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

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Abstract

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 use this together with idiosyncratic shocks from variation in rainfall over time and across space in a difference-in-difference framework. 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.

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The data used in this article can be obtained from the website of LSMS-ISA of the World Bank Group, http://surveys.worldbank.org/lsms/programs/integrated-surveys-agriculture-ISA/tanzania#bootstrap-panel--4

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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 nonexistent—with less than 1 percent of the population having an active mobile money account—in sub-Saharan Africa there are now close to 25 mobile money accounts per 100 adults (Aron *et al.* 2015). In early adopter countries, such as Kenya, as little as four years after the introduction of M-Pesa more than 75 percent of households had at least one active mobile money account, and in June 2014, the monthly value of transactions was about 2 billion USD, equivalent to 60 percent of average monthly GDP (Aron *et al.* 2015). The dramatic expansion of mobile money in sub-Saharan Africa is likely driven by very limited 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 with 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. Jack and Suri (2014) show for Kenya that mobile money has changed

[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.

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 nonusers, the consumption pattern of user households is unaffected. The authors argue 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 (2014) 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 percent. We combine information on mobile money access of households with information on household shocks to estimate the response to shocks for household with and without mobile money accounts. To avoid relying on potentially endogenous household shocks, we focus on rainfall shocks to households depending predominantly on rain-fed agricultural production. Different from Jack and Suri, who use binary, self-reported measures of household shocks, we focus on shocks to households from variation in rainfall.

This has several advantages. First, 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, which we can also test empirically. We show that the distribution of 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. Second, using rainfall shocks, rather than self-reported shocks that rely on recall during the collection of the survey, reduces measurement error. Third, 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.[2] 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 household expenditure and investment in the 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, thus preventing these households from sliding into transient poverty. 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, we find that households' expenditure on preventative health and measures against malaria are protected from negative shocks. We provide further evidence that mobile money preserves investment in the education of children by preventing absenteeism from school and maintaining home study time in the aftermath of household shocks. Effects on educational inputs are particularly pronounced for girls in the household.

We provide suggestive evidence that, in addition to remittances facilitated by mobile money (Jack and Suri 2014, Munyegera and Matsumoto 2016), welfare receipts from NGOs may contribute to the ability of these households to smooth their consumption. 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

[2] 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.

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. Section 5 presents the main and additional results. Section 6 discusses the results and concludes the paper.

2 Background: Tanzania, Mobile Money, and Financial Inclusion

Tanzania is a sub-Saharan African country with an estimated population of 55 million in 2018. The country remains one of the poorest in the world, with about 28 percent of the population being classified under the 1.25 USD poverty line in 2011 (World Bank 2015). Current per capita GNI is 570 USD in 2012, and more recently Tanzania has been described as a development success story with an average growth rate of 7 percent between 2000 and 2011 (World Bank 2013). The Tanzanian economy is still—to a large extent—based on agriculture production, with about 27 percent of GDP and about 80 percent of employment related to the agricultural sector. With its vast landmass, the country is sparsely populated and predominantly rural, creating additional challenges for economic activity, the provision of services, including telecommunication, and access to financial services, including banking.

According to the 2012 World Bank Financial Index in Tanzania, only 17 percent of individuals 15 years and older have a bank account, compared with 97 percent 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.[3] These contrast sharply with 26.4 and 123, respectively, in the United Kingdom. These figures

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

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 in 2007, 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 Survey (CGAP 2016) shows that in 2015, 38 percent of adults in Tanzania had a mobile money account. The household survey data we introduce in the next section shows that in 2012, 41 percent of households had at least one mobile money account, while this number was only 13 percent in 2010, revealing a sharp increase of households with access to the technology.[4] In 2012, 36 percent of all money transfers in Tanzania were made through mobile money transfer services (World Bank 2016).

3 Data

This paper uses data from the World Bank's Living Standard Measurement Studies – Integrated Survey on Agriculture (LSMS-ISA), previously known as the National Panel Survey (NPS), for Tanzania. We use two waves of the panel—LSMS-ISA for 2010/11 (from

[4] 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.

here on 2010) and 2012/13 (from here on 2012)—and focus our analysis on this two-period panel.[5] The data contain very detailed information on individuals and households followed over the two periods and provide 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.[6] The final baseline samples consist of 2,388 households and 9,807 individuals.[7]

The LSMS-ISA collects very detailed information on individuals and the households they live in. Very detailed itemized information on household expenditure allows us to investigate total household and per capita expenditure.[8] Focusing on real total expenditure, rather than a single category for food expenditure, allows us to investigate household poverty, rather than food security only. Additionally, we investigate 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

[5] The 2008/09 wave is part of the LSMS-ISA panel 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.

[6] 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.

[7] Of the 3,924 households in the 2010 survey, 3,776 households were successfully reinterviewed in the 2012 survey, leading to an attrition rate of less than 4 percent 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 the main household section report a sample size of 1,724 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).

[8] The World Bank's LSMS team reports 12-month nominal and real household expenditure for different expenditure classes, ranging from necessity expenditure (e.g., food) to luxury expenditure (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.

decisions, including school enrollment, 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. Using per capita expenditure, about 71 percent of households are classified as living in absolute poverty, and 87 percent of households live on less than 2 per day USD (using per capita expenditure).[9] Seventy-two percent of households live in a rural setup. Twenty-two percent of households have a member that belongs to a SACCO group, while only 16 percent have a formal bank account. Agricultural activities dominate the household labor supply, with 63 percent of adults engaging in such activities.

Table 2 presents summary statistics of the distribution of mobile money agents, the adoption of mobile money in the survey households, the frequency, and the type of service used over the two survey waves. In Panel A of Table 2, we show that over the short period from 2010 to 2012, the mobile money agent network has expanded dramatically. *Agent availability* indicates the presence of a mobile money agent in the village. While in 2010 only 17 percent of all survey villages had a mobile money agent, two years later more than half of all villages had a mobile money agent providing services in the village.

The maps in Figure 1 show the equivalent changes in the mobile money agent distribution over time for all enumeration areas. In the maps, 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. 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.[10] Similarly, the cost of travel to the nearest agent reduced

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

dramatically over the course of two years, from 1,850 TZS to 667 TZS. The table also reports the availability of agents outside of the village for different distances from the village centroid While in 2010, 27 percent of villages had an agent within a 2 km distance, this number increased to 60 percent in 2012. For a 10 km distance, the coverage increases from 52 percent to 82 percent. In Figure A1 in the appendix[11] we depict enumeration areas with a mobile money agent within 10 km distance in 2010 and 2012 in a map demonstrating the universal geographic coverage of the expansion.

The expansion of the mobile money agent network drove an adoption of mobile money accounts in Tanzanian households over the same period. In Figure A2, we show the relationship between distance to the closest agent and the propensity to adopt a mobile money account (see Appendix A3 for details) depicting a strong negative relationship. In Panel B of Table 2, we show that the fraction of households in our sample with at least one mobile money account tripled from 11 percent to 32 percent; the per capita number of mobile money accounts also tripled over the two-year period. This increase is driven by a combination of more households adopting accounts from the market leader M-Pesa, as well as the expansion of Zap and the market entry of the new provider Tigo.

In Panel C of Table 2, we report usage patterns of mobile money services. More than half of users reported using the service only occasionally or for emergency. The reported leading reason, reported in Panel D of Table 2, for mobile money use in both survey waves was sending and receiving money, accounting for roughly 80 percent of the responses, consistent with the low frequent use of mobile money. Together with the expansion of mobile money across households, this shows an increase in both the extensive and intensive margins

[11] The online appendixes can be found at http://jhr.uwpress.org

of mobile money use in these households. A small and stable fraction of 3 percent of households reported using the service for savings.[12]

4 Empirical Strategy

In this paper, we are 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 very fine partitioning of rainfall data available to us across vast geographic space and over time.[13] We then interact the measures of household shocks with the availability of mobile money accounts in the household to understand the impact of mobile money 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.[14] Given their objective nature, rainfall shocks also are not subject to measurement error of self-reported household shocks and the potential endogeneity of such shocks.

In Table A2 in the appendix, we show that the rainfall variation is indeed orthogonal to household characteristics. For this purpose, we regress our rainfall deviation measure on the predetermined household characteristics using the household panel where we include household and year fixed effects.[15] None of the coefficients is significant, and we find no

[12] 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.
[13] In Appendix A1, we discuss in detail the origin of the weather data used to create the rainfall shock measures and how the World Bank created those measures.
[14] In Table A3 in the appendix, we demonstrate the sensitiveness of agricultural yields to variation in rainfall. Using detailed data provided in the agricultural questionnaire of LSMS-ISA for households for which this data is consistently available for standard produce, we estimate the effect of log rainfall on normalized log agricultural yield in kilograms, demonstrating a significant positive relationship. We also estimate the effect on agricultural output expressed in Tanzanian Shilling using market prices for cash crops provided in LSMA-ISA, which results in a marginally significant positive association.
[15] Although it is difficult to define purely predetermined household characteristics, the chosen variables likely represent longer-term characteristics determined prior to the contemporaneous rainfall variation. We alternatively

systematic relationship between household characteristics and the rainfall measure, which supports the assumption of exogeneity of the rainfall deviation. We also include the rainfall measures in the balancing tests of Table A1, demonstrating that rainfall and the frequency of droughts do not differ across treatment status, i.e. households for which access to mobile money agents changes from 2010 to 2012 compared to no change.

We also look at the spatial distribution of rainfall shocks over the two periods. In Figure A3, 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 that 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 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 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 subjected to droughts over both periods (red areas in both maps); and households subjected to average or above 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 for using rainfall shocks for our analysis.

used a full set of household characteristics and find only one significant variable out of 21 (results not reported but available upon request from the authors).

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

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

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 (see Appendix A2 for the construction of rainfall deviation measure).[16] $\mathrm{MM_{ht}}$ X $\mathrm{Rainshock_{ht-1}}$ is the interaction term for mobile money and rainfall shock measure, and $\boldsymbol{\tau}$ 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 of mobile money access 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 include individual (X_{ht}) and household level controls (Z_{ht}). These controls include interaction terms of measures of financial inclusion, other than mobile money, namely access to a bank account and membership with a savings cooperative, with the rainfall measure as these measures may be correlated with mobile money adoption. ε_{ht} denotes an error term, which allows for clustering at the enumeration area level in all estimates accounting for the possibility that regressors and errors might be correlated at the village level.[17] We also allow

[16] Over the two survey periods, we observe no floods, as by standard definition used in the literature (rainfall in excess of a standard deviation rainfall from the long-term mean), which allows us to enter rainfall in equation (1) linearly.

[17] This is more important because our specifications include individual/household fixed effects rather than enumeration area fixed effects that usually account for part of the within enumeration area correlation.

for standard errors to cluster at the district level and provide those in addition to the main estimates.[18]

The causal interpretation of $\boldsymbol{\tau}$ relies not only on the exogeneity of rainfall but also on the mobile money adoption of households. Although the adoption of mobile money accounts by households was largely driven by the expansion of the mobile money network, the individual household decision to adopt mobile money may still be potentially endogenous. In Table A1 in the appendix, we show nevertheless that characteristics of households that adopt mobile money over the two years do not systematically look different from households that do not change "treatment" status. We report the means of the household covariates for households by treatment status, namely 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 differences between the two.[19] The normalized differences between treatment and control households are very small and none exceed one quarter. In particular, the wealth measure is virtually identical across the two groups.

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 A4 reports the coefficients for separate regressions for each measure and year. We find 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

[18] The maps in Figure 2 indicate there is little correlation of rainfall across enumeration areas and over time indicated by the fact that clustering at the district or region level makes little difference to standard errors of estimates.

[19] For the balancing test, we restrict our sample to the observations in the reference households from which observations reported for the main results are drawn. 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.

identification strategy. We repeat the exercise using the 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 A5. Again, we find no significant effects or systematic pattern with the different coefficients.

Alternatively, we estimate the effect of mobile money in response to shocks in an instrumental variable DiD framework, similar to the setting in Duflo (2001), Waldinger (2010), and Jack and Suri (2014), where we instrument for the mobile money adoption in households across survey waves with the information on mobile money agent's presence/ distance to next mobile money agent.[20] First stage results and diagnostic tests are presented in Table A6, where R-squares for both instruments are close to one, ranging from 0.877 to 0.986 in column (2), indicating that the IV-DiD results merely replicate the DiD estimates. We present the coefficient estimates from the second stage regression of IV-DiD for the poverty outcome alongside the DiD results in Table 3.

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 3.[21] In detail, this table contains the DiD coefficients from equation (1), where we use rainfall deviations from the historic mean as exogenous measure for household shocks and include an indicator for mobile money adoption and its interaction with the

[20] 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. The choice of instruments closely follows Jack and Suri (2014). See Appendix A3 for the first stage models of mobile money indicator and its interaction with rainfall shock.

[21] We focus on absolute poverty, as defined by real per capita expenditure of less than 1.25 USD. We created a dummy variable that takes a value of 1 for households with real per capita expenditure of more than 1.25 USD and 0 otherwise, and we estimate the coefficients in Table 3 using a linear probability model. Probit and logit fixed effects models yield biased estimates resulting from the incidental parameter problem (Greene 2003; 2004). We can obtain consistent slope estimate using conditional fixed effects in the logit model, yielding similar results (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).

rainfall variable. We also report the *overall effect* $(\beta_2 + \tau)$ of rainfall shocks on poverty for users of mobile money. We present the IV-DiD results in column (3).

We start with the coefficients from equation (1) without the controls presented in column (1) of Table 3. 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 probability for household poverty as expected. A one standard deviation negative rainfall shock (indicating a drought) raises the likelihood to fall below the poverty line by 4.9 percentage points, a 17 percent increase compared with the mean. 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) and demonstrates the vulnerability of rural households in Tanzania to rainfall shocks.

We then focus on the interaction term between mobile money adoption in the household and rainfall shock. The coefficient on the interaction is negative and statistically significant at the 5 percent level. A one standard deviation negative rainfall shock interacting with the mobile money indicator leads to a 14.6-percentage point decrease in the probability of falling below the poverty line, indicating that households that have adopted mobile money can effectively shield themselves from the negative impact of rainfall shocks.[22] The overall effect of negative rainfall shocks for mobile money users on poverty is negative and statistically significant, indicating that mobile money users overcompensate for the direct negative impact of rainfall shocks. The results suggest that very poor households are enabled by the mobile money technology to smooth their consumption, thereby protecting them from

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

the negative consequences of household shocks and preventing them from sliding into extreme poverty.

In column (2), we include a large set of time-varying household and community covariates.[23] Because mobile money adoption might potentially be correlated with other measures of financial inclusion, for example access to a bank account or to a savings cooperative, we also include their interaction with rainfall shocks as controls. The inclusion of these controls changes the coefficient on the rainfall shock only minimally, confirming the exogenous nature of rainfall shocks. Likewise, the coefficients on the interaction term and the overall effect is reduced only slightly, lending additional credibility to the identification strategy. Because the coefficients are slightly smaller, we adopt the specification of column (2), including the full set of controls as our preferred specification.

Last, in columns (3) we present the IV-DiD results. As expected, given the first stage results presented in Table A6, the coefficients are virtually identical to the regular DiD results, and we hence rely on the DiD framework for all estimates.[24] For each column, standard errors allowing for clustering at the district level are slightly larger but do not have a substantial impact on the precision of the estimated coefficients.

Across the different specifications, we find evidence for a substantial role of mobile money to mitigate the effect of rainfall shocks and even overcompensate for the original negative rainfall shocks. In their 2014 paper, Jack and Suri show how lower transaction costs facilitate risk sharing across larger distances and that mobile money leads to a more diverse group of senders. A broader set of remittance senders may explain the "overcompensating" effect documented in our framework. Overcompensation makes sense in a framework of

[23] The full set of controls include gender of household head, education and occupation categories of household head, household size, average household age, rural dummy, household asset value, number of mobile phones in the household, 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.
[24] Results from the IV-DiD methodology are consistent with the pattern of estimates reported for all other results in the paper (results are available from the authors upon request).

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.[25] Possibly, access to a broad base of senders of remittances facilitated through mobile money makes households with access to mobile money effectively better off after shocks by receiving mobile money transfers that exceed the original income shock.[26] Jack and Suri (2014) find a similar overcompensation effect in some specifications but not generally across different outcomes and different shocks.[27] Riley (2018), who studies the distributional effects of mobile money across adopters and nonadopters in response to shocks in Tanzania, also finds evidence for overcompensation on log per capita consumption. It may also be possible that the timing of the measurement of outcomes in our survey data is at least partially responsible. In the absence of expenditure information over a longer period, but after the shock realization, it is difficult to test for this directly.

Beyond the effect on poverty using per capita household expenditure, we are also interested in the capacity of mobile money to help smooth consumption more generally during periods of rainfall shocks. We therefore estimate equation (1) using the total per capita household expenditure as outcome to test for consumption smoothing. The results are presented in column (1) of Table A7.

While we find the expected sign for the coefficients, and a similar pattern regarding the overcompensation effect compared with the outcomes for poverty in Table 3, none of the coefficients are significant at conventional levels. Moreover, using an outcome of relative poverty of per capita spending below 2 USD a day, we find a similar pattern, but the

[25] This is likely true for both: the 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.

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

[27] 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.

estimates are imprecise. This indicates the poorest of households potentially benefit most from access to mobile money. Focusing hence on overall per capita expenditure may obscure the capacity to effectively smooth consumption for the poorest of households. To investigate this directly, 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.[28] The results are presented in Table 4.

For the first quintile in the wealth distribution of households, we find a substantial negative impact on per capita expenditure from rainfall shocks on log per capita expenditure. A one standard deviation reduction in rainfall leads to a decrease in per capita expenditure of 11 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 indeed 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 3. The interaction term is more than three times larger and of opposite sign compared with the effect of rainfall on per capita expenditure. The coefficient for the overall effect can be used to directly test for consumption smoothing in households in the specified wealth quantiles. While a coefficient close to zero would indicate that households with mobile money can smooth their per capita consumption during droughts, the significant and negative coefficient confirms once more the overcompensating effect of mobile money on consumption.

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,

[28] Focusing on non-agricultural household wealth has the advantage of a more stable measure for household wealth over time, as expenditure maybe directly impacted by the idiosyncratic shocks and the mobile money adoption. The notes of Table 4 provide detail on how we created the household wealth measure.

taken together with the results for poverty presented in Table 3, point to the importance of financial inclusion for the most vulnerable and poorest of households in Tanzania.

Table 2 demonstrated that the vast majority of transactions with mobile money accounts relate to receiving and sending money; savings for emergencies only account for 3 percent of transactions.[29] This is in line with previous research. Jack and Suri (2014) show that mobile money enables consumption smoothing of shocks through informal insurance by increase in remittances.[30] Using information on the origin of remittances from a survey specifically collected by the authors, they find that mobile money increased the average distance travelled of remittances received and expanded the number of senders of remittances.

Unfortunately, the LSMS survey does not contain information that allows us to investigate how mobile money facilitates remittance receipts in our context. The LSMS survey collected some limited information on remittances in the 2012 wave only, and we use this to investigate the differential impact of mobile money on remittances for households with and without bank accounts. In Table A10, we estimate the effect of mobile money in the household on remittances received, an indicator variable taking the value of 1 if the households received remittances over the past 12 months and 0 otherwise, and the natural log of the remittances amount, separately for unbanked households in columns (1) and (2) and for households with bank accounts in columns (3) and (4). Mobile money accounts lead to a large increase in remittances received for unbanked households. We find a 33-percentage point, or 150 percent, increase in the propensity of remittance receipt over the previous 12 month, and a significant increase in the remittances amount for these households. We do not

[29] In other contexts, mobile money has proven to be a useful tool to stimulate savings (Batista and Vicente 2017).
[30] More recently, the integration of international money transfers and mobile money accounts facilitates the receipt of international remittances in rural areas.

find an equivalent effect for banked households, indicating the important role of mobile money for financial inclusion for the poorest of households in Tanzania.[31]

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.[32] Mobile money has been identified by NGOs in Tanzania, including USAID implementing partners (USAID 2013), as an effective way to replace cash when distributing financial aid to households, in particular in rural context. We use information on welfare receipts from NGOs to households in Tanzania to investigate financial aid as an alternative channel in addition to remittances and estimate the effect of shocks and mobile money on financial aid receipts. We present the findings in Table 5. Rainfall shocks have no direct effect on financial aid received, the coefficient is small and insignificant, but we find a substantial and significant effect for mobile money users, suggesting these households benefit from financial aid through mobile money channels in response to negative shocks. Although the absolute value of financial aid is small, financial aid provides another channel through which mobile money helps affected households to smooth consumption.

5.2 Timing of shocks and spatial correlation

We start by investigating the role of 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. In Table A3, we show how rainfall shocks impact agricultural output of the affected households. Planting in Tanzania revolves around two major rainy

[31] 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 0 values to small positive values.

[32] 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 2016).

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.[33] 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 provide 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 further away from the previous harvesting seasons in Tanzania to investigate when exactly household expenditure is impacted after the realization of the rainfall shock.[34] Each survey round takes place between October of the starting year and ends in November of the subsequent year. We split the sample into households observed up to six month after the shock and households observed 6–12 months after the shock.

In column (1) of Table A8, we report the estimates for households nearer to the harvest season (i.e., the first six months from October [harvest year] to March [in the following year]); in column (2), we report the estimates for surveys collected in the second half of the survey year (i.e. from April to September). The coefficients for rainfall shocks within six months of the harvest are positive but much smaller than for the whole sample; likewise, the interaction term of rainfall shock and mobile money is much smaller and not statistically significant. We contrast this with the effect of shocks for the sample observed within 6–12

[33] 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.

[34] 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.

months after the shock and find the effects are much more pronounced, both for the estimates in column (1) and the main estimates from Table 3. These results are consistent with shocks initially absorbed by the consumption of the remaining stock of crops and hence delaying the effect of droughts on poverty; likewise, we find the consumption smoothing effect of mobile money sets in with delay as well.

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). In addition to clustering standard errors at the enumeration level across all estimates, we have shown in Table 3 that clustering at the district level has very little impact on standard errors, indicating that spatial distance across enumeration areas is sufficiently large.

Additionally, we address any remaining concerns regarding spatial correlation of rainfall by following Fujiwara *et al.* (2016) and include various location-specific time trends when estimating equation (1). Cluster specific effects will, in combination with clustered standard errors, very effectively deal with within-enumeration area correlation. In Table A9, we include linear, quadratic, and cubic enumeration area-specific time trends. For ease of comparison, we include the benchmark results from Table 3 in column (1). In column (2), we include an enumeration area-specific linear trend; in columns (3) and (4), we include quadratic and cubic trends, respectively. The estimates are virtually identical to the benchmark in column (1).

5.3 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 as well as household labor supply, as these may impact the ability of households to escape chronic poverty trap associated with intergenerational transmission of poverty.

5.3.1 Preventative health expenditure and health investments

In the sub-Saharan African context, private health expenditure is an important component of human capital investments at the household level. The inadequacy of the public health system compels households to often rely on out-of-pocket health expenditures. To avoid having health expenditures impacted by rainfall shocks through illness,[35] we focus on preventative health expenditure.[36] We also look at a specific private health investment and the use of bed nets and treated bed nets.

Table 6 reports the estimates on preventative health expenditure and bed net use. In column (1), we report the results for an indicator variable (for any preventative health expenditure over the past four weeks). Note, given the short reporting period, only a very small number of individuals have any private preventative health expenditure. In column (2), we report estimates for log real expenditure. First, we show how rainfall shocks impact the ability of households to maintain preventative health expenditure; both the indicator variable and real expenditure are positive and hence negatively impacted by droughts.[37] A one standard deviation negative rainfall shock reduces the propensity for any preventative health expenditure by 0.3 percentage points, a very substantial effect given the low propensity for expenditure in the short four-week window before the survey date. Next, we find that the effects of rainfall shocks are counteracted by mobile money adoption, both for the indicator and the real expenditure outcome. The coefficient of the interaction terms exceed the effect of

[35] 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.

[36] 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.

[37] 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).

rainfall shocks sevenfold for the indicator and about 14 times for log expenditure, a much more pronounced effect than for general per capita expenditure, thus highlighting the importance to separate expenditure components for the analysis.

Because preventative health expenditure is rare and in our instance captures health investments only over a short period before the survey date, we investigate this further by looking at another very important health investment: sleeping under a bed net to protect from vector borne diseases.[38] Bed nets are an effective measure against the transmission of malaria, 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 improve the effectiveness of protection.

In column (3), we present the coefficients for whether a household member slept under a bed net the night prior to the survey; column (4) reports the estimates for whether an individual specifically slept under a treated bed net. For general bed net use, we find a positive, but insignificant, coefficient for rainfall shock and the expected negative coefficient for the interaction term. Once more, we find that mobile money protects households from negative shocks, and we find a marginally significant negative overall effect, indicating once more that mobile money households are indeed overcompensating the negative shock.

When focusing on treated bed nets, we find a similar pattern. A one standard deviation negative rainfall shock reduces treated bed net use by 6.2 percentage points, a 12-percent reduction compared with the mean. The interaction term is again positive and larger

[38] Disease vectors in Tanzania differ by ecological zones and include mosquitos who transmit malaria, filariasis, dengue, chikungunya, and, more recently, Zika.

compared with the mean, but it is not significant. Although not significant at conventional levels, both, coefficients for bed net and treated bed net complement the effects on preventative health expenditure with a very similar picture. Given the importance on long-term health and productivity of preventative health expenditure and the negative consequences of malaria, these estimates are important for the understanding of the negative consequences of rainfall shocks and the potential for mobile money to mitigate those shocks.

5.3.2 Educational 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 enrollment, 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.[39] Similarly, school enrollment 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 7. 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 enrollment as expected.

[39] 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, which, given the timing, might be affected by rainfall shocks. We use information on school absenteeism in the 14 days prior to the survey (column (3)), and the number of hours school age children spend on homework or studying over the week prior to the survey.[40] We would expect school absenteeism to possibly be affected by household shocks if children were helping their parents with economic activities, including in agricultural and nonagricultural production, or needed to help more in the household. We find a significant increase in school absenteeism for children in households affected by droughts.

For a one standard deviation negative rainfall shock, we find an increase in the probability of missing school at least one day over the two weeks prior to the survey by 7.1 percentage points, roughly corresponding to a 26 percent increase compared with the mean. We find a positive and significant coefficient on the interaction term of shocks and mobile money, as well as a positive and large overall effect of 22 percentage points, indicating that children in households with mobile money are shielded from the negative impact of droughts confirming the overcompensating effects of mobile money in line with the estimates on poverty and household expenditure. The estimates on school attendance are reinforced by estimates on the effects on the number of hours of homework children engage in. We find that a one standard deviation negative rainfall shock reduces the number of daily hours of homework school children engage in by 24 percent compared with the mean. Access to mobile money mitigates the negative effect of rainfall shocks on homework, leading to a positive and significant overall effect of negative rainfall shocks on the number of hours of homework.

The joint estimates for boys and girls on educational investments may conceal heterogeneous effects by gender. To investigate this, in Table A12, we present the effects on

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

educational inputs separately for boys and girls and find substantial across gender heterogeneity. 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. The overall effect for girls is more than double the effect we estimate for boys. We find even more profound differences for hours children spend on homework. While the number of hours of homework boys spend on homework is not affected by rainfall shocks, we find that a one standard deviation negative rainfall shock reduces the time spent on homework for girls by about 30 percent compared with the mean. In contrast to boys, we find significant and large effects of mobile money to shield from the effects of rainfall shocks. We find large and precisely estimated overall effects demonstrating that mobile money can play a crucial role for girls to protect their human capital investments during periods of household shocks. Access to mobile money may therefore be particularly important when there are girls in the household, who are impacted much more severely by rainfall shocks. These results are consistent with findings in the literature on the relationship between remittances and child labor and the role of gender differences (Acosta 2011).[41]

Taken together, this is strong evidence in favor of the negative consequences—in particular for girls—droughts can have on inputs in education, namely school attendance and hours of preparatory work for school at home, and the mediating effect mobile money has in response to these shocks.

5.3.3 Labor market participation and child labor

Rural households in Tanzania predominantly engage in agricultural production. In Table 1, we can see that roughly 63 percent of adults in the sample are farmers, and only 10 percent household members are employed in the private or public sector. Droughts may induce

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

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 income by earnings from other wage activities outside the agricultural sector in rural India.[42] 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 nonagricultural labor opportunities in the rural area.

In Table 8, 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.[43] In column (1), we present the estimates for participation in nonagricultural wage labor for adults. We find that a one standard deviation decrease in rainfall increases the likelihood of nonagricultural labor participation of adults slightly by 1.3 percentage points, an 8-percent increase compared with the mean, but the estimate is not significant. The negative coefficient suggests that households in Tanzania react to rainfall shocks by diversifying their income through an increase of nonagricultural labor activities. The interaction term indicates that this effect is counteracted by a 7.7-percentage point decrease in the likelihood of nonagricultural labor participation, counteracting the effect of rainfall shocks, leading to a large and significant overall effect of 6.4 percentage points, which is a 37-percent reduction given the baseline for a one standard deviation negative rainfall shock. This result indicates that households that have adopted mobile money are less likely to diversify their income base, possibly because these households do not need to do so to smooth consumption but are insured against shocks

[42] In another context, other studies demonstrate how nonfarm employment can help rural dwellers oust sliding into poverty during agricultural shocks in Africa and Asia (Kijima *et al.* 2006, Otsuka and Yamano 2006).
[43] 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 the information on labor supply over such long periods.

through remittances facilitated by mobile money. This may enable the affected households to concentrate on agricultural production, maintaining productivity of the farmland in periods after droughts, for example through water resource management, which is particularly relevant for rain-fed agricultural practices (Rockström *et al.* 2010).

Next we are interested in understanding whether we find a similar effect for child labor supply in line with the negative effect we documented for educational investments and the mediating role of mobile money. In Tanzania, as in many Sub-Saharan African countries, children are frequently engaging in child labor, either in agriculture or in formal employment (Kondylis and Manacorda 2012, ILO 2017). In column (2), we report the results for the nonagricultural labor supply of children.[44] Rainfall shocks have an even more pronounced impact on children's labor participation; a one standard deviation negative rainfall shock leads to a 4.2-percentage point increase in child labor supply, which is almost a 100-percent increase compared with the relatively small mean. Once more, mobile money is effective in shielding households from the negative consequences of droughts, reducing the child labor supply in households with mobile money. 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. To complement this result, we estimate the effect of rainfall and mobile money on an indicator variable on whether children participate in household chores, such as fetching water or collecting firewood, the day before the survey.

Finally, we look at the effect of rainfall shocks and mobile money on children engaging in household chores that could also partially explain the findings on school attendance and homework. We find a small positive insignificant effect of rainfall shocks on the probability that children helped with household chores the day prior to the survey, but a large and

[44] While one may be interested in investigating child labor more broadly, for example by investigating participation of children in agricultural production, this information is not available in the LSMS data. We use participation of children in formal employment to investigate child labor

significant effect on the interaction term with mobile money leading to a large significant overall effect. We find that mobile money reduces engagement in household chores in response to rainfall shocks by about 18 percentage points, roughly a 50-percent reduction compared to the mean. Column (5) in Table A11 shows these effects are exclusively driven by the effects on girls. A one standard deviation negative rainfall shock leads to 5.9-percentage point increase in the propensity of girls having to engage with household chores, which is a 22-percent increase given the baseline. Girls in households with mobile money are shielded from the negative consequences of droughts, leading to a large and significant negative effect. These results are important to understand the unequal impact shocks to the household can have for girls and boys in affected households. *Time poverty* of women has been identified as a major barrier to economic inclusion for females in Tanzania, and an increase in household chores for school aged girls may contribute to their underinvestment in education (Fox 2016). Improved financial inclusion may particularly benefit girls in these households by reducing the impact of rainfall shocks on educational investments through child labor and household chores.

6 Final remarks

Financial exclusion remains an important issue in many developing countries. The rural poor are particularly affected by financial exclusion because of their 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 the financial innovation of 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 detailed information on mobile money access through the rapid expansion of the mobile money agent network in a difference-in-differences framework.

We find that mobile money enables the poorest households affected by negative rainfall shocks to smooth their consumption preventing 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 17 percent compared with 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. 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 impacts school expenditure or enrollment in response to shocks, 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 more time fetching water and collecting firewood in response to shocks.

The findings on the role of mobile money to mitigate the effects of droughts are important in the light of changes to the frequency of these events in relation to climate change and may provide a crucial tool for the unbanked poor to smooth consumption and maintain investments in the human capital of both adults and their children. This is particularly important in contexts similar to Tanzania, where there is only limited capacity to adapt because of a high dependence on agricultural small-hold farming (Collier *et al.* 2008).

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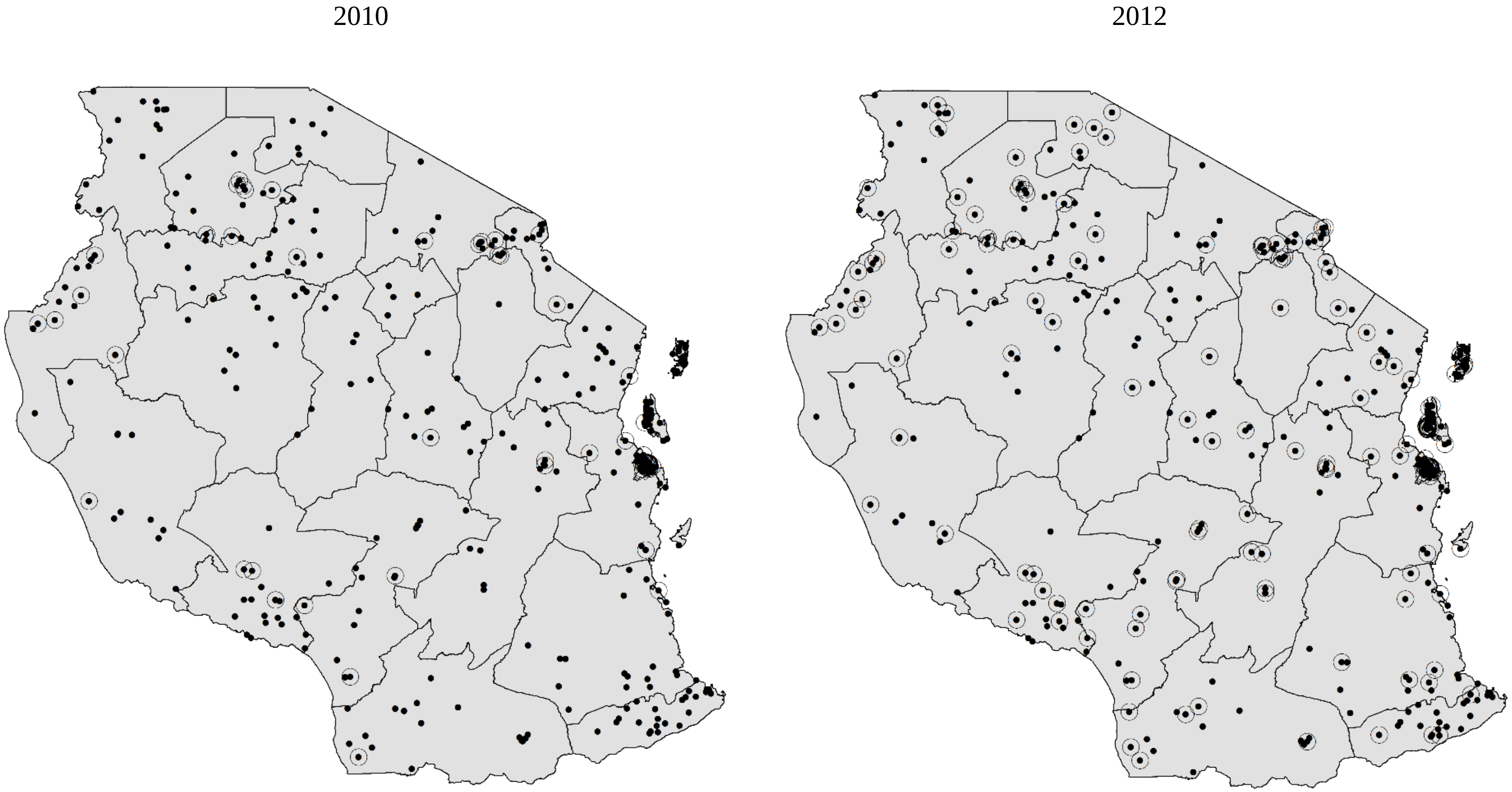
Figures and Tables

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



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.

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
Rainfall measures		
Normalized rainfall-deviation (HH)	-0.062	0.972
Drought indicator (below 1SD of mean)	0.355	0.479

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: HH mobile money composition				
Mobile money (indicator)	0.107	0.309	0.322	0.467
Mobile money accounts per capita	0.032	0.119	0.105	0.232
Mobile money companies used:				
Mpesa	0.103	0.304	0.228	0.420
Zpesa	0.003	0.055	0.003	0.058
Zap	0.003	0.058	0.040	0.196
Tigo	–	–	0.130	0.336
Panel C: 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 D: 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. In Panel A, we present 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 of the table reports summary statistics of mobile money accounts used by the households across the two surveys. The first entry reports the fraction of households with at least one mobile money account. The second entry reports number of mobile money accounts per capita, and lastly we report the different service providers adopted by households (MM provider Tigo was not yet operational in 2010). Panel C presents the frequency of use of mobile money services as a fraction of adopter HHs by year. Panel D 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: Estimates for the Effect of Mobile Money on Poverty Outcome

	Dependent Variable: Absolute Poverty		
Variables	(1)	(2)	(3)
	DiD	DiD	IV-DiD
Mobile money (MM)	-0.042	-0.056	-0.068
	(0.082)	(0.081)	(0.079)
	[0.082]	[0.080]	[0.078]
Rainfall shock (RS)	0.049	0.046	0.046
	(0.016)***	(0.016)***	(0.015)***
	[0.020]**	[0.018]**	[0.018]**
Interaction (MM x RS)	-0.146	-0.125	-0.127
	(0.057)**	(0.057)**	(0.056)**
	[0.066]**	[0.063]**	[0.062]**
Overall effect	-0.097	-0.079	-0.080
	(0.044)**	(0.044)*	(0.043)*
	[0.048]**	[0.048]*	[0.047]*
Mean outcome	0.283	0.283	0.283
Household fixed-effects	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes
Controls	No	Yes	Yes
Observations	3,448	3,448	3,448
R-squared	0.118	0.189	0.189

Notes: 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 propensity to adopt mobile money account (see Appendix A3 for details) at the household level. *Rainfall shock* denotes the deviation from long-term average rainfall, such that a negative value denotes less than the average rainfall. Each column reports the estimates from a separate regression for 3,448 observations (1,724 households). All regressions include household and year fixed-effects. The entries of columns (1) and (2) of the table report the DiD coefficients from a linear probability model of mobile money, rainfall shock and their interaction term on a poverty indicator. In column (3), the variable *Mobile money adoption* is instrumented by the presence of and distance to the nearest mobile money agent such that Mobile money (MM) [interaction] is instrumented by agent availability in the village and distance to nearest agent [interaction of agent availability in the village with rainfall shocks and distance to nearest agent with rainfall shocks]. First stage results are presented in Table A6. The controls used in the estimation of column (2) and (3) 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, number of mobile phones in the household, 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 and the interaction of the financial inclusion variables with the shock variable). Robust standard errors, clustered at the enumeration area are reported in parentheses. Robust standard errors, clustered at the district level are reported in square brackets. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Table 4: DiD Estimates for the Effect of Mobile Money on 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	-0.146	-0.093	-0.081	0.294	-0.428*
	(0.262)	(0.241)	(0.216)	(0.207)	(0.244)
Rainfall shock	0.108**	-0.024	0.010	-0.025	0.015
	(0.048)	(0.039)	(0.043)	(0.032)	(0.041)
Interaction (MM x RS)	-0.376**	0.040	-0.017	0.125	-0.050
	(0.183)	(0.145)	(0.143)	(0.143)	(0.132)
Overall effect	-0.268*	0.016	-0.007	0.100	-0.035
	(0.143)	(0.113)	(0.105)	(0.118)	(0.096)
Household fixed-effects	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	674	688	676	710	700
R-squared	0.143	0.167	0.176	0.134	0.115

Notes: The entries present the coefficients from the DiD coefficients of mobile money, rainfall shock and their interaction term on the log amount per capita expenditure by wealth quintiles. 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 3 (column 2) for the specification and the 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 5: DiD Estimates for Welfare Receipts

	Dependent Variable: ln amount
Variables	(1)
Mobile money	0.030
	(0.164)
Rainfall shock	0.020
	(0.019)
Interaction (MM x RS)	-0.278**
	(0.130)
Overall effect	-0.259**
	(0.118)
Mean outcome	0.071
Household fixed-effects	Yes
Year fixed-effects	Yes
Controls	Yes
Observations	3,448
R-squared	0.049

Notes: The entries of the table report the DiD coefficients 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. 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 3 (column 2) for the specification and the 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 6: DiD Estimates for the Effect of Mobile Money on Health Investments

	Preventative Health Expenditure		Bed net use	
	Indicator	ln Health Expenditure	Untreated	Treated
Variables	(1)	(2)	(3)	(4)
Mobile money	-0.003	-0.031	0.044	-0.027
	(0.007)	(0.105)	(0.129)	(0.166)
Rainfall shock	0.003***	0.048***	0.018	0.062**
	(0.001)	(0.019)	(0.023)	(0.027)
Interaction (MM x RS)	-0.023***	-0.340***	-0.104	-0.119
	(0.009)	(0.128)	(0.070)	(0.087)
Overall effect	-0.020***	-0.292***	-0.086*	-0.057
	(0.008)	(0.114)	(0.050)	(0.066)
Mean outcome	0.003	-6.968	0.707	0.511
Individual fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	14,994	14,994	13,188	13,188
R-squared	0.010	0.009	0.020	0.028

Notes: The entries of the table report the DiD coefficients of mobile money, rainfall shock and their interaction term on a health expenditure and bed net use. 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 preventative healthcare expenditure. The preventative 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). Results in columns 3 and 4 represent estimated coefficients for indicators of bed net use and treated bed net use. Bed net use question refers to sleeping under bed net the night before the survey. See notes in Table 3 (column 2) for the specification and the set of controls used in the estimations. Robust standard errors, clustered at the enumeration area are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Table 7: DiD Estimates for the Effect of Mobile Money on Educational Inputs

Variables	Dependent Variables: School Expenditure (ln)	School Enrolment (indicator)	School Absenteeism (indicator)	Homework (Hours/Day)
	(1)	(2)	(3)	(4)
Mobile money	-0.086	0.080	-0.528**	-0.781***
	(0.268)	(0.072)	(0.209)	(0.225)
Rainfall shock	-0.005	0.005	-0.071*	0.064**
	(0.044)	(0.013)	(0.040)	(0.029)
Interaction (MM x RS)	-0.042	0.003	0.289**	-0.336**
	(0.172)	(0.047)	(0.136)	(0.139)
Overall effect	-0.047	0.008	0.218**	-0.272**
	(0.138)	(0.037)	(0.101)	(0.116)
Mean outcome	2.669	0.875	0.277	0.300
Individual fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	4,232	4,232	3,384	3,382
R-squared	0.026	0.104	0.030	0.099

Notes: The entries of the table report the DiD coefficients of mobile money, rainfall shock and their interaction term on a number of educational inputs. 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. See notes in Table 3 (column 2) for the specification and the set of controls used in the estimations. In addition to household level controls, age, and gender of individuals are used as additional individual controls in all regressions. The number of observations varies across outcomes, as the information on absenteeism and homework is not available in all household questionnaires. Robust standard errors, clustered at the enumeration area are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

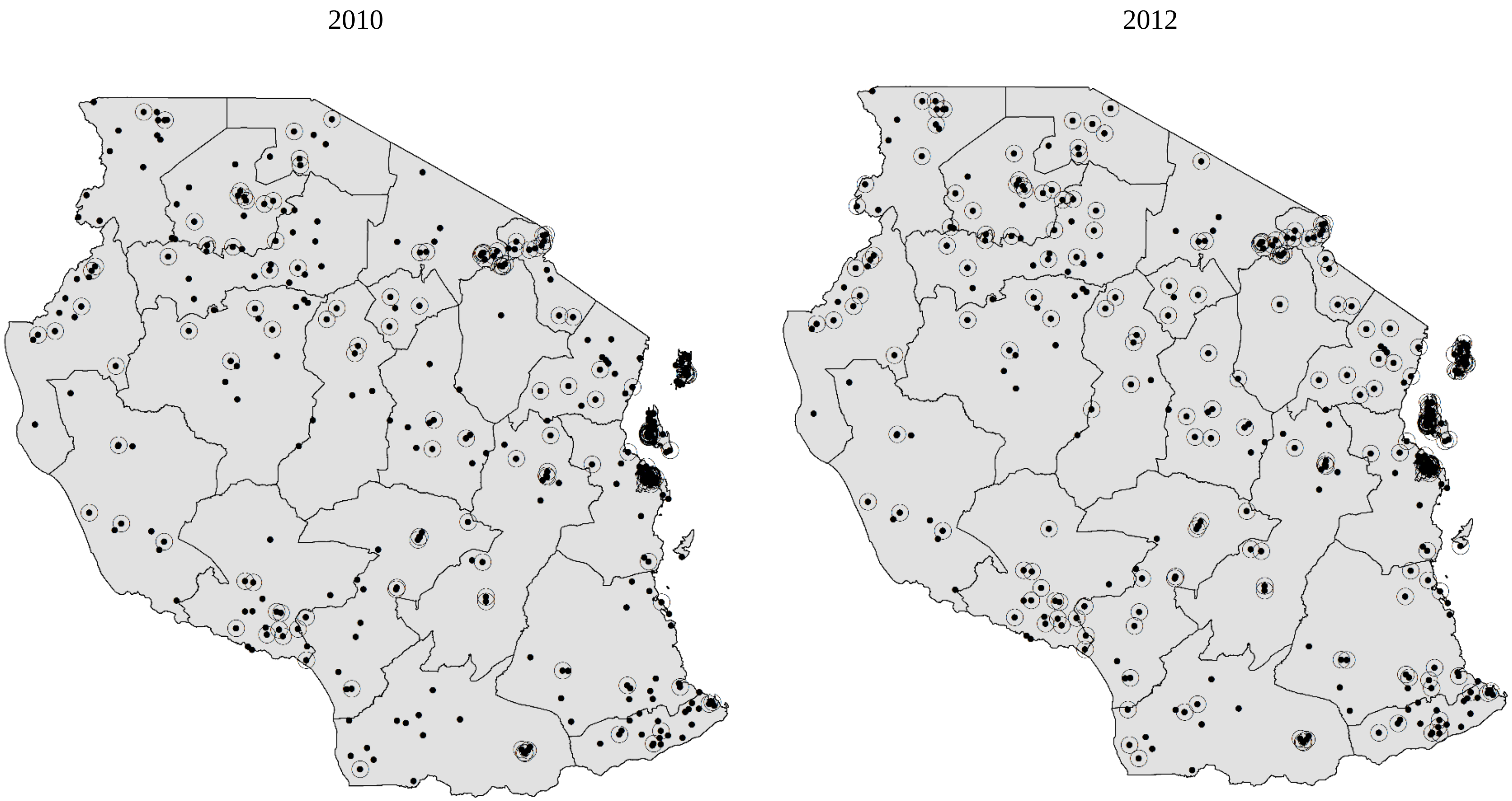
Table 8: DiD Estimates for the Effect of Mobile Money on Labor Supply and Household Chores

Variables	Dependent Variable: Labor Supply Indicator		Household Chores
	Adults	Children	Children
	(1)	(2)	(3)
Mobile money	-0.029	-0.185	0.128
	(0.062)	(0.123)	(0.104)
Rainfall shock	-0.013	-0.042**	-0.029
	(0.010)	(0.018)	(0.019)
Interaction (MM x RS)	0.077*	0.113*	0.184**
	(0.040)	(0.066)	(0.076)
Overall effect	0.064**	0.071	0.155***
	(0.032)	(0.053)	(0.061)
Mean outcome	0.171	0.043	0.317
Individual fixed-effects	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	6,172	1,130	5,230
R-squared	0.142	0.031	0.023

Notes: The entries of the table report the DiD coefficients 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. The outcome variable in column (3) 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. See notes in Table 3 (column 2) for the specification and the set of controls used in the estimations. 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 are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Annex for Online Publication - Financial Inclusion, Shocks, and Poverty: Evidence from the Expansion of Mobile Money in Tanzania

Figure A1: 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 A2: The Relationship between Mobile Money and Distance to Agent

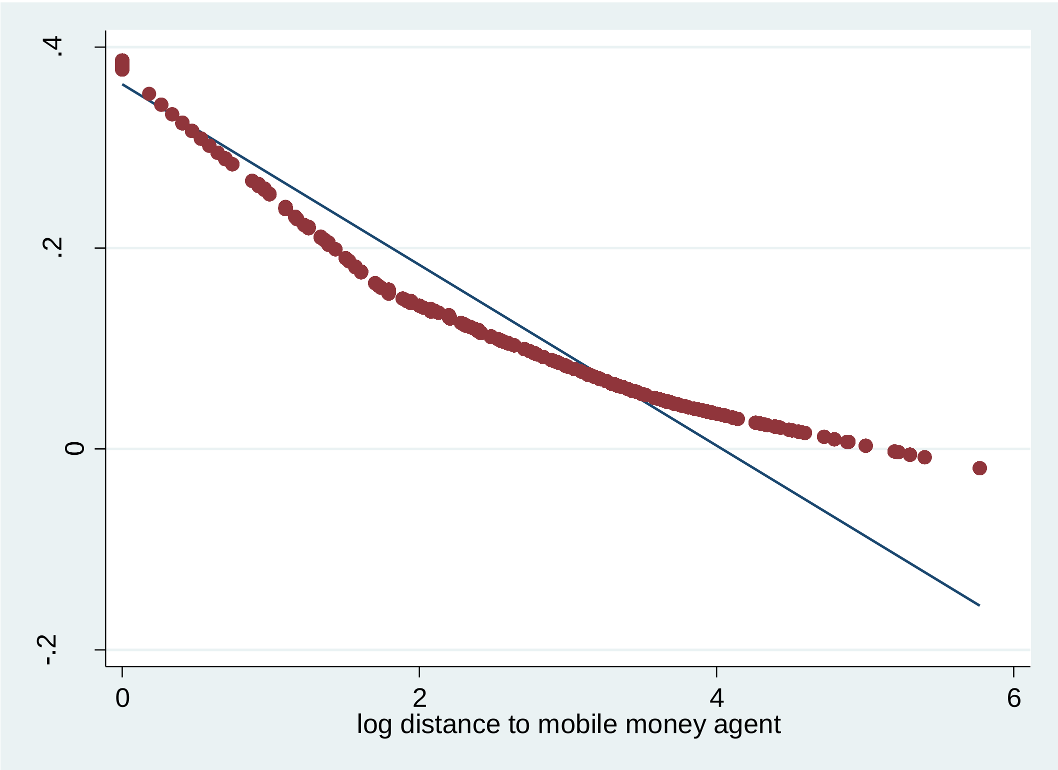
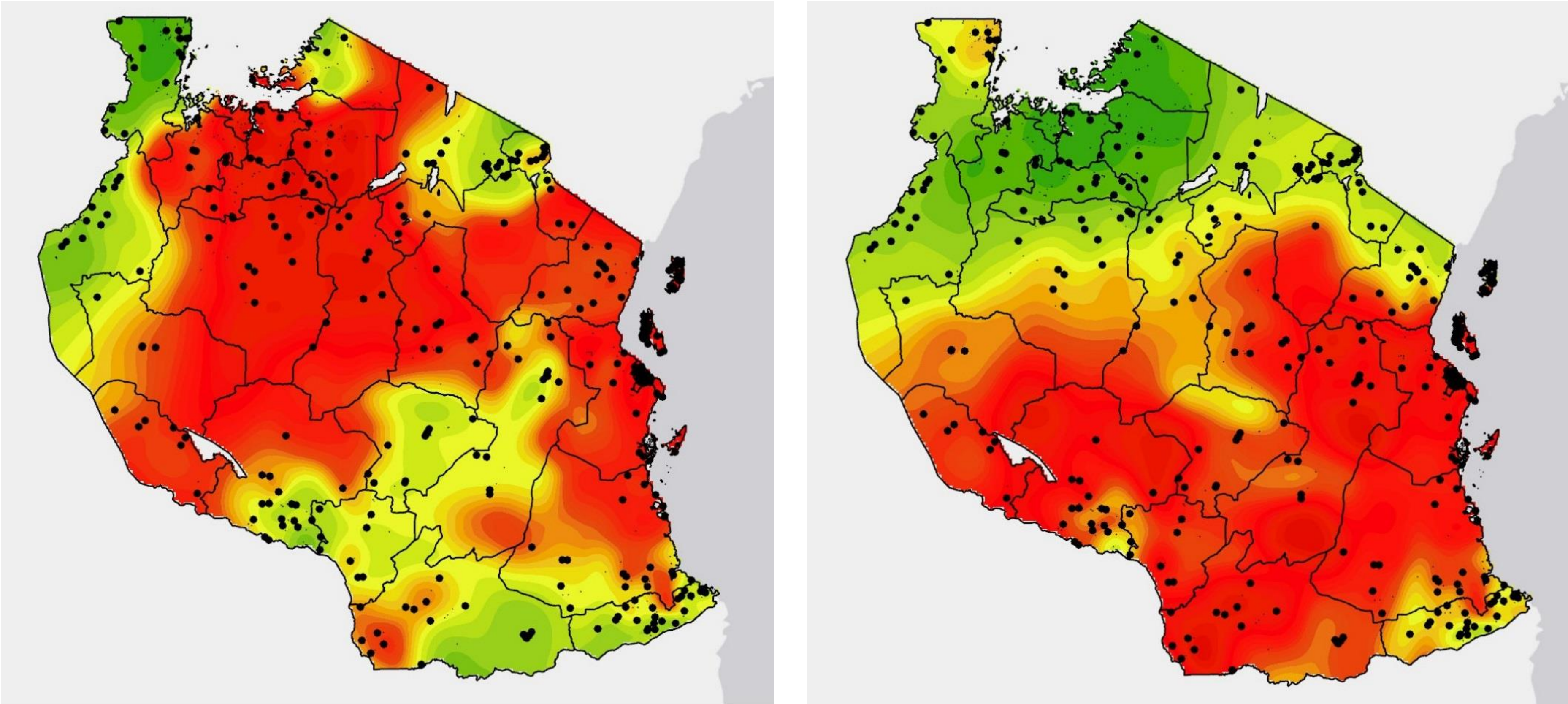


Figure A3: Deviation from Long-term Average Rainfall in the 2010 and 2012 survey years

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 A1: 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 Access	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
Rainfall Shocks					
Normalized rainfall-deviation (HH)	-0.0632	0.9343	-0.1105	0.9624	0.0353
Drought indicator (below 1SD of mean)	0.3645	0.4814	0.3459	0.4758	0.0275

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 A2: Contemporaneous rainfall and household characteristics

Variables	Dependent variable: Rainfall shock
Mean household age	-0.004
	(0.006)
HH head formal schooling	-0.035
	(0.112)
Employment of HH head:	
Agriculture	0.327
	(0.379)
Public servant	-0.264
	(0.480)
Private sector	0.283
	(0.413)
Self-employed	0.352
	(0.398)
Unemployed	0.171
	(0.399)
Married	-0.031
	(0.134)
Female head	-0.117
	(0.217)
Number of children in household	-0.016
	(0.059)
Household size	-0.004
	(0.047)
Household fixed-effects	Yes
Year fixed-effects	Yes
Observations	3,448
R-squared	0.034

Notes: The entries of Table A2 report the coefficients from an OLS regression of the rainfall deviation measure used in the main estimates on the predetermined household characteristics. The regression includes household and year fixed effects. Robust standard errors, clustered at the enumeration area are reported in parentheses.

Table A3: Effect of Agricultural Output and Agricultural Income on Rainfall Deviation

	Dependent variable: Farm output	
	Natural log of Normalized kilogram	Natural log of shillings
Variables	(1)	(2)
ln rainfall	0.302***	0.185*
	(0.105)	(0.097)
Observations	2,374	2,374
R-squared	0.223	0.226

Notes: The entries of column (1) report the results from a regression of the agricultural yield measured in log kilogram of normalized agricultural output on log of rainfall. In column (2), we provide the coefficient from the monetary equivalent using contemporaneous market prices for each cash crop using prices provided by LSMS-ISA. All regressions include the full set of household controls and year fixed effects. Robust standard errors, clustered at the enumeration area are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Table A4: 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)	-0.081				
	(0.152)				
MM agent (5km Radius)		-0.106			
		(0.140)			
MM agent (10km Radius)			-0.006		
			(0.130)		
MM agent (15km Radius)				-0.061	
				(0.127)	
MM agent (20km Radius)					-0.074
					(0.128)
R-squared	0.176	0.177	0.175	0.176	0.176
Panel B	**Dependent variable: Rainfall shock in year 2012**				
2012 agent distribution	(1)	(2)	(3)	(4)	(5)
MM agent (2km Radius)	0.031				
	(0.103)				
MM agent (5km Radius)		0.091			
		(0.107)			
MM agent (10km Radius)			-0.018		
			(0.120)		
MM agent (15km Radius)				-0.074	
				(0.130)	
MM agent (20km Radius)					-0.089
					(0.144)
R-squared	0.256	0.257	0.256	0.256	0.256

Notes: Each column reports the coefficients from separate regressions of rainfall variations in the 2010 (Panel A) and 2012 (Panel B) periods on the distribution of mobile money agents. 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 A5: 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)	0.004				
	(0.037)				
MM agent (5km Radius)		-0.004			
		(0.033)			
MM agent (10km Radius)			-0.038		
			(0.031)		
MM agent (15km Radius)				-0.046	
				(0.030)	
MM agent (20km Radius)					-0.019
					(0.031)
R-squared	0.289	0.289	0.293	0.295	0.290

Panel B	Dependent variable: long-term variability in community rainfall				
2012 agent distribution	(1)	(2)	(3)	(4)	(5)
MM agent (2km Radius)	0.001				
	(0.032)				
MM agent (5km Radius)		0.001			
		(0.032)			
MM agent (10km Radius)			-0.014		
			(0.039)		
MM agent (15km Radius)				-0.007	
				(0.045)	
MM agent (20km Radius)					0.020
					(0.050)
R-squared	0.272	0.272	0.272	0.272	0.273

Notes: Each column presents the coefficients from separate regressions of the long-run variability in rainfall on the distribution of mobile money agents in 2010 (Panel A) and 2012 (Panel B). The long-run variability of rainfall is given by the standard deviation of rainfall over the 30 year period prior to the first survey. We compute the long-run rainfall variability by merging precipitation data from the four closest weather stations to the enumeration area GPS covariates from the University of Delaware weather data repository. 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 A6: First Stage Instrumental Variable Results and Diagnostic Tests.

Panel A: Estimates Panel A: Mobile Money	(1)	(2)
Agent availability	0.083***	0.083***
	(0.004)	(0.004)
Agent distance	-0.069***	-0.069***
	(0.002)	(0.001)
R-squared	0.985	0.986
F-stat (4, 777)	5109	5209
Diagnostic Panel		
Under Identification Test – Chi-Sq. (3, 777)	18786(0.000)	19452(0.000)
Weak Identification Test - F (3, 777)	6243	6419
Panel B: Mobile Money x Rainfall Shock		
Agent availability x rainfall shock	0.076***	0.076***
	(0.004)	(0.004)
Agent distance x rainfall shock	-0.073***	-0.073***
	(0.001)	(0.001)
R-squared	0.875	0.877
F-stat (4, 777)	12118	12334
Diagnostics Panel		
Under Identification Test – Chi-Sq. (3, 777)	51876(0.000)	53173(0.000)
Weak Identification Test - F (3, 777)	17240	17547
Joint significance		
Kleibergen-Paap rk LM statistic (under identification) Chi-Sq. (3)	240(0.000)	241(0.000)
Kleibergen-Paap Wald rk F statistic (weak identification) F	4649	4809
Household fixed-effects	Yes	Yes
Year fixed-effects	Yes	Yes
Controls	No	Yes
Observations	3,448	3,448

Notes: The entries present the first stage estimates obtained from the main results presented in Table 3 Column 3. Total number of observations for the regression is 3,448 (1,724) households. Panel A reports the first stage estimates for agent availability in the village and its distance to the village while Panel B reports results with both interacted with rainfall shocks. Diagnostics Panel reports the diagnostic tests for the first stage estimates where maximum test statistic from Stock-Yogo weak ID F test critical at 10% maximal IV size is 16.87. R-squared values are obtained from the OLS regression of mobile money on agent availability and proximity and their interactions with rainfall shock respectively. 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 3 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 A7: DiD Estimates for the Effect of Mobile Money on Per-capita Expenditure and Relative Poverty

	Dependent Variable:	
	Per-capita Expenditure (ln)	Relative poverty
Variables	(1)	(2)
Mobile money	-0.076	-0.033
	(0.109)	(0.062)
Rainfall shock	0.013	0.008
	(0.017)	(0.011)
Interaction (MM x RS)	-0.027	0.040
	(0.064)	(0.046)
Overall effect	-0.013	0.048
	(0.050)	(0.037)
Mean outcome	13.102	0.123
Household fixed-effects	Yes	Yes
Year fixed-effects	Yes	Yes
Controls	Yes	Yes
Observations	3,448	3,448
R-squared	0.098	0.121

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 (Column 1) and relative poverty (Column 2). See notes in Table 3 (column 2) for details on the specifications and the set of controls used in the estimation. Robust standard errors, clustered at enumeration area are reported in parentheses.

Table A8: DiD Estimates for the Effect of Mobile Money on Poverty Classification, by Time from Harvest

	Within six months of harvest	After six months of harvest
	(1)	(2)
Mobile money	-0.164	0.008
	(0.118)	(0.131)
Rainfall shock	0.021	0.062**
	(0.020)	(0.030)
Interaction (MM x RS)	-0.032	-0.184*
	(0.075)	(0.100)
Overall effect	-0.012	-0.121*
	(0.059)	(0.074)
Mean outcome	0.277	0.279
Household fixed-effects	Yes	Yes
Year fixed-effects	Yes	Yes
Controls	Yes	Yes
Observations	1,444	1,664
R-squared	0.173	0.226
Number of observations	722	832

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. Entries in column (1) present coefficients for households surveyed in the first six months of harvest while column (2) presents the estimates for households surveyed after six months from the main harvest. See notes in Table 3 (column 2) 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 A9: DiD Estimates for the Effect of Mobile Money on Poverty Classification, Including Enumeration Area Trends

	Dependent Variable: Absolute Poverty			
Variables	(1)	(2)	(3)	(4)
Mobile money	-0.056	-0.050	-0.053	-0.055
	(0.081)	(0.081)	(0.081)	(0.081)
Rainfall shock	0.046***	0.045***	0.046***	0.046***
	(0.016)	(0.016)	(0.016)	(0.016)
Interaction (MM x RS)	-0.125**	-0.127**	-0.127**	-0.126**
	(0.057)	(0.057)	(0.057)	(0.057)
Overall effect	-0.079*	-0.082*	-0.081*	-0.080*
	(0.044)	(0.044)	(0.044)	(0.044)
Mean outcome	0.283	0.283	0.283	0.283
Community varying linear trend	No	Yes	No	No
Community varying quadric trend	No	No	Yes	No
Community varying cubic trend	No	No	No	Yes
Household fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	3,448	3,448	3,448	3,448
R-squared	0.189	0.189	0.189	0.189

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 enumeration area specific time varying trends. See Table 3 for the specification and for the controls used in each regression. Each regression is clustered at the enumeration area. Robust standard errors, clustered at the enumeration area are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Table A10: OLS Estimates of the Effect of Mobile Money on Remittances, by Access to Bank Accounts

	Dependent Variable: Remittances			
	Panel A: No bank account		Panel B: Bank account available	
Variables	Indicator	ln Remittance Amount	Indicator	ln Remittance Amount
	(1)	(2)	(3)	(4)
Mobile money	0.325***	3.235***	0.154	2.307
	(0.082)	(0.921)	(0.300)	(3.499)
Mean outcome	0.217	2.210	0.254	2.822
R-squared	0.144	0.132	0.134	0.124
Observations	1,504	1,504	315	315

Notes: This table reports estimates of mobile money adoption in the households on remittances received by households using data from the 2012 LSMS wave. Columns (1) and (2) present estimates for outcomes and specifications for households without bank account, and columns (3) and (4) for households with access to a bank account. See notes in Table 3 for additional details. Robust standard errors clustered at the enumeration area are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

Table A11: DiD Estimates for the Effect of Mobile Money on 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	-0.128	0.066	-0.440*	-0.699**	0.023
	(0.351)	(0.116)	(0.262)	(0.318)	(0.149)
Rainfall shock	0.003	0.000	-0.080*	0.019	0.001
	(0.055)	(0.018)	(0.049)	(0.036)	(0.023)
Interaction (MM x RS)	0.064	0.021	0.225	-0.192	0.004
	(0.223)	(0.068)	(0.166)	(0.188)	(0.096)
Overall effect	0.067	0.021	0.145	-0.173	0.005
	(0.183)	(0.053)	(0.124)	(0.161)	(0.077)
Mean outcome	2.628	0.867	0.270	0.302	0.256
R-squared	0.033	0.101	0.024	0.089	0.015
Observations	1,926	1,926	1,520	1,520	2,438
Panel B : Girls					
Mobile money	0.078	0.040	-0.642***	-0.612**	0.330**
	(0.388)	(0.098)	(0.243)	(0.271)	(0.150)
Rainfall shock	-0.032	0.012	-0.076*	0.099***	-0.059**
	(0.062)	(0.016)	(0.045)	(0.038)	(0.028)
Interaction (MM x RS)	0.030	-0.002	0.413***	-0.418**	0.325***
	(0.275)	(0.060)	(0.152)	(0.163)	(0.109)
Overall effect	-0.002	0.010	0.337***	-0.319**	0.265***
	(0.226)	(0.048)	(0.114)	(0.133)	(0.086)
Mean outcome	2.727	0.893	0.285	0.300	0.383
Observations	1,996	1,996	1,654	1,652	2,360
R-squared	0.042	0.092	0.044	0.122	0.027
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. See notes of Table 7 and 8 for additional details. Robust standard errors, clustered at the enumeration area are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent, respectively.

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.[45] 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

[45] 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.

available in similar household survey data. The intra 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.

Appendix 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. We use annual rainfall because households can choose to cultivate either in the short or long rainy seasons. However, data from the agricultural questionnaire of LSMS-ISA show that households in Tanzania predominantly engage in the long rainy seasons' agricultural activities, perhaps possibly due to higher certainty of agricultural yields from the long rainy seasons between December and February as against short rainy seasons in June and July cultivation. 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:

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

where $\text{R}_{\text{ht}-1}$ 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 $\text{Rainshock}_{\text{ht}-1}$ 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.[46] 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) (see Appendix A3) to ensure the rainfall shock realization is a measure of the current economic resources of the households.[47]

[46] 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.
[47] 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).

Appendix A3. Details on IV-DiD estimation strategy

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.

$$\mathrm{MM_{ht}} = \boldsymbol{\varphi_1}(\mathrm{Agent_c}) + \boldsymbol{\varphi_2}(\mathrm{Agent\_dist_c}) + \xi_{ht} \tag{3}$$

$$\mathrm{MM_{ht}} * \mathrm{Rainshock_{ht-1}} = \boldsymbol{\varphi_1}(\mathrm{Agent_c} * \mathrm{Rainshock_{ht-1}}) + \boldsymbol{\varphi_2}(\mathrm{Agent\_dist_c} * \mathrm{Rainshock_{ht-1}}) + \varsigma_{ht} \tag{4}$$

where $\mathbf{Agent_c}$ represents an indicator variable for mobile money agent availability, and $\mathbf{Agent\_dist_c}$ 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.

We estimate equation (1) using two-stage least squares (2SLS). In equations (3) and (4), 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 we use the smoothed values of the mobile money indicator variable for mobile money access propensity 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.