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ABSTRACT

Financial Inclusion, Shocks and Poverty: Evidence from the Expansion of Mobile Money in Tanzania*

We estimate the effect of mobile money adoption on consumption smoothing, poverty and human capital investments in Tanzania. We exploit the rapid expansion of the mobile money agent network between 2010 and 2012 and combine this with idiosyncratic shocks from variation in rainfall over time and across space in an instrumented DiD methodology. We find that adopter households are able to smooth consumption during periods of shocks and maintain their investments in human capital. Results on time use of children and labor force participation complement the findings on the important role of mobile money for the intergenerational transmission of poverty.

JEL Classification: G23, H31, I31, I32

Keywords: mobile money, household shocks, rainfall, poverty, human capital accumulation, Tanzania

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1 Introduction

Recently, the introduction of mobile money has transformed access to 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, Jack and Suri 2016).[1] Mobile money – a financial innovation that allows individuals to transfer and store 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 (Munyegera and Matsumoto 2018). While in Europe and North America mobile money services are practically non-existent – with less than 1 per cent 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 of M-Pesa more than 75 per cent of households had at least one active mobile money account and in June 2014, the monthly value of transactions was about US$2 billion, equivalent to 60 per cent of average monthly GDP (Aron *et al.* 2015). The dramatic expansion of mobile money in sub-Saharan Africa is likely driven by very limited existing traditional 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 increases 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.

[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.

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 due to improved risk sharing facilitated by reduced transaction costs from mobile money. With this paper, we contribute to the literature on financial inclusion by focusing on the welfare consequences of mobile money adoption beyond consumption smoothing. We expand on Jack and Suri and make use of the rapid expansion of the mobile money agent network in Tanzania over the period from 2010 to 2013 during which the mobile money uptake by households increased from 13 to 41 per cent lending for an instrumented difference-in-difference (IV-DiD). Our identification strategy makes use of changes in measures of agent proximity, including the availability of agent within locality, distance and cost to the nearest agent, as instruments to identify the impact of mobile money on a variety of measures of household expenditure, poverty and human capital investments.

We are particularly interested in how mobile money affects these outcomes of households that are subjected to shocks.[2] To circumvent the endogeneity problem of household shocks, we focus on rainfall shocks to households that largely depend on rain-fed agricultural production. Different from Jack and Suri (2014) who rely on binary, self-reported measures of household shocks, we focus on shocks to households from variation in rainfall at the household level. This has several advantages:

Firstly, the deviation of rainfall from the historical mean – where we can exploit household level variation over two periods – allows us to construct an exogenous measure of household shocks, something we can also test empirically. We show that the distribution of

[2] This framework is different from similar studies that investigate mobile money and consumption patterns without incorporating shock dynamics in similar settings (Batista and Vicente 2013, Munyegera and Matsumoto 2016).

mobile money agents is orthogonal to rainfall deviations from the long-term mean and the long-term variability of rainfall for either period. We also show that household characteristics are balanced across households for which we observe a change in 'treatment' status. Secondly, using rainfall shocks, rather than self-reported shocks which rely on recall during the collection of the survey, reduces measurement error. Thirdly, rather than focusing on a binary shock indicator for household shocks, using rainfall deviation allows us to quantify the size of the shock and estimate the effect of a continuous variable, namely rainfall deviation from the historic mean. This enables us to document an overcompensation effect, where we demonstrate across a number of outcomes that households with mobile money access are more than compensated for the negative direct impact of the shock.[3] Lastly, and related to the previous point, this allows us to combine negative and positive in one measure so that we are not restricted to negative shocks only.[4] We are particularly interested in understanding the effects of mobile money on the poorest households in relation to how shocks and mobile money adoption affect their expenditure patterns, and how these may affect investments in human capital of adults and children in these households.

We find that per capita expenditure is smoothed for the poorest of households by mobile money adoption during periods of rainfall shocks, preventing these households from sliding into transient poverty. We provide evidence that consumption smoothing is achieved through a combination of increased remittances received in response to shocks and welfare receipts facilitated through mobile money accounts. We also find that expenditure components related to human capital investments of adults and children in the household are protected from the negative effect of rainfall shocks by having access to a mobile money account. In particular,

[3] Because of the binary nature of the self-reported household shocks, Jack and Suri (2014) cannot quantify the consumption smoothing effect relative to the shock and therefore also cannot identify any potential overcompensation effect.
[4] In the absence of sufficient 'positive' shocks, Jack and Suri (2014) focus on dummies for (i) overall negative shocks and (ii) illness shocks to households.

we find that households' expenditure on preventative health and measures against malaria are protected from negative shocks.

We also provide evidence that mobile money preserves investment in education of children, by preventing absenteeism from school and maintaining home study time during periods of household shocks. Effects on educational inputs are particularly pronounced for girls in the household. We find that the positive effects of mobile money adoption more than counteract the negative effect of rainfall shocks for essentially all of the outcomes affected by rainfall shocks. This finding is consistent with an informal insurance mechanism where affected households receive mobile money transfers from a variety of (uncoordinated) senders and in a framework where there is uncertainty about the size and precise timing of the realization of the negative shocks.

The remainder of the paper is structured as follows. Section 2 provides background on financial inclusion and the expansion of mobile money in Tanzania. Section 3 introduces the data sources and summarizes important variables at the individual and household levels. Section 4 presents the empirical strategy for identification and the first stage results. Section 5 presents the main and additional results. Section 6 discusses the results and concludes.

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 one of the poorest countries in the world, with about 28 per cent of the population being classified under the US$1.25 poverty line in 2011 (World Bank 2015). Current per capita GNI is US$570 in 2012, and more recently Tanzania has been described as a development success story with average growth rate of 7 per cent between 2000 and 2011 (World Bank 2013). The Tanzanian economy is still – to a large extent – based on agriculture production, with about 27 per cent of GDP and about 80 per cent 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 per cent of individuals 15 years and older have a bank account, compared to 97 per cent in the United Kingdom for the same age group. In addition, on average there are 1.56 commercial bank branches and 2.22 ATMs per 100,000 population between 2004 and 2011 in Tanzania.[5] 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 due to the lack of formal financial services, mobile money in Tanzania has been extremely successful since its introduction in 2009. The proximity to Kenya, where mobile money had been first introduced very successfully, likely also contributed to the quick adoption of the services in Tanzania, which is currently catching-up with its neighbor 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 its own mobile money services.

The Financial Inclusion Insights Surveys (CGAP 2016) shows that in 2015, 38 per cent of adults in Tanzania had a mobile money account. The household survey data we introduce in

[5] Given the vast geographic coverage of the country, similar statistics reveal 0.41 and 0.60 commercial banks and ATMs coverage, receptively, for every 1,000 km^2 in Tanzania (IMF 2012).

the next section shows that in 2012, 41 per cent of households had at least one mobile money account, while this number was only 13 per cent in 2010, revealing a sharp increase of households with access to the technology.[6] In 2012, 36 per cent of all money transfers in Tanzania were made through mobile money transfer services (World Bank 2016a).

3 Data

This paper uses data from the World Bank's Living Standard Measurement Studies – Integrated Survey on Agriculture (LSMS-ISA), previously also known as National Panel Survey (NPS), for Tanzania. We use two waves of the panel – LSMS-ISA for 2010/11 (from here on 2010) and 2012/13 (from here on 2012) – and focus our analysis on this two-period panel.[7] The data contains very detailed information on individuals and households followed over the two periods and provides detailed community level information.

The points in the maps of Figure 1 depict the enumeration areas of the survey, showcasing the broad geographic coverage enumeration village, and confirming the geographically representative nature of the survey.[8] The final baseline samples consist of 2,388 households and 9,807 individuals.[9]

[6] These figures are not directly comparable because while the CGAP survey reports mobile money accounts at the individual level, the LSMS survey we use only reports mobile money accounts at the household level. In addition, because of our focus on households largely depends on rain-fed agricultural practices, our sample is not representative for the entire population in Tanzania, but oversamples the rural population.

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

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

[9] Of the 3,924 households in the 2010 survey, 3,776 households were successfully re-interviewed in the 2012 survey, leading to an attrition rate of less than 4 per cent between the two waves. However, only 2,388 are eligible for regression when matched with rainfall and agent data. Similarly, the panel nature of the survey allows us to follow 18,669 individuals over time from these households where only 9,807 are eligible for estimation due to the aforementioned reason. Number of observations reported in our summary statistics and result tables vary based on the variability of coverage for outcome variables in the final baseline samples. For instance, results and identification checks for main household section report a sample size of 1,803 households out of the sample baseline of 2,338 households. The attrition rate for the Tanzania LSMS is comparable to most field experiments with follow-up survey for a panel data analysis (see Dupas and Robinson 2013).

The LSMS-ISA collects very detailed information on individuals and the households they live in. This includes 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 in a Savings and Credit Cooperative Organization (SACCO), household membership in any other credit and savings society, household access to loans, bank account possession, number of mobile phones the household possesses and value of air time voucher the household purchases in recent times.

Very detailed itemized information on household expenditure allows us to investigate total household and per capita expenditure.[10] 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-ISA 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 at the individual level. The survey also collects 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.

Table 1 presents summary statistics of the household and individual characteristics. Households consist of just above 5 members, on average, with most children below the age of 18. Using per capita expenditure, about 70 per cent of households are classified as living in absolute poverty and 87 per cent of households live on less than US$2 per day (using per capita

[10] 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 (e.g. sporting items). The timing of the 12-month household expenditure figures coincides with the period following the rainfall shock variable extracted from the geospatial variable file that reports 12-month household (plot level) rainfall patterns.

expenditure).[11] The average age of the individuals surveyed in the data is 26 years, showcasing the low population age in Tanzania. Seventy-two per cent of households live in a rural setup. Twenty-two per cent of households have a member that belongs to a SACCO group, while only 16 per cent have a formal bank account. The vast majority (75 per cent) of households have a male household head. Agricultural activities dominate the household labor supply, with 63 per cent of adults engaging in such activities. Fourteen per cent of individuals in the survey at working age are self-employed; 6 and 4 per cent work in the private and public sector, respectively; and 13 per cent are unemployed.

Table 2 presents summary statistics of the distribution of mobile money agents, the frequency and the type of service used over the two survey waves. Agent availability indicates the presence of a mobile money agent in the village. While in 2010 only 17 per cent of all survey villages had a mobile money agent, only two years later more than half of all villages had a mobile money agent providing services in the village. For villages without a mobile money agent, the distance to the closest available agent also reduced dramatically over time, from close to 24 km to just over 6 km.[12] Similarly, the cost of travel to the nearest agent reduced dramatically over the course of two years, from 1,850 Tanzanian shillings to 667 Tanzanian shillings.

The table also reports the availability of agents outside of the village. While in 2010, 27 per cent of villages had an agent within a 2 km distance, this number increased to 60 per cent in 2012; the last entry shows the quasi-universal coverage of mobile agents within a 20 km radius from the villages in 2012. The maps in Figures 1 and 2 show the equivalent changes in the mobile money agent distribution over time for the enumeration areas. In Figure 1,

[11] This is based on real per capita household consumption across all expenditure categories and excludes consumption of food items produced through subsistence farming.
[12] The distance to the next available mobile money agent is measured from the centroid of the village.

enumeration areas marked with a circle show villages where a mobile money agent operates in the village. The maps reveal how markedly the mobile agent distribution expanded over the course of two years and that this expansion took place across the entire country. In the maps of Figure 2, we show villages where a mobile money agent operates within a 10 km radius from the village centroid, showcasing the rapid expansion and improved access of mobile money agents in the proximity to villages between 2010 and 2012.

The reported leading reason, reported in Table 2, for mobile money use in both survey waves was sending and receiving money, accounting for roughly 80 per cent of the responses. This is consistent with the low frequent use of mobile money. More than half of users reported using the service only occasionally or for emergency. Over the two waves, there is tendency for a more frequent use of the service, as the occasional use goes down from 62 per cent to 55 per cent and weekly and daily use increases from 6 to 10 and 2 to 5 per cent, respectively. 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. Mobile money is also used for a variety of other transaction types and services, including buying airtime (8 per cent over the two waves), paying daily expenses (3 per cent) and receiving payment for sales. A small and stable fraction of 3 per cent of households reported using the service for savings.[13]

4 Empirical Strategy

In this paper, we are primarily interested in the effect of mobile money 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 the

[13] This is a striking feature, as storing cash in mobile money accounts does not pay interest. In the absence of a bank account, storing cash using a mobile money account nevertheless protects from accidental loss or theft.

very fine partitioning of rainfall data available to us across vast geographic space and over time.[14] We then interact the 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 mean provides a credible source of variation for unanticipated economic shocks to the household and are – given the large dependence of households on smallholding agricultural practices in Tanzania – the most important source of shocks these households face to their income.[15]

By using this variation, we investigate what role mobile money adoption plays in coping with the consequences of negative (or positive) transitory shocks. We estimate the following econometric model:

$$Y_{ht} = \alpha_h + \delta_t + \boldsymbol{\beta_1}(\mathrm{MM_{ht}}) + \boldsymbol{\beta_2}(\mathrm{Rainshock_{ht-1}}) + \boldsymbol{\tau}(\mathrm{MM_{ht}} * \mathrm{Rainshock_{ht-1}}) + X'_{ht}\boldsymbol{\beta}_3 + Z'_{ht}\boldsymbol{\beta_4} + \varepsilon_{ht} \tag{1}$$

where Y_{ht} represents the set of outcome variables at the household and individual level. $\boldsymbol{\beta_1}$ represents the impact of household mobile money usage, while the coefficient $\boldsymbol{\beta_2}$ represents the direct effect of rainfall deviation on the outcome variables. $\mathrm{MM_{ht}}$ 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. Comparing the coefficient estimates for $\boldsymbol{\tau}$ relative to $\boldsymbol{\beta_2}$ will provide us with the overall effect that mobile money access has on the set of outcome variables in response to rainfall shocks. α_h and δ_t are household/individual and year fixed effects. To control for time-varying household and individual characteristics, and to increase the precision of our estimates, we are able to include individual (X_{ht}) and household level controls (Z_{ht}). ε_{ht} denotes an error

[14] In the appendix we discuss in detail the origin of the weather data used to create the rainfall shock measures and details on the way the World Bank created those measures.
[15] In a similar framework for another East African country – Uganda – Björkman-Nyqvist (2013) demonstrated the importance of rainfall patterns as a determinant of household economic resources, including income.

term, which is clustered at the community/household level for household/individual level estimations, respectively.

Because the adoption of mobile money in households is potentially endogenous,[16] we make use of the rapid expansion of the mobile money agent network between the two LSMS-ISA waves and use an IV-DiD strategy similar to the setting in Duflo (2001), Waldinger (2010) and Jack and Suri (2014).[17] From our data, we have two candidates for instruments, *agent availability*, a dummy variable that denotes whether a mobile money agent provides services in the village, and *agent proximity*, which gives a measure to the closest agent from the village centroid.[18] The choice of instruments closely follows Jack and Suri (2014). 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, which are deviations in rainfall from the historic mean. Because equation (1) includes an interaction term ($\mathrm{MM_{ht}} * \mathrm{Rainshock_{ht-1}}$), we interact the two instruments for mobile money adoption with rainfall.

The first stage of the estimation is specified as follows.

$$\mathrm{MM_{ht}} = \boldsymbol{\varphi_1}(\mathrm{Agent_c}) + \boldsymbol{\varphi_2}(\mathrm{Agent\_dist_c}) + \xi_{ht} \quad (2)$$

$$\mathrm{MM_{ht}} * \mathrm{Rainshock_{ht-1}} = \boldsymbol{\varphi_1}(\mathrm{Agent_c} * \mathrm{Rainshock_{ht-1}}) + \boldsymbol{\varphi_2}(\mathrm{Agent\_dist_c} * \mathrm{Rainshock_{ht-1}}) + \varsigma_{ht} \quad (3)$$

[16] For instance, using remittance as an outcome variable in the econometrics specification from equation (1) above could lead to biased results. Mobile money use may be determined by the likelihood (or frequency) of remittance received by the households, leading to a simultaneous bias in coefficient estimates.
[17] To complement this identification strategy, we use a reduced form DiD methodology to measure the impact of shock and the role of mobile money. For mobile money adoption, we directly exploit the variation in the presence of mobile money agents across communities over a two-year period to measure the proximity of the agents to households.
[18] We have available both distance to the next mobile money agent and cost to the next agent, and we experiment with both measures. We find that our main results are very similar when using either variable to instrument for mobile money use (Tables 4 and A7).

where $\mathbf{Agent_c}$ represents an indicator variable for mobile money agent availability while $\mathbf{Agent\_dist_c}$ represents the distance (in kilometres) to the nearest agent. Identification for the instrumented DID strategy relies on the exclusion restriction to hold, namely that agent availability and proximity over time affect poverty (and other outcomes) only through the use of mobile money. The identification strategy relies on the assumption that the outcomes between mobile money user households subjected to rainfall shocks would maintain the same trajectory in the absence of mobile money services, in addition to the assumption that deviations in rainfall are exogenous. While one cannot directly test for the common trend assumption, there is a number of checks we perform. First, we show that household characteristics are balanced across treatment status. Although this is not required for the identification assumptions to hold and would be captured by the household fixed effects, if there were to be a substantial imbalance in characteristics of households that change treatment status, this may raise concerns about the introduction of mobile money agents being systematically different across households. In Table 3 we report the means of the household covariates for households by treatment status, i.e. for treatment households – households for which we observe a change in access to mobile money agents from 2010 to 2012 – and for control households – households without a change in the access to mobile money agent access – and the normalized difference between the two.[19] The normalized differences between treatment and control households are very small and none exceed one quarter. Next, we want to rule out that mobile money agents are placed in response to rainfall shocks. To test for this, we regress a number of variables measuring the mobile money agent distribution on contemporaneous rainfall shock measures for 2010 and 2012. Table A1 reports the coefficients

[19] For the balancing test, we restrict our sample to the observations used for the main results of Table 4. To account for the different group sizes (719 households in the treatment group and 1,084 households in the control group), we report the difference in means scaled by the square root of the sum of the variances, as a scale-free measure of the difference in distributions. Imbens and Wooldridge (2009) suggest as a rule of thumb that the normalized difference should not exceed one quarter.

for separate regressions for each measure and year. We find that the coefficients are generally small and not significant and there is no systematic pattern in the sign across the different measures, which lends further credibility to the validity of the identification strategy. We repeat the exercise using long-term variability of rainfall as an outcome variable. By doing this, we can test whether mobile money agents are more likely placed in villages that observe higher variability in rainfall. We present the results in Table A2. Again, we find no significant effects or systematic pattern with the different coefficients. Lastly, it may be interesting to look at the spatial distribution of rainfall shocks over the two periods. In Figure 3 we plot the deviation in rainfall from the long-term average for 2010 and 2012. Areas in red shades are subject to negative rainfall shocks, such as these areas obtain less rain over the growing season than their long-term average, while areas in green receive more rainfall, we superimpose the enumeration areas (depicted as black points). The maps reveal three important features: First, for each period, we have coverage of households in red and green areas, suggesting that we use variation in rainfall across villages in each period. Second, over time, we observe all four distinct cases: households being subjected to droughts in 2010 (red areas in the map on the left), but not in 2012 (green or yellow areas on the map to the right), households being subjected to droughts in 2012 (red areas in the map to the right), but not in 2010 (green or yellow areas on the map to the left), households being subjected to droughts over both periods (red areas in both maps), and households being subjected to average or more than average rainfall in both periods (yellow and green areas in both maps). Third, any of the four pairings appear in a number of different geographical areas and are not limited to specific regions so that they cover different ethnic and religious groups, soil, topography and agricultural practices and crops. The idiosyncratic variation in rainfall across Tanzania and over the two periods, provides an ideal setting of using rainfall shocks for our analysis.

We estimate equation (2) using two-stage least squares (2SLS). In equations (2) and (3), we use one continuous instrument (distance to agent) and one binary instrument (availability of agent). While the use of a continuous instrument for a binary endogenous variable may yield consistent estimates in our 2SLS estimates, there is some ambiguity about consistency in the context of binary endogenous variables and outcomes (Wooldridge 2010). To avoid any ambiguity, we use a transformation employed in Björkman-Nyqvist (2013) and Blumenstock *et al.* (2016) and use the smoothed values of the mobile money indicator variable over the distance to the nearest agent in our specifications to address this concern. For consistency, we use the same approach for the interaction term between mobile money and rainfall shocks.[20]

4.1 First stage estimates

Table A3 reports the estimates of the first stage regression of our IV-DiD model and diagnostic tests. These first stage outcomes for mobile money and the interaction with rainfall shock refer to equations (2) and (3) above. Estimates for the agent availability indicator and distance to the nearest agent are reported in Panel A.[21] Column (1) reports the coefficients for the specification without household level controls and column (2) includes household controls. We find that mobile money adoption at the household level is significantly related to the availability of mobile money agents within the same communities. The availability of mobile money agents increases the likelihood of mobile money adoption by 8.2 percentage points. For the distance to the next available mobile money agent, we find, as expected, a negative effect on mobile money adoption. We depict this relationship in Figure A1, where we can see a relative constant drop of mobile money adoption with distance to the next available mobile money agent. This

[20] Regression using only smoothened mobile money presents similar pattern for all outcomes. Results are available from the authors upon request.

[21] To deal with zero values of distance to mobile money agents and costs to agents in the log transformation of the variables, we replace zero values with very small distance and monetary values (1 m distance and 1 Tanzanian shilling).

graphical illustration reemphasizes a pattern of relationship between mobile money usage and proximity.[22] We find similar sized coefficients for the interaction term estimates reported in Panel B. All coefficients are significant at the 1 per cent level. We do not find that the inclusion of controls makes any difference to the first stage estimates.

We also report diagnostic tests of the first stage estimates. Focusing on the regressions with controls, we find an *F*-statistics of 678.95 for mobile money usage and an *F*-statistics of 19214.71 for the model including the interaction of mobile money adoption with rainfall. The associated *F*-statistics for the excluded instruments are 2790.67 and 6518.24, respectively, for mobile money usage and the interaction term, respectively. The first stage estimates also pass standard underidentification tests because the results show that the first stage instruments sufficiently identify the impact of the household mobile money usage on poverty and other welfare outcomes. As for the weak identification tests across endogenous variables, results show that both mobile money and interacted mobile money specifications demonstrate resilience for the purpose of identification.[23]

5 Results

5.1 Main results: Household poverty and consumption smoothing

We present the results for the impact of mobile money and household shocks on household poverty in Table 4.[24] In detail, this table contains the coefficients from equation (1) where we

[22] A similar negative trend is demonstrated for the existing relationship between household mobile money usage and natural logarithm of the associated cost to the nearest mobile money agent.

[23] We adopt the Angrist-Pischke (AP) first stage *F*-statistics test for weak identification of each endogenous regressor. Further results from the classic first stage diagnostic tests, such as the Kleibergen-Paap rk LM statistic (for underidentification and weak identification tests) and Kleibergen-Paap rk LM statistic (for underidentification test), supports the robustness of the first stage results.

[24] We focus on absolute poverty, as defined by real per capita expenditure of less than US$1.25. We created a dummy variable that takes a value of 1 for households with real per capita expenditure of more than US$1.25 and 0 otherwise, and we estimate the coefficients in Table 4 using a linear probability model. Probit and logit fixed effects models yield biased estimates resulting from the incidental parameter problem (Greene 2003). We can obtain consistent slope estimate using conditional fixed effects in the logit model, yielding similar results

use rainfall deviations from the historic mean as exogenous measure for household shocks, and instrument mobile money adoption for both, the separate inclusion of mobile money adoption and in the interaction term with shocks.

As a first observation from Table 4, we find that the coefficient for the direct effect of mobile money on poverty is negative, but not significant at conventional levels of significance. Next, we find a positive and significant effect of rainfall shocks on the propensity for household poverty as expected. A one standard deviation negative rainfall shock (indicating a drought) raises the propensity for poverty by around 4.7 percentage points, which is a 15 per cent increase given the baseline. This result is in line with findings elsewhere in the literature on the negative consequences of rainfall shocks and droughts on household poverty (Carter *et al.* 2007; Harttgen *et al.* 2016). This demonstrates the vulnerability of rural households in Tanzania to rainfall shocks. We are interested in the interaction term between mobile money adoption in the household and the rainfall shock. The coefficient on the interaction is negative and statistically significant at the 5 per cent level. A one standard deviation negative rainfall shock interacted with the mobile money indicator leads to a 14 percentage point decrease in the probability of sliding below the poverty line, indicating that households that have adopted mobile money can effectively shield themselves from the negative impact of the rainfall shocks.[25]

In column (2), we include a large set of household level covariates. Their inclusion does not change the coefficient on the rainfall shock or on the interaction term in any meaningful way, lending additional credibility to the identification strategy. Remarkably, the coefficient

(qualitatively and statistically) as the corresponding linear probability model (results available from the authors upon request). However, the magnitudes require cautious comparison in the absence of substantial knowledge of the distribution of fixed effects (Wooldridge 2010). In addition, conditional fixed effects for logit models do not converge when including year fixed effects in our regressions. This is a fundamental problem that is associated with maximum likelihood estimators of coefficients in non-linear models, as elaborated in Greene (2004).

[25] Using a more extreme poverty indicator, for example using a definition based on US$1.00, reveals very similar results compared to the standard US$1.25 definition (results are available from the authors upon request).

exceeds the coefficient of the rainfall shock significantly, so that households affected by rainfall shocks that have adopted mobile money more than make up for the direct impact of the rainfall shock. 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.

Jack and Suri (2014) show how lower transaction costs facilitate risk sharing across larger distances. They also show that mobile money leads to more diverse senders. A broader set of remittance senders may also explain this 'overcompensating' effect. These effects make sense in a framework of informal insurance, where the shock is difficult to quantify (for senders and/or receivers of remittances) and/or where the full magnitude of the shock materializes only with a lag.[26] It is possibly access to a broad base of senders of remittances facilitated through mobile money that makes households with access to mobile money effectively better off after shocks, by receiving remittances that exceed the original income shock.[27] Jack and Suri (2014) find a similar overcompensation effect in some specifications, but not generally across different outcomes and different shocks.[28] Riley (2018), who studies the distributional effects of mobile money across adopters and non-adopters in response to shocks in Tanzania, also finds evidence for overcompensation on log per capita consumption.

We are also interested in the capacity of mobile money to help smooth consumption more generally during periods of idiosyncratic shocks. We therefore estimate equation (1) using total per capita household expenditure as outcome to test for consumption smoothing. The results

[26] This is likely true for both: a lag between the rainfall shock during the growing season and the realization of the harvest and the lag between realization of the harvest and the moment when the food stock from previous harvests start to run low.

[27] This is possibly also the case because senders unlikely co-ordinate when sending remittances. In the next section, we investigate the effect of mobile money adoption on remittances.

[28] They find, for example, evidence of overcompensation not only for the effect of illness shocks on total consumption, but also for all shocks and the full sample. This difference is likely due to the different nature of the shock Jack and Suri (2014) use, a self-reported indicator for shocks. In our context, we use variation in rainfall from the long-term mean rainfall, rather than a shock indicator.

are presented in Table A4. While we find quantitatively similar results and very similar patterns compared to the outcomes for poverty in Table 4, none of the coefficients are significant at conventional levels. These estimates may nevertheless obscure the capacity to smooth consumption for the poorest of households. For this purpose, we estimate the effect of shocks and mobile money on consumption by wealth quintiles using information on household asset holdings across the two survey periods.[29] The results are presented in Table 5.

Strikingly, we find a very similar pattern for the direct impact of the idiosyncratic rainfall shock and the interaction with mobile money compared to the poverty outcome for the poorest of the households. For the first quintile in the wealth distribution of households, we find a substantial negative impact on per capita expenditure from rainfall shocks on per capita expenditure. A one standard deviation reduction in rainfall leads to a decrease in per capita expenditure of 9 percentage points. The interaction term of rainfall shocks and mobile money reveals that households with access to the financial innovation are able to smooth consumption during shocks and more than compensate for the negative effect of rainfall shocks by even increasing their per capita consumption, similar to the results for poverty outcomes in Table 4. The interaction term is about three times larger and opposite-signed compared to the effect of rainfall on per capita expenditure. We do not find similar effects for any other quintile, where estimates for the impact of rainfall shocks on household expenditure and the interaction term are generally much closer to zero and not statistically significant at conventional levels of significance. These effects, taken together with the results for poverty presented in Table 4, point to the importance of financial inclusion for the most vulnerable households of households in Tanzania.

[29] This has the advantage that we can focus on a more stable measure for household wealth over time, as expenditure maybe directly impacted by the idiosyncratic shocks and the mobile money adoption.

5.2 Underlying mechanism

There is substantial literature that shows how access to financial services, for example borrowing facilities, and precautionary savings can help households to cushion the effects of income shocks and aid consumption smoothing (recent examples include Mohanan 2013, Islam and Maitra 2012). Jack and Suri (2014) have shown how mobile money can play a similar role through facilitating remittance payments in informal insurance networks. We therefore investigate the effect of mobile money on remittances as a first underlying channel for consumption smoothing.

The summary statistics reported in Table 2 shows that the vast majority of transactions with mobile money accounts relate to receiving and sending money; savings for emergency only relate to 3 per cent of transactions. Investigating remittances as a mechanism, we are interested in understanding the effect on the likelihood and the amount of remittance received by households in the past 12 months.[30] We estimate the effect of mobile money on these outcomes and instrument for mobile money by distance to the next mobile money agent; the results are presented in Table 6. We find that households with mobile money account are more than 30 per cent more likely to receive remittances over the 12-month period before the survey. The remittance amount households with mobile money accounts receive is also significantly larger; adding the set of control variables does not change the estimates for remittance indicator (column (2)) or the remittance amount (column (4)) significantly.

[30] We use the natural logarithm of the amount of remittance received in Tanzanian shillings when estimating the amount of remittance received in the past 12 months. To deal with zero values before taking logs, we convert zero values to small positive values. Because of a change in the questionnaire regarding remittances after the first wave (which focused on international remittances), we focus on the information on remittances available in the 2012 wave. Because of this, we cannot estimate the effect the mobile money on remittances in the same framework as the poverty outcomes in Table 4. Instead, we focus on the effect of mobile money on remittances using the 2012 cross-section, where we instrument for mobile money in the household with distance to the next mobile money agent.

We further investigate how these results differ by access to more formal financial services and repeat the estimates for the remittance indicator and remittances amount (with the full set of controls) by information on the availability of a bank account in the household. Panel A of Table 7 reports the results for unbanked households and Panel B for households with access to a bank account. While the effect of mobile money for households without bank account on remittances is very similar to the general findings, there is no effect on remittances for households that do have access to a bank account, pointing to mobile money and traditional bank accounts being substitutes for receiving remittances.[31] This suggests that the technology allows previously unbanked households to tap into remittance receipts. This is consistent with the findings in Jack and Suri (2014) and Riley (2018), who show that mobile money helps households to smooth shocks due to increased remittances from family and friends outside the village.[32]

In addition to remittances, welfare transfers have the potential to smooth shocks. In the absence of a national poverty reduction program during our period of interest, support for households affected by negative shocks comes mainly in the form of aid provided by NGOs operating in Tanzania.[33] We estimate the effect of shocks and mobile money on welfare receipts and present the findings in Table 8. We find that mobile money adoption leads to significant increase in welfare receipts during periods of negative rainfall shocks. This effect

[31] We also investigate the role alternative financial services, such as participation in savings societies (SACCO) for consumption smoothing by repeating the specification for Table 6 and splitting the sample by SACCO membership. We do not find a differential effect of mobile money by SACCO membership (results are available from the authors upon request).

[32] More recently, the integration of international money transfers and mobile money accounts facilitates the receipt of international remittances in rural areas.

[33] Tanzania is today home to one of the largest conditional cash transfer programs in Africa, the Productive Social Safety Net (PSSN). The decision to roll out the PSSN nationwide was taken in 2013, only after the collection of the LSMS waves used in this study; hence, the PSSN is not relevant as a source of welfare transfer in the setting of this paper (World Bank 2016b). Because of the significance and size of the PSSN, we do not use the 2015 wave of the LSMS for our analysis.

on welfare payments complements the receipt of remittance facilitated by mobile money and may add to the overcompensating effect of mobile money in response to rainfall shocks.

Lastly, we investigate the timing of the realization of shocks. Most of the households in the Tanzanian LSMS-ISA rely on agricultural smallholder 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 to May and September to October, respectively. This leads to planting for the long rainy season taking place from December (of the previous year) to February to be harvested from May to July each year. Coinciding with the harvest period for the long rainy season is the planting for the short rainy season, which occurs between June and July, with harvesting between November and December.[34] 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 deteriorate 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 separate 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.[35] Each survey round takes place between October of the starting year and ends in November of the subsequent year. We split the sample in households observed up to six month after the shock and households observed 6–12 months after the shock.

[34] The majority of agricultural activities take place within the long rainy season in Tanzania. This is consistent with the nature of rain-fed agricultural practices in most sub-Sahara African communities due to low adoption of irrigation technology for the purpose of crop cultivation.
[35] There is no evidence that the date of collection of the survey was done in such a way that the timing would be correlated with different rainfall realizations. Indeed, the date of the survey collection for each enumeration area was decided long before the survey took place.

In Table A5, in columns (1) and (2), we report the estimates for households nearer to the harvest season, i.e. first six months from October (harvest year) to March (in the following year); in columns (3) and (4), we report the estimates for surveys collected in the second half of the survey year, from April to September. The estimates for shocks and the interaction with mobile money adoption 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 months sample, suggesting that the differences in the estimates of the interaction terms are not driven by a lag in the receipt of remittances. These results are consistent with shocks initially being absorbed by the consumption of the remaining food stock.

5.3 Robustness checks

We perform a number of robustness checks regarding the main estimates in Table 4. First, we use an alternative instrument for the main estimates of Table 4: cost of travel to the nearest agent. This variable is clearly correlated with distance to the nearest agent, but not perfectly because of differences in mode of travel and in cost of using different forms of transport. Table A6 presents the result of this specification. The coefficients for rainfall shocks and the interaction term with mobile money are very similar to the estimates in Table 4, and they are very stable when adding the full set of controls.[36] While the coefficients are all slightly more pronounced, the ratio between the rainfall shock and the interaction term are basically identical compared to the results in Table 4.

Next, we investigate the potential for spatial correlation of the shock variable, the

[36] A formal test shows that none of the differences for the four sets of coefficients is statistically significantly different from each other.

deviation from long-term rainfall average. Recently, concerns regarding potential spurious correlation of weather events have been raised in the literature in settings using rainfall as an exogenous source of variation (Lind 2015). We do not rely on a cross-section, but rather use the panel nature of our data, thereby allowing us to hold constant fixed household characteristics while exploiting rainfall shocks that vary over two periods and limiting the potential for a spurious correlation. In addition, the very fine geographic information in the household and plot level data allows us to use additional variation of rainfall within geographically spread-out villages and agricultural plots of households of the same enumeration area in addition to the cross-village variation in rainfall, alleviating further some of these concerns.

Nevertheless, we would like to address remaining concerns with spatial correlation of rainfall and household expenditure patterns for proximate households. To address these concerns, we follow Fujiwara *et al.* (2016) in including three location-specific time trends when estimating equation (1), and we successively include linear, quadratic and cubic community-specific time trends. The results are presented in Table A7. All specifications include the full set of controls and household fixed-effects. For ease of comparison, we include the benchmark results from Table 4 in column (1). In column (2), we include a community-specific linear trend; in columns (3) and (4), we include quadratic and cubic trends, respectively. The estimates are almost identical to the benchmark estimates in column (1), alleviating remaining concerns related to spatial correlation of rainfall shocks.

As a last check, we also provide estimates from a simple DiD specification for the main estimates, where we use variation in mobile money agents operating in the village over the two survey waves. We provide the results in Table A8. The DiD estimates confirm the role of mobile money as a buffer against sliding into poverty during periods of household shocks. The overcompensating effect from the interaction term is not as accentuated as in the main specification of Table 4.

5.4 Human capital investments

In section 5.1, we establish how mobile money can shield households from sliding into poverty by smoothing consumption for the poorest households. In addition to transient poverty, we are particularly interested in expenditure components and behaviors impacted by shocks that are related to long-term outcomes, such as investments in health and education, and household labor supply, as these may impact the ability of households to escape chronic poverty trap associated with intergenerational transmission of poverty. To investigate how a technology like mobile money may help households to maintain human capital specific investments, we explore the detailed individual and household level data available in the LSMS-ISA on expenditure components related to health and education, and household decisions impacted by economic shocks related to human capital investments.

5.4.1 Preventative health expenditure and health investments

We start the investigation by looking at health expenditure. 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 compel households to often rely on private health expenditure. To avoid that expenditure on health is impacted by rainfall shocks through illness,[37] we focus on preventative health expenditure.[38]

Table 9 reports the estimates on preventative health expenditure. In column (1), we report the results for an indicator variable (for any preventative health expenditure over the past four

[37] In the case of droughts, this could, for example, work through an increase in intestinal infections; for excess rainfall through an increase in vector borne disease, such as malaria.
[38] In the LSMS household questionnaire, this is recorded as the amount the household spent in the past four weeks for medical care not related to an illness, including preventative healthcare, pre-natal visits and check-ups.

weeks in the household); in column (2), we report estimates for log real expenditure, both including the full set of controls. First, we show how rainfall shocks impact the ability of households to maintain preventative health expenditure; both the indicator variable and real expenditure are negatively impacted by droughts.[39] Next, we find that the effects of rainfall shocks are counteracted by mobile money adoption. Both interaction terms exceed the effect of rainfall shocks sevenfold, a much more pronounced effect than for general per capita expenditure in Table 5, highlighting the importance to separate expenditure components for the analysis.

To gain a better understanding of the nature of preventative health expenditure, we study the purchase of bed nets of households mainly to prevent malaria. Bed nets are an effective measure against the disease, particularly for children (Dupas 2014). Households in Tanzania largely rely on purchasing bed nets privately, rather than through public distribution. Dupas (2009) reports cost as the most important factor in households' decisions to invest in treated bed nets in Kenya and 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.

In Table 10, we present the estimates of equation (1) for bed net use. Column (1) presents the findings for whether a household member slept under a bed net the night prior to the survey; column (2) reports the estimates for whether an individual specifically slept under a treated bed net. In column (1), we can see that negative rainfall shocks reduce bed net use in the households, but the coefficient is not significant; whereas the interaction term with mobile

[39] During periods of income shocks, affected poor households may first reduce their expenditure on non-essential items, such as preventative healthcare. This may nevertheless impact the households in the long-term if reductions in preventative health expenditure undermine investments in health. This is particularly important as a large fraction of preventative health expenditure is related to pre-natal health spending, including spending on facility delivery, possibly affecting the health of the next generation (Prata *et al.* 2004).

money indicates that these households are more likely to sleep under bed nets, thereby confirming previous results on 'overcompensation' found for poverty and household expenditure of poor households. In column (2), we find that a one standard deviation negative rainfall shock decreases the use of insecticide treated bed nets by about 8 percentage points, a 15.1 per cent decrease in treated bed nets compared to mean usage, while the interaction term shows an increase of 17 percentage points for mobile money users, which is a 33 per cent increase compared to the mean. This is consistent with transitory shocks having a stronger impact on the recurring treatment of bed nets than on general bed net use. These results are important for the understanding of the negative consequences of income shocks for households and the potential for mobile money to overcome these, given the long-term consequences of Malaria for individuals and household.

To complement our results on preventive health spending, we also look at health outcomes directly by investigating health visits and hospitalizations of household members. There is an extensive literature on the negative effect of droughts on health outcomes, in particular for children. Droughts can impact health directly, for example, through its effect on nutrition, quality of drinking water, vector-borne diseases and air-borne particles (Adhvaryu *et al.* 2017, Maccini and Yang2009, Rocha and Soares 2015, Stanke *et al.* 2013,), and for this purpose we created indicator variables on health visits of household members, reporting the likelihood of attending healthcare facilities in the four weeks prior to the survey, and a hospitalizations indicator reporting hospitalizations 12 months prior to the survey.[40]

Unfortunately, we do not have direct measures of health and ill-health, and we rely on indirect health measures, such as health visits and hospitalizations. Our measures possibly not

[40] Because of the relative low frequency of hospitalizations, the LSMS records these for 12-month intervals prior to the survey date. Therefore, the variable may capture periods prior to the rainfall shock used for this exercise leading to measurement error of the hospitalization variable.

only reflect health realizations but also the willingness to pay for these, which may be impacted by rainfall shocks and associated financial burden of the households affected. Healthcare in Tanzania is funded through a mixed financing mechanism, including cost sharing policies, potentially resulting in substantial financial burden for healthcare utilization for poor households.[41] In addition, droughts, for example, have been shown to negatively affect health outcomes, increasing the demand for health visits and hospitalizations through an illness channel.[42] Rainfall shocks also impact household income and, conditional on underlying demand for health visits and hospitalizations, could reduce the ability to pay for treatment. Mobile money has a similar double counteracting effect working in different directions, and the overall effect is determined by the relative strength of the effects. Table 11 reports the results from these estimates.

We find that a negative rainfall shock increases the probability of a household member attending a clinic or having a home visit during four weeks prior to the survey date, confirming the negative impact of droughts on health. The interaction term of mobile money and rainfall shows the compensating effect of financial inclusion on health outcomes.

Column (1) of Table 11 shows that mobile money increases the likelihood of visitation to a health practitioner or the hospitalization of individuals. The shock coefficient indicates that negative shock increases the likelihood to pay a visit to health practitioner, while the interaction coefficient reduces the probability of visiting healthcare facility after shock. Results in column (2) for hospitalization for any sickness presents negligible estimates and is statistically significant only at the interaction level. However, although estimates from the estimation of

[41] Until the beginning of the 1990s, healthcare was provided for free. As a consequence of rising healthcare cost, cost sharing was introduced from 1990, starting with fees for hospital admissions. A generous system of fee waivers and exemptions aims to maintain access for the poorest households.

[42] An extensive literature documents the health consequences of rainfall shocks particularly for children (Maccini and Yang 2009,

malaria hospitalization indicator in column (3) show a similar pattern, they are not statistically significant. The hospitalization results in columns (2) and (3) re-emphasizes the preventive expenditure results of (treated) bed net use from Table 10. Columns (1) and (2) of Table 11 present evidence in support of the important role that mobile money plays in sustainable health outcomes through preventive health expenditure (Tables 9 and 10).

5.4.2 Human capital investments in children

The investment in human capital through education of offspring is an important channel to limit the intergenerational transmission of poverty. We investigate the impact of rainfall shocks on educational investments and the role of mobile money to mitigate the potential impact of such shocks. The LSMS-ISA household questionnaire provides information on educational expenditure of households, school enrolment, school absenteeism and number of daily hours dedicated to homework/study for each child present in the household. Some of these measures may not accurately capture the effect of rainfall shocks and mitigating factors on human capital investments by households. For example, apart from school supplies and school uniforms – which often are bought at the beginning of the school year – attending public schools is free.[43] Similarly, school enrolment is completed at the beginning of the school year in January and, therefore, should not be affected by events during the calendar year (and for that reason should not be impacted by rainfall shocks during the long rainy season). We report the estimates for these schooling outcomes in columns (1) and (2) of Table 12. We do not find a statistically significant effect of either rainfall or the interaction of rainfall with mobile money in the household for school expenditure and school enrolment as expected.

[43] Tuition fees in primary schools were abolished in 2002; in the mostly rural context of this paper, children rarely attend school beyond primary education.

Next, we look at variables that capture investments in education just prior to the survey date. We use information on school absenteeism in the 14 days prior to the survey (column (3)), the number of hours school age children spend on homework or studying over the week prior to the survey and an indicator variable on children participating in household chores such as fetching water or collecting firewood the day before the survey.[44] We would expect school absenteeism to be affected by household shocks if children rather engage in economic activities in agricultural production or need to help more in the household. We find a significant increase in school absenteeism for children in households affected by droughts. For a standard deviation lower rainfall, we find an increase in the probability of missing school at least one day over the two weeks prior to the survey by 8.2 percentage points, corresponding to roughly a 30 per cent increase compared to the mean absenteeism rate. Children in households with mobile money are shielded from the negative impact of droughts and we confirm the overcompensating effects of mobile money similar to household expenditure. We also find a significant negative effect of negative rainfall shocks on the time children spend on homework and studying and the counteracting effect of mobile money on the time children prepare for school.

Finally, we look at the effect of rainfall shocks and mobile money on children engaging in (unpaid) household chores. We find a small and not significant effect of rainfall shocks on the probability that children helped with household chores the day prior to the survey, but a large and significant effect on the interaction term. Children in households that have adopted mobile money are much less likely to engage in household chores when subjected to shocks, consistent with the findings on homework and school absenteeism. We find that mobile money reduces engagement in household chores in response to rainfall shocks by about 18 percentage points, a 50 per cent reduction compared to the mean.

[44] We restrict the sample to children between ages 5 and 18 for all members of the same household.

We further estimate the effects for educational inputs separately for boys and girls. The results are reported in Table A9 in the annex. We document substantial heterogeneous effects across gender. While we find similar effects for rainfall shocks on school absenteeism, the effect of the interaction term is much more pronounced for girls, than for boys. For homework and household chores, we find that the effects in Table 12 are largely driven by the effects for girls. While we find no significant, and much smaller effects of rainfall shocks for boys, we find pronounced and significant effects for girls, both for number of hours of home study and the indicator for household chores. Mobile money adoption plays a crucial role for girls to protect their human capital investments during periods of household shocks and indeed overcompensates for the negative effect of rainfall shocks. Access to mobile money may therefore be particularly important when there are girls in the household, who are generally more exposed to these activities, and our results are consistent with findings in the literature on the relationship between remittances and child labor and the role of gender differences (Acosta 2011).[45]

5.4.3 Labor market participation and child labor

Rural households in Tanzania predominantly engage in agricultural activities, as reported in Table 1, which reveals that roughly 10 per cent of household members are employed in the private or public sector, and roughly two-thirds of household members work in agriculture. Droughts may induce households to diversify their labor participation outside of agriculture and affect the labor market participation outside of agriculture in a bid to help mitigate the impact of negative shocks (Morduch 1995, Kochar 1999). Kochar (1999) shows that members of rural households diversify hours of labor to compensate for the shortfall in agricultural

[45] The uneven burden of household chores across gender has been well documented and is particularly pronounced in Sub-Saharan Africa (UNICEF 2016).

income by earnings from other wage activities outside the agricultural sector in rural India.[46] Kijima *et al.* (2006) show that the labor diversification strategy tends to be more effective for the poorest household, but hinges strongly on the availability of non-agricultural labor opportunities in the rural area.

In Table 13, we report the estimates of rainfall shocks and its interaction with mobile money on non-agricultural wage labor in the seven days prior to the survey.[47] Columns (1) and (2) of Table 13 present regression estimates for participation in non-agricultural wage labor for adults and children, respectively. Focusing on adult labor supply first, estimates in column (1) show that a one standard deviation decrease in rainfall increases the likelihood of non-agricultural labor participation of adults by 1.5 percentage points, which is a 17 per cent increase compared to the mean (9 per cent of mean off-farm labor participation in the sample of adults) and is significant at the 10 per cent level. This indicates that households in Tanzania react to rainfall shocks by diversifying their income through an increase of non-agricultural labor activities. The interaction term indicates that this effect is counteracted by an 8.3 percentage point decrease in the likelihood of non-agricultural labor participation.

The results indicate that household that have adopted mobile money are less likely to diversify their income base. Possibly these households do not need to do so to smooth consumption, but are insured against shocks through remittances facilitated by mobile money. Possibly, this may enable these households to concentrate on agricultural production, maintaining productivity of the farmland in periods after droughts, for example through water

[46] In another context, other studies demonstrate how non-farm employment can help rural dwellers oust sliding into poverty during agricultural shocks in Africa and Asia (Kijima *et al.* 2006, Otsuka and Yamano 2006).
[47] We focus the estimates using wage labor in the most recent seven days. Whilst wage labor in the previous 12 months is available in the data, the effect of shocks cannot be attributed using data stretching over such long periods.

resource management, which is particularly relevant for rain-fed agricultural practices (Rockström *et al.* 2010).

In column (2), we report the results for labor supply of children.[48] Rainfall shocks have an even more pronounced impact on children's labor participation. While we find a similar magnitude of effect for the interaction term with mobile money, the coefficient is not significant at conventional levels, possibly because of the relatively small number of observations. Overall, the findings are consistent with the effects estimated for educational inputs, where mobile money helped to shield children from the negative impact of rainfall shocks.

5.5 Self-reported well-being

Lastly, we investigate whether the above results on the mediating effect of mobile money during shocks also translate into improvements of subjective wellbeing. The LSMS-ISA survey is unique in collecting information on subjective wellbeing for adults in the household. We focus on self-reported satisfaction with: (1) life overall, (2) the financial situation of the household, (3) employment, (4) housing and living conditions and (5) health status.[49] Table 14 reports the estimates on diverse self-reported adult satisfaction.

We do not find significant effects of rainfall shocks or the interaction with mobile money on overall life satisfaction, although the signs on either coefficient are as expected. Consistent with the findings on poverty and household consumption, we find a significant effect of rainfall shocks on satisfaction with the financial position of the household. A one

[48] While one may be interested in investigating child labor more broadly, by including participation in agricultural production, this information is not available in LSMS. We rely on the participation of children in non-formal labor for this purpose.
[49] Individuals were asked to evaluate their satisfaction in these areas by indicating their satisfaction level, ranging from 'very unsatisfied' to 'very satisfied'. We created relative satisfaction indicators by assigning a value of 1 (satisfied) if their chosen satisfaction level is above the average level and 0 (unsatisfied) for a level below the average.

standard deviation negative rainfall shock leads to a 4 percentage point decrease in the satisfaction indicator for household finance, which is a 13 per cent reduction given the mean satisfaction value. As for the poverty and consumption results, we find an inverse effect for the interaction term of rainfall and mobile money, which overcompensates for the negative effect of rainfall. We do not find significant effects for the other satisfaction indicators for employment, housing and health; the coefficients are generally much smaller and not significant at conventional levels.

6 Final remarks

Financial exclusion remains an important issue in many developing countries. The rural poor are particularly affected by financial exclusion because of the reliance on smallholder rain-fed agricultural practices and the 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 consequences of a financial innovation – mobile money – on the welfare of 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 mobile money during periods of shocks on consumption smoothing, poverty and human capital investments. We combine information on rainfall variation on the household level with an instrumental variable strategy to address the potential endogeneity of mobile money adoption of households in an IV-DiD framework.

We find that mobile money enables the poorest households affected by rainfall shocks to smooth their consumption and prevents these households from sliding into transient poverty. While a one standard deviation reduction in rainfall from the long-term mean increases the risk for households sliding into poverty by 15 per cent compared to the baseline, this negative effect is counteracted for households with mobile money accounts. We find that the interaction term of shocks with mobile money more than neutralizes the negative effect of the shock; indeed, the coefficient on the interaction exceeds the coefficient of rainfall by about a factor of three. This is the first paper to demonstrate systematically how facilitating access to remittances through simple technological advancements makes households better off in response to shocks to their livelihoods. We provide suggestive evidence that increases in remittances received, as well as welfare payments facilitated through mobile money accounts, drive the effects of mobile money on consumption smoothing and poverty reduction. Alternatively, a shift in the timing of remittances in response to shocks may explain the observed overcompensation effect. The available data in the LSMS survey does not allow to investigate the underlying pathways for this overcompensation effect in more detail, and additional research making use of information on the network structure of mobile money users and more high frequency information on remittance transactions may provide more detailed insights on the origin of the overcompensation effect.

We further provide evidence for the potential long-run effects of financial inclusion – in the form of access to mobile money – on 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 – as expected – 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 firewood in response to shocks.

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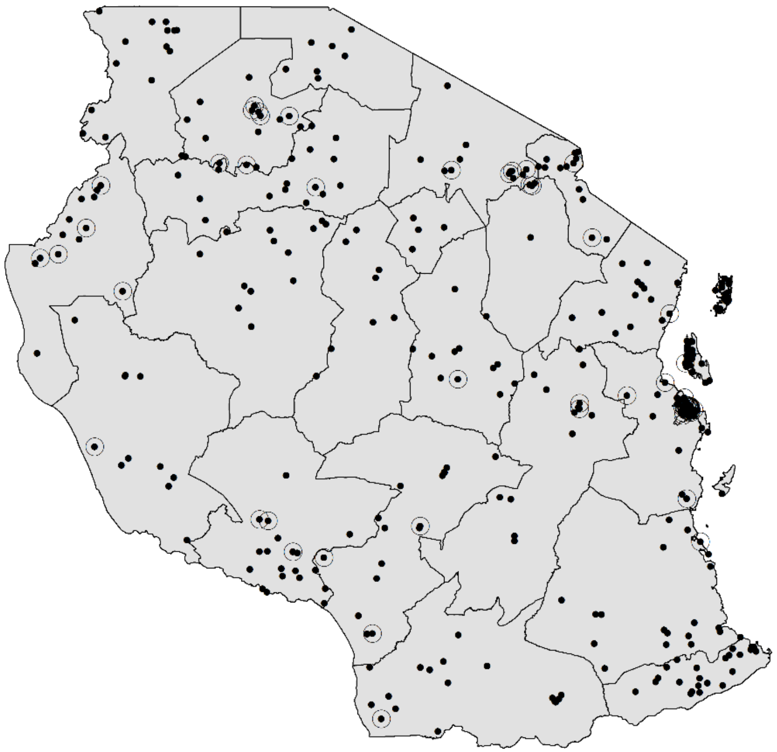
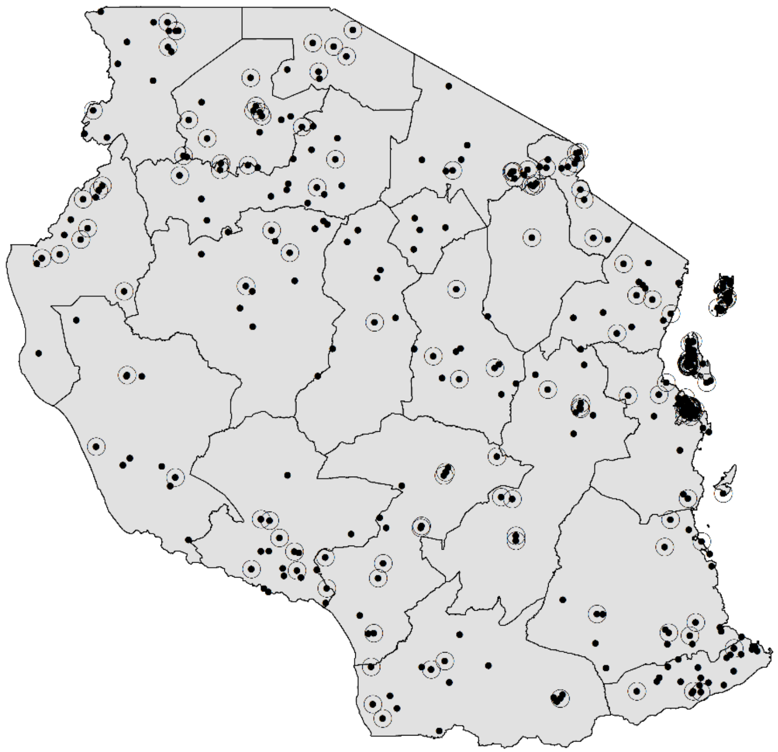
Figures and Tables

Figure 1: Rollout of mobile money agents across LSMS-ISA enumeration areas (agents operating in village)

2010

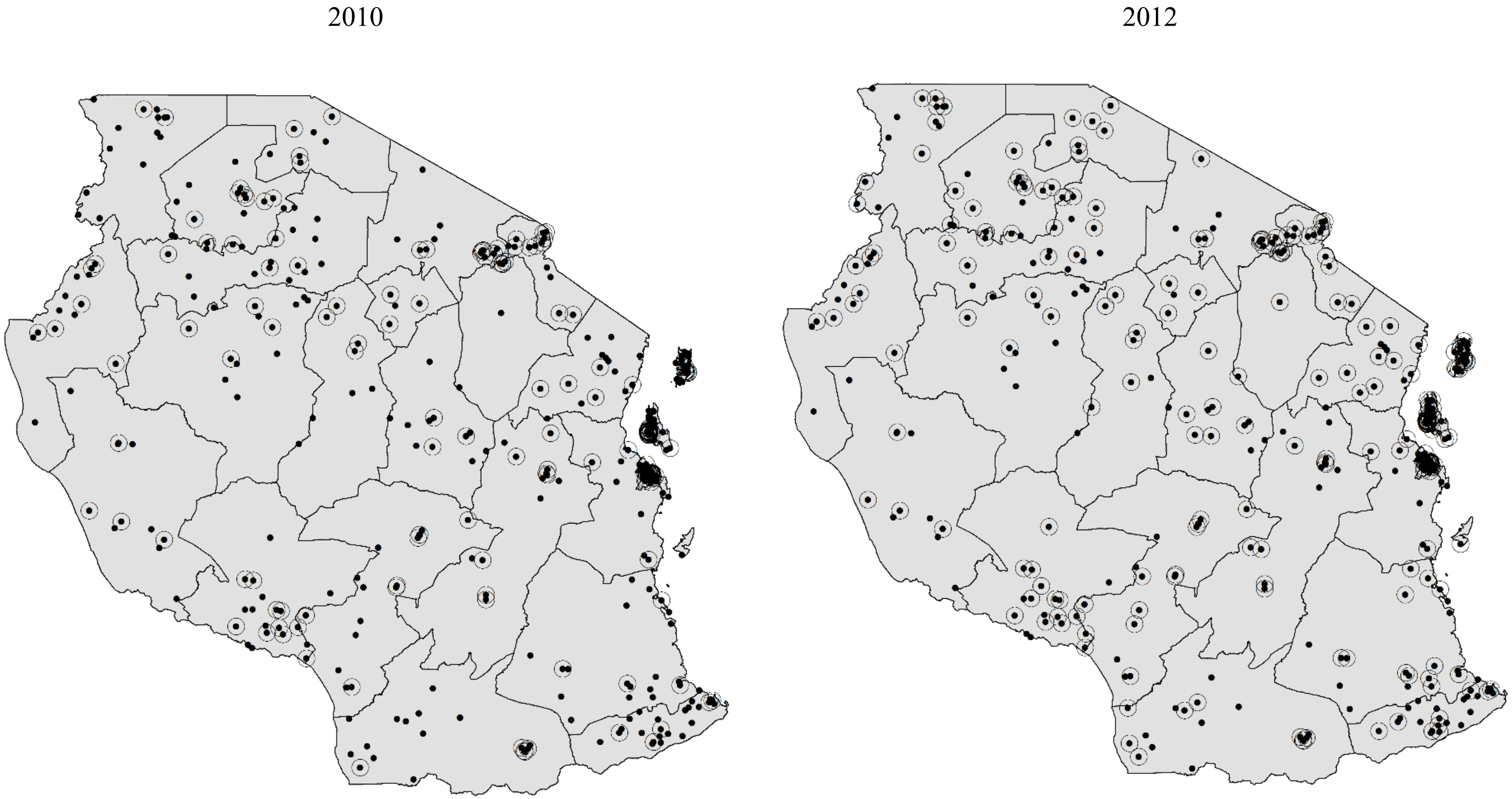


2012



Notes: The maps depict the 26 regions of Tanzania with points representing the enumeration areas from the LSMS-ISA survey. Circles represent enumeration areas with a mobile money agent in operation in the village. The left panel is for the 2010 survey year, the right panel for the 2012 survey year.

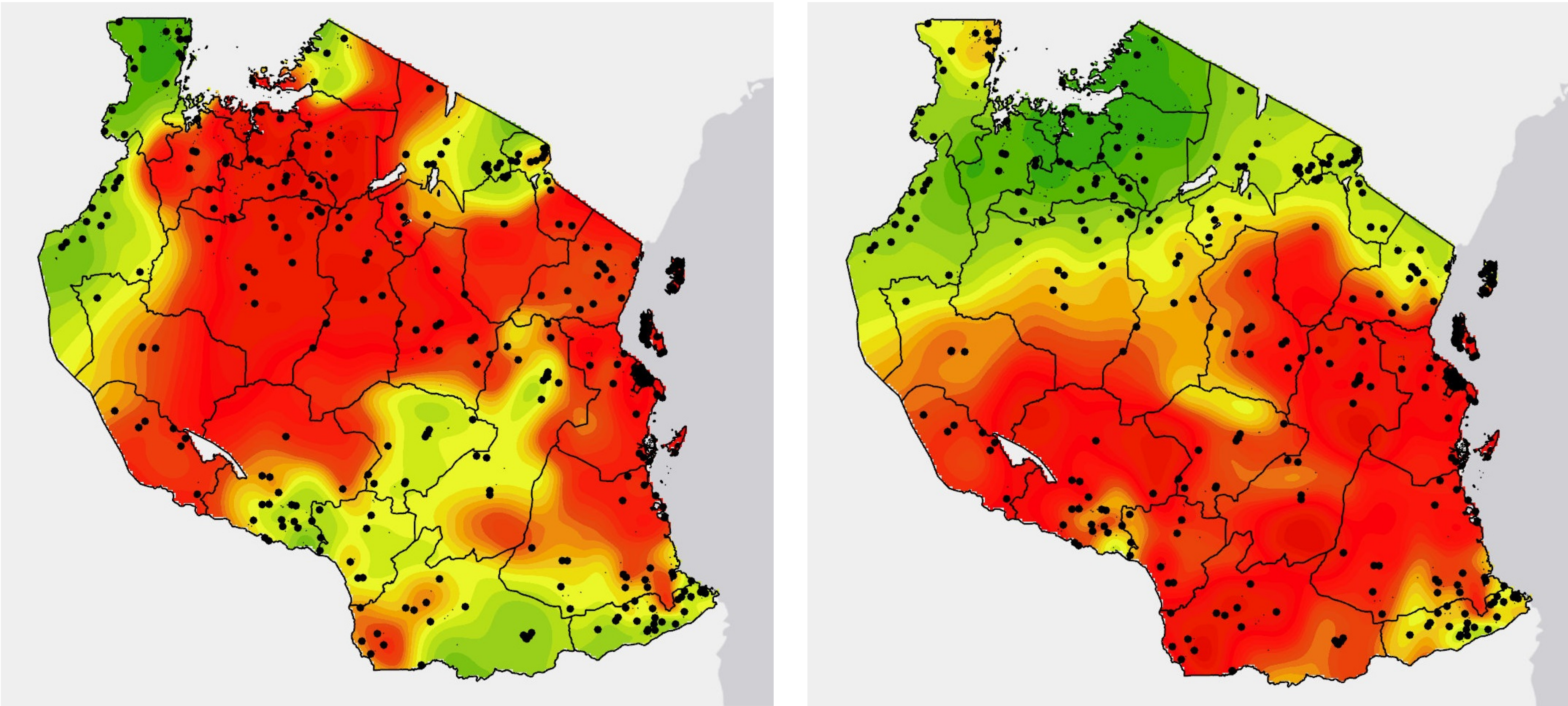
Figure 2: Rollout of mobile money agents across LSMS-ISA enumeration areas (agents operating in 10km radius)



Notes: The maps depict the 26 regions of Tanzania with points representing the enumeration areas from the LSMS-ISA survey. Circles represent enumeration areas with a mobile money agent in operation within a 10km radius around the village. The left panel is for the 2010 survey year, the right panel for the 2012 survey year

Figure 3: Deviation from Long-term Average Rainfall in the 2010 and 2012 survey years

2010 2012



Notes: The maps report the rainfall for the 2010 and 2012 main growing seasons as deviation from long-term average rainfall. Darker red shades represent less than average rainfall; green shades represent more than average rainfall. The 26 regions of Tanzania and Enumeration Areas in the LSMS-ISA used in this paper (black points) superimposed.The left panel is for the 2010 survey year, the right panel for the 2012 survey years.

Table 1: Selected Household and Individual Summary Statistics

Variable	Mean	SD
Household characteristics		
Household Size	5.203	2.704
No. of Children	2.753	2.132
Wealth Measure	73.658	58.576
Absolute poverty (< $1.25)	0.708	0.455
Female Head	0.252	0.434
Rural	0.716	0.451
Mobile Phone Ownership	0.628	0.483
SACCO Membership	0.219	0.414
Bank Account Use	0.162	0.368
Household Head		
Married	0.832	0.374
Formal schooling completed	0.760	0.427
Occupational Categories		
Agriculture	0.629	0.483
Self-Employed	0.162	0.368
Private sector	0.092	0.290
Unemployed	0.063	0.242
Public sector	0.055	0.227
Individual characteristics		
Age	26.142	19.755
Male	0.488	0.500
Married	0.829	0.377
Formal School	0.728	0.445
Occupational Categories		
Agriculture	0.628	0.483
Unemployed	0.134	0.340
Self-Employed	0.135	0.341
Private sector	0.064	0.244
Public sector	0.040	0.195

Notes: Number of observations: 2,338 households, 9,807 individuals. *Female Head, Rural, Mobile Phone Use, SACCO* (Savings and Credit Co-operative Organization) *Membership, Bank Account Use, Male, Married and Formal schooling completed* are all indicator variables. *Married, Formal schooling completed and Occupation Categories* of individuals are restricted to adult individuals. Adulthood is defined as ages 25 or older (8,256 observations – 4,128 adults).

Table 2: Mobile Money Usage and Agent Distribution Between 2010 and 2012

	2010		2012	
	Mean	SD	Mean	SD
Panel A: Distribution of Agents				
Agent Availability (Indicator)	0.166	0.372	0.519	0.500
Distance to Nearest Agent (km)	23.998	37.193	6.162	11.241
Cost to Nearest Agent ('000 TSh)	1.850	3.037	0.667	1.316
Agent Availability (Indicators)				
2km Radius	0.272	0.445	0.598	0.490
5km Radius	0.394	0.489	0.675	0.468
10km Radius	0.521	0.500	0.816	0.387
15km Radius	0.571	0.495	0.873	0.333
20km Radius	0.616	0.487	0.899	0.301
Panel B: Frequency of use				
Occasional (Emergency)	0.624	0.485	0.554	0.497
Half-Yearly	0.016	0.126	0.023	0.149
Quarterly	0.088	0.284	0.049	0.217
Monthly	0.144	0.352	0.182	0.386
Fortnightly	0.052	0.222	0.051	0.219
Weekly	0.060	0.238	0.096	0.295
Daily	0.016	0.126	0.045	0.208
Panel C: Use by transaction type				
Buy Airtime	0.085	0.279	0.082	0.275
Send Airtime	0.004	0.064	0.004	0.063
Send Money	0.375	0.485	0.310	0.463
Receive Money	0.435	0.497	0.497	0.500
Receive Payment for Sales	0.008	0.090	0.020	0.141
Save for Emergency	0.032	0.177	0.031	0.173
Daily Expense	0.060	0.239	0.047	0.212
Large Purchase	–	–	0.008	0.090

Notes: Number of observations: 2,338 households. Panel A of Table 2 presents information on the distribution of mobile money agents across communities over the two waves. *Agent availability* is an indicator variable for the presence of an agent within the enumeration area. *Cost to nearest agent* is calculated based on travel cost given in the LSMS-ISA survey. *Agent availability* is also presented for different radiuses around the village center. Panel B presents the frequency of use of mobile money services as a fraction of adopter HHs by year. Panel C reports the most frequent uses of mobile money services. This shows the overall most-important uses of mobile money services by users as a fraction of all adopter HHs by year. In the 2010 LSMS-ISA survey wave 'Large Purchase' was not listed as possible answer.

Table 3: Balancing tests for HH characteristics by treatment status

Variable	Control Households		Treatment Households		
	Mean	SD	Mean	SD	Normalized Difference
Household Size	5.3180	2.7300	5.0479	2.6840	0.0705
No. of Children	2.8256	2.1571	2.6426	2.1006	0.0608
Mean HH age	26.1030	13.8643	27.5776	14.7667	-0.0728
Wealth Measure	73.3078	58.6164	73.5380	49.6918	-0.0030
Female HH Head	0.2625	0.4401	0.2470	0.4314	0.0252
Rural	0.7214	0.4484	0.7084	0.4547	0.0205
Mobile Phone Ownership	0.6389	0.4804	0.6433	0.4792	-0.0065
No. of Phones	1.1414	1.1949	1.1755	1.2743	-0.0195
Voucher Use	0.6384	0.4806	0.6401	0.4801	-0.0024
Voucher Value	5.8317	4.4688	5.8525	4.4723	-0.0033
SACCO Membership	0.2252	0.4178	0.2017	0.4014	0.0407
Bank Account Use	0.1448	0.3520	0.1966	0.3975	-0.0975
Membership in Loan Group	0.0749	0.2633	0.0842	0.2778	-0.0243
Positive Balance in Loan Group	0.0567	0.2314	0.0587	0.2352	-0.0060
Married	0.8294	0.3763	0.8137	0.3895	0.0290
Formal School	0.7341	0.4419	0.7798	0.4145	-0.0754
Occupational Categories					
Agriculture	0.6545	0.4756	0.5801	0.4937	0.1084
Unemployed	0.0574	0.2327	0.0795	0.2706	-0.0618
Self employed	0.1600	0.3667	0.1737	0.3790	-0.0260
Private	0.0813	0.2733	0.0885	0.2841	-0.0182
Public	0.0468	0.2113	0.0782	0.2686	-0.0919

Notes: Number of observations: treatment households: 719, control households: 1,084. Treatment households refers to households that see a change in access to MM agents from 2010 to 2012, while control households refer to households without change in access to mobile money agents. The normalized difference is calculated as $norm - diff = \frac{\overline{X_0} - \overline{X_1}}{\sqrt{s_{x,0}^2 + s_{x,1}^2}}$, where s^2 denotes the sample variance of x_i.

Table 4: IV-DiD Estimates for Poverty Classification

	Dependent Variable: Absolute Poverty	
	(1)	(2)
Mobile money (MM)	-0.048	-0.051
	(0.077)	(0.075)
Rainfall shock (RS)	0.047**	0.044***
	(0.019)	(0.017)
Interaction (MM x RS)	-0.139**	-0.133**
	(0.063)	(0.059)
R-squared	0.115	0.180
Household fixed-effects	Yes	Yes
Year fixed-effects	Yes	Yes
Controls	No	Yes

Notes: The entries of the table report the IV-DiD coefficients from a linear probability model of mobile money, rainfall shock and their interaction term on a poverty indicator. The poverty index takes a value of 1 for daily real per-capita expenditure above US$1.25; and 0 otherwise. Mobile money denotes the adoption of at least one mobile money account at the household level. The variable *Mobile money* is instrumented by the distance to the nearest mobile money agent. *Rainfall shock* denotes the deviation from long-term average rainfall, such that a negative value denotes less than average rainfall. Each column reports the estimates from a separate regression for 3,606 observations (1,803 households). Mobile money adoption in the interaction term is instrumented by agent availability in the village and distance to nearest agent. Both regressions include household and year fixed-effects. Columns (1) and (2) represent estimations without controls and with controls, respectively. The controls used in the estimation of column (2) include an array of household level covariates (gender of household head, education and occupation categories of household head, household size, average household age, rural dummy, household asset value, indicator variables for household membership of a SACCO group; household membership of any other credit and savings society; household access to loan facilities and bank account ownership). Controls also include number of mobile phones in the household, value of vouchers used by the household in the past month. Each regression is clustered at the enumeration area 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: IV-DiD Estimates for Per-capita Expenditure by Household Wealth Quintiles

	Dependent Variable: Per-capita Expenditure (ln)				
	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Variables	(1)	(2)	(3)	(4)	(5)
Mobile money	-0.017	0.046	-0.138	0.253	-0.570**
	(0.249)	(0.228)	(0.195)	(0.193)	(0.273)
Rainfall shock	0.091**	-0.036	-0.009	-0.023	0.017
	(0.045)	(0.042)	(0.039)	(0.029)	(0.047)
Interaction (MM x RS)	-0.289*	0.117	0.044	0.112	-0.065
	(0.171)	(0.148)	(0.130)	(0.121)	(0.156)
Observations	722	722	720	724	718
Household fixed-effects	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.156	0.159	0.165	0.130	0.126

Notes: The entries present the coefficients from an IV-DiD linear regression model of mobile money, rainfall shock and their interaction term on the log amount per capita expenditure by wealth quintiles, where we instrument for mobile money (including in the interaction term). We use asset-holding details from the 2012 wave. The 2012 survey questionnaire reports two measures for each household asset, the purchase price (when it was bought) and the market price during the time of the interview. We construct current non-agricultural wealth across households by weighing each household asset using the average price between the two asset prices. We then proceed to sum up the worth of each asset holding to measure non-agricultural asset index of the household and produce quintiles of household asset wealth. See notes in Table 4 for the specification and the set of controls used in the estimation. Robust standard errors (clustered at the enumeration area level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table 6: IV Estimates of Mobile Money on Remittances

Variables	Dependent Variable: Remittances			
	Remittance Indicator		ln Remittance Amount	
	(1)	(2)	(3)	(4)
Mobile money	0.346***	0.301***	3.956***	2.916***
	(0.099)	(0.099)	(1.108)	(1.097)
R-squared	0.012	0.129	0.013	0.119
Controls	No	Yes	No	Yes

Notes: This table reports estimates of mobile money adoption in the households on remittances received by households, where we instrument for mobile money use in the household by distance to the next mobile money agent. Columns (1) and (2) B present estimates for a remittance indicator, where the variable takes a value of 1 if the household has received remittances over the past 12 months. Columns (3) and (4) present the coefficients for the natural logarithm of the total cash remittances received (in Tanzanian Shillings) over the same period, respectively. The estimates come from are cross-section regressions restricted to the 2012 wave since questions on remittances are only available in the 2012 wave. See notes in Table 4 for the set of controls used. Number of household observations: 1,819. Robust standard errors (clustered at the enumeration area level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Table 7: IV Estimates of Mobile Money on Remittances, by Access to Bank Accounts

Variables	Dependent Variable: Remittances			
	Panel A: No bank account		Panel B: Bank account available	
	Indicator	ln Remittance Amount	Indicator	ln Remittance Amount
	(1)	(2)	(3)	(4)
Mobile money	0.344***	3.286***	-0.072	-0.554
	(0.099)	(1.089)	(0.335)	(3.704)
R-squared	0.144	0.132	0.132	0.122
Observations	1,504	1,504	315	315
Controls	Yes	Yes	Yes	Yes

Notes: This table reports estimates of mobile money adoption in the households on remittances received by households, where we instrument for mobile money use in the household by distance to the next mobile money agent. Columns (1) and (2) present estimates for outcomes and specifications as in columns (2) and (4) of Table 6 for households without bank account, and columns (3) and (4) for households with access to a bank account. See notes in Tables 4 and 6 for details. Robust standard errors (clustered at the enumeration area level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Table 8: IV-DiD Estimates for Welfare Receipts

Variables	Dependent Variable: ln amount	
	(1)	(2)
Mobile money	0.062	0.036
	(0.169)	(0.162)
Rainfall shock	0.032	0.027
	(0.020)	(0.018)
Interaction (MM x RS)	-0.337*	-0.358**
	(0.177)	(0.166)
R-squared	0.009	0.049
Household fixed-effects	Yes	Yes
Year fixed-effects	Yes	Yes
Controls	No	Yes

Notes: The entries of the table report the IV-DiD coefficients from a linear regression model of mobile money, rainfall shock and their interaction term on the log amount of welfare receipts from government and NGOs over the past 12 months, where we instrument for mobile money (including in the interaction term). The question in the LSMS-ISA questionnaire is 'How much money did your household receive from government or NGOs in the last 12 months?' See notes in Table 4 for the details on the specification and the set of controls used. Robust standard errors (clustered at the enumeration area level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Table 9: IV-DiD Estimates for Health Expenditure

Variables	Dependent Variables: Preventative Health Expenditure	
	Indicator	ln Health Expenditure
	(1)	(2)
Mobile money	-0.004	-0.051
	(0.007)	(0.108)
Rainfall shock	0.003**	0.045**
	(0.001)	(0.019)
Interaction (MM x RS)	-0.022***	-0.328**
	(0.009)	(0.128)
R-squared	0.010	0.009
Individual fixed-effects	Yes	Yes
Year fixed-effects	Yes	Yes
Controls	Yes	Yes

Notes: The entries of the table report the IV-DiD coefficients from a linear probability model of mobile money, rainfall shock and their interaction term on a health expenditure. The entries in column (1) present the coefficients from a linear probability model on an indicator variable for preventative health expenditure; entries in column (2) are from a linear regression on log health preventative health expenditure. The preventive health expenditure indicator in column (1) takes a value of 1 if an individual spends a positive amount on preventative health in the four weeks prior to the survey; and 0 otherwise. Preventative health expenditure in column (2) is calculated as the natural logarithm of real preventative health expenditure (in thousand Tanzanian shillings). The entries in both columns come from separate regressions for 15,536 observations (7,768 individuals). Both regressions include the same set of controls as in Table 4. Robust standard errors (clustered at the enumeration area level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Table 10: IV-DiD Estimates for Bed Net Use

Variables	Dependent Variables: Indicator for use of Bed Net (1)	Treated Bed Net (2)
Mobile money	-0.039	-0.097
	(0.106)	(0.133)
Rainfall shock	0.030	0.077***
	(0.018)	(0.021)
Interaction (MM x RS)	-0.114*	-0.168**
	(0.062)	(0.079)
R-squared	0.015	0.024
Individual fixed-effects	Yes	Yes
Year fixed-effects	Yes	Yes
Controls	Yes	Yes

Notes: The entries of the table report the IV-DiD coefficients from a linear probability model of mobile money, rainfall shock and their interaction term on the individual's use of bed nets, where we instrument for mobile money (including in the interaction term). The bed net use indicator takes a value of 1 if an individual uses mosquito bed nets during sleep; and 0 otherwise. The estimates in column (1) refer to untreated bed nets, and the estimates in column (2) to insecticide-treated bed nets. Treatment of bed nets with an insecticide improves significantly the protection offered by bed nets against mosquitos that are responsible for transmitting malaria. The most commonly used insecticides require regular retreatment. The entries in both columns come from separate regressions 13,658 observations (6,829 individuals). Both regressions include the same set of controls as in Table 4. In addition to household level controls, age, and gender of individuals are used as additional individual controls in all regressions. Robust standard errors (clustered at the enumeration area level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Table 11: IV-DiD Estimates for Health Visits and Hospitalization

Variables	Dependent Variables: Indicators		
	Health visit	Hospitalization	Hospitalization for Malaria
	(1)	(2)	(3)
Mobile money	0.038	0.026	0.020
	(0.053)	(0.035)	(0.026)
Rainfall shock	-0.027***	-0.009	-0.010
	(0.010)	(0.008)	(0.007)
Interaction (MM x RS)	0.069*	0.044*	0.032
	(0.036)	(0.026)	(0.022)
R-squared	0.006	0.005	0.006
Individual fixed-effects	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: The entries of the table report the IV-DiD coefficients from a linear probability model of mobile money, rainfall shock and their interaction term on the indicators for health visits, hospitalization and hospitalization for malaria, where we instrument for mobile money (including in the interaction term). *Health visit* denotes visits to a clinic or home visit by a medical doctor over a period of 4 weeks prior to the survey, while *Hospitalization* denotes admission to hospital over a 12-month period prior to the survey; *Hospitalization for Malaria* refers to hospital admissions exclusively to treat Malaria. All indictors take a value of 1 in case of a health visit, or hospital admission, and 0 otherwise. The entries in both columns come from separate regressions for 15,536 observations (7,768 individuals). All regressions include the same set of controls as in Table 4. In addition to household level controls, age, and gender of individuals are used as additional individual controls in all regressions. Robust standard errors (clustered at the enumeration area level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Table 12: IV-DiD Estimates for Educational Inputs

Variables	Dependent Variables: School Expenditure (ln) (1)	School Enrolment (indicator) (2)	School Absenteeism (indicator) (3)	Homework (Hours/Day) (4)	Household Chores (indicator) (5)
Mobile money	-0.110	0.068	-0.533***	-0.640***	0.150
	(0.270)	(0.073)	(0.173)	(0.218)	(0.110)
Rainfall shock	0.003	0.006	-0.082***	0.075***	-0.026
	(0.043)	(0.013)	(0.031)	(0.029)	(0.019)
Interaction (MM x RS)	-0.087	0.003	0.301***	-0.356**	0.178**
	(0.180)	(0.047)	(0.108)	(0.140)	(0.074)
R-squared	0.027	0.104	0.032	0.102	0.023
Observations	4,346	4,346	3,468	3,466	5,360
Individual fixed-effects	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes: The entries of the table report the IV-DiD coefficients from a linear probability model of mobile money, rainfall shock and their interaction term on a number of educational inputs, where we instrument for mobile money (including in the interaction term). The outcome variable in column (1) is log real per capita school expenditure; the outcome variable in column (2) is in indicator for (current) school enrolment, that takes a value of 1 if the child is currently enrolled at school, and 0 otherwise; the outcome variable in column (3) is an indicator variable that takes a value of 1, if the child has missed school in the two weeks prior to the survey, and zero otherwise; the outcome variable in column (4) is the number of hours that a child spends per day on homework and studying over the week prior to the survey; the outcome variable in column (5) is an indicator and takes a value of 1, if a child participates in household chores (collecting firewood or other fuel material and fetching water), and 0 otherwise, and refers to the day before the survey. All regressions include the same set of controls as in Table 4. In addition to household level controls, age, and gender of individuals are used as additional individual controls in all regressions. Robust standard errors (clustered at the enumeration area level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Table 13: IV-DiD Estimates for Labor Supply (outside agriculture)

Variables	Dependent Variable : Labor Supply Indicator	
	Adults	Children
	(1)	(2)
Mobile money	-0.005	-0.142
	(0.059)	(0.122)
Rainfall shock	-0.015*	-0.033*
	(0.009)	(0.019)
Interaction (MM x RS)	0.083**	0.095
	(0.037)	(0.068)
R-squared	0.152	0.024
Observations	6,442	1,152
Individual fixed-effects	Yes	Yes
Year fixed-effects	Yes	Yes
Controls	Yes	Yes

Notes: The entries of the table report the IV-DiD coefficients from a linear probability model of mobile money, rainfall shock and their interaction term on weekly wage labor supply of individuals. The labor supply indicator takes a value of 1 if an individual engaged in an activity rewarding a wage in the last seven days; and 0 otherwise. Column 1 reports estimates for individuals over 18 years of age, while column 2 reports estimates for children aged 5 – 18. See notes in Table 4 for the details on the specification and set of controls used in the estimation. In addition to household level controls, age, and gender of individuals are used as additional individual controls in all regressions. Robust standard errors (clustered at the enumeration area level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Table 14: IV-DiD Estimates for Measures of Subjective Well-Being

Variables	Dependent Variables: Indicators for Satisfaction with				
	Life	Finance	Employment	Housing	Health
	(1)	(2)	(3)	(4)	(5)
Mobile money	-0.074	-0.058	0.048	0.026	-0.180**
	(0.116)	(0.108)	(0.120)	(0.108)	(0.088)
Rainfall shock	0.008	0.040**	-0.003	0.020	-0.009
	(0.020)	(0.017)	(0.023)	(0.018)	(0.014)
Interaction (MM x RS)	-0.061	-0.170***	0.016	-0.100	0.032
	(0.071)	(0.063)	(0.082)	(0.069)	(0.053)
R-squared	0.013	0.012	0.014	0.007	0.010
Observations	5,962	5,972	4,754	5,962	5,968
Individual fixed-effects	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes: The entries of the table report the IV-DiD coefficients from a linear probability model of mobile money, rainfall shock and their interaction term on measures of subjective wellbeing, where we instrument for mobile money (including in the interaction term). For each category we create indicators that take a value of 1 if an individual reports being satisfied overall with the various component; and 0 otherwise. All regressions include the same set of controls as in Table 4. In addition to household level controls, age, and gender of individuals are used as additional individual controls in all regressions. Robust standard errors (clustered at the enumeration area level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Figure A1: The Relationship between Mobile Money and Distance to Agent

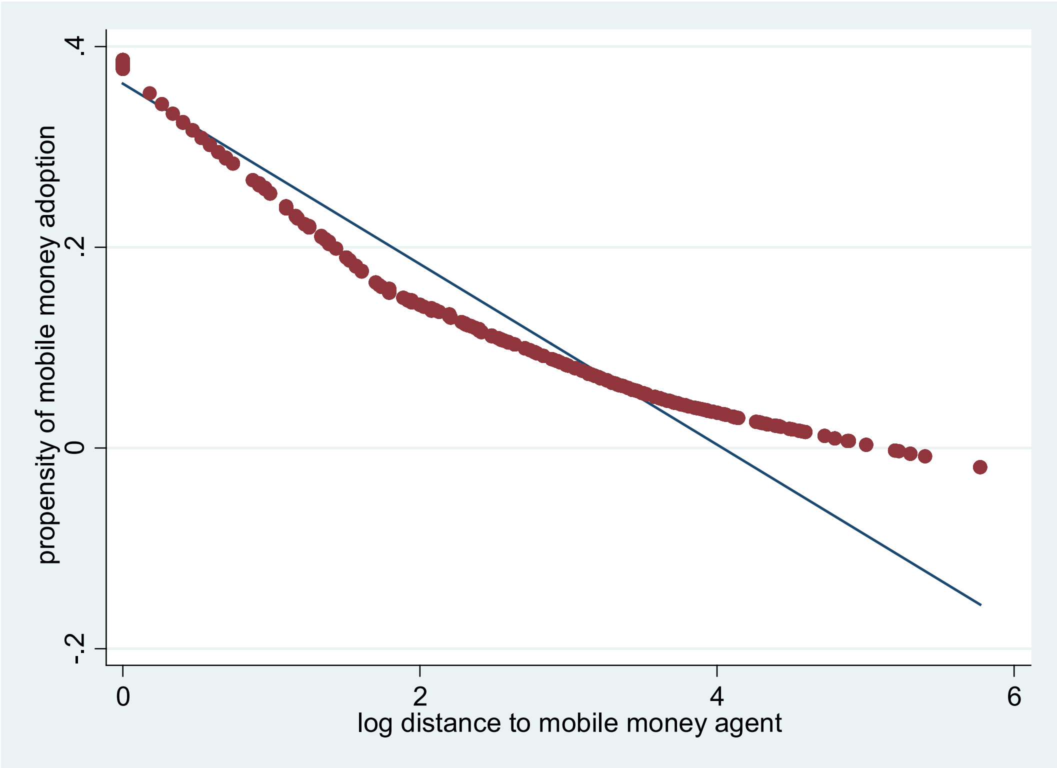


Table A1: Contemporaneous rainfall shocks and mobile money agent distribution for the 2010 and 2012 survey years

Panel A	Dependent variable: Rainfall shock in year 2010				
2010 agent distribution	(1)	(2)	(3)	(4)	(5)
MM agent (2km Radius)	-0.027				
	(0.145)				
MM agent (5km Radius)		-0.066			
		(0.137)			
MM agent (10km Radius)			0.009		
			(0.131)		
MM agent (15km Radius)				-0.069	
				(0.129)	
MM agent (20km Radius)					-0.073
					(0.127)
Constant	0.008	0.017	-0.011	0.081	0.089
	(0.242)	(0.233)	(0.253)	(0.250)	(0.270)
R-squared	0.213	0.214	0.213	0.214	0.214
Panel B	Dependent variable: Rainfall shock in year 2012				
2012 agent distribution	(1)	(2)	(3)	(4)	(5)
MM agent (2km Radius)	0.044				
	(0.117)				
MM agent (5km Radius)		0.058			
		(0.118)			
MM agent (10km Radius)			-0.024		
			(0.128)		
MM agent (15km Radius)				-0.156	
				(0.124)	
MM agent (20km Radius)					-0.204
					(0.140)
Constant	-0.163	-0.174	-0.092	0.023	0.078
	(0.807)	(0.803)	(0.810)	(0.816)	(0.822)
R-squared	0.190	0.191	0.190	0.193	0.194

Notes: Each column reports the coefficients from separate regressions of the distribution of mobile money agents on rainfall variation in the 2010 (Panel A) and 2012 (Panel B) periods. All regressions include community level controls. Robust standard errors clustered at the enumeration area are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively. Results reported for 290 enumeration areas.

Table A2: Long-term rainfall variability and mobile money agent distribution for the 2010 and 2012 survey years

Panel A	Dependent variable: long-term variability in community rainfall				
2010 agent distribution	(1)	(2)	(3)	(4)	(5)
MM agent (2km Radius)	0.020				
	(0.034)				
MM agent (5km Radius)		-0.011			
		(0.028)			
MM agent (10km Radius)			-0.040		
			(0.028)		
MM agent (15km Radius)				-0.054**	
				(0.027)	
MM agent (20km Radius)					-0.030
					(0.029)
Constant	5.281***	5.286***	5.293***	5.297***	5.291***
	(0.079)	(0.080)	(0.081)	(0.081)	(0.080)
R-squared	0.335	0.335	0.339	0.343	0.337
Panel B	Dependent variable: long-run variation in community rainfall				
2012 agent distribution	(1)	(2)	(3)	(4)	(5)
MM agent (2km Radius)	-0.025				
	(0.035)				
MM agent (5km Radius)		-0.036			
		(0.036)			
MM agent (10km Radius)			-0.019		
			(0.040)		
MM agent (15km Radius)				0.015	
				(0.045)	
MM agent (20km Radius)					0.028
					(0.053)
Constant	4.970***	4.943***	4.941***	4.887***	4.875***
	(0.088)	(0.112)	(0.095)	(0.116)	(0.117)
R-squared	0.205	0.207	0.204	0.204	0.205

Notes: Each column presents the coefficients from separate regressions of the distribution of mobile money agents in 2010 (Panel A) and 2012 (Panel B) on the long-run variability in rainfall. The long-run variability of rainfall is given by the standard deviation of rainfall over the 30 year period prior to the first survey. All regressions include community level controls. Robust standard errors clustered at the enumeration area are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Table A3: First Stage Instrumental Variable Results and Diagnostic Tests.

Variables	(1)	(2)
Panel A: Estimates Panel A: Mobile Money		
Agent availability	0.082***	0.082***
	(0.006)	(0.006)
Agent distance	-0.069***	-0.069***
	(0.002)	(0.002)
R-squared	0.987	0.987
F-stat	2374.410	678.950
F-stat (4, 291)	2744.640	2790.670
Diagnostic Tests		
Under Identification Test - Chi-Sq. (3, 291)	NA	10422 (0.000)
Weak Identification Test - F (3, 291)	NA	3434
Panel B: Mobile Money x Rainfall Shock		
Agent availability x rainfall shock	0.075***	0.075***
	(0.005)	(0.005)
Agent distance x rainfall shock	-0.073***	-0.073***
	(0.002)	(0.002)
R-squared	0.998	0.998
F-stat	76412.280	19214.710
F-stat (4, 291)	6436.640	6518.240
Diagnostic Tests		
Under Identification Test - Chi-Sq. (3, 291)	NA	25704 (0.000)
Weak Identification Test - F (3, 291)	NA	8470
Household fixed-effects	Yes	Yes
Year fixed-effects	Yes	Yes
Controls	No	Yes

Notes: The entries present the first stage estimates obtained from the main results presented in Table 4. Total number of observations for the regression is 3,606 (1,803 households). Panel A reports the first stage estimates for agent availability in the village and its distance to the village (along with the interaction with rainfall shocks), respectively. Panel B reports the diagnostic tests for the first stage estimates. The variable mobile money is instrumented by the smoothened distance to the nearest mobile money agent. Rainfall shock denotes the idiosyncratic shock as deviation from the long-term average rainfall, so that a negative value denotes a less than average rainfall. See notes in Table 4 for the precise specification and set of controls used in the estimation. Robust standard errors (clustered at the enumeration area) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Table A4: IV-DiD Estimates for Per-capita Expenditure

	Dependent Variable: Per-capita Expenditure (ln)	
Variables	(1)	(2)
Mobile money	-0.075	-0.072
	(0.130)	(0.124)
Rainfall shock	0.010	0.008
	(0.022)	(0.020)
Interaction (MM x RS)	-0.018	-0.013
	(0.075)	(0.072)
R-squared	0.007	0.099
Household fixed-effects	Yes	Yes
Year fixed-effects	Yes	Yes
Controls	No	Yes

Notes: The entries present the coefficients from a linear regression model of mobile money, rainfall shock and their interaction term on the log amount per capita expenditure, where we instrument for mobile money (including in the interaction term). See notes in Table 4 for details on the specifications and the set of controls used in the estimation. Robust standard errors (clustered at the enumeration area) are reported in parentheses.

Table A5: IV-DiD Estimates for Poverty Classification, by Time from Harvest

	Dependent Variable: Poverty Index			
	Within six months of harvest		After six months of harvest	
	(1)	(2)	(3)	(4)
Mobile money	-0.125	-0.103	0.016	-0.011
	(0.111)	(0.100)	(0.129)	(0.130)
Rainfall shock	0.028	0.020	0.061	0.060*
	(0.020)	(0.018)	(0.039)	(0.035)
Interaction (MM x RS)	-0.054	-0.052	-0.203*	-0.193*
	(0.072)	(0.067)	(0.120)	(0.112)
R-squared	0.086	0.161	0.141	0.216
Observations	1,514	1,514	1,744	1,744
Household fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Notes: Table above entries present the coefficients from a linear probability model of mobile money, rainfall shock and their interaction term on a poverty indicator (absolute poverty) by time from the main harvest, where we instrument for mobile money (including in the interaction term). Entries in columns (1) and (2) present coefficients for households surveyed in the first six months of harvest while columns (3) and (4) present the estimates for households surveyed after six months from the main harvest. See notes in Table 4 for the precise specification and set of controls used in the estimation. Robust standard errors (clustered at the enumeration area) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Table A6: IV-DiD Estimates for Poverty Classification (alternative instrument)

	Dependent Variable: Poverty Index	
Variables	(1)	(2)
Mobile money	0.027	0.024
	(0.093)	(0.091)
Rainfall shock	0.052***	0.051***
	(0.020)	(0.018)
Interaction (MM x RS)	-0.155**	-0.159**
	(0.067)	(0.064)
R-squared	0.115	0.180
Household fixed-effects	Yes	Yes
Year fixed-effects	Yes	Yes
Controls	No	Yes

Notes: Table above entries present the coefficients from a linear probability model of mobile money, rainfall shock and their interaction term on a poverty index. We use an alternative instrument for the mobile money in the interaction term, namely cost to nearest agent. See table 3 for the specification and for the controls used in each regression. Each regression is clustered at the community level. Robust standard errors (clustered at the enumeration area level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Table A8: IV-DiD Estimates for Poverty Classification, Including Community Trends

	Dependent Variable: Absolute Poverty			
Variables	(1)	(2)	(3)	(4)
Mobile money	-0.051	-0.046	-0.048	-0.050
	(0.075)	(0.074)	(0.075)	(0.075)
Rainfall shock	0.044***	0.043***	0.043***	0.043***
	(0.017)	(0.016)	(0.017)	(0.017)
Interaction (MM x RS)	-0.133**	-0.135**	-0.135**	-0.134**
	(0.059)	(0.059)	(0.059)	(0.059)
R-squared	0.180	0.181	0.180	0.180
Household fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Community varying linear trend	No	Yes	No	No
Community varying quadric trend	No	No	Yes	No
Community varying cubic trend	No	No	No	Yes

Notes: The above entries are the coefficients from a linear probability model of mobile money, rainfall shock and their interaction term on a poverty index, where we add sequentially additional community time varying trends. See Table 4 for the specification and for the controls used in each regression. Each regression is clustered at the community level. Robust standard errors (clustered at the enumeration area level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Table A9: Difference-in-Difference Estimates for Poverty Measure

	Dependent Variable: Poverty Index	
Variables	(1)	(2)
Mobile money	0.003	0.000
	(0.022)	(0.022)
Rainfall shock	0.030**	0.030**
	(0.013)	(0.012)
Interaction (MM x RS)	-0.037**	-0.042**
	(0.018)	(0.017)
Household fixed-effects	Yes	Yes
Year fixed-effects	Yes	Yes
Controls	No	Yes

Notes: The above entries are the coefficients from a linear probability model of mobile money, rainfall shock and their interaction term on a poverty index, I a difference-in-difference specification. We use variation of mobile money agents operating in the village over the two survey waves. See table 4 for the controls used in each regression. Each regression is clustered at the community level. Robust standard errors (clustered at the enumeration area level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Table A10: IV-DiD Estimates for Educational Inputs by Gender

	Dependent Variables:				
	School Expenditure (ln)	School Enrolment (indicator)	School Absenteeism (indicator)	Homework (Hours/Day)	Household Chores (indicator)
Variables	(1)	(2)	(3)	(4)	(5)
Panel A : Boys					
Mobile money	-0.172	0.047	-0.528**	-0.614**	0.050
	(0.373)	(0.108)	(0.231)	(0.311)	(0.151)
Rainfall shock	0.004	0.000	-0.086**	0.035	0.002
	(0.058)	(0.018)	(0.042)	(0.035)	(0.024)
Interaction (MM x RS)	0.057	0.023	0.218	-0.209	0.022
	(0.233)	(0.066)	(0.145)	(0.181)	(0.092)
R-squared	0.031	0.099	0.032	0.094	0.015
Observations	1,972	1,972	1,550	1,550	2,496
Panel B : Girls					
Mobile money	0.077	0.040	-0.580***	-0.422	0.343**
	(0.372)	(0.099)	(0.211)	(0.271)	(0.161)
Rainfall shock	-0.008	0.013	-0.091**	0.108***	-0.055**
	(0.060)	(0.016)	(0.036)	(0.039)	(0.028)
Interaction (MM x RS)	-0.066	-0.005	0.439***	-0.431**	0.302***
	(0.260)	(0.063)	(0.127)	(0.173)	(0.109)
R-squared	0.042	0.095	0.042	0.124	0.027
Observations	2,062	2,062	1,706	1,704	2,430
Individual fixed-effects	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes: The entries present the coefficients from a linear regression and linear probability model (for indicator outcomes) of mobile money, rainfall shock and their interaction term on a number of educational inputs by gender, where we instrument for mobile money (including in the interaction term). See notes of Table 13 for details.

Appendix

A1: 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 Center (NOAA CPC), the African Rainfall Estimation Algorithm Version 2.0. The rainfall data from Rainfall Estimate (RFE) v2.0 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.

The 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 technical information received directly from the World Bank's LSMS-ISA team, station data are used to calibrate the merged satellite surfaces. The granularity of the plot-level measure comes from the RFE modelling, as well as the method used to extract the data linking the extrapolated rainfall data at the agricultural plot level. Rainfall values are extracted at household locations using a bilinear interpolation or distance-weighted average of four nearest grid cell values.

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.[50] These data include annual and wet season precipitation measures respectively. While the household level GPS are withheld for confidentiality reasons, these are used to link rainfall estimates to the individual LSMS-ISA households. The spatial distribution of households within enumeration areas in the LSMS-ISA survey for Tanzania adds to the rainfall variation across enumeration area, adding sources of variation not normally available in similar household survey data. The intro enumeration variation of rainfall helps to address potential spatial correlation of rainfall data across broader geographical precipitation variation, such as at the district level or other geographic units of much larger size, which is commonly used in the literature.

[50] Due to the 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.

A2. 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-ISA data), which is available at the plot level.[51] We follow the literature in constructing rainfall shocks and create measures of the deviation in rainfall from the long-run mean for a household by constructing shocks in the following way:

$$\mathrm{Rainshock}_{\mathrm{ht-1}} = ln\, R_{ht-1} - ln\, \overline{R_h} \qquad (4)$$

where $\mathrm{R}_{\mathrm{ht-1}}$ indicates the yearly rainfall in household h for the preceding year's planting season and $\overline{R_h}$ represents the average historical yearly rainfall in household h. Thus, the $\mathrm{Rainshock}_{\mathrm{ht-1}}$ above is equivalent to the shock measure used for the deviation of the natural logarithm of the total rainfall in the 12 months prior to the 2010 and 2012 periods and the natural logarithm of the average yearly historical rainfall in the household h prior to the corresponding years.[52] The rainfall deviation denotes a percentage deviation from mean rainfall (Maccini and Yang 2009). We follow the recent literature when using lagged values of rainfall in equation (4) to ensure the rainfall shock realization is a measure of current economic resources of the households.[53]

[51] 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 agricultural cycle rainfall measures. Yearly rainfall is adopted due to the household's freedom of choice to either cultivate short or long rainy seasons for agricultural yields. However, it is noted from the agricultural data in Tanzanian LSMS-ISA that households partake more in the long rainy seasons' agricultural activities perhaps due to higher certainty of agricultural yields from the long rainy season between December and February as against short rainy seasons in June and July cultivation.

[52] We normalize the rainfall shock variables constructed from equation (4) for each of the two years. This approach aids the comparison of deviation from historical average over the two panel waves and helps with the interpretation of the results.

[53] A substantial number of papers in the economics literature has adopted this procedure. Recent examples include Maccini and Yang (2009), Björkman-Nyqvist (2013) and Rocha and Soares (2015).