Climate Uncertainty and Financial Coping Strategies of Farmers

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Abstract

How does climate uncertainty affect consumption smoothing strategies among poor rural households? This paper investigates how recent exposure to climate uncertainty affects savings behavior as well as the demand, awareness, and uptake of insurance products. It introduces a novel measure of climate uncertainty more relevant for poor farming households relying on rainfed agriculture: *climate unpredictability*, which is the average year-to-year change between dry and wet conditions. Using household finance survey data from Tanzania and a differences-in-differences strategy, I find that households exposed to climate uncertainty in the recent past prepare for future shocks mainly by increasing their savings. I find that the effect is driven only by farming households, that it only affects savings for emergency reasons and not other types of savings, and is determined by exposure to climate unpredictability in the past five years. I find no effects on insurance uptake, demand, or awareness, despite the large welfare gains that would result from increased insurance coverage among this group of households. Instead, I find that households who have faced unexpected climate shocks in the recent past are more likely to partake in semi-formal cooperatives, which effectively substitute for formal insurance services.

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1 Introduction

It is a common but discouraging fact that those households that tend to be the least insured – rural households in low-income countries – are perhaps the most sensitive to income shocks. Most such households tend to rely on rainfed agriculture, which means that they are subject to stochastic income shocks due to climate uncertainty. Moreover, ongoing climate change is projected to only increase rainfall variability, thus increasing both the risk of droughts and floods (Burke et al., 2015). The combination of poverty, financial constraints due to lack of access to insurance and ongoing climate change is thus a particular challenge for rural populations in the global south.

The purpose of this paper is to analyze to what degree households in a low-income Sub-Saharan country, Tanzania, adopt to recent exposure to climate uncertainty by changing their financial behavior, specifically savings and insurance. A novelty of this paper is the introduction of climate *unpredictability*, which I define as the average absolute difference in drought conditions between years and differs from a variability measure such as the standard deviation. To a poor farming household, largely unprotected by insurance and having to invest substantial amounts in seeds and fertilizer each year, an unpredictable climate may be a much more salient and relevant measure of climate uncertainty than the variability itself, and may even be more important than the first-order effect of droughts themselves. As long as drought conditions are persistent, households may be more able to cope to changing conditions through for instance crop choice, but with an unpredictable climate, shifting from dry to wet weather on a year-to-year basis, this may be much more difficult.

The main finding of this paper is that climate unpredictability indeed is more important in determining how households choose to adapt to recent drought shocks. Specifically, I find that households adapt by increasing their savings. This is largely driven by farming households, and specifically affects savings explicitly for emergency reasons. However, climate uncertainty in the recent past, regardless of how it is measured, seems not to affect either insurance demand, awareness or uptake, suggesting an important role for information provision and subsidies, depending on which constraints are critical for adoption.

While the literature on weather-based insurance by now is extensive, there seems to be surprisingly little empirical work on the effects of exposure to climate uncertainty on financial coping mechanisms[1]. Cai, De Janvry and Sadoulet (2020) construct a theoretical model where households with poor insurance knowledge update take-up decisions based on recent exposure to disasters, in a setting very similar to this, and find that improving financial

[1] Except for papers looking at asset dynamics and the selling off of assets to cope with income shocks (Janzen and Carter, 2019)

literacy increases the chance that the take-up instead is permanent. To the best of my knowledge, this has not been empirically verified. Instead, most empirical work has focused directly on uptake itself and causes such as a lack of understanding (Cai, Janvry and Sadoulet, 2015; Giné, Townsend and Vickery, 2008; Patt, Suarez and Hess, 2010), lack of trust (Cole et al., 2013; Giné, Townsend and Vickery, 2008; McIntosh, Povel and Sadoulet, 2019), and liquidity constraints (Cole et al., 2013; Giné, Townsend and Vickery, 2008), but results tend to be ambiguous. Typically, it is often the better-off households that are less vulnerable to drought shocks that are willing to take up insurance (Giné and Yang, 2009). Moreover, and somewhat paradoxically, it seems that demand is especially low among the more risk-averse households (Giné, Townsend and Vickery, 2008). Instead, among the rural poor, it is more common to adopt more direct, but potentially also more vulnerable strategies of using up savings or selling off assets when faced by disasters or negative income shocks, with the poorest households simply cutting down on subsistence consumption (Janzen and Carter, 2019). Thus, the main contribution of this paper is to analyze whether and how recent exposure to climate uncertainty affects households' financial coping strategies among the rural poor, and in particular which aspect of climate uncertainty drives this behavioral adaptation.

This paper is organized as follows: Section 2 provides context for agriculture and financial literacy in Tanzania while Section 3 explains where the data is sourced, how the climate data and treatments are defined and presents the identification strategy. Section 4 presents the results, and section 5 the mechanisms. Section 6 presents robustness checks, while Section 7 concludes with policy implications.

2 Background

2.1 Climate and agriculture in Tanzania

Agriculture is the most important economic sector in terms of labor, employing around half of the total Tanzanian labor force (Bank, 2012) and accounts for up to 75 per cent of rural household income (Komba and Muchapondwa, 2018). Meanwhile, up to 92 per cent of agriculture in Sub-Saharan Africa is rainfed (Bruinsma, 2017), and this is also the most common form of agriculture in Tanzania. This makes rural smallholders in Tanzania exceptionally vulnerable to climate change, and climate variability in general. Since rural households are typically poor, yearly investments in seeds and fertilizer may constitute a large share of total expenditure, and unexpected climate shocks such as droughts and floods thus become a key challenge to escaping the poverty trap.

Moreover, due to the climatic conditions and poor households, droughts are the leading category of disasters in Tanzania and are only expected to increase in frequency with ongoing climate change (Mongi, Majule and Lyimo, 2010), putting even more pressure on households to adapt through coping strategies. According to recent climate change projections, yields of staple crops such as maize, rice and soybean may decline by 45%, and wheat up to 72% by the end of this century due to an increase in rainfall variability (Adhikari, Nejadhashemi and Woznicki, 2015).

2.2 Financial literacy and household coping strategies in Tanzania

The most comprehensive reports on financial literacy in Tanzania provided by the FinMark Trust, who conduct the Finscope national surveys (see description in the next section). Typically, access to financial markets is low, though it has improved by the introduction of mobile banking services. Still, only around 47 per cent of Tanzanian households save money and few, only 10 per cent, have any form of insurance. Savings is thus the most common coping strategy, and Tanzanians tend to rely on savings as their main form of coping mechanism (Finscope, 2023). In the development economics literature, data on monetary savings and insurance uptake has been scarce, and instead most papers tend to use surveys of assets to trace how the dynamic of asset ownership is affected by economic shocks, as an indirect measure of consumption smoothing (Carter et al., 2007; Janzen and Carter, 2019). Hence, in addition to savings and insurance, the selling of assets during hard economic times seems also to be a common coping strategy.

Another challenge is low financial literacy. The dataset analyzed in this paper provides some clues. For instance, only around 60 per cent are aware of insurance and understand its purpose. However, given that uptake is still only around 10 per cent, financial constraints are probably a more likely culprit, and it is indeed the case that a large majority, close to 60 per cent, report wanting insurance but not being able to afford it.

In lieu of formal insurance, many Tanzanian smallholders take part either in informal or semi-formal networks such as Savings and Credit Cooperative Societies (SACCOs). In Tanzania there are around 1400 registered SACCOs, and typically consist of a hundred members (Trærup, 2012). A SACCO is essentially an autonomous collective that provides informal credit and savings services to its members, and hence in practice acts as a substitute to more formal financial institutions such as banks. For example, similar to many insurance products, membership in a SACCO can provide protection against unexpected losses, illness and family deaths (Trærup, 2012).

3 Data and Empirical Strategy

3.1 Household finance survey data

This paper uses large-scale household finance survey data for Tanzanian households from the Finscope National Survey datasets conducted by FinMark Trust[2]. The Finscope National Surveys are nationally representative surveys, carried out since 2006 in 34 low-income countries, especially targeting Sub-Saharan Africa. Its aim is to provide insight into financial literacy and inclusion in poor countries, and provides an unprecedented detail into households' financial literacy and access[3]. 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 level[4]. This makes it an unprecedented dataset in terms of scale and spatial disaggregation, and it enables a difference-in-differences strategy, exploiting sub-national variation in climate uncertainty for the surveyed periods. In total, this yields 22,103 observations clustered in 169 districts, across three waves spanning over 13 years.

Using survey responses, a number of variables capturing financial literacy and coping strategies by households can be analyzed. Since this paper focuses on how households cope with climate uncertainty by financial means, the following variables have been constructed and are used as outcomes:

Save – Whether a household keeps extra savings, for any reason.
Save for emergency reasons – Whether a household saves specifically due to emergency reasons.
Save for other reasons – Whether a household saves for reasons other than emergencies.
Have insurance – Whether a household has insurance or not.
Aware of insurance – Whether a household understands and is aware of insurance and how to get it.
Want insurance, cannot afford – Whether a household reports wanting to purchase insurance but cannot afford it.

Additionally, the survey data includes important individual characteristics such as age, gender, level of education (as a categorical variable in five classes, ranging from no education to tertiary education), occupation and an urban indicator.

[2] The survey data for Tanzania can be accessed here: https://finmark.org.za/data-portal/TZA

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

[4] Unfortunately, the 2013 wave only contains information at the less granular region level, and is thus excluded from the analysis.

3.2 Climate data

To calculate drought incidence, climate variability and climate unpredictability I rely on the Global SPEI database, *SPEIbase*[5], using data covering all of Tanzania for the period 1996-2018.

This long-term climate database contains monthly data on drought conditions all over the world, at to a spatial resolution of 0.5 degrees, covering the period 1901-2020. This makes it suitable for sub-national analysis, even down to the district level.

The data is in form of the SPEI (Standardised Precipitation-Evapotranspiration Index), widely used for drought-monitoring around the world, and 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 drought severity, with mean 0 and standard deviation 1[6]. Negative values indicate drought conditions, and typically values below -1 indicate a severe drought.

The advantages of using SPEI over only rainfall data are several. First, this index is global and standardized, enabling comparisons between countries and over time. 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 (Kubik and Maurel, 2016). Third, this index is increasingly used in the economics literature[7], thus enabling direct comparisons between findings in different settings.

To construct the climate uncertainty variables, I rely on agricultural crop calendars for Tanzania to aggregate the SPEI to the growing season, where soil moisture is critical for crop production. I 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[8].

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

Drought – A district d is considered having experienced a drought in year y if $\text{SPEI}_{d,y} <$

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

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

[7] 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.

[8] 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.

-1, consistent with the literature on droughts. This is used to capture effects of droughts themselves, and the income losses they entail through productivity losses.

Climate variability – The standard deviation of $\{\text{SPEI}_{d,y-5}, ..., \text{SPEI}_{d,y}\}$. This measures is used to capture the effects of a more variable climate.

Climate unpredictability – Defined as the average *absolute difference* in the SPEI between each year in $\{\text{SPEI}_{d,y-5}, ..., \text{SPEI}_{d,y}\}$. This measures is used to capture the effects of the unpredictability of the climate, by focusing on the year-to-year variation.

To illustrate the difference between climate variability and climate unpredictability, consider the evolution of two theoretical SPEI series presented in Figure 1. The red solid line shows a location that was exposed to highly unpredictable climate, while the black dashed line shows a location with a relatively more predictable climate. Yet, both of these series have an equal number of drought events (3), a similar mean SPEI over the time period (0), and similar variance (0.84). However, because the former location had much greater year-to-year variation, it receives a much higher unpredictability score according to the definition above, close to 3 times as high as the latter. In such an unpredictable environment, it may be much harder to cope with climate shocks, as for instance investment in drought-tolerant seeds or crops may fail to cover their investment costs when the following year instead turns wet. Conversely, in an environment of relatively stable droughts or high rainfall, this variation may be easier to cope with because there will be greater return to any adapation by farmers, and hence less need for financial coping mechanisms such as saving and insurance.

3.3 Identification strategy

This paper uses SPEI as a measure of drought exposure, which has two important advantages. First, this better captures effects on crop production than rainfall or temperature alone, and thus improves the signal-to-noise ratio. Second, this index will only partly depend on rainfall, which reduces the risk of not meeting the exclusion restriction[9]. While a large literature have used single indicators of drought, typically rainfall[10] or temperature[11], recent economics papers have recommended multi-variable drought indicators, such as the SPEI[12].

The proposed mechanism is that exogenous variation in soil moisture will affect crop

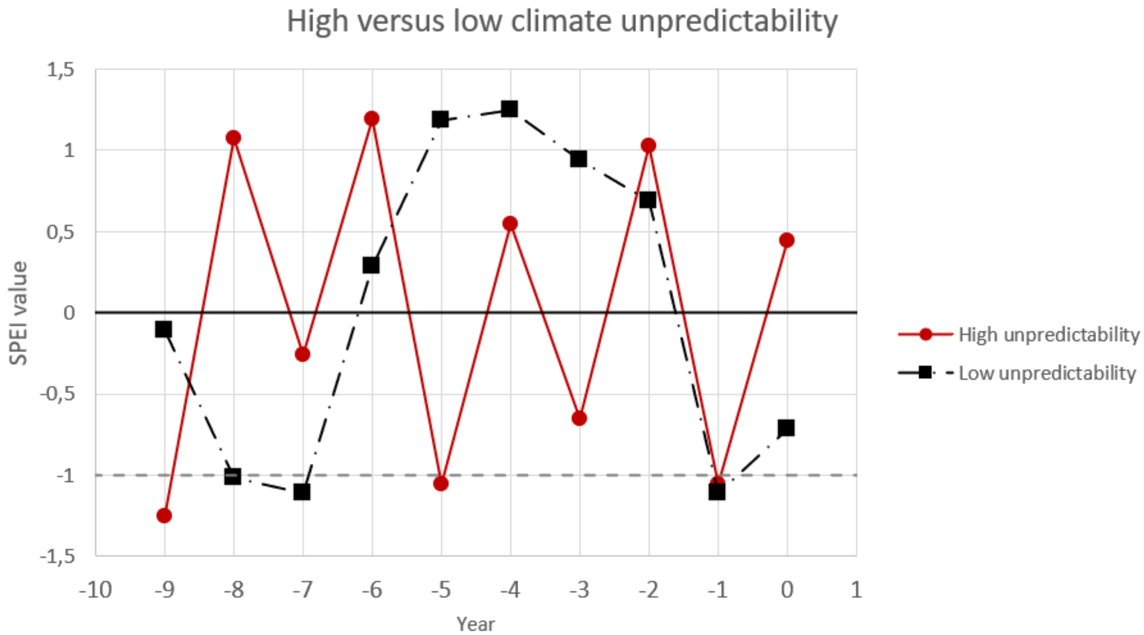
[9] There is a growing literature looking into the problems of using rainfall as an instrumental variable, specifically due to problems of not meeting the exclusion restriction. See for instance Sarsons (2015)

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

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

[12] 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.

Figure 1: Examples of high and a low climate unpredictability over a 10-year period



Notes: This figure shows two hypothetical realizations of SPEI values over the past 10 years in two different locations. The red sold line represents *high* realized climate unpredictability, while the black dashed line represents *low* realized climate unpredictability.

production, and hence differentially affect the income and thus coping behavior of farming relative non-farming households. Kubik and Maurel (2016) shows that negative SPEI values have a large and meaningful effect on crop production in Tanzania. The authors find that a 12-month lagged values are the strongest predictors, and find that a one deviation reduction in the SPEI reduces crop production by 20 to 30 per cent. For households relying on farming as their main source of income, this would thus closely correspond to an income loss of the same magnitude. Hence, the SPEI can be considered a validated proxy to income for farmers in Tanzania.

To see which climate uncertainty variables are most important in shaping households' expectations of their future income, and thus their financial coping strategies, I run a "horse-race" between the number of recent droughts, climate variability and climate unpredictability. The preferred specification is a two-way fixed effects specification, which absorbs both district and wave fixed effects (α_d^1 and α_y^2):

$$Y_{idy} = \alpha_d^1 + \alpha_y^2 + \beta_1 D_{0-5,dy} + \beta_2 D_{5-10,dy} + \gamma V_{0-5,dy} + \gamma V_{5-10,dy} + \delta U_{0-5,dy} + \delta U_{5-10,dy} + \mathbf{X}'_{idy}\Gamma + \varepsilon_{idy} \tag{1}$$

Here, $D_{0-5,dy}$ represents the number of droughts, $V_{0-5,dy}$ is the variability, and $U_{0-5,dy}$ is the unpredictability of the past 5 years, with α, β and γ being the coefficients of interest, respectively.

The specification also adds individual control variables in the vector **X**, to improve precision and to see how this affects coefficient stability, following Oster (2019).

While the two-way fixed effects approach introduces the advantage of not relying on a single event, e.g. a single drought, for the identifying variation, this technique introduces a number of other potential issues, perhaps most well-known that of heterogenous treatment effects, which may introduce negative weights and bias the treatment effects. To adjust for such potential heterogeneity I also use the estimator proposed by De Chaisemartin and d'Haultfoeuille (2020) when running the specification on individual drought years (a binary variable).

Since the treatment is applied at the district level, 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).

3.4 Descriptive statistics

Table 1 provides descriptive statistics for the analyzed sample, grouped by whether the respondents are farmers or not.

In baseline characteristics, farmers and non-farmers differ in expected ways: only 12 % of farmers are located in urban areas, unlike non-farmers who are 44 % likely to be urban. The latter group is also more educated, younger and more likely to be female.

Despite these differences, farmers and non-farmers, as a group, are surprisingly similar when it comes to financial behavior. Around half of the sample reports saving, and roughly 30 % report saving for emergency reasons. Despite this, only around 10 % report having insurance, and awareness of insurance seems not to be a constraint, seeing that over 60 % in both groups report being aware of insurance. Instead, the reason of little insurance uptake seems to be due to financial constraints; around 60 % report wanting to have insurance but not being able to afford it, though the figure is somewhat higher among non-farmers.

Overall, this is very consistent with the most recent Finscope report for Tanzania, which reports that still only 47 % of households save money on the side and 10 % have some form of insurance (Finscope, 2023).

Finally, respondents have a fairly similar experience of recent climate, which should be the case if rainfall is as good as random and there are no systematic climatic differences between rural and non-rural areas in Tanzania. Overall, respondents have on average experienced about 1 drought in the last 5 years, and between 1 and 2 droughts in the prior 5-year period. Climate variability is for both groups and periods close to 1, which over the long run it should be since SPEI is standardized with a mean of 0 and standard deviation of 1. Similarly, climate unpredictability is also close to 1 within each group and five-year period.

Table 1: Descriptive statistics for farmers and non-farmers.

	Farmers		Non-farmers	
	Mean	SD	Mean	SD
Financial behavior				
Save	0.500	0.50	0.507	0.50
Save for emergency reasons	0.296	0.46	0.294	0.46
Save for other reasons	0.276	0.45	0.268	0.44
Have insurance	0.092	0.29	0.107	0.31
Aware of insurance	0.602	0.37	0.630	0.36
Want insurance, cannot afford	0.575	0.49	0.621	0.49
Climate variables				
# droughts in 0-5 y	1.179	0.82	1.323	0.80
# droughts in 5-10 y	1.661	0.78	1.857	0.78
Climate variability in 0-5 y	0.924	0.27	0.896	0.27
Climate variability in 5-10 y	0.926	0.28	1.005	0.29
Climate unpredictability in 0-5 y	1.128	0.40	1.098	0.36
Climate unpredictability in 5-10 y	1.186	0.39	1.331	0.42
Individual characteristics				
Age	39.588	15.12	35.680	20.92
Level of education	1.789	0.69	2.152	0.93
Urban	0.121	0.33	0.437	0.50
Farmer	1.000	0.00	0.000	0.00
Female	0.470	0.50	0.569	0.50
Observations	8,077		14,026	

4 Results

4.1 Effects on savings

Table 2 reports the results of the effect of recent climate uncertainty on overall savings propensity. First, I find that droughts have no significant effect on the savings propensity of Tanzanian farmers. Moreover, the coefficients on droughts are relatively precisely estimated, indicating that this is unlikely to be a false negative. Adding climate variability to the specification changes these results little. However, when climate *unpredictability* is added, I find a large and positive effect of unpredictability on propensity to save. The coefficient is fairly similar for both the most recent 5-year period and the 5-year period prior to this, and is little affected by the addition of control variables. The next section breaks this savings behavior down by reason for saving. If climate uncertainty affects saving by its effect on future expectations of crop income it should differentially affect different reasons of saving.

Table 2: The effect of droughts, climate variability and climate unpredictability on saving propensity

	Farmers			
	(1)	(2)	(3)	(4)
# Droughts (0-5 yrs)	0.014	0.011	0.029	0.029
	(0.021)	(0.022)	(0.026)	(0.026)
# Droughts (5-10 yrs)	–0.009	–0.003	–0.005	–0.004
	(0.019)	(0.021)	(0.019)	(0.018)
Climate variability (0-5 yrs)		0.062	–0.195	–0.172
		(0.088)	(0.142)	(0.140)
Climate variability (5-10 yrs)		–0.014	–0.272*	–0.242*
		(0.107)	(0.150)	(0.144)
Climate unpredictability (0-5 yrs)			0.179**	0.169**
			(0.075)	(0.075)
Climate unpredictability (5-10 yrs)			0.169**	0.153**
			(0.076)	(0.075)
Observations	8,067	8,067	8,067	8,067
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
HH controls				✓

Notes: TWFE estimates with district and year FE. Within each 5-year period *# Droughts* is the number of years with SPEI < -1, *Climate variability* is the standard deviation of the yearly SPEI values and *Climate unpredictability* is the average of the absolute year-to-year changes. Household controls include: gender, age, education level fixed effects, and an urban indicator. Standard errors are clustered at the district level.

4.2 Effects on insurance

Table 3 reports the results on insurance uptake. I find no effects of either climate uncertainty measure on insurance uptake, at least when only considering exposure in the last five years. These results are, at least for droughts and unpredictability, unlikely to be false negatives, since the standard errors are rather low. At best, the effect is unlikely to be economically meaningful, at least when compared to the effects of savings behavior, as seen in Tables 2 and 4.

In the following section on mechanisms, I explore whether a lack of an increase in demand for or awareness of insurance can explain the lack of uptake.

Table 3: The effect of droughts, climate variability and climate unpredictability on insurance uptake

	Farmers			
	(1)	(2)	(3)	(4)
# Droughts (0-5y)	0.003	0.002	0.000	0.000
	(0.012)	(0.011)	(0.013)	(0.012)
# Droughts (5-10y)	–0.004	0.003	0.002	0.001
	(0.009)	(0.011)	(0.011)	(0.011)
Variability, 0-5y		–0.017	–0.025	–0.020
		(0.031)	(0.032)	(0.031)
Variability, 5-10y		–0.101**	–0.085	–0.086
		(0.044)	(0.059)	(0.059)
Unpredictability, 0-5y			0.011	0.010
			(0.022)	(0.021)
Unpredictability, 5-10y			–0.013	–0.011
			(0.029)	(0.029)
Observations	8,035	8,035	8,035	8,035
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
HH controls				✓

Notes: TWFE estimates with district and year FE. Within each 5-year period *# Droughts* is the number of years with SPEI < -1, *Climate variability* is the standard deviation of the yearly SPEI values and *Climate unpredictability* is the average of the absolute year-to-year changes. Household controls include: gender, age, education level fixed effects, and an urban indicator. Standard errors are clustered at the district level.

5 Mechanisms

Having found clear signs that exposure to climate uncertainty in the recent past affect savings behavior, but not insurance uptake, I now investigate potential mechanisms behind these effects, for savings and insurance respectively.

5.1 Savings

5.1.1 Reason for saving

Table 4 reports the results of the effect of recent climate uncertainty on saving for emergencies versus saving for other reasons. Here, I find that droughts do have an effect on saving, but only for saving for emergencies. Moreover, I find that the effect of unpredictability in the past 5 years on savings runs specifically through saving for emergencies. On the other hand, unpredictability in the prior 5-year period affects saving behavior for other reasons. Regardless of controlling for unpredictability, there seems to be no effect of variability itself on saving, for either reason.

Table 4: The effect of droughts, climate variability and climate unpredictability on saving propensity, by reason for saving, farmers only sample

	Saves for emergencies				Saves for other reasons			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
# Droughts (0-5 yrs)	0.045**	0.042*	0.043*	0.043*	–0.028	–0.027	–0.011	–0.010
	(0.021)	(0.023)	(0.023)	(0.023)	(0.018)	(0.018)	(0.020)	(0.020)
# Droughts (5-10 yrs)	0.008	0.017	0.014	0.014	0.026**	0.020	0.020	0.021
	(0.017)	(0.017)	(0.016)	(0.016)	(0.012)	(0.014)	(0.014)	(0.013)
Climate variability (0-5 yrs)		0.013	–0.140	–0.122		0.004	–0.083	–0.083
		(0.086)	(0.123)	(0.123)		(0.069)	(0.083)	(0.084)
Climate variability (5-10 yrs)		–0.079	–0.118	–0.102		0.081	–0.114	–0.108
		(0.069)	(0.120)	(0.120)		(0.073)	(0.079)	(0.080)
Climate unpredictability (0-5 yrs)			0.125**	0.119**			0.039	0.038
			(0.057)	(0.058)			(0.047)	(0.048)
Climate unpredictability (5-10 yrs)			0.012	0.005			0.139***	0.133***
			(0.069)	(0.070)			(0.043)	(0.044)
Observations	7,205	7,205	7,205	7,205	8,040	8,040	8,040	8,040
District FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
HH controls				✓				✓

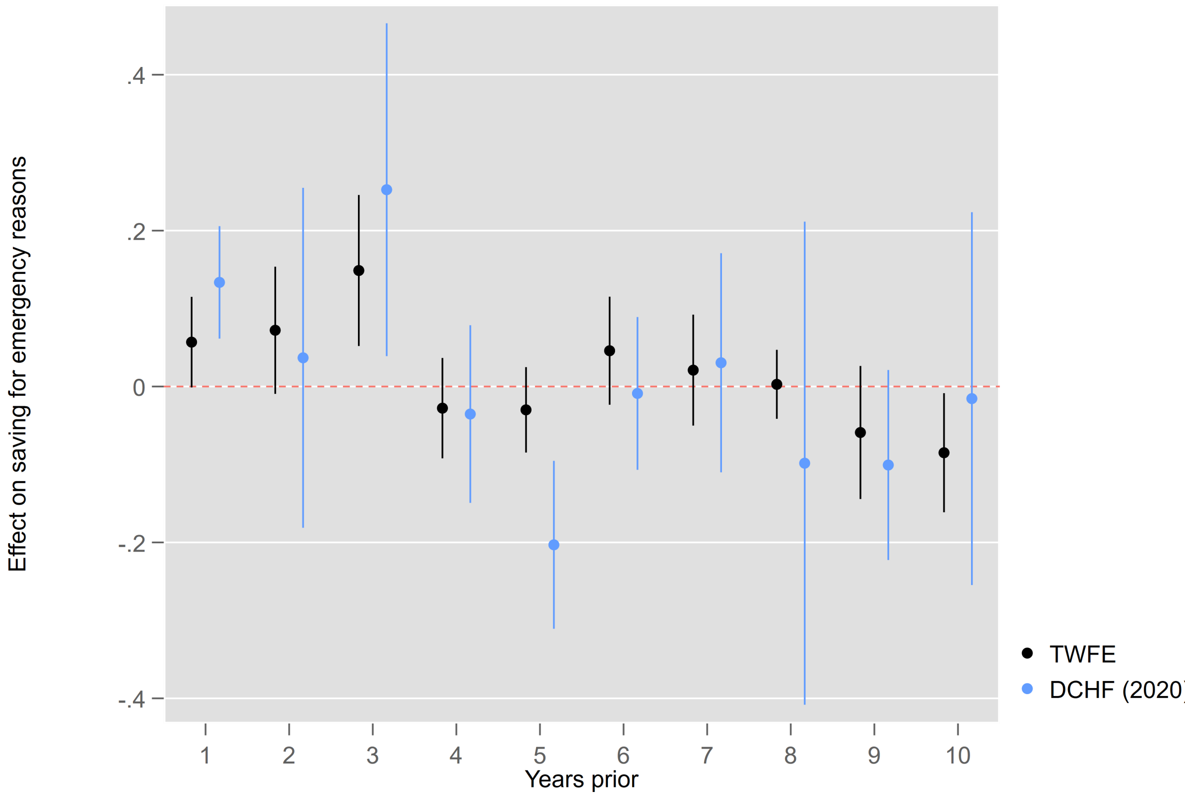
Notes: TWFE estimates with district and year FE. Within each 5-year period *# Droughts* is the number of years with SPEI $<$ -1, *Climate variability* is the standard deviation of the yearly SPEI values and *Climate unpredictability* is the average of the absolute year-to-year changes. Household controls include: gender, age, education level fixed effects, and an urban indicator. Standard errors are clustered at the district level.

5.1.2 Timing of experienced droughts

In order to better disentangle the short-run dynamics of the effects of droughts on savings behavior, I regress saving for emergency reasons on the drought indicator for each year individually, n years prior to the survey date. Since this specification uses single-year values, it cannot be done for the variability and unpredictability measures. Instead the purpose is to shed more light on the short-term behavior of exposure to droughts, and by extension, to experiences with unpredictable weather. Figure 2 presents the coefficients for each year, with and without using an estimator that allows for heterogenous treatment effects (De Chaisemartin and d'Haultfoeuille, 2020).

I find that only droughts in the last three years affect propensity for farmers to save for emergency reasons today. Moreover, adjusting for heterogenous treatment effects increases the effect size for the effects of droughts experienced one and three years ago, although they also reduce precision, as this analysis only leverages a portion of the identifying variation.

Figure 2: Effect of individual droughts on savings behavior by year prior to the survey date.



Notes: This figure shows the average treatment effect of single-year droughts on the propensity for farming households to save for emergency reasons (with 95% confidence intervals), using a TWFE strategy with and without adjusting for heterogenous treatment effects, using the estimator proposed by De Chaisemartin and d'Haultfoeuille (2020).

5.2 Insurance

5.2.1 Demand for insurance

Table 5 reports the results on insurance *demand*. Similar to insurance uptake, I find no or only a small but insignificant effect of recent droughts on insurance demand. Adding climate variability and unpredictability to the specification, I only find significant effects for events in the period 5-10 years back. If anything, unpredictability seems to *reduce* the demand. Why this is the case is not clear, but could potentially be from substitution of an increase in savings, as climate unpredictability for this period leads to an overall increase in saving for "other reasons" which could potentially crowd out the demand for insurance.

Hence, it is not unlikely that the lack of an increase in insurance uptake from recent exposure to climate uncertainty is explained by a lack of an increase in demand, rather than financial constraints imposed by these crises, especially since this exposure increases savings propensity.

Table 5: The effect of droughts, climate variability and climate unpredictability on insurance demand

	Farmers			
	(1)	(2)	(3)	(4)
# Droughts (0-5 yrs)	0.021	0.025	0.009	0.009
	(0.019)	(0.019)	(0.020)	(0.020)
# Droughts (5-10 yrs)	0.016	0.006	0.006	0.008
	(0.017)	(0.017)	(0.018)	(0.018)
Climate variability (0-5 yrs)		–0.095	0.026	0.031
		(0.069)	(0.110)	(0.109)
Climate variability (5-10 yrs)		0.034	0.242*	0.243*
		(0.080)	(0.142)	(0.141)
Climate unpredictability (0-5 yrs)			–0.069	–0.075
			(0.064)	(0.064)
Climate unpredictability (5-10 yrs)			–0.148**	–0.145**
			(0.071)	(0.070)
Observations	7,648	7,648	7,648	7,648
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
HH controls				✓

Notes: TWFE estimates with district and year FE. Within each 5-year period *# Droughts* is the number of years with SPEI $<$ -1, *Climate variability* is the standard deviation of the yearly SPEI values and *Climate unpredictability* is the average of the absolute year-to-year changes. Household controls include: gender, age, education level fixed effects, and an urban indicator. Standard errors are clustered at the district level.

5.2.2 Awareness of insurance

Alternatively, the lack of insurance uptake could also be explained by a lack of awareness, which could also be a constraint on demand itself. Table 6 reports the results on insurance *awareness*. Again, droughts in the past 5 years seem to have no effect on insurance awareness, conditional on droughts in the prior 5-year period. This can likely be explained by the fact that once a household is aware of the technicalities of an insurance product, they are unlikely to "forget" how this works. Adding climate variability and unpredictability to the specification, variability enters negatively and is significant for both 5-year periods, while unpredictability has a positive, albeit insignificant effect. Hence, conditional on the number of experienced droughts, it seems that high variability leads to a lower insurance awareness. Why this is the case is unclear. If insurance awareness is driven by marketing by private firms, one explanation, albeit controversial, could be adverse selection by firms, targeting districts that have had more stable incomes in the recent past.

Table 6: The effect of droughts, climate variability and climate unpredictability on insurance awareness

	Farmers			
	(1)	(2)	(3)	(4)
# Droughts (0-5 yrs)	–0.004	0.001	0.007	0.008
	(0.018)	(0.018)	(0.018)	(0.018)
# Droughts (5-10 yrs)	0.029**	0.027*	0.026*	0.027*
	(0.014)	(0.014)	(0.014)	(0.014)
Climate variability (0-5 yrs)		–0.174***	–0.238**	–0.204**
		(0.051)	(0.095)	(0.092)
Climate variability (5-10 yrs)		–0.127**	–0.219**	–0.190*
		(0.058)	(0.104)	(0.100)
Climate unpredictability (0-5 yrs)			0.040	0.030
			(0.056)	(0.055)
Climate unpredictability (5-10 yrs)			0.062	0.050
			(0.052)	(0.051)
Observations	7,628	7,628	7,628	7,628
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
HH controls				✓

Notes: TWFE estimates with district and year FE. Within each 5-year period *# Droughts* is the number of years with SPEI < -1, *Climate variability* is the standard deviation of the yearly SPEI values and *Climate unpredictability* is the average of the absolute year-to-year changes. Household controls include: gender, age, education level fixed effects, and an urban indicator. Standard errors are clustered at the district level.

5.2.3 SACCO participation

Finally, I investigate whether participation in a SACCO can substitute for insurance, and thus help explain why past exposure to climate uncertainty does not lead to an increase in insurance demand or uptake. Table 7 reports these results. I find that exposure specifically to climate unpredictability in any of the past 5-year periods during the recent decade increases the likelihood of SACCO participation, while exposure to previous droughts only has a small effect, significant only for the previous 5-year period, while variability largely has no significant effect. Hence, it may well be that an increase in SACCO participation crowds out any increase in insurance demand and uptake that would follow exposure to climate uncertainty in the recent past.

Table 7: The effect of droughts, climate variability and climate unpredictability on SACCO participation.

	Farmers			
	(1)	(2)	(3)	(4)
# Droughts (0-5y)	–0.004	–0.004	–0.000	–0.001
	(0.006)	(0.006)	(0.005)	(0.005)
# Droughts (5-10y)	0.011***	0.010**	0.009**	0.008**
	(0.004)	(0.004)	(0.004)	(0.004)
Variability, 0-5y		0.014	–0.029	–0.028
		(0.020)	(0.023)	(0.023)
Variability, 5-10y		0.032*	–0.020	–0.021
		(0.017)	(0.025)	(0.024)
Unpredictability, 0-5y			0.027**	0.027**
			(0.011)	(0.011)
Unpredictability, 5-10y			0.035**	0.035***
			(0.014)	(0.013)
Observations	8,018	8,018	8,018	8,018
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
HH controls				✓

Notes: TWFE estimates with district and year FE. Within each 5-year period *# Droughts* is the number of years with SPEI < -1, *Climate variability* is the standard deviation of the yearly SPEI values and *Climate unpredictability* is the average of the absolute year-to-year changes. Household controls include: gender, age, education level fixed effects, and an urban indicator. Standard errors are clustered at the district level.

6 Robustness checks

Falsification tests: As a falsification test, I run the same specifications for saving and saving for emergencies for non-farming households. Even though non-farmers are likely to be indirectly affected by droughts due to e.g. spatial spillover effects, they are likely to be *less* sensitive in terms of changes to their income. Hence, if climate uncertainty, and in particular climate unpredictability, affects farmers savings through changing their future income expectations, then we would expect to see a strictly smaller effect on non-farmers. Tables A.1-A.2 show that this is the case. While the number of droughts in the recent past seem to affect their savings propensity, climate unpredictability does not. If anything, saving for emergencies for non-farmers is even negatively affected by unpredictability, conditional on the number of droughts and the variability of the recent climate.

Alternative specifications: To analyze the sensitivity of the saving and saving for emergency coefficients to alternative specifications, I run specifications with all the combinations of the climate uncertainty variables where climate unpredictability is always included. This is to ensure that the effect of climate unpredictability is not simply an artifact of collinearity due to correlation with the other climate variables. Table A.3 and Table A.4 reports these estimates. I find a significant effect of climate unpredictability on saving and saving for emergency reasons regardless of specification, which is also similar in magnitude to the main specification.

Alternative time windows: Due to the nature of the treatment, it has to be aggregated over at least a multiple of years. I test the sensitivity of division in 5-year groups by instead using one full 10-year window, where the district fixed effects will capture any climatic variation prior to this period. Tables A.5 and Table A.6 report these results. When aggregating over a single 10-year period, the coefficients on climate unpredictability for saving and saving for emergencies remain largely unchanged in magnitude, but lose precision, with p-values increasing to 0.09 to 0.13. This is likely due to the effect of past exposure running mostly through the *recent* past, something which is seen more clearly in Figure 2.

Robustness to heterogenous and dynamic treatment effects: I run an event study for the past 5 years exposure to climate unpredictability, using the estimator proposed by De Chaisemartin and d'Haultfoeuille (2020) which allows for these effects. To do this, I first transform the treatment variable into a binary variable, indicating whether or not the past 5 years unpredictability is above the sample median, controlling for all other climate variables. Because this 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 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, that the aggregate treatment effect is significant, second, that the effects are similar in magnitude to the effects using a continous treatment variable, and third, that the effect one year after treatment remains largely unchanged, though slightly less precise.

Selection on unobservables: To analyze sensitivity to selection on unobservables, I follow Oster (2019) and calculate an adjusted treatment effect of climate unpredictability in the past 5 years, based on how the coefficient changes as control variables that increase R^2 are added. Table A.7 reports the statistics necessary for this calculation. I assume that selection on observables and unobservables play an equally important role, and use a theoretical R^2 1.3 times the R^2 of the specification with controls. For climate unpredictability in the past 5 years, I find that the adjusted treatment effect on saving is 0.157 and saving on emergencies is 0.072. To completely negate the treatment effects on the two outcomes, selection on unobservables would have to be 14 and 2.5 times greater, respectively, than selection on observables.

7 Conclusion

This paper investigates the effects of past exposure to climate uncertainty on Tanzanian farmers' financial coping mechanisms. I find that exposure to climate uncertainty affects farmers' propensity to save, but not their insurance uptake. I find that the most predictive climate uncertainty variable is unpredictability, which I define as the year-to-year variation in the SPEI. Investigating mechanisms, I find that exposure to climate unpredictability in the past 5 years increases farmers' saving for emergencies specifically, which is consistent with a deliberate strategy used by households to face an unpredictable climate, rather than due to a more general change in risk and time preferences.

My null findings on insurance uptake can partly be explained by the fact that I find no increase in either insurance demand or awareness, and the fact that savings for emergencies acts as a substitute for insurance. However, I find that exposure to climate unpredictability in the recent past increases the likelihood of being a member in a savings cooperate (SACCO), a semi-formal network of local farmers that offers financial services to its members, which may crowd out the demand for insurance. These findings are largely consistent with the previous literature on rainfall insurance, which typically find that farmers believe insurance to be too costly compared to alternative consumption smoothing strategies. This is also in agreement with what is reported in my sample. There is a relatively high financial literacy rate among farmers and non-farmers alike, making a lack of awareness unlikely. Instead, it is commonly reported that the main reason for not purchasing insurance is that it is too expensive.

Since climate change is only expected to lead not only to more droughts, but also to more uncertain rainfall and weather in general, farmers in Sub-Saharan Africa that rely on rainfall are especially vulnerable. The fact that coping mechanisms seem to respond by adjusting their consumption smoothing strategies is thus a positive sign. However, there may be over-adjustment by farmers, such that they only take the recent past into account, consistent with the behavioral literature on the availability heuristic (Tversky and Kahneman, 1973). Since climate is by definition a long-run phenomenon, these may lead to biased expectations, where those who did not face uncertainty underestimate this risk, while those who did overestimate it.

The fact that coping strategies work mostly through savings and semi-formal networks, rather than through formal institutions, may not be optimal, from a policy-making perspective. My findings are thus largely in agreement with the literature that finds that insurance products that safeguard against unforeseen productivity losses, such as weather index insurance, likely have to be redesigned or subsidized in order for their take-up to be more effective, even in the presence of salient climate risks.

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Appendix A

A.1 Falsification tests

Table A.1: The effect of droughts, climate variability and climate unpredictability on overall savings propensity for non-farmers.

	Non-farmers			
	(1)	(2)	(3)	(4)
# Droughts (0-5 yrs)	0.023	0.023	0.034*	0.034**
	(0.016)	(0.016)	(0.018)	(0.017)
# Droughts (5-10 yrs)	–0.006	–0.003	0.002	–0.002
	(0.013)	(0.015)	(0.016)	(0.016)
Climate variability (0-5 yrs)		–0.027	–0.108	–0.068
		(0.068)	(0.105)	(0.097)
Climate variability (5-10 yrs)		–0.042	–0.214*	–0.207*
		(0.065)	(0.114)	(0.112)
Climate unpredictability (0-5 yrs)			0.045	0.030
			(0.051)	(0.049)
Climate unpredictability (5-10 yrs)			0.116*	0.107*
			(0.060)	(0.060)
Observations	14,014	14,014	14,014	14,014
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
HH controls				✓

Notes: TWFE estimates with district and year FE. Within each 5-year period *# Droughts* is the number of years with SPEI $<$ -1, *Climate variability* is the standard deviation of the yearly SPEI values and *Climate unpredictability* is the average of the absolute year-to-year changes. Household controls include: gender, age, education level fixed effects, and an urban indicator. Standard errors are clustered at the district level.

Table A.2: The effect of droughts, climate variability and climate unpredictability on propensity to save for emergencies for non-farmers.

	Non-farmers			
	(1)	(2)	(3)	(4)
# Droughts (0-5 yrs)	0.023**	0.021*	0.023**	0.023**
	(0.010)	(0.011)	(0.011)	(0.011)
# Droughts (5-10 yrs)	0.010	0.018	0.015	0.014
	(0.010)	(0.011)	(0.011)	(0.012)
Climate variability (0-5 yrs)		–0.002	0.077	0.088
		(0.054)	(0.076)	(0.076)
Climate variability (5-10 yrs)		–0.078*	–0.060	–0.062
		(0.044)	(0.073)	(0.073)
Climate unpredictability (0-5 yrs)			–0.065*	–0.068**
			(0.034)	(0.034)
Climate unpredictability (5-10 yrs)			0.001	–0.000
			(0.042)	(0.043)
Observations	12,402	12,402	12,402	12,402
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
HH controls				✓

Notes: TWFE estimates with district and year FE. Within each 5-year period *# Droughts* is the number of years with SPEI < -1, *Climate variability* is the standard deviation of the yearly SPEI values and *Climate unpredictability* is the average of the absolute year-to-year changes. Household controls include: gender, age, education level fixed effects, and an urban indicator. Standard errors are clustered at the district level.

A.2 Alternative specifications

Table A.3: The effect of droughts, climate variability and climate unpredictability on propensity to save for farmers, using alternative specifications.

	Save			
	(1)	(2)	(3)	(4)
Climate unpredictability (0-5 yrs)	0.125***	0.116**	0.173**	0.169**
	(0.044)	(0.048)	(0.079)	(0.075)
Climate unpredictability (5-10 yrs)	0.043	0.056	0.123*	0.153**
	(0.043)	(0.047)	(0.069)	(0.075)
# Droughts (0-5 yrs)		0.017		0.029
		(0.023)		(0.026)
# Droughts (5-10 yrs)		–0.006		–0.004
		(0.019)		(0.018)
Climate variability (0-5 yrs)			–0.147	–0.172
			(0.140)	(0.140)
Climate variability (5-10 yrs)			–0.211	–0.242*
			(0.138)	(0.144)
Observations	8,067	8,067	8,067	8,067
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
HH controls				✓

Notes: TWFE estimates with district and year FE. Within each 5-year period *# Droughts* is the number of years with SPEI < -1, *Climate variability* is the standard deviation of the yearly SPEI values and *Climate unpredictability* is the average of the absolute year-to-year changes. Household controls include: gender, age, education level fixed effects, and an urban indicator. Standard errors are clustered at the district level.

Table A.4: The effect of droughts, climate variability and climate unpredictability on propensity to save for emergencies for farmers, using alternative specifications.

	Save for emergencies			
	(1)	(2)	(3)	(4)
Climate unpredictability (0-5 yrs)	0.086**	0.077*	0.126*	0.119**
	(0.042)	(0.041)	(0.065)	(0.058)
Climate unpredictability (5-10 yrs)	–0.052	–0.035	–0.045	0.005
	(0.039)	(0.040)	(0.069)	(0.070)
# Droughts (0-5 yrs)		0.036		0.043*
		(0.022)		(0.023)
# Droughts (5-10 yrs)		0.015		0.014
		(0.018)		(0.016)
Climate variability (0-5 yrs)			–0.097	–0.122
			(0.134)	(0.123)
Climate variability (5-10 yrs)			–0.033	–0.102
			(0.119)	(0.120)
Observations	7,205	7,205	7,205	7,205
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
HH controls				✓

Notes: TWFE estimates with district and year FE. Within each 5-year period *# Droughts* is the number of years with SPEI < -1, *Climate variability* is the standard deviation of the yearly SPEI values and *Climate unpredictability* is the average of the absolute year-to-year changes. Household controls include: gender, age, education level fixed effects, and an urban indicator. Standard errors are clustered at the district level.

A.3 Alternative time-window

Table A.5: The effect of droughts, climate variability and climate unpredictability on propensity to save for farmers, using a 10-year window.

	Save			
	(1)	(2)	(3)	(4)
# Droughts (0-10 yrs)	0.002	0.003	0.003	0.005
	(0.017)	(0.016)	(0.017)	(0.016)
Climate variability (0-10 yrs)		0.175	–0.142	–0.086
		(0.148)	(0.290)	(0.286)
Climate unpredictability (0-10 yrs)			0.219	0.191
			(0.135)	(0.134)
Observations	8,067	8,067	8,067	8,067
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
HH controls				✓

Notes: TWFE estimates with district and year FE. Within each 5-year period *# Droughts* is the number of years with SPEI < -1, *Climate variability* is the standard deviation of the yearly SPEI values and *Climate unpredictability* is the average of the absolute year-to-year changes. Household controls include: gender, age, education level fixed effects, and an urban indicator. Standard errors are clustered at the district level.

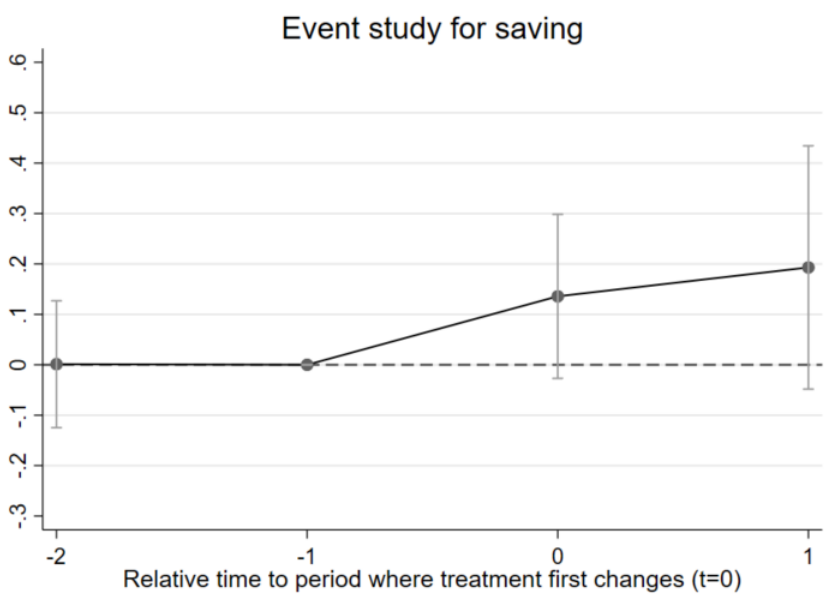
Table A.6: The effect of droughts, climate variability and climate unpredictability on propensity to save for emergencies for farmers, using a 10-year window.

	Save for emergencies			
	(1)	(2)	(3)	(4)
# Droughts (0-10 yrs)	0.026*	0.025*	0.026**	0.026**
	(0.014)	(0.014)	(0.013)	(0.013)
Climate variability (0-10 yrs)		–0.121	–0.370*	–0.336*
		(0.112)	(0.187)	(0.190)
Climate unpredictability (0-10 yrs)			0.166*	0.151
			(0.096)	(0.098)
Observations	7,205	7,205	7,205	7,205
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
HH controls				✓

Notes: TWFE estimates with district and year FE. Within each 5-year period *# Droughts* is the number of years with SPEI < -1, *Climate variability* is the standard deviation of the yearly SPEI values and *Climate unpredictability* is the average of the absolute year-to-year changes. Household controls include: gender, age, education level fixed effects, and an urban indicator. Standard errors are clustered at the district level.

A.4 Robustness to dynamic and heterogeneous treatment effects

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



Notes: This figure shows the event study estimates of switching from below to above median value in past 5 year climate unpredictability, split by the median sample value 1.2, using the estimator proposed by De Chaisemartin and d'Haultfoeuille (2020).

A.5 Selection on unobservables

Table A.7: The effect of droughts, climate variability and climate unpredictability on propensity to save and save for emergencies, respectively, with R^2 without and with additional controls to adjust for selection on unobservables.

	Save		Save for emergencies	
	(1)	(2)	(3)	(4)
# Droughts (0-5 yrs)	0.029	0.029	0.043*	0.043*
	(0.026)	(0.026)	(0.023)	(0.023)
# Droughts (5-10 yrs)	–0.005	–0.004	0.014	0.014
	(0.019)	(0.018)	(0.016)	(0.016)
Climate variability (0-5 yrs)	–0.195	–0.172	–0.140	–0.122
	(0.142)	(0.140)	(0.123)	(0.123)
Climate variability (5-10 yrs)	–0.272*	–0.242*	–0.118	–0.102
	(0.150)	(0.144)	(0.120)	(0.120)
Climate unpredictability (0-5 yrs)	0.179**	0.169**	0.125**	0.119**
	(0.075)	(0.075)	(0.057)	(0.058)
Climate unpredictability (5-10 yrs)	0.169**	0.153**	0.012	0.005
	(0.076)	(0.075)	(0.069)	(0.070)
R^2	0.08	0.11	0.25	0.26
Observations	8,067	8,067	7,205	7,205
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
HH controls		✓		✓

Notes: TWFE estimates with district and year FE. Within each 5-year period *# Droughts* is the number of years with SPEI < -1, *Climate variability* is the standard deviation of the yearly SPEI values and *Climate unpredictability* is the average of the absolute year-to-year changes. Household controls include: gender, age, education level fixed effects, and an urban indicator. Standard errors are clustered at the district level.