Mobile Money and Healthcare Usage: Evidence from East Africa

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Abstract: This paper uses a difference-in-difference framework to explore the effects of mobile money transfer technology (MMT) on healthcare usage in the face of a negative health shock. We use survey data from 2013-16 with quarterly observations on about 1,600 households of 10 villages in the Kisumu region of Western Kenya. We find evidence that MMT helps households increase healthcare expenditures and utilization of formal healthcare services, in terms of visits to a clinic, consultation and medication expenditures, in comparison with the non-users of this technology. This better utilization of formal healthcare services may result in better health and poverty reduction in a meaningful way. These effects can be explained by the decrease in transaction costs related to borrowing and lending and ease of risk sharing due to the use of this technology.

JEL Codes: E42, G22, O16, O17, Z13

Keywords: Mobile Money, Liquidity Constraints, Insurance, Healthcare, Risk Sharing

1. Introduction

Lack of access to financial services restricts the ability of poor households to save and invest and engage in formal insurance mechanisms (Johnson and Nino-Zarazua 2011; Dupas and Robinson 2009). Therefore, poor households of the world rely on informal risk sharing mechanisms during periods of distress. This informal risk sharing and insurance is generally incomplete due to information asymmetries and transaction costs (Gertler and Gruber 2002; Townsend 1995; Kochar 1995; Gertler, Levine and Moretti 2006, 2009). Mobile money transfer technology (MMT) may reduce the transaction costs associated with borrowing and lending and may increase risk sharing in presence of income shocks as it allows its owners to store monetary value on a mobile phone and this value can be sent or received simply by text messages (Jack and Suri 2014; Suri and Jack 2016; Munyegera and Matsumoto 2015; Blumenstock, Eagle and Fafchamps 2011).

The objective of this paper is to test the impact of MMT on risk-sharing in face of a negative health shock. Jack and Suri (2014) use a difference-in-difference specification to examine the changes in the response of consumption to negative unexpected income and health shocks across MMT users and non-users. Our paper builds on this work by using the Socio-Economic Survey (SES) conducted by Kenya Medical Research Institute (KEMRI) and Centers for Disease Control (CDC) and by specifically focusing on the impact of MMT adoption on health expenditures and healthcare use under negative health shocks.

We focus on healthcare use as it has been recognized as pivotal in improving living standards and reducing poverty. Credit constraints and high cost of health services keep more than a billion people in low and middle income countries from using optimal levels of healthcare (Harris et al. 2011; Gouge et al. 2009). By making it easier to borrow money from far off relatives and friends,

MMT can help households overcome these credit constraints. Furthermore, lack of access to formal health and disability insurance in low-income households means that they may have to rely on mechanisms of risk sharing other than formal insurance (Kochar 1995; Gertler, Levine and Moretti 2006, 2009), and MMT can be one such mechanism that can allow households to use more formal healthcare. Healthcare use is particularly important in our setting as communicable diseases like malaria, diarrhea and respiratory disorders are endemic in the region (Thumbi et al. 2015).

Jack and Suri (2014) show that users of MMT are able to smooth consumption for total, food and other non-health expenditure categories under these negative shocks and find a positive and significant effect of MMT on risk sharing in these categories; in contrast, our results indicate that the risk sharing effects are concentrated on health expenditures and healthcare use in presence of a negative health shock. By using a different dataset and focusing specifically on healthcare use, this paper contributes to the literature by showing that users of MMT are able to use more healthcare, compared to non-users. This suggests that MMT can be an efficient financial tool in overcoming very short-run credit constraints and may lead to necessary medication and formal healthcare use in poor households in the time of need, which may have important repercussions for household health. Furthermore, unlike Jack and Suri (2014), we find that households' quarterly non-health consumption is insured against negative health shocks while the health budget increases with the shock. This may imply that households need money for healthcare use in the very short-run in the face of illness and are able to adjust other expenditures over the quarter.

MMT adoption is endogenous and the validity of our identification strategy rests on the assumption that health shocks are exogenous. We find that health shocks are uncorrelated with

observables, suggesting that these shocks are exogenous and equally affect users and non-users of MMT, rendering our panel difference-in-difference a valid identification design. Like Jack and Suri (2014), we allow for all observable household characteristics to affect risk sharing by interacting them with health shocks. This allows us to control for other changes in household's environment and also for how these changes may affect household's consumption smoothing ability.

MMT can allow for consumption smoothing through liquidation of savings or through increased remittances and loans. Jack and Suri (2014) and Munyegera and Matsumoto (2015) find that remittances are the main mechanism through which households are able to smooth consumption. We test the impact of MMT on likelihood of acquiring a loan with our difference-in-difference strategy. We find that MMT users are 5 percentage points more likely to acquire loans than non-users during a negative health shock, indicating that borrowing may be the main mechanism.

In other studies, MMT has been associated with an increase in the privacy of transactions, thereby providing more freedom to women in choosing where to spend their money and also improving the gender parity situation within households (Aker et al. 2011; Jackiela and Ozier 2011). Users of mobile money spent cash on more diverse items, sold fewer non-durable assets and cultivated more diverse crops in the randomized control trial conducted by Aker et al. (2011). In smallholder setting, financial inclusion and MMT adoption has been linked with higher farm input use, higher farm profits and off-farm employment (Suri and Jack 2016; Kikulwe et al. 2014).

The article is organized as follows. Section 2 consists of the data and background. The econometric framework is described in Section 3. A discussion of results is in section 4, and section 5 concludes.

2. Background and Data

Mobile money was started in 2007 and its adoption grew steadily over time. The owners of MMT, which is provided by Safaricom, Airtel, Orange and Essar, can exchange cash for e-money at any "mobile money agent" locations which are easily accessible even in rural areas. Further, they can send this money to anyone in the country with a text message, even if recipient is not a registered mobile money holder and even if the phone operates on another network. Depositing funds for e-money is free, while an SMS costs about 30 Kenyan Shillings (40 cents). Withdrawals are charged at about 1-2 percent and the price is higher if the recipient is not a registered owner of the facility or uses a different cellular network.[1]

Our data have been drawn from the longitudinal Socio-Economic Survey (SES)[2], conducted in the Kisumu Region, near Lake Victoria, of Kenya. The SES is compiled from quarterly visits to about 1600 households in 10 villages. The survey period was roughly from February 2013 to December 2016.

Table 1 provides descriptions of the variables. Table 2 provides the means and standard deviations of the variables of interest. Average *Total Expenditure* during a quarter is about

[1] Registration only requires a National ID card or Passport. Detailed information regarding pricing for one of the cellular service is available at https://www.safaricom.co.ke/personal/m-pesa/getting-started/m-pesa-rates

[2] This survey was launched by Paul G. Allen School for Global Animal Health at Washington State University in collaboration with the Kenya Medical Research Institute and U.S. Centers for Disease Control and Prevention (known as the KEMRI/CDC Research and Public Health Collaboration) and the University of Washington with a goal to reduce poverty and hunger and improve health and education.

10,127.8 Kshs. (~$101) with education and other expenditures constituting the largest expenditure categories. Other expenditures may include expenditures related to livestock and crop farming, or recreation.

We define healthcare use through three variables; *Visits Made* to a clinic, whether or not medication expenditure was incurred (*Medication*) and whether or not a consultation fee was paid during the last quarter (*Consultation*). Number of visits to a clinic indicates the use of formal healthcare facility, but does not indicate if such a facility was used to just buy medicines or used for doctor consultation. In the region, one of the hospitals charges no consultation fee and the visits variable in such a case may only capture opportunity cost of time and transportation costs. We also want to examine if users of *MMT* are more likely to use this technology for medication expenditures or consultation expenditures or both and *Medication* and *Consultation* variables help us determine that.

The user rates of *MMT* remain around 60 percent at the household level in our sample during all time periods while the overall cell phone ownership remains around 70 percent. In our region and sample, the rate of penetration of this technology hasn't been increasing over time, whereas other studies of mobile money report an increasing trend in the adoption of this technology (Munyegera and Matsumoto 2015; Jack and Suri 2011, 2014). Barriers to use this technology include failed transactions, dissatisfaction over mobile carriers' customer service and cash float shortages especially in rural areas (Morawczynski and Pickens 2009).

Shock is an indicator variable equal to 1 if any household member has been sick (could not go to work or go to school) in the past 3 months, 0 otherwise. In the sample, health shocks are the most dominant shocks compared to livestock health shocks and crop loss. On average, 42% of the households report illness incidence within the household in the preceding quarter. In some

of the time periods, as high as 52% households report illness, suggesting that risk due to disease is a dominant feature in these households.

Table 2 also reports the level of cash savings and the percentage of households that take a loan (formally or informally) during the survey period. 10% of the households report that they took a loan during the survey period. Only 44% of the population reported that they had positive cash savings, and mostly the savings were less than 5,000 Kshs. (~$50), while 56% reported that they had no cash savings. There were significant difference in the wealth of households. The wealth variable is constructed from farm and off-farm incomes, value of livestock and value of crop inventory. This component of wealth can also be thought of as savings, since livestock are often used as precautionary savings assets (McPeak 2006). Other assets that could help in risk sharing like acres of land owned and ownership of a phone enter as independent variables in the analysis.

3. Empirical Framework

Our focus is to determine the impact of *MMT* on consumption and healthcare use in face of a health shock. Following Jack and Suri (2014), we employ the following difference-in-difference specification to test whether consumption and healthcare usage of users and non-users of MMT differs under health shocks:

$$y_{ivt} = \alpha_i + \gamma shock_{ivt} + \beta shock_{ivt} * MMT_{ivt} + \lambda MMT_{ivt} + \mu X_{ivt} + \delta_{vt} + \epsilon_{ivt} \qquad (1)$$

where y_{ivt} is (a) expenditures for different consumption categories, and (b) healthcare usage captured by visits to a clinic and expenditures on medication and consultation, in household i, village v, and time t. $shock_{ivt}$ is a dummy variable equal to 1 if the household reported illness in the preceding quarter, 0 otherwise. MMT_{ivt} is a dummy variable equal to 1 if any member of the household is a user of mobile money technology, 0 otherwise. α_i are the household fixed effects

and δ_{vt} are village by time dummy variables that control for time invariant household heterogeneity and aggregate level shocks, respectively. X_{ivt} contains occupational dummy variables, whether or not a household owns a mobile phone or not, travel time to the hospital/clinic, highest educational attainment of the household, total adult household members and children, total household wealth, household's savings level, owned acres and whether or not a household took a loan. This empirical strategy also closely emulates Gertler and Gruber (2002) and Gertler, Levine and Moretti (2006, 2009).

There are two main concerns that may cause problems in the interpretation of β in the above specification. First is the endogeneity of MMT adoption. The validity of our identification strategy rests on the assumption that health shocks are exogenous and are equally likely to affect users and non-users of MMT. If health shock is not exogenous and is correlated to observables or MMT adoption, then β may not capture the causal effect of MMT use on risk sharing. Following Jack and Suri (2014), we test the exogeneity of health shocks by examining if they are correlated to adoption of MMT or a number of household-level variables.

$$shock_{ivt} = \alpha_i + \eta MMT_{ivt} + \rho X_{ivt} + \delta_{vt} + e_{ivt} \qquad (2)$$

The results for this regression have been reported in Table 3. Our $shock_{ivt}$ variables are not correlated with the MMT_{ivt} variable, alleviating the concern that adoption of MMT may be correlated with the bad health state. Further, we do not find evidence of strong correlations between $shock_{ivt}$ and X_{ivt}, which may suggest that $shock_{ivt}$ is also uncorrelated with the unobserved error term.

The second main concern is that exogeneity of $shock_{ivt}$ may not be enough for a consistent interpretation of β in equation (1). Since *MMT* is correlated with observables like education, owning a cell phone and wealth, and these variables may also be used for risk sharing and

consumption smoothing, which implies that β may not necessarily be capturing the effect of *MMT* on risk sharing. We follow Jack and Suri's (2014) strategy of interacting X_{ivt} with the $shock_{ivt}$ to control for these other mechanisms through which risk sharing can happen and alleviate concerns around the interpretation of β. Therefore, the following regression is our preferred specification:

$$y_{ivt} = \alpha_i + \gamma shock_{ivt} + \beta shock_{ivt} * MMT_{ivt} + \lambda MMT_{ivt} + \mu X_{ivt} + \theta shock_{ivt} * X_{ivt} + \delta_{vt} + \epsilon_{ivt} \quad (3)$$

where all of the variables are the same as equation (1), while the term $shock_{ivt} * \boldsymbol{X_{ivt}}$ is included to control for risk-sharing effects through mechanisms other than *MMT*.

To test for the mechanism of risk sharing, we examine the impact of *MMT* on loans with the following linear probability model.

$$loan_{ivt} = \alpha_i + \gamma shock_{ivt} + \beta shock_{ivt} * MMT_{ivt} + \lambda MMT_{ivt} + \mu X_{ivt} + \theta shock_{ivt} * X_{ivt} + \delta_{vt} + \epsilon_{ivt} \quad (4)$$

where $loan_{ivt}$ is a dummy variable equal to 1 if household acquired a loan (formally or informally) in the past quarter and 0 otherwise.

Standard errors are clustered at the household level to account for the serial and intra-household correlation in errors for all regressions and specifications.

4. Results

4.1. Effect on Expenditures

The results of the difference-in-difference regressions for per capita expenditures in different categories under a health shock are reported in Table 4. Jack and Suri (2014) find that health shocks decrease the consumption of non-users of *MMT*; in contrast, we find that health shocks do not significantly affect the non-health expenditures. This result suggests that households are able

to smooth their consumption against human illness shocks. Robustness checks for per capita expenditure regressions are provided in the Table A1 and A2 of the Appendix. These results are in line with the results presented by Genoni (2012) and Islam and Maitra (2012) who suggest that households may be well insured against human sickness.

We find that all households experience a large jump in health expenditures during an illness shock. However, users of technology are able to spend 67% more per capita than the non-users during the time of *shock*, suggesting that *MMT* could help in using formal health facilities and more health inputs in the time of need. Since the non-health expenditures are not affected by health shock and risk sharing is only concentrated in healthcare expenditures, this could mean that households may need payments for the very short-term to go to a doctor and later, they are able to adjust their budget over the course of the quarter. This also indicates that even though all households spend more on healthcare during a health shock; however, they may still want to spend even more to be able to use optimal or best healthcare facilities, but cannot because of budget constraints.

The MMT dummy variable is positively and significantly related to per capita expenditures in most of the regression specifications, indicating that selective adoption of MMT is perhaps correlated with and captures the effect of wealth and other variables that affect expenditures. However, since *shock* is exogenous and users and non-users are equally likely to experience it, this does not pose a threat to the validity of our identification strategy.

4.2. Effect on HealthCare Use

Table 5 provides the estimates of the impact of *MMT* on *Visits Made* to a clinic/hospital in presence of health shock. Column 1, Table 5 reports results for baseline OLS regression with only time by village fixed effects included to control for aggregate village-level shocks.

According to this specification, users of *MMT* are able to visit a formal healthcare facility 0.63 times more than non-users in presence of a *shock*. In Column 2 through 4, we add household fixed effects, covariates, and covariates and interaction of covariates with the *shock*, respectively. By adding household fixed effects, the time invariant endogeneity due to unobserved household characteristics is controlled for and the coefficient on *MMT***Shock* is 0.56. Adding the covariates (Column 3) do not change this estimate, while adding covariates and their interaction with the *shock* results in coefficient of 0.49 on *MMT***Shock*. The changes across column 2 to 4 are fairly small and the results are robust across these specifications. Since the correlation between *MMT* and other covariates can obscure the interpretation of the coefficient on *MMT***Shock*, as discussed in the empirical framework section, therefore, the paper allows for risk sharing through other mechanisms via interaction of *shock* with covariates, making column 4 the preferred specification. Coefficients on *MMT***Shock* are statistically significant at 1% level of significance (p-value < 0.001) for all specifications.

One concern could be that the use of *MMT* may change the financial environment of the households in terms of use of savings and other financial instruments, so controlling for them may cause ambiguities in the effect of *MMT*. However, the results in column 2 and 4 differ by only 0.06 times for the coefficient of *MMT***Shock*, indicating that the impact is robust across specifications, alleviating this concern.

Table 6 presents the role of *MMT* in medication use. The paper finds evidence that users of MMT are 0.16 percentage points more likely to spend on medication during illness periods than the non-users. Kisumu region is associated with high malarial incidence, respiratory problems and febrile illness (Thumbi et al. 2015) and timely medication like anti-malarials can significantly improve regional health. The results are robust across the specifications.

Table 7 presents the role of *MMT* in covering consultation costs. Results suggest that users are 0.15 times more likely to incur a consultation cost during illness period as compared to the non-users and the coefficient is statistically significant at 1% level of significance, suggesting an improvement in healthcare use for the *MMT* users. Tables 5, 6 and 7 provide evidence on the role of *MMT* in improving healthcare access during illness periods. This is an important result as households in developing countries are either not able to use formal healthcare or because of credit constraints are unable to buy optimal amount of healthcare, which results in prolonged illness, higher morbidity and mortality rates and loss of income (Jutting 2004; Schultz and Tansel 1997). Even though formal healthcare facilities are inadequate in developing countries (Das, Hammer, and Leonard 2008), pursuing formal healthcare can still significantly improve health outcomes through timely receipt of treatment and medication (Adhvaryu and Nyshadham 2015).

There could be two potential mechanisms through which *MMT* can help in risk sharing. One, this technology could be connected to a bank account and can help in liquidation of savings. Two, remittances and loans from relatives that live in far off regions or transactions within tribal and family circles could help in risk sharing. We control for the savings level and interact savings level with shocks to ensure that the savings mechanism is controlled for. Furthermore, about 90% of our sample reports that they have savings of less than $50, suggesting that risk sharing might be happening through transactions and informal borrowing rather than savings. Table 8 shows the role of *MMT* in the likelihood of acquiring a loan. Users of *MMT* are 13 percentage points more likely acquire a loan in general and about 2 to 5 percentage points more likely to acquire a loan in face of a health shock, compared to non-users, depending on different specifications. This may suggest that borrowing is the main mechanism for risk sharing in

presence of an adverse health shock. The literature on the effects of mobile money also suggests that it is the remittances that play a major role in risk sharing (Jack and Suri 2014; Munyegera and Matsumoto 2015). The small effect of MMT during a health shock may be explained by the fact that the *Took Loan* variable may only capture a partial effect of these remittances as remittances from relatives can be voluntary and may not be constituted as loans.

5. Conclusion

The paper examines the role of MMT on risk sharing in consumption and builds on the work of Jack and Suri (2014) by using a different dataset and specifically focusing on healthcare expenditures and use, which has not been the focus of their study or any other study related to MMT. We find that, during times of illness, users of MMT are able to spend, per capita, 67% more, are 16 percentage points more likely to spend on medication, 15 percentage points more likely to spend on consultation fees, and are 0.49 times more likely to visit formal healthcare facilities than non-users of the technology. These results imply that the technology can be used to overcome credit constraints which hamper the ability of the households to use necessary healthcare and this may have far-reaching consequences for household health outcomes, especially in poor households.

In contrast to Jack and Suri's (2014) findings, this paper shows that the risk sharing effects of MMT are concentrated on healthcare expenditures and use, instead of non-health expenditures, in presence of negative health shocks. These results may imply that users of MMT are able to use necessary healthcare better than non-users, which can potentially lead to important health outcomes for households. Since all households in our sample are able to smooth consumption in presence of a health shock, and the expenditure on healthcare increases for all households (for MMT users more than non-users), this could imply that the technology is especially beneficial in

getting very short-term loans/remittances for going to a doctor and then households are able to adjust their budget during the course of the quarter.

6. References

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Table 1: Data Description

Variable	Description
MMT	Indicator variable = 1 if any member of the household owns a mobile money savings and transfer (MMT) account, 0 otherwise.
Shock	Indicator variable = 1 if any household member has been sick (could not go to work or go to school) in the past 3 months, 0 otherwise.
Visits Made	Number of visits made to a hospital/clinic in the past 3 months.

Medication	Indicator variable = 1 if the household spent on medicines in the past 3 months, 0 otherwise.
Consultation	Indicator variable = 1 if the household spent on consultation (doctor or traditional healer) in the past 3 months, 0 otherwise.
Education Expenditure	The natural log of the total per capita expenditure on education by the household in the last 3 months.
Healthcare Expenditure	The natural log of the total per capita expenditure on health care by the household in the last 3 months.
Clothing Expenditure	The natural log of the total per capita expenditure on clothing by the household in the last 3 months.
Food Expenditure	The natural log of the total per capita expenditure on food by the household in the last 3 months.
Other Expenditure	The natural log of total per capita expenditure on 'other' things – not captured by categories above by the household in the last 3 months.
Total Expenditure	The natural log of the total per capita expenditure by the household in the last 3 months.
Children	Household members of age less than or equal to 10.
Adult HH members	Household members of age greater than 10.
College Education	Indicator variable = 1 if highest education attainment of the household is college education, 0 otherwise.
Secondary Education	Indicator variable = 1 if highest education attainment of the household is secondary education, 0 otherwise.
Primary Education	Indicator variable = 1 if highest education attainment of the household is primary education, 0 otherwise.
Savings < $70	Indicator variable = 1 if households cash savings are < $70, 0 otherwise.
$70 < Savings < $175	Indicator variable = 1 if households cash savings are between $70 and $175, 0 otherwise.
Savings > $175	Indicator variable = 1, if household cash savings are greater than $175, 0 otherwise.
Took Loan	Indicator variable = 1 if household received a loan in the past 3 months, 0 otherwise.
Cell Phone Ownership	Indicator variable = 1, if household owns a mobile phone, 0 otherwise.
Owned Acres	Acres of land owned by the household
Wealth	Income from crops, livestock and off-farm activities plus the market value of the livestock and crop inventories.
Farmer	Indicator variable = 1 if household head's primary occupation is farming, 0 otherwise.
Self Employed	Indicator variable = 1 if household head's primary occupation is off-farm self-employed, 0 otherwise
Household Help	Indicator variable = 1 if household head's primary occupation is household help, 0 otherwise

Table 2: Summary Statistics

	Mean	**SD**
Food Expenditure (Kshs)	778.9	583.7
Healthcare Expenditure (Kshs)	516.46	3,515.8
Education Expenditure (Kshs)	3,907.01	11,563.31
Clothing Expenditure (Kshs)	464.64	1,174.9
Other Expenditure (Kshs)	3,726.87	5,252.12
Total Expenditure	10,127.8	74,223.34
Visits Made to Clinic	1.06	1.70
Consultation (percent)	0.087	0.28
Medication (percent)	0.30	0.45
MMT (percent)	0.61	0.48
College Education (percent)	0.05	0.23
Primary Education (percent)	0.45	0.49
Secondary Education (percent)	0.29	0.45
Shock (percent)	0.42	0.49
Wealth (Kshs.)	84,921	77,183
Adult HH Members	4.45	2.36
Children < Age 10	1.62	1.81
Cell Phone Ownership (percent)	0.72	0.47
Owned Acres	0.70	5.92
Household Head Occupation Dummies (percent)		
Farmer	0.43	0.49
Self Employed	0.14	0.34
Salaried	0.03	0.19
Other	0.08	0.27
Household Help	0.32	0.43
Financial Instruments		
No Savings (percent)	0.56	0.48
Savings < $70 (percent)	0.43	0.49
$70 < Savings < $175	0.005	0.07
Savings > $175	0.003	0.05
Took Loan (percent)	0.106	0.31

Table 3: Correlates of Health Shock – Linear Probability Model

	Health Shock
MMT	0.09
	(0.08)
Wealth	0.0004
	(0.0003)
Savings	-0.092
	(0.063)
College Education	0.065
	(0.047)
Primary Education	0.036
	(0.035)
Secondary Education	0.045
	(0.042)
Children	0.011**
	(0.005)
Total Household Members	0.02**
	(0.006)
Occupation - House help	0.061
	(0.081)
Occupation - Self Employed	-0.021
	(0.033)
Occupation - Salaried	-0.102
	(0.083)
Cell Phone Ownership	-0.037
	(0.029)
Took Loan	0.063**
	(0.025)
Owned Acres	-0.0003
	(0.0002)
R-Squared	0.04
No. of Observations	12,149

Table 4: The Effect of Mobile Money on Expenditure (in Logs) during a Health Shock

	Education Expenditure	*Health Expenditure*	*Food Expenditure*	*Clothing Expenditure*	*Other Expenditure*	*Total Expenditure*	*Non-Health Expenditure*
Shock	0.074	2.02***	-0.009	0.053	0.082	0.39	0.028
	(0.12)	(0.20)	(0.113)	(0.107)	(0.10)	(0.31)	(0.118)
MMT	0.90***	0.21**	0.152	0.995***	0.093	0.446***	0.45***
	(0.12)	(0.09)	(0.35)	(0.115)	(0.067)	(0.055)	(0.055)
*Shock*MMT*	0.056	0.67***	-0.058	0.322*	0.011	0.089	0.046
	(0.18)	(0.148)	(0.047)	(0.174)	(0.103)	(0.079)	(0.078)
No. of Observations	14,603	14,604	14,608	14,607	14,601	14,599	14,602
Time by Village Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls*Shock	Yes	Yes	Yes	Yes	Yes	Yes	Yes

***, **, * indicate significance at 1, 5 and 10%.
Standard Errors are clustered at the household level

Table 5: The Effect of Mobile Money on Visits to a Clinic

Dependent Variable *Visits Made to Clinic*	(1)	(2)	(3)	(4)
Shock	1.19***	1.10***	0.964***	0.791***
	(0.073)	(0.084)	(0.023)	(0.146)
MMT	0.271***	0.294***	0.13	0.18
	(0.036)	(0.045)	(0.08)	(0.16)
*Shock*MMT*	0.633***	0.556***	0.588***	0.486***
	(0.084)	(0.097)	(0.059)	(0.088)
No. of Observations	15,392	15,392	14,613	14,613
Time by Village Effects	Yes	Yes	Yes	Yes
Household Fixed Effects	No	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Controls*Shocks	No	No	No	Yes

***, **, * indicate significance at 1, 5 and 10% respectively.
Standard errors are clustered at the household level.

Table 6: The Effect of Mobile Money on Medication – Linear Probability Model

Dependent Variable *Medication (Yes/No)*	(1)	(2)	(3)	(4)
Shock	0.214***	0.192***	0.186***	0.317***
	(0.011)	(0.012)	(0.012)	(0.036)
MMT	0.103***	0.12***	0.089***	0.10***
	(0.008)	(0.009)	(0.017)	(0.02)
*Shock*MMT*	0.144***	0.129***	0.141***	0.161***
	(0.015)	(0.016)	(0.016)	(0.031)
No. of Observations	15,385	15,385	14,607	14,607
Time by Village Effects	Yes	Yes	Yes	Yes
Household Fixed Effects	No	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Controls*Shock	No	No	No	Yes

***, **, * indicate significance at 1, 5 and 10% respectively.
Standard errors are clustered at the household level.

Table 7: The Effect of Mobile Money on Consultation – Linear Probability Model

Dependent Variable *Consultation (Yes/No)*	(1)	(2)	(3)	(4)
Shock	0.082***	0.07***	0.07***	0.08***
	(0.007)	(0.007)	(0.008)	(0.02)
MMT	0.014***	0.016***	0.033***	0.0032
	(0.003)	(0.01)	(0.001)	(0.011)
*Shock*MMT*	0.084***	0.016***	0.076***	0.15***
	(0.01)	(0.005)	(0.01)	(0.02)
No. of Observations	15,385	15,385	14,607	14,607
Time by Village Effects	Yes	Yes	Yes	Yes
Household Fixed Effects	No	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Controls*Shock	No	No	No	Yes

***, **, * indicate significance at 1, 5 and 10%.
Standard Errors are clustered at the household level

Table 8: The Effect of Mobile Money on Acquisition of Loans – Linear Probability Model

Dependent Variable *Took Loan (Yes/No)*	(1)	(2)	(3)	(4)
Shock	0.014***	0.0079*	0.0082*	0.0069
	(0.003)	(0.004)	(0.004)	(0.011)
MMT	0.016*	0.018**	0.022**	0.056**
	(0.008)	(0.008)	(0.008)	(0.022)
*Shock*MMT*	0.145***	0.116***	0.137***	0.175***
	(0.006)	(0.006)	(0.013)	(0.017)
No. of Observations	15,392	15,392	14,609	14,609
Time by Village Effects	Yes	Yes	Yes	Yes
Household Fixed Effects	No	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Controls*Shocks	No	No	No	Yes

***, **, * indicate significance at 1, 5 and 10% respectively.
Standard errors are clustered at the household level.

Appendix

Table A1: The Effect of Mobile Money on Education, Health and Food Expenditures (in Logs) during a Human Illness Shock – Robustness Checks

	Education Expenditure	Education Expenditure	Health Expenditure	Health Expenditure	Food Expenditure	Food Expenditure
Shock	0.12*	0.075	1.25***	1.25***	0.005	0.038
	(0.069)	(0.068)	(0.066)	(0.067)	(0.027)	(0.027)
MMT	1.04***	0.894***	0.301***	0.239***	0.177***	0.135***
	(0.063)	(0.096)	(0.047)	(0.081)	(0.02)	(0.029)
Shock*MMT	0.063	0.068	0.479***	0.519***	0.01	0.009
	(0.085)	(0.086)	(0.082)	(0.084)	(0.031)	(0.03)
No. of Observations	15,375	14,603	15,377	14,604	15,381	14,608
Time By Village Effects	Yes	Yes	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Controls*Shock	No	No	No	No	No	No

***, **, * indicate significance at 1, 5 and 10%.
Standard Errors are clustered at the household level

Table A2: The Effect of Mobile Money on Clothing, Other, Total and Total Non-Health Expenditures (in Logs) during a Human Illness Shock – Robustness Checks

	Clothing Expenditure	Clothing Expenditure	Other Expenditure	Other Expenditure	Total Expenditure	Total Expenditure	Non-Health Expenditure	Non-Health Expenditure
Shock	0.024	0.031	0.091	0.088	0.17***	0.189***	0.017	0.036
	(0.05)	(0.05)	(0.11)	(0.10)	(0.035)	(0.048)	(0.035)	(0.035)
MMT	1.10***	1.07***	0.151*	0.101	0.567***	0.784***	0.576***	0.497***
	(0.053)	(0.09)	(0.067)	(0.07)	(0.029)	(0.052)	(0.029)	(0.044)
Shock*MMT	0.032	0.032	0.019	0.012	0.11	0.16	0.029	0.038
	(0.073)	(0.074)	(0.11)	(0.107)	(0.41)	(0.47)	(0.049)	(0.041)
No. of Observations	15,380	14,607	15,338	14,601	15,374	14,594	15,374	14,602
Time by Village Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Controls*Shock	No	No	No	No	No	No	No	No

***, **, * indicate significance at 1, 5 and 10%.
Standard Errors are clustered at the household level