Risk Sharing and Transaction Costs: Evidence from Kenya's Mobile Money Revolution, A Replication Study of Jack and Suri (2014)

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Abstract:

M-PESA, a mobile phone-based technology for transferring money, provides a gateway to formal financial services for populations that otherwise would not have access to those services. Jack and Suri (2014), henceforth JS, analyse a panel of 2,282 Kenyan households over the period 2008 – 2010 to estimate how M-PESA has enabled financial risk sharing. They focus on negative income shocks, such as illness or drought, and analyse how family members and friends share financial resources during these adverse events. A key finding is that M-PESA users, relative to non-users, are largely able to protect their consumption when faced with negative income shocks. They are more likely to receive remittances in the face of unexpected negative shocks, receiving both a greater number and higher value of remittances. They also receive remittances over greater distances and from larger networks. This study aims to replicate the results represented in the original paper along with measurement and estimation analysis to provide more support for the validity of the findings. The theory of change analysis may help to provide additional insights regarding the effectiveness of mobile money innovation.

Original Study:

Jack, W., and Suri, T. (2014). Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution. *The American Economic Review, 104*(1), 183-223.

1. Introduction

Mobile money, a financial inclusion instrument, has had a revolutionary impact on the lives of poor who previously had limited access if any to formal financial services. Recently, a growing body of academic research has focused on understanding the economic impact of mobile money as a poverty alleviation tool in developing economies (Burgess and Pande, 2004; Levine, 2005; Aker and Mbiti, 2010; Mbiti and Weil, 2011; Jack and Suri, 2011). M-PESA[1], Kenya's world-leading mobile phone-based service, has facilitated a range of financial transactions including deposit, withdrawal, and transferring capabilities. Despite the wide range of services offered, person to person (P2P) transfers dominate M-PESA use due mainly to the growing pace of the rural-to-urban migration which is accelerating demand for secure, fast, and affordable means to send remittances home (Aker and Mbiti, 2010). In Kenya, a large population are vulnerable to income fluctuations due to various risks such as unemployment, sickness and natural disasters. Given the poor access to formal insurance, informal networks such as family members and friends can play a crucial role to share risks in the event of any negative shocks. Therefore, strategies like lowering transaction costs may enhance the development of the informal financial market in developing nations such as Kenya.

Jack and Suri (2004) explore the impact of mobile money on informal risk sharing. They use panel data to analyse how mobile money can improve the ability of households to smooth consumption in response to negative idiosyncratic shocks. They find that the introduction of M-PESA facilitates the redistribution across geographical distances. This improved households' ability to spread risk is mainly attributed to the associated reduction in transaction costs. As a result, M-PESA has lifted Kenyan households out of poverty.

This replication study therefore attempts to make three contributions to the existing literature: first and foremost, to confirm the robustness of findings represented in the selected study; second, to extend the years of analysis to the most recent available, so that the period of analysis covers the years 2008 – 2014; and finally, to provide more insights and recommendations particularly by conducting the theory of change analysis. Jack and Suri (2014) provide convincing evidence that M-PESA has had a positive impact on people's financial health. The financial benefits derived from such mobile money innovation can play a critical role in combating world poverty. M-PESA can be potentially implemented in other

[1] M-PESA (M for mobile, M-PESA is Swahili for money).

developing nations where a large proportion of population live close to subsistence and M-PESA can offer significant benefits. The extension of the years of analysis will allow us to overcome shortcomings attributed to the short time period applied. It can help us to examine the consistency of research findings over a longer period. Finally, by changing the focus of analysis from the entire population including both rural and urban residents to rural segment of the population supposedly excluded by formal financial services, we may be able to assess whether M-PESA has not abandoned its initial promise, “banking for the unbanked”. Policy makers should take one crucial step to adopt enabling policies that allows competing firms to offer innovative new technologies such as M-PESA. Such market-based innovations can play a vital role in combating world poverty.

This study proceeds as follows. Section 2 presents the study selected for the replication. Section 3 explains the proposed plan including both Measurement and estimation Analysis (MEA) and Theory of Change Analysis (TCA). Section 4 summarizes the replication study.

2. Presentation of the selected study

Due to the benefits and potential impacts of mobile money, especially for promoting financial inclusion in the developing world, a growing body of literature is devoted to this topic. Among those, a widely cited and highly influential study is Jack and Suri (2014), henceforth JS, with a total of 191 citations in three years after its publication (Google Scholar Citation, April 2, 2017). JS study the impact of reduced transaction costs on informal risk sharing. To do so, they conduct an observational study on data from a large household panel survey designed and administered in Kenya over the three-year period (late 2008 through early 2010). JS employ a panel difference-in-differences specification in which household fixed effects are included to compare changes in consumption and remittances in response to shocks by M-PESA users versus nonusers.

JS undertake a survey of 3,000 randomly selected households in September 2008 across a large part of Kenya. [2] They randomly select ten households from each of 300 enumeration areas in 118 locations. The follow-up survey of these households is administered in December 2009. Given the high attrition rates in round 2 (about 24 percent), the third round interview is designed in June 2010 with the hope of finding households in the original sample

[2] The northern and north-eastern parts (8% of population) were excluded from the sample due to mainly to limited M-PESA agent coverage.

who are missed in the previous round. In this way, a two-period, balanced panel of 2,282 households is constructed. Additionally, in order to construct detailed rollout data, a population of 7,700 M-PESA agents across the country are surveyed in March 2010 and their GPS locations are recorded. The households' and agents' data are then integrated by matching the relevant agent variables to the households.

Theory provided in the paper illustrates a framework through which transaction costs can play a crucial role in risk sharing. Accordingly, the following three hypotheses are tested:

(i) Consumptions should respond less to shocks for M-PESA users than nonusers.

(ii) Remittances should respond more to shocks for M-PESA users than nonusers.

(iii) The network of active participants should be larger for M-PESA users than nonusers.

The authors present convincing evidence that mobile money has had a significant impact on the ability of households to spread risk, and attribute this to the associated reduction in transaction costs. The results show that households that do not use mobile money suffer a 7 percent drop in consumption when hit by negative shocks. Further, mobile money users are more likely to receive remittances in the face of negative shocks. They receive both a greater number and higher value of remittances. Importantly, they are also able to receive remittances over greater distances and from larger networks.

These findings are especially important in the context of developing countries like Kenya, where a large number of people live close to the subsistence level. The success of mobile money in general and M-PESA in particular, has had a transformative impact on the lives of millions of poor households. It has also prompted other developing countries' policy makers and private partners to introduce similar innovations in mobile money to achieve financial inclusion objectives as well as providing a cost effective alternative to brick and mortar banks.

3. The proposed replication plan

This replication study consists of three parts: (i) a pure replication of the original study (ii) a measurement and estimation analysis (MEA), and (iii) the theory of change analysis.

3.1. Pure replication

The aim of pure replication is to reproduce the analyses reported in the original paper using the data and code provided by the authors. As mentioned earlier, this study has been conducted over three rounds (two periods). The first period (round 1) of data was collected by the Financial Sector Deepening Trust in Kenya and requires permission to use.[3] However, the data for the second period (round 2 and 3) as well as the associated programming codes are publicly available via the following link:

https://www.aeaweb.org/articles?id=10.1257/aer.104.1.183

In addition to the two-period balanced panel results available in the paper (Table 1A – Table 9), a subset of the three-period unbalanced panel are posted in an additional online appendix at: http://www.mit.edu/~tavneet/Jack_Suri_Web.pdf

All the above-mentioned tables as well as the figures will be reproduced.

3.2. Measurement and Estimation Analysis (MEA)

Although Jack and Suri (2014) did a thorough analysis, there are further robustness checks that can be conducted to test the sensitivity of the findings presented in the original paper.

3.2.1. Outliers

An outlier is considered as an observation that lies far outside the norm of a variable. The deleterious effects of outliers on statistical analysis have been discussed extensively by Osborn and Overbay (2004). Most importantly the presence of outliers can lead to error variance and therefore a reduction in the power of statistical tests. They can also distort estimates of regression. There are several potential reasons why outliers may arise but they are mainly caused by human errors. This problem seems more pronounced in the survey data. Therefore, checking for the presence of outliers is worth considering.

[3] Permission has already been issued. We attempted to independently reconstruct the variables of interests using the existing raw data available via the following link:
https://dataverse.harvard.edu/dataverse.xhtml?alias=mobilemoney.
However, we were not able to reconstruct the datasets fully. It seems that some key variables were dropped as they contain personal identifiable information (PII).

3.2.2. Placebo test

As a first robustness check, we will run a placebo regression. The idea is that the counterfactual levels for M-PESA users and non-users can be different but the time trends must be the same. This strategy will allow us to assure whether the differences in consumption/remittances between M-PESA users and non-users are solely derived from M-PESA adoption. To do so, we are using the data prior to the advent of M-PESA (data from a four-period panel household agricultural survey collected by Tegemeo Institute over 1997-2007). We will then create a dummy variable for the households using the M-PESA after its introduction in 2007 to estimate the following specification:

$$C_{ijt} = \alpha_i + \gamma Shock_{ijt} + \mu MPUser_{ijt} + \beta MPUser_{ijt} \times Shock_{ijt} + \theta^S X_{ijt} \times Shock_{ijt} + \theta^M X_{ijt} + \eta_{jt} + \pi_{rt} + \varepsilon_{ijt} , \quad (1)$$

where $MPUser_{ijt}$ is a dummy variable which takes a value of one if a household used M-PESA later (after its introduction in 2007) and zero otherwise. If the common trends assumption holds then the dummy for future M-PESA use, $MPUser_{ijt}$, will not be significant for the past data and therefore confirming that it is not unobservable characteristics of households or location of agents which derives the results. Thus, the significant relationship between user and consumption/remittances could be attributed to the M-PESA adoption.

3.2.3. Propensity score matching

To further evaluate the impact of M-PESA adoption on consumption/remittances, we will use propensity score matching. Propensity score matching was developed to help one to design and analyse non-randomized observational studies so that it mimics some of the characteristics of a randomized control trials. It will allow us to account for the possible differences in wealth, education, and other socioeconomic characteristics between M-PESA users and non-users. Matching involves constructing a new control group using observable characteristics so that for every treated (M-PESA user) observation there is an untreated one (nonuser) as similar as possible in observable characteristics. This will be done by running a binary probit or logit regression on M-PESA use on the set of observable baseline characteristics. The probability that a household adopts M-PESA conditional on its characteristics can be written as:

$$\Pr(x) = \Pr[P = 1 | X = x] , \quad (2)$$

where $P = 1$ for households using M-PESA and 0 otherwise, and X is a vector of characteristics. The propensity scores will then be used to match the M-PESA users with the corresponding non-users with the closest score, thereby constructing a new control group as similar as possible to the M-PESA users. Therefore, propensity score matching will try to mimic the random assignment to both treatment and control group by choosing a sample for the control group with the most similar properties to the treatment group. Each matched non-user will be assigned a frequency weight equal to the number of users it will be matched to. We will then use these frequency weights to run the following specification:

$$C_{ijt} = \alpha_i + \gamma Shock_{ijt} + \mu User_{ijt} + \beta User_{ijt} \times Shock_{ijt} + \theta^s X_{ijt} \times Shock_{ijt} + \theta^M X_{ijt} + \eta_{jt} + \pi_{rt} + \varepsilon_{ijt} \quad (3)$$

3.2.4. Tobit model

According to the following equation (reported as EQ (8) in the original paper):

$$r_{ijt} = \alpha_i + \gamma Shock_{ijt} + \mu User_{ijt} + \beta User_{ijt} \times Shock_{ijt} + \theta X_{ijt} + \theta^M X_{ijt} \times Shock_{ijt} + \eta_{jt} + \pi_{rt} + \varepsilon_{ijt}, \quad (4)$$

where the dependent variable, r_{ijt}, is a measure of remittances over the past six months. This variable can be measured either as: (i) the probability of receiving remittances (ii) the number of remittances received, or (iii) the total value received.

All of the above-mentioned outcome variables are continuous. However, if the households are not receiving any remittances then these variables are not available and therefore take the value of zero. Given the zeros for non-users, these variables have a skewed distribution. Using the common linear specification with a censored dependent variable may potentially lead to biased estimates. In order to avoid such bias, we will use a Tobit estimator.

3.2.5. Heterogeneous slopes

In order to address the potential bias resulting from unobserved time invariant household heterogeneity, the fixed effects model has been estimated throughout the original paper. However, as a further robustness check, we will allow for heterogeneous individual specific slope on the shock variable. The following specification control for such possibility:

$$C_{ijt} = \alpha_i + \gamma Shock_{ijt} + \mu User_{ijt} + \beta User_{ijt} \times Shock_{ijt} + \theta^S X_{ijt} \times Shock_{ijt} + \theta^M X_{ijt} + \omega \alpha_i Shock_{ijt} + \varepsilon_{ijt} \quad (5)$$

One problem with this approach is that the associated estimates are biased when the time series is short. However, given the fact that JS conducted five rounds of a household panel survey over 2008 and 2014, this is not a concern anymore.

3.2.6. Endogeneity and IV regressions

JS provide a discussion of the sources of endogeneity in the basic specification (EQ (7) in the paper):

$$C_{ijt} = \alpha_i + \gamma Shock_{ijt} + \mu User_{ijt} + \beta User_{ijt} \times Shock_{ijt} + \theta^S X_{ijt} \times Shock_{ijt} + \theta X_{ijt} + \eta_{jt} + \pi_{rt} + \varepsilon_{ijt} \quad (6)$$

They then explain in order to identify the causal effect of M-PESA on risk-sharing; we must assume the interaction term $User_{ijt} \times Shock_{ijt}$ is exogenous or uncorrelated with error term.

I. Endogeneity of Shocks

JS emphasize that their identification assumption is satisfied if **shocks** are truly **exogenous**. They argue that for two reasons, this may be reasonable:

(i) Households were asked in the survey to report only unexpected events that affect them.

(ii) Reported shocks are not systematically correlated with a number of household-level variables.

Income shocks are correlated with consumption changes and remittances, as would be expected, but they are not correlated with other household characteristics nor with access to agents or M-PESA use. They report these correlations in Table3, page 202.

II. Endogeneity of M-PESA Use

JS also emphasize that the endogeneity of M-PESA use due to selective adoption associated with wealth or other unobservable is absorbed in the main effect of being a user (self-selection effects into using M-PESA are absorbed into coefficient μ on $User_{ijt}$).

However, it is reasonable to argue that mobile money users are richer and better educated compare to non-users (JS did not provide the summary statistics indicating the above argument by comparing these characteristics for users and nonusers). They did not provide the correlation of M-PESA use but it is highly likely to observe that being wealthier, owning a mobile phone, having loans and having a bank account all increase the probability of a household adopting M-PESA. JS control for all these variables by adding X_{ijt} (a vector of controls, in particular, household demographics, household head years of education and occupation dummies, the use of financial instruments, and a dummy for cell phone ownership) in all the regressions. They also control for unobservable characteristics of households by using fixed effects. However, fixed effects cannot take to account time varying unobservable characteristics such as technology preference or risk preference. For instance, people who are more willing to try new technologies may adopt M-PESA more compared to their counterparts or poor people might live in places that experience more shocks and use M-PESA so that they can receive remittances from other family members or friends elsewhere, resulting in a bias in the variable of interest, the coefficient on the interaction between shocks and M-PESA use.

They argue that the difference-in-differences specification allows for unobservable to be correlated with M-PESA use, as long as those unobservables do not interact with the response to shock.

In order to deal with these concerns they propose two strategies:

(i) The first extends equation (6) to include the interactions of the shock with all observable covariates.

(ii) The second strategy uses the agent rollout data.

JS then use the second strategy, using the agent rollout data, to use standard IV method.

$$C_{ijt} = \alpha_i + \gamma Shock_{ijt} + \vartheta Agent_{ijt} + \beta Agent_{ijt} \times Shock_{ijt} + \theta^M X_{ijt} + \eta_{jt} + \pi_{rt} + \varepsilon_{ijt} \quad (7)$$

They argue that the agent measures (geographic proximity to the agents as indicators of access) are exogenous.

However, there is evidence that M-PESA agents are not exogenous as it is assumed in the original paper. It is worth mentioning that M-PESA agents receive a commission on a sliding scale for both deposits and withdrawals but not transactions, so there might be an incentive for M-PESA agents to locate where they can gain more profit such as the wealthier area where the households' income is relatively high and therefore they are better able to smooth consumption regardless.

We will firstly address this concern by controlling for the interactions between observable individual characteristics and shock. The specification would then be as follows:

$$C_{ijt} = \alpha_i + \gamma Shock_{ijt} + \vartheta Agent_{ijt} + \beta Agent_{ijt} \times Shock_{ijt} + \theta^S X_{ijt} \times Shock_{ijt} + \theta^M X_{ijt} + \eta_{jt} + \pi_{rt} + \varepsilon_{ijt} \quad (8)$$

The next step is to report the results for the first-stage regression as JS did not provide those results. However, it is mentioned that the first stage for predicting the M-PESA use is not precise in some cases.

We will then evaluate whether the instrument applied in the original paper is weak and if so we replace the instrument. The proposed instruments for the use of M-PESA and their interactions with shock according to paper are as follows:

(i) Distance to the closest agent.
(ii) The number of agents within 5 km of the household.
(iii) The interaction of each with the shock

We need an instrument (or a set of instruments) to be correlated with M-PESA use (relevant) but do not affect consumption smoothing (exogenous). In the literature, Mbiti and Weil (2011) apply an alternative instrument for M-PESA use in Kenya. They focus on the 2006 perception data (before the advent of M-PESA in 2007) and explain that the survey include a question referring to the perceptions of the most common money transfer methods. The households were then asked to identify the slowest, riskiest, and costly transfer methods. They conclude that those households who feel their means of transfer is not efficient are more likely to adopt M-PESA after its introduction. We will check the agricultural survey collected by Tegemeo Institute over 1997-2007 (prior to the introduction of M-PESA) to see whether this perception question is available and if so, that would be an alternative instrument.

3.2.7. Longer period balanced and unbalanced panel

JS conducted five rounds of a household panel survey over 2008 and 2014 (Suri and Jack, 2016). However, in the original study two rounds of data were applied. We will run all the main specifications using 5 rounds of data to confirm the validity of findings reported in the original paper.

3.3. Theory of Change Analysis (TCA)

The main focus of JS (2014) study is the Kenyan households across a large part of country regardless of their residence locations (rural or urban area).[4] According to the discussion provided in the original study, urban households have higher rate of attrition compared to their counterparts in the rural area. For this and other reasons, most of the analysis is limited to the non-Nairobi sample.[5] While this concern has merit, less is known about the impact of M-PESA on the risk sharing capability of rural households in particular.

[4] Due to the limited coverage of both cell phone tower and M-PESA agent, the residents of north and northeast parts of the country were excluded from the sample.
[5] Nairobi is the capital and largest city of Kenya.

While adoption of M-PESA in Kenya has helped a large number of individuals to smooth their consumption in the face of negative shocks, the remaining question is whether the effect is heterogeneous depending on the rural-urban status. Given the heterogeneity observed in availability of alternative financial services in rural and urban area, it would be of great interest to see whether the risk sharing impact of M-PESA adoption differs depending on the residence location.

According to the literature, the empirical evidence particularly focused on the rural area is scanty. However, Munyegera and Matsumoto (2016) focus their analysis on an exclusively rural sample as they believe most formal financial institutions are concentrated in the urban area where people are more able to smooth their consumption against negative shocks. They find that remittances receipt is a crucial source of informal insurance for poor rural households in Uganda.

We will run the regressions separately for the two samples including urban and rural areas. Further, as the data includes information on the exact location of households including the districts, we can check the robustness of the research findings accordingly.

4. Conclusion

This replication study will start with a pure replication of Jack and Suri (2014) to reproduce the original study results, followed by consistency tests and robustness checks. We will then generate new insights to the topic by conducting the theory of change analysis. This replication will provide more insights to mobile money innovation, M-PESA, and will help developing countries to achieve border policy goals. It is possible that M-PESA could “trickle up” from developing countries to developed nations.

Note regarding the status of obtaining data and codes:

As mentioned earlier, the required data for the pure replication includes two rounds (two-period panel of 2,282 households, 4,564 households in total). While the second round of data is available online on American Economic Review website, https://www.aeaweb.org/articles?id=10.1257/aer.104.1.183, the first round is not available online. On the PDF file named "Data Read Me File" provided by the authors as additional materials, explicitly mentioned the permission from the Financial Sector Deepening Trust (FSD) in Kenya is required to attain the final extract they are using in the paper. Despite proving the permission, we have not received the extract yet. A couple of emails sent to the authors regarding the data acquisition, however, we just have access to the raw data via the following links: https://dataverse.harvard.edu/dataverse.xhtml?alias=mobilemoney. It is worth noting that the raw data for each round includes 24 individual data sets. We have tried to construct all the variables required but given the fact that some variables were dropped (they may include personally identifiable information) from these datasets, we were not able to construct all the variables of interest. It seems that all the codes are available via AER website, though.

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