | (0.017) |
| N | 9,648 | 2525 | 7,123 | 744 | 8,904 |
| R-squared | 0.488 | 0.905 | 0.099 | 0.319 | 0.100 |
| Mean of dependent variable | | 6434.51 | 6476.67 | 6221.86 | 6486.00 |

Notes: The dependent variable in all regression is realized consumption. Each column reports estimates from equation (1) for the indicated outcome variable. Columns: (1) main specification with SPEI-6_drought, (2) as in column 1 but restricting sample to households in the nearby district town, (3) as in column 1 but restricting sample to households in the remote district town, (4) as in column 1 but restricting sample to households in the nearby health post, and (5) as in column 1 but restricting sample to households remote health post. Population weights are used in each regression. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The coefficient estimates in Table 4 for the nearby sub sample (from the district town—less than 10 km) is negative and insignificant while the coefficient of the remote—greater than 10 km is negative

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5 The 2015 World Bank report confirmed remoteness of basic services as defining characteristics of extreme poverty in rural Ethiopia, indicating the increase of poverty rates by 7% with every 10 km of distance from a market town (World Bank, 2015).

6 Based on the 2011-2012 ESS, the World Bank (2015) categorized remoteness of district towns in Ethiopia into three: (1) less than 10 km; (2) between 10 and 20 km; and (3) 20 km or more. For this study, we use 10 km as a remoteness of district town benchmark—those located in less or greater than 10 km.

7 According to the 2011 welfare monitoring survey, a health post is available within a 5 km radius for 62.5% rural households and about 50.4% of the rural population have to travel at least 10 km to reach the nearest health post (CSA, 2012)

8 Unlike household level resilience indicators, community level indicators don't vary much over time for the majority of households, and the type of variation that could be captured with the same methodology as before is not the type we are interested in. Ideally, one should use household fixed effects for separating the causes of changes within households, but cannot be used if anyone wants to analyze variables like our community indicators, which may vary over time but not between households. Therefore, our separate estimation not only address this problem but also helps to address we are interested in by estimating the impact climate shocks on consumption for those who are in nearby and far away from these indicators.

and significant on the realized consumption. This indicates households who are located in remote areas are exposed to drought and achieve lower consumption compared to those located in nearby. Similarly, the coefficient of health post faraway—greater than 5 km in column (5) is negative and significant on the realized consumption. This confirms the importance of better access to basic services in improving resilience against droughts. For probabilistic consumption, table 5 reports estimation results for remoteness beyond the specified kilometer radius from district town and health post.

**Table 5.** Estimates of the impact of drought on probabilistic consumption, by basic service resilience indicators

| | Main impact | District town | | Health post | |
|---|---|---|---|---|---|
| | | Nearby | Remote | Nearby | Remote |
| | (1) | (2) | (3) | (4) | (5) |
| SPEI-6_drought | -0.007*** | 0.012*** | 0.007*** | 0.012 | 0.008*** |
| | (0.002) | (0.004) | (0.002) | (0.009) | (0.001) |
| N | 6,291 | 1,668 | 4,623 | 499 | 5,792 |
| R-squared | 0.949 | 0.901 | 0.892 | 0.970 | 0.887 |
| Mean of dependent variable | | 0.54 | 0.54 | 0.53 | 0.52 |

Notes: The dependent variable in all regression is probabilistic consumption. Each column reports estimates from equation (1) for the indicated outcome variable. Columns: (1) main specification with SPEI-6_drought, (2) as in column 1 but restricting sample to households in the nearby district town, (3) as in column 1 but restricting sample to households in the remote district town, (4) as in column 1 but restricting sample to households in the nearby health post, and (5) as in column 1 but restricting sample to households remote health post. Population weights are used in each regression. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

We consider some alternative panel specifications, alongside our preferred model setups to examine the consistency of our results. These results are robust to some econometric concerns. First, we consider alternative panel specifications, alongside our preferred model setups to examine the consistency of our results. Supplementary Table 6 shows a comparison of our preferred model setup (equation 3 and 7) and the result in Table 3 when running fixed effects with no area fixed effects. The exclusion of region fixed effects does not substantially differ from the main result, as shown in supplementary table 3, depicting the consistency of results in broader terms.

Another important check is to consider magnitude of shock as an alternative formulation of the shock variable in table 3. In equations 3 and 7, we include interactions between continuous shock variable and resilience indicators in place of interactions between dummy shock variable and resilience indicators. Column (1) of Table 7 reports results using equation 3, while column (2) reports results using equation 7.

# 6. DISCUSSION

Policies to reduce the impact of climate shocks either aim to eliminate the climate risk factors in the household's environment, mitigate the household's exposure to them, or strengthen its resilience capacity to cope with them. We assess in particular the effects of drought on household consumption and further explore whether these effects are mitigated by household and community level resilience indicators. Our results suggest that drought, both short-term and long-term, adversely affects household consumption, whereas among the resilience indicators examined through two popular approaches—resilience as capacity and resilience as a normative condition, only a few set of indicators are found to be effective in mitigating the adverse impacts of these droughts on household consumption. Herein we discuss the above main results.

## 6.1. Effect of climate shocks on consumption

An in-depth understanding of the main climate shocks and how these shocks and possibly induced changes in household economic conditions can affect household wellbeing outcomes is an important question, especially in the context of rural Ethiopia. Since better nationally representative data sets become available from developing countries, researchers can analyze them to provide information that would be useful to policymakers. This paper assembles nationally representative socio-economic panel data from ESS and climate data from CEDA to assess the effects of drought on realized household consumption. This is a welcome development for Ethiopia given the adverse impact of drought and type data sets to assess drought's effects on different wellbeing outcomes. We estimated the impacts of short and long-term droughts on household consumption, without ignoring the importance of rainfall anomaly magnitudes and nonlinearities in their effects.

We find negative and statistically significant effects of drought on consumption among rural households in Ethiopia. Our findings suggest multiple pathways may underlie the relationship between climate shock and household consumption. Adverse climatic shocks may reduce agricultural productivity, which lowers household consumption as well as food availability. Indeed, we find links between short-term and long-term droughts and lower household consumption, greater food insecurity, and poverty. Our analysis adds to the previous literature investigating the consequences of climate shocks for poverty reduction and food security in Ethiopia. Many of these studies provide preliminary pieces evidences of the relationship between drought and different wellbeing outcomes (e.g., Hill, R. V. & Porter, C., 2017). In addition to showing the association and impact of drought events on the various well-being outcomes, these studies further suggest that well-being outcomes vary systematically across different types of households due to differences in their capacity to deal with shocks.

Building on the existing literature on the relationship between wellbeing outcomes and drought, our work delves deeper into the impacts of drought on household wellbeing outcomes in two important aspects, which could be important to inform policymakers. First, in addition to drought exposure, we estimate the magnitude and the possible nonlinear effects of drought on household consumption to a get full picture regarding its impacts on household consumption. Such robust climate impact information might be very useful for making resource allocation decisions within government drought shock assistance programs.

Second, droughts are complex climate shocks that may occur over a wide variety of timescales (Vicente-Serrano et al., 2010), ranging from a one-month moisture stress to decades of water deficit. We, therefore, make use of climate indicators that reflect the varying levels and timing of rainfall anomalies to relate the complex aspects of droughts to household consumption. The short-term and long-term drought measures used in our study provide a sound quantitative synthesis on the relationships between different droughts and household wellbeing outcomes that can help policymakers from the indirect links between the provision of drought shock assistance and the food security impacts that these programs seek to mitigate. This is one of the main ways in which previous work couldn't investigate deeper into the impacts of drought on household wellbeing outcomes. Therefore, recognizing the importance of temporal patterns of shocks, our analysis looked at effects for both short-term and long-term droughts, suggesting the need to have wider temporal scopes for planning drought response interventions compared to the typical timeframe used by Ethiopia's emergency management system.

## 6.2. Bridging development resilience approaches traditions

The results in section 5.3 suggest that development resilience from the resilience as capacity and resilience as a normative condition approaches depicts the usefulness to consider the goals of development resilience study, which can, in turn, inform policy. We designed our study to examine how these two distinct development resilience approaches to resilience can generate complementary sets of insights about the dynamic relationship between climate shocks and wellbeing outcomes. The resilience as capacity and resilience as a normative condition approaches we tested reflect two different ways of inferring resilience outcomes, demonstrating the unique offering of each approach concerning the potential of resilience to climate shocks. Our findings implied an important dimension of future work—bridging the resilience as capacity and resilience as a normative condition approaches traditions by conducting empirical studies that apply both perspectives. Herein our discussion focuses on two main issues: (1) resilience indicators associated with attenuating the adverse impacts of drought shocks on either realized consumption or probabilistic consumption measures of wellbeing as well as insights to bridge the resilience as capacity and resilience as a normative condition approaches traditions; and (2) limitations of our study and roots forward.

### 6.2.1. Attenuating resilience indicators and bridging resilience approaches

Studying the extent that resilience indicators attenuate climate shocks is an important area of research. In the resilience as capacity and resilience as a normative condition approaches, the climate shock—wellbeing outcome nexus primarily occurs via resilience indicators. Several pieces of evidence from both approaches broadly identify the set of resilience indicators that have the potential to buffer shock impacts (e.g., d'Errico et al., 2018; Brück et al., 2019; Knippenberg et al., 2019; Phadera et al., 2019; Vaitla et al., 2020), with less clear evidence on the resilience indicators that mediate the impact of climate shocks on wellbeing. Resilience indicator is of the first-order importance for writing down a plausible resilience function in both approaches. However, many of the resilience indicators used are not based on rigorous empirical evidence.

In the case of the resilience as a normative condition approach, the existing literature is limited almost entirely to using the original Cissé and Barrett (2018) econometric method, which estimates resilience as a conditional probability of satisfying normative standard of living through the estimation of the conditional mean and variance of a well-being indicator, combined with an assumed two-parameter distribution. However, the Cissé and Barrett (2018) method has also an alternative (and potentially complementary) reduced-form estimation approach, focusing on the probabilistic distribution on the outcome variable per se. This "reduced resilience score" is yet used than the original form, but makes relatively few identification assumptions and allows unusually strong causative interpretation. The reduced form estimation approach adopted in this study offers two important forward steps beyond the studies on impact evaluation or resilience analysis studies discussed above. First, it better reflects broader realized wellbeing outcome, rather than the condition that reflects one's capacity to avoid adverse wellbeing states the focus of the original normative condition model. As such, this measure is better suited and reconciled with the resilience as the capacity approach outcome variable. Second, this form of specification, which does include resilience indicators and shocks for mean and variance estimation, enables us to explicitly model resilience indicators by exploiting the panel data estimation approach.

We, therefore, look at the resilience indicators that mediate the impacts of shocks on both approaches wellbeing outcomes—realized consumption as an outcome variable in the resilience as capacity (equation 3) and probabilistic consumption as an outcome variable in the resilience as a normative condition (equation 7) to understand what is associated with the ability to withstand or recover quickly from shocks. Despite our expectation of all of the resilience indicators to buffer the impact of climate shocks on household wellbeing, our model results in section 5.3.1 reveal only some of the resilience indicators did influence the relationship between climate shocks and our two related wellbeing measures—realized and probabilistic household consumption. From the resilience indicators included in our models, we find wealth index, informal transfer, and formal transfer as important resilience indicators to capture a household's resilience to mediate climate shocks, while income diversification, livestock diversification, and agricultural asset from our normative approach model. Our separate model results in section 5.3.1 also reveal households' access to the district town and health post indicators as important community level resilience indicators in mitigating adverse climate shock impacts on household consumption. The sets of resilience indicators, obtained from two distinct development resilience approaches framings, which are found effective in mitigating the effects of drought, may reflect the clear opportunity of these approaches to be reconciled to identify which approach is best suited to which indicators.

While the resilience as capacity approach fits to identify sets of indicators that may contribute to protecting rural households from transitory consumption gaps, the resilience as a normative condition approach fits best to identify sets of indicators that have roles in maintaining consumption resilience in the face of droughts. Both are important aspects of development resilience. Policy interventions aimed at increasing household resilience in Ethiopia should therefore focus on these resilience indicators. Given the adverse effects of climate shocks on household wellbeing outcomes, policy interventions that yield pay-offs in the short and long run may be appropriate. In addition, panel-based evidence on resilience indicators is currently limited, especially in the resilience as capacity and resilience as a normative condition approaches.

In addition to identifying the specific indicators that are associated with attenuating the adverse impacts of drought shocks on well-being outcomes, the identification by equation (3) and equation (7) gives the opportunity to which empirical research from the resilience as capacity and resilience as a normative condition approaches can most directly speak and implications for breadth and heterogeneity as well as functional forms.

First, we look at the specific resilience indicators that are associated with the adverse impacts of drought on two closely parallel measures of well-being (realized and probabilistic measures of consumption). Our estimation strategy is the household fixed effects model, a preferred model our panel data and interest—panel model can incorporate the potential of resilience indicators by interacting the vector of climate shock variables with variables of 'hypothesized resilience indicators'. To do so, we run two panel specifications for realized consumption and probabilistic consumption interacting climate shock variables with variables of 'hypothesized resilience indicators'. Noting that standard targeting is not only based on realized wellbeing outcome but possibly by considering stochasticity of wellbeing outcome, the setting and estimates in equation (7) is perhaps the closest empirical analogue to the structural equation of interest for realized wellbeing outcome in equation (3).

Second, the estimates in equation (3) and equation (7) speak the functional forms of resilience as capacity and resilience a normative condition approaches. While both approaches use wellbeing indicators, shocks, and resilience indicators as input variables but model resilience in somewhat distinct ways. In the case of the resilience as capacity approach, we estimate equation (3), where the key interest resilience variable, $R_{it}$ is a right-hand side and explanatory variable, and the dependent variable is realized consumption, $y_{it}$. In contrast, we estimate equation (7), where the interest resilience variable, $\hat{\rho}_{it}$ is a left-hand side and dependent variable, and $R_{it}$ is an explanatory variable. As they stand, the resilience as capacity and resilience as a normative condition approaches based estimates already raises important questions about current practices in assessing the potential of resilience (Barrett et al., 2021). The question of whether resilience is a right-hand or left-hand side variable is the central question that divides these approaches and is also consequential for policy design. The identification framing in equation (3) and equation (7) provide a highly relevant setting to speak about these approaches' functional forms, especially provide insight to bridge the resilience as capacity and resilience as a normative condition approaches classic debate with the question of whether resilience is a right-hand or left-hand side variable.

### 6.2.2. Limitations and routs forward

In reflecting on the implications of our findings, we highlight several important considerations. First, our findings are based on short-run panel estimates from equations (3) and (7). Future research based on a longer time scale can be used to credibly provide evidence about the effectiveness of resilience indicators in mediating the impacts of shocks on well-being. Second, while some of our resilience indicators appear to be important resilience channels, we acknowledge none of our resilience indicators as plausibly exogenous.

Understanding resilience indicators is of first-order importance for writing down a plausible resilience function in both the resilience as capacity and resilience as a normative condition approaches. One way to learn the potential of resilience indicators as mitigating mechanisms for climate shock is by interacting climate variables with indicators of shocks using panel specifications. Our interest variables are constructed by interacting exogenous terms with the potentially endogenous variables. Our study is an initial step toward a broader understanding of the potential resilience indicators. Our results underline the importance of further examination of questions in the literature relating to resilience indicators and which types of climate shocks matter most.

Although identification opportunity provided by equation (3) and equation (7) allowed us to reveal compelling evidence about the potential of resilience indicators as a channel of climate shock—wellbeing linkages, our study is based on short panel data—limited to short time periods and small fluctuations in our interest variables. Bridging the well-identified results from the resilience as the capacity approach to the resilience as a normative condition approach is a clear opportunity and an interesting topic for further rigorous research using long-term panel data and estimation methods.

# 7. CONCLUSIONS

Overall, our findings have significant implications for both research and policy in the areas of climate shocks and resilience. While most studies on the impacts of climate shocks on wellbeing over part or whole of Ethiopia are based on self-reported shock data, they are admittedly problematic as they are based on a sample of only short periods per household and derived from subjective reports. Therefore, an assessment of climate shock impacts that take into account the objective measures and that attempts to establish the link between climate shocks and resilience in a comprehensive manner are a welcome development within the literature, especially given the increasing adversity of climate shocks and the focus on resilience in the policy arena. In this regard, we make use of a high-resolution SPEI dataset for measuring rainfall extremes— droughts at different time scales, reflecting the different features of its complex phenomenon, including short-term dryness during key crop growing seasons (agricultural droughts) and longer-term dryness conditions that may lead to hydrological droughts.

Drawing on historical observations of climate events and household information from the three waves of ESS surveys, we find evidence that climate shocks, especially droughts, are associated with reduced household consumption. We also demonstrate that the effects of climate shocks on consumption are mitigated by various household resilience indicators, an implication for breadth and functional forms for development resilience literature. We model a range of household resilience indicators in interaction with shock exposure status, and we identify resilience indicators that influence whether or not climate shocks are associated with reduced consumption (both realized and probabilistic). While private and public transfers play positive roles in mitigating drought effects on current consumption, indicators such as productive asset holdings as well as crop and income diversification have resilience building roles against droughts. This is particularly important to inform resilience programming that has to identify an optimal mix of strategies to meet immediate needs (protecting household consumption from transitory shock effects) as well as to address underlying causes of climate shocks. Finally, given the importance of climate shocks and data availability, further research that applies a similar methodology could generate policy relevant insights while contributing to bridging between development resilience approaches, at both conceptual as well as empirical levels.

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# ANNEX: ADDITIONAL TABLES AND FIGURES

**Table 6.** Resilience indicators associated with attenuating the adverse effects of drought on realized and probabilistic consumption

| | Realized consumption | Probabilistic consumption |
|---|---|---|
| | (1) | (2) |
| SPEI-6_drought | 0.103* | 0.001 |
| | (0.059) | (0.004) |
| Income diversification × SPEI-6_drought | -0.070* | 0.005* |
| | (0.037) | (0.003) |
| Crop diversification × SPEI-6_drought | -0.057 | -0.002 |
| | (0.036) | (0.003) |
| Livestock diversification × SPEI-6_drought | -0.029 | 0.007*** |
| | (0.036) | (0.003) |
| Agricultural asset × SPEI-6_drought | -0.148*** | 0.005* |
| | (0.037) | (0.003) |
| Wealth index × SPEI-6_drought | 0.069* | -0.003 |
| | (0.040) | (0.003) |
| Informal transfer × SPEI-6_drought | -0.070 | -0.005 |
| | (0.058) | (0.005) |
| Formal transfer × SPEI-6_drought | -0.006 | -0.003 |
| | (0.068) | (0.006) |
| N | 9,648 | 6,291 |
| R-squared | 0.100 | 0.883 |

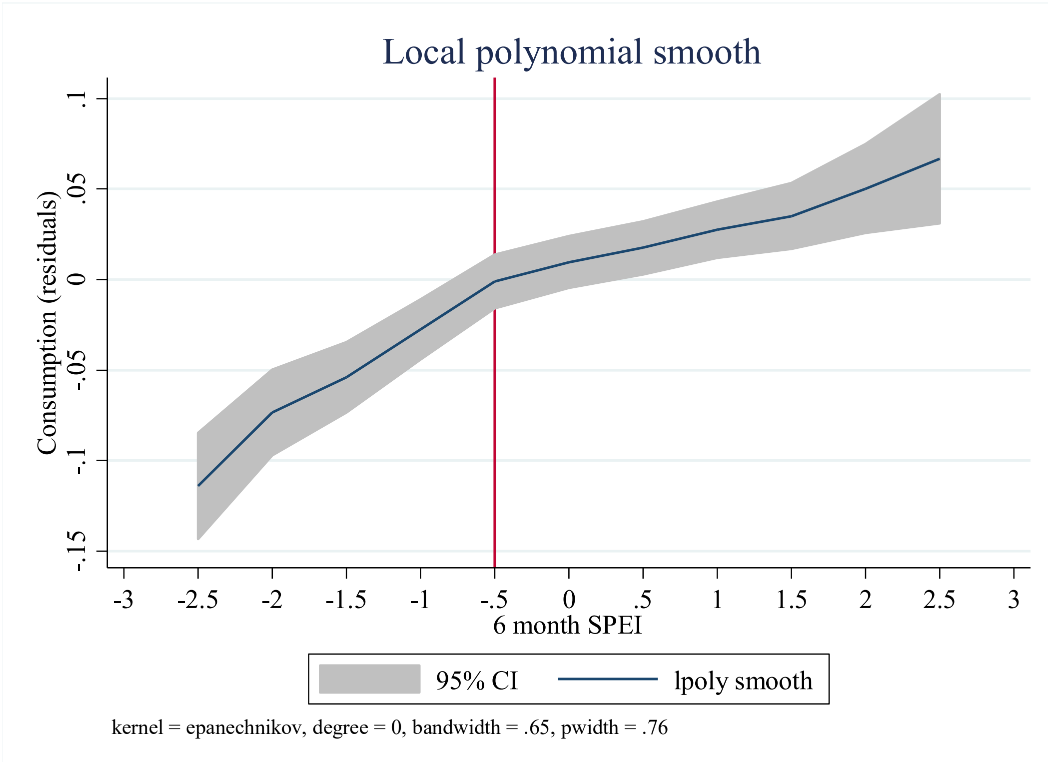
*Notes:* All specifications use CEDA & ESS data and include household FE, and household control variables. Robust standard errors are in parentheses, adjusted for clustering at enumeration area level. The variables (labeled "Income diversification × SPEI-6_drought", etc.) refer to interaction term between drought variable and resilience indicators. All resilience indicator variables are binary dummies. *** p<0.01, ** p<0.05, *

**Table 7.** Resilience indicators associated with attenuating the adverse effects of drought on realized and probabilistic consumption

| | Realized consumption | Probabilistic consumption |
|---|---|---|
| | (1) | (2) |
| SPEI-6 | -0.048** | -0.003 |
| | (0.023) | (0.002) |
| Income diversification × SPEI-6 | 0.040*** | -0.002 |
| | (0.016) | (0.001) |
| Crop diversification × SPEI-6 | 0.044*** | 0.003** |
| | (0.015) | (0.001) |
| Livestock diversification × SPEI-6 | 0.057*** | -0.002* |
| | (0.015) | (0.001) |
| Agricultural asset × SPEI-6 | 0.007 | -0.000 |
| | (0.015) | (0.001) |
| Wealth index × SPEI-6 | -0.031* | 0.001 |
| | (0.017) | (0.001) |
| Informal transfer × SPEI-6 | 0.014 | 0.001 |
| | (0.026) | (0.002) |
| Formal transfer × SPEI-6 | -0.026 | 0.000 |
| | (0.029) | (0.003) |
| N | 9,648 | 6,291 |
| R-squared | 0.102 | 0.883 |

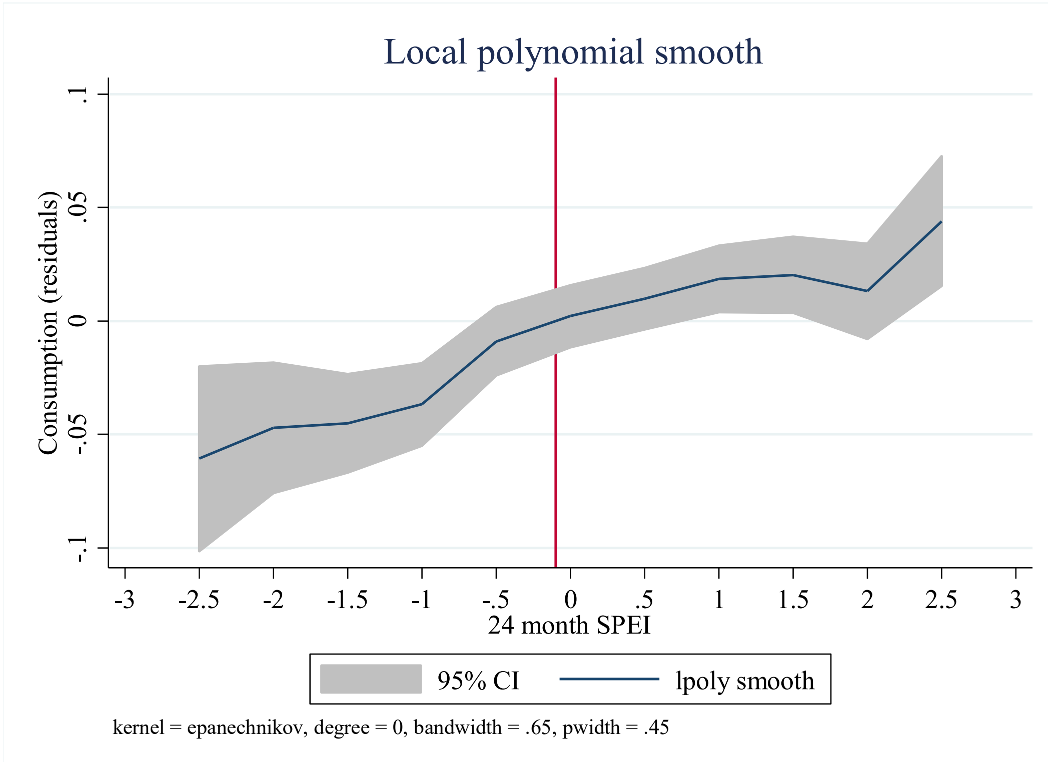
*Notes:* All specifications use CEDA & ESS data and include household FE, and household control variables. Robust standard errors are in parentheses, adjusted for clustering at enumeration area level. The variables (labeled "Income diversification × SPEI-6", etc.) refer to interaction term between drought variable and resilience indicators. All resilience indicator variables are binary dummies. *** $p<0.01$, ** $p<0.05$, *

**Figure 2.** Plot of predicted log of annual per adult equivalent of realized consumption in 2016 terms at different levels of SPEI-6.




Notes: Data used is the CEDA & ESS 3-wave panel. Residuals were estimated from the model that specifies consumption as a function of household characteristics. The fitted curve shows that households have higher consumption when rainfall is above the threshold line (SPEI=-0.5) compared to other household-level factors would otherwise predict (residual >0).In contrast rainfall below the same threshold is associated with reduced consumption compared to other household-level factors would otherwise predict (residual <0). Blueline is a local polynomial regression and the shaded area is its corresponding 95% confidence interval.

**Figure 3.** Plot of predicted log of annual per adult equivalent of realized consumption in 2016 terms at different levels of SPEI-24.




Notes: Data used is the CEDA & ESS 3-wave panel. Residuals were estimated from the model that specifies consumption as a function of household characteristics. The fitted curve shows households have higher consumption when rainfall is above the threshold line (SPEI=-0.1) compared to other household-level factors would otherwise predict (residual >0). In contrast rainfall below the same threshold is associated with reduced consumption compared to other household-level factors would otherwise predict (residual<0). Blueline is a local polynomial regression and the shaded area is its corresponding 95% confidence interval.