The Role of Mobile Money on Household Food Security During Drought Shocks: An Evaluation of Key Pathways

Olukorede Abiona

Working Paper 009 -2025

Bringing Rigour and Evidence to Economic Policy Making in Africa

AFRICAN ECONOMIC RESEARCH CONSORTIUM
CONSORTIUM POUR LA RECHERCHE ÉCONOMIQUE EN AFRIQUE

The Role of Mobile Money on Household Food Security During Drought Shocks: An Evaluation of Key Pathways

By

Olukorede Abiona
Macquarie University Centre for the Health Economy (MUCHE)
Macquarie University Business School (MQBS) and
Australian Institute of Health Innovation (AIHI).

AERC Working Paper 009-2025
African Economic Research Consortium, Nairobi
May 2025

THIS RESEARCH STUDY was supported by a grant from the African Economic Research Consortium. The findings, opinions and recommendations are, however, those of the author and do not necessarily reflect the views of the Consortium, its individual members, or the AERC Secretariat.

Published by: The African Economic Research Consortium
P.O. Box 62882 – City Square
Nairobi 00200, Kenya

Acknowledgments

I wish to express my deep appreciation to African Economic Research Consortium (AERC) for providing financial support to carry out this research – Grant No. RT22517. I am also grateful to the resource persons and members of AERC's thematic group on Agriculture, Climate Change and Natural Resource Management for various comments and suggestions that helped the evolution of this study from its inception to completion. I thank seminar participants at the Australasian Development Economics Workshop (ADEW) for a very useful feedback session on the paper. I would like to express further appreciation to two anonymous referees for very insightful comments and feedback which were instrumental to the transformation of the paper during the review process. The findings and opinions expressed in this paper are exclusively those of the author and cannot be attributed to AERC in any way. The author is also solely responsible for content and any errors.

Abstract

This paper investigates the interaction between mobile money use and exposure to drought events among smallholder farmers in rural Tanzania. We examine the impact of drought on household food security for mobile money adopters relative to non-adopters. To investigate this pattern, we use household and agricultural datasets from the Tanzanian National Panel surveys (TNPS) between 2010 and 2020 in a difference-in-difference framework. Our findings demonstrate an added advantage of drought-mitigating strategies for adopter households by way of strategic farm inputs to improve yields as pathways. This paper contributes to the literature by building unique empirical evidence relating to innovative behaviours from mobile money adoption to support agricultural investment for sustainable household food security over a long-term period. Access to credits is revealed as the channel of transmission.

JEL Classifications: D15, G23, G52, Q12, Q14, Q16

Keywords: drought, mobile money, agricultural investments, insurance, household food security

1. Introduction

Smallholder farmers in low-income countries face frequent regimes of weather events that impact their welfare outcomes. This impact is persistent within sub-Saharan African countries due to a lack of universal support programs during weather shocks. Tanzania, the country of interest in this study, is a predominantly an agrarian economy encompassing approximately 80 percent of its labour force (USAID, 2013). The agricultural sector also accounts for around 28 percent of Tanzania's Gross Domestic Product (USAID, 2013). Low levels of agricultural productivity emanating from extreme weather patterns put significant pressure on the economic sustainability of Tanzania both from the household and macro-economic perspectives. At the micro level, households engage in temporary adaptation strategies such as migration across local communities to navigate persistent weather shocks (Kubik and Maurel, 2016, Kangalawe et al., 2017). These measures present only a temporary mitigation pathway and are not sustainable for agricultural practice. Tanzania is frequently exposed to extreme weather patterns reflected to six drought events over three decades[1] – between 1983 and 2013 (USAID, 2013). There is also a projection that climate change may result in adverse precipitation and temperature levels within the country putting further pressure on agricultural practices. Annual rainfall pattern is predicted to vary significantly between a 1 percent decrease and an 18 percent increase by 2060 while temperature levels may rise by up to 2.7°C (USAID, 2013). The resultant effect of this weather pattern is a persistent decline in farm productivity which may cascade to other adverse welfare outcomes such as food insecurity (Stathers et al., 2013).

The impact of weather shocks on the agricultural productivity of smallholder farmers in Tanzania is worsened by a lack of access to credit facilities. This gap is created by the weak coverage of formal financial services, especially for households living in rural areas (Girabi and Mwakaje, 2013). This infrastructural deficit also imposes some limitations on the opportunities to invest in climate adaptation activities at the household level and deters timely response towards climate resilience for sustainable agricultural practice by smallholder farmers. In general, the composition of the financial inclusion index within Tanzania is low compared to similar sub-Saharan African countries (World Bank, 2014; 2016). Only 17 percent of adults had access to a bank account in 2012 while approximately 2 bank branches and ATMs were

[1] Further statistics show a decrease of 3.3 percent per decade in Tanzanian rainfall patterns from 1960-2006 and an average annual increased by 1°C over the same period.

available per 100,000 population between 2004 and 2011 (IMF, 2012). Mobile money has emerged as a novel financial inclusion technology that bridges this financial inclusion gap thereby helping to serve the underserved group in low–income countries[2]. With financial services from four major providers – M-Pesa, Tigo Pesa, Airtel Money, and Ezy Pesa – mobile money has deepened financial inclusion in Tanzania by way of consistent expansion towards other important banking services beyond remittance. These include other services such as payment for goods and services, savings, access to credit and loan facilities, bill payments etc (CGAP, 2016).

This paper's main objective is to address the question of how bridging access to financial services, using mobile money as a case study, impacts food security in the face of shocks. The overarching research question focuses on the role of mobile money in mitigating risks against food insecurity for rural households. The secondary research question investigates the contributions of agricultural investments and productivity in achieving household food security. The second research question tests the pathway to achieving food security. For example, it helps to understand how an increase in agricultural productivity and crop yields can lead to an increase in food consumption or improve nutrient intake. This approach is quite systematic in that it aims to link three important outcome variables namely household food security, agricultural investment, and productivity. The two research questions are interrelated in that the usage of mobile money for agricultural investment purposes may enhance sustainable endpoint outcomes such as household food security in the long-term. To investigate our research questions, we use detailed questionnaires documenting farm input and productivity measures from agricultural surveys and food security measures from household surveys.

We estimate the effect of drought and its interaction term with mobile money on household food security as the main outcome; followed by agricultural investments and productivity as pathway outcomes. Results from the difference-in-differences (DiD) models show that rural households mitigate the adverse impacts of shocks using strategic agricultural inputs. This pattern confirms the relevance of mobile money adoption for the expansion of agricultural inputs as a precursor for productivity and food security. In general, our results provide evidence consistent with reallocation of resources from credit facilities to agricultural investment priorities. This includes a preference for drought-resistant seedlings, fertilizer applications, and farm tools. We also

[2] Mobile money emerged as a financial innovation that allows individuals to transfer and store funds using short message services (Abiona and Koppensteiner 2022). It thrived upon remittance transfers across unbanked poor in low-income countries.

find some complementary results on productivity – harvest value & land areas harvested. The mitigating factor from mobile money is embedded within the cultivation of maize and nuts – which are the most common staples in Tanzania.

This paper contributes to the extensive literature exploring the mechanisms for designing sustainable insurance pathways for rural households facing risks. The research context in this paper is motivated to fill the gap in this literature and extend the knowledge frontiers (using contexts previously unexplored from empirical evidence). The results presented in this paper stage the potential for the transformation of insurance into a productive investment associated with the accumulation of economic resources (Banerjee et al., 2022). More specifically, our findings demonstrate a pathway for the transition of social protection programs to effective and sustainable investment behaviors[3]. This may be attributed to long-term experience through learning-by-doing. Our findings also provide hope for building internal resilience strategies as against the traditional social protection pathways, with depleting domestic and international support as a result of the global economic meltdown. Unrestricted flow of remittance through an extensive community network may provide a sustainable risk-sharing capacity to mitigate shocks, especially for rural households. Finally, the research fills the knowledge gap about emerging evidence on the role of mobile phones in household nutrition diversity in low-income countries (Parlasca et al., 2020).

The remainder of this paper is organized as follows. Section 2 explores the relevant literature on the mitigating role of mobile money and provides a suitable context for our research questions. In Section 3, we provide a conceptual framework for the research questions. Section 4 presents the data framework while Section 5 outlines the empirical methods used for the analysis. We present the results of the analysis in Section 6 and conclude in Section 7.

2. Relevant literature and research setting

There is a growing literature on the penetration of mobile money for effective financial inclusion in low-income countries (Suri, 2017; Aron, 2018; Ahmad et al., 2020). Most of the studies focus on mobile money welfare transition

[3] This transition depicts vertical scalability of safety net programs measured by progressive evolution of outcomes across different stages of production without external intervention over a reasonable period.

impacts, with or without shocks, across sub-Saharan Africa[4]. Jack and Suri (2011; 2014) provide evidence on the protective role of mobile money against reduced expenditure patterns during shocks in Kenya. Munyegera and Matsumoto (2016; 2018) and Wieser et al. (2019) report the transformative role of mobile money on household expenditure patterns, remittance, and financial behaviour in Uganda. Abiona and Koppensteiner (2022) provide evidence in support of the importance of the adoption of mobile money services for mitigating transient poverty and preservation of human capital investments during rainfall shocks underlying scarce economic resources while Economides and Jeziorski (2017) present evidence of reduced transaction costs and safety in Tanzania. Jack and Suri (2016) show an interaction of poverty reduction and female empowerment capacity for mobile money holders in Kenya. This is achieved through financial resilience, savings, and labour market outcomes. In response to covariate shocks, Riley (2018) shows that mobile money adoption provides positive consumption externalities across households in Tanzania in periods of droughts. The transmission mechanism for the mobile money support in these papers is the expansion of uncoordinated remittance transfers through timely access and reduction in remittance costs. The datasets explored for the above empirical studies on the adaptation role of mobile money focus on short- to medium-term contexts. Our paper extends this literature by examining other outcomes over a long-term period.

While a large body of literature focuses on consumption and expenditure patterns, there is growing evidence of the impact of mobile money adoption on other complementary socio-economic activities of smallholder farmers. The expansion of financial inclusion to rural poor has paved the way for several financial services and this may result in the adoption of suitable and timely agricultural practices especially over a long-term period. These agricultural investment practices include the adoption of climate-smart technologies as an adaptation strategy against adverse impacts of extreme weather events[5]. These adaptation strategies may provide a sustainable pathway for enhanced agricultural productivity thereby leading to household food security in rural areas. Batista and Vicente (2020) show improved savings with mobile money

---

[4] Another strand of the literature explores the welfare impacts of other forms of digital transfers (such as airtimes) which is distinctive from mobile money (Blumenstock et al. 2016). Remittance transfers constitute only one component of mobile money services in low-income countries.

[5] High cost of deployment has been identified as the main barrier of climate smart technologies in Africa (Ndhlovu and Mhlanga 2023). This includes adoption of resilient seeds, technologically driven irrigation systems, preservation of crops against diseases etc. Access to credit facilities through mobile money helps to facilitate this, especially in low-income countries with longstanding barriers to rural banking.

accounts when provided to smallholder farmers in Mozambique. The authors demonstrate that interest-domiciled savings and fertilizer investments became popular because of the intervention. These results provide exploratory evidence regarding adaptation mechanisms that target agricultural inputs. Aker et al. (2016) unveil a similar promising role of mobile money transfers for agricultural investments through a conditional cash transfer program in Niger. The impacts manifest through an increase in the cultivation of a variety of marginal crops. These papers provide an important framework for the role of mobile money in agricultural investment practices for smallholder farmers who are affected by unanticipated economic shocks. The closest research to our paper is presented by Tabetando et al. (2022) which shows improved adoption of modern agricultural inputs and income. In this paper, we explore further avenues to provide a deeper understanding using alternative contexts for the evaluation of the adoption of mobile money by smallholder farmers.

Linking food security outcomes to investment decisions can be considered an important cornerstone for sustainable welfare outcomes for rural households. In this study, we focus on Tanzania where the food security index is reportedly low[6]. According to a report by the Global Food Security Index 2020 (GFSI, 2020), Tanzania ranks 89 out of 113 countries on the overall food security index. The breakdown according to affordability, availability, and quality/safety in this report places Tanzania within the 94th, 72nd, and 88th positions respectively[7]. These features typically explain why micro and macro food security indices in Tanzania may be highly elastic to climate change events—especially droughts—while leaving the country highly susceptible to chronic food insecurity (Arndt et al., 2012; Afifi et al., 2014). Also, structural economic conditions exacerbate this vulnerability. Enhancement of investment in timely, better and more modern operations through mobile money may provide rural households with sustainable agricultural practices (Economides and Jeziorski, 2017).

3. Conceptual framework

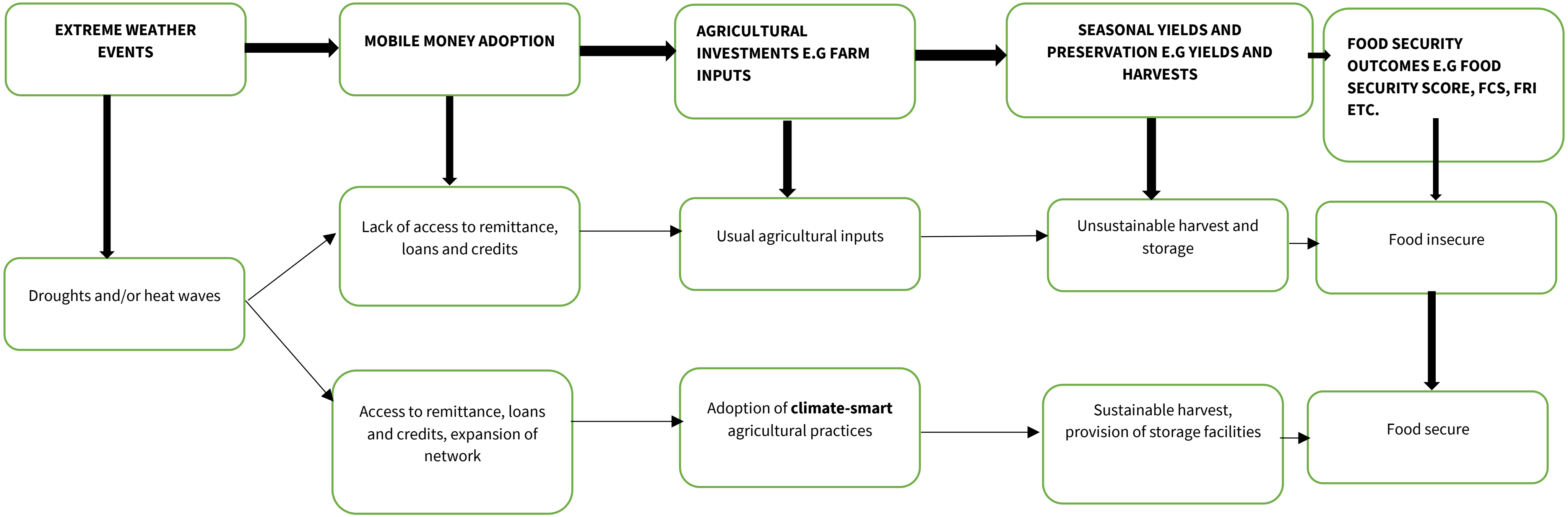
In this research, we consider the adverse effect of extreme weather events on household food security of rural households which is attainable through agricultural productivity in Tanzania (Arndt et al., 2012). In Figure 1, mobile money aids access to remittance, loans, and credit facilities which may

[6] This rating suggests Tanzania's exposure to frequent drought shocks may have undermined the agricultural productivity in the last decade thereby aggravating food insecurity.

[7] https://foodsecurityindex.eiu.com/Country/Details#Tanzania

counteract the negative impacts of adverse shocks on agricultural productivity vis-à-vis household food security. Household food security can be achieved directly by (i) increased household food expenditure and (ii) improved household food diversity and nutrient intake. Both require no direct farm investment which can be interpreted as a responsive mechanism towards achieving food security. Mobile money diffusion can play a role for adopter households in this regard but not necessarily mitigate adverse shock. However, exploring credit and loan facilities for improved productivity pathways to secure food outcomes can be interpreted as an investment strategy by smallholder farmers. This is also common for adverse shock mitigating processes. This framework demonstrates an investment capacity and safety net support with spillover effects achieved through easing access to loans and credits with the use of mobile money. Adopter households have access to both formal and informal loans and credit facilities from a large network of lenders across the country which includes institutions (Murendo et al.' 2018; Afawubo et al., 2020). The main channel of transmission is the expansion of the remittance landscape provided by the mobile wallet. Non-adopter households may suffer food insecurity due to reduced capacity to mitigate risks from such capacities.

Figure 1: Pathways to smallholder household food security during drought shocks



4. Data

In this paper, we use the Tanzanian National Panel Surveys (TNPS) also known as the Living Standard Measurement Studies – Integrated Survey on Agriculture (LSMS–ISA) from the World Bank. We focus on four waves of the World Bank survey using different components of the surveys between 2010 and 2020. These surveys were conducted in collaboration with the Tanzanian National Bureau of Statistics (NBS). The survey design separates household from agricultural questionnaire thereby providing detailed agricultural practice variables for rural households in Tanzania. In addition to this, the surveys provide distribution (accessibility) of service provision across enumeration areas including the location of mobile money agents. The extensive nature of the data enables us to explore household, agricultural, and enumeration area datasets to address the empirical questions specified in the introduction. For our analysis, we focus on an unbalanced sample of households followed over 10 years[8].

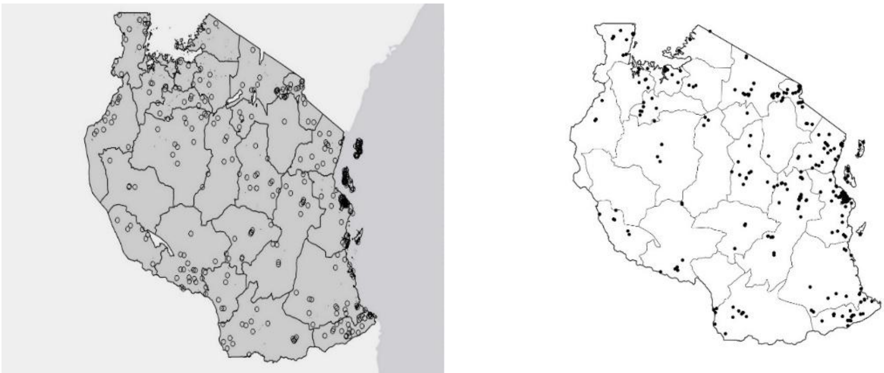
The survey design captures a national representative distribution of survey locations across the 26 regions of Tanzania (see Figure 5A for the spatial distribution of enumeration areas within districts for the Tanzanian map in the LSMS–ISA survey)[9]. In the study, we focus on an unbalanced panel of households from limited EAs across four surveys from the 2010–11, 2012–13, 2014–2015, and 2019–20 waves (Figure 5B). Further, we conduct a supplementary analysis using a balanced panel aimed at sensitivity tests for attrition and distortion of the household sample. The inclusion of discontinued and new entrant households in the estimation process helps to check the impact of attrition and alternative data structure on the main results.

[8] The composition of household observations within this timeline enables us to investigate the long-term impacts of the adoption of mobile money while incorporating transitory and persistent shocks in the models.

[9] The panel structure follows a set of 26 regions across Tanzanian geographical map instituted for the Tanzanian National Panel Survey in the 2008-09 survey. Tanzanian landscape has been updated to 32 regions from 2010.

Figure 5: Survey Enumeration Areas for Tanzanian LSMS–ISA (2010 – 2020)

5A. Baseline Enumeration Areas (2008) 5B. Panel Enumeration Areas (2010 – 2020**)**



In addition, we use datasets from the weather data archive of the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Centre (CPC). The CPC global daily unified gauge-based analysis of daily precipitation and temperature datasets is provided at a 0.50–degree latitude x 0.50–degree longitude daily grid covering terrestrial areas across the globe. This weather data archive provides improved accuracy of both precipitation and temperature measures by combining necessary sources of available information within CPC (Chen et al., 2008a, 2008b). The precipitation data leverages the optimal interpolation objective analysis technique (Xie et al. 2007) while the temperature data uses the Shepard Algorithm to provide minimum and maximum variables. The datasets are available from 1979 to 2022. We extract GPS coordinates (latitude and longitude) provided within the geospatial datasets of TNPS to compute baseline precipitation and temperature datasets for aggregation. Following similar studies, we compute estimates of precipitation and temperature levels by way of matching districts to nearby weather stations from these repositories for each survey period (further details of this linkage process are available from the author upon request).

5. Empirical strategy

In the analysis of this paper, we use a sample of smallholder farmers faced with different weather patterns in rural Tanzania. We investigate food consumption patterns for mobile money adopters in comparison with non-adopter households using four waves of household and agricultural datasets. The study exploits a rapid increase in the adoption/use of mobile money (and expansion of agent network thereof) across districts and over time for identification of the impacts of financial inclusion. Table 1 shows that the adoption of mobile money is nearly saturated among Tanzanian households with 75 percent ownership reported in 2020, increasing from 13 percent in 2010 across a cohort of households[10]. In the analysis, we explore alternative methodologies and data structure. Each strategy enables us to control for time-invariant unobserved characteristics while also controlling for common shocks experienced by all households with the inclusion of year-fixed effects[11].

Methods – Agricultural shocks

In this paper, we allocate precipitation and temperature patterns by agricultural cycle across enumeration areas (EA). This approach helps to understand risk mitigating efforts of smallholder farmers who predominantly rely on the cultivation of cereals – including paddy crops such as maize, millet, and sorghum – in a subsistence manner. We construct alternative indices of drought-induced agricultural shocks (using low rainfall and extreme heat) within each EA as proxies of economic resources available to rural households over some time. The first step for drought computation is the aggregation of precipitation measures for each planting season (November to May) across EA followed by comparison to the norm. Only extreme departures from norm precipitation levels are categorized as seasonal droughts which are benchmarked against the 25th percentile distribution around the long-term seasonal levels.[12] This approach follows the standard method in the literature by constructing drought shock as an indicator variable using an appropriate threshold framework from percentile (Corno et al. 2020) and standard deviation benchmarks (Rocha and Soares 2015, Carrillo 2020). Equation 1 shows the computation methods for drought events for each year:

$\text{drought shock}_{lt-1} = 1 \; if \; \text{Rainfall}_{lt-1} < \text{Rainfall}_{l,25th\;percentile}$, and zero otherwise (1)

where Rainfall_{lt} indicates the cumulative precipitation for the recent agricultural season within EA *l* for period *t*, and $\text{Rainfall}_{l,25th\;percentile}$ is the 25th percentile benchmark of historical yearly precipitation of the EA over a 30-year cycle. Thus, $\text{drought shock}_{lt-1}$ is an indicator variable measuring the

[10] There is also a complementary striking coverage of above 90 percent for mobile money agents in 2020 from about 18 percent in 2010.

[11] We also include a covid indicator using the precise data on interview year provided in the survey. This helps to control for the onset of covid on macroeconomic cycles including within the agricultural sector.

[12] The seasonal standard deviation movements is also captured over a 30-year historical rainfall period within the same district similar to the timeline used for historical average.

relative performance of seasonal precipitation levels before each year compared to the norm. The drought variable is captured from the lead-up period to the outcomes (especially food security) to ameliorate concerns from simultaneity bias. Our drought variable also aligns with the timing of the investment (input) and productivity (outputs) outcomes, given that the investment intervention and harvests take place within a similar time frame. For robustness check, we use an alternative precipitation variation method known as Standardised Precipitation Index (SPI). This index provides a continuous variable depicting the composition of exposure of each EA to drought shock over the past 3 – 6 months. Finally, we capture extreme heat during the recent agricultural season as another form of drought in Equation 2.

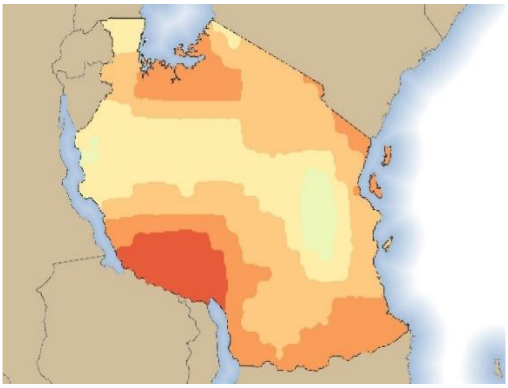
$$\text{extreme heat}_{lt-1} = \frac{frequency\ of\ days\ with\ \text{temperature}\ (\text{Temperature}_{lt-1,d}) > 90th\ percentile\ distribution}{Total\ number\ of\ seasonal\ days} \quad (2)$$

where $\text{Temperature}_{lt-1,d}$ indicates the daily maximum temperature levels for the previous agricultural season within EA *l* for period *t-1* and day *d*. The 90th percentile threshold is computed using a 30-year maximum temperature distribution period within the planting season across EAs. $\text{extreme heat}_{lt-1}$ captures the severity index for excessive heat with the capacity to distort crop yields (Donat et al. 2013, Vogel et al. 2019). Equations (1) and (2) above present credible sources of exogenous shocks while supporting the evaluation of the impacts of alternative extreme weather shocks – droughts and heatwaves – and adaptation strategies from extensive mobile money services.

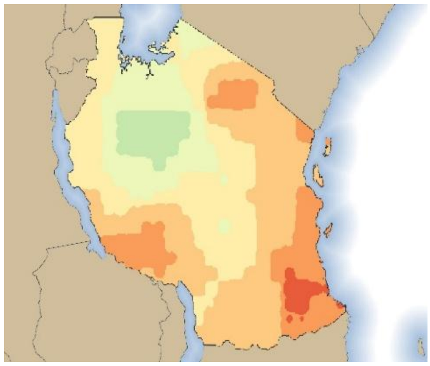
Figure 6 presents variations in the movements of rainfall patterns relative to historical means. Deep red colours indicate patterns below the norm and green above. The extremely low rainfall patterns (droughts) shift around Tanzanian districts between 2010 – 2014 (from Southwest to Southeast to South South) while most districts in 2020 experienced above average precipitation levels. This is complemented by the historical drought composition of enumeration areas that are exposed to drought in Table A2. This pattern enables us to exploit the temporal and spatial distribution of weather events across districts over 10 years as a plausible measure of variation in household economic resources.

Figure 6: Tanzanian historical drought patterns using enumeration area distribution of rainfall around the mean (2010 – 2020)

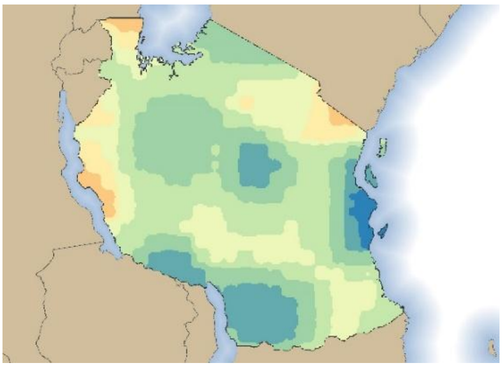
6A. Drought exposure – 2010



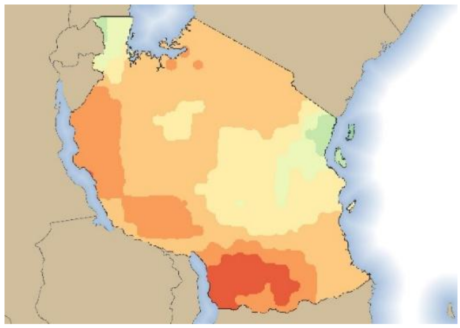
6B. Drought exposure – 2012



6C. Drought exposure – 2014



6D. Drought exposure – 2020



Analysis – Regression model

The regression model is estimated using the specification in equation 3. There are two stages of the model, first between agricultural investment and productivity for investment-productivity phase (Garcia-Verdu et al., 2022, Hirpa Tufa et al., 2022) and the second stage linking productivity to food security for productivity-food security phase (Villacis et al., 2022). In equation 3, we model the three outcomes separately using microlevel datasets as against macro evidence in the literature (Baquedano et al., 2022, Chavas et al., 2022).

$$Y_{ht} = \alpha_h + \delta_t + \boldsymbol{\tau}(\text{MM\_agent}_{\text{lt}-1} * \text{drought shock}_{\text{lt}-1}) + \boldsymbol{\beta_4}(\text{drought shock}_{\text{lt}-1}) + \boldsymbol{\beta_3}(\text{MM\_agent}_{\text{lt}-1}) + X'_{ht}\boldsymbol{\beta}_2 + Z'_{ht}\boldsymbol{\beta_1} + \varepsilon_{ht} \tag{3}$$

Where Y_{ht} represent diverse outcome variables at the household level. $\text{MM\_agent}_{\text{lt}-1} * \text{drought shock}_{\text{lt}-1}$ is the interaction term between mobile money and covariate drought shock from the previous season; where parameter $\boldsymbol{\tau}$ is the coefficient of interest in this model. $\boldsymbol{\beta_3}$ represents the parameter for availability of mobile money agent within EA (an indicator variable)[13] on the outcome variables while the $\boldsymbol{\beta_4}$ represents the direct effect of drought. α_h and δ_t represent the nt community and year-fixed effects respectively. The estimate of $\boldsymbol{\tau}$ relative to $\boldsymbol{\beta_4}$ gives us the relative risk-mitigating factor between mobile money adopter households and non-adopters. We include household head (X_{ht}) and household level (Z_{ht}) covariates to account for changes in household demographic characteristics over time. We include control for additional variables from the survey that may impact the interaction of mobile money and the outcome variables. Household controls include household size, number of household members who are children (under 16 years of age), number of household members who are aged (above 70 years of age), and mean age of household members. We also control for household head-specific characteristics such as age, gender, education, and occupation categories. Finally, we control for mobile phone ownership indicator at the household level to avoid confounders between this variable and the adoption of mobile money. At the community level, we control for access to banks and SACCO using the community-level indicators for the availability of these services, and rural indicators for the location of household residence. Finally, we include another geographical covariate for mainland versus island districts captured during the survey to control for household heterogeneity across regions[14]. We repeat similar regressions for SPI and $\text{extreme heat}_{lt-1}$ as alternative measures of drought. In the regression equations, we cluster error term (ε_{ht}) at the enumeration area level to account for spatial correlation of the interaction of weather patterns and welfare outcomes to ensure robust standard errors during the estimation process.

[13] We reference 'mobile money use' to the variables designated as 'frequency of mobile money remittance' (transferred or received) and 'designated use' (Table A1). These variables represent actual use of mobile money beyond the question on HH adoption of at least one mobile money account. It is important to note that there is a minor difference between the two variables with lack of significant impacts for alternative models using each variable.

[14] Approximately 10 percent of the sample is selected from the Tanzanian islands (Unguja and Pemba). Designated regions in these islands include Kaskazini Unguja, Kusini Unguja, Mjini/Magharibi Unguja, Kaskazini Pemba, Kusini Pemba.

First, we estimate regressions for the food security variables using household nutrition-based food security measures[15]. We follow the approach used in the literature to construct household food security outcomes. In general, self-reported food security measures are subjective and unreliable due to recall bias amidst other issues such as lack of standardisation. Hence, food security measures captured against the benchmark are more appropriate for our study in this paper. We focus on household nutrition-based food security measures. The reasons behind the preference for the diversity of nutritional status of household food baskets within our food security measures are as follows. First, they help to simultaneously test both responsive and investment capacities indicated earlier in the paper. Second, they capture extensive consumption patterns of households in a way that is not covered by other food security measures. For example, similar food security measures such as the food resilience index (FRI) and food security score (FSS)[16] use qualitative indicators for benchmarks (without detailed adjustment for different components of classes of food within the aggregate food basket). Third, they help to provide a policy framework for targeted household resilience that may have a direct impact on the human capital development of children. This provides an important background for the policy relevance context of this research. Lastly, the adoption of nutrition-based food security outcomes fills an important gap in the literature to complement other papers that examine the impacts of mobile money on non-nutritional-based food security (Murendo and Wollni, 2016; Wieser et al., 2019). A food consumption score is computed following WFP guidelines and aims to capture both dietary diversity and food frequency. This is calculated as the weighted sum of the number of days the household

[15] We simultaneously explore data on household 12-monthly loans, credit and remittance patterns to track the channels through which mobile money adoption mitigates contemporaneous shocks for these outcomes of interest.

[16] Food security score (FSS) is constructed according to World Food Program (WFP) guidelines and takes on a value of −1, −2, −3, or −4 (a lower absolute value indicates greater security). The food security score is −1 if in the past seven days, the household reports not worrying about having enough food and reports zero days that they: (a) rely on less preferred and/or less expensive foods, (b) limit portion size at meal-times, (c) reduce number of meals eaten in a day, (d) restrict consumption by adults so that small children may eat, or (e) borrow food, or rely on help from a friend or relative. The food security score is −2 if the household reports that it worried about having enough food and reports zero days for categories a-e. The food security score is −3 if the household reports that it relied on less preferred and/or less expensive foods and b-e are zero. The food security score is −4 if the household reports any days for b-e. Larger values indicate improved food security. Food resilience index (FRI) is the negative of the World Food Program coping strategy index. The index is calculated as the negative of the weighted sum of the number of days in the past seven days that households had to reduce the quantity and quality of food consumed.

ate foods from eight food groups within the recent week. The score is calculated based on the sum of weighted number of days in the last week the household ate food from eight food groups (2 * number of days of cereals, grains, maize grain/flour, millet, sorghum, flour, bread and pasta, roots, tubers, and plantains) + (3 * number of days of nuts and pulses) + (number of days of vegetables) + (4 * number of days of meat, fish, other meat, and eggs) + (number of days of fruits) + (4 * number of days of milk products) + (0.5 * number of days of fats and oils) + (0.5 * number of days of sugar, sugar products, and honey). Spices and condiments are excluded. It has a maximum value of 126. We also used non-standardised combination of the food classes from the Household Dietary Diversity Score (HDDS) as a supplementary food security outcome. Pathway outcome variables in equation (3) include agricultural investment (input) variables namely seedlings (improved and traditional), soil improvement practices (herbicides, fertilizers, and pesticides), paid labour services, irrigation activities, agricultural extension services, and hiring of farm machinery for cultivation. We also estimate 'productivity' variables using harvests and yields as measures of agricultural productivity.

Given that access to mobile money agents is not randomly assigned across households, we use an entropy balancing method. This matching approach is appropriate for observational data where randomized controlled trials are not undertaken (Athey and Imbens, 2017; Hainmueller, 2012; Hainmueller and Xu, 2013). The method involves assessing a binary 'treatment' variable which in this case is the availability of mobile money agents at the community. The variables used to match observations include age, gender, and school attendance of household head, household size, and mean age. Entropy balancing aims to match the two groups by weighting the control group to produce covariate moments that match the treatment group as closely as possible. The identification strategy relies on community-fixed effects and year-fixed effects. Thus, the results are essentially capturing the difference between households with and without mobile money within a community. While adoption rates increased over time, across survey rounds, the underlying variation in the specification is coming from this comparison of households within a community. Thus, what we learn from the paper is how different types of households are impacted by the drought and its interaction with mobile money using an exogenous variation in community-level access to the service over time similar to other studies.

6. Results

Summary statistics – mobile money adoption and use

Table 1 presents the distribution of mobile money adoption across tracked households over the four waves. This pattern shows an expansion in access to mobile money services at extensive margins. Further investigation of the main drivers of this pattern in Table A1 demonstrates that there is a shift towards intensive use of mobile money services aside from inward and outward remittance flows which constitute the largest component of the preference for mobile money use across the 10 years (Table A1 Panel B)[17]. For example, the use of mobile money as an acceptable means of payment for goods and services has increased by approximately 360 percent while saving mobile money as an economic resource for emergency use increased by 142 percent. Its use for large purchases has also increased by 195 percent. The occasional usage of mobile money which constitutes adoption in emergency represents the widest application of services over the four waves (Table A1 Panel A) but there is increasing momentum for a wider use (Table A1 Panel B). This shows additional variation at the intensive margins which suggests an interaction of adoption towards behavioural evolution (spread in application) in Panel B with the largest contribution from emergency usage (occasional adoption) in Panel A.

Table 1: Mobile money adoption rate in Tanzania (2010 – 2020)

	Survey year			
Household mobile money adoption rate (percent)	2010-11	2012-13	2014-15	2019-20
Tracked households	0.12	0.40	0.53	0.71
All households	0.13	0.41	0.59	0.75

Notes: Table 1 presents summary statistics of household mobile money adoption rate across four waves of the Tanzania National Panel Survey (LSMS-ISA). The rate is presented for a tracked 992 households (3,968 observations) over the 10 years and all households. These sample groups constitute balanced and unbalanced panel for the data analysis.

Main Results

Our empirical framework compares outcomes for households exposed to drought shocks with a particular interest in how mobile money adopter households respond by using the services as a coping strategy relative to non-

[17] The most important use of mobile money remains to receive and send money, an indication of remittance valuation, rather than savings application within the country (Abiona and Koppensteiner, 2022).

users over time. We report DiD coefficient estimates from reduced form models in equation (3). All regressions include control variables, year fixed-effects, and enumeration area fixed-effects. Coefficient estimates of interest for each dependent variable are those from parameters of drought ($\boldsymbol{\beta_4}$) and its interaction term with mobile money ($\boldsymbol{\tau}$). The reduced-form models use the distribution of mobile money agents to capture access at the household level[18]. The underlying assumption for causal interpretation of our results is that droughts are exogenously determined in the model. However, the interpretation of the combined effect from drought shock and its interaction with mobile money ($\boldsymbol{\beta_4} + \boldsymbol{\tau}$) may not be causal because those with access to mobile money are almost certainly different to those who don't have it. We follow the literature to establish the exogenous nature of rainfall by estimating the impact of household covariates on drought indicators. This estimation process follows the approach in similar mobile money studies with self-reported HH shocks (Jack and Suri, 2014) and rainfall-related shocks (Riley, 2018; Abiona and Koppensteiner, 2022). The result shows there is no relationship between the drought outcome and the covariates as expected in support of our empirical strategy[19]. The pattern reinforces that drought shocks are exogenously determined lending credence to causal interpretation of our results in general. Below, we report baseline results for food security outcomes (6.2.1) followed by agricultural investment results (6.2.2) and productivity results (6.2.3).

Household food security

In this section, we focus on two household food security measures – the Food Consumption Score (FCS) and the Household Dietary Diversity Score (HDDS). These are standardised food security outcomes by the World Health Organisation that measures the nutritional quality and diversity of food consumption patterns (household food items) within a specific period. The main focus here is the nutrient composition of food intake for a balanced diet, an indication of healthy living. This approach aims to provide an understanding of the nutrition dynamics of drought and mobile money use. Table 2 reports the estimated impacts of droughts and the role of mobile

[18] In the main results, we explore the availability of agents at the community level to measure variation in mobile money access across households. Results from complementary variables such as distance and cost to the nearest agent provide similar results.

[19] Results are available from the authors upon request. This estimation approach involves regression of equation 3 using drought shock as a dependent variable on covariates (used as controls for the main regressions) and includes enumeration area and year fixed effects.

money on these measures. Table 2 reports the results from Equation (3) – the reduced–form specification. We estimate our regressions for alternative food security measures in Columns 1 and 2, respectively for FCS and HDDS. In Columns 1 and 2, we observe a responsive impact of FCS and HDDS on our focus explanatory variables where the parameters for both drought and interaction terms are statistically significant and consistent with a priori expectation. More specifically, the incidence of drought reduces FCS (HDDS) by a factor of 5.24 (0.51) for non-users while this is counteracted by an increase of 5.46 (0.54) for users. This indicates that mobile money users can mitigate the negative impact of drought shock on the nutritional quality of household consumption. The emerging patterns for the household nutrition-based food security reported in Table 1 are striking as the nutrition components of household food baskets may not necessarily be the focus of mobile money usage following drought shocks[20]. In other words, the mitigating role of mobile money may be primarily geared towards closing the food consumption gap by limiting yield loss rather than improving nutrition components in such periods. This evidence suggests that mobile money may be used as both a responsive and investment tool. This implies that mobile money services may aid the strategic deployment of economic resources towards pathways of sustainable household food security on one hand but may also enhance nutrition diversity directly – both of which are not accessible to non-adopter households. The latter may be achieved through partial sales of yields in addition to the consumption from agricultural production. To investigate this further, we estimate regression models using measures of harvests sold and household food production (within consumption). The results from this regression reported in Table A5 show significant estimates of drought and interaction terms for both outcomes. Next, we proceed to investigate potential the pathways through agricultural investments and productivity.

[20] It is reassuring to see complementary patterns from estimated results from FCS and HDDS in columns 1 and 2. This demonstrates robustness of estimation models to alternative metrics for nutritional quality of household food consumption patterns.

Table 2: The interactive impacts of drought and mobile money on current household food security outcomes

	Dependent variables:	
	Food consumption score (FCS)	**Household Dietary Diversity Score (HDDS)**
Variables	**(1)**	**(2)**
Mobile money	1.4943*	-0.0107
	(0.8259)	(0.0741)
Drought	-5.2379**	-0.5124**
	(2.4283)	(0.2491)
Mobile money * Drought	5.4634**	0.5397**
	(2.6533)	(0.2614)
Constant	39.4054***	7.8325***
	(3.2046)	(0.2255)
Controls	Yes	Yes
Year FE	Yes	Yes
Enumeration area FE	Yes	Yes
R-squared	0.2293	0.1602
Observations	6,624	6,624

Notes: The outcome variables in the above Table includes alternative metrics of nutrition-based food security measures – Food Consumption Score (FCS) (column 1) and Household Dietary Diversity Score (HDDS) (column 2). HDDS consists of linear combination of HH food composition within the last 7 days. This measure combines the food group information collected within the survey using 12 food groups following the international dietary data expansion project (INDDEX). Using the INDEX approach HDDS is calculated using an indicator across food classes where each is assigned 1 if consumed in the last 7 days and 0 otherwise. Once allocated HDDS equals Cereals + Roots and tubers + Vegetables + Fruits + Meat, poultry, offal + Eggs + Fish and seafood + Pulses, legumes, nuts + Milk and milk products + Oil/fats + Sugar/honey + Miscellaneous. On the other hand, FCS uses a non-linear combination of the food classes within HDDS using the scaling methods specified in section 5.3 to prioritise nutrient components for expected balanced diet within consumption. Drought variable follows locality reference methodology in equation (1) for extreme drought shock using 25th percentile seasonal precipitation threshold movements below the enumeration area norm. All columns include controls, enumeration area and the survey year fixed effects. Household controls include household size, age composition of HH members (# under 16 years of age and # above 70 years of age), mean age within household and HH mobile phone ownership. We also control for household head demographic characteristics such as age, gender, education and occupation categories. At the EA level, we include an indicator variable for access to bank and SACCO. In addition, we include geographical exposure covariates for the rurailty of the location of HH residence and mainland versus island. Finally, we include a variable for exposure to the onset of covid in early 2020. See section 5.3 for more details on the covariates used as controls in the regression analysis.

Robust standard errors clustered at the enumeration area level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Agricultural investments and inputs

We present the results for agricultural investment patterns concerning inputs in Tables 3 – 5. Table 3 reports results for the interactive impacts of drought and mobile money on the type of seedlings utilised for agricultural cultivation. Table 3 columns (1) – (2) report coefficients from reduced form estimation methods using agent distribution across enumeration areas for access to mobile money. Columns 1 and 2 of the table present estimation results using an indicator variable for recycled (traditional) and improved (chemical) seedlings during the previous planting season. In Table 3, Column 1, the estimated coefficients are consistent for drought and interaction terms with mobile money at traditional statistical levels. Specifically, drought reduces the likelihood of utilization of recycled seedlings by 15 percentage points while the interaction term increases this input by a marginally superior value of 18 percent. In contrast, the pattern of estimated coefficients for improved seeds –Table 3 Column 2 – is nuanced. There is some evidence that recovery of usage of traditional recycled seedlings during drought may be taking place because of access to mobile money for users. These results may be attributed to improved storage capacity for user households following the preceding season.

In Table 4, we explore the role of mobile money on soil improvement practices during drought. Columns 1 – 4 present results for organic fertilizer, inorganic fertilizer, herbicides, and pesticides respectively. There is no documented evidence of the impacts of drought and interaction terms on the application of organic fertilizers (Table 4, Column 1), pesticides (Table 4, Column 3), and herbicides (Table 4, Column 4). On the other hand, Table 4 column 2 shows that drought reduces the use of inorganic fertilizers for non-user households. This adverse impact is reversed for the users as demonstrated by the interaction term with a marginal difference. Both coefficients are statistically significant at the 1 percent level. The reported reduced impacts of drought on soil improvement practices should be interpreted with caution as the list of outcomes here does not capture exhaustive potential pathways. Evidence of impacts from the adoption of the inorganic fertilizers component of this practice suggests that non-targeted transfers may be reliable for intervention programs aiming to provide a sustainable pathway for agricultural practice in the use of soil improvement practices. It is unclear why there is no evidence for other soil improvement attributes in Table 4. One explanation for this lack of coordinated impacts is the need for a support system for other inputs in this category. For example, agricultural extension service officers may be required to coordinate the use of organic fertilizers, pesticides, and herbicides which is not the case for inorganic fertilizers as smallholder households are familiar with the application of these component[21]. Another reason could be the cost directly associated with the process for any of the non-responsive soil improvement practices.

Lastly, we turn to investment in farm tools. In this analysis, we use cost variables associated with hiring farm tools as the dependent variable rather than an indicator variable for adopting such tools[22]. Table 5 presents the impacts of drought and interactive mobile money for non-user and user households. The estimated impacts are considerably smaller compared to the coefficients across other inputs (Tables 3 and 4). Nevertheless, there is some evidence that drought adversely impacts farm tool investments for non-users, which is counteracted for mobile money user households. The findings in this input category partially contradict the paid farm labour inputs where we did not find any results. More specifically, plough and harrow provide more compensating coefficients of mobile money use relative to planting tractors. In rural agricultural settings, smallholder households utilize their tools while performing farm tasks but also hire manpower and tools to enhance agricultural productivity when necessary (Bojnec and Fertő, 2022). However, our results show that there may be perceived additional benefit of hiring farm machinery without a paid workforce, especially as it relates to the allocation of scarce economic resources across competing farmer needs. For completion, we also estimate the regression models for other subsistence farm equipment to investigate the adoption of a complementary investment strategy. These include costs for hiring hoes and cutlasses, spray, water cans, jerry cans, hand mill, etc[23]. We do not find any impacts of drought or interaction terms for any

[21] Engagement with extension service officers often interact with intervention programs from government and non-governmental institutions (Ragasa and Mazunda 2018). This study provides an alternative non-coordinated pathway to sustainable agricultural pathway as a departure from targeted intervention programs. To test this argument, we conduct a regression on the interactive impacts of drought and mobile money on access to the agricultural extension services. Our result shows no impact from either drought incidence or interaction with mobile money (results available from the author upon request).

[22] The cost data is extracted as the amount of Tanzanian shillings paid to borrow each tool from the agricultural datasets. While we perceive that this may not be accurate, it is the best data available for the intended analysis. More importantly, the variable on the likelihood to adopt farm tools does not capture investment patterns compared to the associated cost.

[23] Note that we do not have data on costs for other effective agricultural inputs in Tables 2 and 3 (for improved and recycled seedlings categories) restricting our capacity to investigate this further. This means that we are unable to investigate a potential rise in cost of production associated with better inputs adopted in this regard.

of these[24]. This may be related to the inclination that most of the smallholder households have the aforementioned while borrowing farm machinery will be considered a priority capital investment. This decision may also be attributed to the potentially long-lasting impacts of such investments on soil improvement when combined with fertilizer application. In low-income countries where government and non-governmental intervention is somewhat weak, farmers often have to obtain loans or credit facilities for capital-intensive projects such as the use of machinery for more efficient agricultural cultivation (Mohamed and Temu, 2008). We test for complementary results across human and physical capital by estimating our model on hired external labour engagements during the planting season. There is no evidence of mobile money usage on the former. Preference for investment in machinery may be considered more efficient for rural farmers who may be considering upgrading from subsistence to mechanized farming.

Overall, results reported in Tables 3 – 5 provide evidence of cross-substitution of investment across and within selected agricultural inputs. The preference inputs include recycled seeds (seedlings adoption), inorganic fertilizers (soil improvement practices), and farm equipment hiring (hiring practices). While this looks compatible with facilitating coordinated input, it is unclear if this combination will lead to optimal agricultural productivity within the scope of resource constraints faced by smallholder farmers (Ubabukoh and Imai, 2022). This is particularly important in consideration of numerous alternative agricultural input choices. More importantly, these results provide suggestive evidence in support of subsistence farming improvements rather than semi-commercial or market (fully mechanized) agricultural practice.

Table 3: The interactive impacts of drought and mobile money on the type of seedlings utilised during the last planting season

	Dependent variables:	
	Recycled seedlings (indicator)	**Improved seedlings (indicator)**
Variables	**(1)**	**(2)**
Mobile money	-0.0828***	-0.0294
	(0.0280)	(0.0269)
Drought	-0.1505***	-0.0217

[24] Results available from the authors upon request. Lack of results may be driven by substitution effects between investment in additional subsistence tools (required for external labour engagements) and farm machineries.

	(0.0487)	(0.0669)
Mobile money * Drought	0.1757***	-0.0534
	(0.0674)	(0.0674)
Constant	0.0279	-0.2898*
	(0.1003)	(0.1533)
Controls	Yes	Yes
Year FE	Yes	Yes
Enumeration area FE	Yes	Yes
R-squared	0.0961	0.1134
Observations	5,348	5,348

Notes: The outcome variables are indicators for use of improved seedlings enhanced by chemical components (column 2) and recycled (traditional) seedlings usually adopted from storage from the harvests from previous season (column 1). These are designated as 1 if each of these seedling categories are adopted on any HH plot; and zero otherwise. Drought variable follows locality reference methodology in equation (1) for extreme drought shock using 25th percentile seasonal precipitation threshold movements below the enumeration area norm. All columns include enumeration area and the survey year fixed effects. See Table 2 and section 5.3 for more details on the covariates used as controls in the regression analysis. Robust standard errors clustered at the enumeration area level are reported in parentheses. * p < 0.1; ** p < 0.05; *** p < 0.01.

Table 4: The interactive impacts of drought and mobile money on soil improvement practices during the last planting season

	Dependent variables:			
	Organic fertilizer	**Inorganic fertilizer**	**Pesticides**	**Herbicides**
	(indicator)	**(indicator)**	**(indicator)**	**(indicator)**
Variables	**(1)**	**(2)**	**(3)**	**(4)**
Mobile money	0.0332	-0.0535	0.0049	-0.0259
	(0.0245)	(0.0387)	(0.0088)	(0.0270)
Drought	-0.0413	-0.1748***	0.0065	0.0576
	(0.0442)	(0.0417)	(0.0248)	(0.0698)
Mobile money * Drought	-0.0053	0.1652***	0.0096	-0.0257
	(0.0475)	(0.0510)	(0.0308)	(0.0812)
Constant	-0.4740***	-0.1121	0.0667	-0.2710***
	(0.0805)	(0.1008)	(0.0440)	(0.0492)

Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Enumeration area FE	Yes	Yes	Yes	Yes
R-squared	0.1223	0.1161	0.0936	0.0789
Observations	5,534	5,534	5,534	5,534

Notes: The outcome variables are indicators for use of organic fertilizers (column 1), inorganic fertilizer (column 2), pesticides (column 3) and herbicides (column 4). These are designated as 1 if each of these soil improvement categories are adopted on any HH plot; and zero otherwise. Drought variable follows locality reference methodology in equation (1) for extreme drought shock using 25th percentile seasonal precipitation threshold movements below the enumeration area norm. All columns include enumeration area and the survey year fixed effects. See Table 2 and section 5.3 for more details on the covariates used as controls in the regression analysis. Robust standard errors clustered at the enumeration area level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: The interactive impacts of drought and mobile money on farm equipment hiring during the last planting season

	Dependent variables:		
	Tractor cost	Plough cost	Harrow cost
	(natural log)	(natural log)	(natural log)
Variables	(1)	(2)	(3)
Mobile money	-0.0000	-0.0002	-0.0004**
	(0.0001)	(0.0003)	(0.0002)
Drought	-0.0002***	-0.0006	-0.0005***
	(0.0000)	(0.0005)	(0.0002)
Mobile money * Drought	0.0001*	0.0016*	0.0007*
	(0.0001)	(0.0009)	(0.0004)
Constant	0.0003	0.0428***	0.0003
	(0.0003)	(0.0104)	(0.0006)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Enumeration area FE	Yes	Yes	Yes
R-squared	0.0253	0.1686	0.0766
Observations	3,982	3,987	3,985

Notes: The outcome variables are natural logarithms for the costs of common agricultural equipment loans. These include costs associated with loans of tractors (column 1), ploughs (column 2), and harrows (column 3). To enhance preservation of sample observations, zero costs for sample HHs are converted to 1s before the log transformation. Drought variable follows locality reference methodology in equation (1) for extreme drought shock using 25th percentile seasonal precipitation threshold movements below the enumeration area norm. All columns include enumeration area and the survey year fixed effects. See Table 2 and section 5.3 for more details on the covariates used as controls in the regression analysis. Robust standard errors clustered at the enumeration area level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Agricultural harvests and yields

The systematic pattern in agricultural inputs signifies a behavioural response to drought shocks consistent with proactive mitigating role of mobile money. This means that impact of exposure to rainfall shocks for smallholder farmers may be mediated for mobile money user households leading to bountiful harvest patterns. This is achievable from alternative potential investment decisions attributed to the adoption of mobile money[25] (rather than direct expenditure patterns widely insinuated in the literature) as documented by Tabetando et al., (2022). Thus, we expect harvest from the seasonal agricultural practice with drought incidence to be different between users and non-users. While certain households may be more (or less) susceptible to the impact of drought due to underlying socioeconomic differences, drought regimes in rural areas are generally covariate in nature and any safety net programs are likely to be evenly distributed. To examine the mitigating role of mobile money on farm productivity, we regress reduced form specification in Equation (3) for measures of harvest and yields. This approach is important to enable the linkage for households' pathway towards easing agricultural shocks faced by smallholder households in two folds. First, the results establish a unique non-market pathway between agricultural practice and food security for mobile money user households. Second, mobile money-user households may be able to establish a resilience pathway to mitigate resource shocks underlying unexpected rainfall patterns thereby cushioning the impact of the shock on household food security.

The results for the harvest and yield outcomes are presented in Table 6. Patterns of estimated effects for mobile money and the interaction terms are similar across Columns 1 – 6. This pattern signifies the robustness of the mitigating impact of mobile money across different factors. Coefficients in Columns 1 and 2 indicate that the incidence of drought regime, regardless of mobile money usage, leads to a decline in household harvest levels by a factor of approximately 2.01 and 0.29, for volume and area covered respectively.

[25] The underlying assumption of this argument is that mobile money user households have access in advance of the exposure to drought shocks.

Whereas the interaction term coefficients show that user households are sheltered from this decline in drought shock exposure with an increase of 2.36 and 0.29, respectively. This provides at least enough compensation to counter the decline in agricultural engagements caused by droughts in both cases. To understand the exact nature of the mitigating role of mobile money, we explore the likelihood of planting selected crops using the data available from the agricultural survey. Complementary results from Table 6 Panel B show that similar patterns are reported for maize and nut while paddy and beans turn out insignificant. One prominent feature of the estimated effects for maize and nuts is the matching compensation received because of the mobile money role against the adverse shock for users. This can be explained by improved yields and productivity from investments in agricultural inputs as documented in the previous section. These results provide additional evidence on the scale effects of financial inclusion on agricultural productivity (Hu et al., 2021, Tabetando et al., 2022).

In summary, the investment-productivity results suggest evidence of the reallocation of resources among agricultural investment priorities. This involves a preference for drought-resistant seedlings, and the application of inorganic fertilizers and machinery, which in effect lead to improved cultivation and harvests – which is driven by the cultivation of maize – the most common staple in Tanzania – and nuts.

Table 6: The interactive impacts of drought and mobile money on yields and harvests during the last planting season

	Dependent variables:					
	Panel A: Harvest measures		Panel B: Crop designations			
	Harvest volume (natural log)	Harvest area – htrs (natural log)	Maize (indicator)	Paddy (indicator)	Beans (indicator)	Nuts (indicator)
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Mobile money	-0.7100***	-0.1038***	-0.0324	-0.0060	0.0032	-0.0249
	(0.1858)	(0.0353)	(0.0204)	(0.0297)	(0.0152)	(0.0179)
Drought	-2.0059***	-0.2882***	-0.2335***	0.0256	-0.0736**	-0.0784***
	(0.6710)	(0.0478)	(0.0416)	(0.0499)	(0.0371)	(0.0255)
Mobile money * Drought	2.3575***	0.2923***	0.2578***	0.0192	0.0009	0.0960***
	(0.6988)	(0.0595)	(0.0458)	(0.0508)	(0.0422)	(0.0296)

Constant	1.8350**	-0.2967***	-0.0769	0.2156***	-0.1080**	-0.1262***
	(0.7158)	(0.0860)	(0.0683)	(0.0666)	(0.0499)	(0.0395)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Enumeration area FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.4369	0.3736	0.3847	0.1304	0.1369	0.0954
Observations	5,534	5,534	5,534	5,534	5,534	5,534

Notes: The outcome variables in Panel A include crop cultivation (column 1) and harvest (column 2) measures. These are entered into the regression models as natural logarithms transformation of the harvest volumes and areas harvested, in kilograms and hectares respectively. To enhance preservation of sample observations, zero costs for sample HHs are converted to 1s before the log transformation. Panel B consists of specific crop details. The outcome variables are indicators for the cultivation of maize (column 3), paddy (column 4), beans (column 5) and nuts (column 6). These are designated as 1 if each of these crop categories are cultivated on any HH plot; and zero otherwise. Drought variable follows locality reference methodology in equation (1) for extreme drought shock using 25th percentile seasonal precipitation threshold movements below the enumeration area norm. All columns include enumeration area and the survey year fixed effects. See Table 2 and section 5.3 for more details on the covariates used as controls in the regression analysis. Robust standard errors clustered at the enumeration area level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Robustness and sensitivity checks

This study explores tracked households from LSMS-ISA surveys for Tanzania between 2010 and 2020. There are two main panel structures from different baselines. This consists of (i) the 2008-09 baseline with three waves from 2008-09, 2010-11 & 2012-13; and (ii) the 2014-15 baseline with two waves from 2014-15 & 2019-20. The analysis above relies on the overlap between the panel rounds to form long-term panel data required for the analyses conducted in this paper[26]. This includes 992 balanced household panels per wave between 2010[27] to 2020 – 3968 total observations as observed in Table 1. Our reliance on the overlap constitutes a data limitation that requires a few tests. First, the graphical representation of the enumeration areas of the location of the balanced panel in Figure 5B demonstrates the retention of a nationally representative sample across baselines. To check for the impact of attrition, we conduct a t-test for equality of means of covariates between the treatment

[26] In general, the regression analysis uses unbalanced panel data in a repeated cross-section structure where the identification strategy includes enumeration area (community) fixed effects. We also use IV DiD approach for a balanced panel households to test the robustness of the main results to variation in data structure.

[27] Note that we exclude year 2008 from the main analysis due to lack of information on mobile money adoption or agent availability and location. However, this wave is used for falsification tests later in the paper.

and control households for the unbalanced panel data (Table A3). The results show that the covariates are largely equal with normalised z scores mostly below a quarter as suggested by Imbens and Wooldridge, (2009). Similarly, Table A4 reports the covariate balance test by migration status of households over the 10 years. This test between relocated households (unbalanced group) and the permanent household (strongly balanced group) helps to validate the comparison of our findings between the balanced and unbalanced panels in the results section. We also conducted a t-test to show equality of means between the panel households used for our analysis and the remaining households not tracked. This test is to enhance the external validity of the reported results for interpretation. Finally, it is unclear if the spillover effects from ownership of a mobile phone are the main driver of our results as this will negate the intended interpretation of the financial inclusion background as the shock-absorption framework[28]. To check this pattern, we performed a robustness check using phone ownership across households over the period in place of mobile money. The estimated patterns of phone indicator and interaction with drought shock is neither consistent with the baseline results nor statistically significant across household food security metrics.

Discussion and Policy Implications

In this paper, we seek to extend the risk-sharing and insurance models for mobile money adoption. We examine the risk-mitigating impacts of mobile money on food security while also investigating potential pathways through agricultural investments and productivity. We use the nationally representative household panel dataset from Tanzania to estimate the role of mobile money in responding to adverse impacts of drought shocks on agricultural inputs – termed as agricultural investment variables – to boost farm harvest and yields (productivity) towards household food security (targeted outcome). This approach presents the first pathway for a comprehensive linkage of inputs to end products as a way of novel contribution to the body of literature. This method disentangles how mobile money can facilitate investment rather than respond to shocks for consumption smoothing.

Our findings show that mobile money smoothens a range of investment-productivity variables against drought shocks. The results establish mitigating evidence for a value chain system. This includes interrelated variables across

[28] The mobile phone ownership increases at a slower rate compared to mobile money adoption over the research period considered for our analysis. Household phone ownership rates are 65 percent, 72 percent, 78 percent and 84 percent for 2010-11, 2012-13, 2014-15 and 2019-20, respectively, compared to mobile money adoption rates of 12 percent, 40 percent, 53 percent and 71 percent.

a broad range of input, productivity, and outcome variables. This evidence provides an important basis to reinforce the widespread welfare protection role of mobile money in the literature. While the incidence of drought reduces the likelihood and value of agricultural investment in improved (drought-resistant) seedlings, fertilizer application, and farm tools, these patterns are counteracted for mobile money adopter households. On the other hand, we did not find evidence for hired labour, irrigation practice, or extension services. This selection provides some evidence of the strategic allocation of credit facilities received by smallholder farmers to achieve optimal productivity.

We further provide complementary evidence for the impacts of mobile money use on farm cultivation practices and yields. Our results show that user households can smooth the farm outcome variables from drought-induced losses while non-adopter households maintain reduced productivity levels[29]. This paper expands the emerging literature on the impacts of mobile money on crop-specific outcomes in low-income countries by examining the impacts on a variety of crops (Abdul-Rahaman and Abdulai 2022). Lastly, we find that access to mobile money helps to smooth nutritional-based household food security measures – the food consumption score and HDDS. Supplementary evidence on food outcomes shows that access to mobile money deepens household food production and enhances sales. We provide sensitivity analysis and robustness checks using an alternative identification strategy and drought reference[30]. Results for alternative drought from SPI reported in Table A6 show similar patterns with the percentile precipitation threshold drought shock measure reported in Table 2 for FCS. On the other hand, the heatwave benchmark presented in Table A7 shows statistically significant interaction term coefficients for FCS and HDDS both overcompensating the associated drought coefficients (not statistically significant). Finally, we repeat the estimation of Equation 3 using a 2SLS-IV estimation approach to tackle the endogeneity of household-level mobile money adoption as the main explanatory variable. We present the coefficient estimates from this regression in Table A8 where drought and the interaction term coefficients are significant at 1 percent for the FCS outcome.

Our main results demonstrate that mobile money may be equally useful to mitigate the effects of droughts for rural households in a broader fashion than

[29] This may also be attributed to efficiency gains from alternative crop choices (not documented in our analysis) resulting from credit accessibility by adopter households (Ubabukoh and Imai, 2022) while lack of investment in agricultural inputs by non-adopter households may limit similar capacity.

[30] These analyses focus on food security outcomes from Table 6.

earlier documented in the literature. The implication of these results is the sustainability of the investment patterns considering the level of exposure of rural smallholder farmers to climate change. The innovative tool for the unbanked poor may be helpful to maintain nutritional uptake in food consumption above what is captured in the consumption smoothing framework. This linkage also has implications for household human capital accumulation thereby providing additional positive externalities for future generations. The evidence in this paper complements initial findings across low-income countries in Africa. More importantly, these results signpost mobile money as an efficient intervention tool for governments, non-governmental bodies, and international organisations looking to secure a sustainable intervention platform for smallholder farmers in sub-Saharan Africa[31]. In another context, the findings in this paper provide evidence in support of our proposed investment hypothesis. In the regression models, we find that mobile money uses itself can be associated with a reduction in selected agricultural inputs and productivity which can be explained as a potentially perverse behavioural response to excessive remittance flows without equivalent support requirements. This result presents a new counterintuitive pattern of mobile money adoption in the absence of shock. Most importantly, the coefficients of interaction terms are larger than the independent mobile money variable in each case of the counterintuitive (negative) result. This suggests that the impact of mobile money during drought shock overshadows the independent perverse impact. To understand the channel of our findings, we estimate Equation 3 for credits and remittance outcomes. While we do not find evidence in support of the remittance channel, there are indications that adopter households have greater access to loan and credit facilities (Table A9). Finally, this paper bridges an important gap for a large body of evidence on a similar pattern between safety net programs and household food security outcomes in low-income countries (Gilligan et al., 2009, Berhane et al., 2014, Schmidt et al., 2016).

Finally, we acknowledge that further information regarding the exact allocation of economic resources generated from mobile money especially relating to purchases of agricultural inputs is important to make conclusive statements on household investment decisions for the inputs results. For example, cost data for seedlings or soil improvement practices may help tease out the rising cost of production and how this impacts net welfare outcomes. This kind of data may help to tackle potential endogeneity problems in the adoption of mobile money between adopter and non-adopter households.

[31] The landscape of mobile money users in Tanzania (75 adoption rate from the data) provides an important leverage for effective intervention program deployment.

However, the LSMS data does not provide in-depth data on the exact use of mobile money as it relates to agricultural inputs beyond the limited narrative of the sectors that mobile money allocation goes into (Table A1 Panel B). This is an important data limitation for our study and indicates that our results may be speculative on the allocation of mobile money resources on inputs that generate productivity and food security measures. This area provides an avenue for further research using targeted surveys through primary data collection.

7. Conclusion

This paper unravels evidence for alternative long-term climate change risk-mitigating measures for smallholder farmers. Findings from our empirical analysis strengthen the evidence that mobile money safety net may be useful for policy intervention designs among rural households in Sub-Saharan Africa. In the study, we propose an investment framework and test it empirically. We achieve this by exploring an interaction of investment and welfare outcomes underlying the consumption and risk–sharing models of mobile money adoption. The investment capacity of mobile money is inherent in the expansion of its services which is more likely to take effect after a sustained period of adoption. Another contribution of this research is the evidence on how mobile money plays a safety net role within the agricultural value chain system — from cultivation practice to food production and consumption — especially within the context of rainfed agricultural practice for smallholder farmers in low-income countries.

Our findings demonstrate that mobile money is effective in mitigating adverse economic shocks for rural households more broadly than earlier documented in the literature[32]. More specifically, results from this study complement existing research on the level of reliability of mobile money for safety nets and social protection programs. This evidence bridges the knowledge gap on the sustainability of mobile money and provides a structure for scaling it towards welfare-targeting programs.

[32] The body of literature portrays mobile money as a responsive tool for short-term consumption smoothing while neglecting its capacity for driving long–term microlevel targeted investment decisions.

8. References

Abdul-Rahaman, A., Abdulai, A. 2022. Mobile money adoption, input use, and farm output among smallholder rice farmers in Ghana. *Agribusiness.* 38, (1), 236-255.

Abiona, O., Koppensteiner, M. F. 2022. Financial Inclusion, Shocks and Welfare: Evidence from the Expansion of Mobile Money in Tanzania. *Journal of Human Resources.* 57(2), 435-464.

Afawubo, K., Couchoro, M. K., Agbaglah, M., Gbandi, T. (2020) Mobile money adoption and households' vulnerability to shocks: Evidence from Togo. *Applied Economics.* 52(10), 1141-1162.

Afifi, T., Liwenga, E., Kwezi, L. 2014. Rainfall-induced crop failure, food insecurity and out-migration in Same-Kilimanjaro, Tanzania. *Climate and Development*. 6(1), 53-60.

Aggarwal, S., Brailovskaya, V., Robinson, J. 2020. Cashing In (and Out): Experimental Evidence on the Effects of Mobile Money in Malawi. *AEA Papers and Proceedings.* 110, 599-604.

Ahmad, A. H., Green, C. Jiang, F. 2020. Mobile Money, Financial Inclusion and Development: A Review with Reference to African Experience. *Journal of Economic Surveys*. 34(4), 753-792.

Arndt, C., Farmer, W., Strzepek, K., Thurlow, J. 2012. Climate Change, Agriculture and Food Security in Tanzania. *Review of Development Economics*. 16(3), 378-393.

Athey, S., Imbens, G.W., 2017. The State of Applied Econometrics: Causality and Policy Evaluation. Journal of Economic Perspectives 31, 3–32. https://doi.org/10.1257/jep.31.2.3

Aker, J. C., Boumnijel, R., McClelland, A., Tierney, N. 2016. Payment Mechanisms and Antipoverty Programs: Evidence from a Mobile Money Cash Transfer Experiment in Niger. *Economic Development and Cultural Change*. 65(1), 1-37.

Aron, J. 2018. Mobile Money and the Economy: A Review of the Evidence. *World Bank Research Observer.* 33(2), 135-188.

Batista, C., Vicente, P. C., 2020. Improving Access to Savings Through Mobile Money: Experimental evidence from smallholder farmers in Mozambique. *World Development.* 129(C) 104905.

Berhane, G., Gilligan, D. O, Hoddinott, J., Kumar, N., Taffesse, A. S. 2014. Can Social Protection Work in Africa? The Impact of Ethiopia's Productive Safety Net Programme. *Economic Development and Cultural Change*. 63 (1), 1-26.

Banerjee, A., Karlan, D., Osei, R., Trachtman, H., Udry, C. 2022. Unpacking a multi-faceted program to build sustainable income for the very poor. *Journal of Development Economics.* 155(C). Forthcoming.

Baquedano, F., Jelliffe, J., Beckman, J., Ivanic, M., Zereyesus, Y., Johnson, M. 2022. Food security implications for low- and middle-income countries under agricultural input reduction: The case of the European Union's farm to fork and biodiversity strategies. *Applied Economic Perspectives and Policy*. 44(4), 1942-1954.

Blumenstock, J., Eagle, N., Fafchamps, M. 2016. Airtime transfers and mobile communications: evidence in the aftermath of natural disasters. *Journal of Development Economics.* 120,157–181.

Bojnec, Š, Fertő, I. 2022. Do different types of Common Agricultural Policy subsidies promote farm employment? *Land Use Policy.* 105823. Forthcoming.

Carrillo, B. 2020. Early rainfall shocks and later-life outcomes: evidence from Colombia.

The World Bank Economic Review. 34(1), 179–209.

CGAP. 2016. National Survey and Segmentation of Smallholder Households in Tanzania: Understanding their demand for financial, agricultural and digital solutions. Working paper. Available online: http://www.cgap.org/sites/default/files/Working-Paper-Smallholder-Survey-Tanzania-May-2016.pdf

Chavas, J-P., Rivieccio, G., Di Falco, S., De Luca, G., Capitanio, F. 2022. Agricultural diversification, productivity, and food security across time and space. *Agricultural Economics.* 53(S1), 41-58.

Chen, M., Shi, W., Xie, P., Silva, V. B. S., Kousky, V. E., Wayne Higgins, R., Janowiak, J. E. 2008a. Assessing objective techniques for gauge-based analyses of global daily precipitation. *Journal of Geophysical Research.* 113, D04110.

Chen, M., Xie, P., and Co-authors. 2008b. CPC Unified Gauge-based Analysis of Global Daily Precipitation, Western Pacific Geophysics Meeting, Cairns, Australia, 29 July - 1 August 2008.

Corno, L., Hildebrandt, N., Voena, A. 2020. Age of Marriage, Weather Shocks, and the Direction of Marriage Payments. *Econometrica.* 88 (3), 879–915.

Donat, M. G. et al 2013. Updated analyses of temperature and precipitation extreme indices since the beginning of the twentieth century: the HadEX2 dataset. *Journal of Geophysical Research*: *Atmospheres.* 118 (5), 2098–2118.

Duflo, E. 2001. Schooling and Labor Market Consequences of School Construction in Indonesia: Evidence from an Unusual Policy Experiment. *American Economic Review.* 91 (4), 795-813.

Economides, N., Jeziorski, P. 2017. Mobile Money in Tanzania. *Marketing Science.* 36(6), 815-837.

GFSI. (2020) The Global Food Security Index. Accessed on http://foodsecurityindex.eiu.com/ on 06/05/2021.

Garcia-Verdu, R., Meyer-Cirkel, A., Sasahara, A., Weisfeld, H. 2022. Importing inputs for climate change mitigation: The case of agricultural productivity. *Review of International Economics*. 30(1), 34-56.

Gilligan, D. O., Hoddinott, J., Taffesse, A. S. 2009. The Impact of Ethiopia's Productive Safety Net Programme and its Linkages. *The Journal of Development Studies.* 45(10), 1684-1706.

Girabi, F., Mwakaje, A. E. G. 2013. Impact of Microfinance on Smallholder Farm Productivity in Tanzania: The Case of Iramba District. *Asian Economic and Financial Review*, *3*(2), 227–242.

Hainmueller, J., 2012. Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies. Political Analysis 20, 25–46. https://doi.org/10.1093/pan/mpr025

Hainmueller, J., Xu, Y., 2013. ebalance : A Stata Package for Entropy Balancing. J Stat Softw 54. https://doi.org/10.18637/jss.v054.i07

Hirpa Tufa, A., Alene, A. D., Cole, S. M., Manda, J., Feleke, S., Abdoulaye, T., Chikoye, D., Manyong, V. 2022. "Gender differences in technology adoption and agricultural productivity: Evidence from Malawi. *World Development.* 159(C) 106027.

Hu, Y., Liu, C., Peng, J. 2021. Financial inclusion and agricultural total factor productivity growth in China. *Economic Modelling.* 96(C), 68-82.

Imbens, G.W., Wooldridge J.M. 2009. Recent developments in the econometrics of program evaluation. *Journal of Economic Literature.* 47(1):5–86.

IMF. 2012. World Economic Outlook: Growth Resuming, Dangers Remain. Washington DC.

Jack, W., Suri, T., 2011. Mobile Money: The Economics of M-PESA. *NBER Working Papers 16721. National Bureau of Economic Research.*

Jack, W., Suri, T., 2014. Risk Sharing and Transactions Costs: Evidence from Kenya's Mobile Money Revolution. *American Economic Review.* 104(1), 183-223.

Jack, W., Suri, T., 2016. The Long-run Poverty and Gender Impacts of Mobile Money. *Science*. 354(6317), 1288-1292.

Kangalawe, R. Y.M., Mung'ong'o, C. G., Mwakaje, A. G., Kalumanga, E. Yanda, P. Z. 2017. Climate change and variability impacts on agricultural production and livelihood systems in Western Tanzania. *Climate and Development.* 9(3), 202-216.

Kubik, Z., Maurel, M. 2016. Weather Shocks, Agricultural Production and Migration: Evidence from Tanzania, *The Journal of Development Studies,* 52(5), 665-680.

Kurukulasuriya, P., Rosenthal, S. 2013. Climate Change and Agriculture: A Review of Impacts and Adaptations. *Environment department papers; no. 91.* Climate change series. World Bank, Washington, DC.

Mohamed, K.S., Temu, A.E. 2008. Access to credit and its effect on the adoption of agricultural technologies: the case of Zanzibar. *African Review of Money Finance and Banking.* 1, 45–89.

Munyegera, G. K., Matsumoto, T. 2016. Mobile Money, Remittances, and Household Welfare: Panel Evidence from Rural Uganda. *World Development.* 79, 127-137.

Munyegera, G. K., Matsumoto, T. 2018. ICT for Financial Inclusion: Mobile Money and the Financial Behavior of Rural Households in Uganda. *Review of Development Economics.* 22, 45-66.

Murendo, C., Wollni, M., De Brauw, A., Mugabi, N. 2018. Social Network Effects on Mobile Money Adoption in Uganda. *Journal of Development Studies.* 54(2), 327-342.

Murendo, C., Wollni, M. 2016. Mobile money and household food security in Uganda. *Global Food Discussion Papers No. 76*. Georg-August-Universitaet Goettingen, GlobalFood, Department of Agricultural Economics and Rural Development.

Ndhlovu, E., Mhlanga, D. 2023. Smart Technologies, Climate Change, and Smallholder Farmer Production in Zimbabwe. In: Mhlanga, D., Ndhlovu, E. (eds) The Fourth Industrial Revolution in Africa. Advances in African Economic, Social and Political Development. Springer, Cham. https://doi.org/10.1007/978-3-031-28686-5_15

Parlasca, M. C., Mußhoff, O., Qaim, M. 2020. Can mobile phones improve nutrition among pastoral communities? Panel data evidence from Northern Kenya. *Agricultural Economics.* 51(3), 475-488.

Praveen, B., Sharma, P. 2019. A review of literature on climate change and its impacts on agriculture productivity. *Journal of Public Affairs.* 19: e1960.

Ragasa, C., Mazunda, J. 2018. The impact of agricultural extension services in the context of a heavily subsidized input system: The case of Malawi. *World Development.* 105(C), 25-47.

Riley, E., 2018. Mobile Money and Risk Sharing Against Aggregate Shocks. *Journal of Development Economics.* 135, 43-58.

Rocha, R., Soares, R. R., 2015. Water scarcity and birth outcomes in the Brazilian semiarid. *Journal of Development Economics.* 112(C), 72-91.

Schmidt, L., Shore-Sheppard, L. Watson, T. 2016. The Effect of Safety-Net Programs on Food Insecurity. *Journal of Human Resources.* 51(3), 589-614.

Stathers, T., Lamboll, R., Mvumi, B.M. 2013. Postharvest agriculture in changing climates: its importance to African smallholder farmers. *Food Security.* 5, 361–392.

Suri, T. 2017. Mobile Money. *Annual Review of Economics*. 9(1), 497-520.

Tabetando, R., Matsumoto, T., Fani, D. C. R. 2022. Mobile Money, Agricultural Intensification, and Household Welfare: Panel Evidence from Rural Uganda. *Journal of Agricultural and Applied Economics.* 54(3), 515-530.

Villacis, A. H., Mayorga, J., Mishra, A. K., 2022. Experience-based food insecurity and agricultural productivity in Nigeria. *Food Policy.* 113(C) 102286.

Vogel, E., Donat, M. G., Alexander, L. V., Meinshausen, M., Ray, D. K., Karoly, D., Meinshausen, N., Frieler, K. 2019. The effects of climate extremes on global agricultural yields. *Environmental Research Letters.* 14, 054010.

Waldinger, F. 2010. Quality Matters: The Expulsion of Professors and the Consequences for PhD Student Outcomes in Nazi Germany. *Journal of Political Economy.* 118 (4), 787-831.

Wieser, C., Bruhn, M., Kinzinger, J., Ruckteschler, C. Heitmann, S. 2019. The Impact of Mobile Money on Poor Rural Households: Experimental Evidence from Uganda. *World Bank Policy Research Working Paper No. 8913.*

Ubabukoh K., Imai, K. 2022. Are Farmers “Efficient but Poor”? The Impact of Crop Choices on Technical Efficiency and Poverty in Nigeria. *Journal of Agricultural Economics.* Forthcoming.

USAID. 2013 Climate Change Adaptation in Tanzania. Accessed on 15 July 2022.

https://www.climatelinks.org/sites/default/files/asset/document/tanzania_climate_vulnerability_profile_jan2013.pdf

World Bank. 2014. World Development Indicators. World Bank Group, Washington D.C.

World Bank. 2016. Evaluating Tanzania's Productive Social Safety Net: targeting performance, beneficiary profile, and other baseline findings. World Bank Group, Washington D.C.

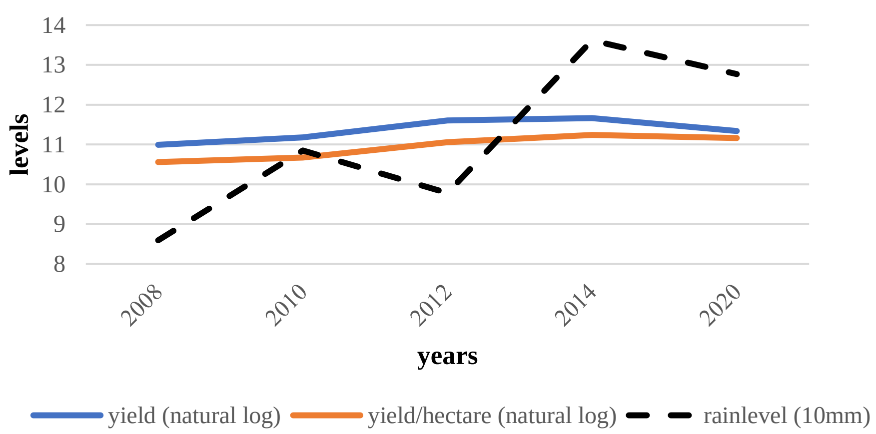
Xie, P., Yatagai, A., Chen, M., Hayasaka, T., Fukushima, Y., Liu, C., Yang, S. 2007. A gauge-based analysis of daily precipitation over East Asia. *Journal of Hydrometeorology.* 8, 607-626.

9. Appendices

Appendix A: Rainfall pattern and agricultural productivity

The body of literature presents extensive evidence on the adverse effect of extreme weather events on agricultural productivity in low-income countries (Kurukulasuriya and Rosenthal 2013, Praveen and Sharma 2019). Figure A1 shows a weak positive correlation between rainfall level and yield patterns within the last decade in rural Tanzania. The pattern shows a prevalence of low rainfall levels in earlier years accompanied by low agricultural productivity. The incidence of low rainfall level is similar to the density of regional distribution of drought shocks in Figure 6. Lack of investment capacity exacerbates the extent of the impact on household welfare. Figure 2 shows that access to credits and loans can mitigate the seasonal productivity risks associated with drought events and excessive heats. However, this requires a timely intervention to secure agricultural inputs and investments for sustainable yields. Mobile money provides a reliable and secure platform for this safety net (adaptative) pathway by navigating the economic, institutional, political, and social challenges facing expansion of financial inclusion in Tanzania. Remittance through mobile money facilitates access to informal credits and loans received from a large network across locations which may be channeled towards agricultural inputs for sustainable harvests (CGAP 2016). Evidence shows that the use of mobile money provides an effective channel between access to loans, credit and savings facilities, and agricultural investments and productivity (Aker et al. 2016, Aggarwal et al. 2020, Batista and Vicente 2020). Batista and Vicente (2020) further shows that savings with mobile money facilitates increased fertilizer inputs for smallholder farmers. Figure 3 shows a similar mitigation pathway towards household food security. We follow the existing literature to provide an indirect link between household use of mobile money, access to credits and loans, and agricultural inputs and productivity using World Bank datasets[33]. We also explore the data to strengthen the link between agricultural productivity and household food security. To achieve this, we use data on crop storage facilities as an intermediary between increased productivity and household food security. However, it is important to note that household food security measures may be directly impacted by remittance outside of agricultural yields. We tease out this effect by examining the impact of household food production component of overall consumption.

Figure A1: Trends of yield and rainfall levels in rural Tanzania (2008 - 2020)



Source: Author's calculations from the World Bank surveys and NOAA-CPC weather data archive.

Appendix B: Estimation Methods – Reduced form analysis and two-stage least squares instrumental variable (2SLS-IV) approach

For the regression analysis, we explore two variants of difference-in-difference (DiD) methodology for equation (3). First, we explore exogenous distribution of mobile money agents across communities to investigate the long-term role of mobile money in this context. This is a known as a reduced form DiD analysis

33 The body of literature relies on primary data from field experiments and randomised control trials to investigate this link. Most of the studies provide targeted intervention support for rural households while evaluating the impact of the programs against control group.

attributing adoption to variation in access to agent distribution over the four waves. Second, we explore the mobile money adoption at the household level. Household mobile money adoption is potentially endogenous as identified in other studies, and the interaction between mobile money and weather patterns may not yield causal estimates when estimating the effects on household welfare outcomes. To resolve this problem, we estimate the effect of mobile money in response to shocks using an instrumental variable DiD (IV DiD) approach similar to the identification strategy in Duflo (2001), Waldinger (2010), Jack and Suri (2014) and Abiona and Koppensteiner (2022). We instrument for mobile money adoption in households across survey waves with the information on mobile money agent's presence and proximity measures (distance and cost) within each community. Proposed specifications for the first stage regressions of mobile money adoption and its interaction with drought are presented in equations (4) and (5) respectively:

$$\mathrm{MM_{ht}} = \boldsymbol{\varphi_1}(\mathrm{Agent_c}) + \boldsymbol{\varphi_2}(\mathrm{Agent\_dist_c}) + \xi_{ht} \qquad (4)$$

$$\mathrm{MM_{ht}} * \text{drought shock}_{\mathrm{ht}} = \boldsymbol{\varphi_1}(\mathrm{Agent_c} * \text{drought shock}_{\mathrm{ht}}) + \boldsymbol{\varphi_2}(\mathrm{Agent\_dist_c} * \text{drought shock}_{\mathrm{ht}}) + \varsigma_{ht} \qquad (5)$$

where $\mathrm{Agent_c}$ is the indicator variable for agent availability within the community and $\mathrm{Agent\_dist_c}$ is the distance to the nearest agent from the centroid.

Table A1: Distribution of household adoption frequency and preference for mobile money

	Survey year:			
	2010	2012	2014	2020
Panel A: Frequency of mobile money use (Proportion)				
Daily	0.0417	0.0124	0.0463	0.0211
Weekly	0.0625	0.1180	0.0880	0.0772
Fortnightly	0.0625	0.0435	0.0509	0.0070
Monthly	0.1667	0.1739	0.1204	0.1754
Quarterly	0.1042	0.0807	0.0278	0.0526
Biannually	0.0208	0.0186	0.0278	0.0105
Occasionally	**0.5417**	**0.5528**	**0.6389**	**0.6561**
Panel B: Designated mobile money use (Proportion)				
Buy airtime	0.0817	0.0898	0.0562	0.1087
Send airtime	0.0058	0.0044	0.0017	0.0011

Send money (Outward remittance transfers)	**0.4066**	**0.3371**	**0.3237**	**0.3038**
Receive money (Inward remittance transfers)	**0.4319**	**0.4522**	**0.4889**	**0.4339**
Receive payment	0.0078	0.0122	0.0153	0.0359
Save for emergency	0.0292	0.0639	0.0801	0.0706
Save for expenses	0.0350	0.0346	0.0290	0.0404
Save for large purchase	0.0019	0.0059	0.0051	0.0056

Note: The Table above provides the composition of frequency and designation (most important use categories) of use for mobile money users for a yearly user HH sample.

Table A2: Summary statistics of rainfall patterns (2010 – 2020)

Year	Mean difference	Median difference	Drought exposure - indicator
	(1)	(2)	(3)
2010	89.49	82.49	0.0209
2012	47.83	37.87	0.1346
2014	240.40	237.82	0.0000
2020	675.40	651.04	0.0000
Overall	122.30	112.66	0.0887

Notes: In the Table above, columns (1) and (2) report mean and median difference between aggregate rainfall patterns across comparison in comparison with combined historical mean. Column (3) report the comparison of seasonal rainfall pattern to reference threshold (using 25th percentile) in equation 1.

Table A3: Covariate balance of means test by drought exposure categories

	control (no exposure group)		treatment (exposure group)		Norm-Difference
Variable	Mean	SD	Mean	SD	
Community					
Bank availability (indicator)	0.2868	0.4523	0.3486	0.4766	-0.0940
SACCO availability (indicator)	0.6523	0.4763	0.8122	0.3906	-0.2596
Household					
household size	5.1321	3.1534	4.9943	2.8219	0.0326
Children under 16 years (#)	2.4008	2.1834	2.1977	1.9217	0.0698
Adults over 70 (#)	0.1592	0.4231	0.1454	0.4074	0.0234
Average age	25.6099	12.8469	26.1369	12.4145	-0.0295
Phone ownership (indicator)	0.6413	0.4796	0.7377	0.4400	-0.1482
Household head					

Household head age	45.5646	15.9837	45.8022	15.6583	-0.0106
Male Household head	0.7534	0.4311	0.7582	0.4283	-0.0079
Education (High school = 1)	0.7855	0.4105	0.8038	0.3972	-0.0321
Occupation categories					
agriculture	0.5931	0.4913	0.4014	0.4903	0.2763
government	0.0571	0.2320	0.0887	0.2844	-0.0862
private_ngo	0.1237	0.3293	0.1693	0.3751	-0.0913
self employed	0.1709	0.3764	0.2543	0.4356	-0.1450
family	0.0114	0.1062	0.0164	0.1272	-0.0304
unemployed	0.0438	0.2047	0.0698	0.2549	-0.0796

Notes: Table A3 reports balance of means test for covariates across drought exposure groups using the method invented by Imbens and Wooldridge (2009). Covariate balancing test in the Table above between no exposure HHs (the control group) and exposure HHs (the treatment group) utilizes the normalized difference approach in the paper where variables with **above a quarter (0.25) norm-difference in absolute terms** are perceived as significantly different between the two groups. The normalized difference is calculated as $norm - diff = \frac{\bar{X}_0 - \bar{X}_1}{\sqrt{s_{x,0}^2 + s_{x,1}^2}}$, where s^2 denotes the sample variance of x_i.

Table A4: Covariate balance of means test by household migration tracking status/characteristics

	relocated households (unbalanced group)		permanent households (strongly balanced group)		Norm-Difference
Variable	**Mean**	**SD**	**Mean**	**SD**	
Community					
Bank availability (indicator)	0.2970	0.4570	0.3034	0.4599	-0.0100
SACCO availability (indicator)	0.6917	0.4618	0.6218	0.4851	0.1045
Household					
household size	5.0365	3.0914	5.5350	3.1668	-0.1126
Children under 16 years (no)	2.3335	2.1266	2.5583	2.2684	-0.0723
Adults over 70 (no)	0.1531	0.4170	0.1801	0.4421	-0.0446
Average age	25.3585	12.5611	27.8277	13.8216	-0.1322
Phone ownership (indicator)	0.6530	0.4761	0.6918	0.4619	-0.0586
Household head					

Household head age	44.7770	15.9656	50.6241	14.6774	-0.2696
Male Household head	0.7562	0.4294	0.7408	0.4383	0.0250
Education (High school = 1)	0.7873	0.4093	0.7948	0.4039	-0.0131
Occupation categories					
agriculture	0.5545	0.4970	0.5964	0.4907	-0.0600
government	0.0652	0.2468	0.0465	0.2105	0.0577
private_ngo	0.1344	0.3411	0.1149	0.3190	0.0417
self employed	0.1874	0.3903	0.1708	0.3765	0.0306
family	0.0126	0.1116	0.0100	0.0995	0.0175
Unemployed	0.0460	0.2094	0.0614	0.2402	-0.0485

Notes: Table A4 reports balance of means test for covariates across HHs by migration status using the method invented by Imbens and Wooldridge (2009). Covariate balancing test in the table above between relocated HHs (the unbalanced sample) and permanent residence HHs (the strongly balanced group) uses the normalised difference approach in the paper where variables with **above a quarter (0.25) norm-difference in absolute terms** are perceived as significantly different between the two groups. The normalised difference is calculated as $norm - diff = \frac{\bar{X}_0 - \bar{X}_1}{\sqrt{s^2_{x,0} + s^2_{x,1}}}$, where s^2 denotes the sample variance of x_i.

Table A5: The interactive impacts of drought and mobile money on sales of harvest and household food production (within consumption)

	Dependent variables:			
	Crop sales in KG	Crop sales in TZSH	Food production in KG	Food production in
	(natural log)	(natural log)	(natural log)	(natural log)
VARIABLES	(1)	(2)	(3)	(4)
Mobile money	-0.3493**	-0.8340***	-0.1050***	-0.0024
	(0.1355)	(0.2386)	(0.0279)	(0.0709)
Drought	-0.6836**	-1.3402**	-0.1654**	-0.1216
	(0.2974)	(0.5820)	(0.0814)	(0.2500)
Mobile money * Drought	0.7103**	1.5157***	0.1702*	0.1863
	(0.3009)	(0.5828)	(0.0880)	(0.2790)
Constant	1.3210**	3.2997***	0.0944	6.7576***
	(0.5325)	(1.0923)	(0.0848)	(0.3067)

Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Enumeration area FE	Yes	Yes	Yes	Yes
R-squared	0.2983	0.3053	0.5070	0.1587
Observations	5,018	5,018	6,624	6,624

Notes: The Table above reports estimated coefficients of drought and interaction terms for HH crop sales and food consumption component from production. Columns 1 – 4 report results for natural logarithm of the sum of crop sales (KG), crop sales (TZSH), food production (KG) and food production (TZSH). Drought variable follows locality reference methodology in equation (1) for extreme drought shock using 25th percentile seasonal precipitation threshold movements below the enumeration area norm. All columns include enumeration area and the survey year fixed effects. See notes in Table 2 and section 5.3 for more details on the covariates used as controls in the regression analysis. Robust standard errors clustered at the enumeration area level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: The interactive impacts of drought and mobile money on current household food security outcomes – Robustness test using drought from Standardised Precipitation Index (SPI)

	Dependent variables:	
	Food consumption score (FCS)	**Household Dietary Diversity Score (HDDS)**
Variables	**(1)**	**(2)**
Mobile money	0.4446	0.0333
	(0.9906)	(0.0731)
Drought (SPI)	-6.2074***	0.1926
	(1.7877)	(0.1781)
Mobile money * Drought (SPI)	5.8798**	-0.0696
	(2.4057)	(0.2291)
Constant	40.0605***	7.7674***
	(3.0201)	(0.2408)
Controls	Yes	Yes
Year FE	Yes	Yes
Enumeration area FE	Yes	Yes
R-squared	0.2255	0.1600

Observations	6,394	6,394

Notes: The Table above reports estimated coefficients of a repeat estimation of outcomes of Table 6 using alternative drought measure namely Standardised Precipitation Index (SPI). Standardised Precipitation Index (SPI) measures the composition of drought variations across enumeration areas. All columns include enumeration area and the survey year fixed effects. See notes of Table 6 for additional notes. Also, see notes in Table 2 and section 5.3 for more details on the covariates used as controls in the regression analysis. Robust standard errors clustered at the enumeration area level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: The interactive impacts of drought and mobile money on current household food security outcomes – Robustness test using drought from extreme heat

	Dependent variables:	
	Food consumption score (FCS)	**Household Dietary Diversity Score (HDDS)**
Variables	**(1)**	**(2)**
Mobile money	-0.0623	-0.1860
	(1.4171)	(0.1251)
Drought (extreme heat)	-5.2064	-0.4516
	(4.0846)	(0.3518)
Mobile money * Drought (extreme heat)	7.6865*	0.9247**
	(4.4098)	(0.4003)
Constant	39.0699***	7.6221***
	(3.6834)	(0.3099)
Controls	Yes	Yes
Year FE	Yes	Yes
Enumeration area FE	Yes	Yes
R-squared	0.2188	0.1568
Observations	6,098	6,098

Notes: The Table above reports estimated coefficients of a repeat estimation of outcomes of Table 6 using alternative drought measure namely extreme heat indicator. See equation 2 for the definition of extreme heat measure capturing locality temperature levels above 90^{th} percentile threshold of historical norms. All columns include enumeration area and the survey year fixed effects. See notes of Table 6 for additional notes. Also, see notes in Table 2 and section 5.3 for more details on the covariates used as controls in the regression analysis. Robust standard errors clustered at the enumeration area level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A8: The interactive impacts of drought and mobile money on current household food security outcomes – Robustness test from an instrumental variable approach

	Dependent variables:	
	Food consumption score (FCS)	Household Dietary Diversity Score (HDDS)
Variables	(1)	(2)
Mobile money	-11.1473***	-0.7777**
	(3.6582)	(0.3321)
Drought	-9.2129***	-0.1840
	(2.8960)	(0.3395)
Mobile money * Drought	20.5552***	0.2275
	(7.2385)	(0.8115)
Constant	57.2427***	9.5381***
	(3.5692)	(0.2521)
Controls	Yes	Yes
Year FE	Yes	Yes
Enumeration area FE	Yes	Yes
R-squared	0.2265	0.1579
Observations	6,624	6,624

Notes: The Table above reports estimated coefficients of a repeat estimation of outcomes of Table 6 using two-stage least square instrumental variable (2SLS-IV) approach. Drought variable follows locality reference methodology in equation (1) for extreme drought shock using 25th percentile seasonal precipitation threshold movements below the enumeration area norm. All columns include enumeration area and the survey year fixed effects. See Appendix 1 for details of the instruments and notes of Table 6 for additional details. Also, see notes in Table 2 and section 5.3 for more details on the covariates used as controls in the regression analysis. Robust standard errors clustered at the enumeration area level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A9: The interactive impacts of drought and mobile money on HH credits and remittance

	Dependent variables:	
	Credits (natural log)	Remittance (indicator)
Variables	(1)	(2)
Mobile money	-0.0457	0.0137
	(0.1442)	(0.0097)
Drought	-0.6635**	0.0110
	(0.2945)	(0.0363)
Mobile money * Drought	0.6488*	-0.0169
	(0.3689)	(0.0392)
Constant	-5.3182***	0.0269
	(0.5670)	(0.0405)
Controls	Yes	Yes
Year FE	Yes	Yes
Enumeration area FE	Yes	Yes
R-squared	0.1235	0.1818
Observations	6,624	6,620

Notes: The Table above reports estimated coefficients of drought and interaction terms for HH credits and remittance in the past 12 months. Column 1 report results for natural logarithm of the sum of HH credits while column 2 reports results for indicator remittance – 1 for any remittance received within past 12 months; and 0 otherwise. Drought variable follows locality reference methodology in equation (1) for extreme drought shock using 25th percentile seasonal precipitation threshold movements below the enumeration area norm. All columns include enumeration area and the survey year fixed effects. See notes in Table 2 and section 5.3 for more details on the covariates used as controls in the regression analysis. Robust standard errors clustered at the enumeration area level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Mission

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

The mission rests on two basic premises: that development is more likely to occur where there is sustained sound management of the economy, and that such management is more likely to happen where there is an active, well-informed group of locally based professional economists to conduct policy-relevant research.

Bringing Rigour and Evidence to Economic Policy Making in Africa

- Improve quality.
- Ensure Sustainability.
- Expand influence.

www.aercafrica.org

Learn More

www.facebook.com/aercafrica

www.instagram.com/aercafrica_official/

twitter.com/aercafrica

www.linkedin.com/school/aercafrica/

Contact Us
African Economic Research Consortium
Consortium pour la Recherche Economique en Afrique
Middle East Bank Towers,
3rd Floor, Jakaya Kikwete Road
Nairobi 00200, Kenya
Tel: +254 (0) 20 273 4150
communications@aercafrica.org