Drought and Financial Services: Evidence from Tanzania

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1 Introduction

Farming households in the developing world face considerable risk. The smallholder paradigm common in developing countries leaves most farming households vulnerable to idiosyncratic shocks. In sub-Saharan Africa, where 80% of farms are smaller than 2 hectares and account for 40% of total cultivated area, household income depends on within-year harvest cycles and across-year variation in weather (Lowder et al., 2016). Agriculture on smallholder farms is predominantly rain-fed and does not rely on irrigation, which means that yields will vary idiosyncratically from year to year (Conning and Udry, 2005). Variation in agricultural yields correspond to variation in household income, consumption, and well-being.

Agricultural households in sub-Saharan Africa have developed a wide variety of techniques to smooth their consumption in response to these unavoidable and potentially livelihood-threatening risks. These techniques range in their level of formality — that is, their degree of regularity, contractuality, and institutionalization (La Porta and Shleifer, 2014). Formal methods include crop insurance, the optimal method of consumption smoothing across uncertain agroclimatic states, and credit from banks or microfinance institutions (MFIs) (Conning and Udry, 2005). Less formal methods include SACCOs (Savings and Credit Cooperatives), open and voluntary associations of households who meet regularly to deposit into a common pool and disburse loans to selected households within the group. This method can be suboptimal because the risk of default is contained within the group, rather than diluted across the portfolio of a larger financial institution, but their social informality makes them relatively more accessible in the developing world.

Nonetheless, these institutional financial services suffer from several problems in the developing world. Information asymmetries between credit issuers and customers can cause adverse selection and moral hazard, and poor institutional infrastructure can result in inconsistent enforcement of financial contracts even if information is perfect. Moreover, financial regulation and undeveloped infrastructure in rural areas makes it costly for banks to enter new areas, and thereby costly for potential customers to use new financial services. SACCOs avoid the former of these problems by leveraging social networks to reveal important information about potential borrowers and enforce contracts but cannot avoid the latter because they require the existence of a commercial bank to operate in a community.

In addition to these loan products, households can also use non-contractual financial services to informally smooth their consumption when faced with adverse climatic conditions. Bank accounts, for example, allow households to sell valuable assets like livestock, timber, crops, or land and store liquidity to maintain their well-being amidst unexpectedly low agricultural income, but suffer from the same access issues described above (Fafchamps et al., 1998; Tabetando et al., 2023).

Mobile money services offer a relatively inexpensive and accessible alternative to an institutional bank account. Mobile money providers allow customers to operate a conventional bank account from their cell phone. Unlike commercial banks, which face high capital and institutional barriers to operate in a particular region, mobile money networks only require dense usage of cell phones and a few individuals willing to serve as agents who are authorized to make deposits and withdrawals from the network on behalf of clients. Users can transfer money to others within the same mobile money network, transport money over short distances, and save money for extended periods of time. This allows for the same informal means of financial intermediation described above — households can sell fixed assets and save and spend the resulting liquidity using their mobile money account. It also connects rural households with urban areas and allows them to receive remittances in times of stress, opening an additional informal means of intermediation to farming households.

This thesis is concerned with the relationship between drought and the take-up of financial services among rural households in Tanzania. After a literature review, I describe two measures of climatic stress on agriculture — seasonal instability and lack of moisture — and test for their effects on the usage of loans, SACCOs, bank accounts, and mobile money.

2 Literature Review

2.1 Drought

The FAO defines agricultural drought as a condition of insufficient soil moisture to meet the needs of a particular crop at a particular time (Allen et al., 1998). Drought is especially dangerous for smallholder farming households in Tanzania because production is not technologically intensive. That is, the majority of farms lack the complex and intensive irrigation, plowing, and harvesting technologies that make agriculture in the developed world highly efficient. It is well established that drought causes significant negative effects on consumption and wellbeing for households involved with agriculture, primarily through loss of income and fluctuations in food prices (Koo et al., 2021; Letta et al., 2022; Arslan et al., 2016; Kudamatsu et al., 2012).

Climate change has increased average air temperatures both globally and in Tanzania, which, all else equal, makes droughts more frequent and more severe. Precipitation, the other key control on drought, shows signs of moderate decrease during the period of interest for this study, 2010-2014. Climate change has been shown to threaten agricultural productivity because it causes more frequent, more severe, and less predictable drought events (for example, Opoku et al. (2021)). Figure 1 displays these trends — increases in temperature or decreases in precipitation can both cause drought if they are severe.

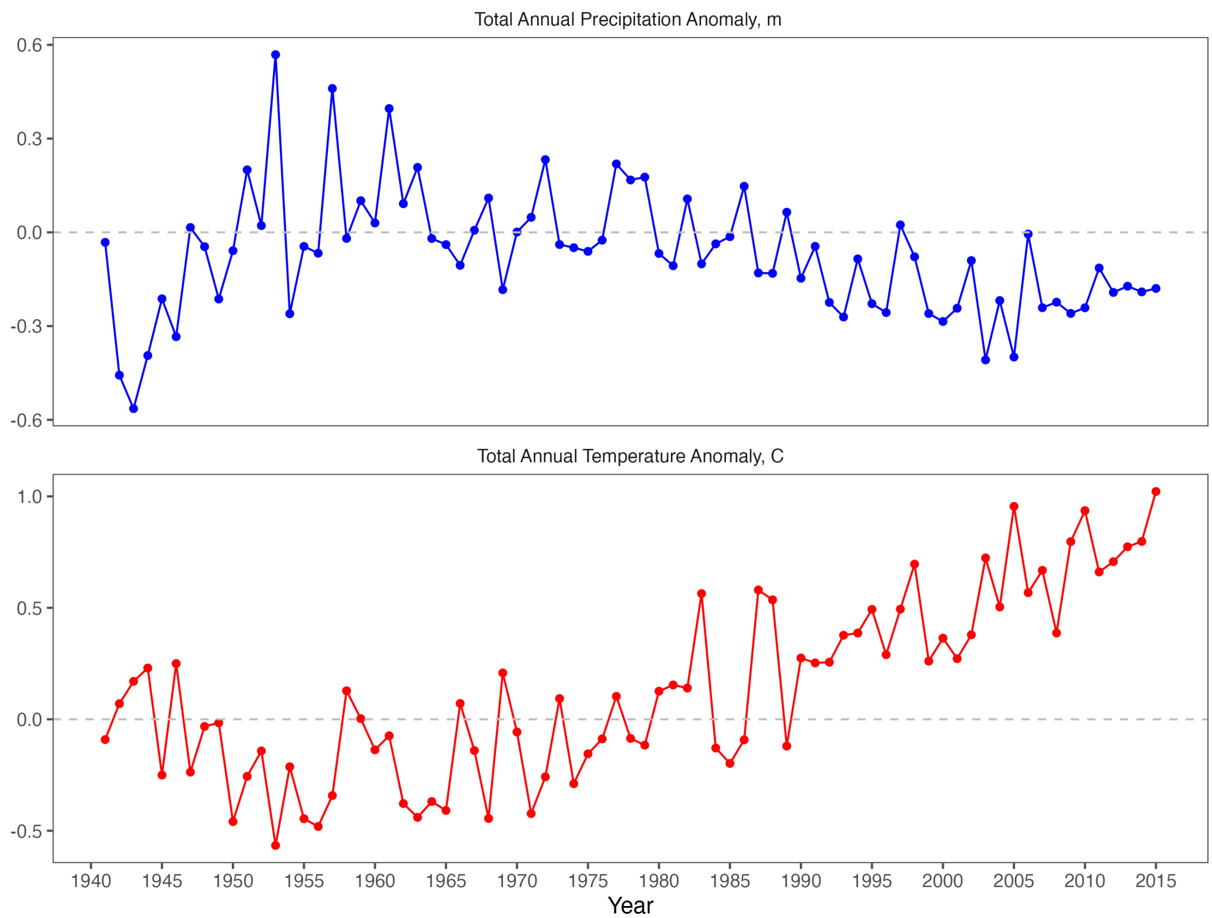

Figure 1: Precipitation and Temperature Anomalies in Tanzania, 1940-2015. *Source:* ClimateReanalyzer.com

The majority of the literature on agricultural drought uses simple measures of rainfall and temperature as the identifying explanatory variable. For example, Alem and Colmer (2022) find that mean-preserving increases in rainfall variability decrease wellbeing among households engaged in agriculture. In a similar vein, Arslan et al. (2016) (2016) find that negative rainfall and temperature shocks decrease household welfare, and that the effect is greatest among households in the bottom income quintiles. Rosenzweig and Udry (2014) use variation in rainfall to study agricultural labor decisions in response to positive/poor forecasts, finding that positive forecasts in a village decrease outmigration on net. Many studies use variation in rainfall to study changes in the use of agricultural inputs: Tione and Holden (2021), for example, study responses in land rental markets, and Marenya et al. (2020) study responses among households' fertilizer take-up. In general, this literature finds unsurprisingly that negative rainfall shocks and overall low rainfall have negative impacts on agricultural productivity and smallholder wellbeing. Mitigating technologies and consumption-smoothing mechanisms like fertilizer and land rental are more likely to be used when a household is faced with low rainfall. On a larger scale, Barrios et al. (2010) find that persistently low levels of rainfall in sub-Saharan Africa have hampered the region's ability to transition away from the low-productivity smallholder regime and towards highly-productive large farms that require a relatively smaller portion of the total workforce. The paper's scope and methods are far afield from the present study, but nonetheless shows that rainfall is an important predictor of development even on long time scales.

Other studies have used nominal weather events to identify weather effects on agricultural and economic outcomes. Anttila-Hughes and Hsiang (2013), for example, use typhoon events in India to study the wide-ranging effects of environmental disaster. A raft of literature studies the economic effects of the El Nino Southern Oscillation (ENSO). Koo et al. (2021), for instance, measures decline in food availability and Collier et al. (2011) study portfolio management responses at regional banks. These nominal shocks aim to capture the multi-faceted nature of a weather event on the livelihoods of agricultural households and other agents. Rainfall, despite its usefulness as an explanatory variable in smallholder agricultural research on a variety of timescales, is an imprecise measure because it is only one among many variables that influence the amount of moisture available to the crops on a given plot of land. Nominal shocks are able to capture a variety of weather changes in one identified event.

Both of these approaches do not precisely capture agricultural drought. Measures of rainfall alone cannot precisely estimate the amount of moisture available to a given plot of agricultural land at a given time. Other variables, including the level of vegetation, cloud cover, sun exposure, topography, and soil composition influence the amount of water stored on the landscape (Allen et al., 1998; Thornthwaite, 1948). A region suffering from drought might experience the same levels of temperature and precipitation as a region without drought, because it has less vegetation to store moisture over time. Nominal approaches avoid this problem because they can better capture the multi-scalar nature of agricultural drought, but they are often hard to identify unless they are regular — like the ENSO — or very severe. In these cases, however, farming households are likely to be aware of regular inter-annual changes in rainfall and will adjust their farming practices as a result. Nominal shocks like the ENSO cannot identify an unexpected, exogenous shock to the climatic conditions faced by farming households.

I use two measures to capture agriculturally-relevant drought in Tanzania, because drought is plausibly stressful in two different ways. First, drought can result from an unexpected lack of moisture, which can be measured by the Standardized Precipitation and Evapotranspiration Index. Second, drought can result from an unexpected change in the seasonal pattern of rainfall in a region. Even if yearly moisture levels remain the same, a change in when during the year that moisture arrives can cause crop failure and reduced yields. I develop a dichotomous variable that indicates a short-term change from long-term expected seasonal conditions in an area, based on the seasonality classification from Herrmann and Mohr (2011).

The Standardized Precipitation and Evapotranspiration Index

In order to precisely identify agricultural drought as a complex phenomenon of ranging severity, meteorologists have developed a number of multi-scalar drought indices that indicate drought severity on a normalized continuous scale (Ayugi et al., 2020). These indices apply a formula to a range of climatic variables that together capture the physical processes that occur during drought. The raw climatic data comes from reanalysis datasets that interpolate conditions between measurement stations using climate models. As computational and conceptual techniques have progressed, drought indices have used a greater range of variables and more precise formulae to best reflect drought conditions.

As of now, the state-of-the-art index is the Standardized Precipitation and Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010). The SPEI uses precipitation and temperature data to model the climatic water balance, or the difference between precipitation and potential evapotranspiration (PET). Precipitation measures the influx of moisture into the soil, and potential evapotranspiration predicts the maximum amount of moisture that would evaporate from the landscape given the meteorological conditions (it is "potential" and not "actual" because measuring actual evapotranspiration, or AET, requires precise data on the amount of moisture present in the soil, which is hard to measure and for which no effective model exists) (Thornthwaite, 1948). Nonetheless, estimation of the PET is difficult because of the involvement of numerous meteorological parameters, including surface temperature, air humidity, soil incoming radiation, water vapor pressure, and ground–atmosphere latent and sensible heat fluxes (Allen et al., 1998). There are many methods used to calculate PET. The standard method, used by the Food and Agriculture Organization of the United Nations (FAO) and the authors of the drought dataset in this paper, is the Penman-Monteith method (Beguería et al., 2023). This method relies on a physically-based model of PET and requires values for solar radiation, temperature, wind speed, and relative humidity (Vicente-Serrano et al., 2010). As such, it is more reliable than other methods which empirically estimate the PET from a smaller set of variables.

Several papers have used the SPEI to identify agriculturally relevant drought shocks. In the Tanzanian setting, where there is a unimodal rainy season (November–April) in the south and a bimodal rainy season (March–May and October–December) in the north, Kubik and Maurel (2016) take the average value of the SPEI for the months January–June. Since they "do not know the distribution of households between the two rainfall regimes," they corroborate their results with SPEI values from the months March–May. It is unclear how this approach properly identifies agriculturally relevant drought because it does not distinguish by rainfall regime and, as a result, it does not take SPEI values from only the growing season months experienced by a household to classify a household as experiencing drought. In this paper I use spatial precipitation and temperature data to classify households by the rainfall regime they experience. This classification is important for selecting which months of rainfall are agriculturally relevant for each household.

Two more recent papers use cutoff values to assign drought shocks. In nearby Kenya and Uganda, which do not experience different rainfall regimes, Tabetando et al. (2023) construct SPEI using a 3 months' resolution during the rainy season. From these values, they create a dummy variable for drought if the value of SPEI was less than -1.0, and a dummy variable for flood if the value of the SPEI was greater than 1.0. Di Falco et al. (2020) construct a dosage-style drought shock for households in Ethiopia by counting the number of months across the two rainy seasons in which the SPEI was lower than .5, then dividing this number by 6. The resulting shock variable gives a "dosage" of drought for the given year that varies between 0 and 1. Though these approaches do not suffer from the season identification problems in Kubik and Maurel (2016), it is not obvious that the selected cutoff points are the appropriate values for assigning flood and drought, respectively. Though rainy seasons vary meaningfully based on which crops a household decides to grow, these decisions cannot be incorporated into the identification of agriculturally relevant drought because they are endogenous to the household's existing knowledge of their local patterns and rainfall and drought. Nonetheless, the unimodal and bimodal rainfall patterns and the division of the two bimodal rainy seasons effectively approximate the agriculturally relevant months for all households regardless of crop cultivation decisions.

Seasonality Classification

In addition to the SPEI, which measures unexpectedly dry conditions throughout the course of the year, I use a classification of the seasonal rainfall pattern to describe when in the year precipitation is expected to occur, and to indicate whether the expected pattern holds in any given year. This is relevant because Tanzania experiences multiple seasonal rainfall patterns for multiple crops (see Figure 2). The center and southwest of the country experiences one rainy season and one dry season per year, also called unimodal

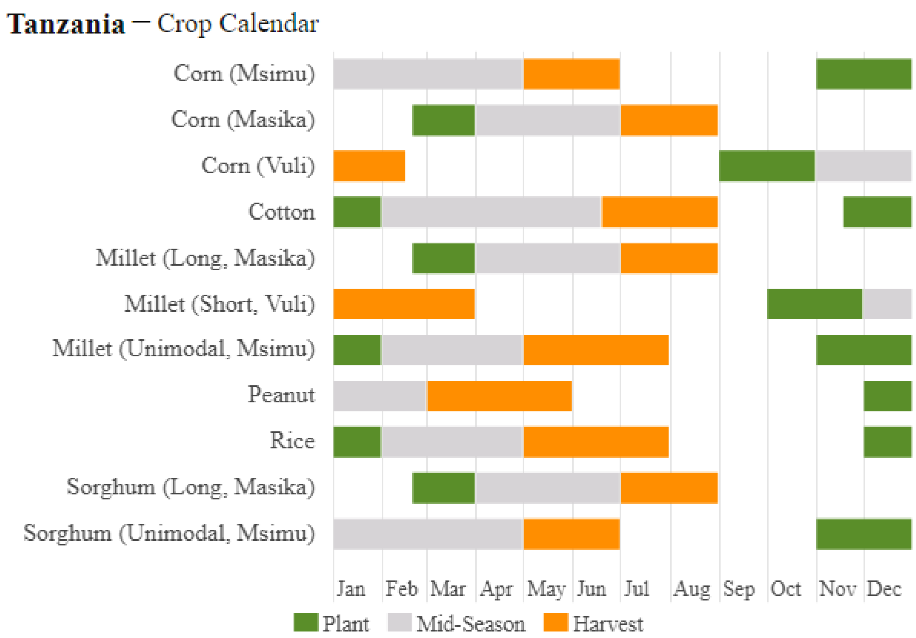

Figure 2: Tanzania experiences a high degree of variability in the timing of growing seasons across region and crop. *Source:* USDA Foreign Agricultural Service

seasonality. The northwest of the country experiences two rainy seasons and two dry seasons, or bimodal seasonality. These seasonal patterns of rainfall determine which crops farmers plant, and they determine when in the year farmers should plant them. Even if the amount of moisture present in a region over the course of the year is within expected norms (this would be indicated by values of the SPEI close to 0), it must be present on the landscape during the expected months, when planting occurs. A household may experience a negative agricultural shock even if they do not experience a dramatic decline in yearly levels of moisture because the moisture arrives at unexpected times and their crop fails as a result.

There is no agreed-upon method of seasonality classification in the climatology literature. Zhao and Zhang (2021) present a review of different methods with a regional concern in Mexico. Various factors influence the selection of a classification method. Some approaches produce a discrete classification of regions and others produce a continuous index of bimodality. Some approaches use daily annual data within years, and other approaches account for year-on-year variation using climatological time series data. These climatological data can also vary in their resolution: monthly data is most common, but some approaches use pentadal and daily time scales.

I follow Herrmann and Mohr (2011), who focus on rainfall seasonality classification in Africa and present fine-grained results for east Africa, where several rainfall regimes meet. Their approach is also intended "to characterize rainfall seasonality as experienced on the ground," which makes it well-suited for this agricultural application. Their method produces a categorical classification of rainfall regimes which is also useful for agricultural application and aligns with the dichotomous treatment of regimes in the LSMS survey data. Rather than a dichotomous classification of pixels as either unimodal or bimodal, Herrmann and Mohr (2011) classify each pixel as one of several possible rainfall regimes. There are three regimes that occur in Tanzania: (1) one unimodal rainy season per year, (2) two unimodal rainy seasons per year, or (3) one bimodal rainy season per year. (3) is different from (2) because the rainy season is not divided by a period of arid conditions, but still has two distinct peaks of rainfall within one season.

In order to establish seasonality at half-degree latitude by half-degree longitude resolution across the African continent, Herrmann and Mohr (2011) compare precipitation levels in millimeters with multiples of temperature levels in degrees Celsius. Following Walter and Lieth (1967), they define an arid month as "one in which the precipitation P in millimeters is less than 2 times the temperature T_a in degrees Celsius (i.e., $P < 2T_a$)." This comparison is justifiable because, according to previous studies, $2T_a$ is "linearly related to annual potential evapotranspiration across many different climate zones" and can serve "as a proxy for evapotranspiration", for which directly measured values are only available at a few meteorological stations. When precipitation is less than twice the amount of moisture that evaporated off the landscape in a given month, Walter and Leith classify that month as an arid month. When precipitation is greater than twice the evapotranpiration, the month is classified as humid.

The "temporal sequence of arid and dry months" across the average year determines the rainfall regime at each pixel location. When both humid and arid months are present, that location experiences a seasonal regime. "A wet season is a consecutive stretch of one or more humid months, and a dry season is a consecutive stretch of one or more arid months." When only one wet season occurs in the average year, that location is classified as experiencing a single-wet-season regime. Two wet seasons separated by at least one arid month indicate a dual-wet-season regime, and multiple wet seasons of at least one month, each separated by at least one arid month indicate a multiple-wet-season regime.

The regime classification system described so far is from Walter and Lieth (1967). Herrmann and Mohr (2011) improve on this system by including a third category for months. In their scheme, "dry months within each wet season are identified for which the precipitation is less than 4 times but greater than 2 times the temperature ($2T_a < P < 4T_a$). A dry month is thus less extreme than an arid month." In this new system arid months are classified in the same way, but some months that in Walter and Leith's system would have been classified as humid are now classified instead as dry. $4T_a$ corresponds to a value of 100 for much of tropical Africa (four times a "realistic" monthly average temperature of 25° C), and 100 mm is an "often-cited monthly rainfall threshold" below which the water requirements for many crops are not satisfied and the short root systems of annual grasses suffer water stress (Todorov and Steyaert, 1983; Creswell and

Martin, Creswell and Martin).

Dry months are incorporated into the classification of rainfall regimes at each pixel location in the following way. The presence of a dry month between periods of humid months constitute a break in the rainy season, as in Walter and Lieth (1967)'s approach. Instead, they separate two distinct modes within one rainy season. This means that, in addition to classifying the number of rainy seasons experienced by a location over the course of the average year, Herrmann and Mohr (2011) also classify the modality of each of those rainy seasons. Rainy seasons with only one stretch of humid months, perhaps bounded by a period of dry months, are classified as unimodal rainy seasons. Rainy seasons with two periods of humid months separated only by a period of dry months (not arid months) are classified as a single bimodal rainy season.

This more complex classification system results in eight different rainfall regime classifications for pixel locations on the African continent. (1) Arid seasonality indicates only arid months, (2) humid seasonality indicates only humid months (3) one unimodal wet season indicates one period of humidity unbroken by dry months, (4) one bimodal wet season indicates two periods of humidity separated by some number of dry months, (5) one multimodal wet season indicates more than two periods of humidity separated only by dry months, (6) two wet seasons, unimodal-unimodal, indicate two periods of humidity separated by some number of arid and dry months, (7) two wet seasons, unimodal-bimodal, indicates two periods of humidity separated by some number of arid and dry months, one of which periods of humidity is itself separated only by a period of dry months, and (8) multiple wet seasons indicates more than two period of humidity each separated by some number of arid and dry months. Other combinations of humid, dry, and arid months are theoretically possible based on this system, but Herrmann and Mohr (2011) only found these eight to present on the African continent within the time period of interest.

In effect, this system raises the precipitation threshold for the end of a rainy season. In Walter and Lieth (1967)'s approach, the rainy season ends whenever precipitation falls below $2T_a$. In Herrmann and Mohr (2011)'s system, the rainy season is allowed to continue until precipitation falls below $4T_a$. Those months with precipitation between $2T_a$ and $4T_a$ are interpreted as "off-peak" times within a rainy season rather than as periods of aridity.

2.2 Financial Services

Rural households in Tanzania face significant variation in income, both within and across years, because of the weather-dependent nature of agriculture. Financial products can be used to smooth consumption, asset use, and risk across time and unrealized states of the world (Conning and Udry, 2005). The risk of agricultural drought would be best mitigated by an actuarially fair insurance market, but insurance is widely unavailable in the developing world (Collins et al., 2009; Karlan et al., 2014). Instead of insurance, households can use various forms of credit to smooth their consumption across a transitory income shock caused by agricultural drought.

Consumption smoothing is optimal because households face diminishing marginal returns to consumption (Perloff, 2004). Without a means of smoothing consumption, households would consume at a low level in one time-period/state of the world, and at a high level in a second time-period/state of the world. After smoothing, households would consume at the same or similar levels in both time-periods/states. Households prefer smoothing because consumption below some subsistence level is very costly, and marginal returns to consumption above that level are diminishing.

However, financial contracts of all kinds are especially prone to information asymmetries in the developing world (Conning and Udry, 2005). Furthermore, government institutions may be less able to enforce the contractual obligations made between creditors and debtors, making the prospect of lending much riskier than in a developed setting. Credit is only a trustworthy means of financial intermediation when creditors can claim a legal and enforcable right to interest payments, regardless of the debtors' ability to make those payments. In order to mitigate these asymmetries and risks, financial institutions in the developing world can charge much higher interests rates than would be expected in an efficient credit market. These high interest rates can increase stress on households experiencing agricultural drought and the accompanying loss of income. Information asymmetries and regulations can also introduce restrictions on the kinds of financial contracts that banks offer. In order to protect themselves from the associated costs, banks may write into contracts preventive measures against adverse selection, moral hazard, opportunistic default, and other potential complications. First and foremost, these restrictions and increased costs will lead to less-than-efficient usage of financial instrumentation, and they may also make loan repayment stressful for households who do take out loans.

These two stories about the impact of credit on household well-being — either as a beneficial means of consumption smoothing or as a costly financial stress — are the main focus of this study. The use of observational data from the LSMS is advantageous in this regard because households who use credit will pay interest rates reflective of the conditions faced by the credit-issuing institutions from whom they borrow in terms of information asymmetries and regulation. Liquidity interventions in randomized controlled trials (RCTs) can estimate with high internal validity the direct effects of credit on agricultural and welfare outcomes (see Conning and Udry (2005) for a review), but they do not estimate with external validity the prevalence of conventional, "*in situ*" credit usage among farming households in developing countries.

Productivity Growth

The empirical literature on financial services use among smallholder households can be divided into two categories. The first examines credit as a constraint on agricultural productivity growth. Though not directly related to my research question, this literature deals with an important moderating variable. A primary mechanism by which drought impacts household income, consumption, and well-being is agricultural productivity (Kubik and Maurel, 2016). For example, losses in productivity are linked to child malnutrition , and it is well-established that agricultural productivity growth ameliorates poverty (Suri and Glennerster, 2023; Janvry and Sadoulet, 2015). Therefore, it is important to understand the effects of credit on agricultural productivity, both in the short- and long-term.

Credit is one of the many constraints on agricultural productivity growth (Suri and Udry, 2022). A large body of literature studies the effects of easing liquidity constraints in general on agricultural activities, finding that input subsidies have significant but relatively small effects on agricultural intensification and increased productivity (Jayne et al., 2018). Access to credit or release from a liquidity constraint can increase fertilizer use, depending on weather conditions and lack of rainfall (Marenya et al., 2020; Nakano and Magezi, 2020; Duflo et al., 2011). Along with education and technology, credit increases agricultural product quality and productivity (Deutschmann et al., 2023). Microcredit, a particular kind of loan product that uses social pressure to prevent default, has been found to have mixed effects on agricultural activity. It increases profits in self-employed nonagricultural activities, increases focus on agricultural activities, and increases further borrowing, but has not been found to increase agricultural productivity or household consumption (Ely et al., 2019; Crépon et al., 2015; Deutschmann et al., 2023; Tarozzi et al., 2015). One possible explanation for these limited effects is a lack of trust in formalized financial services (Mukherjee et al., 2021).

On longer time scales, there is consensus that credit is a meaningful constraint on long-term productivity growth and structural transformation, but that other constraints are more critical (Suri and Udry, 2022; Banerjee and Duflo, 2010; Herrendorf et al., 2013). Improved access to agricultural technology and education will have larger and more permanent effects.

Consumption Smoothing

Though not a critical constraint on long-term productivity growth, credit has been shown to be an important means of consumption smoothing across transitory shocks. In particular, Fink et al. (2020) show that access to loans during the "lean season," the time in the agricultural cycle when savings run low after many months without income from crop sales, improve agricultural productivity and household wellbeing. Christiaensen et al. (2007) find that household ownership of assets improves consumption outcomes after a shock, and Freudenreich and Kebede (2022) show that wealthier households are less sensitive to changing expectations about a future shock.

The household decision to take up one type of financial service over another is not well-studied because most approaches focus on only one strategy. There is significant literature on the use of assets to smooth consumption over time. Early literature found that households do not kill their livestock for sustenance during a shock; they prefer to sell livestock and purchase grain (Bernus, 1980; Loutan, 2012; Reardon, 1993). Later literature suggests that this mechanism is used less than early studies suggested, and studied other assets, including grain stores, as means of consumption smoothing (Fafchamps et al., 1998; Udry, 1995). Drawdown of grain stores is preferable to livestock sale when faced with a shock because households face constant marginal returns to grain sale but not to livestock. Kazianga and Udry (2006) find that households do not use inter-household cash transfers to share risk during a shock, instead only depleting grain stores.Much of this literature also finds that consumption smoothing does not occur at estimated optimal levels for the household. More recent studies have studied consumption-smoothing via a wide variety of mechanisms. Mazur (2023) finds that communities use shared irrigation resources to smooth drought risk across households, and that the smoothing was only effective when the irrigation resource was excludable. Tione and Holden (2021) and Tabetando et al. (2023) study changes in land rentals and land sales, respectively, in response to drought shocks. They find that households adjust their land usage to smooth consumption across a drought shock, selling or renting land that they own to supplement their income. Kubik and Maurel (2016)) study the migration of household members as a response to drought. When a household faces diminished consumption as a result of a drought shock, they are more likely to send a household member to another village, where labor opportunities may be unaffected by the shock in their village.

If households use other mechanisms, rather than credit, to smooth consumption after a shock, literature suggests that households may be averse to default risk. The risk of default is severe in many developing countries because banks often demand high-collateral loans (Dupas et al., 2012). This risk disincentivizes potential creditors from taking out loans, which is suboptimal because risk-averse creditors are ideal clients for lenders (Boucher et al., 2008; Karlan et al., 2011). However, Brune et al. (2017) find that households manage cash savings to smooth consumption across shocks, suggesting that formal financial inclusion does not meaningfully affect household outcomes.

Barriers to Traditional Financial Services

Information asymmetries and weak enforcement mechanisms in developing countries can prevent efficient financial intermediation in developing countries. Conning and Udry (2005) summarize: "The defining characteristic of all financial contracts is that they involve the exchange of state-contingent promises or IOUs. But the fear that promises may be broken can limit the set of credible promises that a would-be issuer can commit to keeping. In a world of complete markets this problem was abstracted away by simply assuming that all potential contract breaches could be immediately detected and costlessly deterred, but most of the modern literature on financial contracting focuses on how asymmetric information and limited enforcement problems may together limit the set of feasible commitments. This theory has proven powerful and rich at providing insights with which to interpret the shape of real world financial contracts and institutional arrangements." In the developing world, would-be issuers of loans cannot "immediately detect and costlessly deter" breaches of financial contracts. As a result, those issuers limit the kinds of contracts they are willing to make, with sometimes adverse consequences for those with whom they contract.

In the context of financial intermediation, information asymmetries present themselves in two ways: adverse selection and moral hazard (Conning and Udry, 2005). Adverse selection occurs when the credit-issuing institution does not have access to private characteristics of their potential customers that would determine their credit-worthiness. In the developed world, banks use credit scores to determine credit-worthiness, and the calculation of credit scores requires access to a wide array of variables about an individual's past financial behavior, income levels, and anything else that may predict the likelihood of default. In the developing world, banks often do not have access to these kinds of data. For example, if a farming household defaults on a loan as the result of a poor harvest, the bank may be unable to determine whether the farmer was a responsible for the poor harvest. It may be the case the farmer decided to plant less productive strains of crop, planted at a sub-optimal time, or used ineffective irrigation or fertilization techniques. But it could also be the case that the farmer made all of these decisions correctly, but because of adverse weather conditions — made harder to predict and generalize because of the important of micro-climatic conditions in agriculture — nonetheless suffered low crop yields and the consequential loss of income. Because the bank may not known which of these possibilities led to the farmer's default, it may not be able to use the known characteristics of the farmer as predictive of future credit-worthiness for similar farmers. Worse still, those farmers who are most likely to default are also those who have the highest demand for loans. In this way, banks can "adversely select" for the credit-worthiness of potential lendees as a result of the imperfect availability of information about those lendees.

When banks raise their interest rates in order to mitigate adverse selection, they can initiate a vicious cycle of that worsens adverse selection over time (Conning and Udry, 2005). If a bank is worried about profitability as a result of default from untrustworthy lendees, they may raise interest rates on future borrowers. At the margin, these higher interest rates will dis-incentivize risk-averse potential borrowers from taking out loans from the bank, because the higher interest rates make the loan riskier for the household. As a result, the customers the bank would prefer to lend to — conscientious, risk-averse borrowers — no longer want to borrow from the bank. The remaining borrowers are on average less risk-averse and more likely to default on their commitments, thereby further threatening the profitability of the bank. From here the cycle begins again: in order to protect profits, the bank will raise interest rates even higher, pushing out a greater number of risk-averse customers from among the bank's borrowers and further increasing the risk of default for the bank.

In this context, moral hazard poses additional risks for the credit-issuing institution (Conning and Udry, 2005). Even when a farming household experiences a successful harvest and receives sufficient income to fulfill their obligations to their creditors, they face two "morally hazardous" decisions. First, they are incentivized to make sub-optimal management choices thanks to the cushion of liquidity provided by the loan. This "ex-ante moral hazard" is a threat because farmers who have received loans may make riskier decisions and further expose themselves to risk of default than they would have without the additional liquidity provided by the loan. Second, farmers may decide untruthfully report a poor harvest in order to escape their contractual obligations to the bank. This is called "ex-post moral hazard." If the bank is unable to verify after the fact that the household did, in fact, produce a successful harvest, it cannot evaluate whether that household can credibly default on the loan. The household has every incentive to hide the evidence of its successful harvest and thereby avoid its contractual obligations to the bank. In the case of both ex-ante and ex-post moral hazard, the bank must carefully monitor the financial and agricultural health of its lendees, which can be very costly, especially in rural areas where transportation and communication are relatively undeveloped.

Even if a bank in a developing country is able to protect itself from the threat of adverse selection by effectively determining the credit-worthiness of its potential borrowers, and from the threat of moral hazard by appropriately monitoring the households and projects that receive loans, it nonetheless faces risks when default occurs as a result of weak contractual enforcement in developing countries. As Conning and Udry (2005) describe, "problems of commitment can also arise even when information is perfect and symmetric because even though actions and outcomes are observed, agents may still be able to simply renege or walk away from their commitments unless they face credible and effective sanctions to dissuade such opportunistic default." This risk of opportunistic default occurs when the legal, cultural, and institutional mechanisms of contractual enforcement cannot effectively motivate borrowers to make payments even when they face losses.

The effects of risk from adverse selection, moral hazard, and opportunistic default all amount to increased costs on behalf of the credit-issuing institution. Banks must spend significant resources to appropriately select, monitor, and enforce their lending contracts. This means that potential borrowers face higher interests rates than what would be expected in perfectly integrated and efficient financial markets (Conning and Udry, 2005).

Recent innovations in financial intermediation in the developing world, like microfinance and savings groups (including ROSCAs), attempt to ameliorate the costs associated with costs by establishing social institutions among groups of borrowers that bear some of the responsibility for selecting, monitoring, and enforcing financial contracts. By indexing punishments for default to social groups rather than individuals, all members of the group are incentivized to allow selective entry to the group only to those they deem credit-worthy. They are also incentivized to keep tabs on other group members while they have outstanding financial commitments, and encourage other group members to meet those commitments, lest the entire group suffer the consequences of default.

Government regulation and administrative barriers also impose costs on efficient financial intermediation in developing countries. Interests rate caps, state-directed credit, and other government interventions have been "a principal culprit" of more effective financial intermediation in developing countries. In Tanzania, the history of the government's participation in financial markets can be divided into three periods (Odhiambo, 2008). From 1961 to 1966, interest rate policy was determined by credit markets in London. From 1967 until 1986, interest rates were set directly by administrative policy. Since 1987 interest rate policy has been slowly deregulated. In 1992 financial institutions were freed to set their own interest rates, and in the following year caps on lending interests rates and real deposit rates were abolished. Odhiambo (2008) find that interest rate policy liberalization increases financial depth — the amount of economic output that passes through the financial sector — and thereby improves the efficiency of financial markets.

Mobile Money

Given the barriers to accessibility associated with institutional financial services, "mobile money" technology has played an important role in expanding financial access in developing countries. High costs passed to customers as high interest rates, regulatory barriers, and undeveloped infrastructure can lead to *institutional voids* (see Palepu and Khanna (1998)) — mobile money can fill these voids because it allows customers to operate a traditional bank account through their cell phone. It offers financial services that are relatively trustworthy and inexpensive in comparison to conventional banks. Suri and Jack (2016) find that, in the long run, mobile money in Kenya increased the allocation of consumption and household labor over time, contributing to significant decreases in poverty. In a similar vein, Abiona and Koppensteiner (2022) use data from Tanzania to show that households use mobile money to smooth consumption during idiosyncratic shocks and thereby reduce poverty levels over time. My results corroborate these findings and investigate in greater detail the determinants of the take-up of mobile money. (Abiona and Koppensteiner (2022), for example, assume as part of their identification strategy that the expansion of mobile money networks is randomly assigned across Tanzania — my approach does not make this assumption.)

Users of mobile money services can deposit and withdraw money from their account through a network of local agents that serve as ATMs. Unlike traditional banks, which need to surmount high capital and regulatory barriers to enter and operate in a community, mobile money networks leverage the existing cell phone network to reach customers. Additionally, the only capital requirement to become an agent — those who facilitate deposits and withdrawals — is the ownership of a cellphone. Transfer fees on the same mobile money network are relatively low — 1.1% on average — while conversion from mobile money to cash is relatively more expensive — a fee of 7.3% on average. Despite these costs, mobile money provides an inexpensive and accessible alternative to traditional commercial banking services.

In the national cross-section, almost 35% Tanzanian of households have at least one mobile money account. The market is dominated by three major mobile money network providers: Vodacom has a 53% market share in the country, Tigo has an 18% share, and Airtel has a 13% share. Customers can transfer money only with other users on the same network.

There are three features available in mobile money services that ameliorate different aspects of financial exclusion. First, users can execute instantaneous peer-to-peer transfers of money. Compared to the alternatives of transporting money in-person, intermediating through a bus driver, or through a traditional commercial banks, mobile money transfers are inexpensive, immediate, and trustworthy. These transfers are most often used to send remittances from urban to rural areas, which is one of the important functions mobile money can provide for rural households facing unexpected stressful climatic conditions.

Second, mobile money networks can be used to securely carry money over short distances, typically up to 10 kilometers. These transactions begin by depositing money through a local agent at one location and then withdrawing money after traveling to a new location from the local agent in that location. These kinds of transactions are intended to mitigate the risk of robbery while carrying large amounts of money, and the high withdrawal fee of 7.3% suggests that these risks are considerable and consumers who use this service have a high willingness to pay to avoid them.

Third, mobile money networks can store money for short and medium periods of time. This use of the network is not very prevalent — 90% of the money leaves the network within five days of being cashed in. Nonetheless, this use of mobile money is an important consideration in the context of agricultural stress because it provides the ability for households to exchange fixed agricultural assets for liquidity. For example, a household may decide to sell livestock, timber, or another valuable asset in order to supplement their income during a period of unexpected stress. The ability to safely and inexpensively store the resulting liquidity in a mobile money account — even if only for a short time before it is used to purchase other goods — is an important part of this informal means of financial intermediation. If households lack a mobile money account or another way to bank their money, they may decide against making such a sale.

The first of these three features is the primary mechanism by which I hypothesize that adverse climatic conditions will affect the take-up of mobile money. When a drought-affected household is able to receive a remittance from a family member living elsewhere in Tanzania, it experiences the same benefits of additional liquidity that would be provided by a loan or SACCO, but the household does not need to overcome the barriers to accessibility of those services. Mobile money agents are numerous and widespread in Tanzania, and the only capital constraint on the take-up of mobile money is the purchase of a cell-phone, which is relatively cheap and accessible (Economides and Jeziorski, 2017). In keeping with this hypothesis, Economides and Jeziorski (2017) find that mobile money users in Tanzania have a relatively high willingness-to-pay in transaction fees for long distance peer-to-peer transfers, the feature used to send remittances, which suggests that these remittances may be used when the receiving household faces a severe liquidity constraint.

In addition to these endogenous characteristics of mobile money, the Tanzanian government pursued policies designed to promote financial inclusion that emphasize accessibility of mobile money, beginning in 2014. Their National Financial Inclusion framework for the years 2014-2016 notes the dramatic increase in mobile money services made available in the preceding several years, and point to the technology as a key tool for reaching their national financial inclusion goals (Ndulu, 2014). In particular, the framework emphasizes proximity to financial access points as a key indicator of financial inclusion, and they note the ease with which mobile money can expand its reach through the recruitment of local agents and low capital costs.

Though mobile money seems to be of particular interest to the Tanzanian government, the Financial Inclusion Framework emphasizes a market-oriented approach and does not promulgate subsidies or other specific incentives for mobile money. Nonetheless, their description of key indicators and areas of regulatory reform focus on improving the regulatory environment for mobile money and expanding its national reach.

2.3 Contributions

This study will contribute to the literature on drought and financial services in Tanzania in two ways. First, I demonstrate a novel approach to measuring year-to-year instability in the seasonal pattern of rainfall. Existing studies use only aggregate rainfall or anomalies in climatic water balance (e.g. the SPEI) to identify exogenous rainfall shocks, but this approach captures only one of two ways that agriculturally relevant drought can occur. A household may experience normal levels of soil moisture, but at unexpected times, which can adversely affect the household's agricultural success in that year. I use a spatial precipitation and temperature data to classify long-term "expected" seasonal patterns of rainfall in Tanzania, and then identify when villages experience instability in that long-term pattern.

Second, I use observational panel data to compare the responses of four different financial services to adverse climatic conditions. Many studies focuses only on one service — especially RCTs that directly engage households with an experimental intervention. This study will comment on the differences in the take-up of commercial credit, SACCOS, traditional bank accounts, and mobile money, before further analysis of mobile money.

As discussed above, traditional commercial credit faces significant barriers to accessibility despite its theoretically preferable ability to contractually intermediate across time and space. Formal commercial bank accounts avoid the costs associated with adverse selection and moral hazard that result from contractual credit, but it suffers from the same institutional and cost barriers. SACCOs make themselves somewhat more accessible by leveraging social networks to execute the vital information-gathering and enforcement mechanisms that make commercial credit so costly, but they less effectively intermediate between regions, which is an important function in response to spatially correlated drought events. They also do not completely avoid institutional barriers, because SACCOs require that at least one member of the group hold a traditional bank account that stores the deposits of the group and issues withdrawals to certain members. For all of these reasons, take-up of these services is low across Tanzania in comparison to mobile money, and we expect to find similarly smaller responses in the take-up of these services in response to drought.

The remainder of this paper will answer the following question: How does drought affect the take-up of financial services among rural households in Tanzania? I will describe the data sources used in this paper and the classification approach for rainfall seasonality before presenting regression results using OLS and fixed effects.

3 Data

The data used in this study can be separated into three categories. (1) I use global data products of precipitation and temperature to classify regions of Tanzania as experiencing either a bimodal or unimodal annual pattern of rainfall. This classification determines the use of the second source of data, (2) a global dataset of the Standardized Precipitation Evapotranspiration Index, the climatological state-of-the-art for measuring drought and moisture conditions on the landscape. The rainfall regime classification determines which months of SPEI data will be applied to each household in the third source of data, (3) the Living Standards Measurement Survey, a semi-annual survey of Tanzanian households implemented by the Tanzanian National Bureau of Statistics and funded by the World Bank. Though the survey was performed five times between 2008 and 2020, I use only the data collected in 2010 because of limited question availability in the other years of the survey. These data have spatial information at the level of the enumeration area, which means that rainfall classification and SPEI assignment both occur at the enumeration-area-level. A given enumeration area recieves a rainfall regime classification from (1), a measure of agriculturally-relevant drought severity from (2), and each household in that enumeration area is incorporated into econometric models using a variety of data from (3). The following sections explain the use of these data in detail.

3.1 Seasonality Data

Hermann and Mohr use monthly averages across a multi-decade period of complete data collection for each of these measures. They use thirteen years of precipitation data from the Tropical Rainfall Measuring Mission Multisatellite Precipitation Analysis (TMPA) 3B43 product at 0.258 spatial resolution, from 1998 to 2010 (Huffman et al. 2007). They combine this data with a second temperature product from a longer time period, the Global Precipitation Climatology Project (GPCP), version 2.1, product at 2.58 spatial resolution from 1979–2008 (Huffman et al. 2009). These data are averaged by month across all years and both datasets to produce monthly average levels of precipitation.

Temperature data comes from the The Moderate Resolution Imaging Spectroradiometer (MODIS) monthly mean land surface temperature product (MOD11C3), measured at 0.058 spatial resolution for the period 2000 to 2010. This product provides the daytime and nighttime monthly averages of land surface temperature used in Hermann and Mohr's analysis. They average mean nightly temperatures per month from MODIS, which underestimate minimum air temperature, and mean daily temperatures per month from MODIS, which overestimate maximum air temperature, to produce a single estimate of air temperature per month averaged across the ten years of data collection. The mean of daily and nightly temperatures is intended to reduce the upward and downward bias of each of those estimates, respectively.

3.2 The Standardized Precipitation and Evapotranspiration Index

Drought data comes from a global dataset of SPEI values calculated at a resolution of .5 degrees-longitude by .5 degrees-latitude, from Beguería et al. (2023) and accessed on Google Earth Engine. The SPEI can be calculated at any time scale 1 to 24 months and varies between -3 (very dry) and 3 (very wet). It can be interpreted as a standardized score that describes the variation in the given time period's climatic water balance when compared to long-term conditions in that region for that month of the year. (It is not a true z-score because the probability distribution that describes the variation in climate water balance is log-logistic and not normal.) As a result, the index measures inter-annual variation in drought conditions. Dry conditions do not register on the index if they are similar to long-term conditions at that time of year — only conditions that are much drier than expected register as negative values. Given random variation in the severity of drought in a given area over time, this shock is plausibly exogenous (Dell et al., 2014).

In order to join the SPEI with yearly panel data, I take the average value of the 1-month time-scale of the SPEI for all 12 months of the calendar year prior to the survey interview. For households surveyed in the 2010-2011 round of the LSMS, I take the average of the SPEI in 2010. For households surveyed in the 2012-2013 round, I take the average of the SPEI in 2012. For households surveyed in the 2014-2015 round, I take the average of the SPEI in 2014.

The variable *Average SPEI*, should be interpreted as the average deviation in climatic water balance in the calendar year prior to the survey interview. I present results using only the 1-month time scale of the SPEI, because shorter time scales better reflect moisture availability on the landscape. Tabetando et al. (2023). According to Vicente-Serrano et al. (2010), "short time scales are mainly related to soil water content and river discharge in headwater areas." Soil water content during the growing season plays a dominant role in root growth and development for crops — short time-scales of the SPEI will most accurately reflect these agriculturally relevant drought conditions (Haj-Amor et al., 2023).

Figure 3 presents the historical variation in the yearly average of the SPEI index. While there is significant variation at any one location from year to year, abnormally dry or wet events occur at a large enough scale to divide many nearby villages from those further away. This poses a threat to the causal interpretation of the SPEI index as an independent variable because it may be correlated with a number of unobservable characteristics about certain regions in Tanzania. I address these concerns in SECTION X with village-level fixed effects.

Each enumeration area is assigned a value of the SPEI index based on its location — presented in Figure 4 — which is then applied to all households in that enumeration area.

3.3 The Living Standards Measurement Survey

Household-level survey data on agricultural activities, credit access and take-up, and consumption outcomes comes from the Living Standards Measurement Survey (LSMS), a panel survey funded by the World Bank and administered in Tanzania by the Tanzania National Bureau of Statistics every 2 years between 2008 and 2014. The survey is clustered by enumeration area (EA), which in rural areas is equivalent to the village and in urban areas is equivalent to the neighborhood. The locations of these EAs are presented in Figure 4. Because this study is focused on households whose primary income source is agriculture, I only use household data from rural enumeration areas. This means that I exclude EAs that the LSMS classifies as urban, and any EAs within 20 miles of Dar es Salaam, the capital of Tanzania. The survey only provides spatial information at the EA-level in order to maintain household privacy, which means that all climatological variables, including those indicates the SPEI and seasonality, are identified at the EA-level. In order to capture the expansion financial services in Tanzania over time, I structure the LSMS data as a panel with three periods: 2010, 2012, 2014. (Though the LSMS was performed in 2008, that round of the survey was missing several variables used in this analysis). The OLS results below have robust standard errors at the village-level. To correct for spatial correlation with unobserved confounds, I then present regressions

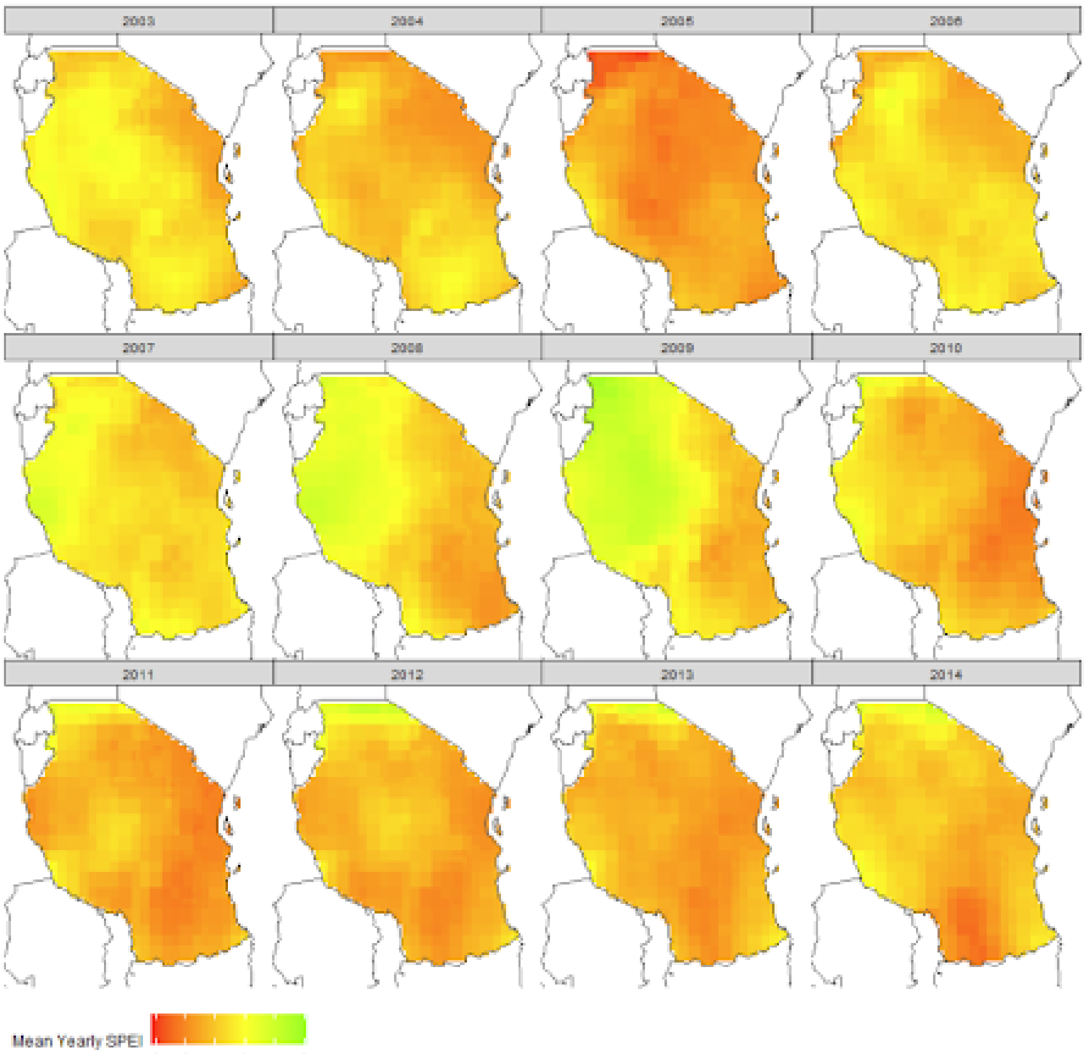

Figure 3: Yearly SPEI in Tanzania, 2003-2014

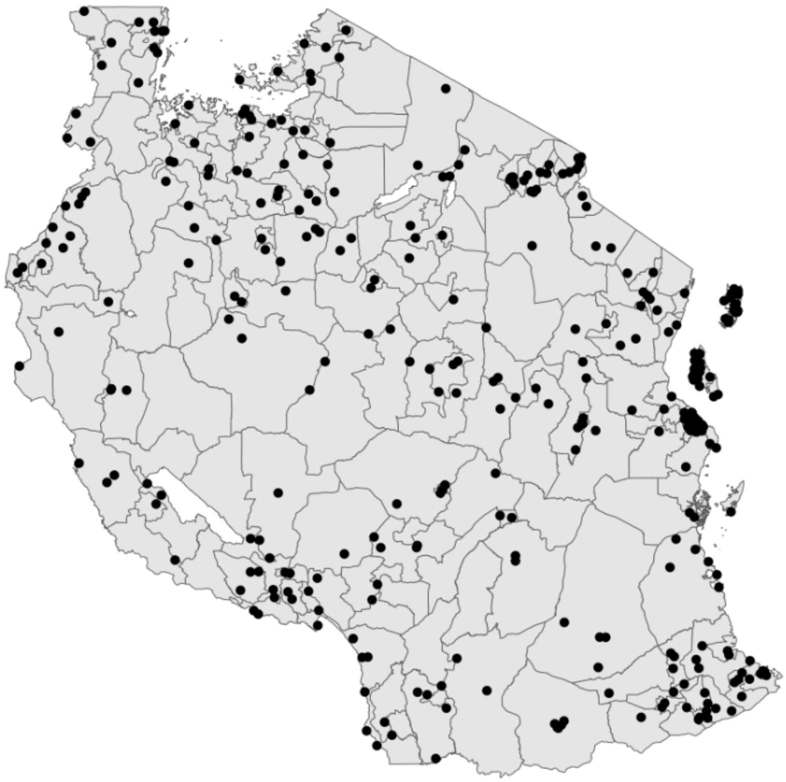

Figure 4: Enumeration Areas in the Living Standards Measurement Survey.

using EA-level fixed effects.

4 Results

The results of this study fall into two categories. First, I present an intermediate set of results that describe seasonality classification for the African continent and analyze seasonal "stability" over time. In other words, I determine how likely it is that an individual year will follow the long-term average seasonal pattern. These results, along with the SPEI, are important for characterizing the degree to which households face agricultural stress as a result of climatic conditions. Next, I combine the seasonality and SPEI data with the LSMS panel and present robust OLS and fixed-effects regressions that estimate the impact of adverse climatic conditions (measured by the SPEI and seasonality data) on the use of financial services.

4.1 Seasonality Classification

Figure 5 below reproduces Figure 1 from Hermann and Mohr (though with different data sources, which produces minor discrepancies in the classifications). It shows that the Sahara experiences arid seasonality;

concentrated regions in the Congo basin, eastern Madagascar, and coastal Guinea experiences year-round humidity, and most of the rest of the continent experiences one unimodal rain season. The region just south of the Horn of Africa, including northeastern Tanzania, experiences a complicated mix of twice-yearly patterns. Some locations, including most of Kenya and nearby areas just south of its border with Tanzania, experience two unimodal wet seasons, while much of Rwanda, Burundi and the rest of northeastern Tanzania experience a single bimodal wet season. In their Figure 3, Hermann and Mohr identify the the two different rainfall regimes in Tanzania by their Tanzanian names: the bimodal *vuli* and *masika* rainy seasons in the northeast, and the unimodal *msimu* rainy season in the rest of the country.

I classify enumerations areas in locations of either two unimodal rainy seasons or one bimodal rainy season — in Hermann and Mohr's language — as experiencing a bimodal rainfall regime. This classification best deals with the ambiguity in the assignment of "dry" months as not causing the end of a rainy season in Hermann and Mohr's system, and it best aligns with the agriculturally relevant considerations for seasonal planting in relation to rainfall patterns. It also most closely aligns with administrative maps that identify the regions that experience *vuli* and *masika* seasons by district in order to provide accurate and agriculturally relevant weather forecasts. These maps include the entire northeast of the country, extending west to the shores of Lake Victoria and south close to Dar es Salaam.

This seasonality assignment, however, does not capture precisely the climatic conditions that would hypothetically cause increased take-up of financial services. If a certain region experiences a predictable and stable bimodal rainfall pattern, then they would be able to plan their agricultural and financial management accordingly. On its own, bimodality should not predict an increased use of financial services. Instead, the year-to-year variability in the seasonal pattern of rainfall may cause unexpected changes in the timing of peak climatic water balance, which can cause agricultural stress and prompt a household to seek financial services.

Hermann and Mohr capture this seasonal instability in their Figure 6. They display the percentage of individual years of rainfall and precipitation data that fall into the same rainfall regime classification as that of the average monthly data on which their Figure 1 is based. The region of dual-seasonality and bimodality in the northeastern part of Tanzania is among the least stable on the content. Hermann and Mohr note that the most frequent fluctuations "in East Africa [are] from dual season to single season or multiple seasons." This means that the area experiencing the *vuli* and *masika* rainy seasons is relatively likely to record only one rainy season or more than two rainy seasons in some years.

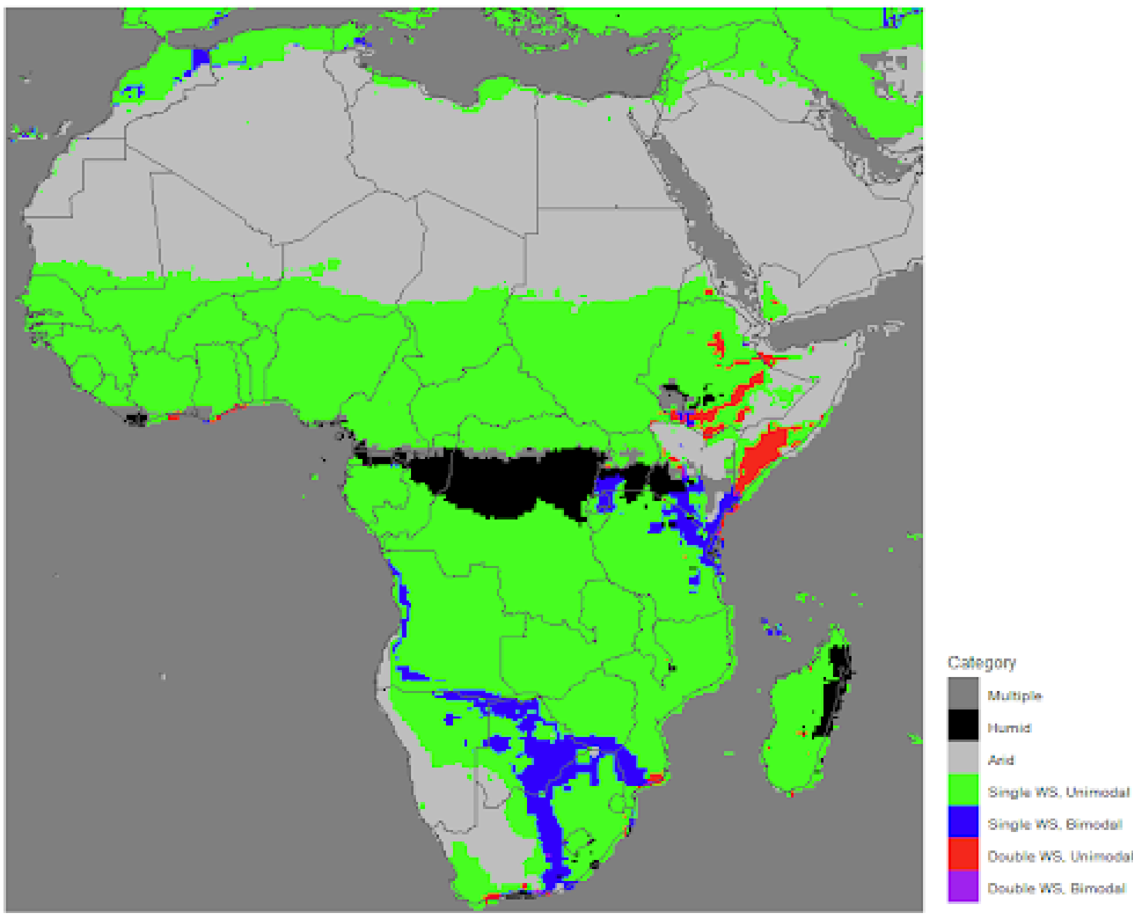

Figure 5: Rainfall regime classification in Africa, 2000-2010.

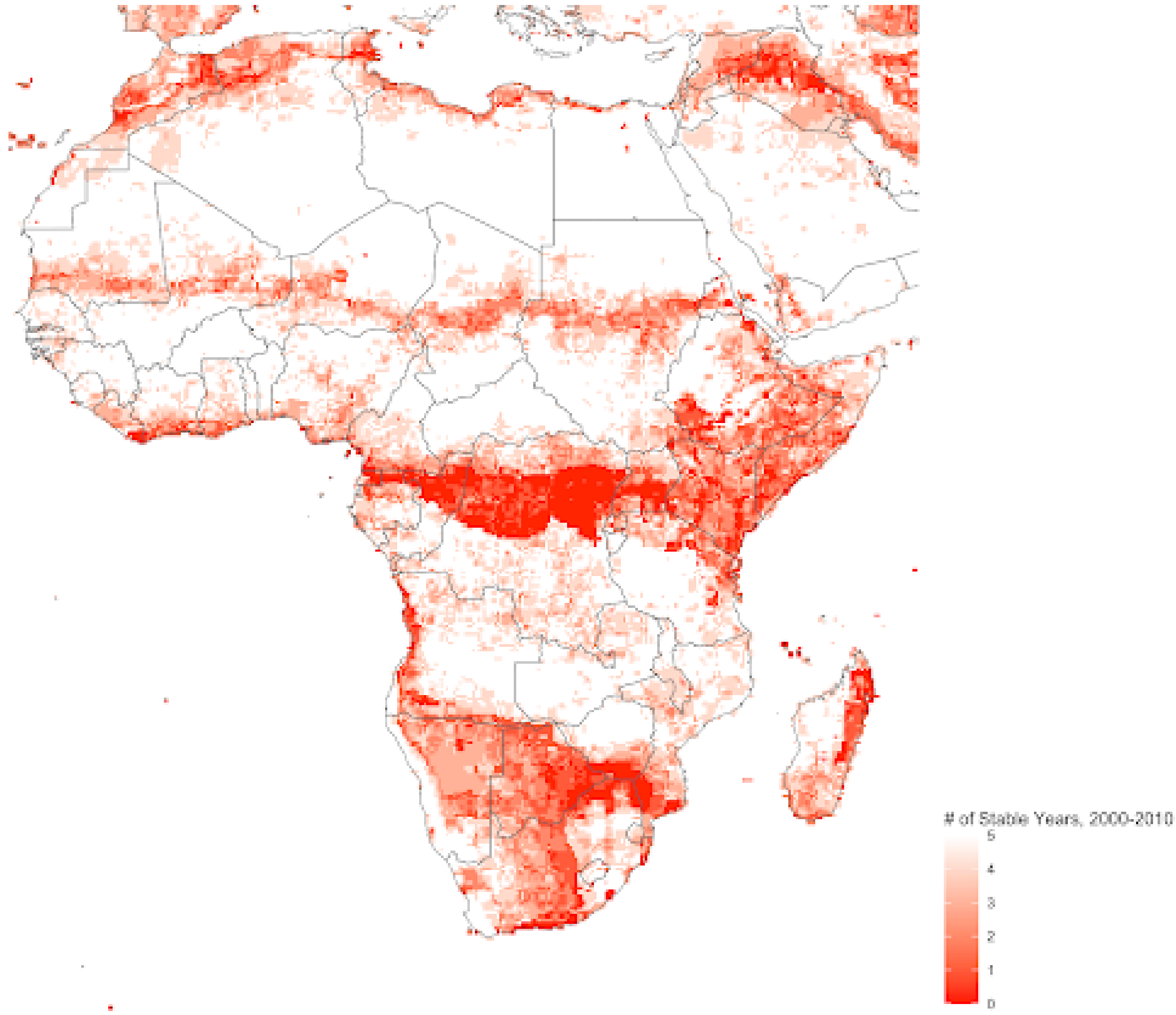

Figure 6: Rainfall regime stability in Africa, 2000-2010.

The regions of Tanzania that experience bimodal rainfall are also much more likely to experience year-to-year instability in the pattern of rainfall, as demonstrated in Figure 6. In the period 2000-2010, the northeastern edge of the country experienced a far greater number of years where the rainfall pattern was different than the mode in that location during the ten-year period. This variable identifies the unexpected climatic conditions that would prompt a household to take up a financial service, in order to receive additional liquidity or intermediation to respond to a drought. During the period of interest for this study (2010-2014), households would expect to experience the pattern that occurred most often during that time, and they would have confidence in the certainty of that expectation to the degree that the pattern was consistent during that time. I use two variables to capture these two expectations. First, *Unstable This Year* indicates whether or not the household's village experienced a pattern of seasonality in the given year (2000, 2012, or 2014) different from the mode 2000-2010. Second, *Long-term Stability* is the proportion of years 2000-

2010 whose seasonality matches the most frequent seasonality in that location. In the regressions presented below, this variable controls for the degree to which households in regularly unstable regions "expect the unexpected" — there is reason to believe households may take up additional financial services as a matter of course because of greater seasonal unpredictability across years, and not because they experience adverse climatic conditions in the given year.

Before moving to the regression models involving the LSMS data, I will briefly explain some of the caveats to this rainfall regime classification.

First and foremost, this discrete categorization approach is an undoubtedly simplistic model of climate water balance as it is experienced by households farming in Tanzania from year to year. Especially in unstable regions, the classification of certain years as either unimodal or bimodal may not reflect other predictable patterns in agriculturally-relevant climatic conditions. I attempt to account for this using the *Long-term Stability* variable in the regressions below, which controls for the long-term level of predictability that a region experiences according to this model of seasonality. Nonetheless, this discrete approach is simplistic and cannot quantitatively measure the degree of anomaly in a given year's seasonal pattern of rainfall.

Second, Hermann and Mohr's method for classifying the rainfall regime relies on the use of temperature as a "proxy" for potential evapotranspiration (PET). According to Walter and Leith, temperature "has been found to be linearly related to annual potential evapotranspiration recorded from lysimeters across different climate zones," therefore "it can be used as a proxy for evapotranspiration..." This results from the fact that average atmospheric thermal energy is the primary control on moisture evaporation on the land surface — temperature is the most important variable when modeling PET. In very dry places, however, like the Saharah and Namib deserts, and in very wet places, like the Congo river basin and western Madagascar, temperature is not a particularly effective proxy for PET. It performs relatively well as a proxy in semi-arid seasonal climates like those found in Tanzania, so the use of temperature in this classification does not pose a meaningful concern for this methodology.

4.2 Variable Description

The seasonal classifications presented above are intermediate results, which contribute the variables *Unstable This Year* and *Long-term Stability* to the regressions models below . In addition to these variables (which are assigned at the village level, the lowest level of the LSMS for which spatial data is provided), I use several household-level variables from the LSMS, described in Table 1. *In Sacco*, *Has Loan*, *Has Bank Account*, and *Has Mobile Money* are the outcome variable of interests. They are each dichotomous variables which describe whether or not households have taken up that financial service in the 12 months prior to the survey date.

The two independent variables of interest are *Unstable This Year* and *Average SPEI*. *Unstable This Year* is dichotomous and indicates whether or not the household's village experienced a rainfall pattern in the given year different from the mode experienced by the village. *Average SPEI* is continuous, and its units are in standard deviations of the log-logistic distribution that describes long-term variability in climatic water balance at each village location. Negative values of this variable can be interpreted as "drier-than-expected" conditions, and positive values can be interpreted as "wetter-than-expected" conditions.

Also included in the regressions are two important control variables. As described above, *Long-term Stability* controls for the long-term expectation of seasonal instability. *Above Median Education* is a dummy variable that indicates whether or not the highest level of education achieved by a member of the household is above the median highest level of education achieved across households, and it controls for the effect of increases in education on the likelihood of the take-up a financial service. Additional education may allow households to overcome some barriers to the accessibility of financial services, whether by gaining the skills required to manage those services, or by connecting households with individuals who can connect them to service providers.

Variable Name	**Description**
In SACCO	Is HH a member of a SACCO?
Has Loan	Has the HH taken a loan in past 12 mo.?
Has Bank Account	Does HH have a bank account?
Has Mobile Money	Does HH use a mobile money service?
Average SPEI	Yearly average SPEI in HH's village
Long-term Stability	# of years of seasonality that match the mode, 2000-2010
Unstable This Year	Does this year's seasonality match the mode?
Above Median Education	Is a member of HH above median education level?
Village N	# of HH in village

Table 1: List of Variables

Characteristic	**2010**, N = 2,147[1]	**2012**, N = 1,817[1]	**2014**, N = 1,463[1]
In SACCO	0.05 (0.22)	0.05 (0.22)	0.05 (0.22)
Has Loan	0.08 (0.27)	0.09 (0.29)	0.11 (0.31)
Has Bank Account	0.09 (0.28)	0.09 (0.29)	0.12 (0.32)
Has Mobile Money	0.07 (0.26)	0.27 (0.44)	0.42 (0.49)
Average SPEI	-0.10 (0.24)	-0.39 (0.20)	-0.23 (0.28)
Long-term Stability	0.72 (0.32)	0.72 (0.32)	0.67 (0.36)
Unstable This Year	0.20 (0.40)	0.26 (0.44)	0.46 (0.50)
Above Median Education	0.15 (0.35)	0.19 (0.39)	0.36 (0.48)
Year	2,010.00 (0.00)	2,012.00 (0.00)	2,014.00 (0.00)
Village N	8 (2)	8 (2)	8 (3)
Has Non-Farm Enterprise	NO DATA	0.32 (0.47)	0.27 (0.44)
# of Sold Animals	2.3 (13.3)	2.4 (14.2)	2.4 (19.4)

Table 2: Statistics by Year

4.3 Difference in Means

Table 2, Table 3, and Table 4 present summary statistics by year and by the two independent variables of interest, respectively.

Financial inclusion, especially via mobile money, dry and unstable climatic conditions, and education all significantly increase from 2010 to 2014, with the largest increases occuring between 2012 and 2014. This is consistent with the hypothesis that adverse climatic conditions increase the take-up of financial services, but it is also consistent with the fact that education and financial inclusion are increasing over time as a result of Tanzania's development over the past several decades. It may be the case that these secular trends are causing the increases measured by the LSMS from 2010 to 2014, and the concomitant increases in climatic adversity are not causally related. I test this hypothesis in the regression models below.

Also note that take-up of SACCOs, commercial loans, and formal bank accounts remain low throughout the period of interest. This is the consistent with the fact that these services face significant barriers to accessibility that are not ameliorated over time.

Table 3 and Table 4 are consistent with the observation that adverse climatic conditions, in terms of seasonal instability and in terms of unexpected dryness, cause increased take-up of some financial services.

Characteristic	**Stable**, N = 3,846[1]	**Unstable**, N = 1,582[1]	*p*-**value**[2]
In SACCO	0.04 (0.20)	0.07 (0.25)	0.076
Has Loan	0.09 (0.28)	0.10 (0.29)	0.7
Has Bank Account	0.09 (0.28)	0.12 (0.33)	0.055
Has Mobile Money	0.21 (0.41)	0.28 (0.45)	0.020
Average SPEI	-0.25 (0.27)	-0.18 (0.25)	<0.001
Long-term Stability	0.80 (0.28)	0.49 (0.33)	<0.001
Above Median Education	0.18 (0.38)	0.32 (0.47)	<0.001
Year	2,011.52 (1.54)	2,012.30 (1.64)	<0.001
Village N	8 (2)	8 (2)	0.6
Has Non-Farm Enterprise	0.34 (0.47)	0.22 (0.41)	<0.001
# of Sold Animals	2.4 (17.0)	2.1 (10.1)	0.4

Table 3: Statistics by Instability

At $\alpha = .05$, seasonal instability is significantly correlated with increased use of bank accounts and mobile money, and unexpected dryness is significantly correlated with increased use of mobile money. Again, the unresponsiveness of SACCO and commercial credit use to these measures of climatic instability is indicative of the significant barriers to accessibility for these services.

4.4 OLS

In order to compare the responsiveness of financial service use to climatic adversity, I present OLS regressions according to the following equation:

$$\mathrm{T}_{it} = c_1 + \beta_1 \mathrm{D}_{vt} + \beta_2 \mathrm{U}_{vt} + \mathbf{C}_{it} + \epsilon_{it} \tag{1}$$

where T_{it} is a dummy variable that equals 1 if household i is using the given financial service in year t and 0 otherwise, D_{vt} is a dummy variable that equals 1 if village v experienced an SPEI value less than -.25 in year t and 0 otherwise, U_{vt} is a dummy variable that equals one if the seasonality in village v during year t is different than its average seasonality and 0 otherwise, S_{vt} is the proportion of years 2000-2010 where the seasonality in village v matched its average seasonality, and $\mathbf{C}_{it}$ is a matrix of control variables. In Table 5,

Characteristic	**SPEI** $> -.25$, N = 2,751[1]	**SPEI** $< -.25$, N = 2,700[1]	p**-value**[2]
In SACCO	0.06 (0.24)	0.04 (0.20)	0.094
Has Loan	0.08 (0.28)	0.10 (0.30)	0.3
Has Bank Account	0.10 (0.30)	0.09 (0.29)	0.6
Has Mobile Money	0.20 (0.40)	0.26 (0.44)	0.011
Average SPEI	-0.02 (0.17)	-0.45 (0.16)	<0.001
Long-term Stability	0.68 (0.30)	0.73 (0.35)	<0.001
Unstable This Year	0.32 (0.47)	0.26 (0.44)	0.004
Above Median Education	0.23 (0.42)	0.20 (0.40)	0.2
Year	2,011.43 (1.75)	2,012.07 (1.39)	<0.001
VillageN	9 (2)	8 (2)	<0.001
Has Non-Farm Enterprise	0.28 (0.45)	0.31 (0.46)	0.4
# of Sold Animals	1.8 (8.2)	3.0 (20.1)	<0.001

Table 4: Statistics by SPEI

$\mathbf{C}_{it}$ includes only *Long-term Stability*, which indicates on a scale from 0 to 1 how predictable the seasonal pattern of rainfall is for each village.

The results in Table 5 confirm the pattern visible in the difference-in-means tables, but not without complication. Mobile money is the only service that significantly responds to climatic adversity at $\alpha = .05$. Net of the effect of instability, an increase by one standard deviation in the severity of dry conditions will increase the likelihood of taking up mobile money by 0.16. Net of moisture conditions and long-term instability, instability in the present year no longer has a significant effect in the OLS models. Only long-term instability significantly increases the take-up of mobile money. This would suggest that households "expect the unexpected" and are more likely to use mobile money as a matter of course, because they live in a region with a higher degree of instability in the pattern of seasonal rainfall.

However, these OLS results cannot be interpreted as causal because of spatial omitted variable bias (OVB). Dryness and seasonal instability are both regionally correlated in any given year, and it may the case that these results are only demonstrative of regional differences in financial inclusion across Tanzania. It may be the case that the northeast regions of the country happen to be more developed and financially included for a variety of unobservable reasons, and so these OLS results erroneously overestimate the response of financial services to year-to-year climatic adversity.

	(1) In SACCO	(2) Has Loan	(3) Has Bank Account	(4) Has Mobile Money
(Intercept)	0.069**	0.080**	0.148***	0.264***
	(0.022)	(0.029)	(0.039)	(0.053)
Unstable This Year	0.018	0.009	0.011	0.040
	(0.024)	(0.020)	(0.029)	(0.039)
Average SPEI	0.041	−0.029	0.017	−0.160**
	(0.037)	(0.028)	(0.036)	(0.050)
Long-term Stability	−0.020	0.003	−0.072+	−0.115*
	(0.025)	(0.032)	(0.042)	(0.058)
Num.Obs.	5407	5407	5406	5407
R2	0.006	0.001	0.008	0.021
R2 Adj.	0.006	0.000	0.008	0.021
AIC	1523.3	4469.2	4692.8	8497.9
BIC	1556.2	4502.2	4725.8	8530.9
RMSE	0.22	0.26	0.31	0.38
Std.Errors	by: Village	by: Village	by: Village	by: Village

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 5: Naive OLS

4.5 Fixed Effects

In order to control for spatial OVB, I estimate the "within-village" effect of climatic adversity on the take-up of mobile money using village-level fixed effects. This approach is equivalent to running the OLS model for each village individually and then averaging the resulting effect sizes across all villages. In order to ensure valid within-village variation between stable and unstable years, these fixed-effect models must be run on subsets of the sample. In the the following regressions, $\mathbf{C}_{it}$ includes *Long-term Stability* and *Above Median Education.*

First, I run the fixed effects model on all villages with only *Average SPEI* and other controls as right-hand-side variables according to Equation 2. This is possible to perform on all villages in the sample because *Average SPEI* is continuous and varies from year to year within all village.

$$\mathrm{T}_{it} = c_1 + \beta_1 \mathrm{D}_{vt} + \mathbf{C}_{it} + \mathbf{V}_v + \epsilon_{it} \tag{2}$$

Table 6 shows that, net of spatial variation and household education, a one-standard deviation increase in the level of dryness experienced by a household is associated with a .328 increase in the likelihood that that household uses a mobile money service in the same year.

	(1)	(2)	(3)
Average SPEI	−0.143***	−0.340***	−0.328***
	(0.021)	(0.027)	(0.027)
Above Median Education			0.210***
			(0.014)
Village FEs	No	Yes	Yes
Num.Obs.	5407	5407	5407
R2	0.008	0.259	0.290
R2 Adj.	0.008	0.192	0.225
AIC	8565.5	7888.5	7662.2
BIC	8585.3	10 876.3	10 656.5
Log.Lik.	−4279.774	−3491.258	−3377.081
F	45.547	3.845	4.474
RMSE	0.37	0.33	0.32
Std.Errors	by: Village	by: Village	by: Village

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 6: Fixed effects, complete sample, response variable: *Has Mobile Money*

However, the variable *Unstable This Year* is dichotomous and so varies from year to year only in some villages. The villages that do not experience variation in *Unstable This Year* must be excluded from the fixed-effects models that include *Unstable This Year* as a right-hand-side variable because comparisons between stable and unstable years cannot be made within that village. Table 7 shows the results of these models, according to Equation 3.

$$\mathrm{T}_{it} = c_1 + \beta_1 \mathrm{D}_{vt} + \beta_2 \mathrm{U}_{vt} + \mathbf{C}_{it} + \mathbf{V}_v + \epsilon_{it} \tag{3}$$

Two conclusions can be drawn from these tables. First, OVB on the coefficient of *Average SPEI* in the naive regression in Table 5 is positive in comparison to the coefficients in Table 6 and Table 7, which means that unobserved spatial variation was positively correlated with the outcome *Has Mobile Money.* Even after controlling for *Unstable This Year* in Table 7, *Average SPEI* still has a more negative effect than that predicted in the naive regression. A standard-deviation increase in the intensity of dry conditions makes households on average .285 more likely to use a mobile money service, after controlling for seasonal instability, education, and unobserved spatial variation.

Second, OVB in the naive OLS models was negative on the coefficient for *Unstable This Year* and positive on the coefficient for *Long-term Stability.* As a result, seasonal instability in the given year has a positive effect on the take-up of mobile money: a household facing seasonal instability in the given year is .074 more likely to use a mobile money service in that year, after controlling for unexpected dry conditions, the

	(1)	(2)	(3)
Unstable This Year	0.153***	0.080***	0.074**
	(0.023)	(0.023)	(0.022)
Average SPEI	0.012	−0.258***	−0.285***
	(0.049)	(0.064)	(0.062)
Above Median Education			0.269***
			(0.027)
Village FEs	No	Yes	Yes
Num.Obs.	1427	1427	1427
R2	0.029	0.299	0.349
R2 Adj.	0.028	0.237	0.291
AIC	2391.9	2153.8	2049.6
BIC	2413.0	2769.6	2670.7
Log.Lik.	−1191.958	−959.887	−906.812
F	21.444	4.857	6.055
RMSE	0.38	0.32	0.32
Std.Errors	by: Village	by: Village	by: Village

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 7: Fixed effects, only villages with year-to-year variation in seasonal stability, response variable: *Has Mobile Money*

long-term level of seasonal instability, and the education level of the household.

For a binned specification of the SPEI (which tests for possible non-linear effects of unexpectedly dry/wet conditions) and a placebo test on urban households, see the Appendix. In sum, both unexpectedly dry conditions (*Average SPEI*) and unexpected changes in the seasonal pattern of rainfall (*Unstable This Year*) cause a significant increase in the likelihood that a household uses mobile money.

4.6 Caveats

In order to strengthen these results, I test for a variety of potential caveats. First, I determine whether concomitant increases in drought, seasonal instability, and mobile money take-up are the result of a secular trend of economic development in Tanzania, rather than a direct causal relationship. Second, I test for the take-up of non-farm sources of income in response to drought or seasonal instability. It is important to determine whether financial services are the only strategy that households use to respond to climatic adversity, or if there is evidence that others are used. Third, I discuss the potential for individuals or entire households to migrate in response to regionally-correlated climatic adversity (though I do not test for this phenomenon because of a lack of migration data in the LSMS). Last, I clarify that these results do not directly describe how households use mobile money in response to drought — in order to answer that question, transaction-level data from mobile money providers would be required.

Secular Trends

In order to strength the causal interpretation of the fixed-effects results presented above, I test the null hypothesis that the relationship between adverse climatic conditions (*Average SPEI* and *Unstable This Year*) and the take-up of mobile money are the result of a coincidence between secular trends in increasing financial inclusion and increasing climate-changed caused dryness and seasonal instability in Tanzania. What appears to be a causal effect in the fixed-effects models above may only reflect these secular trends. The fact that the above results persist after controlling for spatial unobservables and changes in education strengthen the causal interpretation, but they are not proof-positive that the take-up of mobile money would respond similarly if climatic conditions became less adverse over time. In this case, if the models above are to be interpreted causally, we would expect the take-up of mobile money to defy the secular trend and decline over time even if climatic conditions become less adverse from year to year.

In order to test the null hypothesis of secular trends, I filter the dataset on only those households who experience the "anti-trend" in climatic conditions from 2010 to 2014. The regression in column (1) of TABLE includes only those households that move from unstable to stable in either 2010/2012 or 2012/2014. Similarly, the regression in column (2) includes only those households who experience moisture conditions in each year that are wetter than the previous ($SPEI_{2010} < SPEI_{2012} < SPEI_{2014}$).

After subsetting the data in this way and running fixed-effects models according to Equation 3, I can reject the null hypothesis that the relationship between unexpectedly dry conditions (*Average SPEI*) is only related to the take-up of mobile money as a result of coincedental secular trends. Instead, it appears that, among households where moisture conditions become wetter over time, take-up of mobile money declines over time. This results in a coefficient on *Average SPEI* of the same sign and roughly the same magnitude as those in Table 6, meaning that the same effect identified in the entire sample holds among only the anti-trend households.

The same cannot be said for the effect of seasonal instability on the take-up of mobile money. Among households who experience a "stable" season after experiencing an "unstable" season — the anti-trend for seasonal rainfall patterns — the effect of *Unstable This Year* is no longer significantly predictive of the take-up of mobile money, at $\alpha = .1$. This means that I cannot reject the null hypothesis that seasonal instability and the take-up of mobile only appear to be related as a result of coincidental nationwide secular trends.

	(1)	(2)
Unstable This Year	-0.010	0.139
	(0.040)	(0.104)
Long-term Stability	-0.124	-2.912
	(1.723)	(2.370)
Average SPEI	-0.283*	-0.367***
	(0.128)	(0.088)
Above Median Education	0.278***	0.199***
	(0.040)	(0.049)
Village FEs	Yes	Yes
Subset	Unstable	Drought
Num.Obs.	588	298
R2	0.312	0.435
R2 Adj.	0.250	0.379
AIC	1028.2	433.9
BIC	1247.0	541.1
Log.Lik.	-464.076	-187.936
RMSE	0.34	0.39
Std.Errors	by: Village	by: Village

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 8: Test for secular trends, response variable: *Has Mobile Money*

Non-Farm Income

In addition to financial services, households may also use other sources of non-farm income to smooth their consumption in response to climatic adversity. I examine the effects of drought and and seasonal instability on two sources of non-farm income.

The first source is not literally "non-farm," but it is detached from the seasonal cycle of agriculture so it can be considered a non-farm source of income for the purposes of this paper. Livestock are a store of value for smallholder farms, and when they lose agricultural income as a result of a drought, evidence suggests that smallholders may sell livestock to replace the lost liquidity from crop sales (Udry, 1995).

However, I found no evidence of this occurring in Tanzania 2010-2014 (Tables 9 and 10, according to Equations 2 and 3, respectively, where T is the number of animals sold by household i in year t). Without fixed-effects, there is a positive correlation between drought and the number of sold animals. But with fixed effects, there is no longer a significant relationship between drought and the sale of animals. In neither specification is seasonal instability related to the sale of animals. This pattern of results suggests that, as a matter of course, households that tend to be in drier areas tend to sell more animals, for any number of climatic reasons. Animal husbandry is water-intensive and households in dry areas may exchange animals more frequently as a result. However, there is no evidence that, within villages, drought causes households to sell their animals with increased likelihood.

	(1)	(2)	(3)
Average SPEI	−2.173*	0.385	0.402
	(1.090)	(0.315)	(0.318)
Above Median Ed			0.406
			(0.309)
Village FEs	No	Yes	Yes
Num.Obs.	5201	5201	5201
R2	0.001	0.766	0.766
R2 Adj.	0.001	0.744	0.744
AIC	45 642.8	38 983.7	38 983.9
BIC	45 662.5	41 881.7	41 888.4
RMSE	19.95	12.85	12.85
Std.Errors	by: Village	by: Village	by: Village

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Effect of drought on livestock sales, response variable: *Sold Livestock*

	(1)	(2)	(3)
Unstable This Year	−0.201	−0.469	−0.469
	(0.485)	(0.345)	(0.347)
Average SPEI	−2.146*	0.311	0.327
	(1.044)	(0.270)	(0.274)
Above Median Ed			0.406
			(0.310)
Village FEs	No	Yes	Yes
Num.Obs.	5201	5201	5201
R2	0.001	0.766	0.766
R2 Adj.	0.001	0.744	0.744
AIC	45 644.7	38 984.6	38 984.8
BIC	45 670.9	41 889.2	41 895.9
RMSE	19.94	12.85	12.84
Std.Errors	by: Village	by: Village	by: Village

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Effect of drought and seasonal instability on livestock sales, response variable: *Sold Livestock*

	(1)	(2)	(3)
Average SPEI	−0.131	−0.050	−0.064
	(0.086)	(0.113)	(0.111)
Above Median Ed			0.077+
			(0.039)
Village FEs	No	Yes	Yes
Num.Obs.	2634	2634	2634
R2	0.005	0.228	0.232
R2 Adj.	0.004	0.073	0.077
AIC	4997.5	5205.7	5195.4
BIC	5015.1	7803.0	7798.5
RMSE	0.47	0.42	0.42
Std.Errors	by: Village	by: Village	by: Village

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 11: Effect of drought on take-up of non-farm enterprises, response variable: *Has Non-Farm Enterprise*

In addition to selling livestock, households may take up any number of other non-farm income generating activities in order to smooth their income in response to a drought. The LSMS measures whether a household, in the past year, has received any income from a non-agricultural business enterprise.

Hypothetically, these non-farm enterprises would respond to drought similarly to costly and relatively inaccessible forms of credit like commercial loans. For a household to begin a non-farm enterprise, they would need access to the necessary capital, labor, and liquidity to develop this new non-farm source of income. Indeed, they may also require access to commercial credit in order to overcome capital or liquidity constraints. For these reasons, I predict that drought and seasonal instability will not cause a significant increase in the likelihood that a household engages in a non-farm business enterprise. In Tables 11 and 12 (according to Equations 2 and 3, respectively, where T is a dichotomous variable indicating whether or not household i in year t engaged in an non-agricultural income generating activity), I test this hypothesis.

These tables show that drought has no significant effect on the take-up of non-farm enterprises, net of spatial variation and education. Table 12 suggests that, in fact, that seasonal instability has a moderate negative effect on the take-up of non-farm enterprises. This may occur because the unexpected loss of income from seasonal instability prevents households from building the necessary liquidity and taking the necessary risks to engage in a profitable non-farm enterprise.

Note that these data come only from 2012 and 2014, because the LSMS did not include the non-farm enterprise module in the 2010 iteration of the survey. Consequently, these results must be interpreted with a degree of caution. These village fixed-effects regressions on panel data with only two periods amount to means comparison within each village between the first and second period. Idiosyncratic changes from 2012

	(1)	(2)	(3)
Unstable This YEar	−0.113**	−0.168**	−0.153**
	(0.036)	(0.057)	(0.052)
Average SPEI	−0.072	−0.046	−0.060
	(0.076)	(0.107)	(0.106)
Above Median Ed			0.074+
			(0.040)
Village FEs	No	Yes	Yes
Num.Obs.	2634	2634	2634
R2	0.018	0.230	0.233
R2 Adj.	0.017	0.075	0.079
AIC	4965.8	5202.2	5192.7
BIC	4989.3	7805.4	7801.8
RMSE	0.47	0.42	0.42
Std.Errors	by: Village	by: Village	by: Village

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Effect of drought and seasonal instability on take-up of non-farm enterprises, response variable: *Has Non-Farm Enterprise*

to 2014 may have an outsized influence on the coefficients in Tables 11 and 12.

Household Composition and Migration

Unfortunately, the LSMS does not publish information about household composition and migration in their panel data products, so I cannot test the responsiveness of these characteristics to climatic instability. Nonetheless, it is important to note that this may be an important mechanism by which households respond to spatially correlated shocks to income like agroclimatic adversity. If the households in a certain region all suffer from a drought, they may decide to send individual family members to other regions in order to recoup income and decouple their wellbeing from the climatic conditions in their local area. If conditions become severe enough, households may also decide to migrate away from that area. Indeed, Kubik and Maurel (2016) find that "a 1 per cent reduction in agricultural income induced by weather shock increases the probability of migration by 13 percentage points on average within the following year" in the Tanzanian setting. I am unable to test this phenomenon directly because of the limits of the LSMS data, but it is safe to assume that this another potential means for households to smooth their consumption in response to climatic adversity.

However, it is also safe to assume that a household's decision to migrate is constrained by household liquidity and a variety of risks. As a result, migration as a strategy to mitigate agricultural income losses may only be available to those households with adequate liquidity, education, or information to overcome those constraints. Mobile money remains uniquely unencumbered by these constraints.

Mobile Money Transaction Data

Without mobile money transaction data — like that used by Economides and Jeziorski (2017) — I cannot draw any specific conclusions about household-level use of mobile money. The results presented here only show that climatic adversity makes household more likely to use mobile money; they do not neccesarily show that households use mobile money mechanistically to respond to climatic adversity. Based on Economides and Jeziorski (2017), it is reasonable to assume that they do, because urban-rural remittances were found to be the most common use-case for mobile money in Tanzania. However, the evidence presented in this paper does not explicitly show that households use these remittances in response to climatic adversity.

5 Conclusion

Adverse climatic conditions cause an increase in the likelihood of households in rural Tanzania to use mobile money. In particular, unexpectedly dry soil moisture conditions cause statistically and substantively significant increases on the take-up of mobile money, and this effect holds even among households who defy secular increases in dryness over the period of interest. Similar evidence exists from village-level fixed-effect models for a causal relationship between seasonal instability and the take-up of mobile money, but I cannot reject the null hypothesis that this relationship is the result of nationwide secular trends.

These results are consistent with the state of financial inclusion in Tanzania, and across the developing world. Traditional financial institutions face unfavorable regulation, infrastructural barriers, and uniquely costly information asymmetries in developing that prevent the provision of optimal financial intermediation for most rural farming households. Insurance markets are incredibly rare, and sub-optimal alternatives like commercial credit and formal bank accounts rarely overcome these barriers to accessibility. Financial services that attempt to overcome some of these barriers while remaining connected to the formal financial system — in this study, SACCOs — appear to remain largely hamstrung by those barriers.

Mobile money, which exists outside of the formal financial system and experiences much lower capital requirements and operational costs as a result, offers a useful and relatively popular alternative to traditional financial services. I have shown that, in addition to high rates of take-up in the cross-section, mobile money take-up also increases significantly in response to unexpectedly adverse climatic conditions. Because it is relatively inexpensive and easy to access, mobile money provides the most common mechanism by which rural Tanzanian households financially intermediate when faced with agricultural hardship. Mobile money connects rural households with family members in other regions of Tanzania, who may not have suffered the same climatic adversity and are able to send remittances using mobile money. It also allows households to inexpensively transfer money to other mobile money users, easily exchange agricultural assets for liquidity stored in their mobile money account, and safely travel with large amounts of money. All of these functions may be crucial for households to withstand agricultural hardship by providing additional liquidity, allowing households to sell assets and to buy necessities easily, and ensuring that travel to make unexpected purchases is theft-free. Evidence suggests that the first of these functions is the most common, in the form of liquid remittances sent by far-away family members often living in the urban areas.

This study prompts two areas of further research. First, the regression models presented above would be improved by a continuous variable for seasonal instability. In the climatology literature, existing approaches to seasonality classification do no statistically define year-to-year anomalies in the seasonal pattern of rainfall. Such a method would perform the same function as the variables *Unstable This Year* and *Long-term Stability* and more precisely describe the how anomalous a given year's pattern of rainfall was. This would improve these results in two ways. First, it would obviate the need to include only those households that experience variation in *Unstable This Year* in the models that test for the effect of seasonal instability. Second, it would offer a more precise identification of seasonal instability as it is experienced by farming households, who no doubt have intimate knowledge of the agro-ecological conditions they experience over the course of many years. My approach, using the *Unstable This Year* and *Long-term Stability* variables, represents only a small step towards an effective model of these conditions.

Second, these results could be corroborated and improved upon by spatially-linked transaction-level data from a mobile money provider in Tanzania, as was used in Economides and Jeziorski (2017). These authors study the differential use of the various feature options of mobile money, but not with reference to climatic conditions. Using these data and my approach to drought modeling, it would be possible to determine which transactions are most common during and after drought. The hypothesis that remittances from family members living elsewhere are the primary way households use mobile money during climatic adversity could be empirically tested, and the timing of financial behavior during and after drought could be studied with more granularity.

6 Appendix

6.1 Binned SPEI

In order to test for potential non-linear effects of dryness, I specify the variable *Average SPEI* as a set of three dummy variables and one excluded category, according to Figure 7. The results of these regressions are presented in Tables 13 and 14, according to Equations 2 and 3, respectively, where T is a dichotomous variable indicating the take-up of mobile money by household i in year t.

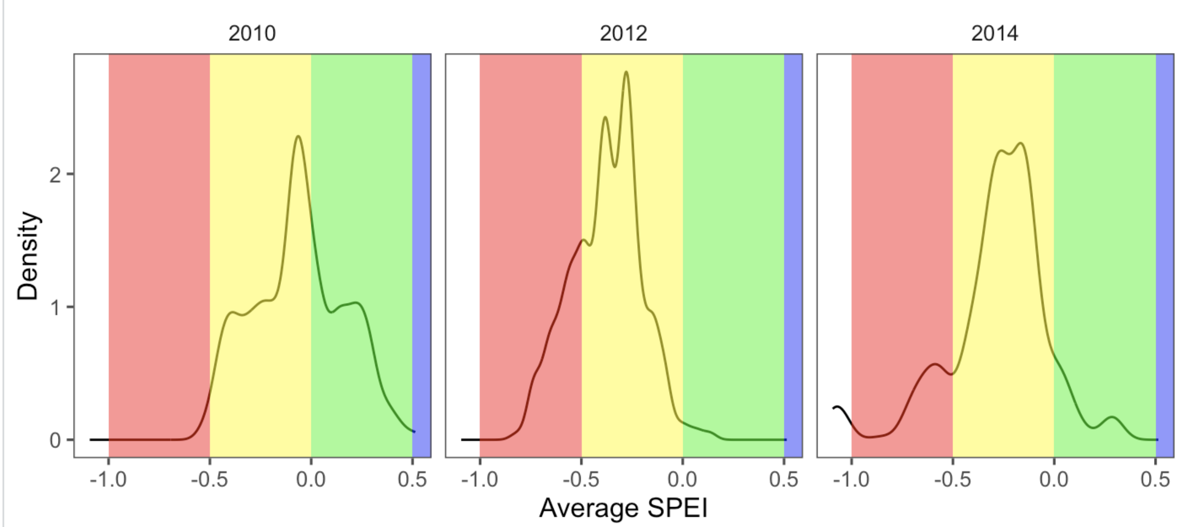

Figure 7: Bins specified for *Average SPEI* in Tables 13 and 14 ($0 < SPEI < .5$ is the excluded category).

	(1)	(2)	(3)
Above Median Ed			0.199***
			(0.037)
$-.5 < AverageSPEI < 0$	0.052+	0.061**	0.068**
	(0.029)	(0.023)	(0.023)
$.5 < AverageSPEI < 2$	−0.186***	−0.062**	−0.030
	(0.024)	(0.023)	(0.022)
Village FEs	No	Yes	Yes
Num.Obs.	5201	5201	5201
R2	0.004	0.246	0.274
R2 Adj.	0.004	0.177	0.207
AIC	8033.0	7461.7	7270.1
BIC	8059.3	10 366.2	10 181.2
RMSE	0.37	0.32	0.32
Std.Errors	by: Village	by: Village	by: Village

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001
Excluded category of the SPEI: $0 < SPEI < 0.5$

Table 13: Effect of drought and seasonal instability take-up of mobile money, response variable: *Has Mobile Money*. Categorical specification of the SPEI.

	(1)	(2)	(3)
Unstable This Year		0.104**	0.103**
		(0.034)	(0.033)
Above Median Ed			0.199***
			(0.036)
$-.5 < AverageSPEI < 0$	0.052+	0.063**	0.070**
	(0.029)	(0.023)	(0.022)
$.5 < AverageSPEI < 2$	−0.186***	−0.164***	−0.131***
	(0.024)	(0.040)	(0.039)
Village FEs	No	Yes	Yes
Num.Obs.	5201	5201	5201
R2	0.004	0.250	0.277
R2 Adj.	0.004	0.180	0.210
AIC	8033.0	7440.4	7248.4
BIC	8059.3	10 351.5	10 166.1
RMSE	0.37	0.32	0.32
Std.Errors	by: Village	by: Village	by: Village

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001
Excluded category of the SPEI: $0 < SPEI < 0.5$

Table 14: Effect of drought and seasonal instability take-up of mobile money, response variable: *Has Mobile Money*. Categorical specification of the SPEI.

These results confirm those found in the main body of this paper: both drought and seasonal instability cause households to take up mobile money with a greater likelihood. Because most households in Tanzania experienced expected or moderately unexpectedly dry conditions (roughly $-1 < AverageSPEI < 0$) over the course of the period of interest, I do not find any evidence for non-linear effects of moisture conditions. If some households experienced extraordinarily wet conditions, then we might expect to find increased take-up of mobile money among those households as well, because of the negative shocks to income associated with extremely wet events like rainstorms or floods. Those events, however, did not occur among the households in this dataset. As a result, negative values of the SPEI ($-.5 < SPEI < 0$) contribute to an increased likelihood to take up mobile money, and positive values of the SPEI contribute to a decreased likelihood to take up mobile money ($.5 < AverageSPEI < 2$). This pattern is most clearly visible in the coefficients presented in Table 14, where, after controlling for seasonal instability, education, and spatial variation, the category $-.5 < AverageSPEI < 0$ is significantly more likely to take up mobile money and the category $.5 < AverageSPEI < 2$ is significantly less likely to take up mobile money.

6.2 Placebo Test

I also present regression results for Tanzanian households in urban areas, in order to compare with the main results of this paper, which only apply to households in rural areas. This resembles a placebo test, because there are some reasons to think that the effect of climatic adversity on the take-up of mobile-money may only occur in rural areas, where households face significant constraints to engage in non-farm income generating activities. However, it turns out that the effect of climatic adversity on the take-up of mobile money (in terms of both drought and seasonal instability) holds in urban areas, likely because many households in urban areas still rely at least partially on agriculture as a source of income, and many urban households are linked to the surrounding rural areas by family connections and may take-up mobile money in order to send remittances to those nearby rural households when drought occurs. Because I do not have data on familial relationships between households, I cannot test for these effects specifically. However, Tables 15 and 16 (according to Equations 2 and 3, respectively, where T is a dichotomous variable indicating the take-up of mobile money by household i in year t) show that urban households experience the same effects of climatic adversity on mobile money take-up as rural households.

	(1)	(2)	(3)
Average SPEI	−0.146***	−0.333***	−0.322***
	(0.022)	(0.029)	(0.028)
Above Median Ed			0.212***
			(0.015)
Village FEs	No	Yes	Yes
Num.Obs.	5037	5037	5037
R2	0.008	0.219	0.251
R2 Adj.	0.008	0.167	0.201
AIC	7986.5	7414.3	7200.6
BIC	8006.1	9482.6	9275.4
Log.Lik.	−3990.244	−3390.171	−3282.288
F	42.783	4.194	5.016
RMSE	0.37	0.33	0.33

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Effect of drought on take-up of mobile money, response variable: *Has Mobile Money*. Urban households.

	(1)	(2)	(3)
Unstable This Year	0.162***	0.089***	0.084***
	(0.025)	(0.025)	(0.024)
Average SPEI	0.076	−0.236**	−0.273***
	(0.054)	(0.073)	(0.071)
Above Median Ed			0.266***
			(0.028)
Village FEs	No	Yes	Yes
Num.Obs.	1290	1290	1290
R2	0.033	0.258	0.310
R2 Adj.	0.031	0.212	0.267
AIC	2195.8	1999.7	1908.0
BIC	2216.4	2397.3	2310.6
Log.Lik.	−1093.882	−922.874	−875.978
F	21.627	5.623	7.167
RMSE	0.38	0.33	0.32

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Effect of drought and seasonal instability on take-up of mobile money, response variable: *Has Mobile Money*. Urban households.

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