Risk Sharing and Transactions Costs: Evidence from Kenya's Mobile Money Revolution

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Abstract

We explore the impact of reduced transaction costs on risk sharing by estimating the effect of mobile money on household consumption. Over a two-year period, household adoption increased from 43 to 70 percent, while the number of cash-in and cash-out agents increased four-fold. Using panel data we collected, we find that while shocks reduce per capita consumption by 7 percent for non-user households, the consumption of households with access is unaffected. The mechanism underlying this effect is an increase in remittances received, in number, size, and diversity of senders. A falsification test using data prior to the innovation supports these results.

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In developing countries, informal networks provide an important means by which individuals and households share risk, although the insurance they provide is often incomplete. Economists have proposed a number of reasons for this incompleteness, including information asymmetries, manifest in problems of moral hazard and limited commitment, both of which induce positive correlations between realized income and consumption. In this paper we emphasize a complementary source of incompleteness, transaction costs – literally, the costs of transferring resources between individuals. We test the impact of transaction costs on risk sharing by analyzing data from a large panel household survey that we designed and administered in Kenya over a three-year period to capture the expansion of "mobile money". This financial innovation has allowed individuals to transfer purchasing power by simple SMS technology, and has dramatically reduced the cost of sending money across large distances.

Mobile money is a recent innovation in developing economies - one of the first and most successful examples to date is Kenya's "M-PESA".[2] In just four years since its launch, M-PESA has been adopted by nearly 70 percent of Kenya's adult population and three quarters of Kenyan households have at least one user. The product's rapid adoption is due in part to the growth in a network of "agents", small business outlets that provide cash-in and cash-out services. The agents exchange cash for so-called "e-money", the electronic balances that can be sent from one account to another via SMS. In a country with 850 bank branches in total, the roughly 28,000 M-PESA agents (as of April 2011) have dramatically expanded access to what we argue is a very basic financial service - the ability to smooth risk.

Families and other social networks in Kenya are dispersed over large distances, due to internal migration, motivated by employment and other opportunities. Lowering transaction costs could have important impacts on the size and frequency of domestic remittances and hence the ability to smooth risk. The predominant use of M-PESA has been, and continues to be, person to person remittances. Before the technology was available, most households delivered remittances via hand or informally through friends or bus drivers. This process was expensive, fraught with delays, and involved substantial losses due to theft. For example, remittances in our data come from an average of 200km away, about a $5 bus ride. Now, all households need to do is send an SMS. Not only are the actual monetary costs of the transfers lower, but the safety and certainty of the process has meant substantial reductions in the costs of sending and receiving money.

To study how M-PESA has affected risk sharing in Kenya, we analyze data from a large household panel survey that we designed and administered over an eighteen month period between late 2008 and early 2010. First, we use a panel difference-in-differences specification, in which we include household fixed effects to compare *changes* in the response of consumption to

[2] "M" is for mobile, and "PESA" means money in Swahili. Mobile payment systems have also been developed in the Philippines, South Africa, Afghanistan, Sudan, Ghana, and in a number of countries in Latin America and the Middle East (Mas (2009) and Ivatury and Pickens (2006)). M-PESA itself has been started in Tanzania and South Africa. For related overviews, see Mas and Rotman (2008) and Mas and Kumar (2008). For qualitative analyses of M-PESA, see Morawczynski (2008), Mas and Morawczynski (2009), Morawczynski and Pickens (2009) Haas, Plyler and Nagarajan (2010) and Plyler, Haas and Nagarajan (2010). Also see Jack and Suri (2011) for more on the adoption of M-PESA and Jack, Suri and Townsend (2010) for the monetary implications.

shocks across M-PESA users and non-users. Importantly, we also allow for all individual characteristics we observe to affect risk sharing by controlling for their interactions with income shocks. This allows us to control for changes in the financial environment over this period, which we argue are minor, as well as for how these changes may affect the ability of households to smooth risk. We also present robustness checks in which we control for the interaction of household fixed effects with the income shocks.

Furthermore, we use household proximity to the agent network, which grew five-fold over the eighteen-month period between the survey rounds, as a proxy for access to the service to assess the robustness of our results. Again, using the panel structure of our data, we compare changes in the response of consumption to shocks (i) of households that experience greater increases in the density of agents around them to those who see smaller changes, and (ii) of households that have larger reductions in the distance to the closest agent. As a further robustness check, we present instrumental variable results using these agent rollout measures as a source of plausibly exogenous variation in utilization. In support of this identifying assumption, we show that agent location is not systematically correlated with households' ability to smooth risk in two ways: first, we show that the growth in the agent network is not correlated with any observables; and second, we perform a falsification test using data from prior to the advent of M-PESA.

Across these various specifications, we find that per capita consumption falls for a non-user household when they experience a negative income shock, as it does for households who lack good access to the agent network. On the other hand, M-PESA user households experience no such fall in per capita consumption. In particular, while non-users see on average a 7-10 percent reduction in consumption in the event of a negative shock, the point estimate for the response of consumption of users is much smaller and is often statistically indistinguishable from zero. The effects we find are more evident for the bottom three quintiles of the income distribution - this is expected as those in the top quintile of the income distribution were likely to be able to smooth risk even before the advent of M-PESA.

We show that these effects are indeed at least partially due to improved risk sharing and not due to liquidity effects that M-PESA may provide. Users of M-PESA achieve some of these improvements in their ability to smooth risk via remittances: in the face of a negative shock, user households are more likely to receive any remittances, they receive more remittances, and they receive a larger total value. In particular, households are about 13 percent more likely to receive remittances, which on average amount to between 6 and 10 percent of annual consumption in total. We also find that users receive remittances from a wider network of sources and a larger fraction of their network in response to a negative shock.

Townsend (1994, 1995), Udry (1994) and Rosenzweig and Stark (1989) made early contributions documenting the methods and extent to which households in developing countries are able to insure themselves partially against risk, through such mechanisms as informal inter-household transfers, state-contingent loan repayments, marriage and precautionary saving. Suri (2011) provides evidence for Kenya prior to M-PESA and finds that food consumption is well smoothed. Gertler and Gruber (2002) and DeWeerdt and Dercon (2006) observe that informal insurance helps finance the expenditure needs of individuals who suffer negative health shocks.

While these findings provide evidence that households engage in risk-spreading trades, the insurance they afford remains incomplete. One explanation for such incompleteness, modeled, for example, by Attanasio and Pavoni (2009), is that private information induces inefficiencies in resource allocation that optimally limit moral hazard costs. Alternatively, following the early work of Thomas and Worrall (1990) and Coate and Ravallion (1993), models of complete information with limited commitment have been developed (also see Phelan (1998), Ligon (1998), Ligon, Thomas and Worrall (2002) and Genicot and Ray (2003)). These models focus on maintaining incentives to participate in an insurance pool, and provide a framework that unifies insurance and state-contingent loans. Recent work by Kaplan (2006) and Kinnan (2010) has examined how these alternative theories of incomplete insurance can be tested against each other, with the latter also including a test for a model of hidden income.

There has also been interest in understanding the way in which insurance networks form, and the sociological links that determine the membership and the durability of risk sharing relationships.[3] For example, Attanasio et al. (2009) use a field experiment in Colombia to examine the role of trust and family ties in determining the identity of participants in risk sharing networks. Fafchamps and Lund (2003) and Fafchamps and Gubert (2007) study the formation of insurance networks in the Philippines. Kinnan and Townsend (2010) also analyze kinship as an integral element of financial inclusion and insurance and Chiappori et al. (2011) find that households with family members in the same village are able to spread risk better.[4] Our interpretation of these findings is that while family ties may limit commitment problems by making it more costly to quit a network, geographically distant family members participate less in risk sharing because of either exacerbated information constraints and the associated moral hazard problems, or transaction costs.

Few studies have incorporated explicit transaction costs into the analysis of informal risk sharing institutions. These costs can be substantial in developing countries, with under-developed financial systems and limited infrastructure. Many transfers take place in person, imposing large real resource costs for all but the smallest of transactions over the shortest of distances.

Yang and Choi (2007) and Ashraf et al. (2010) provide two pieces of evidence that remittances and transaction costs could be important for informal insurance networks. Yang and Choi (2007) find that the receipt of international remittances by households in the Philippines is associated with shocks to income (instrumented by rainfall), suggesting that remittances act to smooth consumption. Ashraf et al. (2010) show that lower remittance fees lead to increases in the frequency of remittances but do not change the per transaction amount. Finally, Schulhofer-Wohl (2009) and Angelucci et al. (2010) allow theoretically for transaction costs to generate

[3] The more general literature on social networks is outside the scope of this paper - good reviews can be found in Jackson (2009, 2010).

[4] Also see Bloch, Genicot and Ray (2008) and Ambrus et al (2010).

incomplete insurance, but do not empirically test their impact on consumption smoothing.[5]

The rest of the paper is structured as follows. In the next section we provide background information on the nature and adoption of M-PESA in Kenya. In section II we present a simple model of insurance with fixed transaction costs. In section III we provide a description of our survey data and follow this with a discussion of our empirical framework in section IV. In section V, we present our results and we conclude in section VI.

I Background on Mobile Money and M-PESA

M-PESA, launched in 2007 by Safaricom,[6] the dominant mobile network operator, is the most widely adopted mobile phone-based financial service in the world.[7] As shown in Figure 1A, the number of registered M-PESA users has grown consistently since the product's launch, and by April 2011 it had reached about 14 million accounts.[8] Ignoring multiple accounts and those held by foreigners, this implies that about 70 percent of the adult population had gained access to M-PESA in four years and, from our survey data, three quarters of households have at least one user. The number of M-PESA agents has grown in tandem, as illustrated in Figure 1B, and by April 2011 there were about 28,000 agents across the country. Over this same period, the number of bank branches across the country grew from 887 in 2008 to 1,063 in 2010 and the ATM network expanded from 1,325 to 1,979, both tiny changes relative to the growth of the M-PESA network. The fast adoption of M-PESA would not have been possible without the creation of this dense network of agents who convert cash to e-money and vice versa for customers. Typically, agents operate other businesses, which are often related to the mobile phone industry (such as mobile phone retail outlets, airtime distribution stores), but also include grocery stores, gas stations, tailors, bank branches, etc. The growth in M-PESA has also been enabled by expansion of the mobile phone network in Kenya,[9] which serves a total of 25 million subscribers (Communications Commission of Kenya (2011)) in a population of 40 million people (i.e. a 62% penetration rate).

Using M-PESA, individuals can exchange cash for e-money at par with any M-PESA agent

[5] We are unaware of any papers that have econometrically assessed the impact of mobile money on risk sharing. Early analysis of the economic impact of cell phones focused on their role in facilitating access to information, particularly with regard to prices (Jensen (2007), Aker (2010), Aker and Mbiti (2010)), and found that they improved the efficiency of market allocations.

[6] Safaricom controlled 78 percent of the market in 2010, ahead of its three nearest rivals (Zain/Airtel, Yu and Orange). In 2010, revenue was just over $1 billion (almost double revenue in 2007), and profit was $0.2 billion. In addition, 11% of Safaricom's revenue in 2010 came from M-PESA, 12% from other data services, and 69% from voice. Appendix Figure 2 shows strong and persistent growth in revenue from M-PESA since 2009, though M-PESA was a loss-maker for Safaricom for the first twelve to eighteen months.

[7] Cell phone users in Kenya and across the developing world are able to purchase and then send "air-time" (i.e., pre-paid cell phone credit) to others via SMA, thereby effecting long distance transfers of stored value. M-PESA formalizes this by creating e-money balances that can be converted to cash one for one (minus some transaction cost) and that can be accessed and transferred by SMS.

[8] Once you have a cell phone, registration is simple, requiring an official form of identification (typically a national ID card or a passport) but no other validation documents are necessary. Opening a bank account is much more difficult.

[9] Cell phones have reached a 50 percent penetration rate across Africa. There are just over 500 million subscribers across the continent, a number that was under 250 million in 2008 (Rao (2011)).

across the country,[10] and transfer these balances via SMS to any other cell phone in the country (including to sellers of goods and services), even if the recipient is not registered with M-PESA and even if the phone operates on a competitor network. Depositing funds is free, there is a fixed fee of 30 Kenyan shillings (about 40 cents) per SMS transfer, and withdrawals are charged according to a step function at a cost of 1-2 percent (the price is higher if the recipient is not a registered M-PESA user).[11] These fees are deducted from users' accounts, and shared by Safaricom on a commission basis with the relevant agent. No interest is earned on account balances, and M-PESA does not make loans. During the period over which our data were collected, central bank regulations limited individual M-PESA transactions to 35,000 shillings (about $470), and imposed a cap of 50,000 shillings (about $670) on account balances.[12]

As shown in Figure 2A, virtually all M-PESA users use the service to make person-to-person remittances (96 percent). It is used to save and to buy airtime with accumulated balances by 42 and 75 percent of users, and a small share (15-25 percent) use it to pay bills, services, and wages. Figure 2B shows the frequency at which households engage in each of these transactions. Of the 1,000 users individually interviewed in 2010, 74% report using use it at least once a month.

II Theoretical framework

In this section, we present a simple theoretical framework that highlights the role of transaction costs in risk sharing. The standard theory suggests that risk-averse households will attempt to smooth their consumption in response to variations in income and/or needs. If income variability is the only source of uncertainty, and if the marginal utility of consumption is independent of income shocks, then full insurance is reflected in fully smoothed consumption across states.[13] Smoothing consumption requires the state-contingent transfer of resources among households who jointly form an insurance network. The simplest theory of insurance assumes that this network is exogenously determined and fixed and that transferring resources among members is costless. In practice, especially in developing countries, these assumptions are not valid. Here we show that in the presence of transaction costs, the smoothing will not be perfect.

At a theoretical level, fixed costs of making transfers mean that small shocks will typically not be smoothed, but that larger ones will. If on the other hand transaction costs are proportional to the size of the transfer (and there is no fixed cost), then all shocks will likely be associated with transfers, but none will be fully offset. If money or goods are transferred in person, then

[10] The cash collected by M-PESA agents is deposited by Safaricom in bank accounts called M-PESA trust accounts at three different commercial banks. Agents are required to have bank accounts so that these transfers can be made electronically. These trust accounts act like regular current accounts with no restrictions on Safaricom's access to funds. In turn, the banks face no special reserve requirements with regard to M-PESA deposits, which are treated as any other current account deposit in terms of the regulatory policy of the Central Bank.

[11] The most recent complete tariff schedule is available at http://www.safaricom.co.ke/index.php?id=255.

[12] These limits were doubled in early 2011, after all the data used in this paper was collected.

[13] On the other hand, shocks that affect the consumption value of certain goods and services – e.g., health shocks that increase the usefulness of medical care – call for smoothing the marginal utility of consumption, but not necessarily consumption itself, across states.

the fixed costs include travel and time costs, which can vary with the distance that separates the individuals (but not with the amount sent). The variable costs may include the expected losses due to theft or loss during long-distance travel. Mobile money is a technology that significantly lowers both the fixed and variable costs of transferring money, thereby enabling households to smooth consumption more effectively. There are at least two mechanisms by which such improved smoothing can arise: first, for a given network of households who provide protection for each other, lower costs both allow a wider range of shocks to be offset by transfers and increase the share of each shock that is compensated; and second, lower transactions costs can expand the scope of the network involved in smoothing risk.

We present a model below in which three ex ante identical individuals form a mutual insurance network, and in which there is a fixed cost per transaction. There is complete information about realized incomes of each member of the network, and they can commit to implementing any budget-feasible ex post reallocation of resources. But the transaction costs might limit the number of members who optimally participate actively in the transfer of resources in any particular state of nature. We show that reductions in transaction costs expand the number of active network participants,[14] and hence the extent to which shocks can be smoothed.

A A model

Consider a static, one-period, model, with full commitment and complete information in which a group of three individuals, $i = 1, 2, 3$ insure each other. In state $s \in \{1, 2, ..., S\}$, incomes are x_i^s, and aggregate income is $x^s = \sum_i x_i^s = 1$, so there is no aggregate uncertainty. Each individual derives the same (state-independent) utility from consumption c, $u(c)$, and individual i's expected utility is

$$\overline{u}(c_i) = \sum_{s=1}^{S} p^s u(c_i^s) \tag{1}$$

where $c_i = (c_i^1, c_i^2, ..., c_i^S)$ is the vector of i's consumption across states, and p^s is the probability of state s.

When transaction costs are zero, Pareto efficiency requires that consumption plans satisfy

$$\max_{c_1^s, c_2^s, c_3^s} \overline{u}(c_1) \quad \text{s.t.} \begin{cases} \overline{u}(c_2) = v_2 \\ \overline{u}(c_3) = v_3 \\ \sum_i c_i^s = 1 \quad \text{for each} \quad s \end{cases} \tag{2}$$

for some fixed v_2 and v_3, or alternatively that they solve

$$\max_{c_1^s, c_2^s, c_3^s} \sum_i \mu_i u(c_i^s) \quad \text{s.t.} \quad \sum_i c_i^s = 1 \quad \text{for each} \quad s \tag{3}$$

[14] It is possible that the lower fixed costs of sending money over long distances are accompanied by higher monitoring costs, if previously those transfers that were made were delivered in person. If these monitoring and induced moral hazard costs were large enough, the lower transaction costs might not result in any change in behavior. This however does not appear to be the case in our empirical work.

for non-negative Pareto weights μ_i. Because this expression is independent of the probabilities p^s, and since there is no aggregate uncertainty, from now on we drop the s superscript. If $\mu_i = 1$ for each i, then total income in each state should be shared equally. For expositional convenience we maintain this assumption, and refer to $W(c) = \sum_i u(c_i)$ as ex post welfare.

For almost all income realizations, the optimum is characterized by two transfers, as illustrated in Figure 3A: either one individual makes transfers to the other two, or two individuals each make a transfer to the third. In all cases, the efficient allocation of consumption yields ex post welfare of $W^* = 3u\left(\frac{1}{3}\right)$.

Suppose there is a fixed cost k associated with each transfer of resources between any two individuals, and consider income realizations $x = (x_1, x_2, x_3) \in R^{213}$, where R^{213} is the sub-region of the 2-simplex satisfying $x_2 > x_1 > x_3$. Other sub-regions of the simplex are symmetric. If resources are shared equally, then almost everywhere, two transactions are needed and ex post welfare is $W^*(k) = 3u(\frac{1-2k}{3})$. Alternatively, if only a single transfer is undertaken, it will optimally be from the person with the highest income realization to the one with the lowest income realization: for $x \in R^{213}$, from individual 2 to individual 3, who share their incomes equally, net of k, while person 1 retains her endowment. Ex post welfare is then

$$\widehat{W}(x_1, k) = u(x_1) + 2u\left(\frac{1 - x_1 - k}{2}\right). \tag{4}$$

Finally, with no sharing, each individual consumes her realized endowment, and welfare is

$$W(x) = \sum_{i=1}^{3} u(x_i). \tag{5}$$

We define three sub-regions of R^{213} as follows:

$$\begin{aligned}
R_0^{213}(k) &= \{x \in R^{213} \text{ s.t. } W(x) > W^*(k) \text{ and } W(x) > \widehat{W}(x_1, k)\} \\
R_1^{213}(k) &= \{x \in R^{213} \text{ s.t. } \widehat{W}(x_1, k) > W^*(k) \text{ and } \widehat{W}(x_1, k) > W(x)\} \\
R_2^{213}(k) &= \{x \in R^{213} \text{ s.t. } W^*(k) > \widehat{W}(x_1, k) \text{ and } W^*(k) > W(x)\}
\end{aligned}$$

For $x \in R^{213}$, the optimal insurance agreement specifies the following consumption allocations:

$$c(x, k) = \begin{cases} (x_1, x_2, x_3) & \text{if } x \in R_0^{213} \\ (x_1, \frac{1-x_1-k}{2}, \frac{1-x_1-k}{2}) & \text{if } x \in R_1^{213} \\ (\frac{1-2k}{3}, \frac{1-2k}{3}, \frac{1-2k}{3}) & \text{if } x \in R_2^{213} \end{cases}. \tag{6}$$

Finally for $l = 0, 1, 2$ we define

$$R_l = \bigcup_{i \neq j \neq k} R_l^{ijk}$$

For all $x \in R_0$, no ex post sharing occurs; if $x \in R_1$ then one transaction is effected ex post; and if $x \in R_2$ then two transactions occur. In the appendix, we characterize these sub-regions of the simplex, which are illustrated below in Figure 3B. In R_0 differences in income at the realized endowment are small enough that it is not worth incurring any transaction cost to smooth consumption. In R_2 either aggregate income is sufficiently concentrated in the hands of one individual (at the corners of the simplex) that she should share it with both of the others, or one individual has sufficiently few resources and the rest is shared sufficiently equally between the other two (on the edges of the simplex) that each of the latter should share with the former, again inducing two transactions. Otherwise, in R_1, a single transfer should be made from the individual with the largest realized income endowment to the individual with the smallest.

We also show in the enclosed appendix (not for publication) that as the transaction cost decreases, a larger measure of income realizations are shared among all three members (i.e., R_2 expands), and a smaller measure of realizations are not shared at all (i.e., R_0 shrinks). That is, the number of active network members rises with a decrease in k. Allowing the transaction cost to vary with the size of the transfer, while maintaining the fixed cost component, would modify these results, but we propose that the underlying qualitative structure of network participation would not change. However, those transfers that take place would, in general, not fully smooth consumption across participating members, and conditional on participation, insurance would be incomplete.

Overall, this simple model highlights the three following implications of reduced transaction costs that we test empirically: (i) shocks are better smoothed, (ii) the number of transactions in a network increases, and (iii) the number of active network members increases.

III Data and Summary Statistics

In September 2008, we undertook a survey of 3,000 randomly selected households across a large part of Kenya. At the time, both cell phone tower and M-PESA agent coverage were very limited in the remote and sparsely populated northern and north eastern parts of the country, so these areas were excluded from the sample frame. The area covered by the sample frame included 92 percent of Kenya's population, and 98 percent of M-PESA agents as of April 2008. We randomly selected 118 locations[15] with at least one agent. In order to increase our chances of interviewing households with M-PESA users, we over-sampled locations on the basis of the number of M-PESA agents present in that location.[16] All the analysis presented below has been reweighted accordingly. In these 118 locations, there were a total of 300 enumeration areas that were part of the master sample kept by the Kenyan National Bureau of Statistics. We sampled

[15] Locations are the third largest administrative unit in the country. Kenya is divided into districts, then divisions, then about 2,400 locations and further about 6,600 sublocations. The average population of each location is about 3,000 households.

[16] At the time we designed our sampling strategy the subsequent rapid adoption of M-PESA was unanticipated, and there were real concerns that we might not find enough users to make statistically meaningful observations. Once M-PESA took off, we attempted to supplement our sample with areas that were not sampled during the first round. However, the Kenyan government was conducting its census in 2009, which made adding a sample from the previous sampling frame impossible because the census staff were overwhelmed with the logistics and collection of the new census.

ten households randomly from each of these enumeration areas to take part in the survey. The GPS-recorded locations of the households are shown in Figure 4 (Appendix Figure 1 shows population density across the country).

Follow-up surveys of the same households were administered in December 2009 and June 2010.[17] Attrition was unfortunately non-negligible, but we designed the interview strategy for the third round with an eye toward finding households missed in the second round. In 2009 we re-interviewed 2,018 households, and in 2010 we were able to find 1,595 of the original sample, 265 of whom were not interviewed in 2009. In this paper, we use the balanced panel of the 2,018 households from rounds 1 and 2, and add a second panel of 265 households using data from rounds 1 and 3. We control for the difference in the timing of the survey between rounds 2 and 3 for this sample of households throughout the regression analysis presented below. This strategy allows us to construct a two period panel of 2,283 households, with an attrition rate of about 24 percent. Because sample attrition is generally higher from urban areas, most of our analysis is limited to the non-Nairobi sample where the attrition rate is closer to 20 percent.[18] We discuss the attrition issues more in Section V.

We focus our analysis on this balanced two-period panel instead of the unbalanced three-period version.[19] In addition to natural concerns over potential biases that an unbalanced panel may introduce, we lack fully complete data on agents that would be relevant for the third round. In particular, our agent data was collected starting in late March 2010, a few months before households were surveyed in round 3. Our measures of agent access for all households in round 3 may therefore be imperfect. For households that we capture in all three periods, the change in their agent access between rounds 2 and 3 is small. Also, rounds 2 and 3 were not far apart so there were not immense changes in agent access between these two rounds. Across the country, there was about a 20 percent increase in the number of agents between these two rounds, compared to a four fold increase between rounds 1 and 2. A subset of the three period unbalanced panel results are posted in a web appendix at http://www.mit.edu/~tavneet/Jack_Suri_Web.pdf.

[17] These dates indicate the start of the survey. Each survey round lasts between 8 and 12 weeks in the field so only a short period of time elapsed between rounds 2 and 3.

[18] These attrition rates are not different from those found in other studies. We reviewed existing panel datasets to document attrition rates. Ashraf et al. (2011), in a remittances study among El Salvador immigrants, were able to follow up on 56.2 percent of the DC area immigrants, and for about 42.7 percent of the sample, they were able to follow both the DC area immigrants as well as the recipient households in El Salvador (they were only able to survey 82 percent of the recipients in El Salvador to begin with). Baird et al. (2008) get follow up rates of between 84 percent and 88 percent, though this is over a much longer period and for only a rural sample. Dercon and Shapiro (2007) document attrition rates across a number of panel studies (again mostly rural), with mean attrition rates for dwellings of about 33 percent, the mean with local tracking being about 14 percent and the mean with extensive tracking being about 7 percent (though all low attrition countries in this group are in Asia). Alderman et al. (2001) also document attrition rates - in an urban Bolivia survey over two years the total attrition was 35 percent with 19.4 percent annual attrition rates. A survey in rural Kwa Zulu Natal in South Africa had an attrition rate of 16 percent over five years. Heeringa (1997) documents an attrition rate of 39.8 percent in the urban Moscow/St Petersburg area in the Russia Longitudinal Monitoring Survey. Lam et al. (2007) use the Cape Area Panel Study where the attrition rates were about 17 percent between waves.

[19] The three period balanced panel covers only 1,311 households.

The surveys we conducted solicited information on basic household composition and demographics, household wealth and assets, consumption, positive and negative shocks, and remittances (both sending and receiving). We also asked for information on the use of financial services, savings, etc., and collected detailed data on cell phone use and knowledge in general, and on the use of M-PESA in particular. Basic patterns in the data are documented in Jack and Suri (2011). Here, we focus only on the data that is relevant to risk sharing.

Table 1A reports summary statistics for the analysis sample of households. Over the two survey periods, the share of households that reported owning at least one cell phone rose from 69 percent to 76 percent, while the share with at least one M-PESA user increased from about 43 percent to 70 percent. Annual per capita consumption was approximately 73,000 Kenyan shillings (or about $975) in period 1, but fell to about 64,000 KSh ($850) in period 2. This drop is attributable to a drought that hit Kenya in late 2008 and continued through 2009. Food consumption is roughly half of total consumption, and wealth is about twice total consumption.

While half of all households had at least one bank account, fully three quarters report that they save money at home "under the mattress". Furthermore, about 18 percent use a savings and credit cooperative and over 40 percent are members of rotating savings and credit associations. Due to security concerns, households are unwilling to report actual amounts saved in each instrument. Jack and Suri (2011) provide more information on how households use M-PESA, on its quality and accessibility, and the differences between users and non-users, and how these indicators have changed over time. M-PESA is used often, with 40 percent of those having ever used it reporting that they use it at least once a month.

By far, the dominant reason for M-PESA use during the period covered by the survey was for sending and receiving remittances. In the first round of the survey, for 25 percent of M-PESA-using households, the most important use was sending money, and for another 29 percent it was receiving money, while for 14 and 8 percent, the most important function was buying airtime for themselves or others, respectively. As shown in Figures 2A and 2B, even in the latest round of the data collected in 2010, well over 90 percent of M-PESA users say they use the service to send or receive money, and of those who do, over 70 percent use it at least monthly. Domestic remittances, not just by M-PESA, are an important part of the financial lives of many households in our sample. As reported in Table 1A, in both the 2008 and 2009 rounds of the survey, nearly half reported that they sent at least one remittance, while the share who reported receiving a transfer rose from 39 percent in period 1 to 42 percent in period 2. International remittances were small by comparison, amounting to less than 1 percent of total remittances.

Similarly, risk is a dominant feature of the lives of Kenyans. In period 1, which likely included some of the lingering effects of the aftermath of post-election violence of early 2008 and the accompanying price hikes, 50 percent of our survey respondents reported a negative shock in the preceding six months.[20] Nearly 57 percent reported such a shock in the six months

[20]In the first period, we collected data on shocks during the eight to nine months preceding the survey since the first round followed the post-election crisis and we opted to include those months. For all the analysis in the paper, we focus only on those shocks experienced in the six months prior to the survey to keep round 1 comparable

preceding the period 2 survey. Positive shocks were far less common. In much of our analysis, we combine all types of negative shocks into a single variable, but we also look separately at weather and illness shocks. In our data, between 4 and 13 percent of households experience a weather shock and 24 to 40 percent an illness shock.

Table 1B disaggregates the period 2 data of Table 1A by M-PESA user status. In particular, we distinguish among three groups of households: early adopters (who had an M-PESA user in both periods 1 and 2), late adopters (who had a user in period 2, but not in period 1), and non-adopters (who had a user in neither periods 1 nor 2).[21] Early adopters are wealthier and more educated, and are more likely to use formal financial products (such as bank accounts) than late adopters, who are similarly positioned vis-a-vis never adopters. Table 2A provides more detailed data on the nature of domestic remittances.[22] In the two periods, households sent on average about 2-3 remittances per month, and received about 2 per month. In each period, the total value of remittances sent and received over the prior six months to the survey was close, making up between 3 and 5 percent of annual household consumption. The gross volume amounted to about 9 percent of monthly consumption in period 1 and somewhat less (6 percent) in period 2. Reflecting the often large geographic separation of families and kin, remittances travel on average more than 200 km, suggesting the potential for important efficiency gains from electronic money transfer technologies.

The bottom two panels of Table 2A disaggregate all domestic remittances by the method of transmission - i.e., via M-PESA or another means. Note that this table does not split the remittances by user status, but by whether M-PESA was used, since even households that use M-PESA continue to send remittances by other means. From Table 2A, the number of remittances both sent and received by M-PESA grew between the two periods, although the total value of receipts fell by just over 50 percent. By comparison, the amounts both sent and received by means other than M-PESA fell by more than 50 percent between the two periods. Importantly, the distance traveled by remittances is higher for those delivered by M-PESA than for others, except for those received in period 2 (which cover the same distance, about 230 km). Despite the expansion of M-PESA, Table 2A reveals little change in the total number of remittances households report sending or receiving between the two survey rounds. However, as the lower panel of Table 2A also illustrates, there was quite a dramatic switch to M-PESA. We also note that average per capita consumption levels were lower in round 2, and that fewer negative shocks were reported, each of which might be associated with less frequent remittances.

In Table 2B, we report data on transaction costs from the first round of our survey. In particular, we report the average cost of sending remittances according to the different methods used. The monetary transaction costs of using M-PESA are much lower than most alternatives,

with round 2 where we only asked about the last six months.

[21] Four percent of the sample switched from having a user in period 1 to not having one in period 2. These households are not included in this table (but they are included in all our results).

[22] All the figures in this table are conditional on non-zero use, i.e., the sending statistics are conditional on households sending at least one remittance and the receiving statistics are conditional on the households receiving at least one remittance.

except those that are delivered by hand. However, reported costs of hand delivered remittances do not include transport costs, which can be substantial. For example, the average distance a remittance comes from is about 200km which alone would cost at least KShs 400 (about $5) in travel costs one way for an individual.

In addition to the household survey data, starting in March 2010, we visited nearly 7,700 M-PESA agents across the country. The sample covered the entire population of agents in each of the administrative locations from which our household sample had been drawn. In addition to administering a short survey, we recorded the GPS locations of the agents, and the dates on which they first conducted M-PESA business. We were thus able to construct detailed rollout data on the agents, and determine when our households first got easy access to M-PESA.[23]

At the national level, the agent network grew from about 4,000 agents at the time of the first round of the survey to close to 20,000 by the third round (Figure 1B). Between 2008 and 2010, there was therefore a five fold increase in the number of agents, a period over which bank branches across the country grew by 20 percent (from 887 to 1,063). Figure 5 illustrates this growth in M-PESA agents in more detail for our sample of 7,700 agents: on the left we show the location of agents in existence in June 2008, and on the right we include those operating in early 2010 (agents that began operations more recently are shaded more heavily).[24] Many of the agents had existing business relationships with Safaricom prior to the advent of M-PESA, and about 75 percent report sales of cell phones or Safaricom products as their main business.

Table 3 reports data on household access to agents, as measured by the average number of agents within certain distances of households and by the distance to the closest agent. The density of agents more or less doubled between periods 1 and 2, although these measures may be a little misleading because they also include zeros. The distance to the closest agent changed dramatically throughout the distribution - for example, the average distance in the bottom quintile fell by 40% and that in the top quintile by 33%. As a comparison, Suri (2011) documents the change in the distance to fertilizer distributors between 1997 and 2004 - the distance to the closest fertilizer distributor fell by 45% over this seven year period. The second panel of Table 3 shows the difference in distance between the closest agent and the second closest agent for households (as a fraction of the distance to the closest agent). This difference was just over 80 percent in round 1 of the survey - this means that the second closest agent to a household was almost twice as far as the closest. By round 2, this difference had fallen to only 40 percent.

Our surveys also collected a number of agent-level operational indicators - agents conduct an average of 10 transactions a day (customers visit agents only for cash-in or cash-out services, not to make transfers). We report measures of the ability of agents to manage inventories of both cash and e-money, which are needed if customers are to withdraw and deposit funds, respectively.

[23] Some M-PESA agents may have shut down between 2007 and our survey, but we cannot measure that turnover. This is less likely to be an issue given the growth in total agents over this period.

[24] Appendix Figure 1 shows population density across Kenya. The cell phone network follows a similar pattern, with very little investment in towers in the Northern part of the country, given the low population densities and the semi-nomadic nature of livelihoods there.

In addition, when taking a cash deposit, an agent sends e-money from his/her own M-PESA agent account to the depositor. The agents must therefore maintain sufficient inventories of e-money to effect these transactions. Improvements in the density of the agent network will increase access to both forms of liquidity and improve the effectiveness of M-PESA as a service.

IV Empirical Framework

If M-PESA significantly reduces the transaction costs of transferring money, especially over long distances, our theory suggests the following testable hypotheses:

1. The consumption of M-PESA users should respond less to shocks than that of non-users;

2. To the extent that these differences arise from differences in remittance behavior, remittances should respond more to shocks for M-PESA users than for non-users;

3. The network of active participants should be larger for users than non-users.

We test these hypotheses both by using household-level data on consumption and shocks, and by combining these data with information on access to the network of M-PESA agents. Here, we describe our various empirical specifications and identification assumptions, as well as a falsification test using household survey data collected prior to the advent of M-PESA.

A Basic Specification

We first use a simple difference-in-differences strategy to examine the impacts of M-PESA on risk sharing by comparing the response of the consumption of M-PESA users and non-users to reported income shocks in the following specification that closely mirrors that of Gertler and Gruber (2002) and Gertler, Levine and Moretti (2006, 2009),

$$c_{ijt} = \delta + \alpha_i + \gamma Shock_{ijt} + \mu User_{ijt} + \beta User_{ijt} * Shock_{ijt} + \theta X_{ijt} + \eta_{jt} + \varepsilon_{ijt} \tag{7}$$

where c_{ijt} is annual per capita consumption for household i in location j in period t, α_i is a household fixed effect, η_{jt} are a set of location by time dummies, $Shock_{ijt}$ is a dummy variable equal to one if the household reports experiencing a negative shock to income in the last six months, $User_{ijt}$ is a dummy for whether there is an M-PESA user in the household at the time of the survey, and X_{ijt} is a vector of controls (in particular household demographics, years of education of the household head, household head occupation dummies (we use three categories: farmer, business operator and professional), the use of financial instruments (including bank accounts, savings and credit cooperatives and rotating savings and credit associations), and a dummy for cell phone ownership). The η_{jt} in equation (7) are included to control for aggregate location-level aspects shocks. In the empirical work, we confirm that these location-by-time dummies have little impact on our results.

Equation (7) allows for a reduced form test of the effect of transaction costs on risk sharing. If both user and non-user households can smooth consumption in the face of income shocks, the coefficients γ and β should both be zero.[25] If, however, households are in general unable to fully insure themselves, then γ will be negative. The coefficient β then tests whether the users of M-PESA are better able to smooth risk. In addition, if the null hypothesis, $H_0 : \beta + \gamma = 0$, cannot be rejected, then we cannot reject the null that M-PESA users are fully insured.

Using this strategy, we can also assess the mechanisms by which M-PESA facilitates risk sharing, in particular the role of remittances, by estimating the following version of equation (7)

$$r_{ijt} = \delta + \alpha_i + \gamma Shock_{ijt} + \mu User_{ijt} + \beta User_{ijt} * Shock_{ijt} + \theta X_{ijt} + \eta_{jt} + \varepsilon_{ijt} \tag{8}$$

where r_{ijt} is a measure of remittances over the past six months, either the probability of receiving a remittance, the number of remittances received or the total value received. We also look at whether remittances travel a longer distance and whether they come from a larger number of members of a household's network.

Next, we discuss the identification assumptions behind specifications like equations (7) and (8), and then how we use the agent data to complement our core analysis. We leave further robustness checks and attrition issues to Section V after we present our main results.

B Identification and Assumptions

For equations (7) and (8) to identify the causal effect of M-PESA on risk sharing, we must assume that the interaction term $User_{ijt} * Shock_{ijt}$ is exogenous, or uncorrelated with the error ε_{ijt}, conditional on the main effects of being a user and of experiencing a shock, the household fixed effects and the other covariates. Here, we describe the situations under which this assumption holds and we address failures of it in the next subsection. Note that the specification in equation (7) already includes a set of household fixed effects as well as a complete set of location-by-time dummies. The former controls for unobserved but fixed characteristics of households and the second for any aggregate shocks, including the decisions of agents to provide services in a given location in a given period.

Our identification assumption is satisfied if shocks are truly exogenous. This may be reasonable for two reasons: first, households were asked in the survey to report only unexpected events that affected them[26]; and, second, reported shocks are not systematically correlated with

[25] In most empirical work, including in developing countries, the hypothesis that households are perfectly insured is rejected, although there is strong evidence that partial risk sharing does take place (see Townsend (1994, 1995), DeWeerdt et al. (2006), Fafchamps and Lund (2003), Fafchamps and Gubert (2007), Deaton (1990, 1992, 1997), Goldstein (1999) and Grimard (1997), among others). Suri (2011) looks at the specific case of Kenya and provides evidence on the extent of risk sharing. There is also a vast literature studying the efficiency of consumption smoothing in the developed world. Examples include Blundell, Pistaferri and Preston (2008), Cochrane (1991), Gertler and Gruber (2002), Hayashi, Altonji and Kotlikoff (1996), Mace (1991), among others.

[26] The survey question reads, "Which of the following unexpected events has this household experienced in the last six months?" The household can also specify other events that are not on the pre-specified list. For round 1, for example, the responses included price shocks as well as the post-election crisis.

a number of household-level variables. In particular, we find that income shocks are correlated with consumption changes and remittances, as would be expected, but that they are not correlated with other household characteristics, such as education of the household head and the use of various financial instruments. Similarly, we find no evidence that shocks - overall as well as illness and weather shocks separately - are correlated with access to the network of M-PESA agents. We report these correlations in Appendix Table 1.

In equation (7), the endogeneity of M-PESA use, say due to selective adoption associated with wealth and/or education, is absorbed in the main effect of being a user. We exploit the panel structure of our data and include household fixed effects to control for other sources of endogeneity, In particular, the difference-in-differences specification in equation (7) allows for unobservables to be correlated with and indeed to drive the use of M-PESA, as long as those unobservables are not attributes that also help the households smooth risk better (i.e., they should not interact with the response to the shock).[27]

As already noted, M-PESA use is correlated with education and the use of other financial instruments, both of which may help households smooth risk. In light of this, we propose two different strategies to account for this. The first extends equation (7) by including the interactions of the shock with all observable covariates using the following specification

$$c_{ijt} = \delta + \alpha_i + \gamma Shock_{ijt} + \mu User_{ijt} + \beta User_{ijt} * Shock_{ijt} + \theta^S X_{ijt} * Shock_{ijt} + \theta^M X_{ijt} + \eta_{jt} + \varepsilon_{ijt} \quad (9)$$

where X_{ijt} is the same vector of controls as above. The second strategy uses the agent rollout data we collected, as described in subsection C below.

Equation (9) represents our preferred specification throughout the paper. This specification controls for the interactions of the shock with measures of household demographics, the years of education of the household head, household head occupation dummies, the use of bank accounts, the use of savings and credit cooperatives, the use of rotating savings and credit associations, and a dummy for cell phone ownership. From Table 1A, we can see that there were small increases in the use of bank accounts and rotating savings and credit associations between the two periods. The specification in equation (9) controls for any effects this may have had on the ability to smooth income shocks. It also controls for any effects the other covariates have on the ability to smooth shocks - for example, the increase in the use of cell phones may have provided better information on shocks but we control for any such information effects by including the interaction of the use of the cell phone with the income shock in the $X_{ijt} * Shock_{ijt}$ term above. Note that we cannot control for the level of savings in each of these instruments interacted with the shock as data on the level of savings was not collected, as mentioned above.

[27] We can think of equation (7) as similar to looking at treatment effect heterogeneity, where the complement to treatment here is the exposure to an exogenous income shock.

C Using Agent Data

Effective use of M-PESA requires access to agents who provide cash-in and cash-out services so that consumers can easily convert e-money to cash, or *vice versa*.[28] We use the data from our agent survey to construct a time profile of the rapid expansion of the agent network as a complement to our analysis above.

C.1 Reduced Form Analysis

We first adopt a reduced form version of the simple difference-in-differences strategy used above, with measures of geographic proximity to the agents as indicators of access, according to the following specification

$$c_{ijt} = \delta + \alpha_i + \gamma Shock_{ijt} + \nu Agent_{ijt} + \beta Agent_{ijt} * Shock_{ijt} + \theta^S X_{ijt} * Shock_{ijt} + \theta^M X_{ijt} + \eta_{jt} + \varepsilon_{ijt} \tag{10}$$

where $Agent_{ijt}$ is a given measure of the access to an M-PESA agent. This specification mirrors that of equation (9) where we also control for the interactions between a set of observables and the income shock in the $X_{ijt} * Shock_{ijt}$ term.

We present these estimates as they are directly comparable to the falsification test we develop below. The assumption behind the specification in equation (10) is that agent density is not systematically correlated with household level *unobservables* that also help households smooth risk. The observables that we control for, both as levels as well as interactions with the income shock, include measures of household demographics, the years of education of the household head, household head occupation dummies, the use of bank accounts, the use of savings and credit cooperatives, the use of rotating savings and credit associations, a dummy for cell phone ownership and the interactions of all these with the income shocks. Our falsification test below provides evidence to support this assumption. In the empirical analysis, we also present results that control for household fixed effects interacted with the negative shock. This specification assumes that improvements in agent density are not correlated with household level unobservables that change between our two survey rounds that also help households smooth risk better.

Over the period covered by our surveys, the number of applications lodged by potential agents with Safaricom far outweighed the number granted. Partly, this was due to bottlenecks in the approval process, as the conditions required for an existing business or entrepreneur to become an agent were, and continue to be, stringent.[29] From discussions with senior M-PESA management, we understand that, given the overwhelming number of agent applications, there was neither the ability, nor an attempt made, to match agent expansion actively to areas with particular characteristics, and that the sequencing of new agent approvals was not directly

[28] Over the long term, it is conceivable that agents will become less important if e-money circulates and is used widely as a medium of exchange. During the period of our surveys, and still now, the density of the agent network has been a crucial component of the service's perceived value and success.

[29] Potential agents need access to the internet, a bank account and must make an up-front investment of about $1200 in purchasing e-money, which is a reasonably large sum for a small scale Kenyan entrepreneur.

controlled or managed on the part of M-PESA in this way.

Strikingly, M-PESA management did not know the administrative locations of their agents[30], so it is hard to believe they were able to seek or approve applications on the basis of information on characteristics of nearby households that we did not collect. The one exception may have been Nairobi, where new agent approvals were discontinued in late 2009 due to a perceived overcrowding of agents. This is the only area where M-PESA management actively made any agent decisions according to location. Accordingly, we present results excluding the province of Nairobi in most of our analysis below.

Due to the service being primarily focused on long distance remittances, the agent network was, early on, quickly rolled out to cover most populated areas of the country, as illustrated in the left panel of Figure 5, albeit with relatively low density compared to subsequent levels. The larger changes over our sample period came from the increased density of agents within locations, and not the expansion to new locations. For example, only about 5% of sublocations in our sample saw the arrival of their first agent between the first and second rounds of our survey. Similarly, only about 4 percent of households have a change in whether there is access to at least one agent within a specified distance (within 1 km, for example) between the two rounds. On the other hand, conditional on having access to an agent within 1 km in the first survey period (for the non-Nairobi sample), there was about a 120 percent increase in the number of agents within 1 km between the two survey periods. Increases for the 2 km, 5 km and 10 km agent densities were 120, 130 and 140 percent, respectively. The second panel in Table 3 shows further evidence of the improvements in agent density over this period. Because agents run out of cash and/or e-money extremely often (see Table 3), these increases in density reflect significant improvements in the access and functionality of M-PESA.

Finally, we confirm that the roll out of agents is uncorrelated with observables in our data, including wealth, cell phone ownership, literacy and education of the household head, use of a bank account and other financial instruments, income shocks, and distance to Nairobi.

C.2 Falsification Test

The agent data also allows us to perform a falsification test using household survey data from the years before M-PESA. For this exercise we use data from a four-period panel household agricultural survey collected over 1997-2007 by Tegemeo Institute of Agricultural Policy in Nairobi, Kenya, the same data used to study risk sharing in Suri (2011).[31] There are two main differences between these data and the data collected for the purpose of the current paper. First, it is a sample of only rural households and, second, the consumption module covered a limited

[30] In the first round of our household survey, we oversampled administrative locations with more agents. We had to collect the data on the number of agents in each location in the country ourselves as Safaricom simply did not maintain a database with this information. This was still true at the time of our agent survey in 2010. Safaricom finally collected the GPS coordinates for a subset of its agent network after our agent survey.

[31] For space reasons, and given this is just a falsification test and a small part of this paper, we do not describe the data in detail here. It is described in detail in Suri (2011).

number of items, including maize consumption and some other components of food consumption (the survey was focused on income and agriculture). As described in Suri (2011), maize is the main staple food in Kenya and the consumption of maize in this data covers purchases of both processed and unprocessed maize as well as own production. We use this as our first measure of consumption. The second measure includes consumption of all food from own production, which on its own covers well over 40 percent of total consumption. In this falsification test, we replicate the strategy we used above with the agent data in equation (10). In particular, we assess the extent of differential risk sharing across households that later experienced differential access to the agents. We use the agent access measures as of 2009 (the results are robust to using agent data at other times). Since there was no M-PESA at the time of the Tegemeo survey, and hence no M-PESA agents, future agent access should not improve risk sharing. We compare the results of this falsification test both with those using our full panel, as well as for a restricted sample of poor, agricultural/rural households to closely reflect the Tegemeo sample.

C.3 Instrumental Variable Regressions

We can also use the agent rollout data to create a set of instruments and use standard IV methods to control for the endogeneity of M-PESA user. Given there are two endogenous variables, the use of M-PESA and its interaction with the negative income shock, we need to instrument for each. As excluded instruments, we therefore use the distance to the closest agent and the number of agents within 5km of the household, as well as the interactions of each with the relevant shock variable. These two measures of agent access are used because of their relatively low correlation with each other ($\rho \approx 0.5$).

V Results

Following the empirical strategies outlined above, we estimate the impact of M-PESA on the ability of households to smooth consumption. We look at the evidence on the mechanisms underlying these results to illustrate that the effects are indeed due in part to risk sharing and the reduction in transaction costs that M-PESA provides and not just due to any liquidity effects it may provide. We then present results of our analysis using the agent rollout data and the accompanying falsification test.

A Difference in Differences Results

Table 4A presents results of our basic specification, equation (7), controlling for a set of covariates. We also report results for the specification in equation (9) in which the covariates are interacted with the shock. In addition to the regression coefficients, in the bottom panel of the table we report mean effects of a negative shock for the full sample (though this is heavily driven by the users who constitute a large fraction of the sample), and for M-PESA users and non-users separately to allow us to compare how these two groups respond to negative shocks. For the effects of the shock for users (non-users), we evaluate the overall effects of the shock at the mean characteristics of the users (non-users). Finally, we also report the effects of the shock for the non-users when evaluated at the mean characteristics of the users - the aim is to understand the role of M-PESA conditional on other observables being similar across users and non-users.

Column (1) in Table 4A reports OLS results (for comparison) with no controls except time fixed effects. In the absence of shocks, consumption is about 55 percent higher for M-PESA users than non-users, reflecting mostly selection effects. Shocks reduce per capita consumption of households without an M-PESA user by 21 percent, but households with an M-PESA user are able to somewhat protect themselves against these shocks, seeing per capita consumption fall by only 11 percent. While this effect is significantly different from zero (see bottom panel), it is also significantly smaller than the 21 percent drop in consumption experienced by non-users. In column (2) we show that the results are very similar for the non-Nairobi sample, which most of our subsequent analysis is based on. M-PESA users appear to be able to smooth a large portion of negative shocks, while non-users are subject to more volatile consumption patterns.

Some of the differences in responses to shocks between users and non-users in columns (1) and (2) could be due to observable differences along other dimensions that allow households to smooth risk better. To allow for this, in column (3) we use the panel specification with a household fixed effect and include the full set of covariates as well as the interactions of the negative shock with the covariates, as per equation (9) above. The coefficients on the shock in columns (1) and (3) cannot be directly compared since column (3) includes interactions - instead in the lower panel we report the overall effects of the shock as well as the effects for users and non-users separately that are comparable across columns.[32] The results are robust to adding these covariates and interactions. In column (4) we add the location-by-time dummies (η_{jt}). The results across columns (1) through (4) are very similar: as reported in the bottom panel, non-users suffer approximately a 7 percent reduction in consumption while users are able to smooth shocks perfectly and experience no significant reduction in consumption. Finally, in columns (5) and (6) we show very similar results for the non-Nairobi sample, while column (7) reports results excluding Mombasa, Kenya's second largest city.

In column (8), we restrict the sample to households that were in the bottom three quintiles of the wealth distribution in the sample in the first round. The aim is to check whether the effects we find are mostly concentrated in the poor households, as we expect the richer households to be able to smooth shocks effectively even before the advent of M-PESA. As column (8) illustrates, we indeed find that the effects are strong for the bottom three quintiles of the wealth distribution (we find effects that are no different from zero for the top two quintiles).

In Table 4B, we report the impact of weather shocks (columns (1) and (2)) and illness

[32] The first row reports the mean effect of the negative shock for the sample, evaluated at the mean of the covariates. The second row reports the mean effect of the negative shock for users, where we evaluate the effect of the shock at the mean level of covariates for users (education, occupation, household demographics and use of financial services), which are different from those of non-users. The third row reports effects for non-users, evaluated at the mean level of covariates for them. The final row reports the effects for non-users when evaluated at the mean covariates of the users.

shocks (columns (3) through (6)) on consumption, using the specifications in equations (7) and (9). Column (1) controls for our core set of covariates and their interactions with the weather shock. In column (2), we additionally control for location-by-time dummies. We find similar effects to Table 4A. For non-users, the weather shocks lower consumption by 20%, all of which the users seem able to smooth. Note that the weather shocks are picking up the drought that parts of Kenya experienced over this period, which accounts for the large effects.

Columns (3) and (4) examine the impact of illness shocks - here users see an increase in their consumption in response to a negative shock, while the consumption of non-users is unresponsive, or even falls. This pattern appears to reflect the ability of user households to finance necessary health care expenditures (most likely from remittances) without compromising other consumption, while non-users must reduce non-medical spending in the presence of health care needs. Columns (5) and (6) confirm these results: the impact of illness shocks on a measure of consumption that does not include health care expenses[33] is negative (an 8 to 13 percent drop) for M-PESA non-users, but is statistically not different from zero for users.[34]

B Mechanisms

The most natural route by which M-PESA improves the ability of households to share risk is through remittances, but other mechanisms could be at work. For example, by providing a safe though unremunerated savings vehicle, it may induce households to build up precautionary savings balances. Alternatively, households might be considered more credit worthy if they have M-PESA and may be more able to borrow money in an emergency. This mechanism is closely related to the remittance story, as it would rely on the belief by creditors that debtor households can make repayments more efficiently and reliably (via the money transfer feature).[35] However, in our data very few remittances (only about 7 percent) are reported as being for the repayment of debts. In this subsection, we confirm that the consumption smoothing effects documented above are due at least in part to risk sharing agreements between households that are implemented via remittances. We use the detailed survey data on remittances to estimate

$$r_{ijt} = \delta + \alpha_i + \gamma Shock_{ijt} + \mu User_{ijt} + \beta User_{ijt} * Shock_{ijt} + \theta^S X_{ijt} * Shock_{ijt} + \theta^M X_{ijt} + \eta_{jt} + \varepsilon_{ijt} \tag{11}$$

where r_{ijt} is a measure of remittances and β is the coefficient of interest. We collected data on remittances during the six months prior to each of our surveys - every remittance the household sent or received over this period was recorded and a number of accompanying questions asked (including the relationship of the person sending or receiving it, the method, the costs, the

[33] Much of the literature on household responses to illness shocks uses this measure of consumption, see for example Gertler and Gruber (2002) and Gertler, Levine and Moretti (2006, 2009).

[34] Non-user households give up other consumption items to cover their medical expenses. They tend to give up subsistence non-food items and are significantly less likely to spend on education in response to a health shock.

[35] Recall that in models without commitment, network members are willing to provide transfers to those hit by negative shocks in return for promises of future payments. Access to M-PESA could make these promises more credible.

purpose, etc.). Our consumption data is annual but is collected, according to standard practice, in a module that varies recall by item. In particular, only large durables are asked with an annual recall, most other items are short term recall and will therefore include the effects of the shocks. The specification in equation (11) is similar to that in equation (9). As dependent variables, we include the probability that a household receives any remittance, the total number of remittances the household receives and the total value of received remittances. Table 5A reports these results.

Columns (1) through (6) report results for the overall shock and columns (7) and (8) for the illness shock. For the overall shock, we first report results with and without the location-by-time dummies, though the results are similar in both cases for all specifications. Across Table 5A, the relevant interaction term is uniformly positive and significant, indicating that users who suffer negative shocks have greater access to remittances, in terms of the probability of receiving a remittance, the number of remittances they receive, and the total revenue they receive.[36] To interpret these findings, the mean effects reported in the bottom panel of the table suggest that for an average M-PESA user, a negative shock significantly increases the likelihood of receiving any remittances by 7 percent and increases the (square root of the) total value received. For a typical non-user, a negative shock has no effect on these indicators of remittance receipt.

We find similar effects for the sample excluding Mombasa in columns (5) and (6) as well as for illness shocks as reported in columns (7) and (8). When faced with such events, users are more likely to receive remittances and receive a larger total amount. In theory, lower transaction costs could lead to an increase or a decrease in the size of each remittance received: lower costs mean a larger amount of any given transaction can reach the recipient, but they also make it economical to send smaller amounts more frequently. We find no effects of the impact of M-PESA on transaction size, though, if anything, users receive larger amounts per transaction (for overall shocks this interaction is not significant). Looking at magnitudes, from Tables 4A and 5A, we find that non-users experience about a 6 percent drop in annual consumption in the non-Nairobi sample as a result of income shocks, a drop that non-users do not experience. As a result of the shock, users of M-PESA receive about KShs 1,000 extra over six months. This amounts to about 4 percent of annual consumption, an amount close to the 6 percent less that users of M-PESA would otherwise suffer.

Next, motivated by our theory above, we investigate the impact of M-PESA on the size and nature of networks that people access when receiving support. The first measure of network access we use is the average distance that remittances received travel to reach a household. As reported in columns (1) and (2) of Table 5B, we find little evidence that such remittances originate from greater distances, and if anything, they seem to originate from closer.

However, our data do show that M-PESA allows them to reach deeper into their networks. We examine this by constructing two measures of the number of active members in a network.

[36]To reduce the influence of extreme outliers and bunching at zero we use the square root of the total amount received.

The first is the number of different relatives or friends from whom remittances are received. Although we cannot precisely identify the individuals who sent remittances to a given household, we do know their relationship to the household head in the receiving household and the town/village that the sender lives in. We use this information to create unique relationship-town identifiers that provide a lower bound on the number of different people from whom a given household receives remittances. The second measure of network size we construct is the ratio of this measure to the total potential network size for each household. To construct the potential network size, we aggregate all the unique relationship-town combinations we observe in the data across all rounds of data and across both sending and receiving decisions.

Using both of these measures of network access we find, as reported in columns (3) through (6) of Table 5B, that M-PESA helps households reach deeper into their networks, along both of our network measures, as predicted by our model. M-PESA users are likely to receive remittances from more people (a result that holds for both overall shocks and illness shocks), and that they reach out to a larger fraction of their network when they experience these income shocks.

C Results Using Agent Data

In using the agent rollout data, we first estimate the reduced form difference-in-differences specification in equation (10). We report these results as they are similar to the falsification results we present later and therefore provide a useful comparison. Table 6A reports these results for a number of different measures of agent access, and for the different types of shocks. The first access indicators are density measures - the number of agents within 1, 2, 5 and 20 km of the household. Throughout, to account for the long right tail in the number of agents as well as some density at zero, we take the square root of the number of agents within each of these distances.[37] The second measure of access to agents is simply the distance from the household to the closest agent (measured in log-meters).

Column (1) of Table 6A shows that households with better access to agents are less affected by negative shocks - the coefficients on the interaction between the 1 km agent density measure and the negative shock is positive. In column (2) we also control for location by time dummies, which do not affect the estimated coefficient on the interaction. The results are similar for the weather and illness shocks (columns (3) and (4)) - we find that households with better agent access are better able to smooth these shocks. Columns (5) and (6) examine the responses to overall shocks using the 2 km agent density measure, with and without location by time dummies. The coefficient on the interaction term is similar across these specifications as well as similar in magnitude to those in columns (1) and (2). Columns (7) and (8) show results for the 5 km and 20 km agent density measures, respectively. The coefficient on the interaction is significantly smaller in the 5 km case, and no different from zero in the 20 km case (this latter result also holds true if we use a 10 km density measure). In columns (9) and (10) of Table

[37]Taking the square root allows us to keep households with zero agents in these distance categories. The more conventional log transformation would require us to drop these and look only at the intensive margin.

6A, we use the distance to the closest agent as the measure of agent access. The coefficient on the interaction between this and the shock is negative - the closer a household is to an agent the larger the offset on a negative shock (i.e., the better smoothed the shock). The estimated coefficient is no different across columns (9) and (10). Overall, we find that better access to agents improves a household's ability to smooth risk.

In Table 6B, we look at whether the agent roll out was associated with observables in our data. In particular, we correlate the agent roll out with household wealth, ownership of a cell phone, measures of education of the household head, household access to various financial services and the various income shocks. We find little evidence that the agent roll out is correlated with household level observables (see the top panel of Table 6B). In the lower panel of the table, we correlate the agent roll out with the distance from the agent to Nairobi for various agent access measures. Here, as the distance to Nairobi is fixed for a given household, we look at whether agent measures are correlated with the levels of agent access in round one as well as separately the growth in agent access between the two rounds. We find little evidence of either.[38]

D Falsification Test

Although we have strong reasons to believe that the agent roll out was not targeted to places that were systematically different to other areas, it remains a concern that the agents might have ended up being more heavily concentrated in areas where households were better able to smooth consumption in any case. To confirm that this possibility is not driving our results, we perform a falsification test using data from 1997 to 2007, before the launch of M-PESA.[39] Apart from the period covered, the falsification strategy is identical to the first set of agent regressions reported in Table 7A. We match locational data on rainfall shocks and household consumption (see Suri (2011) for a full description) to two measures of subsequent agent access (the 2 km density and the distance to the nearest agent), and report the results in Table 7A.

This older survey was focused on agriculture and incomes and did not collect complete consumption data, so we focus on the consumption of maize and other crops. We include location and time dummies and a number of demographic controls in the specifications. Here, the shock is the deviation of rainfall from its longer term mean and so, we expect the coefficient on the shock to be positive. Our results confirm that consumption is strongly correlated with rainfall shocks, but that there is no differential effect for households in locations that subsequently experienced differential agent roll-out. These findings hold for both measures of agent access that we use, and provide convincing evidence that unobserved heterogeneity does not contaminate our results.

In Table 7B, we use our M-PESA survey and restrict the sample as closely as we can to match the dataset used in the falsification test, by including only rural and agricultural households. In addition, we drop the top quintile of the income distribution as the agricultural dataset does

[38] We did not collect data on this distance. We use the GPS coordinates of the households and those of Nairobi to create these distances. There is one caveat to this - such a distance measure does not account for the actual roads taken between the households and Nairobi.

[39] We thank Paul Ferraro for this suggestion.

not include large commercial farmers. As shown in Table 7B, we can replicate the earlier results from Tables 4 through 6 for this subsample - indeed, if anything, the results are stronger. This lends further credibility to the falsification test in Table 7A.

E Additional Robustness Checks

In this section, we present a number of robustness checks that support our main findings above. In particular, we report on some of the empirical strategies described in Section IVC and we briefly discuss heterogeneous slopes.

E.1 IV Results

We instrument for the use of M-PESA and its interaction with the income shock using two agent access variables (distance to the closest agent and the number of agents within 5km of the household) and their interactions with the income shock.[40] Table 8 presents these results for both consumption and remittance measures. Throughout this table, we control for our standard set of covariates as above. However, we do not include the location by time dummies - in all the specifications above, the location-by-time dummies did not change the results at all. In the IV specifications, the first stage for predicting M-PESA use using the agent rollout is not precise when we include these location-by-time dummies, as they soak up a lot of the variation we would like to include (i.e. the growth of agents and the growth of M-PESA use over time).

In Table 8, for comparison purposes, we show the cross section estimates in column (1) and in columns (2) through (7) we present the panel versions. For space reasons, we do not show the first stage regressions in Table 8, but we report the F statistic on the excluded instruments. Overall, we find results consistent with our earlier findings. M-PESA users are better able to smooth shocks and we find that these improvements come about due to increased remittances.

Finally, in the last row of Table 8, we report results from a Hausman test. For the cross sectional results, the Hausman tests compare the OLS and IV regressions. For the panel version, the Hausman tests compare the regular fixed effects panel specification to the IV fixed effects specification. Across the board, we are unable to reject the null that the difference in the coefficients under the two specifications is not systematic. From the Hausman test results, therefore, the estimates in Tables 4A and 5A are preferred as they are efficient under the null.

E.2 Allowing for Heterogeneous Slopes

In addition to equation (9) above, we can exploit the panel structure of our data to examine the extent to which our results are robust to allowing for heterogeneous individual specific slopes on

[40] For the purposes of efficiency, we should use as many indicators of agent access and their interactions with the shocks, as possible. However, as the access indicators are highly colinear, we restrict ourselves to the two mentioned above.

the shock variable. A specification of the following form

$$c_{ijt} = \alpha_i + \gamma Shock_{ijt} + \mu User_{ijt} + \beta User_{ijt} * Shock_{ijt} + \theta^S X_{ijt} * Shock_{ijt} + \theta^M X_{ijt} + \phi \alpha_i Shock_{ijt} + \varepsilon_{ijt} \tag{12}$$

captures such a possibility, where we allow for an interaction of a household fixed effect, α_i, with the negative income shock, and thereby account for unobserved but time invariant household specific smoothing mechanisms. However, as this specification suffers from an incidental parameters problem, standard panel approaches to estimate the parameters are inconsistent for small T. Since approaches based on the work of Chamberlain (1984) are consistent,[41] we estimate this model using such methods. In our case, the large degree of extra flexibility accommodated by such an approach resulted in reduced power. We do not report the results of this estimation here, but note that the point estimates we obtain, while imprecise, are very similar in magnitude to our main results.[42]

F Attrition

There is some attrition in the panel, though the magnitudes are not particularly large by the standards of this kind of survey work in developing countries. In Appendix Table 2, we look at attrition directly, and examine how the households that attrited differ from those that remain in the panel in period 1. We separate out the panel sample into two groups: those that were found in round 2 and those that were found in round 3. We can then compare the three groups (attriters, panel sample where the second period is from round 2 and panel sample where the second period is from round 3) and test whether those found in period 2 are any different from those found in period 3 - the last column reports the results from this test. We show that, though there are some differences between the households that attrited and those that did not, there is no difference in the propensity to experience a shock across the panel and non-panel samples. In addition, there is little evidence of differential agent access across these two samples. In the analysis above, we control for all the observables that differ between the panel and non-panel samples. In addition, our robustness checks using the agent rollout data are similar to the results in the basic specifications.

VI Conclusion

In the presence of high transaction costs, the risk sharing benefits of geographic separation and income diversification can go unrealized. Small idiosyncratic risks might be shared within local networks, but larger and more aggregate shocks are likely to affect consumption directly. In this paper we test the importance of transaction costs as a barrier to full insurance in the context of

[41] See Suri (2011) for an example. The specific application of the Chamberlain methods that is needed here is simpler, but Suri provides an illustration of how such methods can be used.

[42] Although the specification with household dummies is inconsistent, those results too are very similar to the ones we obtain from the Chamberlain methods, and now significant.

the rapid expansion of a cost-reducing innovation in Kenya, M-PESA - a cell phone-based money transfer product that has been adopted by a large majority of households in less than four years. The potential for mobile technology, and mobile money specifically, to transform the lives of the poor, while palpable, is so far little documented. In this paper, we present convincing evidence that mobile money has had a significant impact on the ability of households to spread risk, and we attribute this to the associated reduction in transaction costs. The results are robust across various specifications and also when we use the data on the rollout of M-PESA agents across the country, which provides a source of exogenous variation in access to the service. In particular, we find that households who do not use the technology suffer a 7 percent drop in consumption when hit by a negative income shock, while the consumption of households who use M-PESA is unaffected.

Such insurance is valuable in itself – indeed the probability of shocks and their size suggest a back of the envelope calculation of welfare benefits of on average 3-4 percent of income, depending of course on attitudes towards risk. The longer term welfare benefits could be higher, if the dynamics of poverty are driven by random reductions in consumption that lead to persistently low income (Dercon (2006)). Over the longer term, as electronic payments mature and facilitate more frequent and better matched trades, the impact of this financial innovation on the level of consumption, as well as its variance, could be significant. As M-PESA and other mobile money applications are adopted by a broad cross section of businesses, productivity and efficiency gains could be realized as they were following the diffusion of computing technology in the US (for examples, see Bosworth and Triplett (2002) and Brynjolfsson and Hitt (2003)).

Much as the technology also provides a convenient and safe method of saving, which could facilitate self-insurance, we find that an important mechanism that lies behind the improved risk spreading is remittances. When faced with a shock, households with access to the technology are more likely to receive a remittance, they receive a greater number of remittances and also larger amounts of money in total. In addition, the remittances they receive come from further afield and from a larger sample of network members. These results highlight the importance of transaction costs when using social networks to smooth risk. Mobile money appears to increase the effective size of, and number of active participants in, risk sharing networks, seemingly without exacerbating information, monitoring, and commitment costs.

This observation suggests a reappraisal of competing explanations for incomplete risk-spreading in informal networks in developing countries, which have focused on problems of asymmetric information and limited commitment. We find no evidence that the associated constraints are weaker for users of M-PESA than for non-users – indeed, active members of insurance networks of M-PESA users are more geographically dispersed, suggesting that if anything information problems may be more acute and social pressures that enforce commitment to on-going relationships may be less effective for users than for non-users. In this case, the benefits of the lower transaction costs of M-PESA appear to be sufficiently large to offset any incompleteness of insurance that would otherwise arise from information or commitment problems.

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Table 1A: Summary Statistics (Full Sample)

	Round 1		Round 2	
	Mean	SD	Mean	SD
M-PESA User	0.432	0.496	0.698	0.459
Own Cell Phone	0.692	0.462	0.758	0.428
Per Capita Consumption	73137	131229	64025	87078
Per Capita Food Consumption	31825	31123	30092	25612
Total Wealth	129447	422649	136954	700517
HH Size	4.285	2.224	4.398	2.324
Education of Head (Yrs)	6.974	5.670	7.546	5.008
Positive Shock	0.109	0.312	0.066	0.249
Negative Shock	0.500	0.500	0.571	0.495
Weather/Agricultural shock	0.036	0.187	0.131	0.337
Illness Shock	0.239	0.427	0.401	0.490
Send Remittances	0.463	0.499	0.464	0.499
Receive Remittances	0.387	0.487	0.419	0.494
Financial Access Dummies				
Bank account	0.504	0.500	0.515	0.500
Mattress	0.759	0.428	0.750	0.433
Savings and Credit Cooperative (SACCO)	0.189	0.391	0.176	0.381
Rotating Savings and Credit Cooperative (ROSCA)	0.405	0.491	0.460	0.498
Household Head Occupation Dummies				
Farmer	0.289	0.453	0.273	0.445
Public Service	0.036	0.187	0.034	0.180
Professional Occupation	0.232	0.422	0.195	0.397
Househelp	0.093	0.290	0.103	0.304
Run a Business	0.145	0.353	0.162	0.369
Sales	0.049	0.215	0.091	0.288
In Industry	0.032	0.176	0.019	0.136
Other Occupation	0.060	0.237	0.043	0.202
Unemployed	0.063	0.244	0.077	0.267
Number of observations	2283		2283	

Note: The exchange rate during this period was about KShs 75 = US $1.
For the non-Nairobi sample, there are 1,965 observations in each round.

Table 1B: Summary Statistics (Period Two) by Adoption Status (Full Sample)

	Early Adopters		Late Adopters		Non-Adopters	
	Mean	SD	Mean	SD	Mean	SD
Own Cell Phone	0.940	0.237	0.885	0.319	0.368	0.483
Per Capita Consumption	87728	110733	57380	70291	38371	53414
Per Capita Food Consumption	35627	27361	28985	24941	23558	22295
Total Wealth	220865	1013049	109056	472943	58484	228156
HH Size	4.278	2.225	4.735	2.395	4.252	2.384
Education of Head (Yrs)	8.683	5.336	7.701	4.673	5.611	4.366
Positive Shock	0.075	0.263	0.076	0.265	0.050	0.218
Negative Shock	0.604	0.489	0.527	0.500	0.578	0.494
Weather/Agricultural shock	0.126	0.332	0.115	0.320	0.144	0.351
Illness Shock	0.441	0.497	0.357	0.479	0.410	0.492
Send Remittances	0.660	0.474	0.506	0.500	0.167	0.373
Receive Remittances	0.556	0.497	0.484	0.500	0.175	0.380
Financial Access Dummies						
Bank account	0.733	0.443	0.522	0.500	0.184	0.388
Mattress	0.679	0.467	0.745	0.436	0.857	0.351
Savings and Credit Cooperative	0.245	0.431	0.162	0.369	0.098	0.298
Merry Go Round/ ROSCA	0.533	0.499	0.451	0.498	0.372	0.484
Household Head Occupation Dummies						
Farmer	0.169	0.375	0.242	0.429	0.461	0.499
Public Service	0.056	0.230	0.033	0.177	0.004	0.067
Professional Occupation	0.236	0.425	0.222	0.416	0.102	0.303
Househelp	0.113	0.317	0.121	0.327	0.066	0.249
Run a Business	0.178	0.382	0.144	0.351	0.166	0.373
Sales	0.112	0.315	0.099	0.299	0.052	0.221
In Industry	0.024	0.152	0.013	0.115	0.019	0.137
Other Occupation	0.038	0.192	0.050	0.219	0.040	0.196
Unemployed	0.071	0.258	0.075	0.263	0.082	0.275
Number of Observations	1007		670		516	

Note: The exchange rate during this period was about KShs 75 = US $1.
Early adopters are defined as those households who had adopted M-PESA at the time of the first round, and late adopters are those who adopted sometime in between the two rounds of the survey. Four percent of the sample switched from having a user in period 1 to not having one in period 2. These households are not included in this table.
Looking at Round 1, 94.5% of early adopters owned cell phones, 72.1% of late adopters owned cell phones and 38.5% of never adopters owned cell phones.

Table 2A: Remittances for Non-Nairobi Sample (Only Means Reported)

	Round 1		Round 2	
	Sent	Received	Sent	Received
Overall Remittances				
Number of Remittances per Month	2.860	2.211	2.375	1.929
Total Value	10065.8	13006.9	7059.5	5093.7
Total Value (Fraction of Consumption)	0.036	0.050	0.033	0.029
Average Distance (Kms)	234.3	288.6	214.3	235.0
Net Value Remitted	2354.2		-882.3	
M-PESA Remittances				
Number of Remittances	0.931	0.805	1.616	0.847
Total Value	7965.4	9923.7	7879.3	4789.7
Average Distance (Kms)	343.6	335.1	239.1	237.3
Non M-PESA Remittances				
Number of Remittances	1.930	1.406	0.759	1.080
Total Value	9709.4	13674.2	4614.5	5057.5
Average Distance (Kms)	194.6	273.6	172.4	230.8

Note: The exchange rate during this period was about KShs 75 = US $1.
M-PESA remittances here refers to remittances that are sent or received using M-PESA (households that have an M-PESA user do not send and receive all their remittances via M-PESA).

Table 2B: Remittances Received for Non-Nairobi Sample

Method Money/Transfer was Sent	Frequency	Average Cost of Sending[1,2]
Hand delivery by self	13.5%	1.62
Hand delivery by friend	5.3%	1.77
Bus delivery through friend/relative	4.1%	10.00
Bus delivery through driver/courier	3.0%	158.69
Western Union	0.4%	108.00
M-PESA from own/friend's/agent's account	60.8%	49.77
Postal bank	2.9%	173.08
Direct deposit	6.7%	85.00
Other	3.3%	78.04

Note: The exchange rate during this period was about KShs 75 = US $1.
These are round 1 data for all non-Nairobi households at the remittance level (2080 remittances received).
[1] For 35% of remittances, respondents did not know the sending charge. The number of non-missing cost observations are low for Western Union (only 4), Postal bank (13) and Direct deposit (27).
[2] These costs are purely fees and do not include transport or travel costs, which can be substantial.

Table 3: Agent Characteristics

(a) Household Access to Agents

	Full Sample				Non-Nairobi Sample			
	Round 1		Round 2		Round 1		Round 2	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
# Agents w/in 1km	3.23	7.09	6.86	15.01	2.47	5.19	4.94	9.96
# Agents w/in 2km	9.18	29.07	19.23	58.79	4.43	7.83	9.39	16.97
# Agents w/in 5km	29.32	92.44	59.36	177.8	9.35	18.67	20.96	46.02
# Agents w/in 10km	60.54	173.2	126.8	344.6	18.31	43.11	44.07	102.9
# Agents w/in 20km	114.7	275.1	239.1	544.7	53.52	150.0	119.0	301.6
Dist to Closest Agent	4.84	7.82	3.96	7.13	5.02	7.33	4.11	6.72

(b) Agent Distribution

	Full Sample	
	Round 1	Round 2
Difference in Distance Between Closest and Second Closest Agent (% of Distance to Closest Agent)	84%	41%

(c) Agent Level Data (Total Number of Agents = 7691)

Agent Business	Mean	SD
New registrations, Past 7 Days	7.012	8.782
Transactions, Past 7 Days	70.687	49.357
Frequency of Stockouts	E-Money Stockout	Cash Stockout
At least once every 2 weeks	30.8%	15.9%
Once a month	8.5%	4.5%
Less often than that	3.4%	3.5%
Never	57.2%	76.1%

Table 4A: Basic Difference-in-Differences Results
Dependent Variable: Log Total Household Consumption per Capita

	(1) OLS Full Sample	(2) OLS W/out Nairobi	(3) Panel Full Sample	(4) Panel Full Sample	(5) Panel W/out Nairobi	(6) Panel W/out Nairobi	(7) Panel W/out Nairobi & Mombasa	(8) Panel Bottom 3 Wealth Quintiles
M-PESA User	0.5532***	0.5305***	-0.0895**	-0.0155	-0.0858*	-0.0075	0.0135	-0.0352
	[0.0372]	[0.0387]	[0.0360]	[0.0468]	[0.0500]	[0.0491]	[0.0517]	[0.0570]
Negative Shock	-0.2067***	-0.2027***	0.2409**	0.2317	0.1357	0.1203	0.1233	0.3330
	[0.0375]	[0.0385]	[0.1163]	[0.1692]	[0.1423]	[0.1405]	[0.1474]	[0.2049]
User*Negative Shock	0.1014**	0.1072**	0.1762***	0.1558**	0.1789**	0.1495**	0.1496**	0.2038***
	[0.0499]	[0.0519]	[0.0496]	[0.0619]	[0.0702]	[0.0651]	[0.0679]	[0.0775]
Controls + Interactions			Y	Y	Y	Y	Y	
Time FE	Y	Y		Y		Y	Y	
Time*Location FE				Y		Y	Y	
Observations	4,554	3,925	4,537	4,537	3,909	3,909	3,710	2,725
R-squared	0.122	0.123	0.134	0.242	0.138	0.251	0.254	0.263
Negative Shock	-0.1494***	-0.1438***	-0.0006	0.0017	-0.0003	0.0017	0.0012	0.0126
	[0.0248]	[0.0260]	[0.0215]	[0.0270]	[0.0283]	[0.0281]	[0.0290]	[0.0349]
Shock, Users	-0.1053***	-0.0955***	0.0522*	0.0552	0.0497	0.0495	0.0488	0.1071**
	[0.0330]	[0.0350]	[0.0280]	[0.0346]	[0.0372]	[0.0365]	[0.0376]	[0.0466]
Shock, Non-Users	-0.2067***	-0.2027***	-0.0692**	-0.0678	-0.0615	-0.0569	-0.0561	-0.0725
	[0.0375]	[0.0385]	[0.0323]	[0.0427]	[0.0457]	[0.0438]	[0.0452]	[0.0512]
Shock, Non-Users$\vert_{\text{User X's}}$			-0.1240***	-0.1007*	-0.1292**	-0.1001*	-0.1008*	-0.0967
			[0.0422]	[0.0517]	[0.0580]	[0.0542]	[0.0565]	[0.0614]
Mean of User	0.5647	0.5499	0.5652	0.5652	0.5505	0.5505	0.5467	0.4739
Mean of Shock	0.5365	0.5354	0.5365	0.5365	0.5353	0.5353	0.5492	0.5461

Note: Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1

Throughout, the controls are for the demographic composition of the household, education (years) of the household head, occupation dummies for the household head (three main occupational categories of farmer, professional and business), measures of household financial access (use of bank accounts, savings and credit cooperatives and rotating savings and credit associations), and a dummy for household cell phone ownership.

Interactions refer to interactions of all the controls with the negative shock.

Throughout, when interactions with the controls are included, the overall effect of a negative shock is evaluated at the mean of the covariates for the full sample. The effects of a negative shock for users (non-users) are evaluated at the means of the covariates for the sample of users (non-users). The last row in the bottom panel reports the effect for non-users evaluated at the mean characteristics for the users.

Table 4B: Results for Different Shock Types (Panel)
Dependent Variable: Log Household Consumption per Capita

	(1)	(2)	(3)	(4)	(5)	(6)
	Total Consumption Weather Shock		Total Consumption Illness Shock		Non-Health Consumption Illness Shock	
M-PESA User	-0.0260	0.0439	-0.0446	0.0493	-0.0279	0.0571
	[0.0358]	[0.0396]	[0.0420]	[0.0444]	[0.0407]	[0.0430]
Negative Shock	-0.0603	-0.1546	-0.0704	0.0093	-0.2052	-0.1545
	[0.3352]	[0.3094]	[0.1640]	[0.1631]	[0.1686]	[0.1654]
User*Negative Shock	0.3329**	0.3183**	0.1547**	0.0900	0.1595**	0.1010
	[0.1511]	[0.1417]	[0.0738]	[0.0732]	[0.0692]	[0.0693]
Controls + Interactions	Y	Y	Y	Y	Y	Y
Time*Location FE		Y		Y		Y
Observations	3,913	3,913	3,913	3,913	3,913	3,913
R-squared	0.140	0.251	0.130	0.252	0.141	0.260
Shock Effect	-0.1419**	-0.1157*	0.0021	0.0419	-0.0517	-0.0198
	[0.0670]	[0.0662]	[0.0327]	[0.0333]	[0.0316]	[0.0320]
Shock, Users	-0.0878	-0.0538	0.0545	0.0804**	0.0101	0.0296
	[0.0903]	[0.0866]	[0.0418]	[0.0408]	[0.0404]	[0.0394]
Shock, Non-Users	-0.2084**	-0.1917**	-0.0623	-0.0054	-0.1275***	-0.0805*
	[0.0959]	[0.0909]	[0.0500]	[0.0497]	[0.0483]	[0.0480]
Shock, Non-Users$\vert_{\text{User X's}}$	-0.4206***	-0.3721***	-0.1002	-0.0095	-0.1494**	-0.0714
	[0.1383]	[0.1304]	[0.0619]	[0.0639]	[0.0577]	[0.0601]
Mean of Shock	0.0839	0.0839	0.3190	0.3190	0.3190	0.3190

Note: Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1. The mean of user across all columns is 0.5512. When interactions are included, the effect of a negative shock is evaluated at the mean of the covariates for the full sample. The effects of a negative shock for users (non-users) are evaluated at the means for the sample of users (non-users). The bottom panel also reports the effect for non-users evaluated at the mean characteristics for the users.

Table 5A: Mechanisms (Panel)
Dependent Variable: Measures of Household Level Remittances

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Overall Shock: Sample W/out Nairobi				Overall Shock: W/out Mombasa		Illness Shock	
	Prob [Receive]		Number Received	Total Received (Root)	Prob [Receive]	Total Received (Root)	Prob [Receive]	Total Received
M-PESA User	0.2018***	0.1597***	0.2526**	10.771***	0.1216**	10.636**	0.1823***	12.475***
	[0.0462]	[0.0468]	[0.1273]	[3.705]	[0.0495]	[4.543]	[0.0406]	[3.079]
Negative Shock	0.0172	-0.0298	0.0315	2.613	-0.0920	-0.876	-0.1866	-8.556
	[0.1353]	[0.1428]	[0.4271]	[11.695]	[0.1434]	[15.609]	[0.1490]	[11.130]
User*Shock	0.1023*	0.1354**	0.3430*	8.067*	0.1737***	10.845*	0.1436**	8.385
	[0.0621]	[0.0627]	[0.1769]	[4.668]	[0.0655]	[6.212]	[0.0698]	[5.313]
Controls + Interactions	Y	Y	Y	Y	Y	Y	Y	Y
Time*Location FE		Y	Y	Y	Y	Y	Y	Y
Observations	3,913	3,913	3,913	3,875	3,713	3,713	3,913	3,875
R-squared	0.092	0.173	0.137	0.156	0.177	0.145	0.176	0.161
Shock Effect	0.0380	0.0238	0.0153	2.6665	0.0184	1.896	0.0194	3.2842
	[0.0275]	[0.0284]	[0.0840]	[2.2061]	[0.0293]	[3.397]	[0.0311]	[2.3676]
Shock, Users	0.0674*	0.0657*	0.1039	5.1800	0.0724*	5.446	0.0713*	6.4697**
	[0.0355]	[0.0369]	[0.1116]	[3.2828]	[0.0378]	[5.086]	[0.0420]	[3.2886]
Shock, Non-Users	0.0018	-0.0277	-0.0936	-0.3972	-0.0469	-2.401	-0.0443	-0.5989
	[0.0412]	[0.0406]	[0.1196]	[2.6523]	[0.0422]	[3.389]	[0.0441]	[3.0607]
Mean of User	0.5512	0.5512	0.5512	0.5493	0.5475	0.5475	0.5512	0.5493

Note: Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1
Total received (root) and mean received (root) refer to the square root of the total amount received and of the mean amount received per remittance, respectively. The reason for using the square root of these variables is that they both have long right tails as well as a number of zeros.

Table 5B: Where Do Remittances Come From: Distance and the Role of Networks (Panel)
Dependent Variable: Measures of Networks

	(1)	(2)	(3)	(4)	(5)	(6)
	Distance Travelled		Number of Different Senders		Fraction of Network Remitting	
	Overall Shock	Illness Shock	Overall Shock	Illness Shock	Overall Shock	Illness Shock
M-PESA User	71.35	-16.93	0.1740***	0.1936***	0.1017***	0.1158***
	[63.50]	[53.52]	[0.0645]	[0.0531]	[0.0359]	[0.0313]
Shock	-111.70	-111.25	-0.2637	-0.4779**	-0.0237	-0.1992
	[130.59]	[149.52]	[0.2108]	[0.2228]	[0.1310]	[0.1255]
User*Shock	-186.57**	-9.33	0.2033**	0.2531***	0.1009**	0.1103*
	[80.98]	[90.86]	[0.0865]	[0.0969]	[0.0483]	[0.0604]
Controls	Y		Y	Y	Y	Y
Controls + Interactions	Y		Y	Y	Y	Y
Time*Location FE	Y		Y	Y	Y	Y
Observations	1,519	1,519	3,913	3,913	3,396	3,396
R-squared	0.468	0.473	0.153	0.160	0.191	0.198
Shock Effect	-18.96	-27.69	0.0498	0.0414	0.0251	0.0223
	[28.40]	[35.87]	[0.0421]	[0.0437]	[0.0219]	[0.0228]
Shock, Users	-57.71*	-10.03	0.1117**	0.1211**	0.0459*	0.0451*
	[31.31]	[40.46]	[0.0557]	[0.0574]	[0.0237]	[0.0259]
Shock, Non-Users	94.07	-79.23	-0.0263	-0.0565	-0.0074	-0.0135
	[63.49]	[71.99]	[0.0584]	[0.0621]	[0.0381]	[0.0435]
Mean of User	0.740	0.740	0.5512	0.5512	0.6103	0.6103

Note: Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1
The number of different senders refers to the number of unique relationship-town combinations that households report receiving remittances from in each round of the data. The fraction of the network divides this number by the total number of unique relationship-town combinations ever seen in any round of the data, both on the sending side as well as on the receiving side.

Table 6A: Reduced Forms Using Agent Roll Out (Panel)
Dependent Variable: Log Household Consumption per Capita

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Overall Shock		Illness	Rainfall			Overall Shock			
	Agents w/in 1km		Agents w/in 1km	Agents w/in 1km	Agents w/in 2km		Agents w/in 5km	Agents w/in 20km	Distance to Closest Agent	
Negative Shock	0.152	0.152	-0.232	-0.132	0.133	0.122	0.148	-0.176	0.530**	0.619***
	[0.151]	[0.152]	[0.168]	[0.358]	[0.151]	[0.153]	[0.160]	[0.140]	[0.208]	[0.203]
Agents	-0.096***	0.022	-0.078***	-0.064**	-0.080***	-0.003	0.018	-0.002	0.046	0.051
	[0.028]	[0.039]	[0.027]	[0.026]	[0.019]	[0.031]	[0.024]	[0.006]	[0.036]	[0.054]
Agents*Shock	0.063***	0.055***	0.050**	0.102**	0.053***	0.050***	0.021**	-0.002	-0.047***	-0.058***
	[0.020]	[0.019]	[0.021]	[0.044]	[0.015]	[0.015]	[0.010]	[0.005]	[0.018]	[0.019]
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
+ Interactions	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time*Location FE		Y				Y	Y	Y		Y
Observations	3,913	3,913	3,913	3,913	3,913	3,913	3,913	3,913	3,856	3,856
R-squared	0.145	0.259	0.144	0.142	0.148	0.260	0.256	0.588	0.138	0.258
Shock Effect	-0.0028	-0.0050	-0.0345	-0.1075	0.0022	-0.0036	-0.0057	-0.0570**	-0.0096	-0.0022
	[0.0304]	[0.0285]	[0.0317]	[0.0670]	[0.0302]	[0.0284]	[0.0288]	[0.0251]	[0.0311]	[0.0288]
Mean of Agents	1.0938	1.0938	1.0938	1.0938	1.7077	1.7077	2.6838	6.6281	7.3565	7.3565

Note: Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1
Distance to the closest agent is measured as the log of distance (distance measured in meters). All columns include a full set of controls with interactions of the controls with the shock. For all columns, the negative shock effects are evaluated at the mean values of all the covariates. The coefficient on Agents*Shock interaction in columns (3), (4) are not significantly different if time*location fixed effects are included.
Similarly, coefficient on the Agents*Shock interaction in columns (7) and (8) are not significantly different if the time*location fixed effects are not included.

Table 6B: Agent Roll Out
Dependent Variable: Measures of Agent Access

	Agents w/in 2km		Agents w/in 5km		Distance to Agent	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Log Wealth	0.0225*	[0.0124]	0.0091	[0.0154]	0.0022	[0.0052]
Cellphone Ownership	-0.0318	[0.0313]	-0.0272	[0.0347]	-0.0016	[0.0164]
Household Head Can Read	-0.0393	[0.0424]	0.0141	[0.0536]	0.0382*	[0.0218]
Household Head Can Write	-0.0252	[0.0423]	0.0273	[0.0534]	0.0256	[0.0213]
Household Head Years of Education	-0.0024	[0.0029]	0.0011	[0.0031]	-0.0010	[0.0012]
HH Has a Bank account	0.0285	[0.0319]	0.0252	[0.0355]	-0.0011	[0.0161]
HH has a SACCO account	-0.0180	[0.0381]	0.0159	[0.0461]	-0.0128	[0.0170]
HH has a ROSCA	0.0376	[0.0242]	-0.0128	[0.0273]	0.0076	[0.0111]
Negative Shock	0.0240	[0.0236]	0.0002	[0.0251]	0.0023	[0.0129]
Rainfall Shock	-0.0071	[0.0449]	0.0028	[0.0541]	-0.0009	[0.0236]
Illness Shock	-0.0014	[0.0257]	-0.0056	[0.0282]	-0.0037	[0.0140]

Note: Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1
Each row represents a separate panel regression. Each regression controls only for location by time fixed effects.

	Agents w/in 1km		Agents w/in 2km		Agents w/in 5km		Distance to the Closest Agent	
	Period 1	Changes	Period 1	Changes	Period 1	Changes	Period 1	Changes
Distance to Nairobi	-0.0026	-0.0016	-0.0100*	-0.0042	0.0151	-0.0037	0.0001	-0.0020
	[0.0028]	[0.0013]	[0.0055]	[0.0028]	[0.0091]	[0.0045]	[0.0056]	[0.0012]

Note: Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1
Each row represents a separate regression. Each regression controls for location fixed effects.

Table 7A: Falsification Test, 1997-2007
Dependent Variable: Measures of Log Household Consumption per Capita

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Agents w/in 2km				Distance to Closest Agent			
	Maize Consumption		Crop Consumption		Maize Consumption		Crop Consumption	
	OLS	Panel	OLS	Panel	OLS	Panel	OLS	Panel
Shock*Agents	-0.009	-0.058	0.091	0.055	0.070	0.088	-0.046	-0.037
	[0.083]	[0.068]	[0.085]	[0.065]	[0.077]	[0.065]	[0.072]	[0.062]
Shock Measure (Positive Measure)	0.418***	0.412***	0.400***	0.377***	-0.175	-0.341	0.812	0.704
	[0.074]	[0.068]	[0.069]	[0.062]	[0.648]	[0.552]	[0.608]	[0.529]
Agents	-15.181		-13.537		44.036*		28.512	
	[16.855]		[16.796]		[24.018]		[21.443]	
Observations	4,736	4,736	4,736	4,736	4,736	4,736	4,736	4,736
R-squared	0.323	0.345	0.486	0.546	0.324	0.345	0.486	0.546

Note: Standard errors in brackets; *** $p<0.01$, ** $p<0.05$, * $p<0.1$
The shock measure used here is the deviation of main season rainfall from its long term mean. In addition, this specification controls for location and time dummies and measures of household demographics.

Table 7B: Falsification Test: Similar Sample for 2008-2009
Dependent Variable: Measures of Log Household Consumption per Capita

	(1)	(2)	(3)	(4)	(5)	(6)
	Total Consumption	Food Consumption	Total Consumption		Food Consumption	
			Distance to Agent	Agents w/in 2km	Distance to Agent	Agents w/in 2km
M-PESA User	-0.0031	-0.0353				
	[0.0740]	[0.0763]				
Negative Shock	0.1349	0.0446	0.7217**	0.0898	0.6298**	-0.0308
	[0.1915]	[0.1995]	[0.3223]	[0.1897]	[0.2990]	[0.1987]
User*Shock	0.2140**	0.1756**				
	[0.0866]	[0.0872]				
Agent Variable			0.0554	-0.0837	-0.0001	-0.0738
			[0.1037]	[0.0817]	[0.1068]	[0.1023]
Agent*Shock			-0.0757**	0.0937***	-0.0781**	0.1070***
			[0.0337]	[0.0319]	[0.0318]	[0.0350]
Observations	1,736	1,735	1,718	1,736	1,717	1,735
Shock Effect	-0.0770*	-0.0854**				
	[0.0422]	[0.0407]				
Shock, Users	-0.0233	-0.0357				
	[0.0504]	[0.0506]				
Shock, Non-Users	-0.1234**	-0.1282**				
	[0.0601]	[0.0581]				

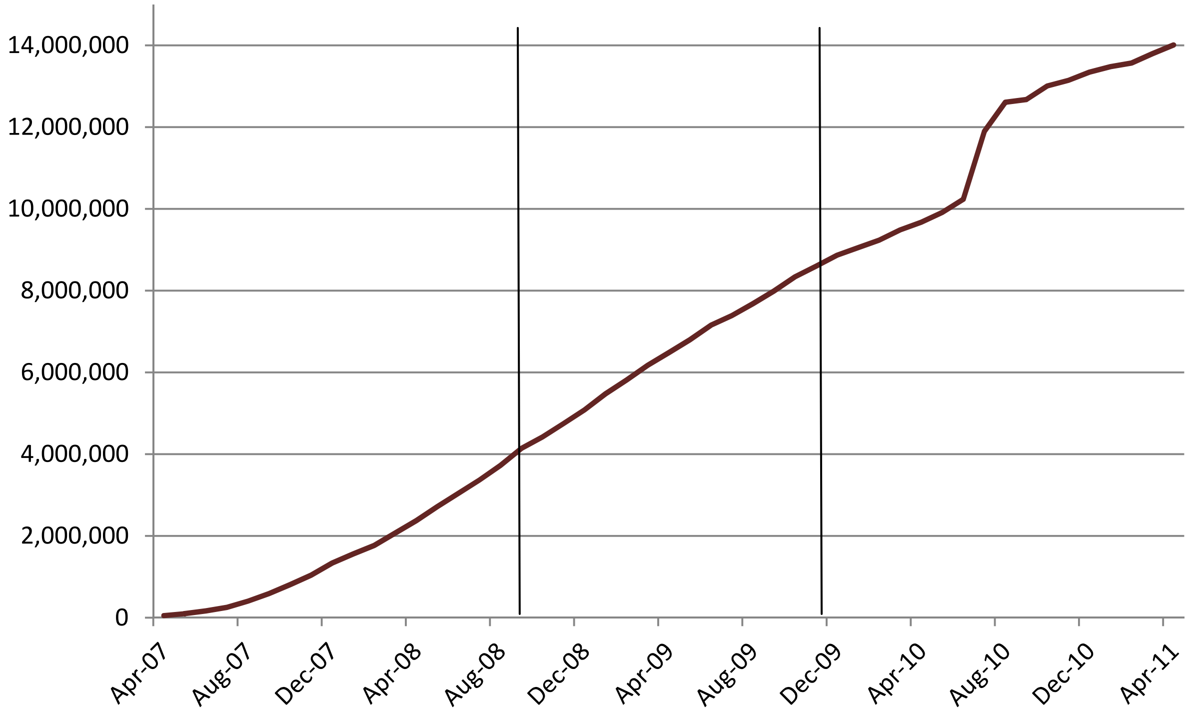
Note: Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1
All specifications control for the full set of covariates as above, their interactions with the shock and location by time dummies.

Table 8: IV Results (Cross Section and Panel)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Total Consumption		Food	Prob [Receive]	Total Received	Prob [Receive]
	Cross Section	Panel	Panel W/out Mombasa	Panel	Panel	Panel	Panel W/out Mombasa
M-PESA User	-0.6331***	-0.7154***	-0.7563***	-0.4274***	0.0182	7.437	-0.0292
	[0.2382]	[0.1671]	[0.1706]	[0.1511]	[0.1447]	[11.398]	[0.1487]
Negative Shock	-0.2700**	-0.2062	-0.2807**	-0.1971*	-0.1667	0.256	-0.2253*
	[0.1195]	[0.1296]	[0.1345]	[0.1192]	[0.1122]	[8.650]	[0.1173]
User*Shock	0.4569**	0.4151*	0.5403**	0.3484*	0.3468*	4.155	0.4399**
	[0.2031]	[0.2169]	[0.2261]	[0.2004]	[0.1877]	[14.559]	[0.1971]
Observations	3,856	3,856	3,668	3,666	3,856	3,820	3,668
Shock Effect	-0.0185	0.0223	0.0150	-0.0064	0.0243	2.5365	0.0154
	[0.0223]	[0.0262]	[0.0269]	[0.0238]	[0.0227]	[1.7692]	[0.0235]
Shock, Users	0.1868**	0.2088**	0.2596***	0.1513*	0.1801**	4.4108	0.2145**
	[0.0882]	[0.0931]	[0.0975]	[0.0863]	[0.0806]	[6.3106]	[0.0850]
Shock, Non-Users	-0.2700**	-0.2062	-0.2807**	-0.1971	-0.1667	0.2559	-0.2253*
	[0.1195]	[0.1296]	[0.1345]	[0.1192]	[0.1122]	[8.6501]	[0.1173]
F-stat on instruments for user	17.09	46.49	50.24	50.24	46.49	46.46	50.24
F-stat on instruments for user*shock	38.94	43.12	43.47	43.47	43.12	44.67	43.47
Hausman test: chi-sq	11.37	24.75	26.01	10.41	11.18	17.51	7.52
[p-value]	[0.91]	[0.17]	[0.13]	[0.94]	[0.92]	[0.56]	[0.99]

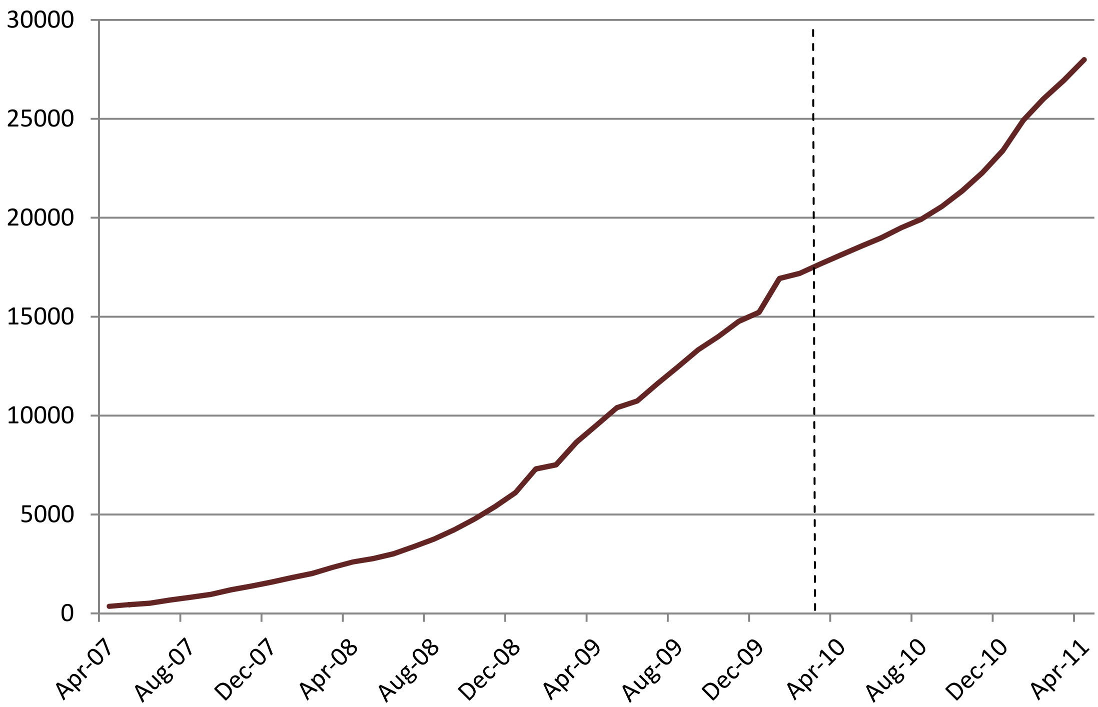
Note: Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1
The excluded instruments are distance to the closest agent and the number of agents within 5km of the household and interactions of each of these with the negative shock. None of these specifications control for location by time fixed effects. The cross section results include location fixed effects.

Figure 1A: M-PESA Customer Registrations



Notes: The solid vertical lines indicate when the household survey rounds were conducted.

Figure 1B: M-PESA Agents



Notes: The dashed vertical line represents when the agent survey was administered.

Figure 2A: Fraction of Households that Use M-PESA, by Transaction Type

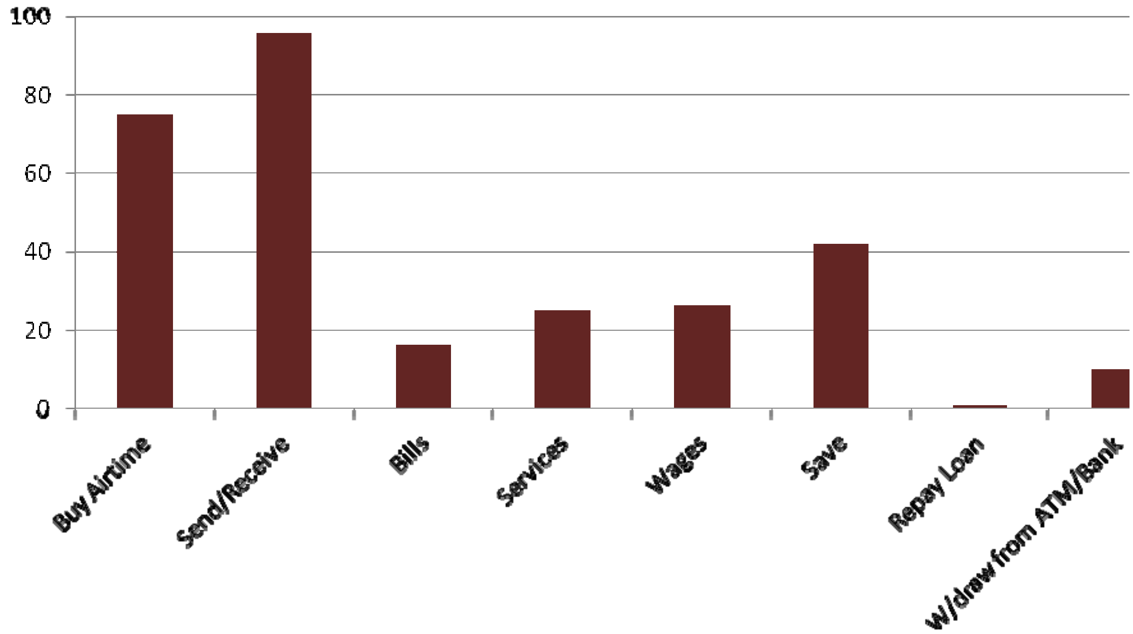
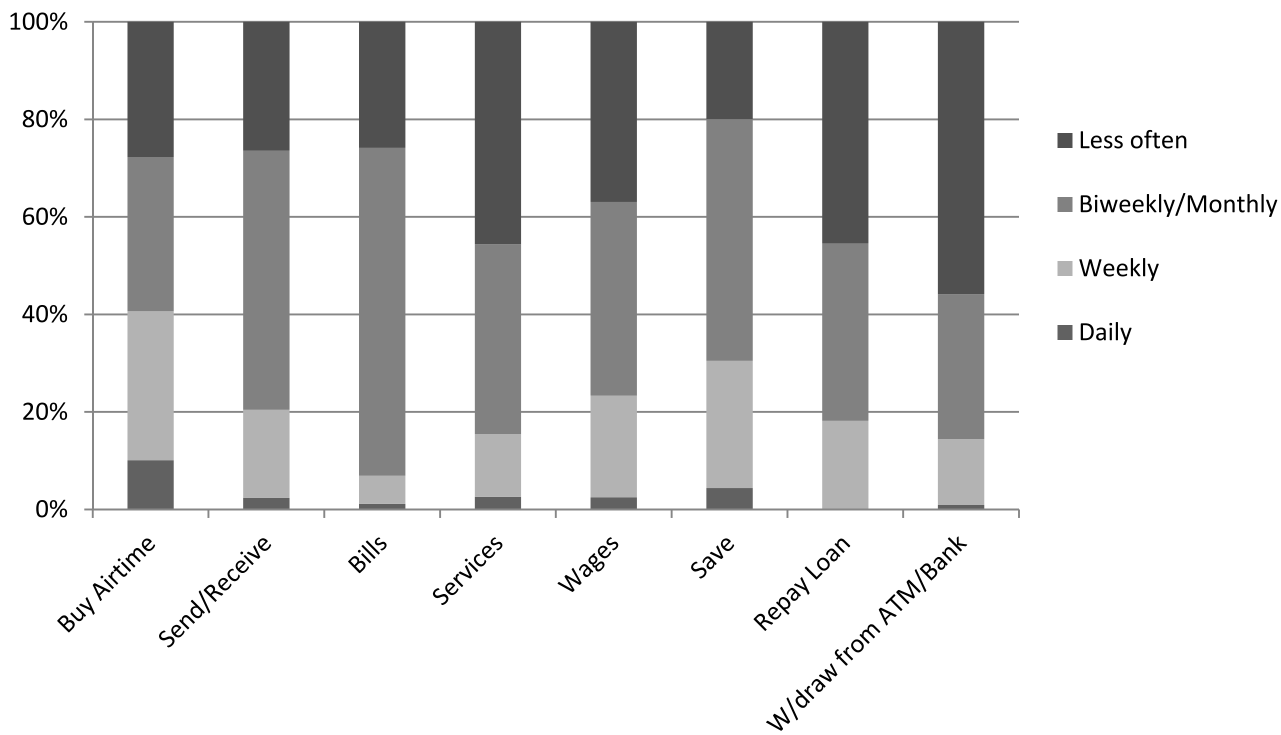
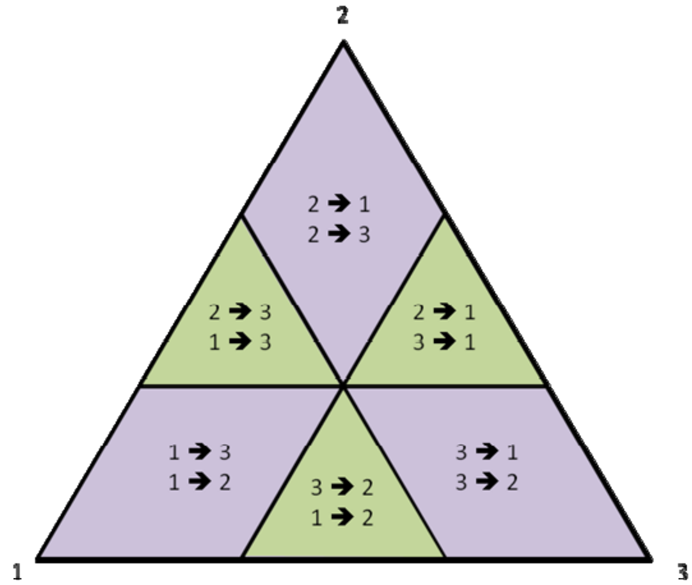


Figure 2B: Frequency of M-PESA Use, by Transaction Type



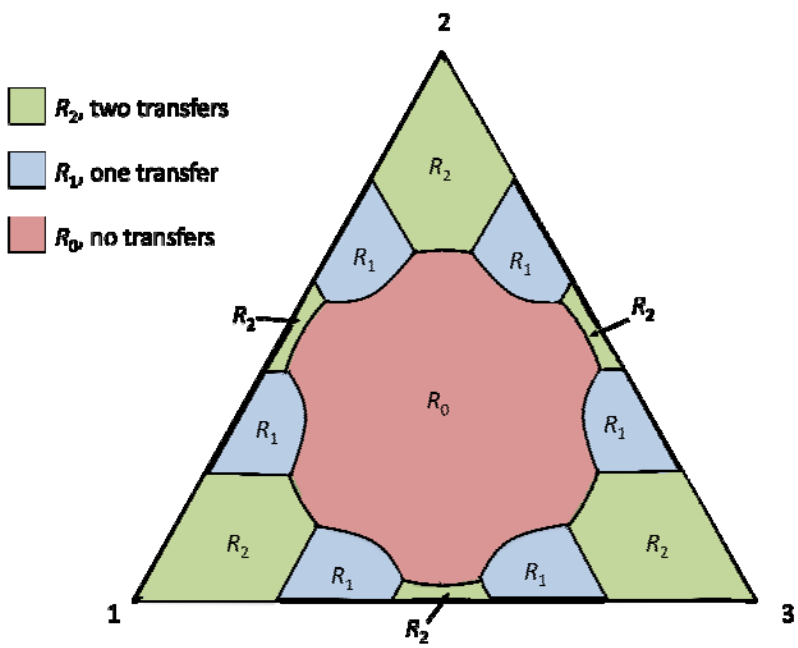
Notes: Figures are based on the 2010 survey covering about 1,000 individual users, which collected data on 31 separate transactions that M-PESA allows. These figures aggregate most of those transactions but do not include balance and pin number checks.

Figure 3A: Insurance Without Transaction Costs



Note: Individuals 1, 2, and 3 are located at the corners of the simplex, each point of which is a realized income endowment. In each of the six areas shown, the direction of optimal risk sharing transfers is indicated.

Figure 3B: Insurance with Transaction costs



Note: In regions marked R_2, R_1, and R_0 respectively, two, one, and zero transfers are undertaken. As transaction costs fall, regions R_0 and R_1 shrink, and more income realizations are smoothed across all three members of the network.

Figure 4: Location of Sampled Households Across Kenya

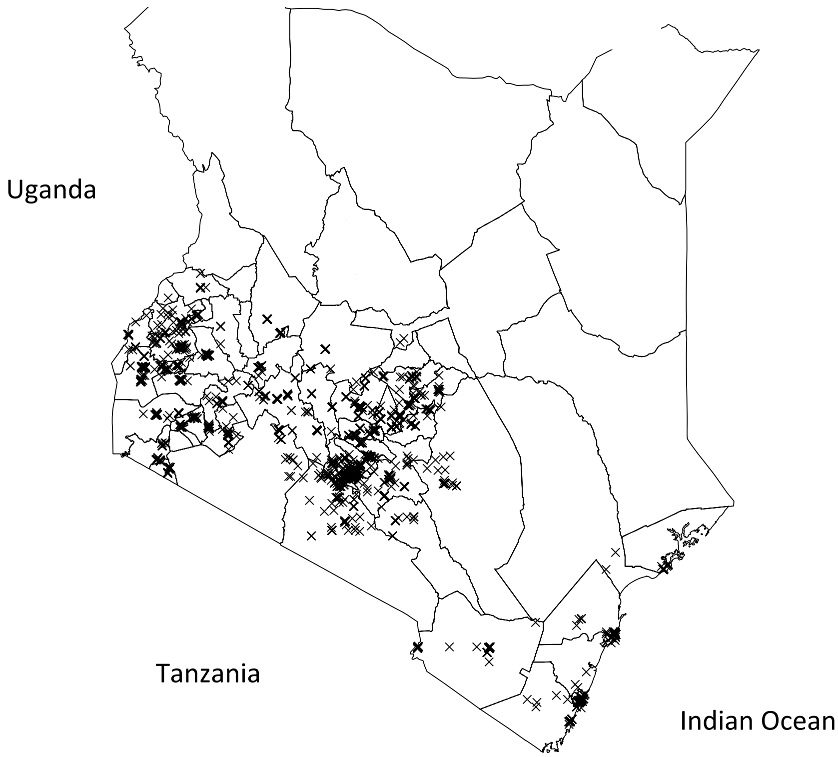
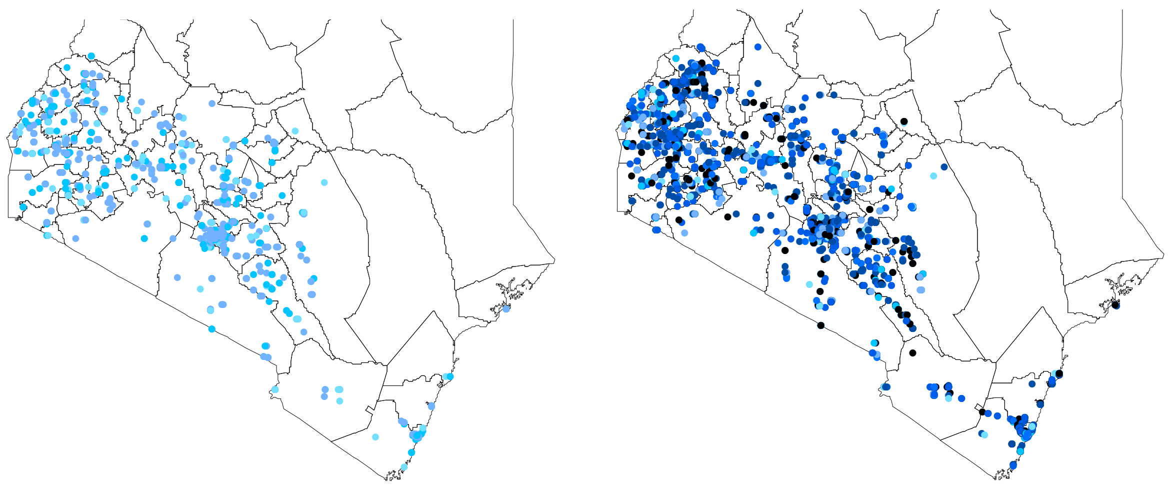


Figure 5: Roll Out of M-PESA Agents Across the Country



Notes: The left panel is at June 2008 and the right panel starting at March 2010. The darker colors represent newer agents (each new shade represents about an additional age of six months from the start of M-PESA in early 2007).

Appendix: Not for Publication

In this appendix we characterize the regions R_i, for $i = 0, 1, 2$, of the simplex in which i transactions optimally take place for a given fixed transaction cost k. We then show how these regions change as k increases, in particular that a smaller number of income realizations are shared among all three members, and a larger number of realizations are not shared at all.

A Characterizing Active Insurance Network Participation

Given a vector of income realizations $x \in R^{213} = \{x : \sum_i x_i = 1 \text{ and } x_2 > x_1 > x_3\}$, ex post welfare is the same under full sharing between all members and partial sharing between individuals 2 and 3 only, if and only if $W^* = \widehat{W}(x_1, k)$, or

$$3u\left(\frac{1-2k}{3}\right) = u(x_1) + 2u\left(\frac{1-x_1-k}{2}\right) \tag{13}$$

Given k, the function $\widehat{W}(x_1, k)$ is defined for $x_1 \in [0, 1-k]$, and has an interior maximum on this domain. In general condition (13) thus has up to two solutions, $x_1 = \hat{x}_1(k)$ and $x = \hat{x}_1'(k)$, with $\hat{x}_1(k) < \hat{x}_1'(k)$. These values define two boundaries, B_{21} and B_{21}' respectively, in R^{213} that are straight lines parallel to the edge of the simplex opposite corner 1. These are illustrated in Appendix Figure 3A, and in turn define three regions: R_{21} and R_{21}' in which sharing of resources among the three individuals by means of two transactions is preferred to sharing between 2 only with a single transaction, and R_{12} in which sharing between two parties (individuals 2 and 3) is preferred to sharing among all three.

Appendix Figure 3B shows the sub-regions of R^{213} in which three-way sharing with two transactions is compared to no sharing. The boundary B_{20} between R_{20} (where three-way sharing is preferred to no sharing) and R_{02} (where no sharing is preferred), is a circle on the simplex, given by

$$u(x_1) + u(x_2) + u(x_3) = 3u\left(\frac{1-2k}{3}\right) \tag{14}$$

Finally, Appendix Figure 3C partitions R^{213} into a sub-region R_{10} in which two-way sharing is preferred to no sharing, and R_{01} in which the opposite holds. The boundary between these sub-regions, B_{10}, is defined by

$$u(x_2) + u(x_3) = 2u\left(\frac{1-x_1-k}{2}\right) \tag{15}$$

To characterize this boundary, fix x_1 at $x_1^0 < \frac{1}{2}$ and consider two points $A = (x_1^A, x_2^A, x_3^A)$ on boundary B_{10} and $B = (x_1^B, x_2^B, x_3^B)$ on boundary B_{20} , with $x_1^A = x_1^B = x_1^0$. We show that for $x_1^0 \in (\hat{x}_1, \hat{x}_1')$ boundary B_{10} lies inside boundary B_{20}, and for x_1^0 outside this range boundary B_{10} lies outside boundary B_{20}.

To see this note that

$$\sum_i u(x_i^B) = u(x_1^B) + 2u\left(\frac{1-x_1^B-k}{2}\right) = u(x_1^A) + 2u\left(\frac{1-x_1^A-k}{2}\right) > 3u\left(\frac{1-2k}{3}\right) \tag{16}$$

if and only if $x_1^0 \in (\hat{x}_1, \hat{x}_1')$. Thus for x_1^0 in this range, at point B it is better for no sharing to take place than for full sharing, so B lies inside the circle defined by boundary B_{20}. For x_1^0 outside this range, B lies outside the circle. Finally, at $x_1^0 = \hat{x}_1$ the three boundaries B_{20}, B_{10}, and B_{21} intersect, and at $x_1^0 = \hat{x}_1'$, boundaries B_{20}, B_{10}, and B_{21}' coincide.

Appendix Figure 3D shows nine areas defined by the juxtaposition of the seven sub-regions defined above. It is straightforward to show that these define four areas in which one sharing arrangement dominates the other two. The partition of the full simplex is illustrated in Figure 3B in the main text.

B Comparative Statics

As k increases, the region R_{21} of Appendix Figure 1 contracts. To show this we first observe that $\hat{x}_1(k) < \frac{1-k}{3}$ by noting that when $x_1 = \frac{1-k}{3}$ the right hand side of condition (13) above is

$$u\left(\frac{1-k}{3}\right) + 2u\left(\frac{1-(\frac{1-k}{3})-k}{2}\right) = 3u\left(\frac{1-k}{3}\right) > 3u\left(\frac{1-2k}{3}\right), \tag{17}$$

where the last term is the left hand side of (13). Thus when $x_1 = \frac{1-k}{3}$ it is strictly better for only individuals 2 and 3 to share than it is for all three to share, and $\hat{x}_1(k) < \frac{1-k}{3}$.

Totally differentiating condition (13), we find

$$\frac{d\hat{x}_1(k)}{dk} = \frac{\left[-\widehat{W}_k(\hat{x}_1,k) - 2u'\left(\frac{1-2k}{3}\right)\right]}{\widehat{W}_x(\hat{x}_1,k)} = \frac{\left[u'\left(\frac{1-x_1-k}{2}\right) - 2u'\left(\frac{1-2k}{3}\right)\right]}{\left[u'(x_1) - u'\left(\frac{1-x_1-k}{2}\right)\right]}. \tag{18}$$

At $x_1 = \hat{x}_1(k)$ the denominator is positive, since $\hat{x}_1 < \frac{1-k}{3}$ and $\frac{1-\hat{x}_1-k}{2} > 1-k > \frac{1-k}{3}$. On the other hand, note that $k < 1$ implies $1-k > \frac{(1-2k)}{3}$, so that at $x_1 = \hat{x}_1(k)$ we have $\frac{(1-\hat{x}_1-k)}{2} > \frac{(1-2k)}{3}$. Thus the numerator is negative at $x_1 = \hat{x}_1(k)$, i.e., $\widehat{W}(\hat{x}_1,k) < 0$, and $\frac{d\hat{x}_1}{dk} < 0$.

The second solution $\hat{x}_1'(k)$ defines the region R_{21}' as shown in Appendix Figure I. As $\widehat{W}(x_1,k)$ has a unique maximum in $[0, 1-k]$ and $\widehat{W}_x(\hat{x}_1,k) > 0$, we know that $\widehat{W}_x(\hat{x}_1',k) < 0$. It immediately follows that

$$\frac{d\hat{x}_1'(k)}{dk} = \frac{\left[-\widehat{W}_k(\hat{x}_1',k) - 2u'\left(\frac{1-2k}{3}\right)\right]}{\widehat{W}_x(\hat{x}_1',k)} > 0 \tag{19}$$

Thus the region R_{21}' also shrinks as k increases. As k increases it is trivial to show that sub-region

R_{02} in Appendix Figure II expands, and R_{20} contracts.

Finally, we can show that as k increases, the region R_{01} in Appendix Figure 3 expands. Fixing x_1, recall that on the boundary B_{10},

$$u(x_2) + u(x_3) = u(x_2) + u(1 - x_2 - x_1) = 2u(\frac{1 - x_1 - k}{2}), \tag{20}$$

so

$$\frac{dx_2}{dk} = \frac{-u'\left(\frac{1-x_1-k}{2}\right)}{[u'(x_2) - u'(1 - x_2 - x_1)]} \tag{21}$$

The numerator is negative, and we seek to show that the denominator is also, which requires that $x_2 > 1 - x_2 - x_1$, or $x_2 > \frac{(1-x_1)}{2}$. First, if $x_1 < \frac{1}{3}$ then $x_2 > 1 - 2x_1$. Thus we require $1 - 2x_1 > \frac{(1-x_1)}{2}$, or $1 > 3x_1$, which is true. Alternatively, if $x_1 > \frac{1}{3}$ then the smallest that x_2 can be is x_1, so we need $x_1 > \frac{(1-x_1)}{2}$ or $3x_1 > 1$, which again is consistent. Thus keeping x_1 constant, $\frac{dx_2}{dk} > 0$ and region R_{01} expands.

Appendix Tables and Figures: Not for Publication

Appendix Table 1: Shock Correlations
Dependent Variable: Overall Shock

	Coefficient	SE	R squared
M-PESA User	-0.0228	[0.0287]	0.108
Cellphone Ownership	-0.0267	[0.0319]	0.108
Log Distance to Closest Agent	0.0089	[0.0490]	0.106
Agents within 1km	0.0033	[0.0263]	0.108
Agents within 2km	0.0228	[0.0223]	0.109
Agents within 5km	0.0002	[0.0183]	0.108
Yrs of Education (HH head)	0.0034	[0.0026]	0.109
Occupation- Farmer	0.0450	[0.0352]	0.108
Occupation- Professional	-0.0130	[0.0338]	0.108
Occupation- Househelp	-0.0265	[0.0431]	0.1100
Occupation- Run a Business	-0.0715**	[0.0353]	0.109
Occupation- Sales	0.0579	[0.0461]	0.110
Occupation - Unemployed	0.1033	[0.0471]	0.108
HH Has a Bank account	0.0033	[0.0310]	0.108
HH has a SACCO account	0.0070	[0.0247]	0.109
HH has a ROSCA	0.0476	[0.0328]	0.109
Fraction of Boys in HH	0.0657	[0.1048]	0.108
Fraction of Girls in HH	0.0121	[0.1148]	0.108
HH Size	0.0106	[0.0105]	0.109

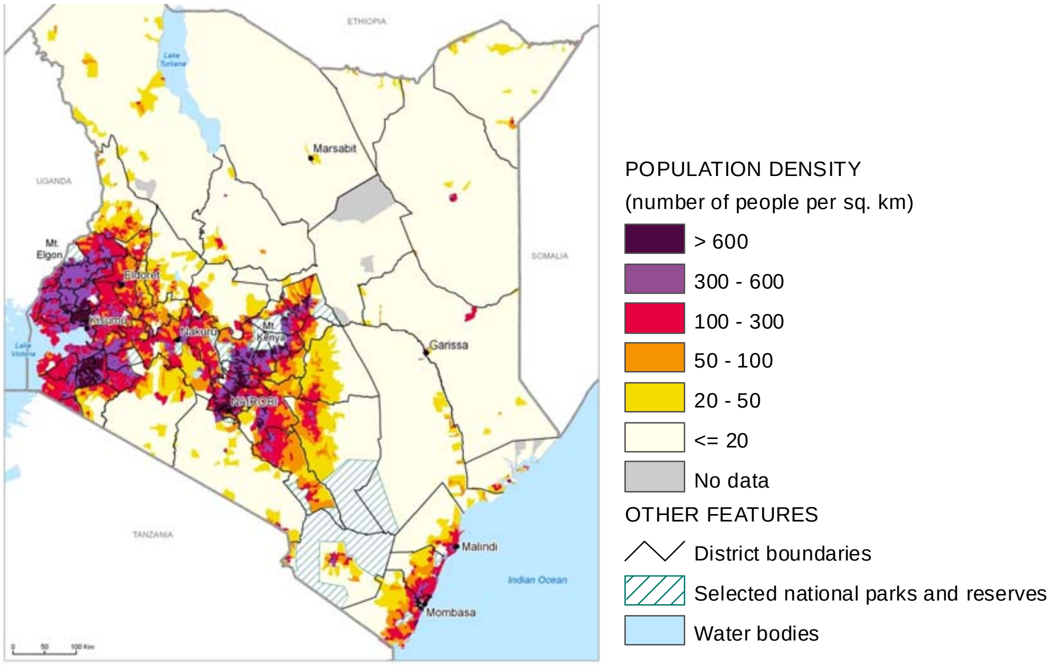
Note: Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1
Each row represents a separate panel regression. All regressions controls for only location by time fixed effects.

Appendix Table 2: Attrition, Rounds 2 and 3 Separated

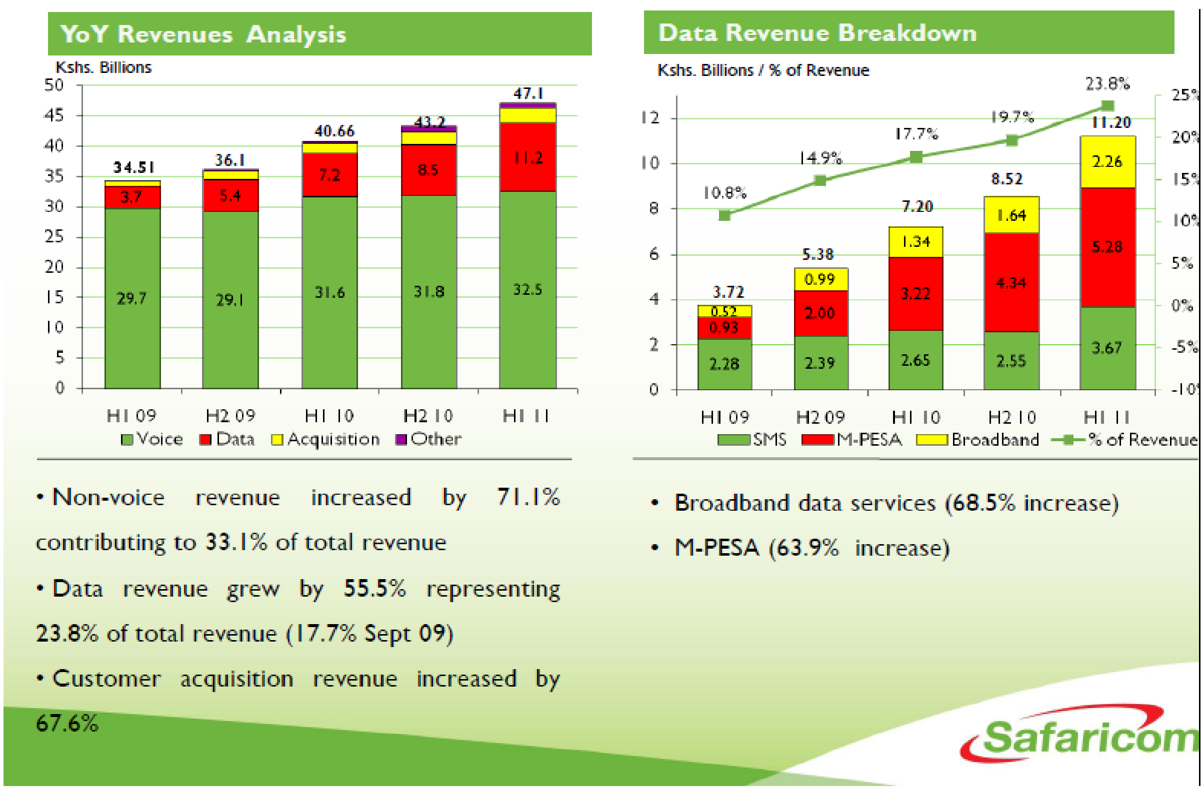
	(1) Second Period is Round 2		(2) Second Period is Round 3		Test (1)=(2) P-Value
	Coefficient	SE	Coefficient	SE	Significance
Log Total Expenditure†	-0.05627	[0.0375]	0.0383	[0.0577]	*
Log Food Expenditure	-0.07527**	[0.0314]	0.0468	[0.0483]	***
M-PESA User	0.0886***	[0.0251]	0.0743*	[0.0386]	
Cellphone Ownership	0.0933***	[0.0222]	0.0799**	[0.0343]	
Log Distance to Agent	0.0880	[0.0537]	0.0282	[0.0823]	
Agents within 1km	-0.6280	[0.3214]	-0.0486	[0.4953]	
Agents within 2km	-0.2885	[0.4076]	-0.0991	[0.6281]	
Agents within 5km	-0.0209	[0.6668]	0.5064	[1.0276]	
Agents within 10km	-0.5052	[1.5735]	2.3009	[2.4247]	
Strong Negative Shock	0.0281	[0.0239]	0.008	[0.0369]	
Rainfall Shock	-0.0113	[0.0079]	-0.0001	[0.0122]	
Illness Shock	0.0158	[0.0176]	0.0261	[0.0271]	
Sent Remittance	0.0309	[0.0254]	-0.0025	[0.0392]	
Received Remittance	0.0101	[0.0253]	0.0441	[0.0389]	
Total Remittance Sent	534.7	[1228.5]	-202.4	[1893.2]	
Total Remittance Received	1780.0	[2169.9]	2459.5	[3343.7]	
Yrs of Education (HH head)	0.1603	[0.2865]	-0.2377	[0.4415]	
Occupation- Farmer	0.0226	[0.0176]	0.0516*	[0.0271]	
Occupation- Professional	-0.0064	[0.0221]	0.0245	[0.0340]	
Occupation- Househelp	-0.0480***	[0.0169]	-0.0493*	[0.0260]	
Occupation- Run a Business	0.0070	[0.0197]	-0.0197	[0.0303]	
Occupation- Sales	0.0196	[0.0121]	-0.0006	[0.0187]	
Occupation - Unemployed	-0.0035	[0.0138]	-0.0026	[0.0212]	
HH Has a Bank account	0.0546**	[0.0242]	0.0354	[0.0372]	
HH has a SACCO account	0.0415**	[0.0202]	0.0103	[0.0311]	
HH has a ROSCA	0.0329	[0.0252]	0.0209	[0.0389]	
Fraction of Boys in HH	0.0114	[0.0097]	-0.0046	[0.0150]	
Fraction of Girls in HH	0.0189*	[0.0096]	-0.0075	[0.0149]	**
HH Size	0.5499***	[0.1064]	0.1716	[0.1640]	***

Note: Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1.
Omitted category is the attrition group (households that were never found). Each row represents a separate regression. All regressions controls for location fixed effects.

Appendix Figure 1: Population Density Across Kenya

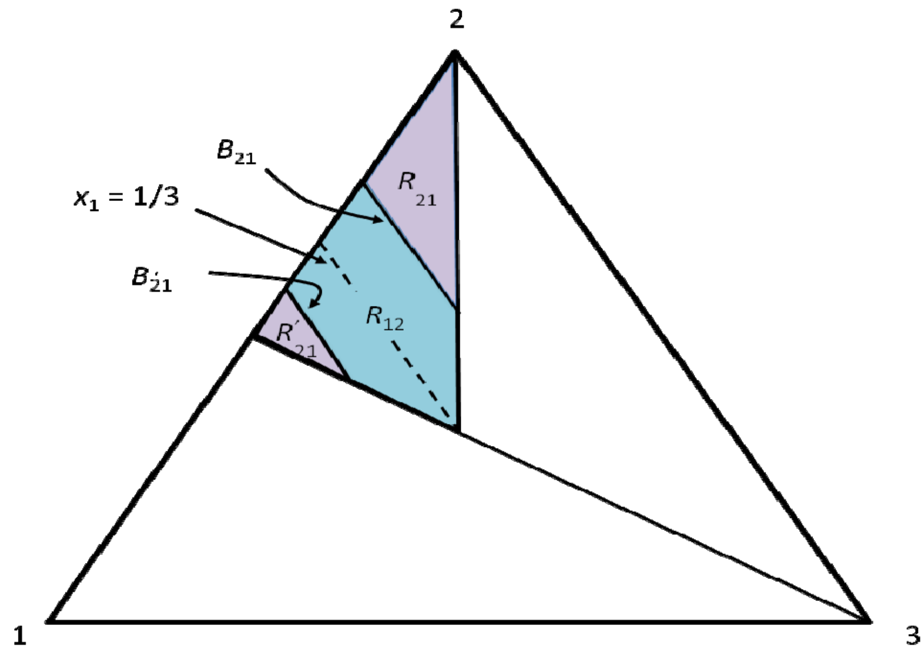


Appendix Figure 2: Safaricom Revenue Breakdown

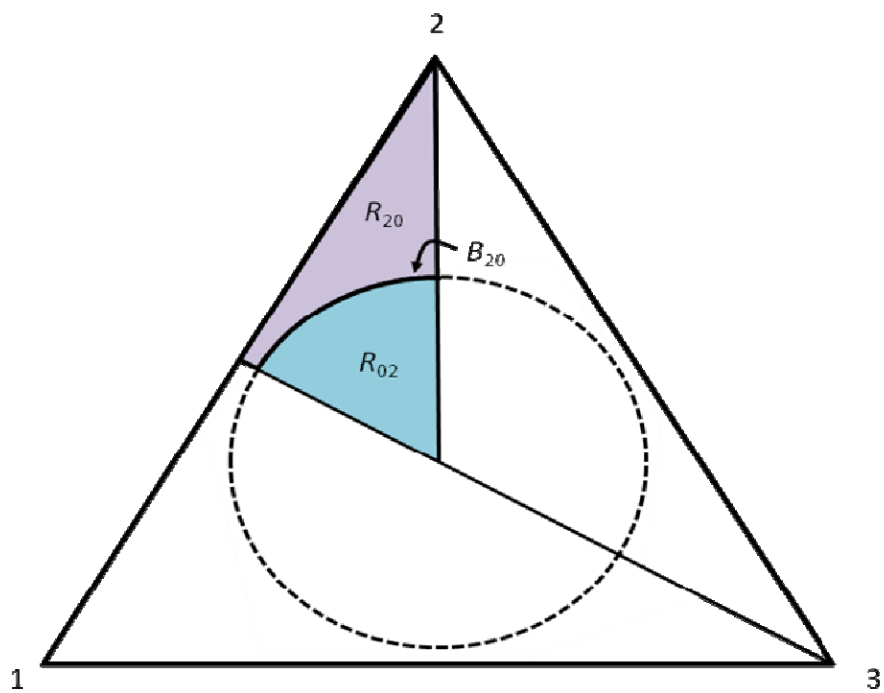


Source: Safaricom annual report, 2010

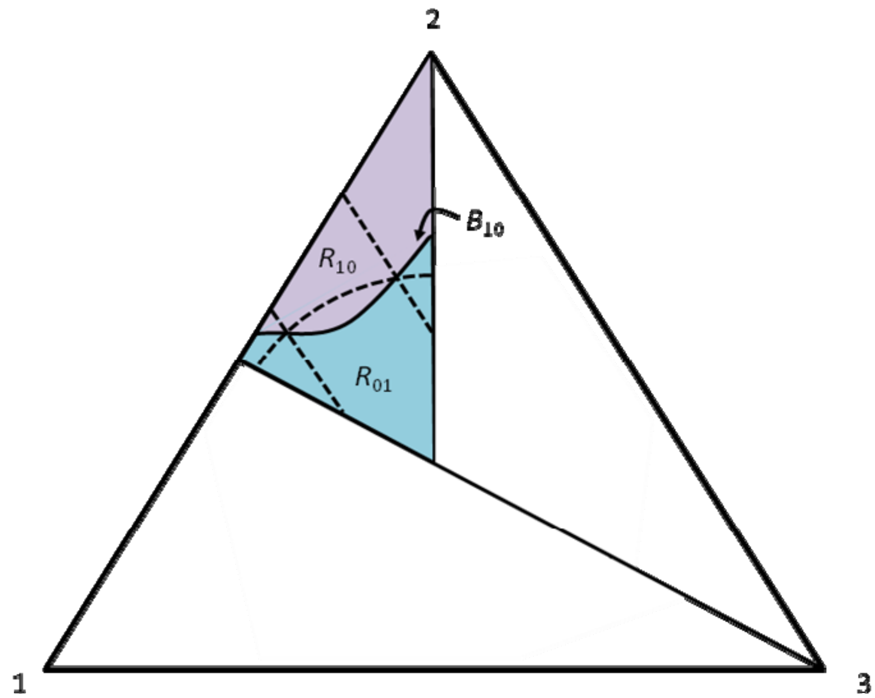
Appendix Figure 3A



Appendix Figure 3B



Appendix Figure 3C



Appendix Figure 3D