Shock-mitigating role of mobile money adoption on household expenditure, poverty, and inequality

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Abstract

In this paper, we examine the impact of mobile money adoption on expenditure patterns, poverty, and inequality in the aftermath of drought shocks. This research extends the literature on the consumption smoothing capacity of mobile money adoption to its capacity to moderate inequality across local communities over the long-term. We use household survey datasets from the Tanzanian National Panel surveys (TZNPS) between 2010 and 2020. The study explores the spatial distribution of drought shocks from extremely high temperature patterns and low rainfall across waves of panel localities while investigating the adaptation mechanisms through increased mobile money agent distribution over the same period in a difference-in-difference framework. Our findings show that access to mobile money agents enhances preference of consumption smoothing towards food, relative to non-food items. This is supported by evidence of results for poverty outcomes. More importantly, the results showcase a mitigating pathway for the inequality-increasing impact of droughts across localities. Our findings are consistent with the effectiveness of basic technological tools for the improvement of economic welfare after an extended period.

JEL classifications: D15, D16, G23, I3, R2

Keywords: Inequality, Mobile Money, Long-term, Covariate shock, Drought

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1. Introduction

The proliferation of mobile phone technology underpins development in low-income countries. For example, beyond aiding communication and network-building capacity, the expansion of mobile phone coverage advances the potential for rapid development of economic activities in Africa (Aker and Mbiti 2010). One of the innovations that has been built on the widespread mobile phone adoption in these settings is the provision of financial services on mobile phones – through the services of mobile money. Mobile money is basically a pay-as-you-go digital medium of exchange and store of value using mobile accounts typically offered by mobile network operators (MNOs) or other entities in partnership with MNOs (IMF 2019)[1]. This platform differs from mobile-based financial services in that it does not require a bank account, traditional financial infrastructure, or internet connections. Although the medium of storage is mobile phones, a network of mobile money agents is important to facilitate transactions, especially in converting cash to electronic money (deposits) and electronic money to cash (withdrawals). However, the establishment of agent banking of this nature is straightforward relative to traditional banks because it serves as a business model through a partnership between local businesses and the MNOs. The use of mobile phones to make financial transactions, particularly by people that do not have access to traditional bank accounts has been heralded as revolutionary for financial inclusion, particularly in developing countries. Mobile money offers the features of easier access, convenience, and lower transaction costs than traditional banking systems or existing informal money transfer systems in developing countries. Thus, it is not surprising that there has been a huge increase in its adoption, particularly in Sub-Saharan Africa, where nearly half of all accounts are registered (GSMA 2019).

There is a growing body of evidence on the role of mobile money in improving the capacity of households to cope with negative shocks from adverse events. Mobile money has been found to help sustain welfare in the face of shocks (Riley, 2018, Batista and Vicente, 2020), improve efficiency in the allocation of labour and consumption over time (Weiser et al., 2019; Suri and Jack, 2016), enable risk sharing (Blumenstock et al., 2016), reduce poverty (Jack and Suri 2014, Suri and Jack 2016, Munyegera and Matsumoto 2016, Sekabira and Qaim 2017, Suri 2017, Riley 2018, Wieser et al., 2019), and aid savings (Ky et al., 2018; Aggarwal et al, 2020; Naito et al., 2021). The mechanism by which this happens typically includes facilitating remittances, preventing negative coping strategies such as reduction in food or medical expenditure, and allowing a more efficient allocation of labour by assisting the shift from less productive agricultural activities to more productive non-farm enterprises – particularly for women. Although there is a lot of evidence at the individual and household level on the shock-mitigating role of mobile money, this has usually been over the short-term. Most of the evidence often rely on analysis based on data that typically span between 3 to 5 years. However, assessing long-term implications is crucial to understanding if the shock-mitigating role of mobile money is inclusive and sustainable, and to also help assist in the design of appropriate regulatory frameworks that unlocks the full potential of mobile money

[1] For example, some banks have partnered with mobile money operators to create digital banking product. This includes M-Shwari in Kenya and M-Pawa in Tanzania.

as a financial inclusion tool. In addition, there also exists a gap in the literature on the role of mobile money for welfare distribution within and across localities. For instance, very little is known about the consequences of mobile money adoption on distribution of consumption patterns within households or within/between communities. This area of study is important as huge transaction costs may create an additional hurdle for access to these services within communities. This means that richer households may be able to benefit more from adopting mobile money relative to poorer ones. Such inequalities in adoption may be propagated through its role in helping adaptation to shocks. Across communities, mobile money may help richer communities adapt and cope to shocks and thus accentuate spatial inequality. Within households, disproportionate access to mobile money may shift bargaining powers of spouses with attendant effect on the incidence of domestic violence. These benefits may accrue only after a sustained adoption of mobile money services following its spread.

This paper makes an important advancement to the literature by examining the long-term shock-mitigating role of mobile money as well as its impact on inequality at the community level. Our focus is on Tanzania, one of the earliest adopters of mobile money, where there is almost one mobile money account for every adult population and where the use of mobile transactions pushed the percentage of Tanzanians using formal financial services from 16 percent to 65 percent between 2009 and 2017 (Makoye 2022). We leverage data spanning over 10 years from four waves of the World Bank's Tanzania Living Standard Measurement Studies–Integrated Survey on Agriculture (LSMS-ISA) to examine long-term mitigating roles of mobile money. We combine information on households' mobile money access with information on exposure to droughts (exogenous shocks) to estimate the response to shocks for households with and without mobile money access and examine the long-term pathways. By leveraging exogenous rainfall shocks to households, we can avoid the endogeneity and measurement error issues that may confound the use of household-self reported shock. In addition, by focusing on households depending predominantly on rain-fed agricultural production, we tease out heterogeneous impacts of mobile money for coping with shocks via food and non-food components of expenditure patterns over the long-term.

We show that droughts have an adverse impact on household consumption, but mobile money adoption mitigates this impact with total (food) consumption increasing in adopter households. This finding is indicative of household preferences for the allocation of resources enabled by mobile money transactions, such as remittances during shock period, towards food consumption. We show that mobile money adoption during drought incidences significantly reduced the probability of households falling into relative poverty (less than US$2) by 16 percent and extreme poverty (less than US$1.25) by 13 percent. These findings are in line with a vast body of literature that showcases the poverty-mitigating impact of mobile money adoption amid climatic shocks (Mizutani 2021, Abiona and Koppensteiner 2022, Djahini-Afawoubo et al. 2023). Distributionally, we find that mobile money serves an inequality-mitigating role in adopter communities post-shock compared to non-adopting communities. Access to mobile money agent reduces within community per-capita expenditure inequality by about 0.035 percentage points after a co-variate shock.

Our study contributes to the growing body of work examining the impact of mobile money as a shock mitigating tool, as well as the wider literature on the effect of widening financial access on economic development (Fonseca and Van Doornik 2022. Muganyi et al. 2022). Our findings have implications for policy especially those designed to promote financial inclusion via mobile technologies in low-income countries. More importantly, understanding the long-term role of mobile money in places such as Tanzania where it has a longer history will provide insights into settings where the mobile money revolution is just beginning[2]. Furthermore, recent events such as the COVID-19 pandemic and climate shocks have highlighted the need to understand household coping strategies and the best tools to help support welfare in those circumstances. The restrictions on face-to-face interactions and the use of cash during the early phase of the COVID-19 pandemic has further driven the adoption of digital methods of payments, with the use of digital systems including mobile money further being mainstreamed into many social protection systems (Demirgüç-Kunt et al., 2022; World Bank, 2022). Our work contributes by providing evidence of the long-term impacts and pathways through which mobile money may affect household welfare and community-level outcomes after experiencing shocks. Covariate welfare shocks such as those from pandemics or climate change are bound to increase in frequency going into the future (Premand and Stoeffler 2022) and our work provides an assessment of the role of mobile money, a promising tool of digital financial inclusion. Specifically, this paper fills the gap on the inequality component of welfare outcomes for rural households in addition to extensive evidence on consumption patterns and poverty. Our results showcase evidence of sustainable welfare through mobile money. The policy dimension of these results cannot be over-emphasized. Notably, many countries have recently adopted (introduced or increased) tax regimes on mobile money transactions[3]. This step is likely to be highly regressive as the burden will fall on the poor who may subsequently reduce their volume of transactions thereby further expanding the inequality gap.

The remainder of the paper is structured as follows. Section 2 provides a review of the existing body of literature to consolidate evidence in this area of research. Section 3 explores the conceptual framework for consumption smoothing through innovative financial inclusion during shocks. In section 4, we present the characteristics of the linked data used to address the research question while section 5 outlines the empirical strategy. In section 6, we present all the results from our analysis including main, heterogeneous, robustness and sensitivity tests. Section 7 discusses the main findings of our analysis and how these are positioned within the literature. We conclude the article with the policy implication and opportunities for further research in section 8.

2. Background and related literature

There has been a steady increase in mobile money adoption across Africa and, subsequently, empirical research into its impact on rural household welfare. Recent literature has found

[2] Following Kenya, Tanzania has the longest history of mobile money adoption in Africa. Both countries are useful East African case studies for emerging late adopter countries in West Africa.
3 In Tanzania, there have actually been concerns with recent hikes in taxes on mobile money that have forced the government to backtrack.

mobile money to improve rural household consumption smoothing, facilitate risk sharing and subsequently reduce their poverty status (Jack and Suri 2014, Munyegera and Matsumoto 2016, Suri and Jack 2016, Sekabira and Qaim 2017, Suri 2017, Riley 2018, Wieser et al. 2019, Baffour et al. 2021, Mizutani 2021, Abiona and Koppensteiner 2022). Studies in Kenya, Tanzania, Uganda, and Ghana have found that mobile money services increase household consumption and reduce poverty levels in the short term (Batista and Vicente 2021, Baffour et al. 2021, Mizutani 2021, Abiona and Koppensteiner 2022). Dizon et al. (2020) report mobile money savings not only reduce risk-sharing but also increase Kenyan women's ability to cope with negative shocks, while Fabregas and Yokossi (2022) using satellite imagery, establish the positive effect of mobile money on economic growth.

Research by Riley (2018), Batista and Vicente (2021), Abiona and Koppensteiner (2022) go further than the norm to investigate the impact of mobile money following a rainfall shock on rural household consumption. Riley (2018) finds that mobile money adopters are less likely to reduce their household consumption after a village-level flood or drought shock than non-adopters. Likewise, Batista and Vicente (2021) using a randomized controlled trial of rural households in Mozambique show that mobile money adoption improved consumption smoothening which subsequently led to reduced vulnerability to weather shocks. Although, they find that mobile money adoption resulted in reduced investments, especially in agriculture. Conversely, Abiona and Koppensteiner (2022) show that during periods of shocks, mobile money adopter households are better able to smooth consumption as well as maintain investments in human capital. These studies provide evidence of the smoothing effect of mobile money services even during an exogenous shock. The latter is an indication of potential forward-looking household decisions when there is access to mobile money which may be related to long-term mobile money impacts evaluated in this paper. Suri and Jack (2016) show that access to mobile money services in Kenya reduced poverty as well as facilitated improvement in the economic status of poor women and female-headed households. Wieser et al. (2019) also find that mobile money agent rollout increases household self-employment and improves their food security. Although their study finds no significant effect of mobile money on poverty and agricultural outcomes.

Our focus in this study is Tanzania, a country with a population of about 61 million people, comprising about 31 million men and 30 million women. Mobile money transactions in Tanzania in 2022 reached a value of 60 billion U.S. dollars from about 4 billion transactions (TCRA, 2023). Apart from Kenya, Tanzania has one of the longest histories of mobile money adoption in Africa. The first mobile money operation started in 2008 leading to quick widespread adoption – the number of registered mobile customers increased from 14,000 in June 2008, to 20.4 million in November 2012. Currently as of December 2022, it is estimated that there are around 40.9 million mobile money accounts (indicative of more than 1 account per adult population). The market share[4] for mobile money is split among Vodacom Tanzania's M-Pesa (40%), followed by Millicom Tigo (27%), Bharti Airtel (22%), Halotel (9%), and TTCL (3%). We explore a 10-year long panel dataset from this setting to examine the long-

[4] Authors' calculations from the Tanzania Communications Regulatory Authority (TCRA) Communication Statistics Report for December 2022.

term impacts of mobile money. The study also investigates the drought shocks mitigating impact of mobile money adoption on household poverty and inequality within communities.

3. Conceptual framework – consumption smoothing hypothesis

The literature highlights unambiguous evidence on the mitigating strategies adopted by households during unanticipated household economic shocks. These responsive behaviours are domiciled within insurance and risk-sharing models of economics (Yang and Choi 2007, Jack and Suri 2014). The theoretical model in this paper considers a coordinated household-level risk-sharing framework which explores an extensive distribution of the geographical location of households within a network. Here, selected group of households are exempted from the negative shock at certain time which may leverage provision of support for affected households through remittance transfers[5]. In our model, the same basic assumption for the existence of pareto-efficient allocation of risk across households in different states of shock hold (Yang and Choi 2007).[6] The welfare state for households exposed to positive and adverse shocks may differ under various circumstances. Consider a network consisting of at least two households, indexed by $h \in \{1,2,\ldots n\}$. We assume that at least one of the households is faced with a different state of shock S^i from that which is experienced by other households mainly from a subset where $i \in \{+, -\}$. S_t^+ and S_t^- represent positive and negative states of shock at period t respectively[7]. We introduce adoption of innovative financial inclusion that expand access into the model to facilitate risk-sharing. This platform helps remittance of funds to and from across network households in diverse states of nature. While other informal safety net strategies continue to play consumption smoothing role for rural households, reduced transaction costs[8] associated with the introduction of mobile money services facilitates sustainable consumption smoothing while preserving household assets. Access to an extensive network – through increasing coverage of mobile money agents (Aron 2018, Ahmad et al. 2020) – increases the propensity and amount of remittance available thereby helping to cushion shocks during an emergency (Jack and Suri, 2014).

We follow Yang and Choi (2007) which states that along the two major states of shock referenced above, households (and individuals therein) face uncertain income in each period t. Consequently, household h consumes $c^h_{s_t^+}$ or $c^h_{s_t^-}$ in either time period, leading to four potential

[5] This model can also be adopted for different exposure levels of economic shocks across geographical locations where partially exposed households may help to cushion the impacts of the shocks for those located in badly affected areas.

[6] A network of households exposed to mutually exclusive dichotomous shock components (positive and negative), in a risk-sharing arrangement, are able to smooth consumption perfectly. This is driven by different but complementary states of household financial positions within a network in different regions of the country. A typical example of the source of such shock exposure comes from precipitation patterns (at a point in time and in reference to historical norm) which affects smallholder households in low-income countries.

[7] Positive and negative state shocks may depict positive short fall and adverse shocks respectively. For smallholder households this may be captured using equal or above average and negative deviation of rainfall pattern in the recent agricultural season compared to the historical norm.

[8] It is important to note that exorbitant transaction cost remains in the traditional remittance systems. These systems also face considerable challenges including associated risk and delay in delivery time of remittance to recipient households. Apart from cost issues with traditional remittance in Tanzania, most of the traditional remittance platforms are not suitable for meeting household emergency demands.

interactions of households across nature of shock and period[9]. We depart from Yang and Choi (2007) by considering the welfare ratio of the same household across periods (either facing the same or different states of shock). If the utility derivable from household consumption ($U_h^t c^h$) is separable over time, and each instantaneous utility is twice differentiable with $U_h' > 0$ and $U_h'' < 0$. The ratio of welfare status of households in two time periods can be written as:

$$\frac{U_h^{1'}(c_{s_1^i}^h)}{U_h^{2'}(c_{s_2^i}^h)} = \frac{\mathrm{W}_1^h}{\mathrm{W}_2^h}, \quad \text{for all } h \text{ and } i. \qquad (1)$$

Where W_1^h and W_2^h are welfare status of household across two periods: first and second periods respectively. In an ideal state, where consumption is perfectly smoothed over the two periods, the right-hand side segment of Equation (1) is equivalent to 1, indicating that negative idiosyncratic shock faced by a household does not affect its consumption pattern across time (Equation 2). This framework is particularly crucial to understand household welfare pattern for those with negative income shock in the second period irrespective of their first period state of shock.

$$\frac{\mathrm{W}_2^h}{\mathrm{W}_1^h} = 1, \text{ for all types of } h. \qquad (2)$$

On the other hand, disparity in the socioeconomic levels across the two time periods may lead to differences between the current welfare state of a household relative to its previous welfare. This is illustrated by eq. (3) below.

$$\frac{\mathrm{W}_2^h}{\mathrm{W}_1^h} \lesseqgtr 1, \text{ for all types of } h. \qquad (3)$$

We disintegrate equation (3) above into two components where the first signifies less than unity relative welfare and the other is greater than unity. The former provides a framework for less than full consumption smoothing (Fafchamps *et al.* 1998) while the later can be classified as households with excess economic resources and may be able to provide remittance or credits/loans through savings. We assume that both households rely on rain-fed agricultural practices but that each household category is resident in a different geographical location which is affected by different weather pattern. Households may be exposed to either positive or adverse shocks which may either deplete or increase their economic resources. Weather patterns provide plausible exogenous shocks that determines available economic resources across households. The most important component of this theory is identifying sustainable

[9] First, a household may be exposed to a positive income shock in periods 1 and 2 respectively. Second, a household may as well experience negative income shocks in two consecutive periods. While this seems to be representative of a static model of shock dispositions, the magnitude across these consecutive periods may play an important role in altering household welfare. Third, a household may be exposed to negative income shock in the first period and consequently have a positive income shock in the second period. The last case is the case where a household experiences a positive income shock and then is faced with a negative income shock in the second period.

support pathway for households with less than 1 relative welfare over the two-period setting. This can be achieved by networking the two types of households presented in Equation 3. This argument underpins the consumption smoothing theory which upholds the findings in many mobile money papers. In some cases, the empirical results support reciprocity where scenarios are interchanged for households who are exposed to diverging shocks over two periods.

Our main objective in this paper is to empirically link financial inclusion to sustainable welfare across expenditure patterns, poverty levels and local inequality. This is particularly relevant with the long-term adoption of mobile money in developing countries where climate change risks are higher, leading to unexpected variation in weather patterns that affect agricultural practice. The consumption smoothing framework using household inter-period welfare states proposed in Equations (2) and (3) may stabilise through mobile money agents in rural settings of Africa due to the capacity to integrate the rural poor into the financial system and sustainably bridge the gap between this group and the urban households. Nevertheless, empirical results vary in the consumption smoothing capacity of mobile money across welfare outcomes. This includes perfect consumption smoothing (Jack and Suri 2014), imperfect smoothing (Tabetando and Matsumoto 2020) and overcompensation (Riley 2018, Abiona and Koppensteiner 2022) in response to idiosyncratic and covariate shocks. In this paper, we test the consumption smoothing hypothesis by exploring inequality in addition to expenditure patterns and poverty levels over a long-term period. This focus helps to provide a new perspective of the impact of mobile money on the potential for shift in the distribution of income composition across the same set of households. The timeframe of our analysis is crucial to match required adjustment timelines for expenditure patterns reflecting adoption of new technology in a new environment (Jiménez 2020). Figure 1 depicts the consumption smoothing process for households exposed to adverse shocks in connection with the pathways and channels of consumption smoothing.

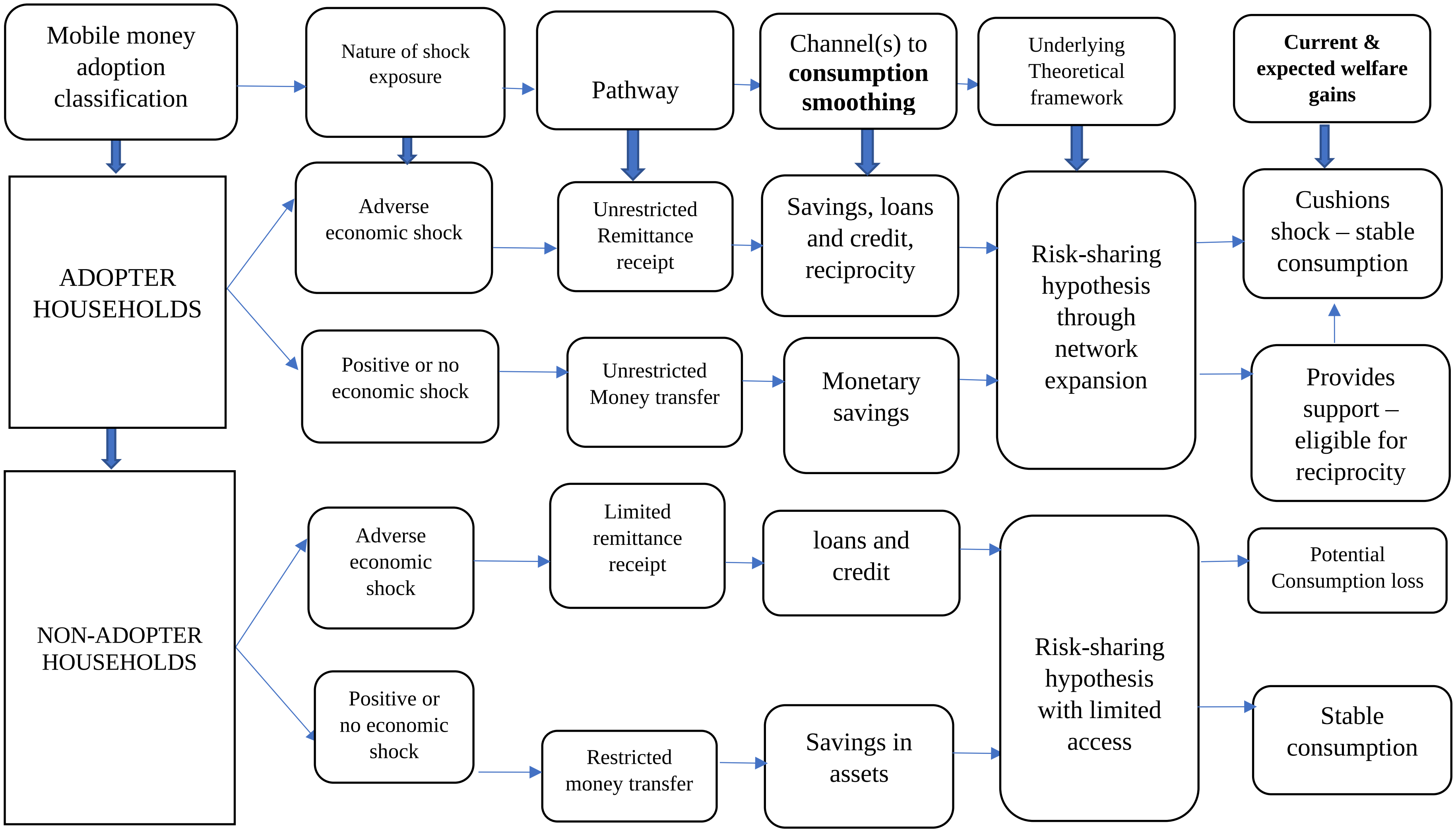

Figure 1: Consumption smoothing pathways through mobile money.

4. Data

We use data from the Tanzania National Panel Survey (TZNPS). The survey is part of the Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA). The TZNPS is a nationally representative household panel survey that collects information on a wide range of topics including agricultural production, non-farm income-generating activities, access to basic services, consumption expenditures, and a wealth of other socioeconomic characteristics. The objective of the survey is to provide high-quality household-level data for monitoring poverty dynamics and evaluating the impact of other major, national-level government policy initiatives (National Bureau of Statistics n.d).

The first wave of the survey was conducted over twelve months from October 2008 to October 2009 with the sample design for the second including re-interviewing the same households in 2010/11 (Wave 2) and 2012/13 (Wave 3) with an almost 96 percent retention at the household level up to Wave 3. However, as with most longitudinal surveys, households leaving the survey (attrition) reduce its representativeness and increases the risk of bias. Thus, the sample was refreshed in a fourth wave (2014/2015) to include new households. In this wave, a nationally representative sub-sample of households from 2008/09 were selected to continue as part of an "extended panel" and subsequently re-interviewed in 2019/20. The sample design for the 2019/20 "extended panel" targeted the sub-sample of households from the initial cohort in 2008/09 and subsequently surveyed in all four consecutive rounds. This consisted of 989 households from the 2014/15 sample to be tracked and interviewed in 2019/20. The final sample for extended panel in 2019/20 and the base sample of our analysis thus included 5,587 individuals in 1,184 households including split-off households identified during data collection (National Bureau of Statistics 2021).

From our panel data covering 2008-2020, we restrict our focus to data from the 2010/11 wave as the first wave survey does not contain information on adoption of mobile money and thus it is not possible for us to distinguish which household has adopted mobile money or not. Unlike previous literature, which usually examines that the impact of mobile money over the short-term, typically a 3 to 5-year period, our data provides us with a panel dataset of around 10 years (2010-2020) to examine long-term pathways through which mobile money affects household welfare after multiple exogenous weather shocks. As the TNZPS is a multi-topic household survey with detailed information on individuals and households including itemized information on household expenditure on food and non-food items, we use this information to examine the heterogeneous impacts of mobile money for coping with shocks via food and non-food components of expenditure patterns over this period.

In addition, we use datasets from the weather data archive of National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (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 for 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 for the period of 1979 – 2022. We extract GPS coordinates (latitude and longitude) provided within the geospatial datasets of TZNPS to compute baseline precipitation and temperature datasets for aggregation. Following a similar approach in the literature, 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 the linkage process are available from the authors upon request).

5. Empirical strategy

We investigate the long-term mediating impact of mobile money adoption on the effect of drought shocks using household survey. This is to assess consumption smoothing hypothesis underpinning mobile money proliferation within long-tern scope. Similar to existing literature, we explore household consumption (expenditure patterns), poverty and inequality as measures of welfare outcome in Tanzania within the context of agricultural shocks (see section 3 for conceptual framework). The study exploits a 10-year incremental variation of mobile money adoption from the Tanzanian Living Standard Measurement Study datasets — Integrated Survey on Agriculture (LSMS – ISA) — for identification strategy.

5.1 Agricultural shock – droughts

The rainy season in Tanzania runs repeatedly for two periods of about 6 months – between mid-March to May as well as October to December of each year. In rural Tanzania, smallholder households mainly undergo subsistence farming where they cultivate major cereals, for instance, paddy crops such as maize, millet and sorghum. Harvests are usually carried out just before the rainy season, though there may be additional cultivation of crops with minimum water requirements during the dry months. We construct rainfall patterns by aggregating precipitation levels for every district from the CPC datasets. We use alternative drought denominations from both precipitation and temperature variations. For the main model in the results section, we construct drought shocks as exposure to heat waves which is captured as the proportion of days within the planting season with temperature shock – above 90th percentile of the temperature variation for the same period in 30 years. The common denominator used for this exposure is the days of the year – 365 days. For robustness, we also used variation in precipitation levels over the same period[10]. We construct the primary drought measure of the paper as follows[11]:

$$heat\ wave_{lt} = \frac{\text{frequency of days with temperature (Temperature}_{ltd}\text{)>90th percentile distribution}}{\text{Total number of seasonal days}} \quad (4)$$

where Temperature_{ltd} indicates the daily maximum temperature levels for the current agricultural season within district *l* for period *t* and day *d*. The 90th percentile threshold is

[10] This includes computing an indicator variable from appropriate threshold frameworks, such as 1 standard deviation movement below locality precipitation historical mean or measures below the 25th percentile of historical precipitation variation. Similar studies use this threshold for the estimation of household shocks and responsive behaviours (Rocha and Soares 2015, Comfort 2016, Carrillo 2020, Corno et al. 2020).

[11] It is important to note that while the drought measure, $heat\ wave_{lt}$, is a continuous variable for the primary drought measure, this is captured as an indicator (binary) variable – using the relative performance of seasonal rainfall level of each year compared to the long-term average – for secondary measures.

computed using a 30-year maximum temperature distribution associated with planting seasons across districts. $heat\ wave_{lt}$ measures the severity index for excessive heat with capacity to distort crop yields which is relevant to this study (Donat et al. 2013, Vogel et al. 2019). The targeting of crop yields here presents credible measure of exogenous shock for households with low adaptation strategies in a low-income country setting.

5.2 Consumption smoothing, poverty and inequality models.

We test whether expanding mobile money adoption has a mediating impact on the effect of an exogenous shock on household consumption, household poverty status and community (or district level) inequality. The empirical analysis is evaluated for the long-term period. The main empirical specification used in this study is as follows:

$$Y_{ilt} = \alpha_i + \boldsymbol{\beta_1}(\mathrm{MM}_{ilt}) + \boldsymbol{\beta_2}(\ heat\ wave_{lt}) + \boldsymbol{\beta_3}(\mathrm{MM}_{ilt} * heat\ wave_{lt}) + \ \boldsymbol{\beta_4}(X'_{ilt}) + \boldsymbol{\beta_5}(Z'_{ilt})\ + \delta_t + \mu_{ilt} \quad (5)$$

Where Y_{ilt} represents consumption, poverty and inequality outcome variables[12] of household i in locality l in year t. MM_{ilt} is a dummy variable that takes the value of 1 if a household have access to mobile money agent within the locality. $heat\ wave_{lt}$ is a continuous variable capturing exposure to extreme temperature as outlined in equation (4)[13]. The coefficient $\boldsymbol{\beta_1}$ captures the impact of household mobile money adoption on the outcome variables while $\boldsymbol{\beta_2}$ presents the direct impact of drought shocks. The coefficient of the interaction between mobile money adoption and drought shocks, $\boldsymbol{\beta_3}$ relative to $\boldsymbol{\beta_2}$ captures the mitigating factor of mobile money access for households accessing mobile money compared to those who do not in periods of unexpected drought shocks. The model also includes household (X'_{ijt}), and household head (Z'_{ijt}) covariates to account for changes in household characteristics during the period. We include controls 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 bank and SACCO using the community level indicators for the availability of these services, and rural indicator for location of HH residence. Finally, we include another geographical covariate for mainland versus island districts captured during the survey to control for household heterogeneity across regions. The term μ_{ilt} is the error term.

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[12] In the analysis, we use standard measures of poverty and inequality. For poverty, we use alternative measures namely relative and extreme poverty with US$1.25 and US$2 per-capita per day for real values of per-capita household expenditure. Similarly, we also use three measures of locality inequality across households– gini coefficient, Theil and Mean Log Deviation – for comparison.

[13] This is also represented as an indicator variable for the secondary measures of drought across households where we designate the variable as 1 if household i experienced drought shocks in locality l and time t and zero otherwise.

5.3 Identification

Equation 5 above is estimated using a difference-in-difference (DiD) approach with locality fixed effects. Specifying the difference-in-difference estimator accounts for biases resulting from difference between mobile money adopters and non-adopters as well as time-variant trends. First, the effect of mobile money adoption on household's ability to withstand drought shocks in the long- term is identified by assuming that the interaction $\mathrm{MM}_{ilt} * heat\ wave_{lt}$ is independent of the error term μ_{ilt}, dependent on the main effects of households adopting mobile money and experiencing a drought shock as well as the household fixed effects, time fixed effects and other control variables. Here, agricultural drought is assumed exogenous to household characteristics. It is important to note that variation in mobile money adoption is matched with distribution of extreme weather events across districts (Figure A1) enabling stronger inference from the difference-in-difference model.

The estimation strategy above assumes parallel trends for causal impacts. This implies that the expenditure patterns would maintain the same trajectory in the treatment and control groups without mobile money. Also, the characteristics of mobile money adopter and non-adopter households are assumed the same to establish a quasi-random assignment of mobile money treatment. Using a lowess smoother transformation for household mobile money adoption rate (indicator), Figure 2 demonstrates an inverse relationship between the adoption and distance/cost of a trip to the nearest mobile money agent from 2010 – 2020. Hence, we posit that the mobile money access instruments can only affect expenditure patterns which is the basis for alternative outcome variables (poverty and inequality) through agent distribution. Empirical strategies in the literature include field experiments (RCT) or using longitudinal surveys combined with evaluation techniques that seeks to uncover causal evidence on the impact of mobile money adoption. Our study falls into the latter group of studies using longitudinal data and exploiting exogenous variation arising from co-variate weather shocks to uncover the shock mitigating impact of mobile money.

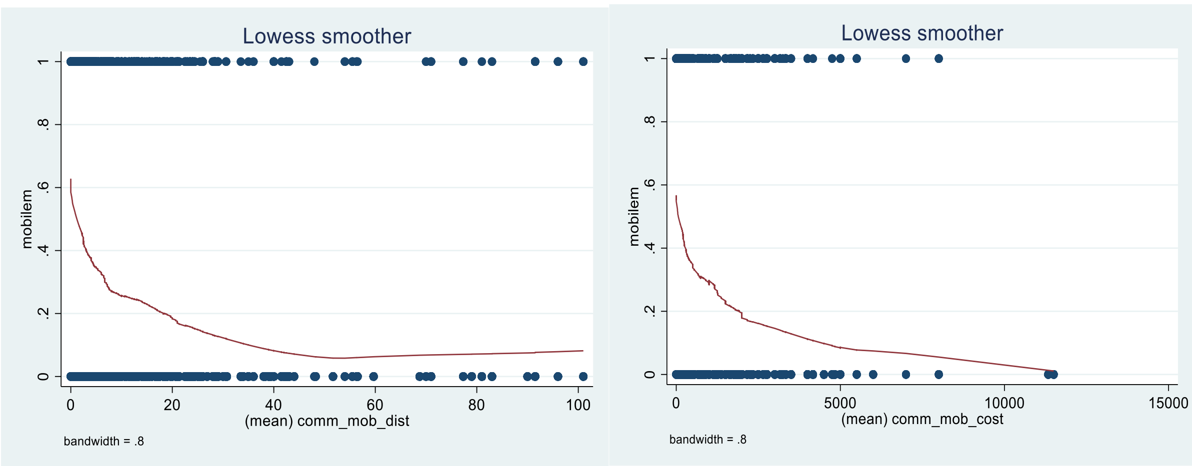


Figure 2: Household mobile money adoption and distance to the nearest agent – lowess smoother.

5.4 Summary statistics

Table 1 presents the summary statistics of household demographic characteristics which are also used as covariates during the estimation process. Using standardised UN poverty thresholds – relative and extreme poverty measures, 25 percent of households are classified as living in relative poverty (using the US$1.25 per-capita per day threshold) while 12 percent are in absolute poverty across households (using the US$2 per-capita per day threshold). About 64 percent of households reside in rural areas, with a mean household size of about 5 members of which about 2 are aged below 16 years. The average age of household members is 26 years, and above 65 percent of households in our sample own mobile phones. On average, household heads are about 46 years with about 25 percent of them nominated as females. A large majority of the household heads completed a basic education at the primary level. More than half of household head in our sample are employed in the agricultural sector with the least being unemployed.

Table 1: Summary statistics

Variable	Mean	Std. dev.
Household level		
HH size	5.0992	3.0993
HH mean age	25.7276	12.7756
Under 16 years (#)	2.3588	2.1440
Over 70 years (#)	0.1569	0.4207
Rural (indicator)	0.6389	0.4803
HH mobile ownership	0.6584	0.4743
Household head		
head age	45.6099	15.9175
female head (indicator)	0.2465	0.4310
have any education	0.7887	0.4082
occupational categories		
agricultural sector	0.5588	0.4965
self employed&family	0.1981	0.3986
service sector	0.1369	0.3438
government	0.0578	0.2334
unemployed	0.0484	0.2146

Notes: Table 1 presents summary statistics of household characteristics across four waves of Tanzania National Panel Survey (LSMS-ISA). The sample constitute an unbalanced household but balanced district panel used for the data analysis.

6.Results

6.1 Main Results

Tables 2 – 4 present baseline coefficient estimates from the reduced form DiD model which explores the variation in the distribution of mobile money agents across locations over the 10-year period. The coefficient estimates of the regressions of the DiD specification from equation (5) follows an Ordinary Least Square (OLS) method for treatment, time and an interaction of both. In the regression equations, we include the basic set of controls for a parsimonious model followed by complete set of controls across alternative outcomes. All regressions include the year fixed-effects and enumeration area (EA) fixed-effects. The former helps to control for differential pricing regimes caused by yearly movements in purchasing power and commodity prices in Tanzania. The inclusion of EA fixed effects controls for variation in the prices across localities. This approach addresses concerns regarding potentially different socioeconomic characteristics of households across different locations[14]. Coefficient estimates associated with the parameters of interest, $\boldsymbol{\beta_2}$ and $\boldsymbol{\beta_3}$, are compared across each column where the estimation results of separate regressions are reported. Post estimation comparator factor ($\boldsymbol{\beta_2} + \boldsymbol{\beta_3}$) namely the total mitigating effect is reported including associated statistical precision for the combined impact.

6.1.1 Expenditure patterns – household-level and per-capita

We present the results for household expenditure patterns in Table 2. Panels A and B of Table 2 present coefficient estimates for household-level and per-capita expenditures respectively. Each panel is further divided into three sub-sections – total, food and non-food expenditure sub-categories. The table report results for each dependent variable twice in each panel while providing estimated results for the parsimonious models (columns 1, 3 and 5) and fully specified regressions (columns 2, 4 and 6). More precisely, Panel A Columns (1) and (2) report the estimated coefficients for total household expenditure. Column (1) shows that drought incidence reduces total expenditure by 29 percent while the interaction term shows that there is an increase in consumption by 52 percent (significant at 5 percent and 1 percent respectively). The coefficient estimates of the total mitigating factor show that the final impact of drought on mobile money adopter households during droughts is an increase of 23 percent – significant at 5 percent. After the inclusion of the full set of controls in column (2), there is a loss of precision in the drought coefficient while the interaction estimate remains statistically significant at 5 percent. More importantly, the total mitigating coefficient shows a similar combined factor of 25 percent – statistically significant at 1 percent. In summary, the results of the impacts of mobile money on adopters during drought suggest that mobile money accessibility helps to reverse the adverse effect that drought imposes on households. This shielding factor is not demonstrated for non-adopter households who particularly reduced the consumption levels in column (1).

We report similar reduced form coefficient estimates for food consumption patterns in columns (3) and (4). The results look similar except for the direct impact of mobile money on food consumption which seems counterintuitive where the direct impact of mobile money on food consumption presents a decline of 38 percent and statistically significant at 1 percent[15]. We focus on column (4) for the interpretation of results on household food expenditure. While the impact of drought conveys adverse effect on food consumption as expected, the interaction coefficient mitigates the impact by increasing food consumption of adopter households. More specifically, while there is a decline of approximately 39 percent (not statistically significant)

[14] For example, the rural-urban composition of EAs across districts may impact the socioeconomic characteristics of the households thereby influencing the prices faced for similar products.
[15] One explanation for this would be the reallocation of remittance transfers between different expenditure categories (food and non-food) especially when there are no unanticipated shocks which requires support. However, this argument may not be plausible as the direct impact of mobile money on non-food expenditure is insignificant and not precisely estimated (columns 5 and 6).

with the incidence of drought for non-adopter households there is an increase of 143 percent (significant at 1 percent) food consumption for the adopter households. This leads to an overcompensated food consumption smoothing of 104 percent (significant at 1 percent).

Finally, we explore the non-food component of household expenditure for our main specifications in columns (5) and (6). It is important to note that this outcome combined with food expenditure patterns in columns (3) and (4) provides a mutually exhaustive total household expenditure in columns (1) and (2). It is unclear if the adoption of mobile money has universal impacts across the different consumption categories or if the smoothing of one category deters the other. The results of the estimated regressions for non-food outcome shows that the patterns are consistent with the a priori expectation across columns (5) and (6) but not sustainable as the inclusion of the full set of controls in column (6) wiped the statistical precision earlier documented in column (5). In particular, the final mitigating factor for both columns are not statistically significant suggesting that the mitigating factor conveyed in columns (1) – (4) is not effective for non-food consumption category. The lack of mitigating support for non-food consumption may reflect household preferences for the allocation of remittance resources from mobile money transactions during shock period.

Table 2: Mobile money and long-term consumption smoothing patterns during drought shock in Tanzania – household expenditures

Panel A – household	Dependent variables: natural log of expenditures					
	total	total	food	food	non-food	non-food
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Mobile money agent	-0.0258	-0.0077	-0.4597***	-0.3760***	0.0270	0.0072
	(0.0444)	(0.0289)	(0.1305)	(0.1324)	(0.0726)	(0.0534)
Drought (heat wave)	-0.2923**	0.0216	-0.5614	-0.3908	-0.5008*	-0.0229
	(0.1292)	(0.0877)	(0.3483)	(0.3424)	(0.2627)	(0.1927)
Interaction term	0.5234***	0.2294**	1.4689***	1.4318***	0.6501**	0.1590
	(0.1337)	(0.0903)	(0.4882)	(0.4918)	(0.2589)	(0.2042)
Total mitigating effect	**0.2311****	**0.2509*****	**0.9075*****	**1.0410*****	**0.1494**	**0.1361**
	(0.0933)	**(0.0702)**	**(0.3172)**	**(0.3208)**	**(0.1419)**	**(0.1015)**
Constant	15.4904***	14.2755***	13.4862***	12.8873***	14.3533***	12.5908***
	(0.0833)	(0.1488)	(0.3188)	(0.4089)	(0.1362)	(0.1733)
Controls	BASIC	FULL	BASIC	FULL	BASIC	FULL
R-squared	0.2098	0.5408	0.0883	0.1860	0.2563	0.5209
Panel B – per-capita	Dependent variables: natural log of per capita expenditures					
	total	total	food	food	non-food	non-food
	(1)	(2)	(3)	(4)	(5)	(6)
Mobile money agent	0.0304	-0.0134	-0.0587	-0.0673**	0.0934	0.0110
	(0.0410)	(0.0298)	(0.0367)	(0.0332)	(0.0713)	(0.0470)
Drought (heat wave)	-0.0625	0.0262	-0.1217	-0.1188	-0.2053	0.0429
	(0.1279)	(0.0923)	(0.1048)	(0.0936)	(0.2417)	(0.1596)
Interaction term	0.3806***	0.2142**	0.3962***	0.3275***	0.4430*	0.0809
	(0.1414)	(0.0958)	(0.1134)	(0.1011)	(0.2597)	(0.1736)
Total mitigating effect	**0.3182*****	**0.2404*****	**0.2744*****	**0.2088*****	**0.2376***	**0.1238**
	(0.0964)	**(0.0798)**	**(0.0881)**	**(0.0796)**	**(0.1402)**	**(0.1058)**
Constant	14.0971***	13.4023***	13.3183***	12.9623***	12.9683***	11.7049***
	(0.0780)	(0.1295)	(0.0704)	(0.1504)	(0.1388)	(0.1689)
R-squared	0.3130	0.5269	0.1398	0.2800	0.3342	0.5404
Observations	8,419	8,373	8,419	8,373	8,419	8,373
Controls	BASIC	FULL	BASIC	FULL	BASIC	FULL
EA FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: The outcome variables are natural logarithms of expenditure patterns for total, food and non-food components respectively. Total expenditure results are reported in columns (1) – (2) followed by food expenditures in columns (3) – (4) while non-food expenditures are reported in columns (5) – (6). In Panel A, we standardise all expenditure categories by adding 1 to ensure these are retained as zeroes on rare occasions of zero expenditures for any of the components. Drought variable follows locality reference methodology in equation (4) for heat wave. We construct drought shocks as exposure to heat waves which is captured as the proportion of days within the planting season with temperature shock – above 90^{th} percentile of the temperature variation for the same period in 30 years. The common denominator used for this exposure is the days of the year – 365 days. All columns include enumeration area and the survey year fixed effects. While the first column of each outcome includes basic controls namely rural indicator of the residential location of HH, mainland or island location of the residential location of HH, covid indicator, and periodic gap indicator, the second column includes all controls. 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 rurality 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. Robust standard errors clustered at the enumeration area level are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

In Table 2 Panel B, we report similar mitigating results for per-capita expenditure patterns which is also established for food per-capita. The non-food component presents partial smoothing for the parsimonious set of controls in column (5) but fades away once the full set of controls are included. In general, Table 2 provides complementary results for the consumption smoothing hypothesis for long-term drought patterns across Tanzania. Next, we explore poverty incidence and inequality across households and potential responsive impacts for mobile money adopters relative to non-adopters.

6.1.2 Poverty incidence – extreme and relative

The mitigating impacts of mobile money documented in Table 2 signifies a strategic deployment of financial inclusion for consumption smoothing of household food consumption. To further understand the underlying factor responsible for the asymmetric response between food and non-food smoothing, we estimate the results for poverty categories. In this section, we use alternative standardised UN poverty thresholds namely relative and extreme poverty indices. We adopt this approach because certain households may be more (or less) susceptible to the impact of drought due to underlying socioeconomic differences, thereby strengthening (weakening) any safety net programs even though they are evenly distributed. More so, it is unclear if mobile money enables the smoothing of drought shocks across different spectrums of poverty incidence. We report the results for the impacts of mobile money on poverty in Table 3.

Table 3 columns 1 and 2 present estimated coefficients for relative poverty incidence using US$2 per-capita per day threshold across households. The estimated coefficients for drought and interaction term show no unique pattern and also lacks statistical power. On the other hand, estimated results for extreme poverty (US$1.25) shows some indicative results for mitigating power of mobile money. We focus on the full specification results (columns 2 and 4) for the interpretation of our results. Drought is associated with an increase of approximately 5 percentage points in the propensity for an average person to consume less than $1.25 per day (not statistically significant). However, this is reversed by a decline of 17 percent in the probability of an average person falling into this bracket (significant at 5 percent). The total mitigating factor indicates a decline in the probability of an average individual falling into poverty by approximately 13 percent which is significant at 1 percent level. Surprisingly, while the isolated drought and interaction terms are not statistically significant, the total mitigating factor for relative poverty poses a 16 percent decline and statistically significant at 1 percent. These results reinforce an overwhelming body of evidence providing support for the positive externality of the adoption of mobile money on risk sharing during covariate shocks.

Table 3: Mobile money and long-term poverty levels with exposure to drought shock in Tanzania

	Dependent variables: poverty incidence			
	relative (< US$2)	relative (< US$2)	extreme (< US$1.25)	extreme (< US$1.25)
VARIABLES	(1)	(2)	(3)	(4)
Mobile money agent	-0.0501*	-0.0301	0.0119	0.0184
	(0.0286)	(0.0237)	(0.0290)	(0.0252)
Drought (heat wave)	-0.0824	-0.1116	0.0693	0.0455
	(0.0929)	(0.0849)	(0.0853)	(0.0772)
Interaction term	-0.0952	-0.0488	-0.2062**	-0.1716**
	(0.0949)	(0.0904)	(0.0958)	(0.0848)
Total mitigating effect	**-0.1776*** **	**-0.1604*** **	**-0.1369*** **	**-0.1260*** **
	(0.0610)	**(0.0554)**	**(0.0485)**	**(0.0397)**
Constant	0.4004***	0.6528***	0.1251***	0.2998***
	(0.0491)	(0.0908)	(0.0401)	(0.0857)
Controls	BASIC	FULL	BASIC	FULL
EA FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
R-squared	0.1806	0.2920	0.1106	0.2238
Observations	8,840	8,792	8,840	8,792

Notes: The outcome variables are indicators of alternative poverty levels. Columns 1 and 2 present results of relative poverty using the US$2 per-capita per-day threshold while columns 3 and 4 present results of the extreme poverty threshold at US$1.25. These are designated as 1 if per-capita expenditure (Table 2 Panel B) levels are lower than the threshold levels; and zero otherwise. Drought variable follows locality reference methodology in equation (4) for heat wave. All columns include enumeration area and the survey year fixed effects. See Table 2 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.

6.1.3 Inequalities – household-level and per-capita

Finally, we test the impact of mobile money on the distribution of consumption patterns. This hypothesis extends the welfare reference commonly used in the evaluation of impact of mobile money adoption in the literature. We repeat the estimation of equation (5) for the inequality results simultaneously for HH and per capita expenditure patterns similar to Table 2. We also use alternative inequality measures – gini coefficient, Theil and Mean Log Deviation – for comparison. Table 4 presents results for inequality across households at the enumeration area level. Columns 1 and 2 report results for gini coefficient for the household and per-capita levels in Panels A and B respectively. In Panel A Column 1 of the Table, the results show that mobile money increases inequality at the baseline. More importantly, an increase in drought exposure at the enumeration area is associated with an increase in inequality while interaction with mobile money reverses this impact. More specifically, an increase in drought exposure by 1 percent increases gini coefficient (indicating the distribution in expenditure pattern across households) by 0.025 percentage points in general. This is partially counteracted by 0.001 percentage points for adopter households with access to an agent. While the drought coefficient in column 2 is no longer statistically significant, the interaction term remains the same and statistically significant at 5 percent. A similar partial compensation pattern is reported for Theil coefficient in columns 3 – 4, and Mean Log Deviation coefficient in columns 5 – 6.

Table 4, Panel B reports regression for per capita expenditure patterns across same measures of inequality. The results show similar pattern to Panel A with reduced precision in drought coefficient. In general, the results indicate a partial offset of the adverse impacts of droughts on inequality. These results are contrary to the overcompensation pattern observed in the consumption smoothing patterns using expenditure and poverty indices. One explanation for reduced capacity of mobile money to match the increasing inequality pattern is the underlying factors of inequality across localities. For example, the network distribution of households may differ within localities to the extent that inadequate support may be accessible when exposed to shocks. This differs from household network accessibility which may range from internal to external to provide tailored support in periods of adverse shocks.

Our findings extend the existing evidence regarding the role of financial inclusion in reducing inequality among disadvantaged households (Bang et al. 2016, Omar and Inaba 2020, Khan et al. 2022). Our findings partially align with evidence from Kling et al. (2022) which posits that there is a higher disparity in income distribution with expansion in the coverage of informal financial inclusion. However, this may contradict our results in consideration of impacts of drought and interaction terms in our models. This paper makes a unique contribution by leveraging an innovative financial inclusion model for poor households for over a decade. More importantly, our study provides disaggregated results on household-level welfare for expenditure, poverty and inequality measures which is yet to be connected in the literature. Our findings provide a unique context for model design for papers within the theoretical literature (Lahcen and Gomis-Porqueras, 2021, Demir et al. 2022, Kling et al. 2022).

Table 4: Mobile money and inequality during drought shock in Tanzania

	Dependent variable: inequality across localities					
	Gini coefficient	Gini coefficient	Theil	Theil	Mean log deviation	Mean log deviation
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Panel A – household						
Mobile money agent	0.00255***	0.00197***	0.00220***	0.00179**	0.00179**	0.00134
	(0.00080)	(0.00076)	(0.00079)	(0.00078)	(0.00087)	(0.00086)
Drought (heat wave)	0.00025**	-0.00025	0.00037***	-0.00005	0.00032***	-0.00012
	(0.00010)	(0.00017)	(0.00014)	(0.00018)	(0.00012)	(0.00018)
Interaction term	-0.00001***	-0.00001**	-0.00001***	-0.00001**	-0.00001**	-0.00001
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Total mitigating effect	**0.00024****	**-0.00025**	**0.00036**	**-0.00006**	**0.00031*****	**-0.00013**
	(0.00010)	**(0.00017)**	**(0.00013)**	**(0.00018)**	**(0.00011)**	**(0.00018)**
Constant	0.21553***	0.13087	0.10859***	0.01271	0.11425***	0.02906
	(0.01390)	(0.12578)	(0.01350)	(0.10725)	(0.01471)	(0.11585)
R-squared	0.80222	0.83197	0.71835	0.74858	0.69704	0.72613
Panel B – per-capita						
Mobile money agent	0.00270***	0.00212***	0.00228***	0.00183**	0.00187**	0.00139*
	(0.00082)	(0.00079)	(0.00085)	(0.00085)	(0.00080)	(0.00079)
Drought (heat wave)	0.00000	-0.00034*	0.00007	-0.00023	0.00000	-0.00026
	(0.00012)	(0.00019)	(0.00016)	(0.00022)	(0.00012)	(0.00020)
Interaction term	-0.00001***	-0.00001**	-0.00001**	-0.00001*	-0.00001**	-0.00001
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Total mitigating effect	**-0.00001**	**-0.00035***	**0.00006**	**-0.00024**	**-0.00001**	**-0.00027**
	(0.00011)	**(0.00019)**	**(0.00015)**	**(0.00022)**	**(0.00012)**	**(0.00020)**
Constant	0.23224***	0.06707	0.13553***	-0.02887	0.13442***	0.00583
	(0.01616)	(0.14730)	(0.01804)	(0.13288)	(0.01740)	(0.13956)
R-squared	0.78304	0.80575	0.67842	0.70315	0.65551	0.68050
Observations	727	727	727	727	727	727
Controls	BASIC	FULL	BASIC	FULL	BASIC	FULL

EA FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: The outcome variables in the Table above present alternative measures of inequality across localities. Columns (1) and (2) present results for Gini coefficient while columns (3) and (4) report the Theil measure. Lastly, columns (5) and (6) present the Mean log deviation index for inequality. The drought variable follows locality reference methodology for heat wave in equation (4). We construct drought shocks as exposure to heat waves which is captured as the proportion of days within the planting season with temperature shock – above 90th percentile of the temperature variation for the same period in 30 years. The common denominator used for this exposure is the days of the year – 365 days. All columns include enumeration area and the survey year fixed effects. While the first column of each outcome includes basic controls, the second column includes all controls. See notes in Table 2 for a list of all controls. Robust standard errors clustered at the enumeration area level are reported in parentheses. * p < 0.1; ** p < 0.05; *** p < 0.01.

6.2 Heterogeneous impacts

Baseline results in Tables 2 and 3 generally test the consumption smoothing hypothesis. The complementary results suggest that the consumption smoothing impacts are concentrated among the poor households (Table 3). We explore the distribution of impacts between the two main residential areas of Tanzania to investigate the role of deepening financial inclusion across locations. We report the results of the estimated results by splitting the sample of observations into rural and urban households in Tables 5 and 6. Henceforth, we focus on the specifications with the full set of controls for subsequent results.

We report estimation results for rural households in Table 5, Panel A. Coefficient estimates for mobile money, drought and the interaction terms are similar across columns (1) to (3) for household-level consumption patterns and columns (4) to (6) for per-capita levels. Similar to observed patterns in the full specification in the baseline results (Table 2), results for rural HHs indicate mitigating impacts of mobile money accessibility for HH-level total and food expenditures (columns 1 and 2). This counteracting effect is also replicated for per-capita components of the spendings (columns 4 and 5). This pattern reinforces the mitigating impact of mobile money for the different categories as highlighted in the main results. On the other hand, estimated results in Panel B for urban households present muted coefficients across all outcome variables for both household-level and per-capita outcomes. In particular, the interaction terms and total mitigating effects lack statistical precision. This suggests that mobile money adoption clearly lack a mitigating role for urban dwellers. This may reflect the reliance of rural households on weather patterns for agricultural productivity thereby supporting the notion that the means to financial inclusion helps to provide an efficient pathway to share risks with counterparts all over the country. Households in urban locations are less likely to be affected in the same way as rural areas which explains the reason for muted results for the mitigating parameter.

Table 6 provides heterogeneous results for extreme poverty. While only results for rural households showcase coefficient estimates for the interaction term consistent, the total mitigating factor coefficients for both rural and urban regions are statistically significant. In general, there is a clear link between the main results in Tables 2 and 3 and the rural components of the heterogeneous results reported in Tables 5 and 6. Also, the effectiveness of mobile money for food consumption patterns is consistent with the poverty results. These results provide a systematic connection for the role of mobile money and how this can be deployed to support intervention designs across low-income countries. From the estimated results, it is clear that mobile money may be useful to assist in mitigating shocks for rural households – the most vulnerable groups to agricultural shocks from weather patterns. This argument is supported by the nature of consumption smoothing that is the focus of the mitigating factor across all our results – food – and the fact that our results are driven by households within rural communities. This argument is further reinforced by the fact that our findings is more pertinent with important regressor (interaction term) of extreme poverty incidence, which is most likely associated with food consumption needs of households, as against relative poverty incidence.

Table 5: Urban-Rural heterogeneous impacts of consumption smoothing

	Dependent variables: natural log of expenditure patterns					
	Household-level			Per-capita level		
	HH total	HH food	HH non-food	per capita	per capita food	per capita non-food
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: rural						
Mobile money agent	-0.0331	-0.3297**	0.0019	-0.0554**	-0.0875***	-0.0080
	(0.0307)	(0.1434)	(0.0668)	(0.0275)	(0.0298)	(0.0566)
Drought (heat wave)	-0.0567	-0.4039	-0.1035	-0.0718	-0.1436	-0.0479
	(0.0941)	(0.3606)	(0.2252)	(0.0973)	(0.1002)	(0.1883)
Interaction term	0.3423***	1.3956***	0.2494	0.3985***	0.4158***	0.2256
	(0.1041)	(0.4827)	(0.2717)	(0.0954)	(0.0900)	(0.2297)
Total mitigating effect	**0.2857*** **	**0.9917*** **	**0.1459**	**0.3267*** **	**0.2722*** **	**0.1777**
	(0.0890)	**(0.2391)**	**(0.1579)**	**(0.0923)**	**(0.0853)**	**(0.1568)**
Constant	14.1709***	13.8536***	12.1611***	13.1773***	13.1205***	11.1452***
	(0.2062)	(0.3247)	(0.1828)	(0.1861)	(0.1620)	(0.1670)
R-squared	0.4743	0.1389	0.3954	0.3950	0.2703	0.3765
Observations	5,402	5,402	5,402	5,402	5,308	5,400
Panel B: urban						
Mobile money agent	0.0678	-0.5097*	0.0123	0.0869	-0.0056	0.0314
	(0.0554)	(0.3060)	(0.0859)	(0.0549)	(0.0667)	(0.0877)
Drought (heat wave)	0.1976	-0.7450	0.1042	0.2220	-0.0716	0.1286
	(0.2069)	(1.1350)	(0.2798)	(0.1854)	(0.1831)	(0.2749)
Interaction term	0.0029	1.5425	0.0345	-0.0745	0.2123	-0.0429
	(0.2045)	(1.2713)	(0.2809)	(0.1902)	(0.2112)	(0.2826)
Total mitigating effect	**0.2005**	**0.7975**	**0.1387**	**0.1474**	**0.1407**	**0.0856**
	(0.0915)	**(0.6311)**	**(0.1300)**	**(0.0987)**	**(0.1200)**	**(0.1358)**
Constant	13.8681***	10.8102***	12.2279***	13.2223***	12.6988***	11.5822***
	(0.1786)	(0.8143)	(0.3200)	(0.1684)	(0.2246)	(0.3176)
R-squared	0.5785	0.2644	0.5475	0.5139	0.2751	0.4979
Observations	2,971	2,971	2,971	2,971	2,813	2,971
Controls	FULL	FULL	FULL	FULL	FULL	FULL
EA FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: Table 5 presents heterogeneous results of the baseline results in Table 2. Panel A report results for rural locations while Panel B reports results for urban locations. All columns include enumeration area, the survey year fixed effects and full set of controls. See Table 2 for more details on the construction of drought shock and composition of 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 6: Rural-urban heterogeneous impacts on extreme poverty level

	Dependent variable: extreme poverty level (< US$1.25)	
	Rural HHs	Urban HHs
Variables	(1)	(2)
Mobile money agent	0.0317	-0.0400
	(0.0307)	(0.0410)
Drought (heat wave)	0.0955	-0.1294
	(0.0884)	(0.1290)
Interaction term	-0.2251**	0.0063
	(0.1079)	(0.1264)
Total mitigating effect	**-0.1296***	**-0.1230*****
	(0.0674)	**(0.0419)**
Constant	0.3502***	0.3636***
	(0.1110)	(0.1208)
R-squared	0.2030	0.2289
Observations	5,620	3,172
Controls	FULL	FULL
EA FE	YES	YES
Year FE	YES	YES

Notes: Table 6 presents heterogeneous results of the baseline results in Table 3 focussing on extreme poverty. Column 1 reports the results for rural households while Column 2 reports results for urban locations. All columns include enumeration area, the survey year fixed effects and full set of controls. See notes in Table 2 for more details on the construction of drought shock and composition of 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.

Finally, we estimate heterogeneous impact of the baseline results for Table 2 (Panel B column 2) by household income groups using a proxy of the household expenditure patterns. This approach seeks to understand the distribution of mobile money mitigating strength by household socio-economic status. In this section, we estimate heterogeneous impacts of mobile money across quartiles of household consumption as a measure of categorising sample households into socioeconomic groups. Table 7 shows that the results for drought and interaction terms are concentrated in the third quartile, however the total mitigating factor presents a U-distribution across quartiles with the turning point (lowest coefficient) obtained within the second quartile. Importantly, the results showcase statistically significant mitigating powers for the first, third and fourth quartiles respectively but with the greatest impact obtained within the first quartile[16]. While this indicates that the mitigating factor may be more effective for the poorest household on one hand, there are indications that the impact of mobile money cuts across socioeconomic groups. This distribution is consistent with the baseline poverty results for both relative and extreme thresholds in Table 3. Although, this pattern may be considered somewhat counterintuitive as the theoretical expectation will be to have the strongest results from the vulnerable household located in the lowest section of the pyramid. One explanation for the observed pattern is the role of wealth status in remittance receipts for

[16] Similar patterns are presented for per-capita food expenditure outcomes across income group quartiles.

each category of household group. This also supports the notion that the associated network that households in each income bracket can form to receive support in periods of need.

Table 7: Distribution of baseline expenditure results across expenditure quartiles

	Dependent variables: natural log of expenditure patterns			
	Expenditure quartiles			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
VARIABLES	(1)	(2)	(3)	(4)
Mobile money agent	-0.0168	0.0351**	-0.0414**	-0.0837
	(0.0411)	(0.0143)	(0.0163)	(0.0579)
Drought (heat wave)	0.0204	0.0418	-0.1391***	-0.1550
	(0.1101)	(0.0396)	(0.0492)	(0.2052)
Interaction term	0.1984	-0.0576	0.2077***	0.3338
	(0.1451)	(0.0576)	(0.0620)	(0.2222)
Total mitigating effect	**0.2189***	**-0.0158**	**0.0686***	**0.1789***
	(0.1189)	**(0.0462)**	**(0.0358)**	**(0.0935)**
Constant	14.0049***	14.5108***	15.0405***	15.2866***
	(0.1774)	(0.0789)	(0.0488)	(0.1392)
Observations	2,105	2,101	2,090	2,077
R-squared	0.2576	0.1238	0.1599	0.3392
Controls	FULL	FULL	FULL	FULL
EA FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: Table 7 presents heterogeneous results of the baseline results in Table 2 focussing on expenditure patterns across HH expenditure quartile groups. Columns 1 – 4 represent lowest HH expenditure quartile to highest quartile respectively. All columns include enumeration area, the survey year fixed effects and full set of controls. See notes in Table 2 for more details on the construction of drought shock and composition of 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.

7. Discussion

Our results on the impact of mobile money adoption during drought incidences imply that mobile money accessibility helps to reverse the adverse effect that drought imposes on households. Our findings are consistent with related literature including results from Riley (2018) and Premand and Stoeffler (2022). In a study of Tanzanian households, Riley (2018) finds that after covariate shocks captured from village-level drought patterns, only households receiving remittance via mobile money were able to sustain their consumption patterns. This evidence suggests that new technologies in the form of mobile money may be used to advance risk sharing capacity not only within their villages but with a wider network of friends and family outside the village. Similarly, Premand and Stoeffler (2022) in a study of households in rural Niger, find that in the midst of drought shocks, cash transfers on average increase household per capita consumption by 10 percent and alleviate poverty. They also argue that the mechanism of effect is mainly through the intensification of agricultural activities leading to improved revenue during climate shock incidences. Conversely, for mobile money non-adopter households, consumption levels decreased during drought shocks.

Our findings in Table 2 indicate that while the impact of drought shocks brings about adverse effects on household food consumption as expected, the interaction coefficient mitigates this impact by increasing total (food) consumption of mobile money adopter households. Specifically, results show that total (food) consumption for mobile money adopter households increases by 23 (143) percent leading to an overcompensated food consumption smoothing of 25 (104) percent. Similar patterns emerge for regression using alternative drought measures from rainfall patterns (Table A1 and A2) where drought against total and food expenditures is mitigated by mobile money accessibility. Findings for the impact on household non-food consumption presented across Tables 2, A1 and A2 are consistent with a priori theoretical expectation, although coefficient estimates of the mitigating factor are statistically insignificant. These two findings taken together is indicative of household preferences for the allocation of resources enabled by mobile money transactions such as remittances during shock period towards food consumption. Results in Table 3 indicate that mobile money adoption during drought incidences significantly reduced the probability of households falling into relative poverty (less than US$2) by 16 percent and extreme poverty (less than US$1.25) by 13 percent. These findings reinforce a vast body of literature that showcase the poverty-mitigating impact of mobile money adoption amidst climatic shocks (Mizutani 2021, Abiona and Koppensteiner 2022, Djahini-Afawoubo et al. 2023). Disaggregating impacts by geographical location of households, the study finds that for households located in rural areas, mobile money adoption significantly mitigates the adverse effect of drought shocks on consumption patterns (household and per capita expenditure) relative to urban areas, but less clear-cut on poverty. This suggests that mobile money adoption may serve as a cushion for climatic and drought shocks directly affecting crop production and yield. This finding supports the literature that highlights financial inclusion as an effective channel for mitigating weather shocks in agricultural productivity for rural dwellers (Afawubo et al., 2020; Koomson et al., 2020) in extension of risk sharing targeting poverty reduction. The results are logical considering that rural households are more vulnerable to agricultural shocks from weather patterns.

This paper departs from the existing literature by estimating the mitigating role of mobile money accessibility on inequality. Results in Table 4 indicate that access to mobile money agent reduces within community per-capita expenditure inequality by about 0.035 percentage points. This finding agrees with results from Vatsa et al. (2022) using data from the 2017 Chinese General Social Survey. Vatsa et al. finds that mobile money adopters have lower food expenditure inequality than non-adopters. Our findings are more robust in that it captures the inequality measure for overall household expenditure and focusses on long-term impacts. These contexts are particularly relevant for developing countries located within South of the Sahel, battling climatic shocks. These results may be useful to inform policy intervention decisions given ongoing efforts to intensify organisation and development of philanthropic interventions and safety nets. The empirical based approach may also help with achieving welfare improvements while combatting the negative impacts of climatic shocks within the region.

Our research complements studies like Riley (2018) by providing longer- term evidence as well as focusing on inequality effects of adoption of mobile money. Examining long-term impacts is important because it allows us to examine the sustainability of mobile money adoption as well as assist in the design of regulatory framework. The impacts of mobile money at the community level are relatively under investigated (Nan et al. 2021). Our findings on consumption (per capita) and inequality indicate that mobile money enhances welfare for adopter households which are typically rural. In the face of a co-variate shock that are likely to reduce consumption and widen inequality, mobile money adoption compensates for this shock and reverses possible inequality-increasing effect of this shock. Our findings on the impact of mobile money are also consistent with findings from other developing country context where there is evidence of adoption of mobile money increasing welfare (Uganda: Munyegera and Matsumoto, 2016). Furthermore, in Niger, evidence from a randomized experiment of a mobile money cash transfer program presents evidence that household diet diversity was 9%–16% higher among households who received mobile transfers, and children ate an additional one-third of a meal per day (Aker et al., 2016). These results were attributed to time savings associated with mobile transfers and shifts in intrahousehold bargaining power for women, further highlighting the potential of mobile money even when integrated with social protection systems. These findings reinforce evidence of mobile money role within the women empowerment literature (Dorfleitner and Nguyen, 2021; Wieser et al., 2019).

8. Conclusion

This paper extends the literature on the consumption smoothing capacity of mobile money adoption to inequality context. The research showcases additional supportive welfare framework for mobile money expansion over a long-term period using Tanzania as a case study. Findings from our empirical analysis strengthens the evidence that mobile money safety net may be leveraged to enhance welfare of adopters in low-income countries, particularly within Sub-Saharan Africa. We achieve this by exploring an interaction of inequality outcomes with droughts extending the consumption smoothing and risk–sharing models of mobile money adoption. This welfare dimension is inherent within the expansion of mobile money services which is more likely to take effect after a sustained period of adoption. It is important to note that the inequality results are embedded with consumption smoothing rather than poised in isolation and more relevant for the poor and rural households as demonstrated in the heterogeneous effects. Our findings demonstrate that mobile money is effective for mitigating adverse economic shocks for rural households in a broader fashion than earlier documented in the literature[17]. More specifically, results from this study complements existing research on the level of reliability of mobile money for safety nets and social protection programs. This evidence bridges the knowledge gap on sustainability of mobile money and provides a structure for scaling towards welfare-targeting programs. Given that co-variate shocks like extreme weather events are likely to increase in frequency and the increased digitization of electronic and mobile payments, including for social protection schemes in developing countries brought about by the Covid-19 pandemic, our analysis provides evidence on the benefits of mobile money as a tool of financial inclusion in addressing poverty and inequality.

[17] 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.

References

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.

Aggarwal, S., Brailovskaya, V., & Robinson, J. (2020, May). Cashing in (and out): Experimental evidence on the effects of mobile money in Malawi. In *AEA papers and proceedings* (Vol. 110, pp. 599-604): American Economic Association.

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.

Aker, J. C., Mbiti, I. M. 2010. Mobile Phones and Economic Development in Africa. *Journal of Economic Perspectives. 24(3), 207 – 232.*

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.

Baffour, P. T., Rahaman, W. A., Mohammed, I. 2021. Impact of mobile money access on internal remittances, consumption expenditure and household welfare in Ghana. *Journal of Economic and Administrative Sciences*. 37(3), 337-354.

Bang, J. T., Mitra, A., & Wunnava, P. V. 2016. Do remittances improve income inequality? An instrumental variable quantile analysis of the Kenyan case. *Economic Modelling.* 58(C), 394-402.

Batista, C., & Vicente, P. C. (2021). *Is mobile money changing rural Africa?: evidence from a field experiment*. Centre for Research and Analysis of Migration, Department of Economics, University College London.

Blumenstock, J. E., Eagle, N., & Fafchamps, M. (2016). Airtime transfers and mobile communications: Evidence in the aftermath of natural disasters. *Journal of Development Economics*, *120*, 157-181.

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

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

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

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.

Comfort, A. B. (2016). Long-term effect of in utero conditions on maternal survival later in life: evidence from Sub-Saharan Africa. *Journal of Population Economics*, *29*, 493-527.

Demir, A., Pesqué-Cela, V., Altunbas, Y., Murinde, . 2022. Fintech, financial inclusion and income inequality: a quantile regression approach. *The European Journal of Finance.* 28(1), 86-107.

Demirgüç-Kunt, A., Klapper, L., Singer, D., & Ansar, S. (2022). *The global findex database 2021: Financial inclusion, digital payments, and resilience in the Age of COVID-19*. World Bank.

Dizon, F., Gong, E., & Jones, K. (2020). The effect of promoting savings on informal risk sharing experimental evidence from vulnerable women in kenya. *Journal of Human Resources*, *55*(3), 963-998.

Djahini-Afawoubo, D. M., Couchoro, M. K., & Atchi, F. K. (2023). Does mobile money contribute to reducing multidimensional poverty?. *Technological Forecasting and Social Change*, *187*, 122194.

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.

Dorfleitner, G., & Nguyen, Q. A. (2022). Mobile money for women's economic empowerment: the mediating role of financial management practices. *Review of Managerial Science*, 1-30.

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.

Fabregas, R., Yokossi, T. 2022. Mobile Money and Economic Activity: Evidence from Kenya. *The World Bank Economic Review*. 36(3), 734-756.

Fafchamps, M., Udry, C., Czukas, K., 1998. Drought and Saving in West Africa: Are Livestock A Buffer Stock? *Journal of Development Economics.* 55(2), 273-305.

Fonseca, J., Van Doornik, B. 2022. Financial development and labor market outcomes: Evidence from Brazil. *Journal of Financial Economics.* 143(1), 550-568.

GSMA. (2019). State of the Industry Report on Mobile Money 2019. GSM Association, Electronic Article.

IMARC (2021). Tanzania Mobile Money Market: Industry Trends, Share, Size, Growth, Opportunity and Forecast 2022-2027. Retrieved from https://www.imarcgroup.com/tanzania-mobile-money-market.

IMF. (2019). Mobile Money Note 2019. Washington, DC: IMF.

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

Jiménez, J. R. P. 2020. Testing the impact of technology diffusion and innovation on long-run growth using cointegration techniques. *The Journal of International Trade & Economic Development.* 29(6), 748-773.

Khan, I. Khan, I., Sayal, A. U., Khan, M. Z. 2022. Does financial inclusion induce poverty, income inequality, and financial stability: empirical evidence from the 54 African countries? *Journal of Economic Studies.* 49 (2), 303-314.

Kling, G., Pesqué-Cela, V., Tian, L., Luo, D. 2022. A theory of financial inclusion and income inequality. *The European Journal of Finance.* 28(1), 137-157.

Koomson, I., Villano, R. A., & Hadley, D. (2020). Effect of financial inclusion on poverty and vulnerability to poverty: Evidence using a multidimensional measure of financial inclusion. *Social Indicators Research*, *149*(2), 613-639.

Ky, S., Rugemintwari, C., & Sauviat, A. (2018). Does mobile money affect saving behaviour? Evidence from a developing country. *Journal of African Economies*, *27*(3), 285-320.

Lahcen, M. A., Gomis-Porqueras, P. 2021. A model of endogenous financial inclusion: implications for inequality and monetary policy. *Journal of Money, Credit and Banking.* 53(5), 1175-1209.

Makoye, K. (2022, June 22). Tanzania slashes controversial mobile money levy. https://www.aa.com.tr/en/africa/tanzania-slashes-controversial-mobile-money-levy/2619506#:~:text=As%20of%20June%202021%2C%20Tanzania,urban%20areas%2C%20official%20data%20show. Anadolu Agency

Mizutani, A. (2021). Can Mobile Money Remittances Reduce Short-Term Poverty? Evidence from Kenya. *Forum of International Development Studies*, *51*(3), 1-18.

Munyegera, G. K., & Matsumoto, T. (2016). Mobile money, remittances, and household welfare: Panel evidence from rural Uganda. *World Development*, *79*, 127-137.

Muganyi, T., Yan, L., Yin, Y. *et al.* 2022. Fintech, regtech, and financial development: evidence from China. *Financial Innovation.* 8, 29. https://doi.org/10.1186/s40854-021-00313-6

Omar, M. A., Inaba, K. 2020. Does financial inclusion reduce poverty and income inequality in developing countries? A panel data analysis. *Journal of Economic Structures.* 9(1), 1-25.

Premand, P., & Stoeffler, Q. (2022). Cash transfers, climatic shocks and resilience in the Sahel. *Journal of Environmental Economics and Management*, *116*, 102744.

Riley, E. (2018). Mobile money and risk sharing against village 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*, 72-91.

Sekabira, H., & Qaim, M. (2017). Mobile money, agricultural marketing, and off-farm income in Uganda. *Agricultural Economics*, *48*(5), 597-611.

National Bureau of Statistics. (n.d). *Basic Information Document National Panel Survey (NPS2008-2009).* National Bureau of Statistics: Tanzania.

National Bureau of Statistics. (n.d). *Basic Information Document National Panel Survey Extended Panel with Sex-Disaggregated Data 2019-2020).* National Bureau of Statistics: Tanzania.

Naito, H., Ismailov, A., & Kimaro, A. B. (2021). The effect of mobile money on borrowing and saving: Evidence from Tanzania. *World Development Perspectives*, *23*, 100342.

Nan, W., Zhu, X., & Lynne Markus, M. (2021). What we know and don't know about the socioeconomic impacts of mobile money in Sub-Saharan Africa: A systematic literature review. *The Electronic Journal of Information Systems in Developing Countries*, *87*(2), e12155.

Suri, T. (2017). Mobile money. *Annual Review of Economics*. 9, 497–520.

Suri, T., & Jack, W. (2016). The long-run poverty and gender impacts of mobile money. *Science*. 354(6317), 1288–1292.

Tabetando, R., Matsumoto, T. 2020. Mobile money, risk sharing, and educational investment: Panel evidence from rural Uganda. *Review of Development Economics.* 24(1), 84-105.

TCRA. (2023). *Second Quarter Communications Statistics Report 2022/2023*: Tanzania Communications Regulatory Authority. https://www.tcra.go.tz/tcra-news/second-quarter-communications-statistics-report-2022-2023

Vatsa, P., Ma, W., & Zheng, H. (2022). Does mobile payment adoption affect the level and inequality of food expenditure? *The Social Science Journal*, 1-13.

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. P., Ruckteschler, C. S., & Heitmann, S. (2019). The impact of mobile money on poor rural households: Experimental evidence from Uganda. World Bank Policy Research Working Paper No:8913. Washington, DC: World Bank.

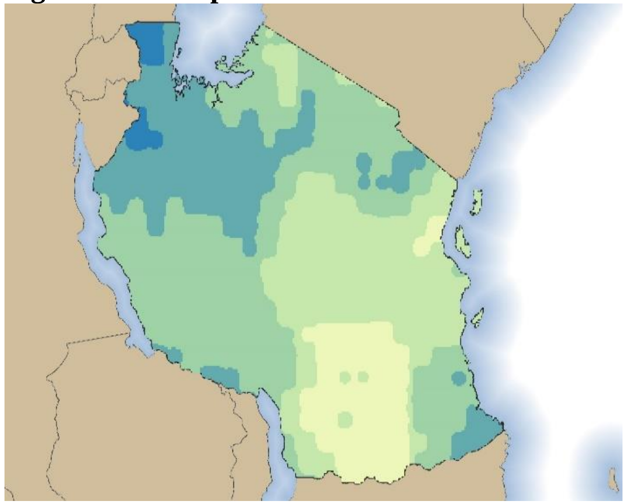
World Bank (2022). *The Role of Digital in the COVID-19 Social Assistance Response*. World Bank: Washington DC.

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.

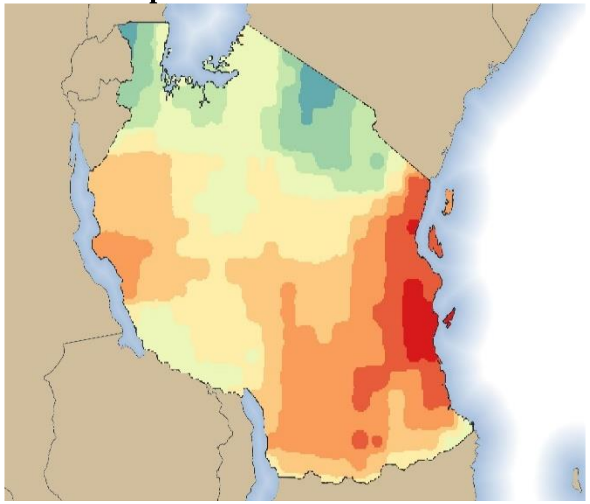
Yang, D., Choi, H., 2007. Are Remittances Insurance? Evidence from Rainfall Shocks in the Philippines. *World Bank Economic Review.* 21(2), 219-248.

Appendix

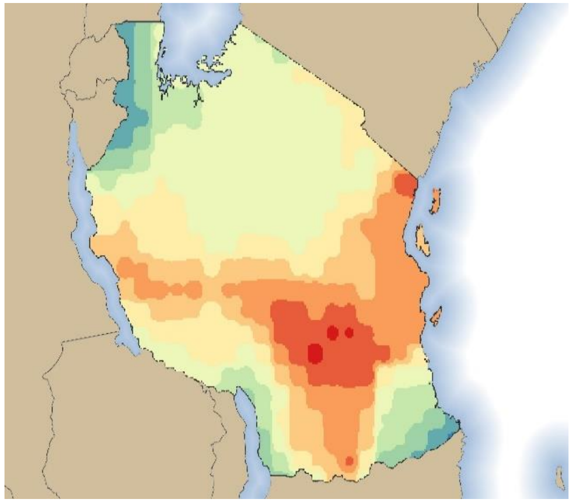
Figure A1: Geospatial distribution of Tanzanian heatwave map between 2008 – 2020.



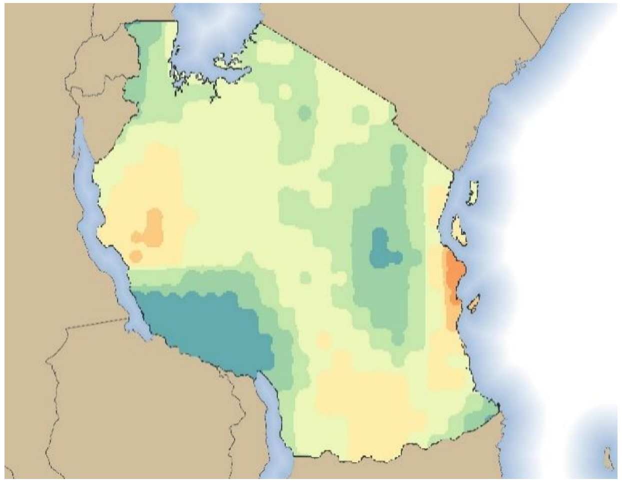
Wave 1 – 2008-09



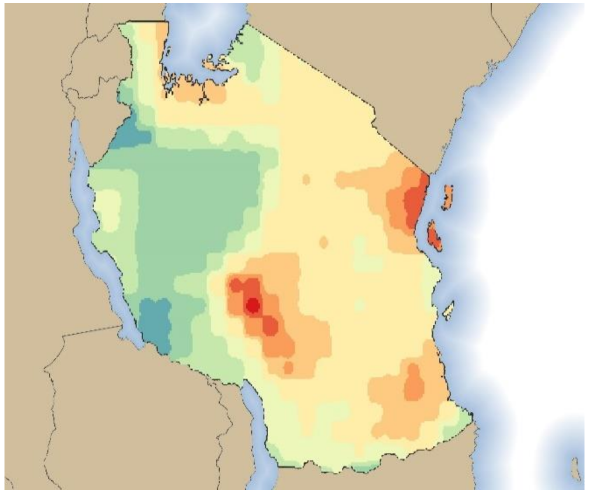
Wave 2 – 2010-11



Wave 3 – 2012-13



Wave 4 – 2014-15



Wave 5 – 2019-20

Table A1: Mobile money and long-term consumption smoothing patterns during drought shock in Tanzania – Rainfall patterns below 1 standard deviation.

	Dependent variables: natural log of expenditures					
	total	total	food	food	non-food	non-food
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Mobile money agent	0.1087***	0.0488***	-0.1677**	-0.0922	0.2000***	0.0543**
	(0.0221)	(0.0165)	(0.0725)	(0.0732)	(0.0328)	(0.0247)
Drought (Rainfall below 1SD)	0.0264	0.0710***	-0.1949*	-0.0845	-0.0219	0.0214
	(0.0321)	(0.0272)	(0.1122)	(0.1086)	(0.0548)	(0.0497)
Interaction term	-0.0329	-0.0608*	0.2837**	0.2342*	-0.0211	-0.0452
	(0.0436)	(0.0323)	(0.1310)	(0.1216)	(0.0689)	(0.0534)
Total mitigating effect	**-0.0065**	**0.0102**	**0.0889**	**0.1497***	**-0.0431**	**-0.0239**
	(0.0295)	**(0.0193)**	**(0.0983)**	**(0.0864)**	**(0.0457)**	**(0.0302)**
Constant	15.4331***	14.3252***	13.6474***	12.5422***	14.2001***	12.6158***
	(0.0600)	(0.1390)	(0.2337)	(0.5912)	(0.1005)	(0.1694)
Observations	9,233	9,174	9,233	9,174	9,233	9,174
R-squared	0.2076	0.5400	0.0846	0.1832	0.2528	0.5196
Controls	BASIC	FULL	BASIC	FULL	BASIC	FULL
EA FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: Table A1 above presents estimation results from regression of equation 5 using alternative drought measure as a robustness for results reported on Table 2 Panel A. Drought measure is captured as rainfall patterns below 1 standard deviation of the historical average. See Table 2 for notes. Robust standard errors clustered at the enumeration area level are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.