Adapting to Climate Instability: Financial Coping Strategies of Low-Income Rural Households

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Abstract

As climate change leads to increasingly erratic weather patterns, how will households reliant on rainfed agriculture adapt to this growing uncertainty? I investigate how exposure to climate instability, defined as the year-to-year change between dry and wet conditions, affects households' financial coping strategies. Using detailed individual-level data on financial inclusion across 29 low-income countries, I find that a one standard deviation increase in climate instability increases the propensity for households to save by up to 7%. This is driven primarily by rural households with low education, who are the most dependent on rainfed agriculture. Saving increases only during wet years, when households attain an agricultural surplus, and the reason for saving is deliberately precautionary, in anticipation of a future negative income shock. Consistent with this finding, lagged climate instability successfully predicts current climate shocks, which suggests that the elicited saving behavior is a rational adaptation. Using household panel data, I find that the increase in saving during wet years is attained through a decrease in non-food expenditures, and this successfully protects against the threat of food shortages. However, uptake of formal financial services is limited, and instead most adaptation is facilitated through community groups and informal networks. Addressing the gaps in financial inclusion and financial literacy may thus be crucial to further increase the resilience of poor rural households against the looming threat of climate change.

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1 Introduction

Rural households in low-income countries represent some of the world's most financially vulnerable. Most of these households rely on rainfed agriculture, with rates of up to 92% in Sub-Saharan Africa (Bruinsma, 2017). This makes them exceptionally vulnerable to climate shocks such as droughts, and climate change, which is expected to dramatically increase rainfall volatility (Wasko et al., 2021). Poor rural households also tend to be financially excluded, with little access to formal banking, credit or insurance, despite the potential massive welfare benefits these services could entail.

We still have very limited knowledge about how exposure to climate uncertainty affects households' *ex-ante* financial coping mechanisms, such as precautionary saving.[1] In this paper, I investigate how poor rural households cope with climate uncertainty through saving, credit, and insurance. I introduce a novel measure of climate uncertainty – *climate instability* – that captures year-to-year shifts in climate conditions. Using three datasets from low-income countries, with analyses at the country, district, and household levels, I find that exposure to climate instability leads to increased saving and credit uptake. Heterogeneity analyses show that this is driven specifically by rural households with low levels of education. Households adapt to climate instability by increasing their savings propensity and uptake of credit in "good" (wet) years, and dissave in "bad" (dry) years. I find that exposure to climate instability, through its positive effects on precautionary savings, ultimately reduces the risk of food shortages, suggesting that the increase in savings propensity from exposure to climate instability may be welfare-increasing.

To motivate how households choose to consume and save, I set up a two-period optimal consumption model. Households are assumed to be risk-averse, which implies that aggregate utility is maximized when consumption is smoothed over the two periods. Households generate income from agricultural production, which is assumed to be a function of climate inputs such as precipitation and evaporation. I measure climate inputs using the Standardized Precipitation-Evapotranspiration Index (SPEI) (Vicente-Serrano, Beguería and López-Moreno, 2010; Beguería et al., 2023). Arguably, the SPEI is preferable to rainfall or temperature measures, since it captures the combined effects of rainfall and temperature on plant growth potential, and has been shown to be more informative for crop production than rainfall or temperature alone (Kubik and Maurel, 2016). Using a global panel on crop production, I confirm that this index is an important determinant of the total production of the six most important staple crops in low-income countries.

[1] Most of the literature use *rainfall variability* as the primary measure of climate uncertainty, and have so far found inconclusive effects on saving, consumption, and credit (Paxson, 1992; Alem and Colmer, 2022; Abay et al., 2022).

Since future climate realizations are unknown, income for period two in the model is inherently uncertain. Using an exponential utility functional form, I show that households must subjectively estimate future climate uncertainty to optimally choose how much to consume and save today, an estimate which I argue will be based on subjective experience of recent climate uncertainty. I use two measures of climate uncertainty, *climate variability*, defined as the standard deviation of the SPEI over the past five years, and *climate instability*, defined as the average absolute difference in yearly SPEI values, over the past five years. In contrast to climate variability, climate instability captures the order and structure of recent climate shocks. I argue that this measure is better rooted in the behavioral literature on how availability bias, contrast effects, and salience affect our perception of experienced events (Tversky and Kahneman, 1973; Bordalo, Gennaioli and Shleifer, 2022). Using data from the Tanzania National Panel Survey, I confirm that exposure to climate instability acts as a more salient measure of subjectively experienced climate uncertainty than climate variability.

For my main outcomes I rely on large-scale household finance survey data from the FinScope National Surveys (FinMark Trust, 2022). These are nationally representative surveys, carried out since 2006, with the aim of improving the state of knowledge of financial inclusion in low-income countries, primarily in Sub-Saharan Africa and South Asia. My three main outcomes are whether a household *i)* saves (and through which means), *ii)* has any credit, and *iii)* is insured. Descriptive statistics reveal that most households still lack access to both credit and insurance, implying that consumption smoothing through precautionary saving is still the most common financial coping strategy in my sample.

Motivated by how memory decays following traumatic natural disasters (Atreya, Ferreira and Michel-Kerjan, 2015) and following the literature on climate variability (Alem and Colmer, 2022), I use climate exposure over a 5-year window as my preferred specification. To disentangle the effects of climate uncertainty from any first-order income effects or systematic differences between districts, I control for the occurrence of droughts and SPEI realizations over the same period, and long-run climate characteristics. Since most countries are surveyed only once, my main specifications rely on a cross-sectional approach, where I exploit within-country short-term deviations in climate instability and variability from the long-term mean as treatment.

I find that climate instability has statistically and economically significant positive effects on saving. In contrast, I find no evidence for an effect from climate variability on any of the outcomes, similar to Paxson (1992). My preferred specification shows that a one standard deviation increase in climate instability leads to a 5% increase in savings propensity (3 pp) for rural households. This is entirely driven by places experiencing "wet" conditions, where the savings propensity increase by 7% (4 pp). Importantly, I find that exposure to climate instability seems to be predictive of a drought in the subsequent year, indicating that the households' heuristic strategy may indeed be a rational adaptation. Furthermore, I find no effects in urban areas, and the positive effect on savings only holds for individuals with no or low skills, as proxied by their education levels, who are more likely to work in agriculture. In addition, I find significant positive effects on the use of credit, but relatively precisely estimated null effects for insurance.

The identifying assumption of my main specification is that climate instability does not correlate with other unobserved variables that vary at the region level and also affect the outcomes. This is arguably a strong assumption, since exposure to climate uncertainty might affect the sample composition through e.g. inter-regional migration. I examine this in two ways. First, I find that within countries, recent climate instability is completely uncorrelated with indicators of compositional change, such as education, age, and urban locations, suggesting that climate instability may provide a source exogenous variation, even with a cross-sectional specification. Introducing informative covariates into the specification also has limited impact on the coefficient of interest, suggesting that selection on unobservables is unlikely (Oster, 2019). Second, I construct a global panel on inter-regional migration using data from Niva et al. (2023) and find precise null results of my climate uncertainty measures on migration. In addition, the main results are robust to outliers (iteratively excluding countries), and to clustering at more aggregated levels which take into account potential large-scale spatial correlation of climate shocks.

To investigate the underlying mechanisms, I build a panel data set at the district-level for Tanzania, one of the few countries with repeated observations in the FinScope dataset. These data are georeferenced at the lower district level, and includes detailed data on type of occupation and the stated reason for saving. This allows me to investigate farming households specifically, while controlling for district fixed effects and relying on a parallel trends assumption. This analysis yields almost identical results: a one standard deviation increase in climate instability increases savings propensity by 6%. I find that this is driven entirely by farming households, and that virtually all of the increase is due to precautionary savings for emergency use. This indicates that farmers adopt a deliberate coping strategy to deal with future shocks, rather than through a latent change in time preferences. These results are robust to heterogeneous and dynamic treatment effects (De Chaisemartin and d'Haultfoeuille, 2020).

Lastly, I use a household panel from the Tanzania National Panel Survey, covering approximately 5,000 households over the period 2008-2014. Using within-household variation to control for unobserved heterogeneity at the household level, I first show that climate instability does not increase the probability of migration, consistent with the global migration analysis. I then replicate my main finding in the global analysis, that climate instability leads to more saving, and specifically for emergency reasons. I find that households exposed to climate instability face a significantly smaller risk of food shortage, likely because of the increase in precautionary savings in good years. Consistent with this, I find that during good years, households who faced climate instability increase the total value of their assets less, suggesting that despite receiving a surplus income from agricultural production, they increase their consumption of durables to a lesser extent, which in turn leads to less risk of food shortage in drought years.

The main contribution of this paper is the introduction of climate instability as an important predictor of saving and credit uptake among poor rural households. The previous literature on *ex-ante* risk mitigation among poor rural households instead focuses on *rainfall variability*, and the evidence so far has been inconclusive, and sometimes even counter-intuitive (Paxson, 1992; Rosenzweig and Binswanger, 1993; Alem and Colmer, 2022; Abay et al., 2022). This paper is most closely related to Paxson (1992), who hypothesizes that exposure to rainfall variability should increase saving, but surprisingly finds no relationship between saving and past exposure to rainfall variability in a sample of rice farmers in Thailand. The paper further relates to Alem and Colmer (2022), who find that exposure to climate variability over the past five years leads to a decrease in consumption, and from this infer an increase in precautionary savings, which they unfortunately cannot test. Rosenzweig and Binswanger (1993) find that past rainfall variability changes the composition of farmers' assets, such that both mean income and income variability are reduced, which perhaps could explain the null results of Paxson (1992). Lastly, Abay et al. (2022) find that rainfall variability negatively affects credit demand among Ethiopian farmers. In contrast, I find that climate instability has a *positive* effect on credit uptake in a global sample of rural households, suggesting that the way in which climate uncertainty is measured matters. A potential limitation of previous studies is that they rely on variation in *rainfall*,[2] while plant water availability is ultimately determined by the combination of precipitation and evaporation. Kubik and Maurel (2016) find by using the SPEI that rainfall and temperature jointly drive agricultural production, of which the most important component is temperature. Consistent with this, Aggarwal (2021) finds that variability in temperature dominates rainfall in explaining effects on consumption among Indian farmers. By using the SPEI to measure climate uncertainty, I am able to jointly capture precipitation and evaporation effects and thus improve on previously used rainfall variables.

The paper further contributes to a larger literature on climate and households' financial coping strategies by using novel Finscope data, which enables me to look explicitly at a key

[2] Alem and Colmer (2022) control for temperature variability, but the treatment variable is rainfall variability.

ex-ante consumption smoothing mechanism: precautionary saving. Similar to Udry (1995), I find that households use precautionary saving in anticipation of a negative income shock in the near future. Previous research generally focuses on how households cope with negative income shocks *ex-post*, through the drawing down of assets (Carter et al., 2007; Janzen and Carter, 2019), livestock (Fafchamps, Udry and Czukas, 1998; Kazianga and Udry, 2006), and grain stocks (Udry, 1995; Cui and Tang, 2024), and by increasing hours worked (Kochar, 1999), reducing investment in children (Jacoby and Skoufias, 1997; Maccini and Yang, 2009), relying on remittances (Yang and Choi, 2007; Jack and Suri, 2014), or alternatively have tried to infer precautionary saving from reported changes in consumption (Janzen and Carter, 2019; Alem and Colmer, 2022). The rapid development of mobile money services provides farmers in low-income countries with important new opportunities to cope with income shocks through *cash savings* instead of other types of saving (Jack and Suri, 2014; Suri, 2017), which is the focus of this paper. Consistent with this, I find that exposure to climate instability leads to an increase in saving for emergency reasons among mobile money users in Tanzania.

Finally, I contribute to the literature by providing generalizable results. This is the largest study to date on how poor rural households cope with climate uncertainty through financial means, with the data covering 29 countries, 42 survey waves, and 223,000 individuals, over the period 2006-2022. Previous work has instead relied on smaller samples and individual countries, such as national panels from Burkina Faso (Fafchamps, Udry and Czukas, 1998; Kazianga and Udry, 2006), China (Yang and Choi, 2007), Ethiopia (Alem and Colmer, 2022), India (Rosenzweig and Binswanger, 1993; Cole et al., 2013; Bjerge and Trifkovic, 2018), Nigeria (Udry, 1995), and Thailand (Paxson, 1992). By using a global sample with rich heterogeneity across climate regimes and levels of development, I show that this is a universal phenomenon among poor rural households that is not driven by any particular location.

The next section provides background on rainfed agriculture and financial inclusion in low-income countries, together with my theoretical model and the hypotheses it predicts. Section 3 introduces the data, empirical strategy and identifying assumptions. Section 4 presents the main results and section 5 the mechanisms. Section 6 presents robustness checks, while section 7 concludes with policy implications.

2 Consumption Smoothing and Climate Anticipation

2.1 Background

Most of the agriculture in the developing world is rainfed, with rates more than 95% in Sub-Saharan Africa, 70% in North Africa, 90% in Latin America, and 60% for South Asia

(FAOSTAT, 2005). In addition to a low baseline income, high reliance on rainfall makes households in these regions particularly vulnerable to climate shocks, which will likely only increase with climate change (Wasko et al., 2021). These regions are also characterized by large yield gaps due to under-investment in agricultural inputs (Molden et al., 2011), which might be worsened by exposure to climate risks due to an unstable climate (Molden et al., 2011). For example, while the total cultivated area of main cereal crops, such as maize, millet and sorghum, in Sub-Saharan Africa has doubled since the 1960s, the yield has remained largely unchanged (Molden et al., 2011).

Among the many margins that rural households can use to smooth their income and consumption, the most straightforward mechanism, especially for credit-constrained households, is through building buffer savings in years of agricultural surplus (Deaton, 1989; Karlan, Ratan and Zinman, 2014). However, most rural households in developing countries still lack access to formal bank services (World Bank, 2023), leading to a greater adaptation of informal services, which can come with higher risks and costs (Karlan, Ratan and Zinman, 2014).

One common method of risk-sharing is through communal saving cooperatives, such as rotating savings and credit associations (ROSCAs).[3] ROSCAs are incredibly common in Sub-Saharan Africa, with membership rates between 50 and 95 percent, and are often the only available saving and credit institution in rural areas (Anderson and Baland, 2002). Members in ROSCAs regularly contribute a fixed amount of money to a common fund, and at each meeting, the pooled funds are given to one member, rotating until everyone has received the lump sum once. In the face of income shocks like droughts affecting agriculture, ROSCAs can provide a financial safety net for members. The lump sum received can be used to cope with the immediate financial strain, such as purchasing food, seeds, or other necessities, thereby offering temporary relief and helping members manage the economic impact more effectively (Beaman, Karlan and Thuysbaert, 2014).

In addition, the mobile technology revolution is rapidly increasing access to financial services, and Sub-Saharan Africa already reports having the highest mobile money account access in the world. This is important, as Jack and Suri (2014) show that mobile money users are less affected by negative income shocks, through their ability to receive remittances from family members and friends. At the same time within-country gaps in financial inclusion between men and women, the rural and urban, and the wealthy and poor are still considerable (Demirguc-Kunt et al., 2018).

In the following section, I set up a simple model of how a rural household deriving most of its income from agricultural production might choose how to optimally consume and save due to future income uncertainty stemming from climate shocks.

[3] In the subsequent empirical analysis, I categorize this type of saving as *informal saving*.

2.2 A Two-Period Optimal Consumption Model with Uncertain Future Income

To model the intertemporal decision-making of households, I follow Bowman, Minehart and Rabin (1999) who set up a two-period optimal consumption model, where income in period two is uncertain. I assume that agents are risk-averse, such that $u'(c) > 0$ and $u''(c) < 0$. The agent's optimization problem can be written:

$$\max_{c_0} U(c_0, c_1) = u(c_0) + \beta u(c_1)$$

$$\text{subject to:}$$

$$c_0 = y_0 - s_0$$

$$c_1 = y_1 + (1+r)s_0$$

Where U is aggregated utility, $0 < \beta \leq 1$ a discount factor, c_0 and c_1 consumption in the current and future period, y_0 and y_1 income in the current and future period, and s_0 savings in the current period. The agent faces the problem of how much of today's income y_0 should be saved to maximize aggregate utility U. This yields the well-known Euler consumption rule:

$$u'(c_0) = \beta(1+r)u'(c_1) \tag{1}$$

I assume that households derive their main income y from agricultural production, which depends on inputs such as labor L, capital K, cultivated area A, and weather W:

$$y = f(L, K, A, W, ...)$$

Since weather in the future period, W_1, is inherently uncertain, future income y_1 will be outside the control of the individual farmer. Since most agriculture in this context is rainfed, and soil moisture is a necessary condition for plant growth, there is likely little to no substitutability between weather and other factors of production. Hence, production approximates a Leontief production function:

$$y_t = min\left(\frac{W_t}{a}, \frac{Z_t}{b}\right)$$

where Z_t represents all other factors of production, and a, b are technological parameters. Assuming that climate can be modelled as a stochastic function with a normally distributed error term, representing random variation in available soil moisture from fluctuations in precipitation and evapotranspiration over time, production, and hence income, can be expressed as[4]:

$$y_t = min\left(\frac{\bar{W}+\epsilon_t}{a}, \frac{Z_t}{b}\right), \quad \epsilon_t \sim N(0, \sigma_w^2)$$

If weather is a binding constraint for production, i.e. $\frac{\bar{W}+\epsilon_t}{a} < \frac{Z_t}{b}$, which is likely during dry conditions and periods of excess labor supply, income in period t can be expressed $y_t = \bar{y} + \epsilon_t/a$, where $\bar{y}$ represents long-term average income. For ease of exposition, I follow Merton (1975) and use an exponential utility formulation[5]: $u(c) = (1 - e^{-\alpha c})/\alpha$ with $\alpha > 0$, which results in the following expression for $E[u(c_1)]$:

$$E[u(c_1)] = 1 - e^{-\alpha(\bar{y}+(1+r)s_0 - \frac{\alpha}{2}\sigma_w^2)}$$

Using the Euler optimal consumption rule in equation (1), with the future utility term replaced by its expectation, I arrive at the optimal savings rate s_0^*:[6]

$$\underbrace{s_0^*}_{\text{Optimal savings}}(2+r) = \underbrace{y_0 - \bar{y}}_{\text{Current surplus}} + \underbrace{\frac{\alpha\sigma_w^2}{2}}_{\text{Risk aversion}} + \underbrace{\frac{\ln(\beta(1+r))}{\alpha}}_{\text{Discounted return}} \tag{2}$$

Optimal savings today will depend on three different aspects captured by each of the terms above, which will motivate my hypotheses. First, when current agricultural surplus is high following a positive climate shock, saving should increase. Second, since agents are risk-averse, saving should increase with the degree of risk aversion α and climate variability σ_w^2. The third term, capturing the effect of the discounted return of saving, is of less relevance to this analysis, since it will not be affected by climate variation, and in addition will approximate zero whenever $\beta(1+r) \approx 1$. Interestingly, I arrive at a linear relationship between savings, current surplus, and risk aversion, which is precisely the relationship that is assumed in Paxson (1992) to motivate the econometric specifications therein.

[4] In an empirical exercise, I validate and use the Standardized Precipitation-Evapotranspiration Index over the last 12 months as my main measure of a climate shock. The empirical distribution of the SPEI, designed to have a mean of 0 and a standard deviation of 1, in my sample reassuringly approximates a normal distribution.

[5] Exponential utility implies constant absolute risk aversion, meaning that risk aversion does not change with wealth. This is often considered unrealistic, however, in this context, most households of interest are at very low (subsistence) levels of consumption, and an exponential utility model will at these lower levels of consumption be indistinguishable from e.g. a CRRA model. As demonstrated by Leland (1968), a CRRA model—or any model with prudent agents—predicts that precautionary saving will increase with future income uncertainty.

[6] See Appendix B.1 for the full proof.

2.3 Estimating Climate Risk from Past Experience

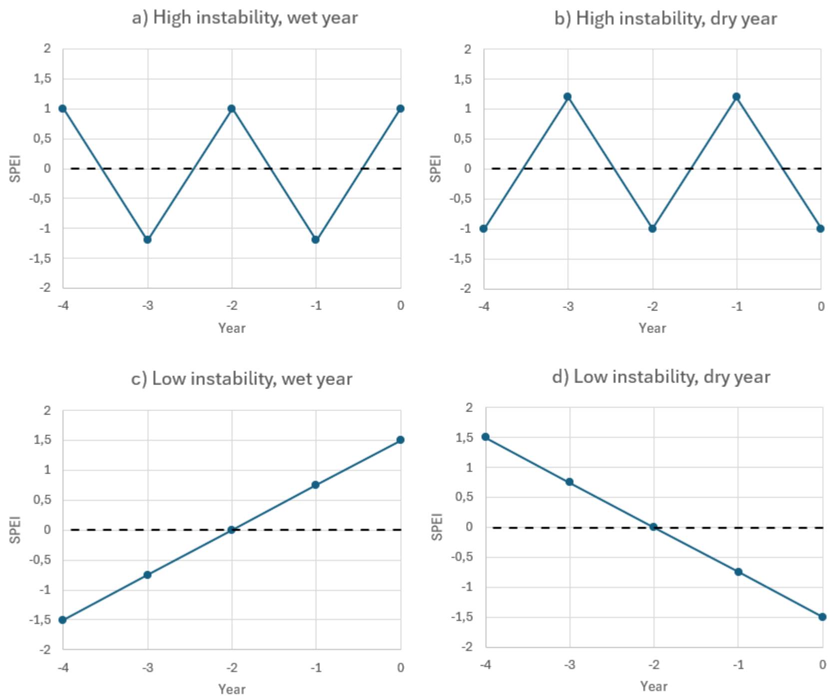
How do households estimate climate variability? A growing literature evaluates how rural low-income households perceive climate change, and has found that climate perceptions are often inconsistent with observed trends over longer periods (De Longueville et al., 2020), and typically biased towards more recent and extreme events (Marx et al., 2007), and events that have a direct impact on livelihoods (Akponikpè, Johnston and Agbossou, 2010). This is consistent with a rich behavioral literature suggesting that individuals tend to overweight recent events more, through availability and recency bias (Tversky and Kahneman, 1973). This suggests that households' estimate $\hat{\sigma_w^2}$ based on subjective experience over a recent time window.

While a variability measure such as the standard deviation of recent shocks might seem like an obvious choice, this measure actually neglects how the shocks are structured and ordered, which may be of importance for individuals' subjective experience. Consider the four hypothetical cases of climate realizations over a five-year period in Figure 1. All cases have been normalized to have the same mean and standard deviation (variability), yet they will arguably have very different effects on the subjective experience of individuals facing these shocks. In cases a) and b), dry and wet years are interleaved, such that the year-to-year differences are high. I classify these as having *high climate instability*. In cases c) and d), variability over the time window is just as high, but here the climate changes smoothly year to year, meaning that they instead have *low climate instability*. Because they all have the same standard deviation, the variability measure is unable to differentiate between these scenarios.

There are several reasons why this would matter for an individual's subjective estimate $\hat{\sigma_w^2}$. First, there is a rich behavioral literature on "contrast effects", where an experience will stand out more if it is compared to more dissimilar experiences (Simonson and Tversky, 1992). In this setting, experiencing a drought after a wet year may make both experiences more *salient* (Bordalo, Gennaioli and Shleifer, 2022), leaving a stronger impression on the need for precautionary saving. I later test and show that this is indeed the case – individuals who faced higher climate instability are more likely to report having experienced more severe shocks, conditional on actual climate shocks, while I do not find the same effect from variability. Additionally, if utility is experienced relative to a recent reference point (Tversky and Kahneman, 1991), such as the previous year, high climate instability will lead to larger utility losses relative to when the climate changes smoothly between years,[7] and the

[7] Using the same exponential utility form as in Section 2.2 and focusing on year-to-year losses in utility, cases a) and b) would dominate case d) in terms of both the sum of utility losses and magnitude of the losses, whereas case c) does not experience any utility loss at all.

Figure 1: Hypothetical climate realizations representing high and low climate instability



Notes: This figure shows four hypothetical realizations of climate outcomes over a recent 5-year period, where all the cases have identical mean (0) and standard deviation (1). Year 0 indicates the climate realization over the past 12 months. Climate realizations are represented by the Standardized Precipitation-Evapotranspiration Index (SPEI).

behavioral literature suggests that losses matter more than gains (Tversky and Kahneman, 1992).

Second, agricultural surpluses should mechanically increase savings, as shown in Equation (7), and repeated interleaved shocks, where precautionary savings repeatedly are built up and consumed, may in turn encourage habit formation in saving (Carroll, Overland and Weil, 2000; Alessie and Teppa, 2010).

Third, high climate instability may undermine farmers' adaptation to a changing climate, since adopting more drought-tolerant crops may backfire when the next year turns unexpectedly wet. Evidence from Ethiopia shows that while access to climate information is one of the most important drivers of farmers' adaptation to climate change, unpredictable weather is a key barrier (Marie et al., 2020). Hence, climate that changes smoothly over time will likely help ease adaptation and hence reduce the need for precautionary saving, versus climate that changes erratically.

Fourth, it may well be that individuals learn of local climate regimes and use this to predict next year's climate. I find evidence that past climate instability does indeed increase the risk of a climate shock in the current period, both in the positive and negative direction, suggesting that farmers may increase their savings in anticipation of an expected future shock.

Based on the above, my main hypotheses are thus that: *i)* households save more during wet years, when there is an agricultural surplus, *ii)* households save more during periods of high climate instability, *iii)* the effect of climate instability on savings should mostly occur in wet years, since households would be expected to consume their savings in dry years, and *iv)* that these effects should be driven by low-skilled labor in rural areas, who are more likely to derive their income from agricultural production. In Section 3.3 I describe the climate data and definitions I use for climate variability and instability to empirically test these hypotheses.

3 Data and Empirical Strategy

For my empirical analysis, I construct five datasets on: household finance, household consumption, climate, agricultural production, and migration, each described separately below.

3.1 Household Finance Survey Data: the FinScope Surveys

3.1.1 Global Dataset

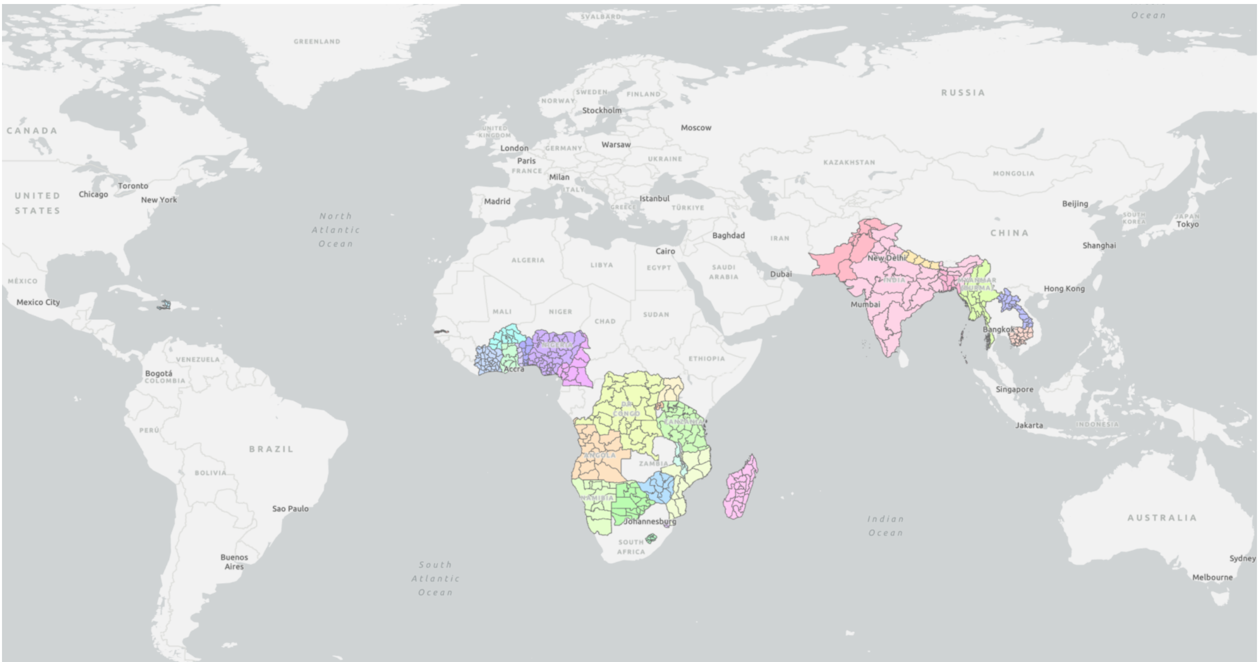
The main purpose of this paper is to investigate how climate uncertainty affects households' saving behavior. To this end, I use the FinScope National Surveys, carried out by the FinMark Trust (FinMark Trust, 2022). The Finscope National Surveys are nationally representative surveys, carried out since 2006 in low-income countries in primarily Sub-Saharan Africa, South Asia, and Southeast Asia. Their aim is to provide insight into financial literacy and inclusion in poor countries, and provides an unprecedented detail into households' financial literacy and access. These surveys have so far received little attention in the economics literature, and have mostly been used in descriptive work documenting the progress towards financial inclusion in the surveyed countries.[8]

The FinScope survey data contains questions on to what extents household use financial services, such as saving accounts, credit and insurance, and which providers they rely on (formal, informal, or family and friends). To build the dataset, I use all available data[9], but exclude small island states, unavailable datasets and surveys that are not georeferenced at the admin 1-level or lower. This results in a sample of 223,670 individual observations, spanning 29 countries, 42 waves, and 16 years, over the period 2006-2022. For a full list of countries and years included in my analysis, see Table A.1.

[8] See Honohan and King (2012) and Ouma, Odongo and Were (2017) for some applications of these datasets.

[9] The survey data can be accessed at: https://finmark.org.za/data-for-financial-markets.

Figure 2: Geographic coverage of the FinScope national survey data



Notes: Each country in the dataset is identified by a unique color. The region boundaries within each country indicate the aggregation level of the climate data.

My main outcomes for financial coping strategies are:

Saved in past 12 months – Whether a household saved in the past 12 months.
Has loans – Whether an individual currently has any loans.
Has insurance – Whether a household has insurance or not.

In addition, the survey data includes important individual characteristics such as age, gender, level of education, occupation and an urban indicator.

3.1.2 Tanzania District Panel

While most countries have been surveyed only once, Tanzania has been surveyed four times (2006, 2009, 2013 and 2016), and furthermore identifies the location of surveyed households down to the district (admin 2) level.[10]. This allows me to use a difference-in-differences strategy, exploiting sub-national variation in climate uncertainty over the survey periods. In total, this yields 22,103 observations clustered in 169 districts, across three waves spanning over 13 years. I use this dataset to examine the effect on saving and to explore the mechanisms underlying this effect. First, I am able to directly identify *farming* households. Second, the

[10]The 2013 wave only contains information at the less granular region level, and is thus excluded from the analysis. The survey data for Tanzania can be accessed at: https://finmark.org.za/data-portal/TZA

surveys within each country are more harmonized, which allows me to identify the reasons why households save. Specifically, I use the following variables as outcomes:

Save for emergency reasons – Whether a household saved specifically due to emergency reasons in the past 12 months.
Save for other reasons – Whether a household saves for reasons other than emergencies in the past 12 months.
Member of a savings group – Whether an individual is a member of an informal savings group.

3.2 Household Consumption Panel: Tanzania National Panel Survey

To further strengthen identification and examine mechanisms more closely, I complement the Tanzania district panel with household panel data from the Tanzania National Panel Survey (NPS), specifically the harmonized dataset covering the period 2008-2015 provided by the World Bank (World Bank, 2021).[11] The Tanzania NPS is a longitudinal survey conducted by the National Bureau of Statistics in Tanzania. The survey aims to provide comprehensive data on household welfare, consumption, and other socio-economic indicators. The uniform dataset from 2008-2015 comprises panel data collected from a nationally representative sample of households across Tanzania. This enables me to look into whether a household moved following climate uncertainty, important for identification, as well as mechanisms such as consumption. I use the following variables as outcomes:

Reported climate shock severity – An index from 0 to 3 representing the severity of a recently experienced climate shock (drought or flood). 0 indicates no shock at all, while 3 indicates maximum severity.
Log Assets – Log of the estimated current market value of household assets, if they were to be sold today.
Food shortage, last 12 months – Whether the household faced a shortage of food in the last 12 months.
Ever moved – Whether the household ever relocated between survey waves.

3.3 Climate Data: SPEIbase

To measure plant water availability, drought incidence, climate variability and climate instability over the survey periods I use the Standardised Precipitation-Evapotranspiration Index

[11] The dataset can be accessed here: https://microdata.worldbank.org/index.php/catalog/3814.

(SPEI) from *SPEIbase*, using data for the entire world for the period 1996-2022.[12] This long-term climate database contains gridded data on drought conditions for the entire world, at a spatial resolution of 0.5 decimal degrees and time scales ranging from 1 to 48 months, covering the period 1901-2023 (Vicente-Serrano, Beguería and López-Moreno, 2010). This makes it suitable for sub-national analysis, even down to the district (admin 2) level.

The SPEI consists of two main components, precipitation and evapotranspiration (derived from temperature). As such, it is widely widely used for drought-monitoring around the world, and is especially suitable for studying the effect of global climate change on droughts (Beguería et al., 2014). The SPEI is in essence a standardized time series of water availability, with mean 0 and standard deviation 1.[13] Negative values indicate dry conditions, and typically values below -1 are used to indicate droughts.

Using SPEI over rainfall or temperature alone provides several advantages. First, this index represents globally harmonized weather data, and adjusted to local grid cell conditions, enabling comparisons between locations and time periods. Second, in addition to precipitation it also takes into account evapotranspiration, hence providing a net measure of of water availability in the soil. For agriculture, especially for rainfed smallholders, the resulting soil moisture from the interaction of rainfall and evapotranspiration is the crucial constraint for crop production, not rainfall per se. Indeed, Kubik and Maurel (2016) evaluates the SPEI for agricultural production in Tanzania, and finds that SPEI 12 m is the most important predictor of agricultural production. In contrast, variation in rainfall is of less importance, and instead, in the context of Tanzanian agriculture, temperature shocks that drive differences in evapotranspiration are more important. SPEI naturally captures both of these effects through variation in net water availability. Third, while a large literature have used single indicators of drought, typically rainfall[14] or temperature[15], the recent economics literature has turned towards multi-variable drought indicators[16], such as the SPEI, which enables a direct comparison of my findings with theirs.

To construct the climate variables, for each observation, I extract climate data in 12-month periods prior to the date of observation[17], I compute country-, region-, and district-level. I

[12]The most recent dataset can be accessed here: https://spei.csic.es/spei_database.

[13]For more details on the definition and derivation of the index and parameter values, see: https://spei.csic.es/home.html.

[14]This literature typically use a standardized precipitation index and examples include Maccini and Yang (2009), Dinkelman (2017) and Shah and Steinberg (2017)

[15]Examples include Adhvaryu, Fenske and Nyshadham (2019) and Jessoe, Manning and Taylor (2018)

[16]See e.g. Couttenier and Soubeyran (2014) who propose using the Palmer Drought Severity Index, a measure that essentially aims to capture soil moisture, and Harari and Ferrara (2018) and Kubik and Maurel (2016) who use SPEI similar to this paper.

[17]In all my survey data, I have either an exact date or month of observation, such that I can compute

then compute district-level average SPEI-values, such that each district d is assigned an SPEI value $\text{SPEI}_{d,y}$ for each year from 1996 to 2018. This enables me to look at the effects of climate uncertainty going back 10 years prior to the first survey date. I can then use these yearly values to construct treatment variables over 5-year periods, to analyze whether households are affected by recent exposure to climate uncertainty[18]. While the specific choice of time window is somewhat arbitrary, a 5-year window is likely near the preferred window size. First, a shorter window such as 3 years will most likely capture individual shocks rather than the pattern of shocks, which I control for regardless, and a longer window such as 20 years will likely result in little variation between regions, as the measure regresses to the mean over time. Second, a literature looking into how people's memories of natural disasters such as floods decay over time has found that most decay seems to occur within 3-4 years (Atreya, Ferreira and Michel-Kerjan, 2015). While this context is slightly different, both types of events still associate with monetary losses stemming from climate shocks. Hence, a window of 5 years would capture the lingering effects of climate shocks. Third, a 5-year window would be consistent with a recent economics literature on climate variability, making my findings more comparable to the existing literature (Alem and Colmer, 2022). I also test robustness to longer time windows and I find that the results still hold for a 10-year window, although with slightly smaller effect sizes.

Specifically, the following climate variables are used in the analysis:

$\mathbf{SPEI_{12m}}$ – The 12-month SPEI aggregated at the country-, region-, or district-level.

$\mathbf{Drought_{12m}}$ – A binary indicator equal to 1 if $\text{SPEI}_{12\text{m}} < -1$, representing conditions drier than 1 standard deviation below the local mean.

Climate variability$_{\mathbf{5y}}$ – The standard deviation of $\{\text{SPEI}_{12m}, ..., \text{SPEI}_{48-60m}\}$, the last five years of yearly SPEI values. This measure is used to capture the effects of an increasing dispersion of water availability relative to the long-term local mean.

Climate instability$_{\mathbf{5y}}$ – Defined as the *average absolute difference* in the SPEI between each year in $\{\text{SPEI}_{12m}, ..., \text{SPEI}_{48-60m}\}$. This measure is used to capture the effects of climate instability, by focusing on the year-to-year variation. Since it correlates strongly with climate variability, I residualize the average absolute differences on climate instability and yearly SPEI values over the last five years to create a climate instability index that is orthogonal to climate variability.[19]

the climate conditions in 12-month intervals preceding this date. For agricultural production data, which records the total harvests per calendar year, I use calendar year averages.

[18] I have initially restricted this analysis to 0-5 and 5-10 years prior to the survey date, and I let district fixed effects capture the remaining climate characteristics prior to these periods.

[19] More formally, I run the regression $ClimInstab_{ry} = \alpha_c^1 + \alpha_y^2 + \sum_{i=1}^{5} \beta_i SPEI_{ry}^i + \gamma ClimVar_{ry} + \varepsilon_{ry}$ where the residuals from this regression constitute my Climate instability index. See section 3.7 for more details.

3.4 Agricultural Production Data: FAOSTAT

To validate the SPEI for agricultural production and analyze to what extent past climate may affect current production, I use global data on yearly agricultural production and yields at the country-level from FAOSTAT (Food and Agriculture Organization of the United Nations, 2024). This dataset contains statistics for 278 agricultural products, and I focus on the six most important food crops in low-income countries: maize, rice, cassava, sorghum, millet, and wheat. For rice, I focus on the share produced through rainfed agriculture. I use all available data for the period 2000-2022.

To match climate data to agricultural production, I use SPAM 2005 (Spatial Production Allocation Model) (You et al., 2014), which provides a global gridded distribution of agricultural production for 42 major crops, representative of 2005. This should arguably be representative of agricultural production for the period 2000-2022, while mostly be unaffected by climate variation during this period. Visual inspection shows that the six included food-crops tend to be clustered in different parts of different countries, largely depending on their respective climate and soil requirements. Hence, while agricultural production is observed at the country level, variation in the country-crop data is driven by sub-national variation in experienced climate. To construct the treatment variables, I aggregate the climate treatment variables at the country $\times$ year $\times$ crop level, by creating yearly weighted averages, where the weight represents the share of the physical area for each crop in a grid cell relative to the country total.

In addition to spatial climate variation, crop growth will also depend on rainfall variability *within* each 12-month period. One way to take this into consideration is to construct crop-specific calendars for each country (Von Uexkull et al., 2016). However, I argue that this potential imprecision is unlikely to be problematic for my analysis. Growing seasons for crops, especially in areas of rainfed agriculture, largely follow the local rainy seasons, since this is when most of the planting and critical growth periods tend to occur. In addition, variation in the 12-month SPEI will mostly be driven by climate variation within the rainy seasons. This is because the 12-month SPEI value takes the accumulated water deficit over the last 12 months into account, which means that relative changes in rainfall in the rainy seasons will have a much larger effect than changes in the dry seasons.[20] To the extent that the 12-month climate variable unadjusted for local crop calendars adds unnecessary variation, adjusting this locally should only increase the precision and magnitude of the estimates from a reduction in classical measurement error. For agricultural production, I use the following outcome variables:

[20] If the 12-month SPEI value instead was calculated as the 12-month average of monthly SPEI values, then the measure would weight relative deviations in wet and dry seasons equally.

Log Production – The log of production (tonnes) of a crop in a country and year.

Log Yield – The log of the production (tonnes) per harvested acre.

3.5 Migration Data: Niva et al. (2023)

Lastly, I construct a global migration panel at the region level using a recent dataset from Niva et al. (2023). This data contains inter-regional migration rates at the admin 1-level. Since my main dataset is identified at this level, I can test whether recent climate uncertainty also affects migration and hence the composition of the households in my sample. While the main purpose of this exercise is for identification purposes, migration could itself be one mechanism by which households smooth their consumption and a potential outcome of interest. I use the following outcome variable:

Net migration rate – The net migration rate per 1000 inhabitants at the region (admin 1) level. Positive values indicate net in-migration, and negative values net out-migration.

3.6 Descriptive Statistics

Table 1 provides descriptive statistics for the full and rural FinScope sample, respectively. Overall, most individuals save (60%), but only a small share saves formally, through e.g. a savings account. Instead, most saving is done through informal means (typically through a village-level savings group) or through family and friends, especially for rural households. Consistent with this, most individuals still do not have access to credit or insurance, with rates at around 31-33% and 13-15%, respectively.

By construction, SPEI_{12m} will have a mean close to zero and a standard deviation close to 1. The slightly negative value indicates that most individuals faced slightly drier-than-normal conditions when surveyed. Similarly, Climate $\text{instability}_{\text{5y}}$ should have a mean close to 0 since it is residualized on Climate $\text{variability}_{\text{5y}}$. Climate $\text{variability}_{\text{5y}}$ should be close to 1 if there is no dependence between climate realizations each year, but this is slightly smaller, at 0.78. This could indicate the presence of long-term dependence, such that deviations from the mean are clustered over time to some degree.

As expected, education levels are relatively low, with the mean education roughly equivalent to having completed primary school. The mean age is in the age category representing 35-44 year-olds. About 35% of the sample lives in urban areas, and a small majority of the sample consists of female individuals.

Table 1: Summary statistics for the full and rural samples in the FinScope dataset

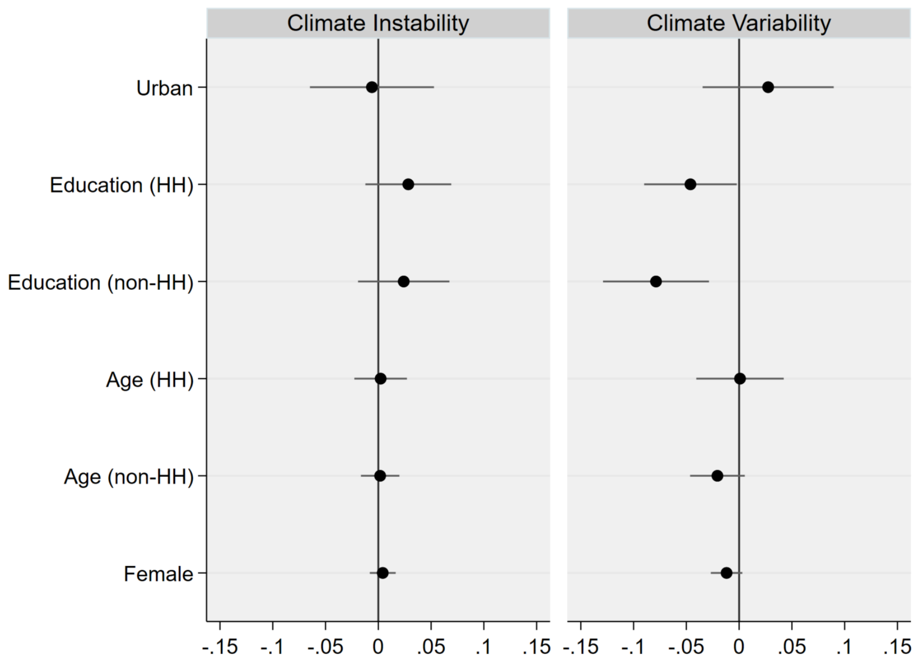
	Full sample		Rural sample	
	Mean	SD	Mean	SD
Outcomes				
Save	0.609	0.49	0.602	0.49
Save formally	0.151	0.36	0.122	0.33
Save informally	0.273	0.45	0.278	0.0.45
Save through family and friends	0.293	0.46	0.316	0.46
Have loans	0.313	0.46	0.333	0.47
Have insurance	0.149	0.36	0.133	0.34
Climate variables				
$\text{SPEI}_{12\text{m}}$	–0.187	0.91	–0.079	0.88
$\text{Drought}_{12\text{m}}$	0.158	0.36	0.129	0.34
Climate $\text{variability}_{5\text{y}}$	0.785	0.36	0.777	0.34
Climate $\text{instability}_{5\text{y}}$	0.000	0.19	0.003	0.18
Individual characteristics				
Age category	3.163	1.43	3.163	1.42
Education level	2.332	1.07	2.158	1.00
Urban	0.349	0.48	0.000	0.00
Female	0.545	0.50	0.537	0.50
Year of observation	2015	3.71	2015	3.53
Observations	223,670		145,503	

Note: Ages are reported as quintile groups, ranging from 16-24 years (1), 25-34 years (2), 35-44 years (3), 45-60 years (4), and 61+ years (5). Education is categorized as: no education or incomplete primary school (1), completed primary school (2), completed secondary school (3), vocational training (4), and completed tertiary education (5).

3.7 Identification Strategy

My main specifications can be interpreted as a reduced form analysis, where I use climate variability and instability as instruments for income uncertainty, to estimate the effect of households' consumption smoothing strategies. For this to identify a causal effect on saving, I need three assumptions to hold. First, climate realizations over the past 5 years must be randomly assigned (the independence assumption). Since this is measured as deviations from the local long-term mean, and weather is mostly random, any violation would most likely instead arise from self-selection, as households may react by selecting into or out of areas depending on past climate outcomes. As a preliminary test, Figure 3 shows covariate balance tests for climate instability and variability, with standardized effect sizes. Reassuringly, climate instability does not correlate significantly with any covariate, while there is significant negative selection for education from climate variability, especially for non-household members, suggesting that households' with younger and more educated members might migrate out of areas facing high climate variability. While the effect size is rather small, it is important to consider this negative selection when interpreting the effects from climate variability. Later, as a robustness check, I investigate the effects of exposure to climate instability and variability on migration directly.

Figure 3: Covariate balance tests for the global FinScope dataset



Notes: All variables are standardized to demonstrate the effect of a one standard deviation increase in climate instability and climate variability, respectively, on each covariate (standardized). *HH* denotes the head of the household, while *non-HH* denotes other household members.

Second, the relevance assumption states that for climate uncertainty to affect income uncertainty it must be the case that current climate has a significant effect on current agricultural production. While this is fairly uncontroversial, it allows me to test the strength of the first stage and also rule out any effects of *past* climate uncertainty on current agricultural production, conditional on current climate. Hence, the first specification that I estimate is:

$$Y_{cy} = \alpha_c^1 + \alpha_y^2 + \beta SPEI_{cy}^{12m} + \gamma ClimVar_{cy}^{5y} + \delta ClimInstab_{cy}^{5y} + \mathbf{X}_{cy}'\Gamma + \varepsilon_{cy} \tag{3}$$

Where Y_{cy} is either Log Production or Log Yield in country c in year y, α_c^1, α_y^2 are country- and year fixed effects, β the coefficient of interest, and $\mathbf{X}$ are climate controls which include climate realizations over the past five years. Lastly, the exclusion restriction states that climate instability and variability should only affect consumption smoothing through effects on income uncertainty. Hence, for a null effect of climate variability and instability on current income, γ and δ should preferably be close to 0.

For my main specification, where I estimate how past climate uncertainty affects current consumption smoothing strategies, I essentially run a "horse-race" between climate variability and climate instability, conditional on current and past climate realizations:

$$Y_{icry} = \alpha_c^1 + \alpha_y^2 + \beta SPEI_{ry}^{12m} + \gamma ClimVar_{ry}^{5y} + \delta ClimInstab_{ry}^{5y} + \mathbf{X}'_{icry}\Gamma + \varepsilon_{icry} \tag{4}$$

where Y_{icry} is whether an individual i in region r, country c, and year y saves, has any credit, or has any insurance. The vector $\mathbf{X}$ includes age category, education level, an urban dummy, and a female dummy.

In additional analyses, I use a similar specification as (4) using the Tanzania district panel and the Tanzania NPS household panel, where I essentially replace the country fixed effects with district and household fixed effects, respectively, and generate climate variables at the district-year level. Since the treatment variables are continuous, the identifying variation comes from different treatment dosages over time within the same district or household. While this helps with identification relative to the cross-sectional global FinScope analysis, it introduces potential bias from heterogeneous and dynamic treatment effects. To check robustness to these sources of bias, I also re-run the analysis using the estimator proposed by De Chaisemartin and d'Haultfoeuille (2020).

Since the treatment is applied at the region- and district levels, standard errors are clustered at this level following Abadie et al. (2023), which also helps to account for within-district serial correlation (Bertrand, Duflo and Mullainathan, 2004).

4 Results

4.1 Climate and Agricultural Production

Table 2, Panel A, reports the results from the regression of agricultural production on climate and climate uncertainty, which I use to validate my theoretical model and empirical strategy. Results are reported for the universe of FAOSTAT-reporting countries ("Global Sample") and for countries within the same regions as the FinScope sample ("FinScope regions", representing Sub-Saharan Africa, South- and Southeast Asia). First, I find a strongly significant positive effect of SPEI_{12m} on log production.[21]. This indicates a significant linear relationship between SPEI_{12m} and agricultural production, which validates the assumption in the theoretical model of additive income shocks from deviations in the SPEI_{12m}. While the model is at the household level and these results represent the country level, assuming

[21] While my analysis is reduced form, the effect of SPEI_{12m} roughly corresponds to F-statistics of 25 to 39, indicating a strong first stage.

a fixed number of households in the short-run, the average household income can be defined as $y = Y/N$ where Y is total country level production and N the number of households in each country, such that $y \propto Y$.

The effect is also economically meaningful: within FinScope regions, a one standard deviation in the SPEI increases production by 7%, and a drought reduces production by 14%. Given that these are aggregated at the country-level, measuring crop production on a more local level would arguably only result in larger estimates. For reference, Kubik and Maurel (2016) shows that negative SPEI values have a large and meaningful effect on crop production in Tanzania, using household-level data. The authors find that $\text{SPEI}_{12\text{m}}$ is the strongest predictor, and find that a one deviation reduction in the $\text{SPEI}_{12\text{m}}$ reduces crop production by 20-30%.[22]

Reassuringly, climate variability and instability does not affect current production, conditional on current and past climate realizations, and these null effects are relatively precisely estimated.

For log yield, defined as the log of production per harvested area unit, I find qualitatively the same results as for production with the global sample, but not in the sample of FinScope regions. This could indicate that in regions that rely on rainfed farming with less inputs and capital, the total area sown and harvested is itself a function of rainfall. Indeed, farmers relying on rainfed agriculture in the drought-prone Sahel belt tend to wait until the rainy season arrives before they start sowing (Bussmann et al., 2016). This indicates that in dry years a smaller area is cultivated, most likely the subset of areas less affected by droughts.

4.2 Climate Uncertainty and Saving Behavior

Table 3 reports the main results: how climate uncertainty affects saving propensity. First, I find only a weak relationship between current climate $\text{SPEI}_{12\text{m}}$ and saving, which interestingly is negative instead of positive, as predicted by the theoretical model and hypothesis *i)*. Instead, the effects from the climate uncertainty variables are more consistently significant. I find a positive effect of climate instability, and a negative effect of climate variability on saving, with the caveat that climate variability may induce negative selection to some extent. Column (6) presents my preferred specification, which is the effect of climate uncertainty within the rural sample. To give an economic interpretation of the effect, a one standard deviation increase in climate instability *increases* the propensity to save by 2 pp, or 4%, whereas the same increase in climate variability *decreases* the propensity to save by 1.5 pp,

[22] Running the regression only on Tanzania yields an (imprecise) 0.35 coefficient on $\text{SPEI}_{12\text{m}}$, similar to Kubik and Maurel (2016). In line with their results, I find limited effects of SPEI realizations prior to the past 12 months (results available upon request).

Table 2: Climate uncertainty and agricultural production

	Global Sample				FinScope Regions			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Log Production				
SPEI_{12m}	0.050***		0.026***	0.028***	0.069***		0.048***	0.053***
	(0.008)		(0.009)	(0.009)	(0.014)		(0.017)	(0.016)
Drought_{12m}		–0.119***	–0.080***	–0.072***		–0.138***	–0.070*	–0.046
		(0.017)	(0.021)	(0.020)		(0.029)	(0.036)	(0.034)
Climate Variability_{5y}				–0.047				–0.120
				(0.035)				(0.073)
Climate Instability_{5y}				–0.008				–0.007
				(0.035)				(0.064)
				Panel B: Log Yield				
SPEI_{12m}	0.023***		0.014*	0.016**	0.008		0.009	0.011
	(0.006)		(0.007)	(0.007)	(0.013)		(0.016)	(0.017)
Drought_{12m}		–0.052***	–0.032*	–0.026		–0.009	0.004	0.012
		(0.013)	(0.016)	(0.016)		(0.027)	(0.032)	(0.032)
Climate Variability_{5y}				–0.030				–0.051
				(0.026)				(0.061)
Climate Instability_{5y}				0.009				–0.023
				(0.029)				(0.073)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Climate controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,181	14,181	14,181	14,181	6,437	6,437	6,437	6,437
Clusters	181	181	181	181	66	66	66	66

Note: Log Production is the log of production (tonnes), while *Log Yield* is the log of production per area harvested (tonnes/ha), for each crop, country, and year. Crops included in the analysis are: rice, wheat, maize, cassava, sorghum and millet. *FinScope Regions* indicate countries located in the regions of the FinScope survey dataset (Sub-Saharan Africa, South Asia and Southeast Asia). $SPEI_{12m}$ is the average SPEI value over the past 12 months aggregated at the country level. $Drought_{12m}$ is a binary variable equal to 1 if $SPEI_{12m}$ < 1. Climate controls include yearly SPEI values for the last 5 years, excluding the last 12 months. *Climate* $variability_{5y}$ is the standard deviation of last 5 years' SPEI values. *Climate* $instability_{5y}$ is the average absolute difference in SPEI over the last 5 years, residualized on Climate variability_{5y}. Regressions are weighted by each crop's contribution to the total agricultural production of each country. Standard errors are clustered at the country level. * p<0.1, ** p<0.05, *** p<0.01.

Table 3: Climate uncertainty and saving behavior

	Saved in past 12 months						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{SPEI}_{12\text{m}}$	−0.009			−0.009	−0.003	0.001	−0.003
	(0.011)			(0.011)	(0.010)	(0.012)	(0.009)
Climate variability$_{5\text{y}}$		−0.040*		−0.037	−0.029	−0.037	−0.019
		(0.023)		(0.023)	(0.021)	(0.023)	(0.022)
Climate instability$_{5\text{y}}$			0.119***	0.114***	0.094***	0.143***	0.007
			(0.038)	(0.037)	(0.033)	(0.038)	(0.035)
Sample	Full	Full	Full	Full	Full	Rural	Urban
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HH controls	No	No	No	No	Yes	Yes	Yes
Observations	223,602	223,602	223,602	223,602	223,602	145,502	78,100
Clusters	384	384	384	384	384	374	363

Note: $SPEI_{12m}$ is the average SPEI value over the past 12 months aggregated at the region (admin 1) level. *Climate variability$_{5y}$* is the standard deviation of last 5 years' SPEI values. *Climate instability$_{5y}$* is the average absolute difference in SPEI over the last 5 years, residualized on Climate variability$_{5\text{y}}$. All regressions include moving averages of the SPEI values for the last 5 and 30 years, and climate variability and instability over the last 30 years. Household controls include: age category, education level, an urban dummy, and a female dummy. Standard errors are clustered at the region (admin 1) level. * p<0.1, ** p<0.05, *** p<0.01.

or 2.4 %. This is largely in line with hypotheses *ii)* and *iv)* which state that savings should go up with climate instability, and primarily for rural households.

4.2.1 Heterogeneity in Climate Uncertainty and Saving Behavior

Rural/urban – As a falsification test, Table 3, column (7) reports the results for the urban sample. In the absence of agricultural spillovers and general equilibrium effects, we do not expect an effect of climate uncertainty in urban areas, where most of the income is non-agricultural. The results show a relatively precisely estimated null effect for the urban sub-sample. Hence I conclude that the effect of climate instability on saving is largely a rural phenomenon.

Labor skill level – Less skilled labor should be more likely to rely on agricultural production as a main source of income. Since labor skills are intimately connected to education, I analyze heterogeneity by education levels. Whether there is heterogeneity by education may be ambiguous ex-ante, however, since higher education has been shown to increase financial literacy (Zhou, Yang and Gan, 2023), which may compensate for the lower probability of depending on agriculture. Table 4 reveals a negative trend from less skilled to more skilled labor, where the largest effects of climate instability on saving is seen for unskilled labor (those

Table 4: Climate uncertainty and saving behavior, by labor skill level

	Saved in past 12 months			
	Unskilled (1)	Low skill (2)	Medium skill (3)	High skill (4)
SPEI_{12m}	0.003	0.005	–0.002	–0.004
	(0.018)	(0.015)	(0.012)	(0.018)
Climate variability_{5y}	–0.071*	–0.029	–0.024	0.058
	(0.039)	(0.030)	(0.022)	(0.038)
Climate instability_{5y}	0.186***	0.156***	0.080**	0.088
	(0.067)	(0.040)	(0.036)	(0.067)
Sample	Rural	Rural	Rural	Rural
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
HH controls	Yes	Yes	Yes	Yes
Observations	41,582	56,664	43,106	4,149
Clusters	365	371	372	285

Note: Unskilled labor is defined as having not completed primary education, *low skill* as having completed only primary education, *medium skill* as having completed secondary education and/or received vocational training, and *high skill* as having completed tertiary education. $SPEI_{12m}$ is the average SPEI value over the past 12 months aggregated at the region (admin 1) level. *Climate* $variability_{5y}$ is the standard deviation of last 5 years' SPEI values. *Climate* $instability_{5y}$ is the average absolute difference in SPEI over the last 5 years, residualized on Climate variability_{5y}. All regressions include moving averages of the SPEI values for the last 5 and 30 years, and climate variability and instability over the last 30 years. Household controls include: age category, education level, an urban dummy, and a female dummy. Standard errors are clustered at the region (admin 1) level. * p<0.1, ** p<0.05, *** p<0.01.

who have not completed primary school), and virtually zero effects on high-skilled labor (those with tertiary education), while the relationship with climate variability is weaker. The saving propensity is the lowest among unskilled labor, about 53%, meaning that the effect size within this group is considerably larger than for the other groups. This group is also likely to be the most vulnerable to climate shocks in general. Here, a one standard deviation increase in climate instability increases the likelihood of saving by more than 5%.[23]

Gender – Research indicates that women are more likely to be excluded from financial services in low-income countries (Morsy, 2020). Consistent with this, the sample means in the FinScope data suggest that females are less likely to save than males. This could be the result of systematic discrimination and that women would be less able to save during a period of high climate instability. However, I find no significant differences in the effect of climate instability between males and females (results available upon request).

[23]The largest effect size is found for unskilled labor within the rural sample, where the effect on saving is 7%.

4.3 Climate Uncertainty, Credit, and Insurance

While credit and insurance are less common than saving as means of financial smoothing in the FinScope sample, they may still be affected by climate uncertainty for the same reasons as saving is. Table 5, Panel A and B, reports these results for credit and insurance respectively, using the same specifications as in Table 3. For credit, I find that it is affected analogously to savings. Climate instability has a positive effect on the uptake of credit, and this is driven specifically by the rural sample, whereas climate variability has no effect. This may indicate that households, in addition to savings, use credit as a means of consumption smoothing when the climate is unstable. In addition to increasing the salience of climate risk, an unstable climate also implies the presence of "good years" in the recent past, which may assist households in qualifying for loans.[24] In contrast, I find no effect of climate instability on insurance uptake. Instead, I find a significant negative effect of climate variability on insurance. One disadvantage of the insurance data in the FinScope surveys is that it mostly consists of non-agricultural insurance, such as e.g. life and health insurance. Hence, it is not clear ex-ante how these would be affected by climate uncertainty. In the sense that it may affect insurance demand through a change in risk preferences, I elaborate on this in Section 5.3.

[24]Similarly to the effect on saving, I find a positive effect on loans only during wet years, which suggests that one channel of credit uptake can be through relaxed credit constraints from positive income shocks, in combination with the expectation of a future drought.

Table 5: Climate uncertainty and uptake of credit and insurance

	Saved in past 12 months						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Has loans						
$\text{SPEI}_{12\text{m}}$	0.006			0.007	0.006	0.001	0.019**
	(0.009)			(0.009)	(0.009)	(0.011)	(0.009)
Climate $\text{variability}_{5\text{y}}$		0.013		0.016	0.018	0.018	0.016
		(0.017)		(0.017)	(0.017)	(0.018)	(0.021)
Climate $\text{instability}_{5\text{y}}$			0.080**	0.082***	0.074**	0.099***	0.046
			(0.031)	(0.031)	(0.031)	(0.036)	(0.029)
	Panel B: Has insurance						
$\text{SPEI}_{12\text{m}}$	0.011			0.010	0.015*	0.014	0.010
	(0.009)			(0.008)	(0.008)	(0.010)	(0.007)
Climate $\text{variability}_{5\text{y}}$		–0.030		–0.030	–0.025	–0.038*	–0.015
		(0.021)		(0.020)	(0.020)	(0.022)	(0.021)
Climate $\text{instability}_{5\text{y}}$			–0.009	–0.011	–0.020	–0.012	–0.033
			(0.028)	(0.028)	(0.027)	(0.023)	(0.040)
Sample	Full	Full	Full	Full	Full	Rural	Urban
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HH controls	No	No	No	No	Yes	Yes	Yes
Observations	223,602	223,602	223,602	223,602	223,602	145,502	78,100
Clusters	384	384	384	384	384	374	363

Note: $\textit{SPEI}_{12m}$ is the average SPEI value over the past 12 months aggregated at the region (admin 1) level. *Climate* $\textit{variability}_{5y}$ is the standard deviation of last 5 years' SPEI values. *Climate* $\textit{instability}_{5y}$ is the average absolute difference in SPEI over the last 5 years, residualized on Climate $\text{variability}_{5\text{y}}$. All regressions include moving averages of the SPEI values for the last 5 and 30 years, and climate variability and instability over the last 30 years. Household controls include: age category, education level, an urban dummy, and a female dummy. Standard errors are clustered at the region (admin 1) level. * p<0.1, ** p<0.05, *** p<0.01.

5 Mechanisms

5.1 Building Up a Savings Buffer in Good Years

Hypothesis *iii)* predicts that climate instability should increase savings specifically in wet years, when households' earn an agricultural surplus and expect coming years to revert to the mean or lower. Table 6 reports the results split by if the past 12 months were "wet" ($\text{SPEI}_{12\text{m}} > 0$) or "dry" ($\text{SPEI}_{12\text{m}} < 0$). I find that the full effect of climate instability is driven by locations that experienced wetter than normal weather in the past 12 months. Here the estimated effect is twice as high as in the main specification, while the effect is essentially zero during dry years. This suggests that households use current favorable conditions to build up buffer savings before the climate again turns dry.

The negative effect of climate variability, on the other hand, seems to be driven by places experiencing dry weather. While the interpretation of effects from climate variability is less clear, individuals facing high climate variability coupled with current dry weather are more likely to be on a "downward trend", as indicated in Figure 1 d). This may make these households especially incapable to put away savings, and may also help to explain the negative selection on education seen for this exposure.

To more precisely look into how these buffer savings are generated, Table 7 breaks down the effect in wet and dry years by the type of saving: formal (bank account), informal (typically a local community-level savings group), or family and friends. Despite the ongoing mobile and fintech revolutions, most of the increase in saving from climate instability occurs through saving informally or through family and friends. Saving informally, i.e. through a local community-level savings group, perhaps reveals the most telling pattern. Savings group operate by allowing their members to save collectively and lend out to those most at need, and some also offer an emergency fund financed by regular contributions (Karlan et al., 2017). The positive effect of climate instability in wet years is almost exactly mirrored by a negative effect in dry years, indicating a cyclical savings pattern, where farming households deposit to the savings group in wet years, and withdraw their savings in dry years. Consistent with this, households facing high climate variability also see a negative effect on this form of saving in dry years, suggesting that they may withdraw their savings in this situation as well. These results thus indicate that local saving groups serve an important purpose in helping agricultural households smooth consumption through periods of high climate and income instability.

Table 6: Climate uncertainty and saving behavior, by current climate conditions

	Saved in past 12 months		
	All years	Wet year	Dry year
	(1)	(2)	(3)
$\text{SPEI}_{12\text{m}}$	0.001	0.041**	0.002
	(0.012)	(0.019)	(0.025)
Climate $\text{variability}_{5\text{y}}$	–0.037	–0.058	–0.048
	(0.023)	(0.040)	(0.043)
Climate $\text{instability}_{5\text{y}}$	0.143***	0.224***	0.013
	(0.038)	(0.056)	(0.061)
Sample	Rural	Rural	Rural
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
HH controls	Yes	Yes	Yes
Observations	145,502	67,072	78,430
Clusters	374	170	238

Note: $SPEI_{12m}$ is the average SPEI value over the past 12 months aggregated at the region (admin 1) level. *Wet year* is the sample where $SPEI_{12m} > 0$ and *Dry year* the sample where $SPEI_{12m} < 0$. *Climate* $variability_{5y}$ is the standard deviation of last 5 years' SPEI values. *Climate* $instability_{5y}$ is the average absolute difference in SPEI over the last 5 years, residualized on Climate $\text{variability}_{5\text{y}}$. All regressions include moving averages of the SPEI values for the last 5 and 30 years, and climate variability and instability over the last 30 years. Household controls include: age category, education level, an urban dummy, and a female dummy. Standard errors are clustered at the region (admin 1) level. * p<0.1, ** p<0.05, *** p<0.01.

5.2 Climate Instability as a Predictive Heuristic

One reason why individuals would build up buffer savings is due to a higher likelihood of mean reversion following a wet year when the climate is unstable. This would make saving rational, even in the presence of behavioral biases, such as the availability heuristic and salience effects. Indeed, I find this to be the case. Table 8 shows that climate instability in particular is predictive of future climate shocks, using climate variables lagged by one year, and current climate as outcomes. First, in column (1), I find that climate instability significantly increases the risk of a drought in the subsequent 12 months. A one standard deviation increase in climate instability increases the probability of a drought by 5 pp, or about 33%. Consistent with this, column (2) reports a negative, though insignificant, effect on $\text{SPEI}_{12\text{m}}$. However, climate instability may be more informative of the second rather than the first moment of the distribution, in that it primarily affects tail risks. Column (3) instead uses the absolute value of $\text{SPEI}_{12\text{m}}$, capturing an effect on more extreme weather in both directions, and here the effect is again significant and economically meaningful. Lastly, column (4) shows that this effect is particularly strong for the left tail (drought risk), as conditional on the current year being dry, high climate instability will strongly increase the risk of severe dryness. In other words, a one standard deviation increase in climate instability

Table 7: Climate uncertainty and saving behavior, by current climate conditions and type of saving

	Saved in past 12 months, by type					
	Wet year			Dry year		
	Formal	Informal	Family and friends	Formal	Informal	Family and friends
SPEI_{12m}	0.004	0.045**	0.020	–0.008	0.011	0.006
	(0.006)	(0.020)	(0.022)	(0.008)	(0.022)	(0.026)
Climate $\text{Variability}_{\text{5y}}$	–0.007	–0.055	0.013	0.013	–0.093**	0.018
	(0.011)	(0.047)	(0.050)	(0.019)	(0.038)	(0.049)
Climate $\text{Instability}_{\text{5y}}$	0.015	0.175***	0.168***	0.083**	–0.145***	0.021
	(0.015)	(0.063)	(0.059)	(0.033)	(0.051)	(0.061)
Sample	Rural	Rural	Rural	Rural	Rural	Rural
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
HH controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67,072	67,072	67,072	78,430	78,430	78,430
Clusters	170	170	170	238	238	238

Note: $SPEI_{12m}$ is the average SPEI value over the past 12 months aggregated at the region (admin 1) level. *Wet year* is the sample where $SPEI_{12m} > 0$ and *Dry year* the sample where $SPEI_{12m} < 0$. *Climate variability*$_{5y}$ is the standard deviation of last 5 years' SPEI values. *Climate instability*$_{5y}$ is the average absolute difference in SPEI over the last 5 years, residualized on Climate variability$_{\text{5y}}$. All regressions include moving averages of the SPEI values for the last 5 and 30 years, and climate variability and instability over the last 30 years. Household controls include: age category, education level, an urban dummy, and a female dummy. Standard errors are clustered at the region (admin 1) level. * p<0.1, ** p<0.05, *** p<0.01.

increases next year's dryness by about 10% of a standard deviation, conditional on that year being dry.

5.3 Deliberate Savings Strategy or a Change in Time or Risk preferences?

Exposure to past shocks may affect saving behavior through a change in latent time or risk preferences. For example, natural disaster such as the 2004 Tsunami led to substantial long-lasting increases in both risk aversion and impatience (Cassar, Healy and Von Kessler, 2017). In the theoretical model, risk aversion is captured by the parameter α, and this is one mechanism through which climate uncertainty can affect current saving behavior, in addition to effects on subjective climate risk $\hat{\sigma}_w^2$.

One way to test the effect of risk preferences is a placebo test where insurance uptake is used as an outcome. This is one of the outcomes reported in Table 5. Given that I find no effect of climate instability on insurance, I take this as evidence to suggest that climate instability does not substantially affect risk preferences. In contrast, climate variability has a significant negative effect, suggesting that this effect partially could operate through a change in risk preferences. However, this finding is hard to reconcile with the natural disasters literature, since it would imply that climate variability leads to less risk aversion. If households

Table 8: The predictive ability of recent climate instability for future droughts and extreme weather

	Droughts and SPEI in the past 12 months			
	Drought_{12m} (1)	SPEI_{12m} (2)	$\text{Abs}(\text{SPEI}_{12m})$ (3)	SPEI_{12m}, if $\text{SPEI}_{12m} < 0$ (4)
$\text{SPEI}_{12\text{-}24m}$	0.065**	–0.271***	–0.077	–0.156**
	(0.032)	(0.069)	(0.064)	(0.072)
Climate $\text{variability}_{1\text{-}6y}$	0.107**	–0.176	0.023	–0.289**
	(0.050)	(0.142)	(0.111)	(0.129)
Climate $\text{instability}_{1\text{-}6y}$	0.220***	–0.087	0.223	–0.489***
	(0.077)	(0.139)	(0.155)	(0.169)
Sample	Rural	Rural	Rural	Rural
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
HH controls	Yes	Yes	Yes	Yes
Observations	145,502	145,502	145,502	78,430
Clusters	374	374	374	238

Note: $SPEI_{12m}$ is the average SPEI value over the past 12 months aggregated at the region (admin 1) level. *Climate $variability_{5y}$* is the standard deviation of last 5 years' SPEI values. *Climate $instability_{5y}$* is the average absolute difference in SPEI over the last 5 years, residualized on Climate variability_{5y}. All regressions include moving averages of the SPEI values for the last 5 and 30 years, and climate variability and instability over the last 30 years. Household controls include: age category, education level, an urban dummy, and a female dummy. Standard errors are clustered at the region (admin 1) level. * p<0.1, ** p<0.05, *** p<0.01.

opt out of insurance due to financial constraints, it could be that climate variability, through negative effects on individuals' wealth, alternatively lead to a net reduction in insurance demand.

To disentangle buffer savings from the effect of a change in time preferences, I break down the main result on saving by the *stated* reason of saving. This data is only available for a subset of the surveyed countries, one of which is Tanzania, for which I have panel data at the district level. This allows me to relax some of the identifying assumptions, as I can rely on a parallel trends assumption and not have to worry that climate uncertainty variables pick up region-specific characteristics. I here also have more detailed data on which households rely on agriculture as their main source of income ("Farmers").

Columns (1) and (2) in Table 9 replicate the main results, with overall similar effect sizes as in Table 3. In a sense, this can be seen as an out-of-sample test of the main results, and the main estimates change little by excluding Tanzania from the sample. However, when I break down saving by the stated reason for saving, I find that virtually the full increase in saving propensity is explained by saving for emergencies (column 3). In contrast, I find no effect on saving for other reasons, as reported in column (4), which should pick up a latent change in time preferences. Lastly, column (5) shows that there is a weakly significant positive effect

Table 9: Climate uncertainty and saving behavior, using Tanzania district panel data

	Saved in past 12 months		Saved for emergencies	Saved for other reasons	Member of savings group
	(1)	(2)	(3)	(4)	(5)
$\text{SPEI}_{12\text{m}}$	–0.006	0.029	–0.013	0.015	–0.001
	(0.017)	(0.021)	(0.021)	(0.015)	(0.004)
Climate $\text{variability}_{5\text{y}}$	–0.004	0.009	0.111	-0.124^{**}	-0.034^{*}
	(0.059)	(0.081)	(0.074)	(0.056)	(0.019)
Climate $\text{instability}_{5\text{y}}$	0.115^{*}	0.202^{**}	0.188^{***}	–0.007	0.024^{*}
	(0.060)	(0.089)	(0.070)	(0.055)	(0.013)
Sample	Full	Farmers	Farmers	Farmers	Farmers
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
HH controls	Yes	Yes	Yes	Yes	Yes
Observations	22,081	8,067	7,205	8,040	8,018
Clusters	129	129	129	129	129

Note: $SPEI_{12m}$ is the average SPEI value over the past 12 months aggregated at the district (admin 2) level. *Climate* $variability_{5y}$ is the standard deviation of last 5 years' SPEI values. *Climate* $instability_{5y}$ is the average absolute difference in SPEI over the last 5 years, residualized on Climate $\text{variability}_{5\text{y}}$. All regressions include yearly SPEI values for the last 5 years as climate controls, in addition to the last 12 months. Household controls include: age, education level, an urban dummy, and a female dummy. Standard errors are clustered at the district (admin 2) level. * p<0.1, ** p<0.05, *** p<0.01.

of climate instability on being a member of a local savings group, which links to the results on savings as a buffer in Section 5.1.

5.4 Climate Shock Salience

In Section 2.3 I speculated that one channel of how climate instability can increase saving, in addition to mechanical effects from an agricultural surplus and mean reversion, is due to subjective experience. Shocks that happen in an interleaved fashion may increase the salience of individual shocks, relative to when multiple consecutive shocks cause a new "norm". To test this, I use a third dataset consisting of the Tanzania NPS household panel. In addition to containing information on whether households experienced a severe climate shock in the past five years, this dataset arguably provides the strongest identification, as I can exploit within-household variation in climate uncertainty exposure and not have to worry about selection effects.

Columns (1) and (2) of Table 10 reports the results of this exercise. First, using the main specification I find a positive effect of climate instability on climate shock salience, though imprecise, with a p-value of about 0.15. However, climate shocks consist both of floods and droughts, and hence using the *absolute* value of the SPEI is arguably an appropriate

Table 10: Climate uncertainty, reported shock severity, non-food expenditures and reported food shortages

	Reported a severe climate shock		Log Non-food expenditures		Food shortage, last 12 months	
	(1)	(2)	(3)	(4)	(5)	(6)
SPEI_{12m}	–0.034*		0.032	–1.574	0.025	0.047
	(0.019)		(0.158)	(0.710)	(0.019)	(0.092)
$\text{Abs}(\text{SPEI}_{\text{12m}})$		0.057**				
		(0.029)				
Climate $\text{variability}_{\text{5y}}$	–0.015	0.054	0.655	2.111***	0.174**	0.145
	(0.070)	(0.071)	(0.543)	(0.651)	(0.068)	(0.092)
Climate $\text{instability}_{\text{5y}}$	0.103	0.163**	1.675***	–1.082	–0.221***	–0.095
	(0.072)	(0.064)	(0.559)	(0.989)	(0.062)	(0.153)
Climate $\text{variability}_{\text{5y}}$				1.526**		–0.029
$\times$ SPEI_{12m}				(0.667)		(0.081)
Climate $\text{instability}_{\text{5y}}$				–2.716***		0.116
$\times$ SPEI_{12m}				(0.935)		(0.151)
HH FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,151	17,151	21,530	21,530	15,665	15,665
Clusters	153	153	153	153	155	155

Note: *$SPEI_{12m}$* is the average SPEI value over the past 12 months aggregated at the district (admin 2) level. *Wet year* is the sample where *$SPEI_{12m}$* > -1 and *Dry year* the sample where *$SPEI_{12m}$* < -1. *Reported climate shock severity* is reported severity of a recent climate shock (drought or flood), on a scale from 0 (no shock) to 3 (most severe). *Log Assets* is the log of the current estimated value of all assets. *Food shortage, last 12 months* is a binary variable equal to 1 if the household reported any food shortage in the last 12 months. *Climate $variability_{5y}$* is the standard deviation of last 5 years' SPEI values. *Climate $instability_{5y}$* is the average absolute difference in SPEI over the last 5 years, residualized on Climate $\text{variability}_{\text{5y}}$. All regressions include yearly SPEI values for the last 5 years as climate controls, in addition to the last 12 months. * p<0.1, ** p<0.05, *** p<0.01.

control variable. With this specification, I find strongly significant positive effects of both $\text{Abs}(\text{SPEI}_{\text{12m}})$ and climate variability, even conditional on the absolute value of past years' SPEI realizations. This suggests that when shocks are structured in an interleaved fashion, they are more likely to be remembered as severe incidents, compared to when they occur in clusters, and may thus affect saving through their effect on subjective climate risk $\hat{\sigma}_w^2$.

5.5 How Do Households Save and How is Their Welfare Affected?

Lastly, I use the Tanzania NPS household panel to also investigate *how* households manage to save. Since I find no effects on current income (Table 2), and positive effects on saving (Table 3), it must be that households that face climate instability cut down on their consumption in order to increase their precautionary saving. If the purpose of the emergency savings is to reduce the risk of food shortage and starvation, then we would expect to see a decline in *non-food* expenditures. Table 10, columns (3) and (4) report the results of this exercise. First, and somewhat counter-intuitively, I find that climate instability has a *positive* effect on non-food expenditures. The Tanzania NPS data consists of four different waves which all seem to have taken place in relatively dry years. The median $\text{SPEI}_{12\text{m}}$ is less than -1, indicating drought conditions for the *majority* of the sample across waves, and few households experienced wet conditions at all. Building on my previous results, this suggests that households who face climate instability may currently be withdrawing their savings form previous wet years, and may hence see a smaller negative effect on their overall consumption compared to other households. Second, and consistent with this explanation, the effect of climate instability masks considerable heterogeneity. Interacting climate instability and variability with current climate, column (4) shows that the positive effect of climate instability on non-food consumption is *higher* for those households experiencing more dry conditions. In contrast, climate variability has the opposite effect, and here consumption is instead *lower* when the current climate is drier, consistent with the baseline negative effects of climate variability on saving.

How does this affect the welfare of households? In column (5) I estimate the effect of climate variability and instability on reported food shortages over the last 12 months. Consistent with the effect on precautionary savings, I find that exposure to climate instability has a strong negative effect on the likelihood of having faced food shortages, while climate variability increases this risk. While these survey waves mostly reflect drought conditions, where food shortages arguably should be higher, in column (6) I break down the effect by current climate conditions. I do not find any significant effect by whether local climate conditions were more or less dry, which could either be due to low power, or that households, to avoid food shortages in a dry climate, instead adjust the non-food expenditures margin, as found in column (4), to avoid an acute food shortage. This could still make high climate instability households more protected against food shortages, as seen in column (5), if other unexpected shocks that are orthogonal to local climate conditions, such as increases in international food prices, occur, since these households would be more likely to have built up a precautionary savings buffer. Consistent with this finding, a recent meta-analysis of 27 randomized saving interventions across Sub-Saharan Africa found a small but significant positive effect on food security (Steinert et al., 2018).

6 Robustness Checks

Migration – One threat to the identification strategy is that households may cope by migration, either through moving the whole household or sending off household members. For migration to affect the main results through compositional effects, any effects on migration would have to be at the inter-regional (admin 1) or higher, and it would have to be selective, such that individuals' baseline propensity to save correlates with the likelihood of migrating. The balance tests in Figure 3 do not reveal any significant differences in covariates such as education or age for exposure to climate instability, and these null results are relatively precise and bounded at low effect sizes. However, for climate variability, exposure is negatively correlated with education. This could be the case if there is negative selection on climate variability, such that more educated household members migrate out of regions that have faced higher climate variability recently.

To test whether climate instability and variability affect migration directly, I first use the global region-level migration dataset by (Niva et al., 2023) for the countries in my sample and a two-way fixed effects strategy. Table A.5, column (1) reports these results. I find no significant effects either of from last 12 months SPEI value, nor from climate instability or variability. These results are relatively precise, and suggest that the effect of a one standard deviation increase in climate instability is bounded above at 0.3 migrants/1000 inhabitants. It may still be that this exposure triggers migration *within* rather than *between* regions, which should not be a concern for the identification of the main results. As a second test, I use the household panel from the Tanzania NPS which allows me to capture any potential effects on migration within one of the countries in the main sample. Table A.5, column (2) reports the results. Again, I find relatively precise null effects on whether a household ever moved. While power is low, an upper bound of the effect on on migration is a 4% increase per one standard deviation increase in climate instability. The risk of compositional effects from climate variability is higher, consistent with the covariate imbalance for education in Figure 3. However, comparing the effect sizes on saving and migration, I conclude that it is unlikely that migration is a main driver of the effects on saving.

Alternative time windows – I test the sensitivity of the time window bandwidth by replacing the 5-year window with a 10-year window, while the district fixed effects absorb any long-run variation. Table A.2 reports these results. Overall, I find smaller effect sizes, and only a strongly significant effect of climate instability on saving for the rural subsample. The magnitude, 0.105, is similar to the estimate from my preferred specification, 0.133, however. Since the estimated effects includes exposure from the past five years, this recent exposure is more informative for individuals' decision-making, consistent with the literature on price effects of natural disasters that tend to show a decay in economic effects after 3-4 years (Atreya, Ferreira and Michel-Kerjan, 2015).

Measurement error in the SPEI – Since the SPEI uses interpolated data for grid cells where there are no weather stations, it is potentially sensitive to measurement error with a scarcity of stations. If the measurement error is uncorrelated with the dependent and independent variables it would only bias my estimates downward. To see whether this is the case, I use station density data from the CRU TS climate data Harris et al. (2020), which is used as input to the SPEI. This contains gridded data on the number of weather stations (temperature and precipitation) that contribute to interpolating climate data in a specific grid cell. Similar to the SPEI, I aggregate this measure at the country- and region levels. I define high station density as areas where the number of stations used for interpolation is above the sample median. First, I analyze whether density affects the estimates for agricultural production, reported in Table A.3. I find that the main effect of SPEI is only significant in the sample with above median station density, while it is about 30-50% smaller in areas below median station density. I do not find any significant effects of climate variability or instability on current agricultural production. This suggests that measurement error may also bias my main results on saving downwards. Table A.4 shows the results of the same analysis for my preferred specification (6) in Table 3. I find that the results on saving from climate instability is mostly driven by areas with above median station density, which is reassuring. I find that rainfall stations seem more important than temperature stations in alleviating this bias, likely due to the fact that there is much greater variation in the number of rainfall stations used for interpolation. Overall, I arrive at an estimate around 0.14-0.149 when considering only regions with above median station density, compared to the main effect of 0.133. This suggests that measurement error biases my main results downward, but only to a limited degree.

Heterogenous and dynamic treatment effects – While my main results primarily rely on cross-sectional variation in a reduced-form , some of the specifications that support my main results are TWFE regressions, which may be prone to biased estimates in the presence of heterogeneous and dynamic treatment effects (Goodman-Bacon, 2021). For agricultural production, I use specification (2) in Table 2 with a drought dummy, and the estimator robust to heterogeneous and dynamic treatment effects by De Chaisemartin and d'Haultfoeuille (2020), and find that the estimate for drought is virtually indistinguishable from the TWFE specification. I conclude that the effect of climate on agricultural production is not affected by heterogeneity over time or dynamic effects, conditional on past climate controls. Next, for the Tanzania district panel, I run an event study for the past 5 years exposure to climate instability, using the same estimator. I first binarize climate instability by splitting the sample into above or below the median. Since the estimator excludes the always-treated, and only exploits the first time a group switches into being treated, we should expect to lose precision but reduce potential bias. Figure A.1 visualizes the event study estimates. While there are only two pre-treatment periods, the results of the placebo test in period -2 is suggestive of parallel pre-trends. While none of the individual treatment effects are significant, there are three things to note. First, the aggregate treatment effect is significant (results not reported), second, the effects are similar in magnitude to the baseline results in Table 9, and third, that the effect one year after treatment remains largely unchanged, though slightly less precise, suggesting that the positive effect on saving seems to survive over time.

Selection on unobservables – To analyze sensitivity to selection on unobservables, I follow Oster (2019) and calculate an adjusted treatment effect of climate instability in the past 5 years, based on how the coefficient changes as control variables that increase R^2 are added (selection on observables). I assume that selection on observables and unobservables play an equally important role, and use a theoretical R^2 1.3 times greater than the R^2 of the specification with controls. For climate instability in the past 5 years, and using columns (5) and (6) in Table 3, I find that the adjusted treatment effect on saving for the full sample is 0.066, about 80% of the unadjusted coefficient 0.083. To completely negate the treatment effect, selection on unobservables would have to b almost 5 times greater than selection on observables, and I thus conclude that it is unlikely that the treatment effect is driven by selection on unobservables.[25]

The Tanzania district panel can be used to account for unobservable differences across regions within a country. As Table 9, columns 1-2, show, the effect of climate instability on saving is virtually unaffected by the inclusion of district fixed effects. The main results are thus unlikely to be driven by inherent differences, in the absence of intense short-run compositional effects through selective migration.

Finally, I assess unobserved heterogeneity at the household level by using a subsample of the Tanzania National Panel Survey covering mobile money users. Here, individuals are asked why they rely on mobile money for saving, and the reason why they do so. Table 11 reports the results from a specification where I include household fixed effects to effectively rely on within-household variation in exposure to climate instability and variability. I find that climate instability, but not climate variability, leads to an increase in saving for emergency reasons. In addition, there is a positive effect on saving for everyday purchases, which includes food consumption, but no on big purchases, which can be considered a placebo test. In addition, I

[25] Interestingly, the reverse relationship is seen with the results using a 10-year window, where adding control variables only strengthens the effect of climate instability, meaning that there is positive selection on observables such that this estimate is likely only biased downwards.

Table 11: Climate uncertainty and saving among mobile money users in the Tanzania NPS

	Saved for emergency	Saved for emergency (most important)	Saved for everyday purchases	Saved for big purchases	Received money	Sent money
	(1)	(2)	(3)	(4)	(5)	(6)
Climate variability$_{5y}$	0.093	−0.031	0.010	−0.017	−0.073	0.154
	(0.156)	(0.062)	(0.122)	(0.085)	(0.141)	(0.145)
Climate instability$_{5y}$	0.241	0.168*	0.218*	0.009	0.252**	−0.040
	(0.190)	(0.100)	(0.119)	(0.058)	(0.123)	(0.127)
HH FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,714	2,714	2,714	2,714	2,714	2,714
Clusters	119	119	119	119	119	119
Mean dep. variable	.285	.0549	.138	.0457	.843	.739

Note: $SPEI_{12m}$ is the average SPEI value over the past 12 months aggregated at the district (admin 2) level. *Wet year* is the sample where $SPEI_{12m} > -1$ and *Dry year* the sample where $SPEI_{12m} < -1$. *Reported climate shock severity* is reported severity of a recent climate shock (drought or flood), on a scale from 0 (no shock) to 3 (most severe). *Log Assets* is the log of the current estimated value of all assets. *Food shortage, last 12 months* is a binary variable equal to 1 if the household reported any food shortage in the last 12 months. *Climate variability$_{5y}$* is the standard deviation of last 5 years' SPEI values. *Climate instability$_{5y}$* is the average absolute difference in SPEI over the last 5 years, residualized on Climate variability$_{5y}$. All regressions include yearly SPEI values for the last 5 years as climate controls, in addition to the last 12 months. * p<0.1, ** p<0.05, *** p<0.01.

find that climate instability leads mobile money users to receive, but not send, more money, suggesting that remittances from other family members and relatives may help households achieve precautionary saving following exposure to climate instability. This is consistent with Jack and Suri (2014), who find that mobile money users are protected against negative income shocks, through their ability to receive remittances.

Sensitivity to outliers – Running my preferred specification, column (6) in Table 3, by iteratively leaving out countries yields climate instability coefficients in the range 0.11-0.15 compared to the baseline coefficient of 0.13, with similar significance levels.

7 Conclusion

How does climate uncertainty in the shape of climate *instability* and climate *variability* affect consumption smoothing strategies in a global sample of low-income rural households? I find that exposure to climate instability, defined as the average absolute change in climate conditions year-to-year, increases the propensity to save, and that this effect is specific to rural households and households with low education, who are more likely to derive most of their income from agriculture. Importantly, this also increases additional sources of consumption smoothing, such as credit use, but the effect is only seen when current climate conditions are wet, where households are more likely to generate an agricultural surplus.

The increase in saving can partly be explained by the fact that climate instability seems to predict future droughts, due to a mean-reversion effect, where experiencing a wet year during a period of high climate instability increases the risk of a drought in the following year. Thus, it seems that the increase in saving is a rational adaptation in preparation of future droughts. In addition, I find evidence for a behavioral explanation, where conditional on actual climate realizations, experiencing high climate instability make individuals and households more likely to report having experienced a dramatic climate shock.

Using household panel data from Tanzania, I find that a likely mechanism through which households build up precautionary savings during periods of high climate instability is by reducing non-food expenditures. In turn this protects against food shortages, which seem to spill over to shortages that are not necessary climate-related.

Taken together, my findings suggest that rural households in low-income countries are adapting to local changes in climate conditions. To what extent this may alleviate the burden of climate change is hard to tell, as this will depend not so much on first-order changes in rainfall and temperature, but the way these shocks are structured over time.

Notably, there is limited adoption of formal financial services, and instead most climate adaptation seems facilitated through local initiatives and informal networks. Addressing the gaps in financial inclusion and literacy may thus be crucial to further increase the resilience of poor rural households against the looming threat of climate change.

In contrast to a positive adaptation toward climate instability, I find instead mostly negative effects of climate variability on saving, although they are less precise than the effects of climate instability. Households living in places where climate change may induce longer drought-spells may thus be much less likely to adapt to these changes. Policies that may help to facilitate consumption smoothing among the most marginal households, such as subsidized weather index insurance and improved access to financial services, may be more important to pursue in these locations.

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Online Appendix for "Adapting to Climate Instability: Financial Coping Strategies of Low-Income Rural Households"

A List of Countries in the FinScope Dataset

Table A.1: List of countries and years included in the analysis

Country	Years
Angola	2022
Bangladesh	2016
Benin	2018
Botswana	2020
Burkina Faso	2016
Cambodia	2015
Cameroon	2017
Cote d'Ivoire	2016
Democratic Republic of Congo	2014
Eswatini	2014, 2018
Gambia	2019
Ghana	2010, 2021
Haiti	2018
India	2015
Laos	2014
Lesotho	2021
Madagascar	2016
Malawi	2014
Mozambique	2014, 2015, 2019
Myanmar	2018
Namibia	2011, 2017
Nepal	2015
Nigeria	2016
Pakistan	2008
Rwanda	2008, 2012, 2016
Tanzania	2006, 2009, 2013, 2017
Togo	2016
Uganda	2006, 2009, 2013, 2018
Zimbabwe	2014, 2022

B Proofs

B.1 Optimal Consumption in Two Periods with Uncertain Income

It needs to be shown that:

$$E[u(c_1)] = 1 - e^{-\alpha(\bar{y}+(1+r)s_0-\frac{\alpha}{2}\sigma_w^2)} \tag{5}$$

which together with:

$$u'(c_0) = \beta(1+r)E'[u(c_1)] \tag{6}$$

yield the relationship:

$$\underbrace{s_0^*}_{\text{Optimal savings}}(2+r) = \underbrace{y_0 - \bar{y}}_{\text{Current surplus}} + \underbrace{\frac{\alpha\sigma_w^2}{2}}_{\text{Risk aversion}} + \underbrace{\frac{\ln(\beta(1+r))}{\alpha}}_{\text{Discounted return}} \tag{7}$$

We start by proving (5). Since $u(c) = (1-e^{-\alpha c})/\alpha$ and $y_t = \bar{y}+\epsilon_t/a$ with $\epsilon_t \sim N(0, \sigma_w^2)$, we can decompose utility in period two, $u(c_1)$, into its deterministic and stochastic components:

$$u(c_1) = \frac{1 - e^{-\alpha(\bar{y}+(1+r)s_0+\epsilon_1)}}{\alpha} = \frac{1 - e^{-\alpha(\bar{y}+(1+r)s_0)}e^{-\alpha\epsilon_1}}{\alpha} \tag{8}$$

To find the expectation of the stochastic component $e^{-\alpha\epsilon_1}$, we can use the fact that the moment generating function of a normal distribution $N(x;\mu,\sigma^2)$ can be written:

$$M_x(t) = E(e^{xt}) = e^{\mu t+\sigma^2t^2/2} \tag{9}$$

Since for ϵ_t we have that $\mu = 0$ and $\sigma^2 = \sigma_w^2$, we can express $E[u(c_1)]$ as:

$$E[u(c_1)] = E\left[\frac{1 - e^{-\alpha(\bar{y}+(1+r)s_0)}e^{-\alpha\epsilon_1}}{\alpha}\right] = \frac{1 - e^{-\alpha(\bar{y}+(1+r)s_0)}E[e^{-\alpha\epsilon_1}]}{\alpha} = \frac{1 - e^{-\alpha(\bar{y}+(1+r)s_0)}e^{-\frac{\alpha^2\sigma_w^2}{2}}}{\alpha} \tag{10}$$

We can now solve the first-order derivatives in (6):

$$u'(c_0) = e^{-\alpha c_0} = e^{-\alpha(y_0-s_0)} \tag{11}$$

and:

$$E'[u(c_1)] = e^{-\alpha(\bar{y}+(1+r)s_0-\frac{\alpha}{2}\sigma_w^2)} \tag{12}$$

which yields:

$$e^{-\alpha(y_0-s_0)} = \beta(1+r)e^{-\alpha(\bar{y}+(1+r)s_0-\frac{\alpha}{2}\sigma_w^2)} \tag{13}$$

By taking the natural logarithm of both sides in (13) and rearranging the terms we arrive at the expression in (7).

C Robustness Checks

C.1 Alternative Time-Window

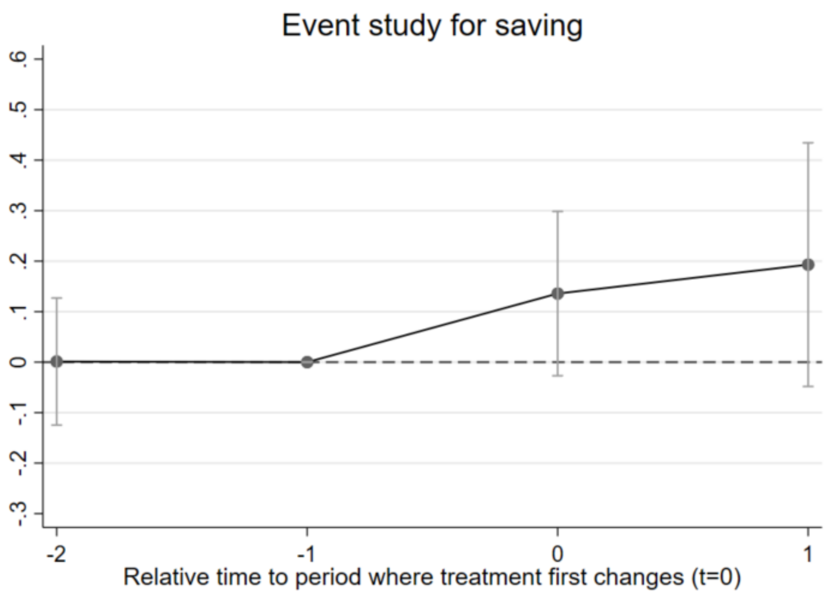
Table A.2: Using a 10-year window for Climate variability and instability

	Saved in past 12 months						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SPEI_{12m}	–0.014			–0.013	–0.005	–0.004	–0.005
	(0.009)			(0.009)	(0.009)	(0.010)	(0.009)
Climate variability_{10y}		–0.037		–0.032	–0.028	–0.035	–0.010
		(0.033)		(0.033)	(0.029)	(0.032)	(0.033)
Climate instability_{10y}			0.047	0.047	0.079*	0.105**	0.026
			(0.051)	(0.051)	(0.043)	(0.049)	(0.043)
Sample	Full	Full	Full	Full	Full	Rural	Urban
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HH controls	No	No	No	No	Yes	Yes	Yes
Observations	223,602	223,602	223,602	223,602	223,602	145,502	78,100
Clusters	384	384	384	384	384	374	363

Note: $\textit{SPEI}_{12m}$ is the average SPEI value over the past 12 months aggregated at the region (admin 1) level. *Climate* $\textit{variability}_{10y}$ is the standard deviation of last 10 years' SPEI values. *Climate* $\textit{instability}_{10y}$ is the average absolute difference in SPEI over the last 10 years, residualized on Climate variability_{10y}. All regressions include yearly SPEI values for the last 10 years as climate controls, in addition to the last 12 months. Household controls include: age category, education level, an urban dummy, and a female dummy. Standard errors are clustered at the region (admin 1) level. * p<0.1, ** p<0.05, *** p<0.01.

C.2 Robustness to Dynamic and Heterogeneous Treatment Effects

Figure A.1: Event study estimates for high climate instability in the past 5 years



Notes: This figure shows the event study estimates from the Tanzania district panel analysis, where the treated group is those who were exposed to above median 5 year climate instability, using an estimator robust to dynamic and heterogenous treatment effects (De Chaisemartin and d'Haultfoeuille, 2020).

C.3 Measurement Error in the SPEI

Table A.3: Sensitivity to measurement error in the SPEI on crop production, for countries in the FinScope regions

	Dependent variable: Log Production			
	Rainfall station density		Temperature station density	
	Above median	Below median	Above median	Below median
SPEI_{12m}	0.060***	0.045	0.074***	0.033
	(0.020)	(0.029)	(0.022)	(0.026)
Drought_{12m}	–0.024	–0.075	–0.005	–0.090*
	(0.045)	(0.048)	(0.046)	(0.046)
Climate Variability_{5y}	–0.093	–0.147	–0.108	–0.172
	(0.095)	(0.112)	(0.090)	(0.135)
Climate Instability_{5y}	0.064	–0.094	0.067	–0.062
	(0.075)	(0.124)	(0.087)	(0.093)
Mean stations	5.64	1.87	7.84	6.55
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Climate controls	Yes	Yes	Yes	Yes
Observations	3,128	3,309	3,152	3,285
Clusters	33	33	33	33

Note: Log Production is the log of production (tonnes) for each crop, country, and year. Crops included in the analysis are: rice, wheat, maize, cassava, sorghum and millet. Only countries located in the regions of the FinScope survey dataset are included in this analysis (Sub-Saharan Africa, South Asia and Southeast Asia). *Rainfall* and *Temperature station density* are the average number of stations used in the interpolation of SPEI values for each country over the time period. $SPEI_{12m}$ is the average SPEI value over the past 12 months aggregated at the country level. $Drought_{12m}$ is a binary variable equal to 1 if $SPEI_{12m} < 1$. Climate controls include yearly SPEI values for the last 5 years, excluding the last 12 months. *Climate* $variability_{5y}$ is the standard deviation of last 5 years' SPEI values. *Climate* $instability_{5y}$ is the average absolute difference in SPEI over the last 5 years, residualized on Climate variability_{5y}. Regressions are weighted by each crop's contribution to the total agricultural production of each country. Standard errors are clustered at the country level. * p<0.1, ** p<0.05, *** p<0.01.

Table A.4: Sensitivity to measurement error in the SPEI on saving behavior

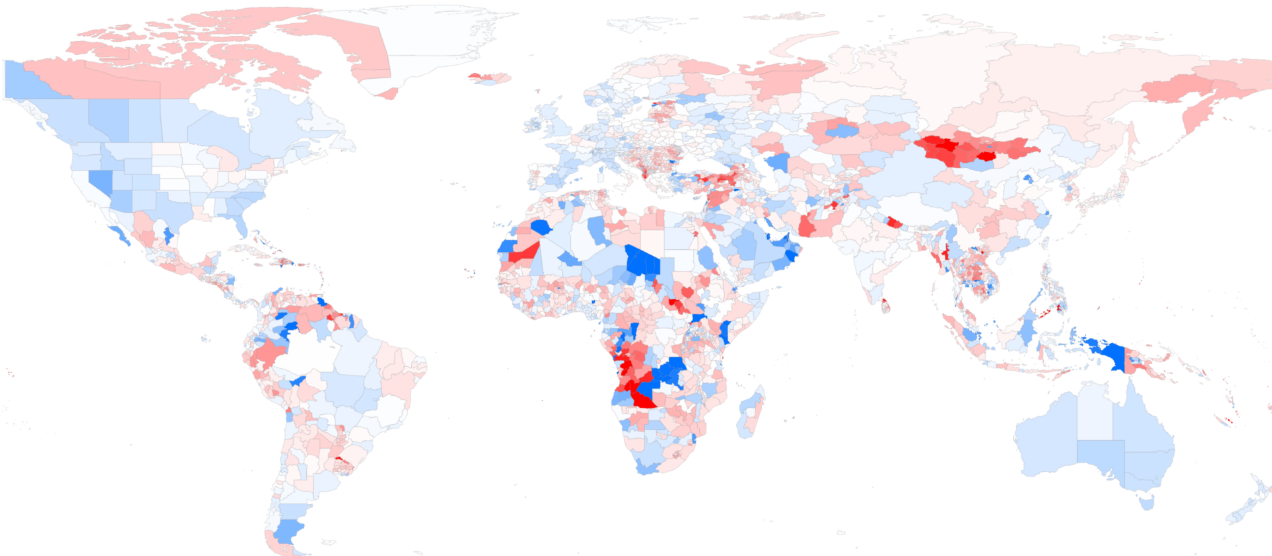
	Dependent variable: Saved in past 12 months			
	Rainfall station density		Temperature station density	
	Above median	Below median	Above median	Below median
$SPEI_{12m}$	0.024	–0.012	0.040**	–0.012
	(0.016)	(0.012)	(0.016)	(0.013)
Climate $Variability_{5y}$	–0.065*	–0.035	–0.074*	–0.040
	(0.038)	(0.028)	(0.041)	(0.025)
Climate $Instability_{5y}$	0.149***	0.030	0.140**	0.096**
	(0.054)	(0.045)	(0.062)	(0.043)
Mean no. stations	5.11	2.18	7.86	6.33
Sample	Rural	Rural	Rural	Rural
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
HH controls	Yes	Yes	Yes	Yes
Observations	73,438	72,064	62,109	83,393
Clusters	197	177	212	162

Note: Rainfall and *Temperature station density* are the average number of stations used in the interpolation of SPEI values for each country over the time period. $SPEI_{12m}$ is the average SPEI value over the past 12 months aggregated at the region (admin 1) level. Climate controls include yearly SPEI values for the last 5 years, excluding the last 12 months. *Climate* $variability_{5y}$ is the standard deviation of last 5 years' SPEI values. *Climate* $instability_{5y}$ is the average absolute difference in SPEI over the last 5 years, residualized on Climate $variability_{5y}$. Standard errors are clustered at the region (admin 1) level. * p<0.1, ** p<0.05, *** p<0.01.

D Mechanisms and Alternative Explanations

D.1 Migration

Figure A.2: Global subnational migration rates at the region (admin 1) level 2000-2019



Notes: This figure shows the average migration rates at the region (admin 1) level for the whole world for the period 2000-2019. Blue indicates positive migration rates (net in-migration), while red indicates negative values (net out-migration), from Niva et al. (2023).

Table A.5: Climate uncertainty and migration

	Net migration rate (global dataset)	Ever moved (Tanzania NPS)
	(1)	(2)
$SPEI_{12m}$	0.038	0.012
	(0.127)	(0.025)
Climate $variability_{5y}$	–0.122	0.043
	(0.645)	(0.098)
Climate $instability_{5y}$	0.596	0.045
	(0.557)	(0.102)
Region or Household FE	Region	Household
Year FE	Yes	Yes
Observations	9,160	11,989
Clusters	458	144

Note: Net migration rate is the net migration rate per 1000 inhabitants in each region, where positives value indicates net in-migration and negative values net out-migration. *Ever moved* is a binary variable equal to 1 if the household relocated between survey waves. $SPEI_{12m}$ is the average SPEI value over the past 12 months aggregated at the region (admin 1) level for column (1) and at the district (admin 2) level for column (2). Climate controls include yearly SPEI values for the last 5 years, excluding the last 12 months. *Climate* $variability_{5y}$ is the standard deviation of last 5 years' SPEI values. *Climate* $instability_{5y}$ is the average absolute difference in SPEI over the last 5 years, residualized on Climate $variability_{5y}$. Standard errors are clustered at the region (admin 1) level for column (1) and at the district (admin 2) level for column (2). * p<0.1, ** p<0.05, *** p<0.01.