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Is Mobile Money Changing Rural Africa? Evidence from a Field Experiment

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Abstract

Rural areas in sub-Saharan Africa are typically underserved by financial services. We measure the economic impact of introducing mobile money in rural villages of Mozambique using a randomized controlled trial. Administrative records show that mobile money availability translated into substantial adoption of these services. It also improved consumption smoothing by treated households, which became less vulnerable to both adverse geo-located weather and idiosyncratic shocks. However, mobile money led to reduced investment, especially in agriculture. Our findings suggest that mobile money facilitated rural out-migration by reducing the transaction costs associated with migrant remittances and thereby improving insurance possibilities.

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Keywords: mobile money, technology adoption, insurance, consumption smoothing, investment, remittances, savings, migration, Mozambique, Africa.

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1. Introduction

Financial inclusion is a challenge in many parts of the world. Even though substantial improvements have been made in recent years, access to financial services in sub-Saharan Africa is still very limited: in 2017, only about one third of adults had a bank account, while less than half of these individuals had formal savings accounts.[1] There are also substantial costs and risks when sending or receiving money transfers in this region: the average cost of sending remittances to sub-Saharan African countries is higher than to all other regions in the world, and the top ten most expensive remittance corridors in the world are all within Africa.[2]

At the same time, the use of mobile phones has been dramatically changing the African landscape: the unique subscriber base of mobile phones nearly doubled between 2007 and 2012, making sub-Saharan Africa the fastest growing region globally for the adoption of mobile communication. By the end of 2016, there were 420 million unique mobile subscribers (and 731 million active SIM connections) in sub-Saharan Africa, surpassing the number of unique mobile phone subscribers in the United States.[3] Access rates to mobile phone services in sub-Saharan Africa are even higher than the referred numbers since entire households often share a single phone. This technological revolution has the potential to make mobile phones used for many more purposes than simple voice communication and text messaging. One such example is mobile money.

Mobile money allows financial transactions to be completed using a cell phone. The four types of transactions typically made available through mobile money services are: (i) cashing-in at a mobile-money agent, i.e., exchanging physical cash for e-money usable on the cell phone; (ii) transferring e-money to another cell phone number; (iii) paying for products or services using e-money; (iv) cashing-out, i.e., exchanging e-money for physical money at a mobile-money agent.

Mobile money was made popular by Safaricom's M-PESA in Kenya, which was launched in March 2007. By September 2009, US$3.7 billion (close to 10 percent of Kenya's GDP) had been transferred through the system. In April 2011, M-PESA had 14 million subscribers (equivalent to around 60 percent of the Kenyan adult population) and close to 28 thousand agents.[4] This was the start of the so-called mobile money revolution, even though no other country in the world could yet replicate the remarkable success of mobile money in Kenya.

[1] See Demirgüç-Kunt et al. (2018) on the latest Findex database.
[2] World Bank. *Remittance Prices Worldwide 2018*.
[3] GSMA Intelligence. *Sub-Saharan Africa Mobile Economy 2017.* Available at www.gsma.com.
[4] See Jack and Suri (2011) and Mbiti and Weil (2013, 2016) for a detailed description of the introduction of M-PESA in Kenya.

This paper presents, to the best of our knowledge, the first experimental evidence on the impact of introducing access to mobile money in rural locations that previously had no formal financial services available. We designed and conducted a randomized field experiment where mobile money was introduced in rural villages of southern Mozambique. Providing access to mobile money services in this context represents a clear potential reduction in transaction costs for remittances and savings, namely when one considers the typical alternatives in place: sending money in person or via bus drivers is slow, expensive and risky; keeping cash 'under the mattress' can be unsafe and is open to temptation spending, lack of self-control and pressure by others.

Our project aims at measuring the economic impact of introducing mobile money for a panel of rural households. We are particularly interested in documenting impact (i) on mobile money adoption patterns, (ii) on fundamental outcomes related to welfare, such as consumption and investment, and (iii) on the patterns of remittances and savings, as mediators for the impact on the more fundamental economic outcomes.

The field experiment took place in 102 rural Enumeration Areas (EAs) in the provinces of Maputo-Province, Gaza, and Inhambane, in southern Mozambique. In half of these locations, randomly chosen, a set of mobile money dissemination activities took place. These activities included the recruitment and training of agents in each treatment location, community theatres and community meetings where mobile money services were explained to the local population, and a set of individual dissemination activities. The individual level activities included registration and experimentation of several mobile money transactions with trial e-money provided by the campaign team.

Measurement in this paper comes from administrative data made available by the mobile money operator that sponsored the interventions. This includes transaction-level details for all transactions performed by our panel of experimental subjects for the three years between June 2012 to May 2015. These administrative data on mobile money adoption are complemented by behavioral measures of adoption that measured both the marginal willingness of respondents to save and remit, as well as their willingness to use mobile money as a substitute for traditional savings and remittance channels. We also make use of administrative data on geo-referenced weather shocks, in order to account for a major flood that took place in some of our sampled locations about 6 months after mobile money had been introduced in these areas. Finally, we also conducted three waves of household surveys in the rural locations included in the study, targeting our panel of respondents. These surveys allow us to measure our main outcomes of interest - consumption, investment, as well as remittances and savings for these households.

We find evidence of strong mKesh adoption in the rural treatment locations. According to administrative data from the mobile money operator, 76 percent of the sample of treated individuals conducted at least one transaction using mobile money in the year after the initial dissemination. Although general adoption decreased slightly over the full duration of our analysis, overall 85 percent of individuals in our sample in treated areas used the service over the three years. The adoption picture taken using the administrative records is very much in line with the findings from the adoption behavioral games played by the experimental subjects. We measured a clear increase in the (marginal) willingness of sampled individuals to send transfers. Interestingly, the magnitude of these effects increased over time in the different survey waves, presumably as familiarity and trust in the mobile money system increased. There was, however, no significant change in the marginal willingness to save when mobile money services were made available. We also report a positive effect on the willingness to use mobile money to conduct transfers and to keep savings instead of alternative traditional transfer and saving methods – a fact that is corroborated by both administrative and survey data.

The experimental results show that the availability of mobile money has likely improved the welfare of rural households since their vulnerability to shocks diminished. Specifically, even though we do not observe significant treatment effects on consumption for households not affected by shocks, we do find important consumption smoothing when households are faced with negative shocks. We also report a reduction in the episodes of hunger experienced by families in treated locations. This result seems to be driven by an increase in remittances received by treated rural households, since (formal and informal) savings did not change significantly.

Importantly, we also find that agricultural activity and investment progressively fell after the introduction of mobile money in treatment rural areas. This pattern of disinvestment is consistent with an increase in out-migration over time from treated rural areas, which we confirm in our data. We explain this migration response in the context of a simple theoretical model where the introduction of mobile money reduces the transaction costs associated with long-distance transfers and thereby improves household-level insurance possibilities, which incentivizes migration.

Our work relates to a growing body of recent literature examining the expansion of mobile money use. This literature was initially focused on the Kenyan success story of M-PESA. The earlier studies by Mbiti and Weil (2013, 2016) and by Jack and Suri (2011), point to internal migrant remittances as the main driving force behind the success of M-PESA.[5] This evidence is consistent with our finding of increased remittances to rural

[5] There is also a number of early descriptive studies about M-PESA – see, for example, Mas and Morawczynski (2009).

households after the introduction of mobile money in our experimental locations. Mbiti and Weil (2013), however, observe estimates of e-money velocity that are consistent with mobile money being used as a storage instrument as well. Jack and Suri (2011) describe the M-PESA experience in detail, while pointing out several possible mechanisms of impact.

More recent contributions relate mobile money to consumption smoothing. Jack et al. (2013) and Jack and Suri (2014) follow a panel of households to show that the consumption of households with access to M-PESA is not hurt by idiosyncratic shocks, which implies that decreased transaction costs for transfers promote risk sharing – a finding that our work replicates using an experimental design. This evidence is also confirmed by Riley (2018), who analyzes a panel of households in Tanzania, and by Lee et al. (2020), who study the experimental impact of incentivizing mobile money usage in Bangladesh among both rural households and their migrant family members in urban areas. These contributions extend the seminal work by Townsend (1994) and Udry (1994), who first documented the importance of informal risk sharing in rural settings for insuring against idiosyncratic risk. A number of related contributions followed. Limited commitment in general equilibrium models is shown to improve our understanding of observed patterns of mutual insurance (e.g., Ligon et al., 2002). Other important studies (Fafchamps and Lund, 2003; DeWeerdt and Dercon, 2006) put the emphasis on network structures within villages to test for the degree of consumption smoothing. Blumenstock et al. (2016) examine the nature of transfers using cell phone airtime (which may be thought of as an early version of mobile money) before and after an earthquake in Rwanda. They also find evidence supportive of risk sharing.

A more recent branch of literature describes the potential of mobile money as a tool to promote economic development in different areas. Suri and Jack (2016) document positive effects of mobile money on savings in Kenya, along with impacts on the occupational choices of women. Their overall poverty-reduction result is in line with Aker et al. (2016), who describe the positive poverty-reduction impact of a cash transfer program implemented using mobile money in Niger after a natural disaster. In a different context, Blumenstock et al. (2018) show how mobile salary payments can increase savings due to default enrollment, even long after salaries are paid. More in line with the lack of impact of our intervention on savings, De Mel et al. (2020) conducted a RCT of an intervention offering different levels of reduced fees to make mobile deposits in Sri Lanka and found that adoption was limited and concentrated on women and those living far from commercial banks - but there were no increases in household savings.

In a different line of work, Jack and Habyarimana (2018) examine the impact of randomizing access to a mobile money savings account in Kenya as a way to successfully increase savings and access to high school. Batista and Vicente (2020b) test the impact of offering interest-bearing savings accounts through mobile money to individual farmers and their networks in Northern Mozambique – thereby exploring the network dimension of mobile money adoption. Batista et al. (2019) also facilitate access to an interest-bearing mobile money savings account, cross-randomized with a busines training program designed to promote microenterprise development in urban areas of Mozambique. Similarly, Bastian et al (2018) and Aggrawal et al. (2020a, 2020b) also conduct experiments promoting mobile money use among microentrepreneurs in Tanzania and Malawi, respectively. In all these studies, mobile money worked as an effective tool to increase savings, although the impact on business performance varied across studies and some results of the latter two projects are not yet available.

This paper is also related to the literatures on the development impact of remittances and savings in developing countries. As made clear in the literature review by Yang (2011), there is limited causal evidence on the development impact of remittances. Yang (2008) employed exchange rate shocks in the Philippines induced by the 1997 Asian financial crisis: he finds that increased migrant resources generated by exchange rate appreciation are used primarily for investment in origin households, rather than for current consumption.[6] Yang and Choi (2007) show evidence that migrant remittances serve as insurance in face of negative weather shocks in the Philippines. Our results are consistent with some of these results, as we observe that lower transaction costs lead to increased remittances and, as consequence, to improvements in consumption smoothing. However, we do not find evidence supportive of productive or investment effects of remittances.

On savings, Karlan and Murdoch (2010) called for an understanding of the impact that introducing new access technology may have on savings, as unintended consequences are possible: liquidity may carry self-control problems and exacerbate social pressure to consume for time inconsistent individuals (as in Ashraf et al., 2006). Despite these concerns, Dupas and Robinson (2013) show that access to non-interest-bearing bank accounts in rural Kenya significantly increased savings, a finding that highlights the potential unmet demand for saving products in rural settings.[7] We do not find a similar result in our experiment, where overall saving behavior did not significantly change. This is likely related to the fact that mobile money is not systematically used as a savings method.

This paper is organized as follows. In Section 2 we provide a background description of Mozambique and of the introduction of mobile money in the country. Section 3 presents the theory of change and hypotheses to be tested in our field experiment. Section 4 describes the experimental design, including sampling, experimental

[6] This investment takes the form of educational expenditures and entrepreneurial activities. Other recent studies focusing on African countries found similar effects of migration: on education in Cape Verde (Batista et al., 2012) and on entrepreneurship in Mozambique (Batista et al., 2017).
[7] Recent work by Callen et al. (2019) shows that when formal savings became available for a sample of Sri Lankan households, they worked more in order to benefit from those additional saving opportunities.

intervention, measurement strategies, balance tests and attrition checks. Section 5 proposes an econometric strategy and displays the empirical specifications to be estimated. Section 6 analyzes results on adoption and on the impact of introducing mobile money on the main outcomes of interest. Section 7 discusses the empirical findings and proposes a simple theoretical model to explain how out-migration from treated villages acts as an important mechanism underlying our results. Finally, Section 8 provides concluding remarks and directions for further research.

2. Background

Mozambique is one of the poorest countries in the world. According to the Word Bank, the latest available numbers show that 82 percent of the population lives in poverty, with less than 3 USD a day, and that 65 percent of the population lives in rural areas.[8] At the same time, there were over six million subscribers of mobile phone services in the country (corresponding to nearly one fourth of the population), and mobile phone geographical coverage extended to 80 percent of the population at the time our randomized intervention started in 2012.[9]

Mozambican authorities passed legislation in 2004 that allows mobile operators to partner with financial institutions in order to provide mobile money services. Under this legislation, complemented with an operating license issued in 2010, Mcel, the main mobile telecommunications operator, established a new company, Carteira Móvel, which started offering mobile money services, branded as mKesh, in January 2011.[10] In an initial effort to recruit mKesh agents, Carteira Móvel recruited around one thousand agents in just a few months after September 2011. However, these agents were based mainly in urban locations, particularly in Maputo city. In this context, Carteira Móvel regarded the launching of this research project as an opportunity to test the impact of mKesh dissemination in rural locations of the country before any systematic efforts in that direction.

The potential of mobile money in rural Mozambique is considerable. Bank branches typically do not reach beyond province capitals and some district capitals.[11] Typical methods for transferring money and saving in rural Mozambique entail significant costs and risks. Bank transfers require significant travel costs to use bank

[8] World Development Indicators, 2018.
[9] Computed from data made available by Mcel and Vodacom, the only two mobile phone operators in Mozambique at this time. A competitive market composed by state-owned Mcel and Vodacom (linked to the multinational Vodafone) was in place since 2003, although a third operating license was awarded to Movitel (linked to the Vietnamese multinational Viettel), which started operating in Mozambique still in 2012.
[10] Note, however, that the formal mKesh launch and first advertising campaign of this service on national media was only aired in September 2011.
[11] From the list of bank agencies made available by the Bank of Mozambique in December 2011, for the 18 districts that we cover in our study, only 37 bank agencies were reported to exist in those districts (just over two on average per district, where each district has an average population of 170,000 inhabitants).

branches. Alternatively, senders need to travel to the location of recipients or use a bus driver as courier (who typically charges a 20 percent fee and may not deliver the money at all). Mozambique is reported to be in the top four countries in terms of most expensive remittances in Sub-Saharan Africa, and formal bank transfers cost on average 22 percent of the value of the transfer in bank fees.[12] Saving methods for the rural population are often limited to hiding money ‘under the mattress’ (often money is hidden in cans and buried underground), keeping money with local traders or authorities, and participating in ROSCAs.[13] None of these arrangements typically pays interest, and some of them carry considerable risks. Mobile money services as provided through mKesh offer the possibility of transferring money and saving at considerably lower costs and risks than the existing alternative channels.

3. Theory of change

Inspired by the remarkable success of the M-Pesa mobile money service in Kenya, our project was designed to experimentally measure the impact of introducing mobile money services in a setting where its economic effects could be substantial. For this reason, we chose to work in rural areas of southern Mozambique where the levels of financial inclusion were low and there were active internal migration corridors to the capital city of the country, Maputo.

The main hypotheses to be tested in this project depart from mobile money substantially reducing the transaction costs associated with long-distance (e.g., urban-rural) transfers. In addition, in face of the very limited supply of formal financial services, the availability of mobile money also greatly decreases the cost of holding formal savings. We conjecture that, faced with this exogenous drop in the cost of long-distance transfers and of holding formal savings, households will adjust their optimal levels of consumption and investment.

Existing evidence shows that increased remittances are used both to raise consumption levels of the recipients, and to boost their investment levels. As documented by several descriptive studies, migrant remittances play an important role in improving consumption levels and limiting poverty of recipient households, especially when these are hit by negative shocks.[14] Other studies, like Yang (2008), have shown that increases in remittances are spent expanding investment in educational expenses and entrepreneurial activities.

[12] See World Bank (2015a), *Remittance Prices Worldwide*.
[13] We report for the sample of rural households that we study the following statistics: 63 percent save money at home, 30 percent save money with a local trader, and 21 percent participate in a ROSCA. Only 21 percent report any money saved in a bank account.
[14] See, for example, Adams and Page (2005), Yang and Choi (2007) and Acosta et al. (2008).

Increased savings could mechanically be achieved by cutting consumption. Boosted household savings could result in additional investment as has been found by several recent experiments. For example, Dupas and Robinson (2013) show that providing access to formal savings accounts in Kenya increased savings and business investment particularly for female business owners. Similarly, Batista et al. (2019) find that female business owners in Mozambique who are offered interest-bearing mobile savings accounts also benefit the most from this intervention. In an agricultural setting in central Mozambique, Batista and Vicente (2020b) obtain that tailored interest-bearing mobile savings accounts offered to smallholder farmers right after harvest promoted fertilizer usage in their agricultural plots.

In this context, we established our main outcome variables of interest to be mobile money adoption (a necessary condition for any subsequent economic impact of mobile money), as well as household levels of consumption and investment - the main welfare determining outcomes of interest for the project. We also examine the impact of introducing mobile money on remittances received and savings, as mediators for the impact of mobile money on consumption and investment.

4. Experimental design

4.1. Sampling and randomization

In order to evaluate the impact of introducing mobile money services in rural Mozambique, we selected a sample of rural areas where mobile money services had never been made available before: 102 rural Enumeration Areas (EAs) were chosen in the provinces of Maputo-Province, Gaza, and Inhambane. These EAs were sampled randomly from the 2008 Mozambican census for the referred provinces.[15] For each EA to be included in our sampling framework two additional criteria had to be met. First, the EA had to be covered by Mcel signal – this was first checked by drawing 5-km radii from the geographical coordinates of each Mcel antenna, and then confirmed by a strong cell signal at the actual location of each EA. Second, there needed to be at least one commercial bank branch in the district of each EA to ensure that mobile money agents could access liquidity for their business at a reasonable (time and money) cost. To define this sampling framework, Mcel made available the geographical data on its antennae, and the Central Bank of Mozambique made available the data on the location of all commercial bank branches in the country.

[15] Note that in Maputo-Province, only its northern districts bordering the Gaza province were considered, as they included all rural locations not in close proximity to the Maputo capital city.

The households that took part in this study were selected at the EA level. We sought household heads while following an n-th house random walk departing from the center of the EA along all walking directions. However, additional conditions had to be observed by households to be included in our sample. All sampled households had to own a Mcel phone number – this was not a binding constraint as Mcel was the only cell phone provider in these rural areas at the time of the baseline survey.

In total, 2004 individuals were included in the baseline survey, which served the purpose of identifying all experimental subjects before the treatment activities at the community and individual levels. We interviewed an average of 20 individuals per EA.

The mKesh dissemination intervention was block-randomized using pairs of EAs from the full set of 102 EAs. The blocks were selected by matching on geographic characteristics. The 51 treatment EAs were then drawn randomly within each block. Figure 1 shows the location of the 102 EAs in our study, split between treatment and control.

<Figure 1 near here>

Note that the individual-level treatment, as well as invitations for community-level dissemination events, was submitted only to a subsample of the survey respondents in treatment locations. This subsample had on average 16 individuals per EA and was drawn randomly within the EA. We call the individuals that were given the individual treatment and the invitations within a treatment EA the ‘targeted individuals’, and the individuals that were not given the individual treatment and the invitations the ‘untargeted individuals’. The specific dissemination interventions that were conducted are described in the following section.

4.2. Randomized intervention

The randomized intervention we evaluate included both the introduction and dissemination of mobile money services in 51 rural locations of the provinces of Maputo Province, Gaza, and Inhambane, in southern Mozambique. We partnered with Carteira Móvel, the only mobile money provider in the country at the time, for this purpose. Because mobile money services were not previously available in any of the rural locations included in our sample, the intervention included three different stages. First, the recruitment and training of mKesh agents. Second, the holding of a community theater and of a community meeting describing and demonstrating mKesh services. Third, the individual dissemination of mKesh to a randomly selected group of villagers.

The first stage consisted of the recruitment of one mobile money agent per location, and took place between March-May 2012. The recruited agents were typically local grocery sellers. Three main criteria were sought when proposing local vendors to become mKesh agents. First, they were required to hold a formal license to operate as vendors, implying they had a legally established business as required by the applicable mobile money regulation. Second, they were required to have a bank account, which ensured minimum levels of financial literacy. Third, they were assessed as having a sufficiently high level of liquidity in their business, which often translated to observing that businesses had full shelves - this was typically the case for the largest business in each village).

After randomization of treatment status, each treatment location was visited on purpose for the on-site recruitment of agents. Training of the agents followed in a second visit. At this point in time, the contract signed by Carteira Móvel, as well as agent materials, were handed out to the agents. The materials included an official poster (to identify the shop as an mKesh agent), other mKesh advertising posters, and an mKesh agent mobile phone to be used exclusively for all mKesh transactions. A briefing describing the remaining dissemination activities in rural areas was held at this point. This included a description of the community theater and meeting to be subsequently held in the village, and a review of all mKesh operations, with an emphasis on registration of clients, cash-ins, purchases in shop, and cash-outs.

The second stage of the intervention included a community theater and a community meeting to disseminate mobile money services at the community level. These events were held one after the other in close proximity to the mobile money agent's shop. These community-level events were advertised with the support of local authorities. The playing of the mKesh jingle from the mKesh shop also helped drawing attention to the events. The script of the community theater was the same for all treatment locations, and answered frequently asked questions – including mentions of mKesh safety (based on a PIN number), transfers using mKesh, savings using mKesh, and the mobile money self-registration process. The context was a village scene, with a household head and his family/neighbors.[16] The community meeting, which had the presence of local village authorities, gave a structured overview of the mKesh service, and allowed interaction with the community as questions and answers followed the initial presentation.

The third and final stage of the dissemination activities was conducted at the individual level for the targeted individuals, i.e., those approached individually by mKesh campaigners. In this context, campaigners distributed a leaflet, which structured the individual treatment. This leaflet had a full description of all the mobile money

[16] This script is available from the authors upon request.

operations available, while also providing the mobile phone menus to be used to perform each operation. The leaflet is displayed in Figure 2.

<Figure 2 near here>

Campaigners described the leaflet and asked targeted individuals whether they wanted to self-register to use the mKesh services. If they did, the campaigners helped individuals follow the self-registration menu. Self-registration required that individuals provided their name and their identity card number. Campaigners then offered 76 MZN (about 3 USD) of free trial money to be cashed-in to the mKesh account of each individual. For this purpose, targeted individuals had to accompany the campaigners to the shop where the mKesh operated in their village. The cash-in menu instructions were then followed at the mKesh agent location with the purpose of cashing-in the 76 MZN to the individual's mKesh account. After the cash-in was made, campaigners helped targeted individuals to check the balance in their mKesh accounts. Subsequently, each targeted individual was asked to buy something in the agent's shop for the value of 20 MZN. This transaction was then made in the presence of the agent, which implied a 1 MZN fee. Finally, targeted individuals were explained how a transfer could be done to another mobile phone and how they could cash-out the remaining 50 MZN from their account - the transfer would cost a 5 MZN fee, which, together with the 1 MZN fee for the in-shop purchase, would add up to the 76 MZN total cashed-in by mKesh campaigners in each individual account. Targeted individuals were also briefed about the pricing structure of the mKesh services - a page in the mKesh leaflet left with each targeted individual provided this information. Figure 2 includes all the specific menus followed by campaigners during the process just described.

The community and theater meetings as well as the individual treatment were conducted in the period June-August 2012. In July-September 2013 and July-September 2014, the communities in our sample were revisited for the purpose of conducting the surveys. Around those moments in time, the agent network was re-evaluated and given particular attention in the field. That implied, from the side of the mobile money operator, an additional effort in solving the problems faced by agents and communities related to the local provision of the mobile money services.

4.3. Measurement

The measurement of the impact of the intervention described in the previous sections is based on four main sources of data. First, we make use of the administrative records of mobile money transactions carried out by all individuals in our sample since the beginning of the project in July 2012. Carteira Móvel made these records available to us for the subsequent three years (until July 2015). The data include for each individual and for each transaction conducted: the date of the transaction, the type of transaction, the transaction amount, and the value of any fees paid.

Between July 2012 and June 2015, a total of 15,971 transactions were recorded in the mobile money system for our sample of experimental subjects. Naturally, all transactions related to the initial individual dissemination activities conducted by mKesh campaigners (namely, initial cash-in, balance check, and in-shop purchase) are excluded for the purpose of our analysis.

Second, we collected geo-referenced data to measure the flood shocks that affected Mozambique in the 2012/2013 rainy season.[17] Specifically, we use the Standardized Precipitation Evapotranspiration Index (SPEI) proposed by Vicente-Serrano et al. (2010) corresponding to each of our EAs since 1981. The SPEI extends the (previously) most commonly used Standardized Precipitation Index (SPI) in that it is based on water balance, i.e., the difference between precipitation and potential evapotranspiration (calculated taking into account average temperatures, wind speed, vapor pressure, and cloud coverage). This provides a much-improved measurement of extreme weather conditions, as evaporation and transpiration can consume a large fraction of rainfall. In our work, we define flood shocks as happening in areas with SPEI values above two standard deviations relative to the average computed for the 1981-2010 period.[18] These data are used in our work to provide a rigorous measure of flood shocks affecting all our experimental locations. Note that the January 2013 flood affected 69 percent of all locations in our sample, evenly balanced across treatment and control locations (balance test with a p-value of 67 percent).

Third, we use behavioral measures of the marginal willingness to remit and to save, as well as of the marginal willingness to substitute between mobile money and conventional remittance and savings mechanisms. These measures were obtained by playing games with all individuals in our sample, both in treatment and control locations, in all survey rounds. The games allowed us to elicit information on how individuals' marginal propensity to save and remit changed after the introduction of mobile money, as well as on the marginal propensity of these individuals to use mobile money as a substitute for traditional saving and remittance mechanisms. These games are described in detail in the Appendix to this paper.

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[17] For a description, see for example the report by the United Nations OCHA Regional Office for Southern Africa (ROSA), available at:
http://reliefweb.int/sites/reliefweb.int/files/resources/Southern%20Africa%20Floods%20Situation%20Report%20No.%205%20%28as%20of%2008%20February%202013%29.pdf (last accessed on April 20, 2019).

[18] Using the longer time spell 1961-2010 for which data are available does not change our results. The earlier periods are however likely to be subject to more noise in measurement, hence our choice, following the literature, to use 1981 as the starting point for our reference long run period.

Finally, we conducted survey measurements targeted at our panel of subjects of our outcome variables of interest. These measures were taken at the baseline survey (conducted between June and August 2012), one-year follow-up survey (conducted between July and September 2013), and two-year endline survey (conducted between July-September 2014). These three household survey rounds included standard demographic, consumption, investment and savings questions, as well as a full module on remittances in the context of household migration.

4.4. Experimental validity: balance and survey attrition

We now turn to testing the experimental validity of our work. We verify the quality of random assignment of locations and households to treatment status in the baseline sample, as well as in the subsamples interviewed in the following data collection waves. The latter is to limit concerns related to differential attrition.

We performed balance tests for a range of baseline variables. Appendix Table 1a shows balance in the characteristics of treatment and control locations. We note that almost all locations have primary schools, although only 39 percent of control locations have a secondary school. Nearly two thirds of the control EAs have a health center, and 61 percent have market vendors. We note that 63 percent of these locations have electricity supply, but only 14 percent have sewage removal systems in place. The quality of cell phone coverage is classified as above average in the baseline survey (4.7 in a 1-5 scale) in the control locations. 26 percent of control EAs have paved road access, and 71 percent have land road access. They are located at an average of 62 minutes from a commercial bank, and transportation to get there costs about 32 MZN (equivalent to slightly above 1 USD at the time of the baseline survey). In terms of balance across treatment and control locations, we only find one difference between treatment and control that is statistically significant: electricity supply is more frequent in control locations.

Appendix Tables 1b and 1c examine demographic traits of the experimental subjects, including basic attributes (age, gender, education, and marital status), occupation, religion and ethnicity, income and property, technology use and financial behavior. We note that the average individual in the control group has 39 years of age, is female with a 63-percent probability, and has 5.5 years of education. 46 percent of control individuals selected farming as their main occupation, and the main ethnic group is Changana (70 percent of control individuals). We also observe that 86 percent of the control sample owns a plot of land ("*machamba*"), and that 27 percent have a bank account. Respondents in our sample report using their cellphone every day (86% of individuals) or several times every week (13%). At the individual level, we do not find differences between treated and control individuals across a range of variables related to basic demographics, occupation, religion/ethnicity, technology and finance. We only observe minor differences in terms of income and property: specifically, owning cars is less frequent among treated individuals, whereas the opposite happens with motorcycle ownership.

Overall, the results of the balance checks show that our randomization procedure seems to have been effective in building comparable treatment and control groups.

We now turn to concerns related to differential attrition. Note that there is no attrition when considering outcomes measured through the administrative records on mobile money transactions as we have access to the full universe of transactions. Our concerns relate to potential differential attrition across survey rounds. To alleviate these concerns, we performed an analysis of mean baseline survey respondents' characteristics in the different survey waves. The results of this analysis are presented in Appendix Tables A2a and A2b for attrition in the second survey wave, and in Appendix Tables A3a and A3b for attrition in the final survey wave. Overall, differential attrition across the survey waves does not seem to be a concern for our analysis as attrition seems to be uncorrelated with treatment status.

5. Empirical strategy

Our empirical approach targets the estimation of intent-to-treat effects on the main outcome variables of interest following from our theoretical framework. Since the mobile money intervention was randomized and we have baseline (pre-treatment) measures for most outcomes, we use a simple ANCOVA specification including baseline values of the dependent variable as a control variable to identify the intent-to-treat effect of interest (β): [19]

$$Y_{il,t} = \alpha + \beta T_l + \gamma Z_l + \theta X_i + \lambda t + Y_{il,-t} + \varepsilon_{il,t} \qquad (1)$$

In this equation, Y is an outcome of interest, i and l are the identifiers for individual i and location l. Note that time is defined either for post-treatment periods (t) or for the baseline pre-treatment period (-t). T_l is a dummy variable taking value 1 for treatment locations since the intervention was randomized at the location (EA) level, and 0 otherwise. Z_l is a location-level vector of controls including regional dummies and X_i is a vector of

[19] McKenzie (2012) underlines large statistical power gains of using ANCOVA compared to difference-in-differences when a baseline is taken and autocorrelations are low between outcomes in different periods.

individual controls. Finally, ε is the error term. Whenever baseline information is not available for our outcome of interest, we employ the same specification as above, but without baseline values of the outcome, as follows:

$$Y_{il,t} = \alpha + \beta T_l + \gamma Z_l + \theta X_i + \lambda t + \varepsilon_{il,t} \qquad (2)$$

For simplicity and transparency in the presentation of results we employ OLS (or Linear Probability Models for binary outcomes) in all regressions in this paper. Throughout our analysis, standard errors are clustered at the unit of randomization level, which is the EA.

Our empirical approach will be to estimate ITT effects of the randomized intervention on the main outcomes of interest put forward by our theoretical framework (namely adoption, consumption, investment, migrant remittances and savings), followed by an exploration of potential mechanisms and heterogeneous responses. For this purpose, we focus our analysis on a few main variables or indexes, while following this investigation with a more detailed examination of the components of those indices – whenever applicable. To address the issue of multiple hypotheses testing, we compute p-values adjusted for family-wise error rate (FWER) using the step-down multiple testing procedure proposed by Romano and Wolf (2016). This procedure improves on the ability to detect false hypotheses by capturing the joint dependence structure of the individual test statistics on the treatment impacts. For our coefficients of interest, we therefore report both naïve standard errors corrected for clustering at the location level, and FWER-adjusted Q-values that adjust for multiple hypothesis testing, based on 1000 simulations.

6. Econometric results

6.1. Adoption of mobile money – administrative and behavioral data

In order to measure adoption of mobile money following its introduction in treatment locations, we use administrative records for all transactions performed by all individuals in our sample - both in treatment and control locations. These records include the date, value and type of transaction of each individual transaction conducted in the three years between July 2012 and June 2015.

We estimate treatment effects on adoption by employing empirical specification (2).[20] Note that there is no relevant contamination (or alternative means of mobile money adoption) by individuals in the control locations. Indeed, as shown in Table 1a, the percentage of individuals in control locations that conducted at least one transaction varied between 0.5 and 1.2 percent in each of the three years following the introduction of the mobile money service. These results are consistent with the fact that no new mobile money agents opened for business in any of the control locations over the three-year period following the initial intervention. In this context, the treatment effects displayed in Tables 1 are a close proxy to the mean adoption rates of mobile money by treated individuals.

As shown in Table 1a, slightly more than three-quarters of the treated individuals in our sample performed at least one mobile money transaction in the first year following the introduction of the service. This percentage decreased to 53 and 54 percent, respectively, in each of the following two years. Overall, 85 percent more targeted individuals performed mobile money transactions than control individuals in our sample, over the three years for which we have administrative records.

<Tables 1 near here>

As shown in Table 1a, the evolution in mobile money adoption patterns displays interesting compositional dynamics over the three years for which we have data available. Indeed, some of the early adopters used the mobile money service mostly to buy airtime, but this effect lost prominence over time: slightly more than 60 percent of the targeted individuals were buying airtime in the first year, compared to 35 and 33 percent in the following couple of years. This evolution can be understood in a context where all mobile phone users are familiar with airtime purchases, even if mobile money does not provide any substantial advantage relative to traditional airtime purchases – the opposite of what happens with long-distance mobile money transfers, which are much faster, inexpensive and safer than traditional transfer methods, although they require another party also agreeing to use mobile money. Consistently, we observe that in the first year following the introduction of the mobile money service, 45 percent of individuals in treated locations received transfers and 30 percent sent transfers, whereas 24 percent made cash-ins and 28 percent made cash-outs. Over the following three years, new users started making these transactions, bringing total usage rates to 52 percent for transfers received, 38 percent for transfers sent, 45 percent for cash-ins, and 39 percent for cash-outs. Remote payments (mostly long-distance payments of services, such as electricity) started at almost zero usage, but became increasingly more frequent:

[20] Since the mobile money service was not available before the intervention, there is no baseline we can employ in our analysis.

in the last year for which we have data, 6 percent of targeted individuals in treatment locations performed at least one long-distance payment.[21]

Tables 1b and 1c describe the adoption patterns of mobile money in more detail. Again, mobile money usage by control individuals was extremely limited, so that treatment effects are very close to mean usage by treated individuals. Table 1b shows that the average number of transactions conducted per individual over the first year after the service was introduced was 7, but this decreased to an average of 3 in the subsequent two years. Table 1c displays the average value of transactions per treated individual, which reached nearly 1000 MZN (about 40USD) in the three years after the introduction of mobile money.

The adoption behavior measured through the administrative records of the mobile money provider is very much consistent with the data generated by behavioral games played by survey respondents and aimed at measuring their willingness to transfer and save when mobile money became available. These games were specifically conducted in order to measure individual willingness to transfer and save in treatment areas, in comparison with control areas.[22] We show treatment effects in Tables 2 and 3 per year and for all years for both willingness to transfer and to save, both in general and using mKesh.

As can be seen from the results in Tables 2, the availability of mobile money in treated rural areas produced a clear increase in the (marginal) willingness of targeted individuals to send transfers. The overall increase relative to the control was 11 percentage points over the three years in which we played the game. Interestingly, the magnitude of these effects increased over time, presumably as trust in the mobile money system improved. We also report a positive treatment effect on the willingness to use mobile money to conduct transfers instead of alternative transfer methods. This effect corresponds to an increase in 27 percentage points in the probability of using mKesh relative to those individuals in the control group that also chose to remit. Given the very poor remittance channels available before the introduction of mobile money, namely making in-person visits to the rural receivers, or using bus drivers as expensive and risky transfer carriers, it is not surprising that the marginal willingness to transfer increases - in particular using mobile money as a substitute for traditional remittance channels.

<Tables 2 near here>

[21] Batista and Vicente (2020a) provide a detailed description of the characteristics of early and late adopters performing different mobile money transactions.
[22] See the Appendix for a detailed description of these behavioral games.

We now turn to the results of our behavioral games relating to subjects' willingness to save. These are displayed in Tables 3. We find that the marginal willingness to save does not significantly increase with treatment - this effect is only close to marginally significant in 2013 (the p-value is 0.15 after accounting for multiple hypothesis testing). However, the likelihood of saving using mKesh as a replacement for traditional saving methods does increase strongly by 24 percentage points. The magnitude of this effect looks rather stable over the three years of our study. This evidence is consistent with a pattern where total savings are not much affected by the availability of mobile money, but where there is substitution from alternative means of saving towards mobile savings.

<Tables 3 near here>

Overall, the results obtained using both administrative data and behavioral games indicate significant levels of adoption of mobile money, which substitutes for traditional alternative methods to remit and save.

6.2. Consumption, vulnerability to shocks, and subjective welfare

Having established the pattern of mobile money adoption in treated locations, we now turn to evaluating its economic impact. We start by examining the effects of the introduction of mobile money on consumption smoothing, vulnerability to shocks, and subjective welfare.

In order to evaluate the impact of introducing mobile money on consumption smoothing and household vulnerability to shocks, we consider two types of shock variables. First, we use the Standardized Precipitation Evapotranspiration Index (SPEI) proposed by Vicente-Serrano et al. (2010)[23] to measure the flood shocks that affected Mozambique in the 2012/2013 rainy season. In our work, we define flood shocks as happening in areas with SPEI values above two standard deviations relative to the average computed for the 1981-2010 period.[24] According to this measure, the January 2013 flood affected 69% of all locations in our sample, evenly balanced across treatment and control locations (balance test with a p-value of 67.3 percent).

[23] As detailed in section 4.3 on Measurement, the SPEI extends the commonly used Standardized Precipitation Index (SPI) in that it is based on water balance, the difference between precipitation and potential evapotranspiration (calculated taking into account average temperatures, wind speed, vapor pressure and cloud coverage). This provides a most rigorous measurement of extreme weather conditions, as evaporation and transpiration can consume a large fraction of rainfall.
[24] Using the longer time spell 1961-2010 for which data are available does not change our results. The earlier periods are however likely to be subject to more noise in measurement, hence our choice, following the literature, to use 1981 as the starting point for our long-run reference period.

Second, we use a binary indicator variable taking value 1 when a rural household experienced a death in the family, a job loss in the household, or significant health problems in the household in the 12 months before the survey interview – as reported by the household head in the 2014 household survey.[25] This idiosyncratic shock had an incidence of 41 percent in our sample, with this fraction of households being affected by at least one of the negative shocks. This variable is evenly balanced across households in treatment and control locations: the balance test has a p-value of 80.9 percent.

Table 4 shows the results related to household consumption. In column (1), we employ the SPEI flood shock that partly affected our sample in January 2013, about six months after the introduction of mobile money. The estimation results show that when the household is hit by this negative shock, the impact of the mobile money availability on log consumption per capita is positive and strongly significant. Indeed, whereas consumption falls (not significantly) on average for households hit by the flood in control areas, consumption expenditure actually increases by an average 44.2 percent for households who suffered a negative shock in treatment areas relative to those affected in control areas. This evidence is supportive of mobile money contributing to household consumption smoothing in face of negative shocks. Note that the consumption of treated households unaffected by negative shocks does not seem to be significantly changed by the availability of mobile money - indicating that treatment effects in the absence of shocks are not sizable.

<Table 4 near here>

We further confirm these results using the idiosyncratic household shock indicator based on the 2014 household survey. Our estimates are shown in column (2) of Table 4. Indeed, there is a significant positive impact of mobile money availability on log consumption of households affected by a negative shock. Specifically, while a negative shock causes consumption to fall (non-significantly) in control areas, total expenditure actually increased by 39.3 percent for households who were located in treatment areas and who were affected by the negative shocks relative to those in control areas also affected by the shock. Finally, we again find that consumption did not seem to be significantly affected for households in treatment areas who did not suffer any negative shock.

Consistent with our results on consumption smoothing, columns (1)-(3) in Table 5a show that following the introduction of mobile money there was a significant reduction in the vulnerability of the treated rural households relative to the control group. The vulnerability index we employ averages equally episodes of

[25] This question was not included in the 2012 and 2013 household surveys.

hunger, lack of access to clean water, lack of medicines, and lack of school supplies. It ranges between 0 and 3.[26] The estimated magnitude of the reduction in vulnerability is 0.14 in both surveys, which is equivalent to a 6 percent reduction relative to the mean in the control group.

<Table 5a near here>

Table 5b examines the impact of mobile money availability on the different components of the vulnerability index over the period of analysis. Specifically, it shows that reduced vulnerability seems to arise mostly through reduced incidence of episodes of hunger among the respondents in treatment villages where mobile money became available. We estimate a 8 to 13 percent decrease in the vulnerability to episodes of hunger relative to the control group – with the largest effect appearing in the first follow-up survey wave right after the flood occurred. These effects are statistically significant at the 1 or 5 percent levels, respectively, as shown in columns (1) and (2) of Table 5b. Table 5b also documents some significant improvements in access to clean water, school supplies and medicines after mobile money is introduced in treatment locations relative to control locations. As shown in columns (4)-(12), these positive effects are stronger in the survey wave after the flood occurrence, and not immediately after the negative flood shock took place.

<Table 5b near here>

Finally, and consistently with the consumption smoothing and decreased vulnerability results just described, we observe a significant positive impact of the introduction of mobile money on the self-reported subjective well-being of rural households, as is shown in columns (4)-(6) of Table 5a. This self-reported welfare measure increased between 5 and 8 percent relative to the control group, with statistical significance between 1 and 5 percent kept after adjusting p-values for multiple hypothesis testing.[27]

6.3. Agricultural activity and investment

Another important dimension for the potential economic impact of introducing mobile money services in rural areas is agricultural activity and investment – recall that more than 90 percent of households reported actively farming at baseline.

[26] Vulnerability is measured using a categorical indicator ranging from 0 to 3, where 0 denotes having suffered more than 5 episodes of no access (to food, clean water, medicines, or school supplies) over the year prior to the survey and 3 denotes never having suffered lack of access in the year prior to the survey.
[27] The scale employed for subjective wellbeing is categorical and ranges from 1 to 5.

Our estimates in Table 6 show that agricultural activity, as measured by a simple binary variable taking value 1 when the respondent is actively farming her land, decreased significantly with the introduction of mobile money in treated locations. The magnitude of the effect is 5.2 percentage points, significant at the 1 percent level, when including both 2013 and 2014 as post-treatment years. In addition, we examine treatment effects on an index of agricultural investment for those farms that remain active – constructed as the arithmetic average of binary variables indicating use of improved seeds, fertilizer, pesticides, hired labor, and extension advice. We estimate a negative and significant treatment effect on this agricultural investment index, especially in the second year after the introduction of mobile money, when the index falls by 7 percentage points – or 37 percent relative to the control group. The timing of this effect also holds when decomposing the investment index in each one of its different components.

<Table 6 near here>

6.4. Business activity

Another dimension of potential economic impact of introducing mobile money technology is business activity. At baseline 23 percent of the rural households in our sample reported running an active business. Table 7 shows treatment effects on running an active business, in general and distinguishing between types of businesses (vendors, restaurants/bars, manual services, and personal services). We do not find significant effects of the introduction of mobile money on running an active business activity in treated locations. When looking for specific types of businesses, one identifies a small 2 percentage points decrease in active restaurants/bars in the second year. Overall, the availability of mobile money does not seem to have affected business activity in rural locations, suggesting that no significant changes in occupational choices took place. This pattern of results also implies that any increase in remittances received because of the introduction of mobile money does not seem to be used in investing in business activity.

<Table 7 near here>

6.5. Migrant remittances

The evidence presented so far shows that making mobile money services available in rural locations contributed to smooth consumption of households in face of negative shocks. One possible channel through which consumption smoothing may operate is that of long-distance migrant remittances, similarly to the evidence documented by Jack and Suri (2014), Riley (2018) and Lee et al. (2020). Given the few, risky, expensive, and slow alternative remittance channels available in the rural areas included in our study, mobile money is arguably an advantageous remittance channel that may allow for quick responses to urgent needs in times of economic distress.

The administrative and behavioral adoption data we examined before showed that mobile money transfers were actively used by individuals in treatment locations following the randomized intervention, and that experimental subjects' marginal willingness to transfer (namely through mKesh) clearly increased with the treatment. We now examine whether patterns of use of mobile money measured through administrative records, and overall remittances measured through the different waves of household surveys, responded to the negative shocks suffered by households.

Figure 3 displays a striking response of mobile money transfers received by all rural households in our sample, as recorded by the mobile money operator, at the time of the January 2013 flood. In January and February 2013, mobile money transfers received became 6 to 7 times larger than the highest monthly transfers received in the previous six months – roughly the time-period over which mobile money had been available in treated locations.

<Figure 3 near here>

When we perform regression analysis on these mobile money transfers administrative data analogously to Table 4, i.e., interacting the treatment with the shocks suffered by the households, we obtain the estimation results shown in Table 8. Note that we average mobile money transfer data over the one year prior to the survey to match the (survey) data on idiosyncratic shocks.

We find that the probability that a household in a treated location affected by the 2013 flood receives mobile money transfers is 11 percentage points higher than that of a household in a treatment area not affected by this negative shock. The corresponding results when the dependent variable is the value of mobile money transfers received are very much consistent: the value of mobile transfers received by a treated household affected by the flood is 73.5 percent higher than the amount received by treated households not affected by the flood. The estimated coefficients on the interactions between the treatment and the negative village-level shock are statistically significant at either the 1 or 5 percent levels. Note that households who suffered this negative shock in control areas see the probability of receiving a mobile money transfer increasing by 2 percentage points and the value of these transfers increase by 11 percent – but these coefficients are imprecisely estimated given the low usage of mobile money in the control group. For this reason, we focus on comparing the effects of mobile money on those affected by the negative shock or not within the treatment group. The impact of mobile money availability on those affected by the shock is much larger (46.2 percentage points and 227 percent, respectively) when we make the comparison relative to the control group.

<Table 8 near here>

We now turn to examining the response of mobile money transfers received by households in treatment locations when these households are hit by an idiosyncratic shock – namely a death in the family, a significant health problem in the household, or job losses in the household.[28] Treated households subject to a negative shock experience a strong increase in the amount of mobile money transfers received (50.5 percent relative to the transfers received by treated households that did not suffer any idiosyncratic shock), but not a significant increase in the probability of receiving a mobile money transfer compared to treated households who did not suffer a negative shock.

The difference in the estimated treatment effects depending on whether households are subject to an aggregate village-level shock or to an idiosyncratic household-level shock is according to what we would theoretically expect: it should be easier to smooth consumption through informal networks at the village level in face of idiosyncratic shocks than in face of aggregate shocks like the 2013 flood. This theoretical hypothesis is consistent with our finding that mobile transfers received by distressed households increased particularly at the time of the 2013 floods, when mobile money could be most useful to channel long-distance remittances.

To assess the effect of introducing mobile money on overall remittances, we analyze the incidence and value of overall migrant remittances in the 12 months before the surveys. Table 9a shows that treated households in areas affected by the 2013 floods saw a 44.1 percentage points increase in the probability of receiving remittances relative to households in control areas also affected by the flood. The value of those remittances is 412.1 percent higher than those received by households in control areas affected by the flood. When examining the different components of migrant remittances (namely regular cash, occasional cash and in-kind remittances), we find that the estimated effect for overall remittances is almost entirely due to a large increase in occasional cash remittances sent in response to the 2013 floods.

<Table 9a near here>

[28] The incidence of these shocks is only available for 2013/2014 because this question was not included in the 2012 and 2013 household surveys.

Table 9b displays estimated treatment effects interacted with idiosyncratic shocks faced by households in 2013/2014. The likelihood of treated households affected by these shocks receiving remittances increased by 20.9 percentage points relative to control households also hit by negative shocks, whereas the value of those remittances increased by 209.6 percent. These effects are again driven by a significant increase in the incidence and value of occasional cash remittances received by treated households when they are subject to idiosyncratic shocks. Similar to when examining mKesh transfers received, the magnitude of these insurance treatment effects is smaller for the case of idiosyncratic household shocks than for the aggregate flood shock, as would be expectable because idiosyncratic shocks can be more easily insured within the village without the need for migrant remittances.

<Table 9b near here>

One interesting finding is that the estimated treatment effect for households who did not report any negative shock is positive and significant in 2013-2014 on both the incidence (13.3 percentage points) and value (105.8 percent) of total remittances. This is unlike what happened in the first year after the introduction of mobile money, when the corresponding effect was positive but insignificant. These increased remittance flows may happen as a result of information dissemination about insurance possibilities via mobile money, as well as of growth in the network of migrants that can provide assistance to distressed rural households - a hypothesis that is supported by the evidence we discuss in the next section of the paper.

6.6. Saving behavior

We now turn to measuring treatment effects on saving behavior. We begin by analyzing whether experimental subjects changed their proclivity to save, or used different means for saving, and how much each of the different types of savings changed with the availability of mobile money. These results are shown in Table 10.

<Table 10 near here>

Our findings show that the availability of mobile money did not have a clear impact on the probability of saving, even though point estimates are positive and the overall probability of saving (in all years) increases marginally with treatment. The magnitude of this effect is 4 percentage points, which is statistically significant at the 10 percent level. This result is consistent with our behavioral evidence pointing to positive, but mostly insignificant changes in the marginal willingness of individuals to save in presence of the newly available mobile money technology. We also find that the total amount saved did not change significantly.

Looking at the disaggregation of savings into different types of saving, the only statistically significant finding is that individuals in our sample report being much more likely to save using mKesh – exactly as predicted by our behavioral experiment on the willingness to save using mKesh. This probability is 64.9 and 51.5 percentage points higher in 2013 and 2014, respectively. Interestingly, the probability of keeping an mKesh balance using the administrative data confirms this increase from self-reported survey data, with similar magnitudes. Likewise, we estimate a treatment effect on the survey-reported mKesh savings value that is very close to the corresponding results in the administrative data mKesh savings value.

7. Mechanisms: Out-migration from rural areas

The impact of introducing mobile money in our experiment seems to be mainly driven by migrant remittances received by treated households - and by their role in providing insurance against shocks. These results are not fully in line with the original testable hypotheses we put forward. Indeed, we found that consumption levels only changed because of consumption smoothing in face of shocks, most probably driven by migrant remittances. But the level and pattern of savings remained mostly unchanged. Most unexpectedly, we observed decreases in agricultural activity and investment following the introduction of mobile money.

To explain the negative impact of mobile money on agricultural activity and investment, we conjectured it may be due to an increase in out-migration from rural areas. This out-migration may be explained by the substantial decrease in the transaction costs associated with sending migrant remittances to rural areas, which led not only to an increase in the value of migrant remittances received by treated rural households, as learnt from our empirical analysis, but also to increased incentives to move away from rural to urban areas – where there is a higher probability of finding a more productive occupation.[29]

To illustrate the mechanisms underlying this effect, we now provide a simple theoretical framework predicting migration as a result of introducing mobile money. For this purpose, we use a modified version of the model proposed by Munshi and Rosenzweig (2016).

[29] An alternative explanation for the agricultural disinvestment result could be that, as Karlan et al. (2014) propose in their model, in the presence of binding credit constraints, improved insurance allowed by mobile money leads to decreased investment. The intuition is that insurance acts as a substitute for savings as it enables transferring resources to some of the future states of nature. We tested this hypothesis, but we did not find supportive evidence for it in our data.

In our framework, rural household members can perfectly insure against idiosyncratic risks (such as getting ill) within their household, but this full insurance is lost if household members migrate because of the transaction costs associated with long-distance transfers – including time delays, transfer unreliability, and high transfer fees (as found in our baseline survey). In this setting, migration decisions are made as a result of the tradeoff between losing insurance when household members migrate and accruing income gains when there are migrants in the family.

When mobile money is made available, there is a substantial decrease in the transaction costs of time-sensitive remittances – which can be sent safely, cheaply and instantaneously when shocks occur. This possibility of low cost instant transfers provides additional insurance possibilities that can offset the insurance loss that takes place when a rural household member migrates. Ceteris paribus, migration should therefore increase when households concerned with consumption-smoothing are faced with this improved technology for short-run transfers.

In our model, we assume a household is composed of several income earning members, which can migrate to higher earning occupations in urban areas. These assumptions closely match the reality in the rural areas where our project was conducted, from where there are strong migration corridors to the capital city of Maputo.

Migration decisions are made at the household level. The household has logarithmic preferences, which allow expressing the expected utility function from consumption as an additively separable function of mean consumption M and normalized risk $R \equiv \frac{V}{M^2}$, where V is the variance of consumption:[30]

$$EU = \log(M) - \frac{1}{2}\frac{V}{M^2} \qquad (3)$$

We assume that incomes of the household members vary over time and so risk-averse individuals benefit from insurance between household members to smooth consumption. We assume that household members can completely risk share ex-post in case they live together. If they do not live together, i.e., there are household members who migrate, we hypothesize that full risk sharing is not possible anymore. This is due to the distance separating household members and to the limitations of the transfer technology between household members.

For simplicity, we make two important assumptions. First, we assume storage and savings are not possible, so that total income of the household is equal to total consumption at any point in time. In addition to being standard

[30] This expression is obtained by evaluating log consumption at mean consumption M and ignoring higher-order terms. For the Taylor expansion to be valid with CRRA preferences, consumption must be in the interval $[0,2M]$.

in similar models of mutual insurance, this assumption does not seem overly restrictive in our context where savings and investment are very low. Second, we rule out information asymmetries between household members. This is a potentially restrictive assumption given that international migrant remittances have been shown to strongly respond to improved communication within the household (Batista and Narciso, 2018). However, in our context, there is widespread internal migration to Maputo (about one third of households in our baseline sample had at least one migrant), which facilitates information flows within households.

Migration decisions made by the household trade-off a household income gain generated by migration with the limitations on risk sharing imposed by long-distance migration. To formalize this decision, suppose first that there is no migration in the household. In this case, there is complete risk sharing within the household and household members have the same expected income (which equals consumption with the assumption that there is no available savings or storage technology). Let M_H, V_H denote the mean and variance of a household's income when there is no migration in the household.

If there is migration, we assume the household's mean income increases to $M_H(1+\tilde{G})$ where $\tilde{G}$ is a random variable representing the gain in income from migration (net of any loss in income due to migration costs). The distribution of $\tilde{G}$ is a continuous and differentiable function over its non-negative support. This gain from migration must be compared to the increased risk that the household faces since it cannot fully insure due to the transaction costs associated with sending long-distance transfers between household members. We assume that in this case the normalized consumption risk becomes $\beta \frac{V_H}{M_H^2}$, where $\beta > 1$ represents the transaction costs of sending long-distance remittances.

In this setting, the household will choose migration if the expected utility from migration is above the expected utility from staying home, i.e., if the expected gain from migration is above the added consumption risk of imperfect risk-sharing due to transaction costs of remittances. This can be depicted as:

$$\log(M_H) - \frac{1}{2}\beta \frac{V_H}{M_H^2} + G > \log(M_H) - \frac{1}{2}\frac{V_H}{M_H^2} \Leftrightarrow G > \frac{1}{2}\frac{V_H}{M_H^2}(\beta - 1) \qquad (4)$$

where $G \equiv \log\left(1+\tilde{G}\right)$. Denoting the probability distribution of G as $F(.)$, we derive that the probability of migration is given by:

$$Prob(Migration) = 1 - F\left[\frac{1}{2}\frac{V_H}{M_H^2}(\beta - 1)\right] \qquad (5)$$

In this setting, the introduction of mobile money will decrease parameter β, since it generates a clear reduction in the transaction costs of long-distance remittances between household members, i.e., migrants and household members who stayed home. This implies that the probability of migration increases when β decreases, i.e.,

$$\frac{\partial Prob(Migration)}{\partial \beta} < 0$$

This is the main prediction that we take to the data in order to explain the fact that some types of investment (namely agricultural) decreased in our experimental setting for the rural households in our sample. Mobile money may have facilitated migration of active household members, who saw attractive opportunities to migrate and share risk with their home households. These migrants may have changed their occupation from agriculture at home (a rural setting) to more productive activities in urban areas, which is consistent with our observed empirical response – a pattern of geographical occupational change, distinct but similar to the mobile money impact on occupational change described by Suri and Jack (2016).

To test this hypothesis, we examine the impact of introducing mobile money on the probability of a household having a migrant, and also on the number of migrants in a household. Migrants are defined as someone who has been away from the household for at least three months.[31] In order to test for the insurance-based migration mechanism proposed by our model, we estimate the interaction effects of the mobile money intervention with the aggregate and the idiosyncratic shocks suffered by household in the two years after the intervention. More specifically, we examine treatment effects interacted with the incidence of the aggregate flood shock in 2013 and with the idiosyncratic self-reported shocks by households in 2014. The results are shown in Tables 11a and 11b.

<Table 11a near here>

<Table 11b near here>

The data confirm the hypothesis that introducing mobile money in rural areas increased both the incidence and the number of migrants in the two years following this intervention.[32] The nature of the treatment effect varies

[31] We conduct our analysis for two different definitions of migrant. The first includes as migrants the household head, his/her spouse, all their children and other individuals who sent remittances to the household. An alternative more restrictive definition of migrant only includes migrants the household head, his/her spouse, and all their children.
[32] This finding is consistent with the findings by Lee et al (2019) in Bangladesh.

however over time and with the incidence of the shocks: the increase in migration one year after the service was made available seems to have happened significantly only in treatment areas that were affected by the flood, where the probability of having a migrant in the family rose 30.6 percentage points (relative to an increase of 10.9 percentage points in the flooded control locations) and the number of migrants in the family rose by 0.54 (compared to 0.14 in control households also affected by the negative shock), as shown in columns (1) and (2) of Table 11a.[33] This finding supports the hypothesis that the increased migration flows were a response to the insurance possibilities opened by mobile money in face of the damages caused by the flood, enabled by the lower costs of remitting from urban areas. Two years after the intervention, the estimated effects are however of a different nature: there are no longer statistically significant differences between the impact on migration for those treatment areas that were affected by the floods and those that were not. Indeed, there is an increase in migration in all treatment areas regardless of the definition of migration that is used, and after adjusting standard errors for multiple hypothesis testing.

The main difference in the treatment effects on the two different measures of migration has to do with the magnitudes of the estimated effects and their evolution over time. As could be expected, effects are larger when adopting a broader measure of migration, as shown in Table 11a relative to Table 11b. Interestingly, the migration impact of mobile money seems to decrease after the flood when the definition of migrants includes all remitters, whereas it actually increases when the definition of migrant includes only core household members. This is consistent with aggregate shocks prompting the financial support of extended household members who possibly are already migrants in urban areas, while migration of core household members took longer to build. This finding suggests that adopting the improved migration technology created by the availability of mobile money may require experimentation, financial resources to overcome liquidity constraints, or information acquisition over time, consistent with Bryan et al. (2014), Angelluci (2015) and Batista and McKenzie (2019). The exact mechanism driving this increase in migration flows over time is an interesting question for future research.

Overall, the results we obtained on the impact of mobile money availability on migration flows are consistent with the negative treatment effects estimated on agricultural activity and investment – which were most strongly concentrated in the second year after mobile money was introduced, suggesting that the absence of core household members to farm the household plot may have led to less agriculture activity and also disinvestment in techniques that could increase agricultural productivity. In this sense, it can be argued that the

[33] Migration flows triggered by rainfall shocks have been documented in the literature by Munshi (2003), Hunter et al. (2013), and Dinkelman (2017), among others. They show up very clearly for untreated households in our estimates in Tables 11.

introduction of mobile money created a specific form of geographical occupational change: a shift from subsistence agricultural activities in rural areas to more productive occupations performed by migrants outside of the rural areas of origin.

8. Concluding remarks

What is the economic impact of introducing a mobile money service? Our study is, to the best of our knowledge, the first to conduct a randomized controlled trial to answer this research question. We evaluate the impact of making mobile money available for the first time in rural locations with limited access to formal financial services in Mozambique, one of the poorest countries in sub-Saharan Africa. We find significant levels of adoption of the mobile money service among rural households in treatment locations. Availability of mobile money translated into stronger resilience to negative shocks in terms of consumption and lower vulnerability, particularly to hunger episodes. We also observe an increase in the migrant remittances received by rural households with access to mobile money services. Importantly, we find evidence of reduced investment in agriculture. This result is consistent with households preferring to invest in migration – a poverty-lifting technology that is much improved by the reduction in long-distance transfer transaction costs provided by mobile money.

Overall, this research indicates that introducing mobile money in poor rural areas may serve an important positive role in decreasing rural households' vulnerability to shocks. This positive impact may however arise side by side with disinvestment in subsistence agriculture. Households seem to prefer to migrate and take higher productivity occupations in urban areas. In this sense, our work shows how financial inclusion can accelerate urbanization and structural change as a path for improved welfare. This result is of course specific to the context where our experiment was conducted. Rural areas of Mozambique are still considerably underserved in terms of financial services and subsistence agricultural activity is dominant. While there are many similar regions in sub-Saharan Africa where our findings are likely to be relevant, it will be interesting to evaluate whether this same mechanism holds in different parts of the world at different stages of development.

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TABLES

Table 1a: Administrative adoption - at least one transaction performed per individual

		Years	2012/2013	2013/2014	2014/2015	All
Dependent variable:			**(1)**	**(2)**	**(3)**	**(4)**
		Coefficient	0.757	0.527	0.533	0.849
	Treatment	**Standard error**	(0.016)	(0.018)	(0.018)	(0.013)
Any transaction		**Q-value**	[0.000]	[0.000]	[0.000]	[0.000]
	Mean dep. variable (control)		0.012	0.006	0.005	0.018
	R-squared adjusted		0.623	0.378	0.382	0.744
Types of transactions:						
		Coefficient	0.229	0.181	0.195	0.430
Cash-in	**Treatment**	**Standard error**	(0.015)	(0.014)	(0.015)	(0.018)
		Q-value	[0.000]	[0.000]	[0.000]	[0.000]
		Coefficient	0.431	0.253	0.216	0.499
Transfer received	**Treatment**	**Standard error**	(0.018)	(0.016)	(-0.015)	(0.018)
		Q-value	[0.000]	[0.000]	[0.000]	[0.000]
		Coefficient	0.284	0.095	0.069	0.367
Transfer sent	**Treatment**	**Standard error**	(0.016)	(0.011)	(0.009)	(0.017)
		Q-value	[0.000]	[0.000]	[0.000]	[0.000]
		Coefficient	0.603	0.338	0.312	0.715
Airtime purchase	**Treatment**	**Standard error**	(0.018)	(0.017)	(0.017)	(0.016)
		Q-value	[0.000]	[0.000]	[0.000]	[0.000]
		Coefficient	0.162	0.086	0.121	0.286
In-store purchases	**Treatment**	**Standard error**	(0.013)	(0.010)	(0.012)	(0.016)
		Q-value	[0.000]	[0.000]	[0.000]	[0.000]
		Coefficient	0.006	0.009	0.049	0.055
Remote payments	**Treatment**	**Standard error**	(0.003)	(0.005)	(0.008)	(0.009)
		Q-value	[0.075]	[0.161]	[0.000]	[0.000]
		Coefficient	0.265	0.107	0.124	0.367
Cash-out	**Treatment**	**Standard error**	(0.016)	(0.011)	(0.012)	(0.017)
		Q-value	[0.000]	[0.000]	[0.000]	[0.000]
Number of observations			1,739	1,739	1,739	1,739

Note: All specifications estimated using OLS. The dependent variable is a binary variable taking value 1 when the corresponding transaction was performed. Controls included in all regressions are age and gender. All regressions include province fixed effects. Standard errors reported in parentheses, clustered at the EA level. Q-values adjusted for multiple hypothesis testing following Romano and Wolf (2016) are presented in brackets.

Table 1b: Administrative adoption - number of transactions performed per individual

		Years	2012/2013	2013/2014	2014/2015	All
Dependent variable:			**(1)**	**(2)**	**(3)**	**(4)**
		Coefficient	6.470	2.551	3.230	12.251
	Treatment	**Standard error**	(0.885)	(0.202)	(0.459)	(1.195)
Any transaction		**Q-value**	[0.000]	[0.000]	[0.000]	[0.000]
	Mean dep. variable (control)		0.057	0.049	0.170	0.277
	R-squared adjusted		0.043	0.107	0.034	0.074
Types of transactions:						
		Coefficient	0.837	0.340	0.475	1.652
Cash-in	**Treatment**	**Standard error**	(0.160)	(0.043)	(0.149)	(0.245)
		Q-value	[0.001]	[0.000]	[0.031]	[0.000]
		Coefficient	0.710	0.335	0.408	1.454
Transfer received	**Treatment**	**Standard error**	(0.042)	(0.025)	(0.033)	(0.079)
		Q-value	[0.000]	[0.000]	[0.000]	[0.000]
		Coefficient	0.369	0.125	0.080	0.574
Transfer sent	**Treatment**	**Standard error**	(0.025)	(0.017)	(0.011)	(0.035)
		Q-value	[0.000]	[0.000]	[0.000]	[0.000]
		Coefficient	3.933	1.461	1.532	6.926
Airtime purchase	**Treatment**	**Standard error**	(0.709)	(0.140)	(0.156)	(0.859)
		Q-value	[0.001]	[0.000]	[0.000]	[0.000]
		Coefficient	0.239	0.110	0.140	0.489
In-store purchases	**Treatment**	**Standard error**	(0.035)	(0.015)	(0.015)	(0.043)
		Q-value	[0.000]	[0.000]	[0.000]	[0.000]
		Coefficient	0.030	0.034	0.445	0.509
Remote payments	**Treatment**	**Standard error**	(0.015)	(0.023)	(0.218)	(0.236)
		Q-value	[0.157]	[0.269]	[0.090]	[0.090]
		Coefficient	0.352	0.146	0.150	0.647
Cash-out	**Treatment**	**Standard error**	(0.034)	(0.020)	(0.021)	(0.059)
		Q-value	[0.000]	[0.000]	[0.000]	[0.000]
Number of observations			1,739	1,739	1,739	1,739

Note: All specifications estimated using OLS. The dependent variable is the number of transactions performed per individual. Controls included in all regressions are age and gender. All regressions include province fixed effects. Standard errors reported in parentheses, clustered at the EA level. Q-values adjusted for multiple hypothesis testing following Romano and Wolf (2016) are presented in brackets.

Table 1c: Administrative adoption - value of transactions performed per individual

		Years	2012/2013	2013/2014	2014/2015	All
Dependent variable:			**(1)**	**(2)**	**(3)**	**(4)**
		Coefficient	502.590	251.541	231.191	985.323
	Treatment	**Standard error**	(66.415)	(50.404)	(82.686)	(160.592)
Any transaction		**Q-value**	[0.000]	[0.001]	[0.015]	[0.001]
	Mean dep. variable (control)		1.061	7.452	30.668	39.181
	R-squared adjusted		0.048	0.025	0.007	0.033
Types of transactions:						
		Coefficient	117.518	79.185	84.548	281.251
Cash-in	**Treatment**	**Standard error**	(25.624)	(24.750)	(39.563)	(71.527)
		Q-value	[0.029]	[0.051]	[0.090]	[0.040]
		Coefficient	108.295	38.299	16.857	163.450
Transfer received	**Treatment**	**Standard error**	(16.526)	(8.351)	(3.210)	(21.161)
		Q-value	[0.000]	[0.002]	[0.001]	[0.000]
		Coefficient	26.901	5.180	5.391	37.472
Transfer sent	**Treatment**	**Standard error**	(4.198)	(0.973)	(2.482)	(5.178)
		Q-value	[0.001]	[0.001]	[0.090]	[0.000]
		Coefficient	98.906	36.345	31.873	167.124
Airtime purchase	**Treatment**	**Standard error**	(14.460)	(4.130)	(4.117)	(18.526)
		Q-value	[0.001]	[0.000]	[0.004]	[0.000]
		Coefficient	13.312	5.477	5.328	24.117
In-store purchases	**Treatment**	**Standard error**	(5.266)	(0.864)	(1.014)	(5.454)
		Q-value	[0.072]	[0.001]	[0.040]	[0.005]
		Coefficient	22.319	36.204	64.431	122.954
Remote payments	**Treatment**	**Standard error**	(11.420)	(18.793)	(36.658)	(57.007)
		Q-value	[0.147]	[0.147]	[0.147]	[0.105]
		Coefficient	115.340	50.851	22.763	188.954
Cash-out	**Treatment**	**Standard error**	(20.113)	(12.088)	(8.650)	(34.678)
		Q-value	[0.000]	[0.008]	[0.072]	[0.001]
Number of observations			1,739	1,739	1,739	1,739

Note: All specifications estimated using OLS. The dependent variable is the value of transactions performed per individual (in MZN). Controls included in all regressions are age and gender. All regressions include province fixed effects. Standard errors reported in parentheses, clustered at the EA level. Q-values adjusted for multiple hypothesis testing following Romano and Wolf (2016) are presented in brackets.

Table 2a: Transfer game - willingness to transfer

Dependent variable ------>		Willingness to transfer in transfer game			
	Year	2012	2013	2014	All
		(1)	**(2)**	**(3)**	**(4)**
	Coefficient	0.059	0.124	0.160	0.107
Treatment	**Standard error**	(0.031)	(0.028)	(0.040)	(0.021)
	Q-value	[0.104]	[0.000]	[0.000]	[0.000]
Mean dep. variable (control)		0.160	0.088	0.226	0.159
R-squared adjusted		0.013	0.032	0.028	0.039
Number of observations		1,257	847	838	2,942

Note: All specifications estimated using OLS. The dependent variable is a binary variable taking value 1 if respondent is willing to transfer. Controls are age and gender. All regressions include province fixed effects. Specification (4) also includes year fixed effects. Standard errors reported in parentheses, clustered at the EA level. Q-values adjusted for multiple hypothesis testing following Romano and Wolf (2016) are presented in brackets.

Table 2b: Transfer game - willingness to transfer using mKesh

Dependent variable ------>		Willingness to transfer using mKesh in transfer game			
	Year	2012	2013	2014	All
		(1)	**(2)**	**(3)**	**(4)**
	Coefficient	0.255	0.390	0.213	0.266
Treatment	**Standard error**	(0.058)	(0.076)	(0.055)	(0.038)
	Q-value	[0.000]	[0.000]	[0.000]	[0.000]
Mean dep. variable (control)		0.466	0.122	0.156	0.286
R-squared adjusted		0.139	0.140	0.076	0.160
Number of observations		234	121	245	600

Note: All specifications estimated using OLS. The dependent variable is a binary variable taking value 1 if respondent is willing to transfer usig mKesh. Controls are age and gender. All regressions include province fixed effects. Specification (4) also includes year fixed effects. Standard errors reported in parentheses, clustered at the EA level. Q-values adjusted for multiple hypothesis testing following Romano and Wolf (2016) are presented in brackets.

Table 3a: Saving game - willingness to save

Dependent variable ------>		Willingness to save in saving game			
	Year	2012	2013	2014	All
		(1)	**(2)**	**(3)**	**(4)**
	Coefficient	0.020	0.036	0.009	0.020
Treatment	**Standard error**	(0.034)	(0.024)	(0.021)	(0.019)
	Q-value	[0.548]	[0.147]	[0.648]	[0.296]
Mean dep. variable (control)		0.589	0.802	0.861	0.734
R-squared adjusted		0.035	0.010	0.005	0.095
Number of observations		1,739	1,207	1,260	4,206

Note: All specifications estimated using OLS. The dependent variable is a binary variable taking value 1 if respondent is willing to save. Controls are age and gender. All regressions include province fixed effects. Specification (4) also includes year fixed effects. Standard errors reported in parentheses, clustered at the EA level. Q-values adjusted for multiple hypothesis testing following Romano and Wolf (2016) are presented in brackets.

Table 3b: Saving game - willingness to save using mKesh

Dependent variable ------>		Willingness to save using mKesh in saving game			
	Year	2012	2013	2014	All
		(1)	**(2)**	**(3)**	**(4)**
	Coefficient	0.232	0.241	0.238	0.237
Treatment	**Standard error**	(0.032)	(0.028)	(0.030)	(0.019)
	Q-value	[0.000]	[0.000]	[0.000]	[0.000]
Mean dep. variable (control)		0.111	0.016	0.070	0.067
R-squared adjusted		0.102	0.133	0.095	0.113
Number of observations		1,039	987	1,091	3,117

Note: All specifications estimated using OLS. The dependent variable is a binary variable taking value 1 if respondent is willing to save using mKesh. Controls are age and gender. All regressions include province fixed effects. Specification (4) also includes year fixed effects. Standard errors reported in parentheses, clustered at the EA level. Q-values adjusted for multiple hypothesis testing following Romano and Wolf (2016) are presented in brackets.

Table 4: Consumption - treatment interacted with shocks

Dependent variable ------>		**Log consumption per capita**	
		Village Flood Index	**Household Shock Index**
		(1)	**(2)**
β1: Treatment * Negative shock	**Coefficient**	0.372	0.311
	Standard error	(0.144)	(0.105)
	Q-value	[0.032]	[0.010]
β2: Treatment	**Coefficient**	0.069	0.082
	Standard error	(0.129)	(0.081)
	Q-value	[0.834]	[0.536]
β3: Negative shock	**Coefficient**	-0.140	-0.091
	Standard error	(0.091)	(0.072)
	Q-value	[0.337]	[0.360]
p-value of tests	$\beta_1 + \beta_2 = 0$	0.000	0.000
	$\beta_1 + \beta_3 = 0$	0.039	0.005
	$\beta_1 + \beta_2 + \beta_3 = 0$	0.001	0.001
Mean dep. variable (control)		8.507	8.297
R-squared adjusted		0.123	0.100
Number of observations		1,034	1,194

Note: All specifications estimated using OLS. The dependent variable in column (1) is log total household consumption in 2012-2013. The dependent variable in column (2) is log total household consumption in 2013-2014. The negative shock in column (1) is defined as SPEI rainfall in EA in the 2012-2013 season being above two standard deviations relative to the 1981-2010 average. The negative household shock in column (2) is defined as having a death in the family, significant health problems in the household, or job losses in the household in 2013-2014. All regressions include the value of the dependent variable at baseline as control, individual controls, and province fixed effects. Individual controls are age and gender. Standard errors reported in parentheses are clustered at the EA level. Q-values adjusted for multiple hypothesis testing following Romano and Wolf (2016) are presented in brackets.

Table 5a: Subjective well-being and vulnerability

Dependent variable ------>		Non-vulnerability index			Subjective well-being		
	Year	2013	2014	All	2013	2014	All
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Coefficient	0.143	0.138	0.142	0.275	0.181	0.230
Treatment	**Standard error**	(0.042)	(0.053)	(0.037)	(0.070)	(0.076)	(0.053)
	Q-value	[0.001]	[0.025]	[0.000]	[0.000]	[0.026]	[0.000]
Mean dep. variable (control)		2.486	2.418	2.452	3.258	3.396	3.328
R-squared adjusted		0.029	0.024	0.027	0.022	0.016	0.017
Number of observations		1,006	1,035	2,041	1,180	1,230	2,410

Note: All specifications estimated using OLS. The non-vulnerability index is the arithmetic average of four indices of access to food, clean water, medicines and school supplies, ranging between 0-3. The subjective well-being dependent variable is categorical, ranging between 1-5. All regressions include the value of the dependent variable at baseline as control, individual controls, and province fixed effects. Individual controls are age and gender. Standard errors reported in parentheses are clustered at the EA level. Q-values adjusted for multiple hypothesis testing following Romano and Wolf (2016) are presented in brackets.

Table 5b: Components of non-vulnerability index

Dependent variable ------>		Access to food			Access to clean water			Access to medicines			Access to school supplies		
	Year	2013	2014	All	2013	2014	All	2013	2014	All	2013	2014	All
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	Coefficient	0.326	0.184	0.255	0.098	0.090	0.096	0.056	0.113	0.086	0.090	0.130	0.111
Treatment	**Standard error**	(0.045)	(0.070)	(0.046)	(0.042)	(0.048)	(0.034)	(0.060)	(0.070)	(0.048)	(0.065)	(0.068)	(0.046)
	Q-value	[0.000]	[0.034]	[0.000]	[0.064]	[0.141]	[0.015]	[0.345]	[0.141]	[0.068]	[0.269]	[0.141]	[0.032]
Mean dep. variable (control)		2.431	2.426	2.428	2.705	2.690	2.698	2.388	2.221	2.302	2.411	2.334	2.372
R-squared adjusted		0.054	0.031	0.039	0.018	0.011	0.008	0.016	0.008	0.016	0.007	0.010	0.008
Number of observations		1,170	1,239	2,409	1,175	1,240	2,415	1,160	1,233	2,393	1,032	1,050	2,082

Note: All specifications estimated using OLS. The dependent variables are categorical, ranging between 0-3, where 0 denotes having suffered more than 5 episodes of no access over the year prior to the survey and 3 denotes never having suffered lack of access in the year prior to the survey. All regressions include the value of the dependent variable at baseline as control, individual controls, and province fixed effects. Individual controls are age and gender. Standard errors reported in parentheses are clustered at the EA level. Q-values adjusted for multiple hypothesis testing following Romano and Wolf (2016) are presented in brackets.

Table 6: Agricultural activity and investment

		Year	2013	2014	All
Dependent variable:			**(1)**	**(2)**	**(3)**
Active farm	**Treatment**	**Coefficient**	-0.044	-0.058	-0.052
		Standard error	(0.018)	(0.022)	(0.016)
		Q-value	[0.029]	[0.014]	[0.004]
	Mean dep. variable (control)		0.948	0.936	0.942
	R-squared adjusted		0.028	0.010	0.013
	Number of observations		969	1,056	2,025
Index of agricultural investment (conditional on farm being active)	**Treatment**	**Coefficient**	-0.026	-0.070	-0.049
		Standard error	(0.016)	(0.020)	(0.015)
		Q-value	[0.092]	[0.002]	[0.002]
	Mean dep. variable (control)		0.164	0.191	0.178
	R-squared adjusted		0.040	0.100	0.068
	Number of observations		772	828	1,600
Investment index components:					
Improved seeds	**Treatment**	**Coefficient**	-0.039	-0.071	-0.055
		Standard error	(0.027)	(0.037)	(0.024)
		Q-value	[0.422]	[0.080]	[0.060]
Fertilizer	**Treatment**	**Coefficient**	-0.049	-0.068	-0.059
		Standard error	(0.033)	(0.032)	(0.027)
		Q-value	[0.422]	[0.080]	[0.060]
Pesticides	**Treatment**	**Coefficient**	-0.040	-0.069	-0.057
		Standard error	(0.023)	(0.025)	(0.019)
		Q-value	[0.357]	[0.022]	[0.011]
Hired labor	**Treatment**	**Coefficient**	0.031	-0.073	-0.021
		Standard error	(0.033)	(0.031)	(0.025)
		Q-value	[0.422]	[0.080]	[0.392]
Extension advice	**Treatment**	**Coefficient**	-0.032	-0.048	-0.040
		Standard error	(0.021)	(0.021)	(0.016)
		Q-value	[0.422]	[0.080]	[0.044]

Note: All specifications estimated using OLS. Active farm is a binary variable taking value 1 when the respondent reports having an active farm. The Index of agricultural investment is the arithmetic average of binary variables indicating use of improved seeds, fertilizer, pesticides, hired workers, and extension advice. All regressions include the value of the dependent variable at baseline as control, individual controls, and province fixed effects. Individual controls are age and gender. Standard errors reported in parentheses are clustered at the EA level. Q-values adjusted for multiple hypothesis testing following Romano and Wolf (2016) are presented in brackets.

Table 7: Business activity

		Year	2013	2014	All
Dependent variable:			**(1)**	**(2)**	**(3)**
		Coefficient	-0.001	-0.024	-0.014
Any active business	**Treatment**	**Standard error**	(0.028)	(0.030)	(0.021)
		Q-value	[0.979]	[0.419]	[0.526]
		Mean dep. variable (control)	0.249	0.339	0.295
		R-squared adjusted	0.076	0.108	0.099
		Number of observations	1,191	1,256	2,447
Types of businesses:					
		Coefficient	-0.023	0.003	-0.011
Vendors	**Treatment**	**Standard error**	(0.025)	(0.027)	(0.018)
		Q-value	[0.726]	[0.994]	[0.784]
		Coefficient	0.004	-0.022	-0.009
Restaurants/bars	**Treatment**	**Standard error**	(0.005)	(0.008)	(0.004)
		Q-value	[0.726]	[0.014]	[0.144]
		Coefficient	0.001	0.007	0.004
Manual services (e.g., mechanic, tailor)	**Treatment**	**Standard error**	(0.005)	(0.008)	(0.005)
		Q-value	[0.769]	[0.766]	[0.784]
		Coefficient	0.010	0.001	0.005
Personal services (e.g., hairdresser)	**Treatment**	**Standard error**	(0.008)	(0.009)	(0.006)
		Q-value	[0.530]	[0.994]	[0.784]

Note: All specifications estimated using OLS. Any active business is a binary variable taking value 1 when the respondent reports having an active business of any type. All regressions include the value of the dependent variable at baseline as control, individual controls, and province fixed effects. Individual controls are age and gender. Standard errors reported in parentheses are clustered at the EA level. Q-values adjusted for multiple hypothesis testing following Romano and Wolf (2016) are presented in brackets.

Table 8: Administrative records on mKesh transfers received - treatment interacted with shocks

Dependent variable ------>		Transfers Received Using mKesh (Administrative Data)			
		Village Flood Index		Household Shock Index	
		Binary	Value	Binary	Value
		(1)	(2)	(3)	(4)
β1: Treatment * Negative shock	Coefficient	0.110	0.735	0.060	0.505
	Standard error	(0.052)	(0.245)	(0.042)	(0.209)
	Q-value	[0.032]	[0.003]	[0.163]	[0.023]
β2: Treatment	Coefficient	0.352	1.535	0.262	1.044
	Standard error	(0.047)	(0.205)	(0.029)	(0.122)
	Q-value	[0.000]	[0.000]	[0.000]	[0.000]
β3: Negative shock	Coefficient	0.020	0.113	-0.001	0.004
	Standard error	(0.012)	(0.065)	(0.004)	(0.016)
	Q-value	[0.104]	[0.104]	[0.882]	[0.882]
p-value of tests	$\beta_1 + \beta_2 = 0$	0.000	0.000	0.000	0.000
	$\beta_1 + \beta_3 = 0$	0.014	0.001	0.164	0.016
	$\beta_1 + \beta_2 + \beta_3 = 0$	0.000	0.000	0.000	0.000
Mean dep. variable (control)		0.010	0.040	0.000	0.000
R-squared adjusted		0.294	0.277	0.186	0.175
Number of observations		1,739	1,739	1,261	1,261

Note: All specifications estimated using OLS. The binary dependent variable takes value 1 when mKesh transfers are received by household. The value of mKesh transfers is obtained using the inverse hyperbolic sine transformation. The dependent variables in columns (1)-(2) regard 2012-2013. The dependent variables in column (3)-(4) regard 2013-2014. The negative shock in columns (1)-(2) is defined as SPEI rainfall in EA in the 2012-2013 season being above two standard deviations relative to the 1981-2010 average. The negative household shock in columns (3)-(4) is defined as having a death in the family, significant health problems in the household, or job losses in the household in 2013-2014. All regressions include the value of the dependent variable at baseline as control, individual controls, and province fixed effects. Individual controls are age and gender. Standard errors reported in parentheses are clustered at the EA level. Q-values adjusted for multiple hypothesis testing following Romano and Wolf (2016) are presented in brackets.

Table 9a: Remittances received - treatment interacted with village flood shock in 2012-2013

Dependent variable ------>		Total remittances		Regular cash remittances		Occasional cash remittances		In-kind remittances	
		Binary	Value	Binary	Value	Binary	Value	Binary	Value
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β1: Treatment * Negative shock	Coefficient	0.391	3.650	0.006	0.151	0.456	4.108	0.070	0.401
	Standard error	(0.065)	(0.568)	(0.041)	(0.389)	(0.035)	(0.309)	(0.047)	(0.353)
	Q-value	[0.000]	[0.000]	[0.898]	[0.790]	[0.000]	[0.000]	[0.317]	[0.480]
β2: Treatment	Coefficient	0.050	0.471	0.061	0.531	-0.006	-0.008	-0.032	-0.127
	Standard error	(0.054)	(0.467)	(0.033)	(0.308)	(0.015)	(0.123)	(0.039)	(0.292)
	Q-value	[0.355]	[0.355]	[0.229]	[0.271]	[0.895]	[0.942]	[0.726]	[0.895]
β3: Negative shock	Coefficient	0.017	0.102	0.024	0.242	0.027	0.224	-0.029	-0.154
	Standard error	(0.047)	(0.391)	(0.019)	(0.187)	(0.016)	(0.130)	(0.032)	(0.204)
	Q-value	[0.792]	[0.792]	[0.410]	[0.410]	[0.283]	[0.283]	[0.464]	[0.464]
p-value of tests	$\beta_1 + \beta_2 = 0$	0.000	0.000	0.004	0.005	0.000	0.000	0.141	0.161
	$\beta_1 + \beta_3 = 0$	0.000	0.000	0.408	0.408	0.000	0.000	0.247	0.401
	$\beta_1 + \beta_2 + \beta_3 = 0$	0.000	0.000	0.000	0.000	0.000	0.000	0.784	0.589
Mean dep. variable (control)		0.209	1.731	0.067	0.673	0.049	0.352	0.119	0.786
R-squared adjusted		0.202	0.214	0.037	0.051	0.307	0.322	0.008	0.003
Number of observations		1,208	1,208	1,208	1,208	1,208	1,208	1,208	1,208

Note: All specifications estimated using OLS. The binary dependent variable takes value 1 when remittances are received by household. The value of remittances is obtained using the inverse hyperbolic sine transformation. The dependent variables regard 2012-2013. The negative shock is defined as SPEI rainfall in EA in the 2012-2013 season being above two standard deviations relative to the 1981-2010 average. All regressions include the value of the dependent variable at baseline as control, individual controls, and province fixed effects. Individual controls are age and gender. Standard errors reported in parentheses are clustered at the EA level. Q-values adjusted for multiple hypothesis testing following Romano and Wolf (2016) are presented in brackets.

Table 9b: Remittances - treatment interacted with household shock index in 2013-2014

Dependent variable ------>		Total remittances		Regular cash remittances		Occasional cash remittances		Inkind remittances	
		Binary	Value	Binary	Value	Binary	Value	Binary	Value
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β1: Treatment * Negative shock	Coefficient	0.076	1.038	-0.001	0.364	0.416	3.783	-0.059	-0.294
	Standard error	(0.063)	(0.568)	(0.043)	(0.440)	(0.057)	(0.491)	(0.061)	(0.493)
	Q-value	[0.214]	[0.087]	[0.976]	[0.715]	[0.000]	[0.000]	[0.653]	[0.795]
β2: Treatment	Coefficient	0.133	1.058	0.072	0.709	-0.002	-0.090	0.077	0.538
	Standard error	(0.044)	(0.408)	(0.030)	(0.293)	(0.018)	(0.140)	(0.046)	0.393
	Q-value	[0.003]	[0.010]	[0.066]	[0.066]	[0.926]	[0.640]	[0.231]	[0.361]
β3: Negative shock	Coefficient	0.085	0.570	0.002	-0.067	0.025	0.198	0.053	0.273
	Standard error	(0.044)	(0.381)	(0.028)	(0.267)	(0.019)	(0.170)	(0.042)	(0.337)
	Q-value	[0.073]	[0.132]	[0.947]	[0.887]	[0.543]	[0.563]	[0.543]	[0.701]
p-value of tests	$\beta_1 + \beta_2 = 0$	0.001	0.000	0.030	0.003	0.000	0.000	0.888	0.544
	$\beta_1 + \beta_3 = 0$	0.000	0.000	0.981	0.401	0.000	0.000	0.723	0.955
	$\beta_1 + \beta_2 + \beta_3 = 0$	0.000	0.000	0.018	0.004	0.000	0.000	0.148	0.216
Mean dep. variable (control)		0.486	4.198	0.116	1.111	0.080	0.591	0.371	3.023
R-squared adjusted		0.066	0.077	0.040	0.059	0.202	0.232	0.032	0.036
Number of observations		1,261	1,261	1,261	1,261	1,261	1,261	1,261	1,261

Note: All specifications estimated using OLS. The binary dependent variable takes value 1 when remittances are received by household. The value of remittances is obtained using the inverse hyperbolic sine transformation. The dependent variables regard 2013-2014. The negative household shock is defined as the average of the occurrence of deaths in the family, significant health problems in the household, and job losses in the household in 2013-2014. All regressions include the value of the dependent variable at baseline as control, individual controls, and province fixed effects. Individual controls are age and gender. Standard errors reported in parentheses are clustered at the EA level. Q-values adjusted for multiple hypothesis testing following Romano and Wolf (2016) are presented in brackets.

Table 10: Household savings

Dependent variable ------>			Probability of saving (binary variable)			Value of savings (inverse hyperbolic sine transformation)		
		Year	2013	2014	all	2013	2014	all
			(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
		Coefficient	0.038	0.036	0.037	0.260	0.153	0.203
	Treatment	**Standard error**	(0.026)	(0.025)	(0.020)	(0.243)	(0.243)	(0.188)
		Q-value	[0.200]	[0.214]	[0.094]	[0.280]	[0.526]	[0.280]
		Mean dep. variable (control)	0.814	0.739	0.770	6.592	5.713	6.079
		R-squared adjusted	0.027	0.015	0.028	0.057	0.055	0.070
		Number of observations	774	1,092	1,866	774	1,092	1,866
Total savings components:								
		Coefficient	-0.054	-0.025	-0.039	0.024	0.022	0.020
Saves using bank account	**Treatment**	**Standard error**	(0.029)	(0.032)	(0.026)	(0.270)	(0.245)	(0.220)
		Q-value	[0.277]	[0.800]	[0.540]	[0.988]	[0.930]	[0.998]
		Coefficient	0.024	-0.030	-0.004	0.124	-0.283	-0.094
Saves at home	**Treatment**	**Standard error**	(0.031)	(0.029)	(0.023)	(0.248)	(0.206)	(0.172)
		Q-value	[0.923]	[0.757]	[0.998]	[0.958]	[0.583]	[0.952]
		Coefficient	-0.025	0.020	-0.003	-0.226	0.253	0.010
Saves in rosca	**Treatment**	**Standard error**	(0.029)	(0.032)	(0.024)	(0.323)	(0.339)	(0.262)
		Q-value	[0.892]	[0.800]	[0.998]	[0.945]	[0.800]	[0.998]
		Coefficient	-0.001	0.021	0.011	-0.017	0.116	0.054
Saves with shopkeeper	**Treatment**	**Standard error**	(0.012)	(0.012)	(0.009)	(0.083)	(0.089)	(0.062)
		Q-value	[0.988]	[0.374]	[0.670]	[0.978]	[0.619]	[0.882]
		Coefficient	-0.009	-0.005	-0.008	0.003	0.039	0.007
Lends money	**Treatment**	**Standard error**	(0.024)	(0.022)	(0.017)	(0.188)	(0.181)	(0.130)
		Q-value	[0.985]	[0.997]	[0.993]	[0.998]	[0.997]	[0.997]
		Coefficient	0.649	0.515	0.580	3.204	2.622	2.906
Saves using mkesh (survey)	**Treatment**	**Standard error**	(0.024)	(0.021)	(0.018)	(0.128)	(0.114)	(0.096)
		Q-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
		Coefficient	0.712	0.808	0.762	2.827	3.147	2.990
Saves using mkesh (admin)	**Treatment**	**Standard error**	(0.022)	(0.016)	(0.016)	(0.112)	(0.103)	(0.094)
		Q-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Note: All specifications estimated using OLS. The binary dependent variable takes value 1 when savings are reported by the household. The value of savings is obtained using the inverse hyperbolic sine transformation. All regressions except those concerning lending money and saving using mKesh include the value of the dependent variable at baseline as control, individual controls, and province fixed effects. The exceptions regard data for which the baseline values of the dependent variables are not available. Individual controls are age and gender. Standard errors reported in parentheses are clustered at the EA level. Q-values adjusted for multiple hypothesis testing following Romano and Wolf (2016) are presented in brackets.

Table 11a: Household migration - treatment interacted with shocks. Migrants include remitters.

Dependent variable ------>		Household Migration					
			Village Flood Index			Household Shock Index	
	Year	2012/2013	2012/2013	2013/2014	2013/2014	2013/2014	2013/2014
		Binary	**Number**	**Binary**	**Number**	**Binary**	**Number**
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
β1: Treatment * Negative shock	**Coefficient**	0.205	0.420	0.042	0.131	0.024	0.307
	Standard error	(0.073)	(0.114)	(0.059)	(0.211)	(0.056)	(0.155)
	Q-value	[0.004]	[0.000]	[0.715]	[0.715]	[0.676]	[0.084]
β2: Treatment	**Coefficient**	0.101	0.121	0.146	0.275	0.163	0.243
	Standard error	(0.062)	(0.080)	(0.039)	(0.167)	(0.042)	(0.113)
	Q-value	[0.149]	[0.149]	[0.000]	[0.102]	[0.000]	[0.029]
β3: Negative shock	**Coefficient**	0.109	0.140	-0.027	0.002	0.074	0.199
	Standard error	(0.049)	(0.072)	(0.051)	(0.149)	(0.044)	(0.089)
	Q-value	[0.031]	[0.048]	[0.809]	[0.989]	[0.095]	[0.047]
p-value of tests	$\beta_1 + \beta_2 = 0$	0.000	0.000	0.000	0.002	0.000	0.000
	$\beta_1 + \beta_3 = 0$	0.000	0.000	0.702	0.419	0.006	0.000
	$\beta_1 + \beta_2 + \beta_3 = 0$	0.000	0.000	0.000	0.001	0.000	0.000
Mean dep. variable (control)		0.346	0.481	0.657	1.253	0.659	1.258
R-squared adjusted		0.123	0.101	0.090	0.143	0.098	0.159
Number of observations		1,208	1,208	1,264	1,264	1,261	1,261

Note: All specifications estimated using OLS. The dependent variables in columns (1)-(2) regard 2012-2013. The dependent variables in column (3)-(6) regard 2013-2014. The negative shock in columns (1)-(4) is defined as SPEI rainfall in EA in the 2012-2013 season being above two standard deviations relative to the 1981-2010 average. The negative household shock in columns (5)-(6) is defined as the average of the occurrence of deaths in the family, significant health problems in the household, and job losses in the household in 2013-2014. All regressions include the value of the dependent variable at baseline as control, individual controls, and province fixed effects. Individual controls are age and gender. Standard errors reported in parentheses are clustered at the EA level. Q-values adjusted for multiple hypothesis testing following Romano and Wolf (2016) are presented in brackets.

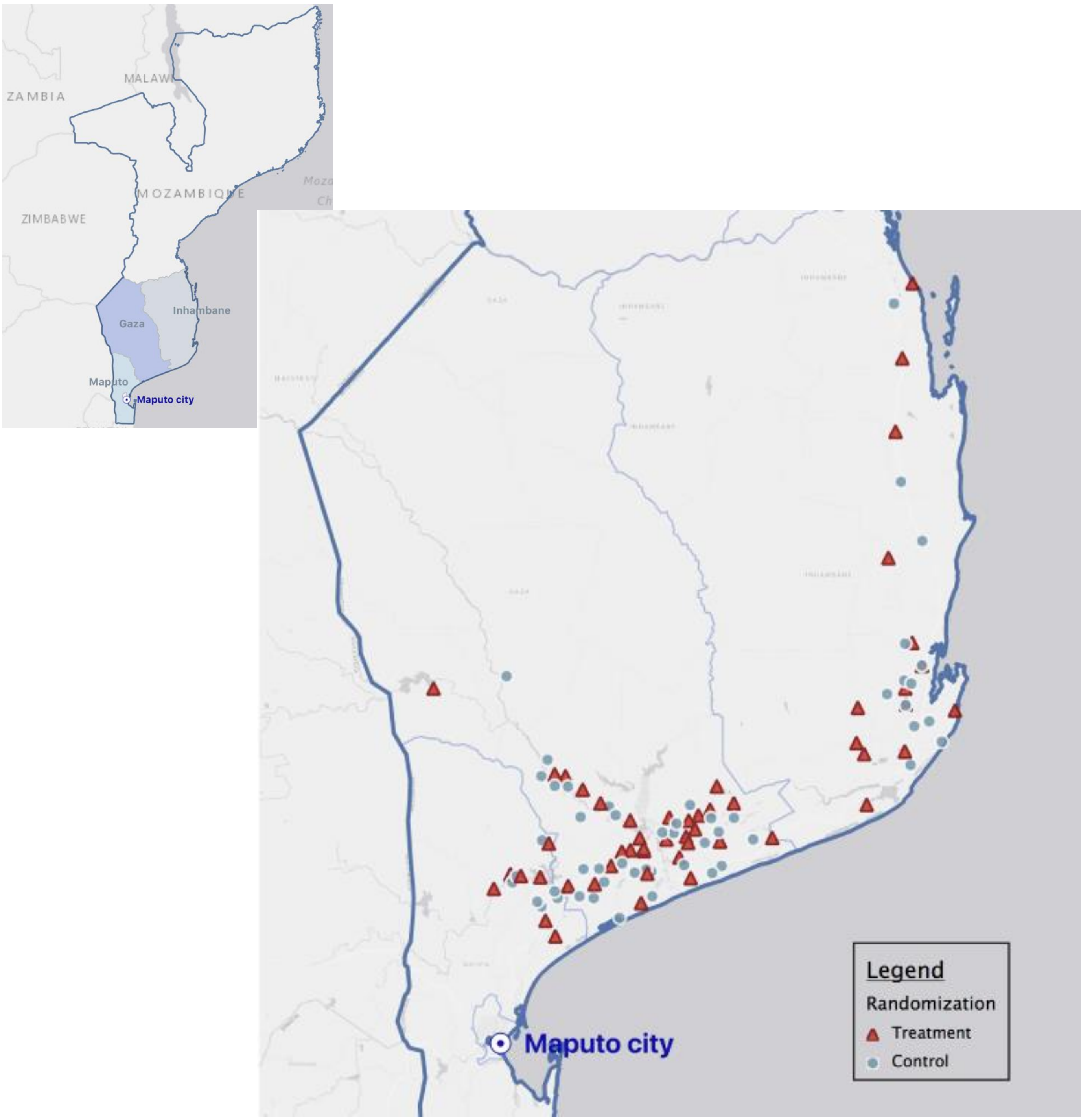
Table 11b: Household migration - treatment interacted with shocks. Migrants include only household head, spouse(s) and their children.

Dependent variable ------>		**Household Migration**					
		Village Flood				**Household Shock Index**	
	Year	2012/2013	2012/2013	2013/2014	2013/2014	2013/2014	2013/2014
		Binary	**Number**	**Binary**	**Number**	**Binary**	**Number**
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
β1: Treatment * Negative shock	**Coefficient**	0.140	0.249	0.060	0.067	0.144	0.337
	Standard error	(0.049)	(0.077)	(0.074)	(0.129)	(0.056)	(0.109)
	Q-value	[0.004]	[0.004]	[0.598]	[0.623]	[0.007]	[0.003]
β2: Treatment	**Coefficient**	0.018	0.017	0.110	0.171	0.096	0.087
	Standard error	(0.032)	(0.042)	(0.063)	(0.103)	(0.038)	(0.070)
	Q-value	[0.689]	[0.703]	[0.125]	[0.125]	[0.021]	[0.223]
β3: Negative shock	**Coefficient**	0.055	0.077	0.045	0.132	0.041	0.072
	Standard error	(0.032)	(0.046)	(0.045)	(0.084)	(0.033)	(0.054)
	Q-value	[0.134]	[0.134]	[0.326]	[0.172]	[0.261]	[0.261]
p-value of tests	$\beta_1 + \beta_2 = 0$	0.000	0.000	0.000	0.002	0.000	0.000
	$\beta_1 + \beta_3 = 0$	0.000	0.000	0.074	0.063	0.000	0.000
	$\beta_1 + \beta_2 + \beta_3 = 0$	0.000	0.000	0.000	0.000	0.000	0.000
Mean dep. variable (control)		0.169	0.225	0.372	0.604	0.374	0.607
R-squared adjusted		0.066	0.056	0.075	0.104	0.085	0.115
Number of observations		1,208	1,208	1,264	1,264	1,261	1,261

Note: All specifications estimated using OLS. The dependent variables in columns (1)-(2) regard 2012-2013. The dependent variables in column (3)-(6) regard 2013-2014. The negative shock in columns (1)-(4) is defined as SPEI rainfall in EA in the 2012-2013 season being above two standard deviations relative to the 1981-2010 average. The negative household shock in columns (5)-(6) is defined as the average of the occurrence of deaths in the family, significant health problems in the household, and job losses in the household in 2013-2014. All regressions include the value of the dependent variable at baseline as control, individual controls, and province fixed effects. Individual controls are age and gender. Standard errors reported in parentheses are clustered at the EA level. Q-values adjusted for multiple hypothesis testing following Romano and Wolf (2016) are presented in brackets.

FIGURES

Figure 1: Map of experimental locations



Source: Basemaps created using ArcGIS software by Esri. Basemaps are used in line with the Esri Master License Agreement, specifically for the inclusion of screen captures in academic publications. We make use of the World Light Gray Base. (Sources: Esri, HERE, Garmin, ® OpenStreetMap contributors, and the GIS User Community).

Figure 2: mKesh leaflet

Main operations: Self-registration.

Cash-in.

Checking balance.

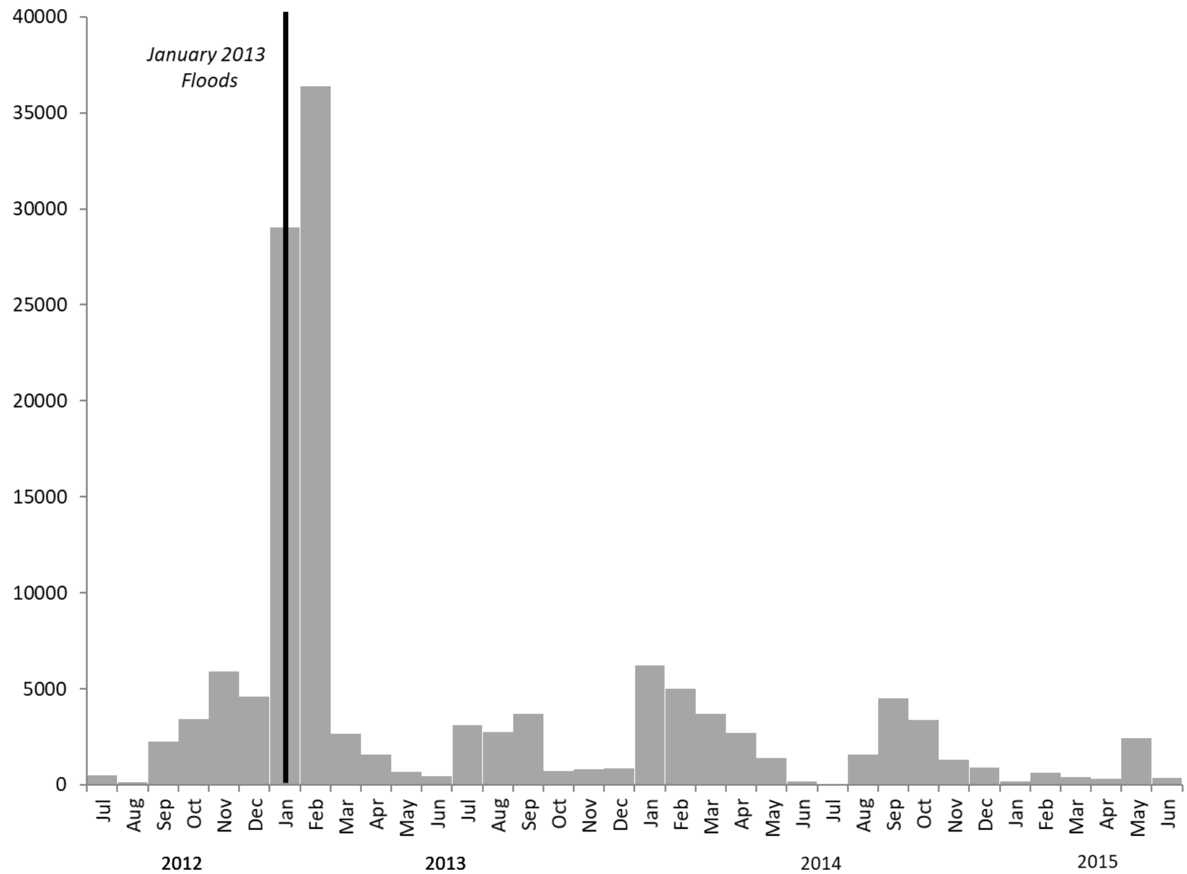
Paying for expenses at the mKesh shop.

Other operations and pricing:Transfer.

Cash-out.

Pricing.

Figure 3: Evolution of total value of monthly mobile money transfers received by all sampled households (in MZN) – administrative data provide by mobile money operator



APPENDIX - Behavioral measures of marginal willingness to remit and to save

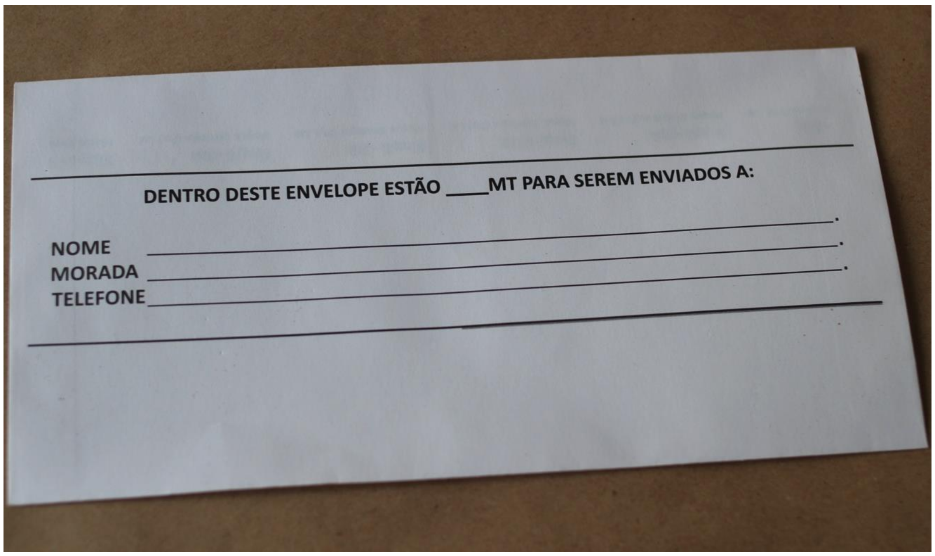
We conducted simple games to experimentally elicit behavioral measures of the marginal willingness to remit and to save, as well as of the marginal willingness to substitute between mobile money and conventional remittance and savings mechanisms. In particular, we measured the marginal willingness to remit to closely related migrants living in the Maputo city area and the marginal willingness to save after the introduction of mobile money services in rural areas of southern Mozambique. In addition, these games allowed us to measure the marginal propensity to use mobile money as a substitute for traditional saving and remittance mechanisms. These measures were obtained by playing games with all individuals in our sample, both in treatment and control locations, in all survey rounds.

The "remittance game" gave all individuals in both treatment and control locations 20 MZN (around 1 USD) in cash. The respondent could either keep the 20 MZN in cash, or remit this amount to a close migrant living in the Maputo city area (chosen by the respondent). If the respondent decided he/she wanted to remit, the respondent had to make an additional decision. The remittance could be sent through transferring the 20 MZN through the respondent's mKesh account, or through default remitting. A default remittance in rural Mozambique typically means sending money through someone, be it a family member, a friend, or a bus driver. So we proposed to send the 20 MZN in an envelope through 'us' (the enumeration team) without any costs. Figure A1 shows the envelope used for this purpose. This should be an attractive alternative to mKesh as our team was offering the money to begin with and there was no reason not to trust that the money would be taken to the migrant. In addition, we did not charge any fee for the remittance - something highly unusual and superior to the typical traditional remittance options people have available in Mozambique, where bus drivers will charge 20 percent fees to bring migrant remittances from Maputo to rural areas and often end up not delivering the transfer.

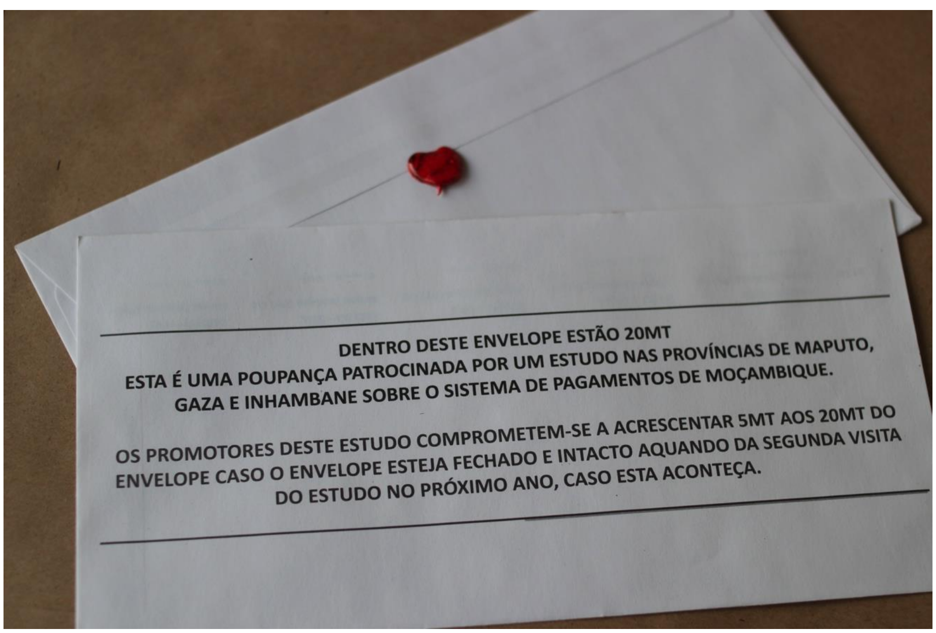
The savings game also gave all individuals in both treatment and control locations 20 MZN (around 1 USD) in cash. The respondent could either keep the 20 MZN in cash or 'save' them. If the respondent answered he/she wanted to 'save', the respondent had to make an additional decision. 'Saving' could be through cashing-in the 20 MZN in the respondent's mKesh account, or through default saving. Default saving in rural Mozambique typically means saving 'under the mattress.' So we proposed the following type of default saving: depositing the 20 MZN on a sealed envelope kept by the respondent, which would give the right to be paid 10 MZN in interest at the time of the next visit of the enumeration team (approximately one-year after, which implied the equivalent to a 50% interest rate), in case the envelope was still sealed at the time of that visit. The sealed envelope used is depicted in Figure A1. Note that the time of the next visit was expected to be in one year's time but it was uncertain when this game was run. The interest payment was meant to break indifference between cash-in-hand and cash-in-envelope. That way, in case there was already money 'under the mattress,' the sealed envelope would become the most valuable 20-MZN bill 'under the mattress.' This default option can then be seen as a very attractive alternative to adopting mKesh for saving.

Figure A1: Envelopes for default options in savings and remittance games

Remittance envelope.



Savings envelope (with sealing wax).



APPENDIX TABLES

Table A1a: Differences between locations in treatment and control groups at baseline

	Control Mean	Difference in Means between Treatment and Control
	(1)	(2)
Has primary school	0.941	0.039
	(0.238)	(0.039)
Has secondary school	0.392	-0.137
	(0.493)	(0.093)
Has health center	0.647	0.078
	(0.483)	(0.092)
Has market vendors	0.608	-0.039
	(0.493)	(0.098)
Has police	0.510	0.000
	(0.505)	(0.100)
Has church	0.980	0.000
	(0.140)	(0.028)
Has meeting point	0.471	-0.078
	(0.504)	(0.099)
Has electricity supply	0.627	-0.196
	(0.488)	(0.098)
Has sewage removal	0.137	-0.039
	(0.348)	(0.064)
Quality of mcel coverage (scale 1-5)	4.725	-2.392
	(13.537)	(1.906)
Has paved road access	0.255	-0.039
	(0.440)	(0.085)
Has land road access	0.706	0.020
	(0.460)	(0.090)
Price of transportation to the nearest bank (MZN)	31.508	-3.397
	(17.946)	(3.156)
Time distance to nearest bank (in minutes)	61.801	43.915
	(47.920)	(39.331)
Number of observations	51	102

Note: Standard deviations in parentheses in column (1). Standard errors reported in parentheses, clustered at the EA level, in column (2).

Table A1b: Differences between individuals in treatment and control groups at baseline

		Control Mean	Difference in Means between Treatment and Control
		(1)	(2)
Basic demographics	Age	38.543	-1.636
		(14.391)	(1.056)
	Gender (female)	0.627	-0.032
		(0.484)	(0.032)
	Years of education	5.547	0.178
		(3.582)	(0.315)
	Single	0.176	0.025
		(0.381)	(0.023)
	Married	0.665	-0.020
		(0.472)	(0.029)
	Separated	0.052	0.003
		(0.222)	(0.011)
	Widowed	0.107	-0.008
		(0.310)	(0.019)
Occupation	Farmer	0.464	-0.039
		(0.499)	(0.040)
	Vendor	0.086	0.020
		(0.281)	(0.019)
	Manual worker	0.065	0.007
		(0.247)	(0.015)
	Teacher	0.049	0.014
		(0.216)	(0.015)
Religion and ethnic group	Non-religious	0.046	0.015
		(0.210)	(0.014)
	Catholic	0.349	-0.041
		(0.477)	(0.036)
	Zion	0.167	0.026
		(0.374)	(0.035)
	Other christian	0.355	0.017
		(0.479)	(0.036)
	Religious intensity (scale 1-5)	3.796	-0.073
		(1.116)	(0.104)
	Changana	0.699	-0.015
		(0.459)	(0.082)
	Bitonga	0.075	-0.011
		(0.263)	(0.041)
	Chitsua	0.130	-0.005
		(0.336)	(0.054)
	Chopi	0.057	0.025
		(0.232)	(0.040)
Number of observations		1,021	1,819

Note: Standard deviations in parentheses in column (1). Standard errors reported in parentheses, clustered at the EA level, in column (2).

Table A1c: Differences between individuals in treatment and control groups at baseline

		Control Mean	Difference in Means between Treatment and Control
		(1)	(2)
Income and property	Per capita monthly expenditure (MZN)	6,421.067	-188.535
		(7,217.013)	(445.412)
	Owns plot of land (*machamba*)	0.864	0.019
		(0.343)	(0.028)
	Owns mosquito net	0.550	0.004
		(0.498)	(0.049)
	Owns fridge	0.145	-0.038
		(0.352)	(0.023)
	Owns sewing machine	0.031	0.011
		(0.172)	(0.010)
	Owns radio	0.512	0.006
		(0.500)	(0.031)
	Owns tv	0.395	-0.038
		(0.489)	(0.044)
	Owns bike	0.161	0.018
		(0.368)	(0.031)
	Owns motorcycle	0.017	0.011
		(0.128)	(0.007)
	Owns car	0.068	-0.023
		(0.252)	(0.010)
Technology and finance	Frequency of mobile phone use (scale 1-5)	4.824	0.003
		(0.467)	(0.032)
	Has bank account	0.265	0.042
		(0.441)	(0.036)
	Participates in rosca	0.166	0.015
		(0.372)	(0.028)
	Total savings (MZN)	4,726.001	574.254
		(13,590.305)	(986.943)
	Has bank loan	0.041	-0.008
		(0.199)	(0.010)
	Has family loan	0.056	-0.015
		(0.230)	(0.012)
Number of observations		1,021	1,819

Note: Standard deviations in parentheses in column (1). Standard errors reported in parentheses, clustered at the EA level, in column (2).

Table A2a: Differences between individuals in treatment and control groups at baseline for households surveyed in Year 2

		Control Mean	Difference in Means between Treatment and Control
		(1)	(2)
Basic demographics	Age	39.462	-1.909
		(14.673)	(1.181)
	Gender (female)	0.622	-0.032
		(0.485)	(0.036)
	Years of education	5.452	0.271
		(3.570)	(0.350)
	Single	0.157	0.028
		(0.364)	(0.025)
	Married	0.682	-0.013
		(0.466)	(0.028)
	Separated	0.052	0.002
		(0.222)	(0.013)
	Widowed	0.109	-0.017
		(0.312)	(0.019)
Occupation	Farmer	0.476	-0.053
		(0.500)	(0.046)
	Vendor	0.084	0.030
		(0.278)	(0.022)
	Manual worker	0.067	0.012
		(0.251)	(0.016)
	Teacher	0.052	0.016
		(0.222)	(0.017)
Religion and ethnic group	Non-religious	0.043	0.016
		(0.203)	(0.014)
	Catholic	0.350	-0.030
		(0.477)	(0.040)
	Zion	0.163	0.025
		(0.370)	(0.035)
	Other christian	0.365	-0.005
		(0.482)	(0.040)
	Religious intensity (1-5)	3.817	-0.035
		(1.093)	(0.097)
	Changana	0.693	-0.024
		(0.461)	(0.085)
	Bitonga	0.077	-0.015
		(0.267)	(0.041)
	Chitsua	0.127	0.014
		(0.333)	(0.057)
	Chopi	0.062	0.021
		(0.241)	(0.043)
Number of observations		727	1,261

Note: Standard deviations in parentheses in column (1). Standard errors reported in parentheses, clustered at the EA level, in column (2).

Table A2b: Differences between individuals in treatment and control groups at baseline for households surveyed in Year 2

		Control Mean	Difference in Means between Treatment and Control
		(1)	(2)
Income and property	Per capita monthly expenditure (MZN)	6,407.012	-333.036
		(7,479.466)	(508.287)
	Owns plot of land (*machamba*)	0.880	0.005
		(0.325)	(0.027)
	Owns mosquito net	0.562	0.014
		(0.497)	(0.051)
	Owns fridge	0.150	-0.032
		(0.357)	(0.026)
	Owns sewing machine	0.033	0.009
		(0.179)	(0.012)
	Owns radio	0.533	0.004
		(0.499)	(0.037)
	Owns tv	0.410	-0.026
		(0.492)	(0.048)
	Owns bike	0.174	0.023
		(0.380)	(0.035)
	Owns motorcycle	0.018	0.010
		(0.133)	(0.008)
	Owns car	0.068	-0.019
		(0.253)	(0.012)
Technology and finance	Frequency of mobile phone use (scale 1-5)	4.824	0.027
		(0.478)	(0.032)
	Has bank account	0.273	0.070
		(0.446)	(0.040)
	Participates in rosca	0.175	0.016
		(0.380)	(0.032)
	Total savings - meticais	4,662.880	711.152
		(12,780.207)	(915.245)
	Has bank loan	0.049	-0.014
		(0.215)	(0.012)
	Has family loan	0.060	-0.031
		(0.239)	(0.014)
Number of observations		727	1,261

Note: Standard deviations in parentheses in column (1). Standard errors reported in parentheses, clustered at the EA level, in column (2).

Table A3a: Differences between individuals in treatment and control groups at baseline for households surveyed in Year 3

		Control Mean	Difference in Means between Treatment and Control
		(1)	(3)
Basic demographics	Age	39.815	-2.267
		(14.435)	(1.147)
	Gender (female)	0.611	-0.001
		(0.488)	(0.034)
	Years of education	5.366	0.344
		(3.519)	(0.347)
	Single	0.162	0.054
		(0.369)	(0.026)
	Married	0.670	-0.048
		(0.470)	(0.032)
	Separated	0.055	-0.004
		(0.228)	(0.012)
	Widowed	0.113	-0.003
		(0.316)	(0.023)
Occupation	Farmer	0.485	-0.062
		(0.500)	(0.047)
	Vendor	0.088	0.024
		(0.284)	(0.021)
	Manual worker	0.062	0.010
		(0.241)	(0.017)
	Teacher	0.044	0.016
		(0.206)	(0.015)
Religion and ethnic group	Non-religious	0.046	0.006
		(0.210)	(0.014)
	Catholic	0.353	-0.056
		(0.478)	(0.040)
	Zion	0.179	0.020
		(0.384)	(0.037)
	Other christian	0.339	0.040
		(0.474)	(0.040)
	Religious intensity (scale 1-5)	3.807	0.031
		(1.111)	(0.095)
	Changana	0.700	0.003
		(0.458)	(0.084)
	Bitonga	0.080	-0.012
		(0.271)	(0.045)
	Chitsua	0.131	-0.009
		(0.338)	(0.055)
	Chopi	0.052	0.014
		(0.223)	(0.036)
Number of observations		764	1,324

Note: Standard deviations in parentheses in column (1). Standard errors reported in parentheses, clustered at the EA level, in column (2).

Table A3b: Differences between individuals in treatment and control groups at baseline for households surveyed in Year 3

		Control Mean	Difference in Means between Treatment and Control
		(1)	(3)
Income and property	Per capita monthly expenditure (MZN)	6,279.001	-301.788
		(7,343.351)	(457.890)
	Owns plot of land (*machamba*)	0.887	-0.000
		(0.316)	(0.027)
	Owns mosquito net	0.563	-0.024
		(0.496)	(0.052)
	Owns fridge	0.142	-0.041
		(0.350)	(0.025)
	Owns sewing machine	0.036	0.010
		(0.185)	(0.011)
	Owns radio	0.531	-0.016
		(0.499)	(0.035)
	Owns tv	0.395	-0.034
		(0.489)	(0.047)
	Owns bike	0.170	0.008
		(0.376)	(0.033)
	Owns motorcycle	0.017	0.010
		(0.130)	(0.007)
	Owns car	0.066	-0.025
		(0.249)	(0.012)
Technology and finance	Frequency of mobile phone use (scale 1-5)	4.822	-0.001
		(0.486)	(0.036)
	Has bank account	0.260	0.038
		(0.439)	(0.039)
	Participates in rosca	0.171	-0.002
		(0.377)	(0.031)
	Total savings - meticais	4,411.044	421.572
		(10,607.118)	(828.848)
	Has bank loan	0.041	-0.007
		(0.199)	(0.011)
	Has family loan	0.056	-0.023
		(0.231)	(0.014)
Number of observations		764	1,324

Note: Standard deviations in parentheses in column (1). Standard errors reported in parentheses, clustered at the EA level, in column (2).