FINANCIAL INCLUSION, SHOCKS AND WELFARE: ***EVIDENCE FROM THE EXPANSION OF MOBILE MONEY IN TANZANIA***

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Abstract

In this paper we investigate the effect of mobile money adoption by households in Tanzania on consumption smoothing, poverty and human capital investments. We exploit the rapid expansion of the mobile money agent network between 2011 and 2013 we instrument for the household adoption of mobile money by using changes in the distance and cost to the nearest mobile money agent. We test for consumption smoothing by focussing on idiosyncratic shocks to households from variation in rainfall in rural areas. Our results show that while per-capita total expenditure is not smoothed within our specifications, per-capita expenditure pattern for the extremely poor households is significantly smoothed in periods of negative idiosyncratic shock for mobile money adopter households. Our results indicate that mobile money adopter households conveniently shield against sliding into transient extreme poverty while there is an increase in head count living below US$1.25 per day for non-adopter households. At the individual level, the effect on children's absenteeism from school as a result of the rainfall-driven income shock is cushioned for mobile money adopter households. This is complemented by more time for school homework and children spending less time engaging in household chores.

JEL Classifications: G23, H31, I31, I32

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1 Introduction

Mobile money as financial innovation has in recent years transformed financial services in many sub-Saharan African countries and helped to overcome gaps in financial inclusion of the unbanked poor in these countries (Jack and Suri 2011).[1] Mobile money–a financial innovation that allows individuals to store and transfer funds using short message services–has transformed mobile phones from simply being a communication tool to enabling low-cost financial services and has seen unprecedented growth in these countries. While in Europe and North America mobile money services are practically inexistent, with less than 1 percent of the population having an active mobile money account, in sub-Saharan Africa there are now close to 25 mobile money accounts per 100 adults (Aron *et al.* 2015). In early adopter countries, such as Kenya, as little as four years after the introduction more than 75 percent of households have at least one active mobile money account and in June 2014 the monthly value of transactions was about US$2 billion, about 60 percent of average monthly GDP (Aron *et al.* 2015). The dramatic expansion of mobile money in sub-Saharan Africa is likely driven by very limited available financial services (in 2011 there were only 850 bank branches in Kenya, but 28,000 mobile money agents) and the already prevailing popularity of mobile phone services as compared to landline telephone services. Tanzania, the country of interest in this paper, has seen similar increase in the use of mobile money since its introduction in 2009. Mobile money led to a dramatic decrease of the transaction cost of transferring funds between users, in particular across large distances allowing individuals to send and receive remittances much more cheaply than before the introduction of the service.

Jack and Suri (2014) show for Kenya that mobile money has changed risk sharing by allowing users to send and receive remittances in cases of negative shocks to the household. They find that while shocks reduce consumption for non-users, the consumption of user households is unaffected. The authors argue that these effects are partially due to improved risk sharing facilitated by reduced transaction costs from mobile money. With this paper we contribute to the literature on mobile money by focusing on the welfare consequences of mobile money access beyond consumption smoothing. We follow Jack and Suri and make use of the rapid expansion of the mobile money agent network in Tanzania over the period from 2011 to 2013 during which the mobile money uptake by households has increased from

[1] One of the first and to date most successful examples of mobile money is M-PESA in Kenya, which launched its service in 2007.

13 to 41 percent lending for an instrumental variable identification strategy while employing household and individual fixed effects. We are particularly interested in how mobile money protects the welfare outcomes of households that are subject to household shocks. To circumvent the endogeneity problem of household shocks we focus on rainfall shocks to households that depend on rain-fed agricultural production. Besides consumption smoothing, we are more focussed on understanding the effects of mobile money on the poorest households and poverty measures. In addition, we are interested in how mobile money can cushion the impact of negative household shocks on individual level human capital investments – education and health – and the overall effect of mobile money on subjective wellbeing and labour diversification of adults during shocks.

We find that while per-capita expenditure is not significantly smoothed within our baseline specification, per-capita expenditure of the most vulnerable households is smoothed in periods of negative idiosyncratic shock for mobile money adopter households. Our results indicate that mobile money adopter households are less likely to slide into transient poverty (using the extreme poverty benchmark[2]) while non-adopter households are more likely to be classed as poor after being subjected to rainfall shocks. At the individual level, the effect on children's absenteeism from school as a result of rainfall-driven income short fall is cushioned for mobile money adopter households. This is complemented by more time for school homework as against engaging in household chores. Similarly, reduction in preventive health expenditure (e.g. treatment of insecticide bed nets) as a result of negative household shock is compensated for mobile money adopter households. We also provide evidence that adults in mobile money adopter households indulge in non-diversification of labour activities to cushion agricultural shocks.

The remainder of the paper is organised as follows. Section 2 provides financial inclusion and mobile money expansion background in Tanzania. Section 3 discusses the data sources and summarizes important variables at the individual and household levels. Section 4 presents the empirical strategy for identification. Sections 5 presents the main results and some heterogeneous results respectively. Section 6 provides concluding remarks.

[2] Households below the $1.25 per capita expenditure per day are categorised as extremely poor.

2 Background: Tanzania, Mobile Money and Financial Inclusion

Tanzania is a sub-Saharan African country with a population of 48 million in 2012. The country remains among the poorest in the world with about 28 percent of the population being classified under the $1.25 poverty line in 2011/12.[3] Current per-capita GNI is $570 in 2012 and more recently Tanzania has been described as a development success story with average growth rate of 7 percent between 2000 and 2011 (World Bank 2013). The Tanzanian economy is still – to a large extent – based on agriculture production with about 27 percent of GDP and about 80 percent of employment related to the agricultural sector. With its vast landmass, the country is sparsely populated and predominantly rural creating additional challenges for economic activity, the provision of services, including telecommunication and access to financial services, including banking.

According to the 2012 World Bank Financial Index in Tanzania, only 17 percent of individuals 15 years and older have a bank account, compared to 97 percent in the United Kingdom for the same age group. Also, on average there are 1.56 commercial bank branches and 2.22 ATMs per 100,000 population between 2004 and 2011 in Tanzania.[4] These contrast sharply with 26.4 and 123 respectively in the United Kingdom. These figures indicate the very weak provision of formal financial services in Tanzania resulting in a financial inclusion gap, especially for the rural population. This is evidenced by the very low position of Tanzania in financial inclusion rankings, even among other sub-Saharan African countries (World Bank 2014).

Tanzania emerged as one of the early adopters of mobile money services. Likely because to the lack of formal financial services, the introduction of mobile money in Tanzania has been extremely successful since its introduction in 2009. The proximity to Kenya, where mobile money has been first introduced very successfully, also contributed to the quick adoption of the services and Tanzania is currently catching-up with its neighbour in terms of the number of users and the volume of mobile money transactions (CGAP 2016). Currently there are four mobile money services on the market: Vodacom's M-Pesa, Tigo Pesa, Airtel Money and Ezy Pesa. The national microfinance bank completes the market with their own mobile money services providing for a competitive mobile money market and lower transaction

[3] World Bank 2015.
[4] Given the vast geographic coverage of the country this equates to 0.41 and 0.60 commercial banks and ATMs respectively for every 1,000km^2 in Tanzania (IMF 2012).

prices than in Kenya. The Financial Inclusion Insights Surveys (CGAP 2016) shows that in 2015, 38 percent of adults in Tanzania have a mobile money account. The household survey data we introduce in the next section, shows that in 2014 41 percent of households have at least one mobile money account, while this number was only 13 percent in 2011, revealing the sharp increase of households with access to the technology. In 2012 36 percent of all money transfers in Tanzania are made through mobile money transfer services (World Bank 2016).

3 Data

This paper uses data from the World Bank's Living Standard Measurement Studies (LSMS) for Tanzania. We use two waves of the panel LSMS for 2010/11 and 2012/13 and focus our analysis on this two-period panel.[5] The data contains very detailed information on individuals and household followed over the two periods and provides detailed community level information.

The map presented in figure 1 below depicts the enumeration areas of the survey showing the broad geographic coverage of the data collection, confirming the representative nature of the survey[6]. From 3,924 households in the 2010/11 survey, 3,776 households were successfully re-interviewed in the 2012/13 survey amounting to an attrition rate of less than 4 percent between the two waves. The panel nature of the survey allows us to follow 18,669 individuals over time from these households.[7]

The LSMS survey collects very detailed information on individual and the households they live in. These include information on age, gender, marital status, education levels and occupation. Household level characteristics include gender of household head, household size, average household age, household location (rural/urban), a very detailed description of basic household assets, household membership of a Savings and Credit Cooperative (SACCO) group, household membership of any other credit and savings society, household access to loan, bank account possession, number of mobile phones the household possesses, value of voucher the household purchases in recent times.

[5] The 2008/09 wave is part of the panel LSMS for Tanzania, but does not contain information on mobile money. Because we cannot rule out that some households nevertheless were already early adopters in 2009, we cannot use the 2008/09 wave of the LSMS, by assuming that no household had access to mobile money.

[6] The original 26 regions across Tanzanian geographical map at the inception of the National Panel Survey in 2008/09 survey are retained over the three waves for consistency.

[7] The attrition rate in our study is comparable to what is obtainable in most field experiments with follow-up survey for a panel data analysis (see Dupas and Robinson 2013).

There is also an abundance of information on educational decisions, including school enrolment, school absenteeism, individual's schooling expenditure, number of after-school hours children spend on homework and domestic work.

Very detailed itemised information on household expenditure allows us to investigate total household and per capita expenditure.[8] Focusing on real total expenditure, rather than a single category for food expenditure, allows us to investigate household poverty, rather than food security only, in addition to a number of other expenditure categories including expenditure on health and education. In addition to the detailed expenditure data, the LSMS provides information on the frequency of visits to health clinics, the acquisition of mosquito bed nets, and self-reported satisfaction along a number of dimensions.

Tables 2 and 3 present summary statistics of the household and individual characteristics, respectively. On average households consist of just above 5 members, with most children below the age of 18. Average age of the individuals surveyed in the data is 26 years showcasing the low population age in Tanzania. 72 percent of the households live in rural areas. 22 percent of the households have a member that belongs to a SACCO group while only 16 percent have a formal bank account. Agricultural activities dominate the household labour supply with 63 percent of adults engaging in such activities. 13 percent of adults are self-employed, and 6 and 4 percent working in the private and public sector, respectively. 14 percent of individuals in the survey are unemployed.

Table 3 reports summary statistics for the use of mobile money over the two survey waves. The reported dominant reason for mobile money use in both survey rounds was sending and receiving money, accounting for roughly 80 percent of the responses. Next is around 8 percent of respondents buying airtime for themselves as their most important use of mobile money, and around 5 percent and 3 percent report to predominantly use it for daily expenses and emergency savings, respectively. About 60 percent report to use mobile money only occasionally, in line with the less frequent use for sending and receiving remittances and for emergency use only. Only a small number report to use mobile money on a weekly or daily

[8] The World Bank's LSMS team reports 12 month nominal and real household expenditure for different expenditure classes ranging from necessity expenditure (e.g. food) to luxury expenditure (such as on sporting items). The timing of the 12 months household expenditure figures coincides with the period following the rainfall shock variable extracted from the geospatial variable file which reports 12 months household (plot level) rainfall patterns.

basis, a pattern consistent with the low reporting of mobile money predominantly being used for daily expenses. The data nevertheless reveals a shift towards more frequent use of mobile money. Together with the expansion of mobile money across households this shows an increase in both, the extensive and intensive margin, of mobile money use in these households.

4 Empirical Strategy

In this paper, we are interested in the effect that mobile money has on consumption smoothing and welfare outcomes for households during periods of shocks. For this purpose we exploit rainfall variation, as measured by deviations from the long-term rainfall, using a very fine partitioning of rainfall data available to us across vast geographic space and over time. We then interact these measures of household shocks with the availability of mobile money accounts in the household to understand the impact mobile money has on our set of household and individual outcomes. Deviation in rainfall from the long-run means provide a credible source of variation for shocks to the household and are, given the large dependence of households to smallhold agricultural production, indeed the most important source of shocks these households face to their resources. By using this variation we investigate whether mobile money adoption plays a role in coping with the consequences of negative transitory shocks. We estimate the following econometric model:

$$Y_{ht} = \alpha_h + \delta_t + \boldsymbol{\tau}(\mathrm{MM_{ht}}\ \mathrm{X}\ \mathrm{Rainshock_{ht-1}}) + \boldsymbol{\beta_4}(\mathrm{Rainshock_{ht-1}}) + \boldsymbol{\beta_3}(\mathrm{MM_{ht}}) + X'_{ht}\boldsymbol{\beta}_2 + Z'_{ht}\boldsymbol{\beta_1} + \varepsilon_{ht} \quad (1)$$

where Y_{ht} represent the set of outcome variables at the household and individual level. $\mathrm{MM_{ht}}\ \mathrm{X}\ \mathrm{Rainshock_{ht-1}}$ is the interaction term for mobile money and rainfall shock measure; $\boldsymbol{\tau}$ *is* the coefficient of interest in our model. $\boldsymbol{\beta_3}$ represents the impact of household mobile money adoption, while the coefficient $\boldsymbol{\beta_4}$ represents the direct effect of rainfall shocks on the outcome variables. α_h and δ_t are household/individual and year fixed effects. Comparing the coefficient estimates for $\boldsymbol{\tau}$ relative to $\boldsymbol{\beta_4}$ will provide us with the overall effect mobile money access has on the set of outcome variables in response to rainfall shocks. To control for time-varying household and individual characteristics and to increase the precision of our estimates we include individual (X_{ht}) and household level controls (Z_{ht}) in some specification. Error term (ε_{ht}) is clustered at the community/ household level for household/ individual level estimations, respectively.

Because the adoption of mobile money in households is potentially endogenous, we make use of the rapid expansion of the mobile money agent network between the two LSMS waves and follow Jack and Suri (2014) by combining household shocks with an instrumental variable strategy in an instrumented difference-in-difference (DiD) strategy. Rather than relying on self-reported recall of household shocks as in Jack and Suri (2014) we use exogenous and objective measures for household shocks, namely deviation from mean rainfall. Because (1) includes an interaction term ($\mathrm{MM}_{\mathrm{ht}}\, \mathrm{X}\, \mathrm{Rainshock}_{\mathrm{ht-1}}$) we interacted the two instruments for mobile money adoption with rainfall shocks and we follow Jack and Suri (2014) in the choice of instruments by using the presence of a mobile money agent in the village and distance (cost) to agent as instruments for mobile money adoption.

Identification for the instrumented DID strategy relies on the exclusion restriction to hold, namely that agent proximity over time to affect poverty (and other outcomes) only through the use of mobile money. In addition, we assume that deviations in rainfall are exogenous.

4.1 Construction of Rainfall Shock Measure

To construct our measure of rainfall shocks we use precipitation data provided by the World Bank (along with the LSMS data) that is available on the plot level.[9] We follow the literature in constructing rainfall shocks and create measures of deviations in rainfall from the long-run mean rainfall for an area by constructing shocks in the following way:

$$\mathrm{Rainshock}_{\mathrm{ht-1}} = ln\, R_{ht-1} - ln\, \overline{R_h} \qquad (2)$$

where $\mathrm{R}_{\mathrm{ht-1}}$ indicates the yearly rainfall in household *h* for the preceding year's planting season and $\overline{R_h}$ is the average historical yearly rainfall in household *h*. Thus, the $\mathrm{Rainshock}_{\mathrm{ht-1}}$ above is equivalent to the shock measure used for deviation of the natural logarithm of the total rainfall in the 12 months prior to the 2010/2011 and 2012/2013 periods and the natural logarithm of the average yearly historical rainfall in the household *h* prior to the corresponding

[9] In the Appendix we provide a full description of the source of rainfall data used in this paper alongside detailed information on the technicalities involved in creating growing season specific rainfall measures. Yearly rainfall is adopted due to household's freedom of choice to either cultivate short or long rainy seasons for agricultural yields. However, it is noted from agricultural data in Tanzanian LSMS that households partake in the long rainy season agricultural activities perhaps due to certainty with agricultural yields from longer rainy season cultivation between December and February as against short rainy seasons in June and July cultivation.

years. The rainfall deviation basically implies a percentage deviation from mean rainfall (Maccini and Yang 2009).[10]

5 Results

5.1 Main Results: Households

5.1.1 Poverty and Consumption Smoothing

We present the results for the impact of mobile money and household shocks on household poverty in Table 4.[11] In detail, this table contains the coefficients from equation (1) where we use our exogenous measure for household shocks, namely rainfall deviations, and instrument mobile money adoption for both, the separate inclusion of mobile money adoption and in the interaction term with shocks in equation (1). We estimate equation (1) using simple OLS in a linear probability framework.[12] As a first observation from Table 4 we find that the coefficients for the direct effect of mobile money are positive as expected, but not significant at any conventional level of significance. Next we are interested in direct effect of shocks and the interaction term. We find that a one standard deviation negative (indicating less than mean rainfall) rainfall shock increases the probability of spending below the poverty line among affected households by around 3.5 percentage points. This result is in line with findings in the literature on the negative consequences of rainfall shocks and droughts on household poverty. The coefficient on the interaction between shocks and mobile money adoption is negative and statistically significant at the 5 percent level. A one standard deviation negative rainfall shock interacted with the mobile money indicator leads to a 10 percentage point decrease in the probability of being poor. Interestingly, when combined with the direct effect of rainfall shocks, this more than counteracts the negative consequences of rainfall shocks. One possible interpretation to explain this unexpected outcome is related to the way households in need

[10] There are a number of examples in the economics literature that have adopted this procedure. Recent examples include Maccini and Yang 2009; Björkman-Nyqvist 2013; Rocha and Soares 2015.

[11] The diagnostic F-statistics are 13.27 for mobile money adoption model; and 21.90 for the interaction of mobile money adoption and rainfall shocks. The associated F-statistics for the excluded instruments are 5.98 and 55.16 with probability value of 0.00 respectively for mobile money adoption and the interaction term first stage regressions.

[12] We use linear specifications because probit and (unconditional) logit with fixed effects yield inconsistent slope estimates due to the incidental parameter problem explained in Greene (2003). Consistent slope estimates can be obtained using conditional fixed effects logit, which yields qualitatively and statistically the same results as the corresponding linear probability model. However, magnitude of estimates requires cautious comparison in the absence of substantial knowledge of the distribution of fixed effects (Wooldridge 2010). The main drawback of conditional fixed effects logit is that estimates do not converge when including year fixed effects in our regressions. This is a general problem associated with maximum likelihood estimators of coefficients in nonlinear models as elaborated in Greene (2004).

receive remittances and seems to suggest that these households possibly receive more remittances than the negative rainfall shock would require. This type of overcompensation is more likely in a framework where remittance transfers are easier because of lower transaction costs. Riley (2016) finds similar evidence for overcompensation in a related framework. This suggests that very poor households with access to mobile money are able to smooth their consumption to protect them from the negative consequences of resource shocks and avoid sliding into extreme poverty and may benefit from a diverse set of senders of remittances and the lower transaction costs enabled by mobile money.

We also estimate equation (1) for total per capita household expenditure to test for general consumption smoothing. The results are presented in Table A1. While we find quantitatively similar results and very similar patterns compared to the outcomes for poverty in Table 4, none of the coefficients are nevertheless significant at conventional levels. This indicates that access to a low-cost financial transaction technology may be most important for the poorest households that are most vulnerable to shocks. Using even more extreme poverty indicators, for example using a definition based on $US 1, reveals very similar results compared to a standard $US1.25 definition (results available from the authors upon request).[13]

As a first robustness check we estimate equation (1) using two alternative sets of instruments. The estimates for the coefficients are very similar when using either *distance to agent* (chart A) or *cost to agent* (chart B) as instrument.

More recently, concerns regarding potential spurious correlation of weather events have been raised in the literature when using rainfall variation as exogenous source of variation (Lind 2015). While the panel nature of our data allows us to hold constant fixed household characteristics, the very fine partitioning of the data does not limit us to the use of across-village variation in rainfall, but allows us to use additional variation of rainfall within geographically spread-out villages and agricultural plots and this additional variation helps us to alleviate some of these concerns. Nevertheless, remaining inter-spatial correlation of rainfall and household expenditure patterns for spatially proximate households may still lead to

[13] Using information on the amount of welfare support received by households during the survey years as outcome in the same framework yields an interesting insight in the use of mobile money during shocks (Table A2). Access to mobile money reduces significantly the amount of welfare received by households; remittances available through mobile money may provide a partial substitute to welfare transfers. Rainfall shocks do not seem to have a significant impact on welfare transfers in a specification including controls (and have the ‘wrong’ sign), the interaction term is significant and reveals a positive effect on welfare transfers as response to negative rainfall shocks. This result could be due some welfare transfers received through mobile money.

spurious inference when using rainfall shocks in our framework. Lind (2015) proposes two solutions to address spurious weather correlation concerns in studies focussing on weather variability as the variable of interest. The first is to conduct a placebo test using an out-of-context rainfall variation on outcome variable of interest while the second pivots around the adoption of spatially varying time trend in rainfall pattern as additional control variable to de-trend the rainfall data. Following Fujiwara *et al.* (2016), we adopt three locality-specific trends for the purpose of de-trending the spatial correlation of rainfall shocks in our estimation of equation (1). We implement a linear, quadratic and cubic community-specific trends respectively in the regression of extreme poverty index. Estimates reported in Table A3 Columns 3 – 5 present the de-trended rainfall shock and interaction term estimates for the corresponding time trends. The estimates vary only very slightly as a result of inclusion of diverse spatially varying time trends and do not differ from the baseline results in Column 2, reducing remaining concerns related to spatial correlation of rainfall shocks further.

5.1.2 Duration between harvest season and interview date

Most of the households in the Tanzanian LSMS rely on agricultural smallhold farming as source of income and own consumption. Planting in Tanzania revolves around two major rainy seasons; the long and the short rainy seasons, which last from February – May and September – October, respectively. This leads to planting for the long rainy season taking place around December (previous year) to February to be harvested from May to July each year. Coinciding with harvest period for the long rainy season is planting for the short rainy season which takes place between June and July with harvesting taking place between November and December.[14] In addition to the timing patterns of planting and harvesting, households can to some extent store produce from the previous harvest for own consumption, so that their consumption will not necessarily be impacted instantaneously after a bad harvest manifests. Our data provides the exact date of the survey of the households and we are able to exploit this information to disintegrate our sample into observations nearer and farther away from the previous harvesting seasons in Tanzania to investigate when exactly household expenditure is impacted after the realization of the rainfall shock. Each survey round takes place between October of the starting

[14] The vast majority of agricultural activities take place within the long rainy season in Tanzania. This is consistent with the nature of rainfed agricultural practices in most sub-Saharan African communities due to low adoption of irrigation technology for the purpose of crop cultivation.

year and ends in November of the subsequent year and we split the sample in households observed up to six month after the shock and households observed 6-12 months after the shock.

Table 5 Panel A reports the estimates for the households nearer to the harvest season, i.e. first six months from October (starting year) to March (following year) while Panel B reports estimates of the regression for second half of the survey year, April to September of the current year. The estimates for the sample observed 6-12 month after the shock are much more pronounced, while the overall pattern of the estimates is preserved in both samples. In particular, the estimates for the rainfall shocks are also smaller for the within six month sample, suggesting that the differences in the estimates of the interaction terms are not driven by a time gap in the receipt of remittances. These results are consistent with shocks initially absorbed through the consumption of remaining stocks.

5.2 Main Results: Individuals

In addition to household outcomes and the effect of shocks contemporaneously on poverty, information from individual household members in the LSMS survey allow us to investigate a number of additional outcomes. In particular, we are interested in understanding the potential of mobile money to mediating the effect of shocks for long-term outcomes and the intergenerational transmission of poverty. Shocks to poor households may for example impact health investments of adults in the household and subsequently their labour supply. Shocks to household resources may also impact the ability of households to invest in the human capital of children in the household through investments in health and education. In addition, we are able to investigate the direct effect mobile money has on a number of subjective wellbeing measures.[15] For educational outcomes we restrict observations to children aged five – 18 and examine individual education expenditure and school enrolment of children for this age bracket. Also, we use an indicator for absenteeism and the number of hours spent on homework outside school as outcome variables. Lastly, we investigate children's likelihood to partake in household chores.

5.2.1 Children

5.2.1.1 Schooling Outcomes

[15] Subjective wellbeing are categorically ranked self-reported wellbeing in general or with reference to base period used as benchmark for unfolding events in the current period. Questions on subjective wellbeing are conducted on a number of areas including health, finance, spouse and life in general.

We start by investigating individual outcomes by looking at schooling outcomes of children, including log school expenditure, school enrolment, school absenteeism and number of daily hours dedicated to homework. Unfortunately, some of these measures may not properly capture human capital investments by households. For example, outside of school supplies and school uniforms – which often are bought at the beginning of the school year – within public schools are free.[16] Similarly, school enrolment is completed at the beginning of the school year in January and therefore may not be affected by events during the calendar year (or for that sake by the realization of rainfall shocks during the long rainy season). We report the instrumented DiD estimates for schooling outcomes separately by gender in Table 6. Indeed we do not find significant effects on school expenditure and school enrolment for either girls or boys. Looking at school absenteeism, we find that a negative rainfall shock leads to a significant increase in absenteeism for boys and girls. This could for example be the result of children engaging in child labour activities. While the interaction term for boys is not statistically significant, the sign is as expected. For girls the coefficient on the interaction term is significant at the 10 percent level. A similar pattern emerges for school absenteeism as did for household poverty, the coefficient on the interaction term of mobile money with shocks reveals an 'overcompensation' of the direct effect of rainfall shocks on absenteeism. During shocks, mobile money protects school attendance of children in affected households. A one standard deviation negative rainfall shock increases the rate of absenteeism by 8 and 6 percentage points for boys and girls, respectively. The interaction effects for mobile money adopters show a reduction of 21 and 26 percentage points for boys and girls, respectively. The results in column (4) on the daily number of hours dedicated to homework reveal some interesting heterogeneous effects by gender. While we estimate small and insignificant effects for rainfall shocks and the interaction term for boys (chart A) we find substantially larger effects (significant at the 10 percent level) for girls. Mobile money shields girls' time dedicated to homework from the negative effect of rainfall shocks.[17]

5.2.1.2 Participation in Unpaid Household Chores

The heterogeneous effects by gender reported for hours dedicated to homework are matched by similar heterogeneous effects for household chores. Two major household chores in the Tanzanian context involve water fetching and firewood gathering. Table 7 Columns 1 to 3

[16] Tuition fees in primary schools were abolished in 2002.

[17] Joint estimates for boys and girls are provided in Table A4, with similar results to Table 6.

report estimates for a combined indicator for any of these two categories as the dependent variable restricted to children between five and 18 for all children, and boys and girls separately.

While none of the rainfall shock estimates are significant, the coefficient on the interaction term for children is positive, revealing that a negative rainfall shock is mediated by the availability of mobile money accounts in the household. These results are almost completely driven by the effects for girls. A one standard deviation negative rainfall shock leads to a 22 percentage point decrease in the likelihood of girls engaging in household chores such as water fetching. Access to mobile money may therefore be particularly important when there are girls in the household, which are generally more exposed to these activities and our results are consistent with findings in the literature on the relationship between remittances and child labour, especially relating to gender differences (Acosta 2011).

5.2.2 Health Outcomes

In the sub-Saharan African context, private health expenditure is an important component of human capital investment at the household level. The inefficiencies of the public health system force households to often rely on private investments in health behaviour. This is exemplified by the role of private purchases of treated malaria bed nets as an effective measure against the disease, particularly for children (Dupas 2014). Dupas (2009) reports cost as the most important factor in households' decisions to invest in treated bed nets in Kenya. In the absence of subsidies, liquidity constraints faced by households may substantially limit investment in bed nets and the recurring treatments with insecticides to maintain the effectiveness of the protection. To investigate the impact of shocks and mobile money accounts on health outcomes we use individual level data on the use of treated bed nets and preventive health expenditures. The question on individual preventive health expenditure reports the amount spent on preventive health expenditure relating to the past four weeks prior to the survey date. Table 8 reports estimates on preventive health expenditure outcomes. This category relates to expenditures made for privately paid pre-natal visits, check-ups, insecticide treatment of bed nets, repellents etc. Column (1) reports the results for an indicator variable (of any such expenditure over the past four weeks in the household) and column (2) report estimates for log real expenditure, both including the full set of controls. For both, the indicator and log health spending, we find effects for the rainfall shocks as expected, and for the interaction term, both significant at the 1 percent level of significance.

In Table 9 we present the estimates of equation (1) for bed net use. Columns (1) presents the findings for whether a household member slept under a bed net the night prior to the survey and column (2) reports the estimates for whether an individual specifically used treated bed nets. We find that a one standard deviation negative rainfall shock decreases the use of insecticide treated bed net by 8 percentage points while the interaction term shows an increase of 25 percentage points for mobile money adopters, confirming previous results on 'overcompensation' for shocks for mobile money users. We find similar, but less accentuated effects for all bed net uses (regardless of insecticide treatment status).

5.2.3 Self-Reported Well Being

Next we investigate whether the above results on the mediating effect of mobile money during shocks also translate into improvements of subjective wellbeing. We focus on self-reported satisfaction with the financial situation of the household, satisfaction with life overall and satisfaction with health status. Satisfaction levels are evaluated using rank system ranging from very unsatisfied to very satisfied. We construct a satisfaction indicator assigned "satisfied" if satisfaction level is above average level and "unsatisfied" for below average level category.

Table 10 reports the estimates on diverse self-reported adult satisfaction outcomes for finance, life and health respectively. Estimates on the satisfaction with the financial situation reveal the expected (negative) impact of negative rainfall shocks on the financial situation in the households. In line with the previous findings, the magnitude of the interaction term exceeds the coefficient estimate for rainfall shock. The simple availability of mobile money does not seem to have a significant effect on financial satisfaction (although the magnitude is relatively large and the estimates are noise). We do not find significant effects on either life satisfaction or health satisfaction.

5.2.4 Labour supply

As a final outcome for individuals we investigate the effect of shocks and mobile money on labour supply in the household. The existing literature points out the role of labour supply diversification into the non-agricultural sector during rainfall shocks that help to mitigate the impact of these shocks. This strategy is usually aimed at smoothing income to enhance consumption smoothing in periods of shock (Morduch 1995; Kochar 1999). Kochar (1999) specifically reveals that members of rural households diversify hours of labour into non-agricultural activities to cover the shortfall in agricultural income by earnings from other wage activities outside the agricultural sector in rural India.[18] As showcased by Kijima *et al.* (2006), the low wage diversification strategy tends to be more effective to mitigate negative agricultural shocks among the more vulnerable units – asset poor segment of the community. However, the diversification of labour activities between agricultural and non-agricultural sectors hinges strongly on the availability of non-agricultural opportunities in the rural area.

Table 11 reports estimates of rainfall shocks and its interaction with mobile money on non-agricultural wage labour in the seven days prior to the survey.[19] Columns 1 and 2 of Table 11 respectively present regression estimates for participation in non-agricultural wage labour for adults and children, respectively. We are particularly interested in understanding the potential effect shocks and mobile money may have on child labour. Focusing on adult labour supply first, estimates from column (1) show that a one standard deviation decrease in rainfall increases the likelihood of off-farm labour participation of adults by 2 percentage points. The interaction term indicates that this effect is counteracted by a 7 percentage points' decrease in the likelihood of non-agricultural wage labour activities by an adult. While it is difficult to interpret this effect from a welfare point of view, the fact that mobile money may decrease engagement in non-agricultural activities in periods of shocks may also indicate a possible perverse effect access to an effective remittance mechanism may have on labour supply. Although results for child labour are qualitatively very similar, pointing to a positive role mobile money may play in reducing child labour, because of the small number of observations the coefficients are not significant at conventional levels.

5.4 Transmission Channels

Numerous papers in the mobile money literature have linked consumption smoothing mechanism by adopters to remittance receipts to cushion the effect of shocks (Jack and Suri 2014; Riley 2016). Similar to these papers, we also investigate the role of remittances in the context of mobile money and shocks. In particular, we are interested in understanding the effect on the likelihood and the amount of remittance received by households in the past twelve

[18] In another context, other studies demonstrate how nonfarm employment can help rural dwellers oust sliding into poverty during agricultural shocks in Africa and Asia (Kijima et al. 2006; Otsuka and Yamano 2006).
[19] We focus on the estimates using wage labour in the most recent seven days. Whilst wage labour in the previous twelve months is available in the data, the effect of shocks cannot be attributed using data stretching over such long periods.

months.[20] Naturally we would prefer remittance measures related to a much shorter time frame, but unfortunately this data is not available. Having previously reported summary statistics on the most common uses of mobile money services - sending and receiving of remittances - it is less likely that savings from electronic money receipts would be a major factor to the impact of mobile money adoption especially in periods of shocks. To establish the role of remittance, Table 12 reports the impact of mobile money adoption, rainfall shock and interaction term on remittance indicator and natural logarithm of amount received in our focus cross-section data.

Our results indicate that mobile money adopter households are more likely to receive domestic remittance transfers and indeed receive greater amounts relative to non-adopters. Negative rainfall shocks increase the likelihood and amount of remittances received by households, but the estimates are noisy. The sign of the interaction effect points to greater chance for remittance transfers and the greater amount received in periods of negative shocks for adopter households relative to non-adopters, but the coefficients are not significant.

6 Conclusion

Financial exclusion remains an important issue in many developing countries. The rural poor are particularly affected by financial exclusion because of the reliance on rainfed agricultural practices and their related vulnerability to rainfall shocks. There is a well-established literature in economics on the consequences of financial exclusion at the macro level, and an emerging literature providing credible evidence on the welfare effects of financial exclusion using micro evidence. In this paper we provide evidence on the effect of a financial innovation – mobile money - on households and the individuals living in these households.

For this purpose we use a national representative household panel data set from Tanzania to estimate the role of the household adoption of mobile money in cushioning the welfare consequences of rainfall shocks to predominantly rural smallholder farmers. We combine information on rainfall variation on the household level with an instrumental variable

[20] The natural logarithm of the amount of remittance received in Tanzanian Shillings is used in the estimation of amount of remittance received in the past twelve months. To ensure that zero remittance values are kept in the regression process, they are converted to ones before computing the logarithmic values of the remittance amounts. Also, we restrict our regression to the last wave owing to the inappropriateness of remittance receipt questionnaire which focuses on remittance from abroad in the first wave. Hence, our estimation strategy borders on cross sectional instrumental variable estimation for observations in the last wave of our data. Our result in this regard should be representative of the use of remittance as a cushioning mechanism against shock on welfare conditional on the representation of the panel data structure in the two waves.

strategy capable of addressing the potential endogeneity of the decision of individual households to adopt mobile money in an instrumented DiD framework.

We find that mobile money access prevents households from sliding into extreme poverty during periods of negative rainfall shocks. Our evidence suggests that the poorest households may benefit most from access to mobile money, as they are also particularly vulnerable to shocks. We further provide evidence for the potential long-run effects financial inclusion may have – in the form of access to mobile money – for human capital accumulation. We find that access to mobile money helps smoothing of preventive health expenditure and increases the fraction of individuals in households sleeping under treated malaria bed nets.

While we do not find that mobile money improves school expenditure or enrolment, we provide evidence that mobile money helps to reduce school absenteeism in the aftermath of rainfall shocks and increases the number of hours dedicated to homework compared to households without mobile money access. This effect is particularly strong for girls. Similarly, we find that mobile money shields girls from spending time fetching water and collecting fire wood in response to shocks.

Lastly, our results also point to potential perverse effects of access to mobile money on non-agricultural labour supply, but without a better understanding of the consequences of moving away from small-hold farming towards other sources of income, the interpretation of the findings on labour supply is beyond the scope of this paper.

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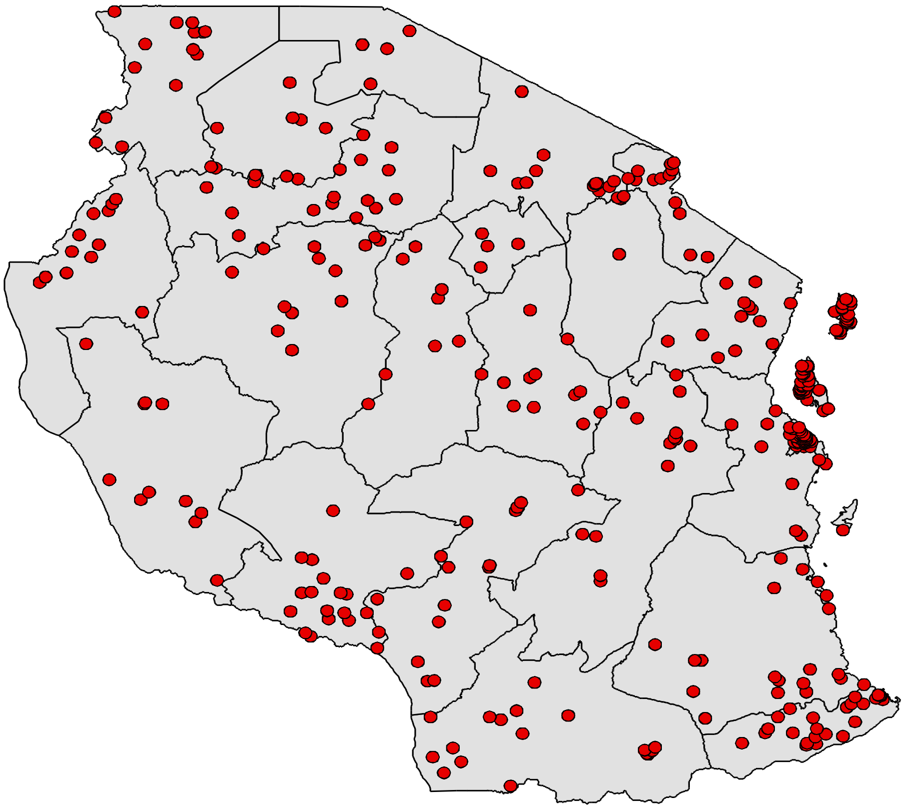
Figures and Tables

Figure 1: Map of the United Republic of Tanzania (Depicting the Enumeration Areas of LSMS Survey).



Notes: The map depicts the 26 regions of Tanzania with the red dots representing the Enumeration Areas in the LSMS-ISA used in this paper.

Figure 2: The Graphical Illustration of the Correlation between mobile money Indicator and Distance to Agent

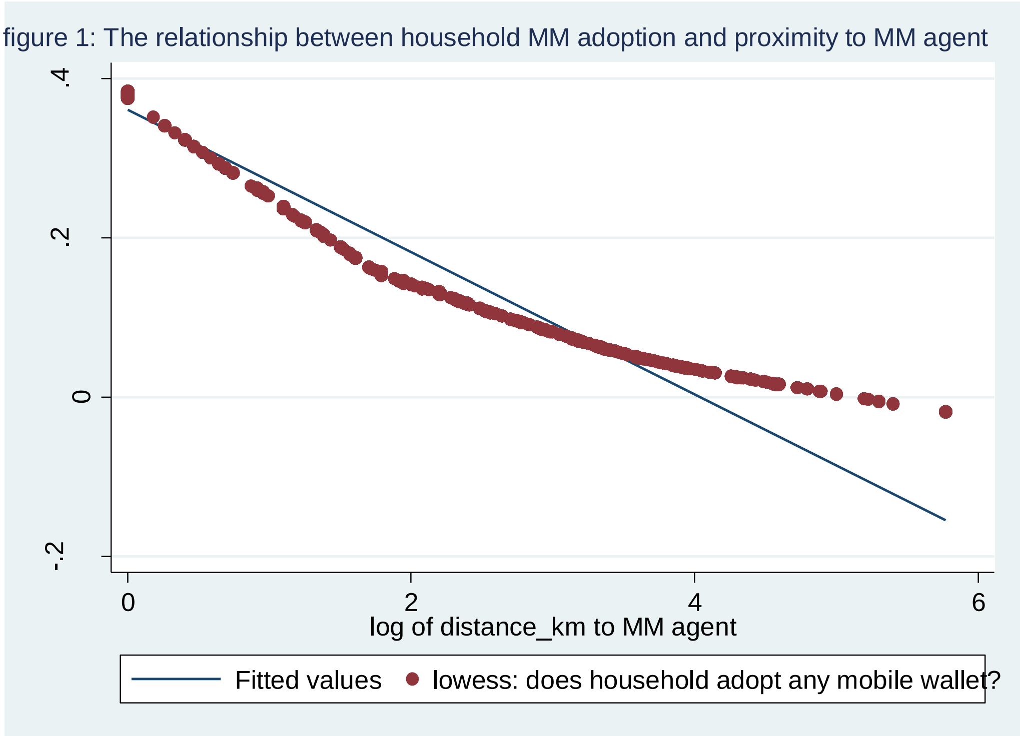


Table 1: Household Summary Statistics.

Variable	Mean	Standard Deviation
Household Size	5.1967	2.6965
No. of Children	2.7447	2.1237
Wealth Measure	73.6435	58.5276
Female Head	0.2506	0.4334
Rural	0.7173	0.4504
HH Phone Possession	0.6294	0.4830
SACCO Membership	0.2186	0.4133
Mobile Money	0.2130	0.4095
Bank Account Ownership	0.1587	0.3654
Self-Reported Shock	0.3610	0.4803
Household Head		
Married	0.8332	0.3728
Formal School	0.7618	0.4261
Occupational Categories		
Agriculture	0.6317	0.4824
Self-Employed	0.1622	0.3686
Private	0.0893	0.2853
Unemployed	0.0627	0.2425
Public	0.0541	0.2263

Notes: The summary statistics reported in Table 1 are for the focus household sample. Female Head, Rural, HH Phone Possession, SACCO Membership, Mobile Money, Bank Account Ownership and Self-Reported Shock are all indicator variables. Self-Reported Shock is an indicator variable measures as 1 for an incidence of shock in the past twelve months within the households; and 0 otherwise. Shock components for Self-Reported Shock indicator includes drought, crop pest infestation, livestock deaths, business collapse, loss of paid job, sale price decrease, food price increase, input price increase, water shortage, land slide, illness, death of breadwinner, death of any member, HH break up, jail sentence for any member, fire incidence, robbery attack on HH, HH damage and others negative shocks.

Table 2: Individual Summary Statistics.

Variable	Mean	Standard Deviation
Age	26.2003	19.7392
Male	0.4889	0.4999
Married	0.8324	0.3735
Formal School	0.7304	0.4438
Occupational Categories		
Agriculture	0.6285	0.4832
Unemployed	0.1386	0.3456
Self-Employed	0.1319	0.3384
Private	0.0617	0.2407
Public	0.0392	0.1942

Notes: The summary statistics reported in Table 2 are for our focus individual of panel observations. Male, Married and Formal School are all indicator variables. Married, Formal School and occupation categories of individuals above are restricted to adult individuals.

Table 3: Service Preference and Frequency of Use of Mobile Money by Adopters in Tanzania Between 2011 and 2013.

Chart A : Service Preference	2011	2013
Buy Airtime	0.0816	0.0759
Send Airtime	0.0082	0.0040
Send Money	0.3837	0.3063
Receive Money	0.4245	0.5020
Receive Payment for Sales	0.0082	0.0200
Save for Emergency	0.0286	0.0280
Daily Expense	0.0571	0.0439
Large Purchase	–	0.0080
Chart B : Frequency of Use		
Occasional (Emergency)	0.6245	0.5699
Half-Yearly	0.0163	0.0200
Quarterly	0.0898	0.0479
Monthly	0.1469	0.1784
Fortnightly	0.0490	0.0453
Weekly	0.0571	0.0919
Daily	0.0163	0.0439

Notes: Chart A of Table 3 above for service preference reports the overall most important use to which mobile financial service is put by adopters as a fraction of entire adopter households by year in the Tanzanian Living Standard Measurement Study by World Bank. Please note that "large purchase service use" category is unavailable for the 2011 wave. Chart B presents the frequency of use of mobile financial service by adopters as a fraction of entire adopter households over two waves in the same survey.

Table 4: Instrumental Variable Estimates of Mobile Money and Interaction With Rainfall Shock for Poverty Indicators.

	Dependent Variable: Extreme Poverty Incidence	
Variables	(1)	(2)
Chat A: Distance to Agents		
Mobile Money	0.2991	0.2381
	(0.2723)	(0.2639)
Rainfall shock	0.0381**	0.0380**
	(0.0168)	(0.0158)
Interaction	-0.1030**	-0.1042**
	(0.0466)	(0.0425)
Chat B: Cost to Agents		
Mobile Money	0.2448	0.1278
	(0.3775)	(0.4122)
Rainfall shock	0.0402**	0.0413***
	(0.0165)	(0.0157)
Interaction	-0.1045**	-0.1049**
	(0.0515)	(0.0473)
Household Fixed-Effect	Yes	Yes
Year Fixed-Effect	Yes	Yes
Controls	No	Yes

Notes: Table 4 above reports the linear probability model (LPM) estimates of mobile money indicator, rainfall shock and their interaction term. Extreme Poverty Incidence is measured as 1 for real per-capita expenditure above US$1.25; and 0 otherwise. Mobile Money indicates mobile money service use at the household level. Interaction implies an interaction term between mobile money indicator and rainfall shock measures (household shocks). Each column is a separate regression for 3,590 observations. Columns (1) – (2) each represents estimation without controls and with controls respectively. The controls used in the estimation of column (2) include an array of household level controls. These are gender of household head, education and occupation categories of household head, household size, average household age, household residential place (rural/urban), household asset valuation, household membership of a SACCO group, household membership of any other credit and savings society, household access to loan, bank account possession within the household, number of mobile phones the household possesses, value of voucher the household purchases in the past. Each regression is clustered at the community level. Robust standard errors (clustered at the community level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table 5: Instrumental Variable Estimates of Mobile Money and Interaction Term on Extreme Poverty Considering the Timing of Planting Seasons

	Dependent Variable: Extreme Poverty Incidence			
	Panel A: Within six months of harvest		Panel B: After six months of harvest	
Variables	(1)	(2)	(3)	(4)
Mobile Money	0.0343	0.0273	0.6152	0.3986
	(0.2879)	(0.3289)	(0.5041)	(0.4031)
Rainfall shock	0.0261	0.0185	0.0548	0.0544*
	(0.0198)	(0.0175)	(0.0349)	(0.0308)
Interaction	-0.0456	-0.0496	-0.1547*	-0.1407*
	(0.0569)	(0.0596)	(0.0916)	(0.0741)
Observations	1,702	1,702	1,905	1,905
Household Fixed-Effect	Yes	Yes	Yes	Yes
Year Fixed-Effect	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes

Notes: Table 5 above reports the linear probability model (LPM) estimates of mobile money indicator, rainfall shock and their interaction term on extreme poverty category from Table 5. Panel A conveys estimates for households surveyed in the first six months of harvest while Panel B reports estimates for households surveyed after six months of harvest. Mobile Money indicates the mobile money service use at the household level. Interaction implies an interaction term between mobile money indicator and rainfall shock measures (idiosyncratic shocks). See notes in Table 4 for a list of all controls used in the regression process. Each regression is clustered at the community level. Robust standard errors (clustered at the community level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table 6: Instrumental Variable Estimates of Mobile Money and Interaction With Rainfall Shock on Children School Outcomes by Gender.

Variables	School Expenditure (Tanzanian Shilling) (1)	School Enrolment (Indicator) (2)	School Absenteeism (Indicator) (3)	Homework (Hours/Day) (4)
	Dependent Variables:			
Chart A : Boys				
Mobile Money	303.3013	0.0734	-0.7845	-0.8013
	(208.7114)	(0.3532)	(1.2006)	(1.6107)
Rainfall shock	7.4557	-0.0012	-0.0838**	0.0228
	(9.5779)	(0.0166)	(0.0403)	(0.0498)
Interaction	-8.0870	0.0260	0.2122	-0.0373
	(34.9972)	(0.0502)	(0.1482)	(0.2169)
Observations	1,898	1,898	1,492	1,492
Chart B : Girls				
Mobile Money	-16.6312	-0.1582	-0.5011	1.7019
	(55.9685)	(0.2051)	(0.6943)	(1.0646)
Rainfall shock	3.0683	0.0031	-0.0604*	0.0978*
	(3.3328)	(0.0157)	(0.0366)	(0.0560)
Interaction	0.2856	0.0194	0.2644*	-0.4091*
	(14.6199)	(0.0534)	(0.1371)	(0.2192)
Observations	2,042	2,042	1,678	1,676
Individual Fixed-Effect	Yes	Yes	Yes	Yes
Year Fixed-Effect	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: Table 6 above reports the estimates of mobile money indicator, rainfall shock and their interaction term. Column 1 displays estimates for natural logarithm of children school expenditure while column 2 reports estimates from linear probability for school enrolment indicator. School enrolment indicator is measured as 1 if a child aged 5 to 18 is currently attending school; and 0 otherwise. On the other hand, school absenteeism indicator in column 3 indicates 1 if an enrolled child missed school in the last two weeks; and 0 otherwise. Column 4 engages in the daily hours used for school homework at home. Mobile Money indicates the mobile money service use at the household level. Interaction implies an interaction term for mobile money indicator and rainfall shock measures (idiosyncratic shocks). Charts A and B reports estimates for boys and girls respectively. Each column follows column 2 Table 4 above in reporting estimates of the regression which includes relevant household controls. In addition to household level controls, age and gender of children are used as additional individual controls for the estimation. Each regression is clustered at the household level. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table 7: Instrumental Variable Estimates of Mobile Money and Interaction With Rainfall Shock on Children Household Chores.

	Dependent Variables: Household Chores		
	Children	Boys	Girls
Variables	(1)	(2)	(3)
Mobile Money	-0.4728	-0.6224	-0.5061
	(0.3324)	(0.5536)	(0.4171)
Rainfall shock	-0.0150	0.0068	-0.0454
	(0.0195)	(0.0253)	(0.0293)
Interaction	0.1157*	0.0287	0.2168**
	(0.0664)	(0.0834)	(0.1058)
Observations	6,956	3,494	3,462
Individual Fixed-Effect	Yes	Yes	Yes
Year Fixed-Effect	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: Table 7 above reports the estimates of mobile money indicator, rainfall shock and their interaction term. Household Chores in columns 1 – 3 is a union of water fetching and firewood gathering duties. This is measured as 1 if a child fetches water or gathers firewood at home; and 0 otherwise. Mobile Money indicates the mobile money use at the household level. Interaction implies an interaction term for mobile money indicator and rainfall shock measures (idiosyncratic shocks). Each column follows column 2 Table 4 above in reporting estimates of the regression which includes relevant household controls. In addition to household level controls, age and gender of children are used as additional individual controls for the estimation. Each regression is clustered at the household level. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table 8: Instrumental Variable Estimates of Mobile Money and Interaction With Rainfall Shock on Preventive Health Expenditure Measures.

	Dependent Variables:	
	Preventive Health Exp. Indicator	Real Preventive Health Expenditure
Variables	(1)	(2)
Mobile Money	-0.0011	-0.0227
	(0.0145)	(0.2144)
Rainfall shock	0.0032***	0.0474***
	(0.0012)	(0.0183)
Interaction	-0.0161***	-0.2353***
	(0.0057)	(0.0849)
Individual Fixed-Effect	Yes	Yes
Year Fixed-Effect	Yes	Yes
Controls	Yes	Yes

Notes: Table 8 above reports the estimates of mobile money indicator, rainfall shock and their interaction term. Preventive Health Expenditure Indicator in column (1) is measured as 1 if an individual spends any amount on preventive health in the past four weeks; and 0 otherwise. Real preventive health expenditure in column (2) is calculated as the natural logarithm of real preventive health expenditure in thousand Tanzanian shillings. Mobile Money indicates the mobile money use at the household level. Interaction implies an interaction term for mobile money indicator and rainfall shock measures (idiosyncratic shocks). Each column follows column 2 Table 4 above in reporting estimates of the regression which includes necessary controls respectively. In addition to household level controls, age, gender, marital status, educational and occupational categories of individuals are used as additional individual controls for the estimation. Each regression is clustered at the household level. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table 9: Instrumental Variable Estimates of Mobile Money and Interaction With Rainfall Shock on Bed Net Adoption and Treatment.

	Dependent Variables:	
	Bed Net Use Indicator	Treated Bed Net Indicator
Variables	(1)	(2)
Mobile Money	0.8244*	0.9259*
	(0.4269)	(0.5100)
Rainfall shock	0.0377	0.0843***
	(0.0247)	(0.0289)
Interaction	-0.1979**	-0.2535**
	(0.0958)	(0.1135)
Individual Fixed-Effect	Yes	Yes
Year Fixed-Effect	Yes	Yes
Controls	Yes	Yes

Notes: Table 9 above reports the estimates of mobile money indicator, rainfall shock and their interaction term. Bednet Use Indicator in column (1) indicates 1 if an individual uses mosquito bednet during sleep; and 0 otherwise while treated bednet indicator in column (2) indicates 1 if an individual specifically uses treated bednet; and 0 otherwise. Mobile Money indicates the mobile money use at the household level. Interaction implies an interaction term for mobile money indicator and rainfall shock measures (idiosyncratic shocks). Each column is a separate regression for 13,350 observations. Each column follows column 2 Table 4 above in reporting estimates of the regression which includes necessary controls respectively. In addition to household level controls, age, gender, marital status, educational and occupational categories of individuals are used as additional individual controls for the estimation. Each regression is clustered at the household level. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table 10: Instrumental Variable Estimates of Mobile Money and Interaction With Rainfall Shock on Subjective Well-Being.

	Dependent Variables:		
	Finance Satisfaction (Indicator)	Life Satisfaction (Indicator)	Health Satisfaction (Indicator)
Variables	(1)	(2)	(3)
Mobile Money	0.3503	0.4103	-0.3641
	(0.3186)	(0.3184)	(0.2528)
Rainfall shock	0.0349*	0.0193	-0.0145
	(0.0193)	(0.0216)	(0.0170)
Interaction	-0.1306*	-0.1046	0.0875
	(0.0685)	(0.0708)	(0.0578)
Observations	5,880	5,870	5,878
Individual Fixed-Effect	Yes	Yes	Yes
Year Fixed-Effect	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: Table 10 above reports the estimates of mobile money indicator, rainfall shock and their interaction term. Satisfaction Dummies in columns (1) – (3) is measured as 1 if an individual if satisfied beyond average reported satisfaction index from the questionnaire; and 0 otherwise. Mobile Money indicates the mobile money use at the household level. Interaction implies an interaction term for mobile money indicator and rainfall shock measures (idiosyncratic shocks). Each column follows column 2 Table 4 above in reporting estimates of the regression which includes necessary controls respectively. In addition to household level controls, age, gender, marital status, educational and occupational categories of individuals are used as additional individual controls for the estimation. Each regression is clustered at the household level. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table 11: Instrumental Variable Estimates of Mobile Money and Interaction With Rainfall Shock on Wage Labour

	Dependent Variable : Weekly Wage Participation Indicator	
	Adults	Children
VARIABLES	(1)	(2)
Mobile Money	0.2036	-0.0341
	(0.1905)	(0.3291)
Rainfall shock	-0.0203**	-0.0370
	(0.0098)	(0.0264)
Interaction	0.0690**	0.0698
	(0.0293)	(0.0593)
Observations	6,326	1,176
Individual Fixed-Effect	Yes	Yes
Year Fixed-Effect	Yes	Yes
Controls	Yes	Yes

Notes: Table 11 above reports the estimates of mobile money indicator, rainfall shock and their interaction term. Weekly Wage Participation Indicator is measured as 1 if an individual engaged in a wage rewarding labour activity in the last seven days; and 0 otherwise. Column 1 reports estimates for adults over 18 years while column 2 reports estimates for children aged 5 – 18. Mobile Money indicates the mobile money use at the household level. Interaction implies an interaction term for mobile money indicator and rainfall shock measures (idiosyncratic shocks). Each column follows column 2 Table 4 above in reporting estimates of the regression which includes necessary controls respectively. In addition to household level controls, age, gender, marital status, educational and occupational categories of individuals are used as additional individual controls for the adult estimation in column 1 while age and gender are used as additional controls in column 2. Each regression is clustered at the household level. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table 12: Instrumental Variable Estimates of Mobile Money and Interaction Term on Remittance

	Dependent Variable: Remittance			
	Panel A: Remittance Indicator		Panel B: ln (amount)	
Variables	(1)	(2)	(3)	(4)
Mobile Money	0.3777***	0.9512***	4.3531***	9.7178***
	(0.0826)	(0.2788)	(0.9347)	(2.8698)
Rainfall shock	-0.0378	-0.0289	-0.2689	-0.1470
	(0.0341)	(0.0346)	(0.3771)	(0.3754)
Interaction	0.0055	-0.0134	-0.0092	-0.1835
	(0.0746)	(0.0758)	(0.8442)	(0.8317)
Observations	1,809	1,809	1,809	1,809
Household Fixed-Effect	Yes	Yes	Yes	Yes
Year Fixed-Effect	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Notes: Table 12 above reports the estimates of mobile money indicator, rainfall shock and their interaction term on remittance receipts by observation households. Panel A and Panel B report estimates for indicator and natural logarithm of remittance receipts (in Tanzanian Shillings) by households respectively. See notes in Table 4 for a list of all controls used in the regression process. Each regression is clustered at the community level. Robust standard errors (clustered at the community level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Appendix

Table A1: Instrumental Variable Estimates of Mobile Money and Interaction With Rainfall Shock on Per-capita Expenditure.

	Dependent Variable: Per-capita Expenditure (ln)	
Variables	(1)	(2)
Chart A: Distance to Agent		
Mobile Money	-0.1154	-0.2843
	(0.3921)	(0.4133)
Rainfall shock	0.0076	0.0130
	(0.0195)	(0.0190)
Interaction	0.0092	0.0048
	(0.0582)	(0.0542)
Chart B: Cost to Agent		
Mobile Money	0.1419	-0.1948
	(0.4613)	(0.4947)
Rainfall shock	0.0082	0.0156
	(0.0189)	(0.0188)
Interaction	-0.0175	-0.0116
	(0.0615)	(0.0561)
Household Fixed-Effect	Yes	Yes
Year Fixed-Effect	Yes	Yes
Controls	No	Yes

Notes: Table A1 above reports the estimates of mobile money indicator, rainfall shock and their interaction term for the natural logarithm of per-capita expenditure. Controls used in column 2 are outlined in the notes of table 4 above. Robust standard errors (clustered at the community level) are reported in parentheses.
***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table A2: Instrumental Variable Estimates of Mobile Money and Interaction With Rainfall Shock on Household Welfare Support.

	Dependent Variable: ln amount	
Variables	(1)	(2)
Mobile Money	-0.8739*	-0.9995*
	(0.5103)	(0.5806)
Rainfall shock	0.0365*	0.0283
	(0.0219)	(0.0225)
Interaction	-0.1969*	-0.2049*
	(0.1171)	(0.1117)
Household Fixed-Effect	Yes	Yes
Year Fixed-Effect	Yes	Yes
Controls	No	Yes

Notes: Table A2 above reports the linear probability model (LPM) estimates of mobile money indicator, rainfall shock and their interaction term on the natural logarithm of the amount of funds solicited from welfare support societies in the past one year. See table 4 for additional notes and controls. Robust standard errors (clustered at the community level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table A3: Spatial Correlation Consideration for Extreme Poverty Results.

	Dependent Variable: Extreme Poverty Indicator				
Variables	(1)	(2)	(3)	(4)	(5)
Mobile Money	0.2991	0.2381	0.3198	0.3386	0.3399
	(0.2723)	(0.2639)	(0.3519)	(0.3538)	(0.3443)
Rainfall shock	0.0381**	0.0380**	0.0376**	0.0374**	0.0377**
	(0.0168)	(0.0158)	(0.0161)	(0.0162)	(0.0161)
Interaction	-0.1030**	-0.1042**	-0.1052**	-0.1038**	-0.1036**
	(0.0466)	(0.0425)	(0.0432)	(0.0428)	(0.0427)
Household Fixed-Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effect	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
Community Varying Linear Trend X Time	No	No	Yes	No	No
Community Varying Quadric Trend X Time	No	No	No	Yes	No
Community Varying Cubic Trend X Time	No	No	No	No	Yes

Notes: Table A3 above reports the linear probability model (LPM) estimates of mobile money indicator, rainfall shock and their interaction term with community varying trends by time controls for spatial correlation. See table 5 for additional notes and controls. Robust standard errors (clustered at the community level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table A4: Instrumental Variable Estimates of Mobile Money and Interaction With Rainfall Shock on Children School Outcomes.

	Dependent Variables:			
	School Expenditure (Tanzanian Shilling)	School Enrolment (Indicator)	School Absenteeism (Indicator)	Homework (Hours/Day)
Variables	(1)	(2)	(3)	(4)
Mobile Money	76.3315	-0.2027	-0.2884	1.2409
	(56.1424)	(0.1965)	(0.7384)	(1.0065)
Rainfall shock	6.0651*	-0.0035	-0.0610**	0.0668*
	(3.4078)	(0.0133)	(0.0289)	(0.0398)
Interaction	-11.8226	0.0364	0.1695	-0.2938*
	(13.4400)	(0.0417)	(0.1090)	(0.1603)
Observations	4,242	4,242	3,374	3,372
Individual Fixed-Effect	Yes	Yes	Yes	Yes
Year Fixed-Effect	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: Table A4 above reports the estimates of mobile money indicator, rainfall shock and their interaction term for children school outcomes. See Table 6 for additional notes. Each regression is clustered at the household level. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

A. Weather Data: Rainfall Data from the LSMS-ISA

The main rainfall data used in this paper are obtained from the National Oceanic and Atmospheric Administration Climate Prediction Centre (NOAA CPC) African Rainfall Estimation Algorithm Version 2.0. The rainfall dataset from Rainfall Estimate (RFE) v2.0 is a valuable component of geographical variables because it provides a standardized time-series for all of the LSMS-ISA countries. Toté *et al.* (2015) provide a validation of the RFE rainfall measure relative to other measurement methods. The RFE outperforms Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) and TAMSAT African Rainfall Climatology and Time-series (TARCAT) v2.0 products, especially in drought detection for Mozambique.

It is important to understand that RFE is a merged product using data from multiple meteorological satellites and rainfall stations. The remote sensing data provide a continuous surface, at a specific resolution, measuring rainfall estimates. According to a sourced technical document from the World Bank's LSMS team, station data are essentially used to calibrate the merged satellite surfaces. The apparent granularity of the household measure comes from the RFE modelling, as well as the method used to extract the data. Rainfall values are extracted at household locations using a bilinear interpolation or distance-weighted average of 4 nearest grid cell values as used in practice.

Seasonal precipitation data gathered from the Tanzanian meteorological weather stations are used in the interpolation of the global positioning system (GPS) of surveyed Tanzanian households[21]. These data include annual and wet season precipitation measures respectively. While the household level GPS are withheld for confidentiality reasons, these are engaged to capture household specific approximates of precipitation measures outlined above. Spatial distribution of households included in the LSMS-ISA survey for Tanzania enhances the credibility of the rainfall variation at the Enumeration Area (EA) level with additional variation achievable within the EA – engaging the household level approximations of the precipitation measures. Preliminary analysis shows that rainfall measures within the same locality are actually correlated but different in absolute terms. It is important to reiterate that while this unique data displays more variation of precipitation measures between EA compared to within EA, availability of such sophisticated level of precipitation augments rainfall shock driven inquiries in the literature.

Furthermore, specific nature of the rainfall data helps to address inter-spatial correlation of rainfall data with broader geographical precipitation variation, such as the district level, commonly used in the literature. Other weather parameters captured are geophysical characteristics at the landscape level including rainy season parameters and soil fertility conditions for agricultural production. While the unmodified household GPS

[21] Due to spatial distribution of household observations in the survey data, enumerators were provided with a technological device that helps to capture exact GPS location of the respondent household and its immediate environs. Households close to each other have exactly the same GPS while households farther away may have different GPS measurements.

measured are not released for confidentiality of survey observations, modified EA level GPS are released as part of the survey data.

B. Conceptual Framework

The response of shock-prone household within the insurance and risk-sharing models aftermath of shock is unambiguous as described in Yang and Choi (2007) and Jack and Suri (2014) respectively. However, our model considers an aggregate economic framework where some households are exempted from the negative shock and can be helpful for remittance transfers to affected households. Assuming the same basic assumption of the existence of pareto-efficient allocation of risk across households, as in Yang and Choi (2007), in different states of shock[22] hold, welfare state for negative income shock households may vary in different dimensions and under varying 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 network household is faced with a different state of shock S^i from that experienced by our focus household mainly from a subset where $i \in \{+,-\}$. S_t^+ and S_t^- represent positive and negative states of shock at period *t* respectively[23]. One important component of our model is the acquisition of innovative financial technology for the purpose of transferring funds back and forth across network of households in diverse states of nature. While asset and livestock sales continues to play consumption smoothing role, reduced transaction costs[24] associated with the emancipation of mobile money facilitates the consumption smoothing process through accessibility to wider network in periods of emergency (Jack and Suri, 2014).

Along the two major states of shock stated above, households (and individuals therein) face uncertain income in each period t, following Yang and Choi (2007). Similarly, household h consume $c^h_{s_t^+}$ or $c^h_{s_t^-}$ in either time period, leading to four potential combinations for each household across shock faced and time frame[25]. However, we deviate from Yang and Choi (2007) with a consideration of welfare ratio of the same household across periods (facing the same or different states of shock). If the utility derivable from

[22] A set of positive and negative shock exposed network of households, 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 with differing rainfall patterns at a point in time.
[23] Positive and negative states of shock respectively refers to quantified positive and negative deviation of household plot level rainfall measure associated with the recent agricultural season from the average of ten years historical rainfall patterns.
[24] It is important to note that exorbitant transaction costs continues to be charged in traditional/antiquated remittance platforms alongside lots of associated risk and requirement for time before delivery of remittance to households. Apart from cost issues with traditional remittance in Tanzania, most of the traditional remittance platforms are not suitable for meeting household emergency demands.
[25] 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 shock in the consecutive periods. While this seems to be representative of a static model of household shock disposition, the magnitude across these consecutive periods may play a dynamic role in affecting 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.

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 across 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 the equation is equivalent to 1, indicating that negative idiosyncratic shock faced by a household does not affect its consumption pattern across time. This is particularly relevant for households with negative income shock in the second period irrespective of their first period state of shock.

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

On the other hand, an inequality may exist between the current welfare state of a household relative to its previous welfare state. This is illustrated by eq. (3) below.

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

Disintegrating the above equation to two welfare ratios where the first is less than unity and the other is greater than unity gives us an idea of the dynamics of less than full consumption smoothing (Fafchamps *et al.* 1998) and greater than full consumption smoothing respectively.

While the use of mobile money has replaced traditional mechanisms as a result of the efficiency of the use of the remittance services in periods of emergency (shock), sales of household assets/livestock and access to existing formal and informal financial system within East African communities may aid smoothing in excess of the impact of shock. More so, a broader network of households, across the different regions of the country, avails the household the tendency of getting more than required funds to cushion shock.

Our main objective in this paper is to empirically establish the dynamics that play out between equations (2) and (3) above using the sparsely populated Tanzanian framework. We may also be able to engage household and individual welfare outcomes to understand consumption smoothing priorities in the use of mobile money for shock affected households.