Financial Inclusion, Climate-Related Shocks, and Food Security in Ethiopia

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Abstract

In this study, we examine the impact of climate-related shocks on the food security status of households in rural Ethiopia and whether access to financial services can mitigate the adverse consequences of climate-related shocks. We use panel data from the Ethiopian Socioeconomic Survey. Climate-related shocks are measured using self-reported shocks, as well as satellite-based weather data. To minimise endogeneity concerns in our regression analysis, we use a panel data correlated random effects (CRE) approach and an estimation approach, which combines a control function approach with the CRE approach. We show evidence of the negative and statistically significant impact of climate-related shocks on food security, meaning that households who have experienced climate-related shocks are more likely to report food insecurity. The findings also show that households that can save money, whether through formal or informal means, are less likely to experience food insecurity. In addition, we show that formal saving helps households reduce the negative impact of climate-related shocks on food security in rural Ethiopia.

Keywords: Climate-related shocks, financial inclusion, food insecurity, welfare, Ethiopia

1. Introduction

Despite the commitment of the Sustainable Development Goal (SDG) to end hunger by 2030, food insecurity remains a serious challenge in most African countries, with the number of hungry people reaching 282 million by 2022, according to the Food and Agriculture Organization (FAO) (FAO, 2024). Adverse weather conditions and other shocks, such as COVID-19 and conflict, have been identified as important contributors to Africa's deteriorating food security situation in recent years (FAO, 2024). Most African countries are vulnerable to the effects of recurring negative effects of climate change because a substantial portion of their population relies on rain-fed agriculture for a living, and they have a relatively low capacity to cope with climate change-related and other shocks (FAO,2022).

Climate-related shocks directly affect food security and well-being in rural areas by reducing agricultural revenue, resulting from a sudden decrease in crop or livestock production and the subsequent increase in food prices (Brown et al., 2015; Hallegatte & Rozenberg, 2017). Low-income and vulnerable households are disproportionately affected by climate-related shocks as they have limited capacity to cope with such disruptions (Hallegatte & Rozenberg, 2017). This situation is exacerbated by significant market failures in the insurance and financial markets, as well as inadequate coverage of social protection systems in most developing countries. In this context, the importance of financial inclusion in enabling vulnerable households to adopt technologies and coping mechanisms that can help them to better adapt to adverse shocks has been recognised (Moore et al., 2019).

Financial inclusion can improve food security by facilitating households' access to credit, insurance, formal savings, and receiving remittance or other payments (Moore et al., 2019; Karlan et al., 2014; Hallegatte, 2016; DeLoach & Smith-Lin, 2018; Janzen & Carter, 2019; Mawejje, 2019). For example, growing empirical evidence documents the mitigating role of access to mobile money during shocks (Jack et al., 2013; Jack & Suri, 2014; Riley, 2018; Koomson et al., 2021; Abiona & Koppensteiner, 2022). Access to mobile money simplifies payment transactions by reducing transaction costs from remittance and other sources. In the absence of formal financial services, households rely on informal mechanisms or costly coping measures, such as selling productive assets, which adversely affects long-term welfare (Janzen & Carter, 2019; Chhatre et al., 2023).

In this paper, we estimate the impact of climate-related shocks on household food security in rural Ethiopia and investigate whether access to financial services mitigates the negative impact of climate-related shocks. We use nationally representative panel data from the Ethiopian Socioeconomic Survey (ESS) collected in 2014 and 2016. This allows us to estimate the impact of the 2015/2016 drought in Ethiopia, which was one of the worst in recent years.

Ethiopia is one of the African countries most frequently hit by climate-related shocks, the most recent of which was the droughts in 2015/16 and in late 2020 (FAO, 2022). Almost 80 % of the population lives in rural areas, with rain-fed subsistence farming accounting for over 69 % of employment. Because fewer than 5 % of the country's irrigable land is irrigated (Haile & Kasa, 2015), households' reliance on rain-fed subsistence agriculture means that weather-induced production shocks often translate into income shocks (Warner & Mann, 2018; Brunckhorst, 2020). However, the extent to which climate-related shocks have a negative impact on welfare outcomes, such as food security, is determined by several factors, including households' coping and resilience capacity to mitigate the negative consequences of climate-related shocks.

Previous empirical evidence on whether climate-related shocks resulted in significant negative welfare effects in Ethiopia is mixed (Gao & Mills, 2018; Warner & Mann, 2018; Brunckhorst, 2020; Gebrehiwot et al., 2021; Tesfahun et al., 2021; Haile, 2022). Negative rainfall shocks in 2015/2016, for example, are associated with reduced consumption, lower agricultural outputs (Brunckhorst, 2020), and a decline in children's food consumption Z-scores in Ethiopia (Haile, 2022). In contrast, the study by Hirvonen et al. (2020) found little evidence that the 2015/2016 drought in Ethiopia caused widespread increases in chronic or acute child malnutrition.

Existing research that examined the role of alternative coping strategies finds that coping strategies such as off-farm employment and receiving financial or in-kind transfers were useful in mitigating the negative effects of drought on consumption (Gao & Mills, 2018; Tesfahun et al., 2021; Haile, 2022). However, Haile (2022) shows that the effectiveness of cash transfers as a climate risk-mitigating instrument diminishes as droughts become more severe.

There is limited research on the impact of financial inclusion on food security and its role in reducing the adverse impacts of climate-related shocks on food security in Ethiopia. From a policy perspective, it is vital to evaluate the extent to which access to financial services can help households manage climate-related risks and help policymakers develop policies that are aligned with the best approaches for improving resilience to food insecurity. Our work contributes to ongoing research that examines the role of various coping strategies in minimising the adverse effects of shocks on household food security and well-being.

Ethiopia's financial sector has improved in recent years, following a government strategy that assigned the banking sector a special role in increasing deposit mobilisation to close the massive financial gap required to achieve the first and second five-year growth and transformation plans objectives (Birru, 2019:168-170). Following this, both government and private banks actively opened branches in previously unbanked areas (Birru, 2019), increasing the total number of bank branches from 970 in 2010 to 5546 in 2017 (see Figure 1A in Appendix A). Despite these developments, financial inclusion remains low in Ethiopia. According to the most recent Global Findex 2021 data (Table A1 in Appendix A), just 37 % of rural and 46 % of urban adult (15+) population in Ethiopia have accounts with financial institutions. Adoption of mobile money, particularly digital payments, is low, with only 2.3 % of rural adults and 5.5 % of urban adults having a mobile money account.

Although financial inclusion is a multidimensional phenomenon, we use whether households save through formal financial institutions as a proxy measure of financial inclusion. This is because most innovative financial inclusion services, such as mobile money, are not widely used in rural regions of Ethiopia, with less than 1 % of households in our sample using mobile money and other innovative financial products during the 2015/2016 survey round. In contrast, nearly 20 % of rural households reported using formal banking institutions to save money in 2015/16. In Ethiopia and other contexts, it is reported that households most commonly rely on precautionary savings to reduce the impact of shocks by households (Moore et al., 2019). For instance, data from Ethiopia shows that 49 % of rural households who have experienced climate-related or other shocks reported that they rely on their own savings to cope with shocks (Figure A2 in Appendix A).

A recent study from India shows the key role of traditional banking in rural areas in mitigating the negative impact of climate-related shocks (Chhatre et al., 2023), as most services in these rural areas are often provided via the banking system. Similarly, an experimental study in Chile found that improving access to savings accounts helped participants better manage their consumption following an income shock (Kast & Pomeranz, 2014). Thus, providing formal saving services and incentives encourages households to save more by reducing impulse spending and providing protection against theft and family pressure (Demirguc-kunt et al. 2017; Kast & Pomeranz, 2014).

We use two indicators to measure food insecurity: The food insecurity experience scale (FIES) and households' response to a question whether, in the 12 months prior to the survey, the household was ever in a situation where they did not have enough food to feed the family.

To measure climate-related shocks, we combine household data with exogenous climate-related shock indicators derived from satellite-based weather data. We also use self-reported shocks to identify households that experienced climate-related shocks. Previous research has primarily relied on either self-reported shocks or satellite-based weather data to measure climate-related shocks. However, it is acknowledged that each approach has its own limitations (Nguyen & Nguyen, 2020; Dubache et al., 2021). Satellite-based weather data is considered an objective measure of climate-related shocks, as it reduces the reporting bias associated with self-reported shocks. However, shocks measured based on satellite-based data can be less accurate in complex topography areas and are frequently aggregated over large areas, failing to capture the heterogeneity of the actual climate-related shock experiences by households (Nguyen & Nguyen, 2020; Dubache et al., 2021). Thus, the self-reported shock indicator can overcome this shortcoming and allows control for non-covariate shocks that can potentially affect food security.

Our econometric strategy relies on the correlated random effects (CRE) approach and an estimation approach that combines the CRE approach with a control function method (Bates et al., 2024). This combination allows us to address potential endogeneity due to heterogeneity and treatment effects. We instrument the use of formal financial services using households' proximity to financial services (financial institutions) in a village/community. Additionally, we use the proportion of community-level reported climate-related shocks to instrument self-report shocks. The results show evidence of a negative and statistically significant impact of climate-related shocks on food security, meaning that households who have experienced climate-related shocks are more likely to report food insecurity. Moreover, households that can save money, whether through formal or informal means, are less likely to experience food insecurity. In addition, we show that formal saving helps households reduce the negative impact of climate-related shocks on food security in rural Ethiopia.

The remainder of this paper is organised as follows: In Section 2, we provide an overview of the financial sector in Ethiopia. In Section 3, we describe the data sources and approaches to measure our main variables of interest. Section 4 describes the empirical strategy adopted. The main findings and discussion are presented in Section 5, while Section 6 provides a conclusion.

2. Financial sector and financial inclusion in Ethiopia: an overview

The financial sector in Ethiopia largely consists of banks, insurance companies, and microfinance institutions, all regulated by the National Bank of Ethiopia (NBE) (Kotiso, 2019; World Bank, 2019; NBE, 2021). The banking sector and microfinance institutions (MFIs) account for 98.6% of the total financial sector (World Bank, 2019). Modern banking in Ethiopia began in 1905 and before the financial sector was opened to the private sector in 1994 there were only three government banks, one commercial bank, and two specialized banks—the Housing and Saving Bank and the Agricultural and Industrial Bank of Ethiopia (now the Development Bank of Ethiopia), and one government-owned insurance company (see Birru, 2019: p161).

The government enacted Proclamation 84/94 in 1994, allowing the private sector (but only Ethiopians) to engage in the banking and insurance sectors (Birru, 2019). The banking sector was assigned a special role in enhancing deposit mobilisation to close the massive financial gap required to achieve the first and second five-year growth and transformation plans (GTP), GTP (2011-2015), and GTP-II (2016-2020) objectives (see Birru, 2019: pp168-170). Following this, the number of bank branches increased significantly, with the CBE taking the lead in opening new banks outside of the capital city, Addis Ababa, paving the way for private banks to follow (Birru, 2019). Furthermore, the NBE introduced the "NBE Bill" in 2011, which requires each private commercial bank to set aside 27% of its monthly loan disbursement to buy this Bill. Thus, to remain operationally competitive and profitable in the financial market, private banks aggressively opened branches in previously unbanked areas (Birru, 2019). These developments resulted in a more than 400 percent growth in the number of bank branches, from 970 in 2010 to 5546 in 2017 (see Figure A1 in Appendix A).

The Ethiopian banking system had 30 banks by the end of the fourth quarter of 2021/22, comprising 28 private and 2 state-owned banks, with a total of 8,944 branches serving the country's population of over 105 million (NBE, 2022). However, the geographic distribution of bank branches is skewed towards large cities and towns, with Addis Ababa alone hosting 32.8 percent of all bank branches (NBE, 2022). Furthermore, despite their small number, state-owned banks have a disproportionately large market share. The two state-owned banks account for 24 percent of all bank branches and 41.5

percent of total capital. There are currently 43 MFIs with a total capital of Birr 15.5 billion and total assets of Birr 58.9 billion (NBE, 2022). As of 2018, the five largest government-affiliated MFIs—Amhara, Dedebit, Oromia, Omo, and Addis Credit and Savings Institutions—accounted for 89 percent of the sector's assets.

Digital financial development in Ethiopia is underdeveloped. As per the latest Global Findex 2021 data (Table A1 in Appendix A), only 37% of the rural adult population and 46% of the urban adult population (aged 15 and above) in Ethiopia possess accounts with financial institutions. The adoption of mobile money, especially digital payments, is minimal, with about 2.3% of rural adults and 5.5% of urban adults possessing a mobile money account. At present, several mobile money services are offered by banks, including CBE-Birr, Hello Cash, Amole, and Awash Mobile Wallet. After the NBE's ratification of new legislation permitting non-bank organisations to provide mobile and electronic financial services, Ethio Telecom, the largest publicly owned telecommunications provider, inaugurated the TeleBirr mobile money service in 2021. Likewise, Safaricom, which entered the Ethiopian telecommunications market in 2022, introduced M-PESA, Safaricom Ethiopia's mobile financial services, in 2023.

Overall, although there is progress in improving the financial services in Ethiopia, the development of financial inclusion remains hampered by both demand and supply side factors (World Bank, 2019; Berhanu Lakew & Azadi, 2020; Alemu et al., 2021). For instance, the expansion of digital finance is hampered by a lack of infrastructure, limited internet access, a lack of competition, and a weak regulatory framework, remoteness, and a lack of finances to mention but a few factors (Alemu et al., 2021). There are large urban-rural divides in internet availability with 17.5% of urban adults reportedly having internet connection while the figure is only 4.6% of rural respondents (Table A1 in Appendix A). Lack of access to internet connection can be a significant challenge in promoting access to digital financial services in Ethiopia.

Although over 40% of the rural and 57% of urban adult (15+) population in Ethiopia reported owning a cell phone, the utilisation of mobile banking is less than 6% (Table A1 in Appendix A). This suggests that mobile banking has tremendous potential for improving access to inclusive financial services in Ethiopia.

3. Materials and Methods

Data sources

The data used is the ESS, a panel data that is collected by the Central Statistical Agency of Ethiopia (CSA) with the support of the Living Standards Measurement Surveys – Integrated Surveys in Agriculture (LSMS-ISA) project of the World Bank. The ESS started in 2011/12 with a sample of 3,969 households from 290 rural and 43 small-town enumeration areas (EAs). Subsequent waves were conducted in 2013/14 and 2015/16. The initial sample was designed to be representative of rural and small-town areas of Ethiopia. To ensure that the ESS data provides nationally representative estimates, the sample was expanded in subsequent waves to include additional households from major cities. The year-to-year attrition rate remains low (below 5 %). The most recent publicly available rounds of the ESS were collected in 2018/19 and 2021/2022. However, these rounds represent new samples and cannot be linked to previous waves.

The ESS collects data on a variety of areas, including demographic and housing characteristics, assets, food and non-food consumption expenditures, land size and agricultural output, income-generating activities, self-reported shock experiences (both idiosyncratic and covariate shocks), and the use of various financial services. The financial inclusion indicators in the ESS survey include account ownership and the type of financial institution (e.g., private banks, Commercial Bank of Ethiopia, microfinance institution), whether households saved in formal or informal institutions, and whether they had formal insurance coverage. However, in rural areas, the use of mobile money, formal insurance or other innovative financial products was less than 1 % in the 2015/2016 survey round. Access to credit from financial institutions is also limited, with about 7.5 % of the sampled households indicating borrowing from financial institutions in 2015/2016 (Table 1). In contrast, nearly 20 % of rural households reported using formal financial institutions (e.g banks and microfinance) to save money in 2015/16. Additionally, saving is an important source of funds for households to deal with various shocks. Figure A2 (in Appendix A) shows that 49 % of rural households who have experienced climate-related or other shocks reported that they rely on their savings to cope with shocks. For these reasons, we use an indicator of household savings through formal accounts at financial institutions, such as banks and microfinance, as a proxy for financial inclusion. Given that we want to investigate the impact of climate-related shocks on food security, we limit our sample to rural households and use data from the 2013/14 and 2015/16 survey rounds. This allows us to estimate the impact of the 2015/2016 drought, which was one of the worst in recent years. However, detailed information on the use of formal financial instruments, such as owning a bank account and a formal savings account, was only collected in the 2015/16 wave. We expect no substantial change in bank expansion between the 2013/2014 and 2015/2016 survey years (see Figure A1 in Appendix A); hence, we believe the financial inclusion variable did not change much between 2014 and 2016.

Climate-related shock measures

In this paper, we use both climate data and self-reported shocks as indicators of climate-related shocks, such as drought or flooding. The use of respondents' self-reported experience with climate-related shocks, as well as meteorological data such as rainfall or vegetation anomalies, are among the most widely used measures (see Dercon & Porter, 2014; Gao & Mills, 2018; Makate et al., 2022). Climate data can be regarded as an objective measure of climate-related shocks, reducing the reporting bias associated with self-reported shocks. However, the accuracy of climate data is lower in areas with complex topography and is frequently aggregated over large areas, which may not capture the heterogeneity of actual climate shock experiences at the household level (Nguyen & Nguyen, 2020; Dubache et al., 2021).

We use the Standardized Precipitation-Evapotranspiration Index (SPEI) from the Global SPEI database.[1] The key advantage of using the SPEI compared to precipitation data alone is that it incorporates both precipitation and potential evaporation data to estimate the likelihood of drought or flooding experiences (see Vicente-Serrano et al., 2010). The data are provided in a format of about 50 km x 50 km grid cells. Using the geo-referenced household-level latitude and longitude coordinates supplied in the ESS, we linked the climatic data with the household-level data at the EA levels. The SPEI is calculated at different time scales (e.g., 1 month, 3 months, 6 months, and 24 months) with short time scales reflecting short-term drought conditions. We use the SPEI with a six-month time scale. The distribution of rural sample households based on the SPEI scores is provided in Figure A3 (in Appendix A). Figure A3 (in Appendix A) indicates that households in rural Ethiopia are more likely to experience droughts than floods, as indicated by the skewed distribution towards the negative scale.

Based on SPEI, negative values indicate dryer conditions (drought), while positive values indicate wet conditions (flooding). Table A2 (in Appendix A) shows the commonly used cut-off points for determining drought or flooding intensity based on the SPEI or other similar indices. We created a dummy variable for the SPEI scores that indicated that households experienced at

[1] https://spei.csic.es/database.html

least mild drought (SPEI <=-0.5) or at least moderate drought (SPEI <=-1). The results in Table 1 show that only 3.71 % of households experienced at least moderate drought (SPEI <=-1) in 2015/2016. However, according to the mild drought indicator (SPEI <=-0.5), 44 % of rural households experienced at least mild drought during this timeframe. Therefore, we use the mild drought indicator (SPEI <=-0.5) in our analysis to measure climate-related shock.

The ESS survey collected self-reported information about several types of shocks experienced by households, including both idiosyncratic and covariate shocks, with a 12-month recall period preceding each survey round. Climate-related shocks include drought, flooding, landslides, and heavy rain. However, drought is one of the most prevalent climate-related shocks reported by sample households (Table 1). Based on the self-report shock indicator, 27 % of households reported experiencing drought in 2015/2016. Additionally, the proportion of households that experienced drought was relatively higher in 2015/2016 compared to 2014/2015 (Table 1). This is consistent with earlier research, which documented that 2015/2016 was the most recent severe drought year that affected the entire country except for a few areas in the southwestern and northeastern parts (FAO, 2022; Kourouma et al.,2022).

Household food insecurity measures

The survey collects data on households' self-assessed food insecurity status. Households were asked whether, in the 12 months preceding the survey, they had faced a situation where they lacked enough food to feed their family. We use this variable as our primary measure of food security, as it reflects the household's food security status over 12 months. In addition, respondents were asked if, in the past 7 days prior to the survey date, they or anyone in the household had relied on less preferred foods, reduced the variety of foods eaten, decreased portion sizes at meal times, reduced the number of meals eaten in a day, restricted food consumption by adults and small children, borrowed food or relied on help from a friend or relative, had no food of any kind in the household, went an entire day and night without eating, worry that your household would not have enough food. We use these indicators to create a food insecurity index similar to the FAO's FIES. The FIES is calculated by counting the number of affirmative responses to the nine food insecurity indicators, with the score ranging from zero to nine. Higher raw scores indicate greater food insecurity. We then create a dummy variable to indicate whether the household experienced at least mild food insecurity based on the FIES indicator. Households with the FIES score of three and above are considered food insecure.

After excluding observations with missing values, we have 3,091 balanced rural households across the two survey rounds. Table 1 presents descriptive statistics about the food security status of rural households, along with other household characteristics. Approximately 31 % of rural households reported experiencing food insecurity in the 12 months prior to the survey in 2016. This proportion increased to 37 % when using the FIES measures, which is based on a seven-day reference period.

Table 1: Descriptive statistics

	2014	2016
	Mean	**Mean**
Food insecurity		
Food insecure in the past 12 months (1, if yes, 0 otherwise)	34.5	30.5
FIES index	0.8	1.2
FIES index dummy (1, if food insecure, 0 otherwise)	28	37.3
Shocks		
SPEI_06 (<= -0.5)	29.5	44.5
SPEI_06 (<= -1)	10.4	3.7
Reported Drought	8.7	27.4
Reported climate shock(all)	12.2	30.5
Reported non-climate shock	24.4	28.6
Household characteristics and access to finance		
Household size	5.2	5.2
Male headed (1, if yes, 0 otherwise)	78.9	78.4
Head age	46.3	48.1
Head – Orthodox Christian (1, if yes, 0 otherwise)	48.5	48.8
Head – Other Christian (1, if yes, 0 otherwise)	23.4	23.2
Head Muslim and other (1, if yes, 0 otherwise)	28.1	28
Higher education (1, if yes, 0 otherwise)	14.8	15.7
Land size in hectares (log)	0.8	0.8
Livestock in TLU (log)	1.3	1.3
Have mobile (1, if yes, 0 otherwise)	37.2	43.2
Formal saving (1, if yes, 0 otherwise)	19.2	19.3
Informal saving (1, if yes, 0 otherwise)	18.3	18.7
Borrowed from financial institutions (1, if yes, 0 otherwise)	12.3	7.5

Borrowed from relatives/friends/neighbours (1, if yes, 0 otherwise)	13.6	13.2
Borrowed from other sources (1, if yes, 0 otherwise)	9.9	5.8
Received transfers (1, if yes, 0 otherwise)	14.8	13.8
Non-agricultural business (1, if yes, 0 otherwise)	21.3	18.6

Source: Authors' illustrations using data from ESS (2013/14, 2015/16)

4. Empirical Strategy

To estimate the impact of climate-related shocks on food security, we specify the following baseline empirical model:

$$Y_{it} = \alpha_i + \psi_t + \delta CLS_{it} + X_{it}\beta + e_{it} \text{--} (1)$$

where: Y_{it} represents the food security status of household *i* at time t, ψ_t is a time dummy, X_{it} is a vector of household-level controls, α_i accounts for time-invariant household heterogeneity, e_{it} is the error term, and CLS_{it} is a binary variable that equals 1 if households experienced climate-related shock and 0 otherwise. Based on satellite weather data, we classify households as having experienced a climate-related shock if they encountered at least mild drought (SPEI_06 <=-0.5) within the 12 months preceding each survey year. In addition, the self-reported climate-related shock indicator is used to measure the CLS_{it} variable. The parameter δ measures the impact of the climate-related shock on Y_{it}. To test whether the use of financial services moderates the impact of climate-related shocks on food security, we introduce an interaction term in equation (1), which interacts the shocks with the use of financial services.

We assume that the climate-related shock indicators based on weather data are exogenous and not affected by individual households. However, the use of financial services is not random and may potentially be endogenous in our regression model. As a result, unobserved household and individual-level factors that affect the use of financial services could be correlated with the error term. The self-reported climate shock measure may also be endogenous in our model, as omitted factors affecting food insecurity might also influence reported shocks. Households with lower levels of welfare, for instance, may be more likely to report shock experiences. This potential endogeneity can be reduced by controlling for various household and village-level characteristics. Specifically, we control for the maximum level of education in the households, household assets (land and livestock), household size, household head characteristics (i.e., age, gender, and religion), and access to mobile services. Additionally, we account for other coping mechanisms and factors that are expected to improve household resilience to food insecurity (Gao & Mills, 2018; Tesfahun et al., 2021; Haile, 2022; Mossie et al., 2024). These factors include ownership of non-farm businesses, access to cash transfers, and whether the household borrows informally or formally.

Estimating Equation (1) using fixed effects estimation can eliminate the effects of time-invariant unobserved household heterogeneity. However, this estimation approach does not address endogeneity due to time-varying unobservable. To account for this, we use the CRE approach to estimate our model, which allows elements of the X_{it} to be correlated with the unobserved individual heterogeneity, α_i (Wooldridge, 2019). Estimating a CRE model involves the inclusion of a term, which includes the average values of the time-variant variables in our model, $\bar{X}_i$ (Mundlak, 1978; Wooldridge, 2019). In the case of balanced panel data, the coefficient estimates for the time-variant variables are equivalent to those obtained through fixed effects regression. The advantage of the CRE model is that it also allows us to estimate coefficients for the time-invariant variables. This is particularly important for the financial inclusion indicator, which is time invariant as it was only measured in 2016.

As a robustness check, we also estimate Equation (1) using an approach that combines a control function approach with the CRE approach (Bates et al., 20). In this process, we include residuals from the first-stage regression of the self-reported shock variables and the formal savings indicator. For the first-stage regressions, we apply pooled ordinary least squares (OLS) with time and region-fixed effects, along with other control variables outlined in Table 1. To instrument the use of formal savings, we use the proximity of households to financial services (financial institutions) in their village or community. The survey's community module collected data on the presence of financial institutions and the distance (in kilometres) to the nearest financial institution. The considerable increase in bank branches following a change in government policy after 2012 can be seen as a quasi-experiment, helping to minimise bias from the placement effect of financial services providers. This expansion is viewed as exogenous to individual households.

To reduce endogeneity and report bias in the self-reported climate shock indicator, we created a community-level variable representing the proportion of reported climate-related shocks within the community (excluding the household in question). This variable is used as an instrument for household-level self-reported shocks in our regression.

5. Results and Discussions

We begin by presenting the estimation results of equation (1) using the CRE approach, excluding the interaction effects. Table 2 displays the estimation results of the impact of shocks on household food security, where food security is measured as a dummy variable indicating whether a household experienced food insecurity in the previous 12 months prior to the survey dates. Columns 1 and 2 of Table 2 show the coefficient estimates and marginal effects of the regression when climate-related shock is measured using the SPEI, while Columns 3 and 4 show the corresponding estimates using the self-report climate shock indicator.

Table 2: The impact of climate-related shocks on food insecurity (12-month food insecurity measure)

	(1)	(2)	(3)	(4)
	Coeff.	Marginal eff.	Coeff.	Marginal eff.
SPEI_06	0.296***	0.0769***		
	(0.0693)	(0.0179)		
Climate shock (reported)			1.348***	0.319***
			(0.0912)	(0.0194)
Other shocks (reported)			0.563***	0.133***
			(0.0718)	(0.0165)
Formal saving	-0.349***	-0.0905***	-0.371***	-0.0877***
	(0.0687)	(0.0176)	(0.0715)	(0.0167)
Informal saving	-0.299***	-0.0774***	-0.316***	-0.0748***
	(0.0629)	(0.0161)	(0.0663)	(0.0155)
Borrowed (financial ins.)	0.0371	0.00963	0.0171	0.00403
	(0.129)	(0.0334)	(0.135)	(0.0318)
Borrowed (non-financial ins.)	0.318**	0.0824**	0.304**	0.0719**
	(0.108)	(0.0278)	(0.112)	(0.0265)
Borrowed (friend/family)	0.238**	0.0617**	0.239**	0.0564**
	(0.0843)	(0.0218)	(0.0868)	(0.0204)
Transfers	0.279**	0.0723**	0.173	0.0409
	(0.0872)	(0.0225)	(0.0900)	(0.0212)
Non-farm business	-0.00753	-0.00195	-0.0227	-0.00536

	(0.0947)	(0.0246)	(0.0982)	(0.0232)
_cons	-0.380*		-0.612***	
	(0.164)		(0.157)	
lnsig2u	-0.905***		-0.921***	
	(0.152)		(0.165)	
N	6182	6182	6182	6182

Source: Authors' estimation using data from ESS (2013/14 & 2015/16). Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions control for the other variable listed in Table 1, as well as time and region-fixed effects.

Table 2 shows that the coefficient estimates for both SPEI and self-reported climate-related shock variables are positive and statistically significant (at a 1 % level of significance). On average, the probability of food insecurity is 0.0769 when climate shock is measured using the SPEI variable, while the corresponding probability is 0.319 for the self-reported climate-related shocks. These findings show that households that experience climate-related shocks are more likely to be food insecure. The coefficient estimate for the self-reported non-climate-related shocks is also positive and significant, implying that households that reported experiencing non-climate-related shocks are more likely to report food insecurity.

The coefficient estimate on the formal saving variable is negative and statistically significant (at a 1 % level of significance), suggesting that households that save through formal financial institutions are less likely to experience food insecurity. Similarly, the coefficient estimate on the informal saving variable is negative and statistically significant, indicating that informal saving is also associated with a lower likelihood of experiencing food insecurity. These findings show that households that save using either formal or informal means are less likely to experience food insecurity.

Regarding other variables, the coefficient on borrowing from financial institutions is not significant in all model specifications. Conversely, the estimates for the variables indicating borrowing from non-financial institutions, friends, and family are positive and significant, implying that households that borrow from informal sources are more likely to experience food insecurity. Similarly, the coefficient on the transfer variable is positive and significant in some of the model specifications (Table 2, columns 1 and 2). Households that received cash or in-kind assistance are more likely to report food insecurity. These findings indicate that poor and vulnerable households are more likely to borrow from informal sources and they are also likely to receive transfers. However, such coping methods are insufficient to address the severity of food insecurity among these households. This is consistent with Haile's (2022) findings that when droughts worsen, the usefulness of cash transfers as a climate risk mitigation tool decline.

We find similar estimation results when we use the FIES indicator to measure food insecurity (Table 3). The negative impact of climate-related shock on food security is statistically significant (at the 1 % level of significance). Similarly, the coefficient on the formal saving indicator is negative and significant, implying that households that saved through formal financial institutions are less likely to experience food insecurity. However, the coefficient on the informal saving variable and other coping variables are not significant, except for borrowing from non-financial institutions.

Table 3: Impact of climate-related shocks on Food insecurity (FIES)

	(1)	(2)	(3)	(4)
	Coeff.	Marginal eff.	Coeff.	Marginal eff.
SPEI_06	0.275***	0.0788***		
	(0.0650)	(0.0185)		
Climate shock (reported)			0.763***	0.212***
			(0.0811)	(0.0216)
Other shocks (reported)			0.272***	0.0756***
			(0.0648)	(0.0179)
Formal saving	-0.169**	-0.0484**	-0.169**	-0.0470**
	(0.0619)	(0.0176)	(0.0619)	(0.0171)
Informal saving	-0.0921	-0.0263	-0.0982	-0.0273
	(0.0576)	(0.0165)	(0.0583)	(0.0162)
Borrowed (financial ins.)	-0.168	-0.0480	-0.181	-0.0502
	(0.127)	(0.0362)	(0.132)	(0.0366)
Borrowed (non-financial ins.)	0.389***	0.111***	0.384***	0.107***
	(0.103)	(0.0293)	(0.104)	(0.0288)
Borrowed (friend/family)	0.144	0.0412	0.157	0.0437
	(0.0795)	(0.0227)	(0.0804)	(0.0223)
Transfers	0.103	0.0295	0.0381	0.0106
	(0.0788)	(0.0225)	(0.0797)	(0.0222)
Non-farm business	0.0205	0.00588	0.0145	0.00403
	(0.0919)	(0.0263)	(0.0935)	(0.0260)

_cons	-0.400**		-0.629***	
	(0.154)		(0.140)	
lnsig2u	-1.293***		-1.352**	
	(0.186)		(0.197)	
N	6182	6182	6182	6182

Source: Authors' estimation using data from ESS (2013/14 & 2015/16). Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions control for the other variable listed in Table 1, as well as time and region-fixed effects.

Our main findings remain the same after controlling for the potential endogeneity of the self-reported climatic shock variables and the formal saving variable. Table 4 presents regression estimates obtained by combining the CRE and control function approaches. In Columns 1 and 2 of Table 4, the estimation results are shown using the SPEI as the climate-related shock indicator after including residuals from the first-stage estimation of the formal saving variable, and Columns 3 and 4 display regression estimates using the self-reported climate and non-climate shock variables, after including residuals from the first-stage regression of the self-reported shock variables and residuals from the first- stage estimation of the formal saving variable. The estimate on the formal saving residual is significant, demonstrating the presence of endogeneity in our model. However, the coefficients on the self-reported shock variables are not significant.

Table A3 (in Appendix A) provides the findings of the first-stage regression on the predictors of formal saving and shocks. In the saving regression, the coefficient estimates on the instrumental variables are negative and significant, implying that households closest to financial institutions are more likely to use formal financial savings. The coefficient estimates on community-level shock variables are positive and significant in the shock regressions, showing that households in locations with more reported shocks are more likely to report individual-level shocks. The coefficient estimates for the other covariates in the formal saving regression align with expectations. Households with higher education levels, larger landholdings, and access to mobile devices are more likely to save through formal financial accounts. Male-headed households are more likely to engage in formal saving than female-headed households, while households with older heads are less inclined to save through formal financial accounts. In contrast, most of the covariates in the shock regression are not statistically significant.

Table 4: Impact of climate-related shocks on food insecurity: Control function with CRE regression

	(1)	(2)	(3)	(4)
	Coeff.	Marginal eff.	Coeff.	Marginal eff.
SPEI_06	0.292***	0.0757***		
	(0.0690)	(0.0178)		
Climate shock (reported)			1.353***	0.319***
			(0.105)	(0.0229)
Other shocks (reported)			0.547***	0.129***
			(0.0920)	(0.0215)
Formal saving	-5.992***	-1.552***	-4.918***	-1.161***
	(0.860)	(0.219)	(0.892)	(0.209)
Informal saving	-0.301***	-0.0779***	-0.320***	-0.0754***
	(0.0619)	(0.0159)	(0.0657)	(0.0153)
Borrowed (financial ins.)	0.0592	0.0153	0.0373	0.00881
	(0.128)	(0.0331)	(0.134)	(0.0316)
Borrowed (non-financial ins.)	0.324**	0.0839**	0.309**	0.0729**
	(0.108)	(0.0278)	(0.113)	(0.0266)
Borrowed (friend/family)	0.241**	0.0624**	0.243**	0.0573**
	(0.0840)	(0.0217)	(0.0867)	(0.0204)
Transfers	0.274**	0.0711**	0.171	0.0403
	(0.0871)	(0.0224)	(0.0898)	(0.0212)
Non-farm business	-0.0176	-0.00456	-0.0334	-0.00788
	(0.0952)	(0.0247)	(0.0983)	(0.0232)
Residual (formal saving)	5.666***	1.467***	4.565***	1.077***
	(0.860)	(0.220)	(0.893)	(0.210)
Residual (climate shock)			-0.0316	-0.00746
			(0.122)	(0.0287)
Residual (non-climate shock)			0.0255	0.00601
			(0.107)	(0.0251)
_cons	0.637**		0.231	
	(0.225)		(0.224)	
lnsig2u	-0.952***		-0.946***	

	(0.157)		(0.169)	
N	6182	6182	6182	6182

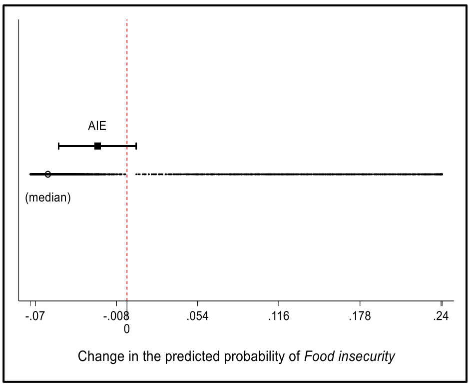
Source: Authors' estimation using data from ESS (2013/14 & 2015/16). Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions control for the other variable listed in Table 1, as well as time and region-fixed effects.

Table A4 in Appendix A shows the estimation findings after introducing interaction variables to evaluate the moderating effect of formal saving on the established positive relationship between climate-related shocks and food insecurity. The estimates on the climate-related shock variables remain positive and statistically significant. Although the coefficient on the interaction term of formal saving and SPEI is positive and significant, Ai and Norton (2003) show that the magnitudes and signs of the interaction effect in nonlinear models are different from those of the interaction term. As a result, the statistical significance of the interaction effect cannot be assessed using a t-test on the coefficient of the interaction term. To accurately calculate the interaction effects, we use the Stata tool 'ginteff' developed by Radean (2023). Figure 1 shows the estimated average interaction effects (AIE), which are represented by a solid square with a 90 % confidence interval. The second line depicts the effects of individual interaction on median values.

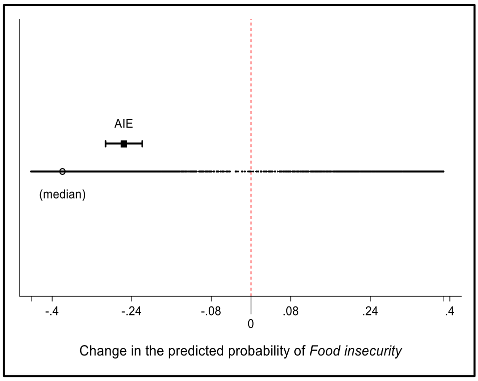
The average interaction coefficients are negative and statistically significant in the models that include the self-reported climate and non-climate shock variables (Figures 1b and 1c). Although the coefficient on the interaction between the SPEI and formal saving is negative, it is not statistically significant (Figure 1a). The negative and significant interaction effects in Figure 1 (1b and 1c) indicate that the positive impact of climate-related and non-climate-related shocks on food insecurity is reduced for households with formal savings. This suggests that formal saving helps households to reduce the negative impact of shocks on food security. Thus, formal saving plays a moderating role in the relationship between shocks and food insecurity.

Figure 1: Testing for interaction effects of shocks and formal saving (12-month food insecurity).

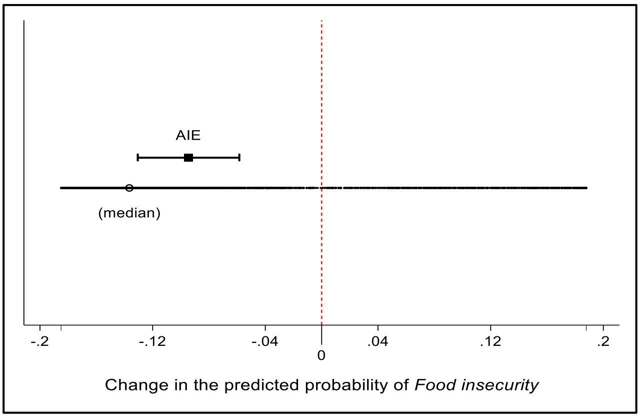
1a) SPEI_06*Formal saving



1b) Self-reported climate shock* formal saving



1c) Non-climate shocks *Formal saving

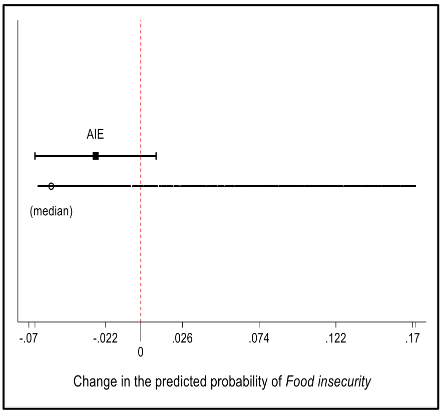


Source: Authors' estimation using data from ESS (2013/14 & 2015/16)

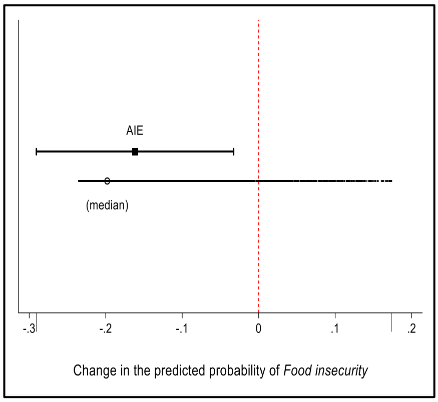
We repeat the interaction effects estimation using the FIES as a measure of food insecurity. Figure 2 presents the estimated AIE and individual interaction effects with 90 % CI. Although the coefficient on the interaction effect is negative in all cases, it is statistically significant only in the case of the interaction between self-reported climate shock and formal saving (Figure 2b). The result indicates that formal saving helps households to mitigate the adverse effect of climate-related shocks on food insecurity.

Figure 2: Testing for interaction effects of shocks and formal saving (seven-day food insecurity)

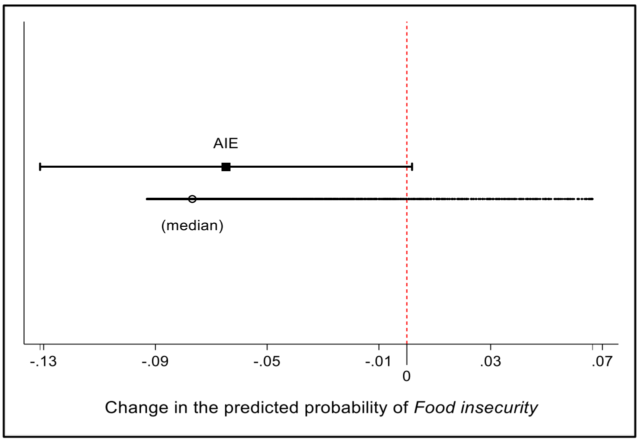
2a) SPEI_06*Fromal saving



2b) Self-reported climate shock* formal saving



2c) Non-climate shocks *Formal saving



Source: Authors' estimation using data from ESS (2013/14 & 2015/16)

Overall, our regression analysis demonstrates that both climate-related and non-climate-related shocks increase rural households' food insecurity. Conversely, households that save via both formal and informal approaches are less likely to experience food insecurity. We also find evidence that formal savings can assist households in mitigating the negative impact of climate-related shocks on food security. This finding aligns with prior evidence indicating that precautionary saving is a crucial strategy for addressing climate and other shocks (see Moore et al., 2019).

6. Conclusion

Recurrent climate-related shocks and food insecurity remain significant challenges in Ethiopia. This study examines the impact of climate-related shocks on household food security in Ethiopia and explores whether formal financial services might assist in attenuating the negative effects of climate-related shocks on food security.

Our results show that climate-related shocks, measured by self-reported drought and SPEI indicators, are associated with increased food insecurity. This is consistent with previous research demonstrating that climate-related shocks have a direct impact on household welfare in rural areas (Brown et al., 2015; Hallegatte & Rozenberg, 2017).

We also find that households that practise precautionary savings through formal and informal methods are less likely to experience food insecurity. In addition, we find evidence indicating that saving through formal financial institutions helps households in mitigating the adverse impacts of climate-related shocks on food security.

Our analysis indicates that while climate-related shocks, such as droughts, may reduce agricultural production and income, the effect of these shocks on individual welfare is affected by factors like household coping capacity. This underscores the necessity of enhancing households' coping capacity and resilience to mitigate the adverse effects of climate-related and other shocks. Policies that enhance the accessibility of financial services in rural areas and promote savings may help households implement diverse coping mechanisms to smooth consumption and improve food security during shocks.

The results have policy implications. Given the evident role of savings products, financial service providers need to design targeted savings products. Moreover, savings products can be a gateway to secondary products such as insurance products that can pay out post-climate shocks, to prevent households from falling below their optimal welfare status.

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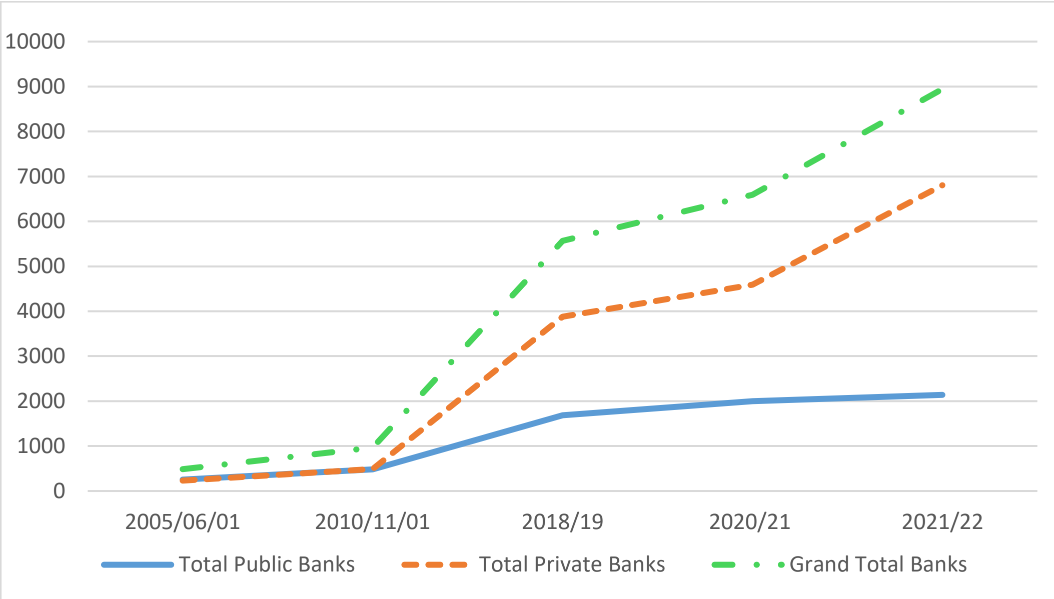
8. Appendices

Appendix A

Figure A1: Branch network of the banking sector



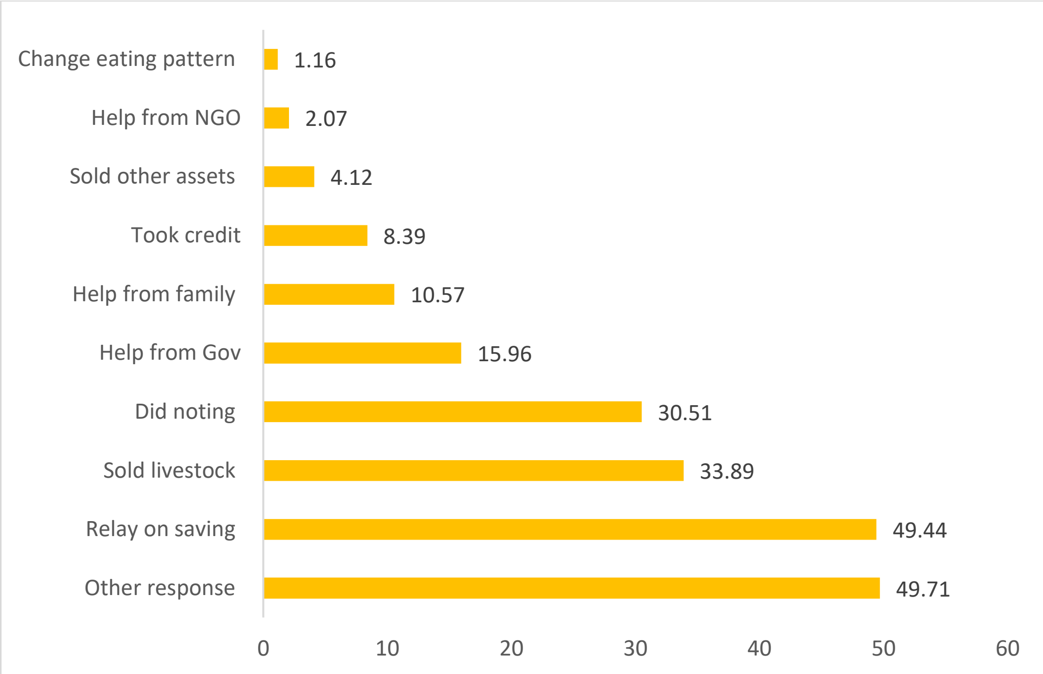
Source: Authors' illustration using data from NBE (2007, 2011, 2019, 2021, 2022).

Table A1: Share of the adult population (aged 15+) with mobile phones and account.

	Rural	Urban	National
Account at financial institutions	36.7	49.5	46.0
Mobile account	2.3	5.5	4.6
Own Mobile	39.9	55.6	51.3
Access to internet	4.6	17.5	14.1

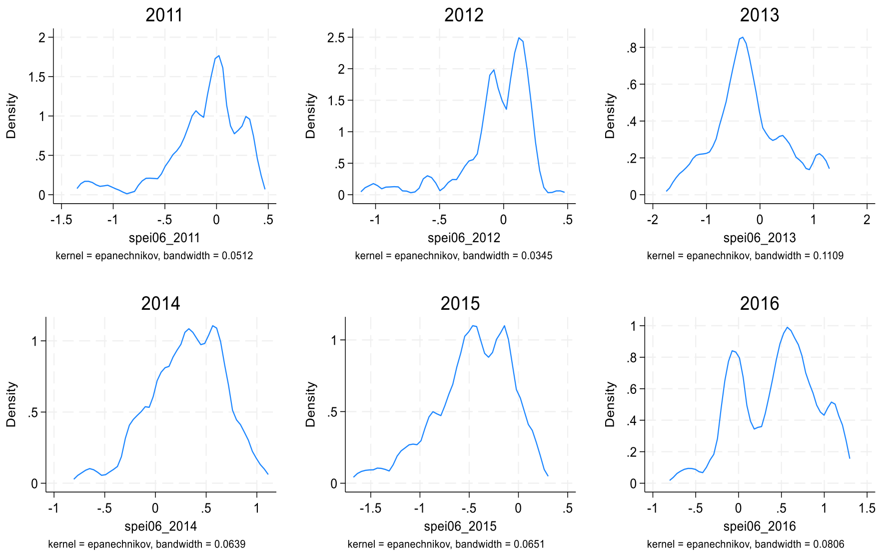
Source: Authors' illustrations using data from The Global Findex 2021.

Figure A2: **Household coping strategies following shocks in rural Ethiopia**



Source: Authors' compilation using data from ESS (2016)

Figure A3: The distribution of sample households based on SPEI_06 (2011-2016)



Source: Authors' compilation using data from Global SPEI database and ESS (2016)

Table A2: Common measures of drought and flood intensity

SPEI Value	Flood and drought intensity
SPEI <=-2.0	Extremely dry
-2.0 <SPEI<=-1.5	Severely dry
-1.5 <SPEI <=-1	Moderately dry
-1<SPEI<=0	Mild drought
0<SPEI<=1	Near normal wet
1 <SPEI<=1.5	Moderately wet
1.5 < SPEI<=2	Very wet
SPEI>2.0	Extremely wet

Source: Edossa et al. [40].

Table A3: First-stage regression of determinants of formal saving and shocks

	(1) Formal Saving	(2) Climate shock	(3) Non-climate shock
Distance to bank (log)	-0.0231**		
	(0.00753)		
Distance to microfinance (log)	-0.00929*		
	(0.00436)		
Non-climate shock (EA)			0.0107***
			(0.000136)
Climate shock (EA)		0.0109***	
		(0.000105)	
Household size	-0.00151	0.00232	0.00652**
	(0.00307)	(0.00152)	(0.00214)
Male headed	0.0364*	-0.00251	-0.0160
	(0.0151)	(0.00763)	(0.0112)
Male age	-0.00218***	0.000612**	0.000451
	(0.000390)	(0.000198)	(0.000281)
Head – Other Christian	0.0966***	-0.0116	0.0120
	(0.0207)	(0.00919)	(0.0129)
Head – Muslim and other	0.00288	-0.00960	-0.00133
	(0.0219)	(0.00982)	(0.0149)
Higher education	0.124***	0.00226	-0.0231
	(0.0201)	(0.00965)	(0.0128)
Land size in hectares (log)	0.0321*	0.00932	-0.0118
	(0.0136)	(0.00625)	(0.00842)
Livestock in TLU (log)	-0.0117	0.000926	-0.0162*
	(0.00964)	(0.00470)	(0.00669)
Have a mobile device	0.165***	-0.0130*	-0.00977
	(0.0133)	(0.00655)	(0.00917)
_cons	0.269***	-0.00801	0.0304
	(0.0457)	(0.0188)	(0.0264)
N	6182	6182	6182

Source: Authors' estimation using data from ESS (2013/14 & 2015/16). Standard errors in parentheses * p < 0.05, ** p < 0.01, *** p < 0.001. All regressions control for the other variable listed in Table 1, as well as time and region-fixed effects.

Table A4: The impact of climate shocks on food insecurity (with interaction terms)

	(1)	(2)
	Coeff.	Coeff.
SPEI_06	0.218**	
	(0.0712)	
Formal saving	-6.303***	-4.840***
	(0.864)	(0.898)
Informal saving	-0.310***	-0.320***
	(0.0619)	(0.0660)
SPEI_06_mild* Formal saving	0.503***	
	(0.121)	
Climate shock (reported)		1.382***
		(0.108)
Climate shock (reported)* Formal saving		-0.189
		(0.147)
Other shocks (reported)		0.552***
		(0.0953)
Other shocks (reported)*Formal saving		0.00865
		(0.143)
Residual (Formal saving)	5.731***	4.538***
	(0.860)	(0.894)
Residual (climate shock)		-0.0307
		(0.122)
Residual (non-climate shock)		0.0222
		(0.106)
_cons	0.671**	0.227
	(0.225)	(0.224)
/		
lnsig2u	-0.959***	-0.942***
	(0.158)	(0.169)

N	6182	6182

Source: Authors' estimation using data from ESS (2013/14 & 2015/16). Standard errors in parentheses * p < 0.05, ** p < 0.01, *** p < 0.001. All regressions control for the other variable listed in Table 1, as well as time and region-fixed effects.

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To strengthen local capacity for conducting independent, rigorous inquiry into the problems facing the management of economies in sub-Saharan Africa.

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