Determinants of Use and Intensity of Use of Mobile Phone-based Money Transfer Services in Smallholder Agriculture: Case of Kenya

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Abstract

Smallholder farmer access to agricultural finance has been a major constraint to agricultural commercialization in developing countries. The ICT revolution in Africa has however brought an opportunity to ease this constraint. The mobile phone-based money transfer (MMT) services that started in Kenya urban centres have spread to rural areas and even other countries. Using these services farmers could receive funds to invest in agricultural financial transactions. This study examines the factors that influence use of MMT services among farm households in Kenya. It also assesses the factors conditioning the intensity of use of such services. The study finds education, distance to a commercial bank, membership to farmer organizations, distance to the m-banking agents and endowment with physical and financial assets affect the use of m-banking services. It discusses the implications of these findings for policy and practice.

Key words: Mobile phones, m-banking services, use, intensity, smallholder farmers, Kenya

1.0 Introduction

Access to financial services has the potential to improve commercialization of smallholder agriculture and contribute to poverty alleviation among rural communities (Kibaara, 2005; Gine et al, 2009). More than 70 percent of Africa's population live in rural areas and experience high incidence of poverty. Majority of these rural dwellers depend on agriculture as source of livelihood. The World Bank (2009) for instance identifies rural finance as crucial factor in achieving pro-poor growth and poverty reduction goals. However, formal financial markets tend to fail for majority of smallholder farmers in developing countries (Besley, 1998).). Consequently, most smallholder farmers depend on 'traditional' informal financial systems which are poorly developed (Financial Sector Deepening (FSD), 2006). Development of rural financial systems is hampered by the high transaction cost of delivering the services to small, widely dispersed farmers (Poulton et al, 2006. Other factors that lead to the failure of formal financial markets for smallholder farmers include high covariate risks, missing markets for managing weather and market risks and the lack of suitable collateral (Onumah, 2002). Transaction costs tend to be particularly high among smallholder farmers due to poor communication and transportation facilities, lack of production and market information, as well as thin and segmented markets (Poulton et al., 2006; Poulton et al, 1998; Shiferaw, 2009).

Lack of working capital and low liquidity (due to inability to access financial services) is one of the key impediments to commercialization of smallholder agriculture (Kibaara, 2005). It especially limits smallholder farmer's ability to purchase productivity-enhancing inputs (e.g., seeds, fertilizers and pesticide) (Nyoro, 2002). Consequently smallholder farmers tend to produce small volumes that exclude them from participating in better-paying output markets that require large volumes (Barrett, 2008). Indeed, smallholder farmers' inability to invest in productivity enhancing inputs (due to lack of agricultural finance) is the reason such farmers remain autarkic and are trapped in low equilibrium poverty trap (Barrett, 2008).

The desire to spur progress in smallholder agriculture has historically led to search for new models of agricultural financing that address the constraints faced by farmers. Among these models are interventions that provide agricultural finance to farmers in groups and attempt to use the Gramean lending model (Okello et al, 2010). Other models link farmers to formal agricultural finance markets through flexible lending systems that allow recovery of loan from sales (i.e., interlinked credit scheme) (Gine, 2009). These models have had limited success due the factors highlighted above. However, most smallholder farmers still lack access to formal financial systems (especially banks).

The recently introduction money transfer services using mobile phones (m-banking) has caused excitement among development agents due the potential it has in resolving some of the financial constraints smallholder farmers face namely, access to finances when needed. The excitement about m-banking emanates from the increase in penetration and use of mobile phones in the rural. Studies suggest that 80-90 percent of Kenyan population now covered by mobile networks (Mason, 2007; Okello et al. 2009). There are approximately 15 million mobile subscribers in Kenya compared to just 5 million individuals with bank accounts Omwansa (2009). At the same time, there were over 12,000 M-PESA agents in 2009 in Kenya, substantially more points of service than the combined number of bank branches (887) and ATM (1,435). Cumulative value of mobile phone-based money transfers had reached $1.5 billion in early 2009, the monthly value of person-to-person transfers was $190.3 million; equivalent to about 10 percent of Kenya's GDP (FSD, 2009). Thus the introduction of m-banking has spurred unprecedented transfers of money among individuals and households in Kenya. To what extent are smallholder farmers aware of this service? Are they using the mobile phone-based money transfer services? If they are, then for what purpose? This paper examines the above questions. It specifically:

i. Assesses the awareness of m-banking services among smallholder farmers.
ii. Examines the use of m-banking services by smallholder farmers.

This paper is focuses on smallholder farmers in three different districts namely Kirinyaga (Central province), Bungoma (Western province) and Migori district (Nyanza province). The districts were selected for survey because they present diversity of social and economic backgrounds. Kirinyaga district has export oriented agriculture with several export crops being produced. Smallholder farmers in Bungoma district grow mainly maize with some sugarcane. In Migori, on the other hand, the main crops are maize and some tobacco. Thus the choice of the districts presents differing levels of commercialization as well as cultural backgrounds. M-banking is an interesting issue to study because it can potentially lower the cost of remitting money from urban to rural households in a timely and cost effective way. The large network of m-banking agents in the rural areas can especially make it easy for agricultural households to reduce the time and cash expense in accessing the funds they need to invest in agriculture.

The rest of this paper is organized as follows: Section 2 characterizes the study farmers; Section 3 presents the study methods; Section 4 presents the results of the study; and Section 5 concludes.

2.0 Characterization of study farmers

Table 1 presents the characteristics of the households interviewed in this study.

Table 1: Household Characteristics

Variable	Mean	Std. Dev.	Minimum	Maximum
Age	43.67	13.84	18	92
Education	8.44	3.66	0	18
Distance to bank	10.12	7.37	1	55
Distance to M-banking agent	2.2	9.6	0.2	40
Farming Experience	20.3	8.99	1	70
HH Size	5.74	2.17	1	14

Of the 379 respondents, the mean age was 43.7 years while the mean household size is 5.7 members. Mean education of respondents was 8.4 years indicating that the farmers have relatively low levels of education. The low level of education has implications on the use of new generation ICT tools (e.g., mobile phones) for money transfer. Previous studies identify literacy as important in the use of mobile phones for information access due to difficulty of navigating through the phone menus, often written in English (Okello et al, 2009). Of the sampled farmers, 191 (50.4 percent) were men while 188 (49.3 percent) were female. The average years of experience in farming was 20 suggesting that the respondents have a lot of experience in agricultural production. Results also show that the mean distance to the nearest m-banking agent was reported to be 2.2 kilometres, while the mean distance to the nearest bank was given as 10.12 kilometres. Hence farmers have better access to m-banking services than services of commercial banks**.**

3.0 Study Methods

3.1. Conceptual method for analyzing use of m-banking

This study uses the Transaction Cost Economics (TCE) paradigm, which is part of the New Institutional Economics – NIE - (Hubbard, 1997; Clague, 1997; Poulton *et al*, 1998). The concept of transaction costs was first introduced about seven decades ago by Coase (1937) and has been widely used in studying agricultural economics and related issues in developing countries (Jaffee, 2003; Fafchamps, 2004; Fafchamps and Hill, 2005; Okello and Swinton, 2007). Coase defines transaction cost as costs associated with information, negotiation, monitoring, coordination, and enforcement of contracts. North (1990) reiterates on the same and defines transaction costs as costs of measuring the valuable attributes of the commodity exchanged and the costs of providing and ensuring the desired attributes.

Transaction costs both in the input and output markets of developing countries can be summed up into four categories; search costs, negotiation costs, monitoring costs and mal-adaption/adjustment costs (Poulton et al., 2006; Fafchamps, 2004; Fafchamps and Gabre-Madhin, 2006 and Okello et al., 2010).

High transaction costs impede smallholder farmer linkage to financial services. For such farmers, the cost of borrowing tends to be high because of lack of information regarding their credit worthiness, difficulty of monitoring the usage of loans, and the systematic risks that affect farmers. Smallholder farmers often lack the collateral needed by commercial banks to secure loans. Hence most credit organizations regard them as credit unworthy. In addition, the geographical dispersion of smallholder farmers and poor organization among them makes monitoring costly to lenders (Poulton et al, 2006). Indeed, the emergence of rural micro-finance organizations and SACOs has been based on the premise that smallholder farmers need unique services that is close to them. However, the poor economic conditions in rural communities make running such organizations and unprofitable. Consequently, most financial organizations tend to be located in commercial centres where there is enough clientele to make their operations profitable. However, such centres tend to be inaccessible to the remotely located smallholder farmers.

Mobile phone-money transfer services can theoretically resolve the constraints smallholder farmers face in accessing finances by reducing the transaction costs farmers face in using banking services. First, they can make money transfer into farming communities easy and instant. Consequently, farmers do not have to incur high time and travel costs to travel to banking facilities. Second, it can include the hitherto excluded farmers into the banking services by reducing the costs of accessing funds and/or depositing savings. The latter is especially important because unlike the commercial banks and savings organizations, the m-banking services attract no ledger fees and minimum balances. At the same time, it attracts a very modest withdrawal fee that is affordable to farmers.

3.2 Empirical methods

Assessing use of MMT services

This study uses a logit model to examine the factors that condition the use of m-banking services. In a logistic regression model, the probability, *p*, that a household is uses m-banking is given by:

$$P = e^{z}/1+e^{z} \tag{1}$$

Central to the use of logistic regression is the logit transformation of *p* given by *Z*

$$Z = ln(p/1-p) \tag{2}$$

Where;

$$Z = X\beta + \varepsilon \tag{3}$$

β is the a vector of regression parameters, *X* is a vector of explanatory variables and ε is the stochastic term assumed to have a logistic distribution. The vector X comprise of farmers' demographic characteristics, physical, human, and social capital endowments, and farm and regional characteristics. Z is a latent variable that takes the value of 1 if the farmer used m-banking services and 0 otherwise.

Assessing intensity of use of MMT services

Intensity of use of mobile phone-based money transfer services in this study refers to the number of times a respondent received and sent money via the mobile phone. The number of times a particular farmer uses mobile phone-based money transfer in a given year assumes integer values of discrete nature and is therefore a nonnegative count variable. Count data are non-normal and hence are not well estimated by OLS regression (Maddala, 2001).

The key models normally used to analyze count data include the Poisson Regression Model (PRM), the Negative Binomial Regression Model (NBRM), the Zero Inflated Poisson (ZIP) and the Zero Inflated Negative Binomial (ZINB). Poisson and negative binomial regression models have become the standard models for the analysis of response variables with nonnegative integer (Winkelmann and Zimmermann, 1995; Greene, 2008). The last two (ZIP and ZINB) are specifically used to account for the frequency of zero counts (when there are more zeros than would be expected in either a Poisson or Negative Binomial Model), which is not the case in this study. Only the PRM and NBRM are therefore discussed here since the response variables were nonnegative integers and with only a few zero counts.

Greene (2003) argued that both PRM and NBRM models (for analyzing count data) are much closer to OLS regression model than other discrete choice models. This is because, just like OLS, the optimality conditions can be derived from the PRM models and that violation of variance assumptions in the models does not necessarily result in inconsistent estimators but rather the coefficient estimates are inefficient and standards errors are potentially biased (Wooldridge, 2002).

Poisson regression

Poisson regression model is normally the first step for most count data analyses (Areal *et al.*, 2008). The model makes an assumption that the dependent variable ***y*** given vector of predictor variables $\boldsymbol{x}$ has a Poisson distribution. The probability density function of $\boldsymbol{y}$ given $\boldsymbol{x}$ is completely determined by the conditional mean

$$\lambda(x) \equiv E(y|x) \tag{4}$$

$$f(y_i|x_i) = \frac{e^{-\lambda(x)}\lambda_i(x)^y}{\Gamma(1+y_i)} \tag{5}$$

Where $\lambda_\mathrm{i} = \exp(\alpha + \mathrm{X}'\beta) \quad \mathrm{y_i} = 0,1,..., i$

PRM specifies that each observation $\boldsymbol{y_i}$ is drawn from a Poisson distribution with parameter $\boldsymbol{\lambda_i}$ which is related to a ray of predictor variables X' (Greene, 2003; 2008).

The PRM is derived from the Poisson distribution by introducing parameters into the relationship between the mean parameter $\boldsymbol{\lambda_i}$ and predictor variables **x**. Wooldridge (2002) and Greene (2003; 2008) show that the expected number of events, $\mathrm{y_i}$, (times of receiving and sending money via mobile phone) per period is given as:

$$E(y_i|x_i) = \mathrm{var}[y_i|x_i] = \lambda_i = \exp(\alpha + \mathrm{X}'\beta) \;\; \textit{for } i = 1, 2,..., n. \tag{6}$$

The log-linear conditional mean function $E(y_i|x_i) = \lambda_i$ and its equi-dispersion $Var(y_i|x_i) = \lambda_i$ assumptions are the main features of Poisson regression model (Greene, 2008). The log-linear regression models accounts for the nonnegative restriction imposed by Poisson on the dependent variable (Winkelmann and Zimmermann, 1995).

The merits of Poisson regression are outlined by Winkelmann and Zimmermann (1995) as: (a) it takes into account the nonnegative and discrete nature of the data (b) the assumption of equality of the variance and conditional mean accounts for the inherent heteroscedasticity and skewed distribution of nonnegative data (c) the log-linear model allows for treatment of zeros. Empirically, parameters of PRM are easier to estimate using maximum likelihood techniques.

The Poisson regression model has found application in various fields. In agriculture, for example, Ramirez and Shultz (2000) used it to explain the adoption of agricultural and natural resource management technologies by small farmers in Central American countries. Maumbe and Swinton (2003) used this model to study the hidden health costs of pesticide use among Zimbabwe's smallholder cotton growers. Similarly, Okello (2005) used the same model to examine the drivers of the number of pesticide induced acute illnesses and the count of gear items used to prevent exposure to pesticides.

Poisson regression model has some limitations in empirical work. In particular, the restrictions imposed by the model on the conditional moments of the dependent variable in most cases violate its application given that the observed data often display overdispersion (Wooldridge, 2002; Greene, 2008). Overdispersion refers to excess variation when the systematic structure of the model is correct (Berk and MacDonald, 2007).

Overdispersion in PRM is as a result of two assumptions (Winkelmann and Zimmermann, 1995). First, the assumption that the Poisson process is a deterministic function of the predictor variables hence does not allow for the unobserved heterogeneity. Secondly, the assumption that events constituting each count are independent and occur randomly over time thus ignoring the fact that present occurrences can influence the probability of future occurrences (Berk and MacDonald, 2007). Overdispersion in the data leads to larger variance of the coefficient estimates than anticipated mean which consequently results in inefficient, potentially biased parameter estimates and spuriously small standard errors (Wooldridge, 2002; Xiang and Lee, 2005).

Violation of the above two assumptions can also lead to underdispersion. This is where the variance is less than the conditional mean which results if the events constituting the counts are negatively related (Berk and MacDonald, 2007). This has the same effect as overdispersion. In presence of under- or over-dispersion, though still consistent, the estimates of the Poisson regression model are inefficient and biased and may lead to misleading inference (Famoye *et al.*, 2005; Greene, 2008).

In practical application, the basic assumption of equality of the mean and variance imposed by PRM is rarely fulfilled. A reliable and practical test for overdispersion therefore is usually important to justify the need for models beyond the standard Poisson regression (Xiang and Lee, 2005). To address the problem of overdispersion or underdispersion, the negative binomial, a variant of Poisson-based regression model, is usually used (Wooldridge, 2002; Famoye *et al.,* 2005; Berk and MacDonald, 2007; Greene, 2008).

Negative binomial regression model (NBRM)

The functional form for the NRBM relaxes the equi-dispersion restriction of the Poisson model and also takes care of any model misspecification (Greene, 2008; Berk and MacDonald, 2007). The introduction of a gamma-distributed stochastic term in the conditional mean of the deterministic PRM accounts for the inherent unobserved latent heterogeneity (Greene, 2007; 2008). NBRM allows variance to exceed the mean (Greene, 2008). Negative binomial regression model does better with over dispersed data.

Following Greene (2007), the negative binomial model can be presented as:

$$E(y_i|x_i,\varepsilon) = \exp(\alpha + X'\beta + \varepsilon) \tag{7}$$

The model requires that:

$$Var(y_i|x_i) = [1 + \alpha \exp(X'\beta)]\exp(X'\beta) \tag{8}$$

Where *X'* is a vector of explanatory variables similar to those included in section 3.2.1. Hence the estimated NBRM is specified as:

m-transfer = m-transfer (age, age squared, gender, distance to the bank, number of enterprises, household size, distance to the mobile phone-based money transfer agent, income, value of assets, education, farming experience, group member, district) + e (9)

3.3 Sampling procedure and data

This study was part of a wider project implemented by Electronic Agricultural Research Network in Africa (eARN-Africa). The aim of the project was to evaluate the effectiveness of ICTs in helping smallholder farmers commercialize. The project had been implemented in three different districts each in a separate province. These include Kirinyaga (Central province), Bungoma (western province) and Migori (Nyanza province). These districts were characterized by poor access to markets by small farmers and reliance on agriculture. The study districts were selected to represent diverse agro-ecological zones, socio-economic environment, cultural diversity and varying production systems. For example, Kirinyaga district is considered a high potential area with export oriented export crops (French beans, baby-corn and Asian vegetables). Bungoma district on the other hand grew mainly maize with sugarcane while Migori is considered low potential area with main crops grown being maize and tobacco. Thus the choice of the districts presents differing levels of commercialization. Kirinyaga district is mainly inhabited by people of Kikuyu ethnic group while Bungoma and Migori districts are mainly inhabited by Luhya and Luo ethnic groups respectively.

Sampling procedure was done in three stages. First, the three districts (project districts) were purposely selected. Second, in each of the district, a location was randomly identified. A list of all farm households was then drawn with the help of local administration (village elders and area agricultural extension officers). Third, the respondents were then randomly sampled from the lists. A total of 379 farmers were interviewed in this study. These comprised of 198 (52%) users of MMT and 181(48%) non-users of MMT. We compare and contrast these respondents in the next section.

The data was collected through personal interviews using pre-tested questionnaire and data entered and analyzed using SPSS and STATA packages. The data collected included household characteristics, socio-economic indicators, household assets, information sources, ownership and use of mobile phones, sources and uses of income, among others. The household survey was conducted during March and April of 2010.

4. Results

Characteristics of users and non users of MMT services

We present differences in the characteristics of users and non-users of MMT services with test of significance in their differences in Table 1.

Table1: Differences in characteristics of users and non users of MMT services (sample mean)

Characteristic	Users (n=198)	Non-Users (n=181)	Difference	t –values
Farmer-specific characteristics				
Age of the household	40.85	41.68	-0.83	-0.62
Gender (Male=1)	0.57	0.44	0.13^{***}	2.58
Occupation (Farming =1)	0.72	0.31	0.24	0.28
Awareness of MMT services (Aware=1)	1.00	0.92	0.08	1.28
Farm-level characteristics				
Distance to bank (km)	8.61	11.75	-3.13^{***}	-4.17
Distance to agric extension agent (km)	6.66	8.59	-1.93	-1.41
Distance to MMT agent (km)	2.17	4.29	7.31^{***}	3.54
Number of enterprises	6.31	3.20	3.03^{***}	1.92
Household size (adult equivalent)	5.64	5.85	0.21	0.93
Asset endowment characteristics				
Education (years)	9.78	6.99	2.78^{***}	7.95
Farming experience (years)	16.49	20.25	-3.76^{***}	-2.82
Group membership (member =1)	0.69	0.34	0.14^{***}	2.84
Agricultural income (KSh.)	8866.19	2706.27	6199.92^{***}	6.02
Non-agricultural income (KSh.)	17854.31	12955.29	4890.72^{**}	1.97
Assets value (KSh.)	39735.49	29436.77	10299.02	1.32
Location characteristics				
Kirinyaga	63	58	5	0.62
Bungoma	69	63	6	0.56
Migori	66	60	6	0.61
Total number of farmers (N)	**198**	**181**		

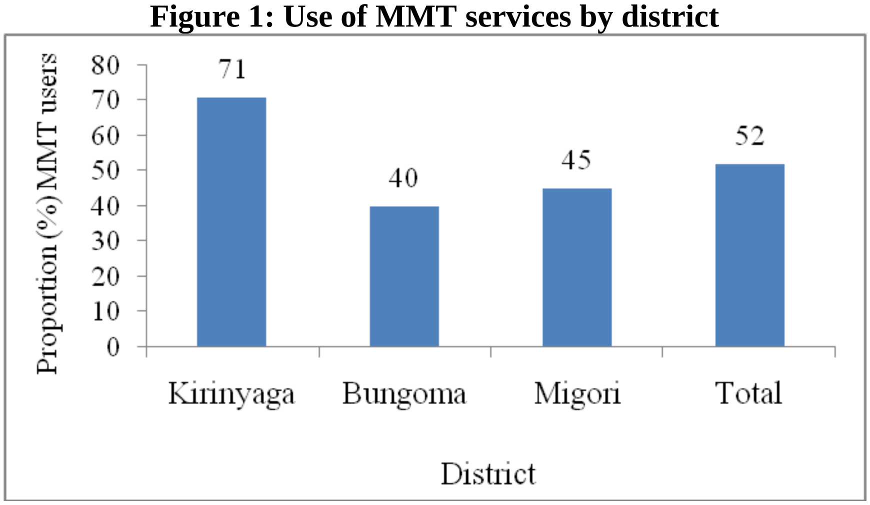
Source: Survey results, 2010. Note: Significance level: *10 %, **5 % and ***1 % levels.

We carried out t-tests for continuous variables and chi-square test for categorical variables. Results suggest that there were differences between users and non-users of MMT with respect to farmer-specific, farm-level and asset endowment characteristics. Specifically, results show that users of MMT services are more educated than their counterparts. Interestingly, non-users of MMT services are more experienced in farming. There are also significant differences among the farm-specific characteristics namely, distance to the bank, distance to the money transfer agent and distance to the agricultural extension agent's office. Users of MMT services have a closer proximity to the MMT agent. Asset endowment (value of current assets) characteristics show no significant difference between the groups.

Use of MMT services among respondents

Overall, 96% of the respondents were aware of the existence of MMT services. Meanwhile 198 (52%) had use these services. However, as expected, the usage differed for different regions (Figure 1). More farmers in Kirinyaga district have used MMT services before than in the other two districts. Two factors may explain this finding. First, the level of agricultural commercialization is much higher in Kirinyaga than in the others. Majority of the respondents interviewed participate in better-paying fresh export vegetable production. Second, ownership of mobile phones was higher in Kirinyaga than in Migori and Bungoma districts.

Figure 1: Use of MMT services by district



Source: Survey results, 2010

Determinants of use of MMT services among farmers

The results of the logistic regression are shown in Table 4. The likelihood ratio shows that the model fits the data well (p-value = 0.0001).

Table 4: Drivers of use MMT services by smallholder farmers: Logit regression

Use of m-banking	Coef.	Std. Err.	p-value
Gender	0.54	0.26	0.041
Age	0.03	0.02	0.118
Education (years)	0.19	0.04	0.000
Distance to nearest m-banking agent	-0.31	0.01	0.001
Group membership	0.71	0.26	0.007
Distance to nearest bank	0.51	0.02	0.009
Household size	-0.09	0.06	0.159
Years of experience in farming	-0.03	0.01	0.064
Agric extension	-0.01	0.02	0.642
Ln assets	0.11	0.05	0.028
Ln income	0.24	0.08	0.005
Constant	-5.1373	1.1543	0.0000

No. Of Observations: 378
Pseudo R^2 : 0.1985
P-Value: 0.0001
Log Likelihood: -207.2917

As hypothesised, distance to the m-banking agent plays a critical role in usage of m-banking. The further away the farmers from m-banking agent the less likely the use of the service. These findings indicate that m-banking therefore has great potential to reduce the exclusion of farmers from banking services caused by lack of access resulting from distance to the service. Indeed, results of the descriptive analysis indicated the m-banking services are located within average distance of 2 km from the farmers interviewed. Indeed, distance to the nearest bank is positively and significantly related to the likelihood of use m-banking services. That is, the further away the famer from the nearest commercial bank, the more likely that farmer will use m-banking services. An increase in distance from a bank by 10 percent increases the likelihood of usage of m-banking services by 5 percent.

Results also shown, that among the household characteristics, gender and education affect the likelihood of using m-banking services. An increased in level of education by 1 year increases the likelihood of using m-banking by 0.02 percent. The finding relating to education supports the earlier argument that literacy affects the awareness and use of m-banking services. Results further show that social capital proxied by membership in farmer organizations also affects the likelihood of using m-banking services. This finding is in-line with those of previous studies that indicate that collective action affects adoption of new techniques of farming.

The other capital endowment variables that affect the likelihood of using m-banking services include possession of physical assets and income. Results show that an increase in the value of assets owned by a respondent by 10% increases the likelihood adoption of m-banking services by 11%. This finding indicates that the likelihood of usage of m-banking services is higher among the more asset endowed farmers than their counterparts. Results further show that the more financially endowed farmers are more likely to use m-banking services than their counterparts. An increase average income by 10% increases the likelihood of use of m-banking services by 24%.

Determinants of intensity of use of MMT services

In order to assess the factors conditioning the extent to which farmers use mobile phone-based money transfer services, this study used Poisson and Negative binomial regression techniques. These count variable models are suitable for dependent variables that are countable finite such as the number of times a farmer uses a service (Gitonga, 2009).

Results for the Poisson regression model (Table 5) shows that the model is highly statistically significant (a p-value = 0.000). Intensity of use of mobile phone-based money transfer in this Poisson model refers to the total number of times the respondent sent/received money via mobile phones

Table 5: Determinants of intensity of use of mobile phone-based money transfer: Poisson and Negative Binomial Regression Models

Definition of variables	Poisson regression model		Negative Binomial model	
Dependent Variable –number of times of using MMT	Coefficient	p-value	Coefficient	p-value
Farmer specific variables				
Age	0.25	0.011	0.22	0.019
Age^2	-0.01	0.014	-0.01	0.024
Gender	0.73	0.563	0.62	0.633
Farm specific variables				
Distance to MMT agent	-0.06	0.029	-0.04	0.016
Distance to the bank	-0.15	0.480	0.06	0.002
Number of enterprises	-0.21	0.112	-0.15	0.078
Household size	-0.13	0.134	-0.32	0.144
Asset endowment variables				
Natural log of household assets	0.03	0.549	0.06	0.190
Natural log of agric income	0.06	0.886	0.08	0.007
Natural log of other income	0.02	0.383	0.03	0.038
Education	0.16	0.000	0.19	0.000
Group membership	0.32	0.121	0.55	0.017
Regional variable				
Region of Survey	2.28	0.222	1.78	0.276
Constant	-2.71	0.041	-4.31	0.000
	Number of obs. = 377 Wald $chi^2(13)$ = 126.34 Prob > chi2 = 0.000 Deviance = 5886.56 Prob > chi^2 (364) Pearson = 6015.44 Log pseudo LH = -3299.87		Number of obs. =377 /natural log of Alpha = 1.31 Alpha = 3.39 Prob > chi^2 = 0.000 Wald $chi^2(9)$ = 144.32 Log pseudo LH = -905.10	

Source: Survey results, 2010.

Total number of mobile phone-based money transfer times is the response (dependent) variable in the Poisson regression. This is a count variable. Underneath the response variable are the predictor variables and the intercept (constant) with their respective regression coefficients and the p-values. The mean deviance and the Pearson chi-square ratio (the Pearson chi-square value divided by its degrees of freedom) are used to assess the degree of fit of the Poisson model. They are used to detect overdispersion or underdispersion in the Poisson regression. Values greater than 1 indicate overdispersion, that is, the true variance is bigger than the mean. Values smaller than 1 indicate underdispersion, the true variance is smaller than the mean. Generally, a Pearson chi-square ratio of between 0.8 and 1.2 indicates that the model can be assumed to be appropriate in modelling the data (Trentacoste, 2000).

The Deviance and Pearson ratios were estimated and results are as shown below:

$$Deviance/df = 5939.68/364 = 16.30 \quad (1)$$

$$Chi\text{-}square/df = 6236.89/364 = 17.13 \quad (2)$$

From the results above, both the ratios of mean Deviance and Pearson Chi-square to the degrees of freedom are significantly greater than 1; thus there is evidence of over-dispersion. This implies that variances of the coefficient estimates are larger than the expected mean. This violates the assumption of the Poisson model that the variance must equal the expected mean. This results in inefficient, potentially biased parameter estimates and spuriously small standard errors (Hilbe, 2007). Evidence of overdispersion indicates inadequate fit of the Poisson model.

Indeed the results of the fitted poisson model suggest that it does not fit the data well. Consequently the discussion below is based on the negative binomial results. The Likelihood Ratio has a p-value of 0.001 showing that the model fits the data well.

As hypothesised, the cost of accessing money sent through mobile phones (proxied by distance to the mobile phone-based money transfer agent) affects the intensity of usage of mobile phone-based money transfer. The further away the farmers are from mobile phone-based money transfer agent (hence the higher the cost of using mobile phone-based money transfer services) the less the degree of use of the service. If the distance to the mobile phone-based money transfer agent were to increase by 1 kilometre, the number of times of using mobile phone-based money transfer services would decrease by 0.04, holding the other variables in the model constant.

Among the human capital characteristics, education level affects the intensity of using mobile phone-based money transfer services. An increased in level of education by 1 year increases expected number of times of using mobile phone-based money transfer services by 0.19, holding the other variables in the model constant. This is consistent with our theoretical expectations and with findings of other studies (Salasya et al., 1996).This positive effect of education on the degree of use of mobile phone-based money transfer services suggests that more educated producers have exposure to new innovations, are more receptive to new ideas and are more willing to adopt, hence the positive relationship. Results also show that intensity of use of mobile phone-based money transfer services increased with age, but at a decreasing rate. The expected number of times of using mobile phone-based money transfer services increased by 0.25 for each year increase; but this increase is accelerated by -0.01 for each year.

Distance to the nearest bank significantly influenced the intensity of use of mobile phone-based money transfer services. The expected number of times of using mobile phone-based money transfer services increases by 0.06 for every one kilometre increase in the distance to the nearest bank, holding other factors constant.

The number of enterprises (proxy for risk) indicates that risks increases the intensity of use of mobile phone-based money transfer services. Expected number of times of using mobile phone-based money transfer services increase by 0.2 units for every one unit increase in number of enterprises.

Income level (both farm income and remittances from family and friends) of the household also affects the intensity of using mobile phone-based money transfer service. An increase in average income by 10 percent increases expected number times of using mobile phone-based money transfer services by 0.8. This is probably because most of the respondents were both senders and receivers of money via mobile phone-based money transfer methods. An increase in earnings means more opportunity to transfer money either to pay school fees, purchase inputs or pay a debt among other uses. This also implies that an increase in farm incomes widens the possibility of adopting an innovation by mitigating the shortage of capital input (Thirtle *et al*., 2003).

Social capital (proxied by group membership) also significantly influences intensity of use of mobile phone-based money transfer services. Expected number of times of using mobile phone-based money transfer is 0.55 higher for group members compared to non-members, holding the other variables in the model constant.

5. Summary, conclusions and policy implications

This study assessed the level of awareness and usage of mobile phone-based money transfer among smallholder farmers in Kenya. It finds that the level awareness of mobile phone is quite high. More than 96 percent of the farmers are aware of mobile phone-based money transfer services. However, the level of awareness has not translated into usage. Only 52 percent of the farmers were found to be users. The study also finds that aware of m-banking services does not vary much among the study regions. However, the usage of mobile phone is significantly higher in regions with greater level of agricultural commercialization. The study also finds that the largest proportion of money received via m-banking (32%) is used on agricultural related purposes (purchase of seed, fertilizer for planting and topdressing, farm equipment/implements, leasing of land for farming, paying for labour).

The study find the factors explaining use of use of m-banking include education, distance to a commercial bank, membership to a farmer organization (a proxy collective action), distance to the m-banking agent, and endowment with physical and financial assets. It study specifically finds that distance to the m-banking agent (which affects transport cost to the m-banking agent and opportunity cost of time spent) has an inverse relationship with the decision to use m-banking service. The further the m-banking agent is from the farmers, the lower the likelihood of usage.

The implication of these findings is that there is need to expand the coverage of m-banking services in rural areas since it resolves one idiosyncratic market failures farmers face namely access to financial services. In addition, attention should be given to infrastructural constraints facing rural areas namely the lack of electricity (needed to charge mobile phones). It also implies that m-banking service providers should consider expanding the availability of sufficient “float” of funds to expedite transfers into and from farming communities. Indeed, lack of adequate float was also cited as one of the major constraints to the use of m-banking in remote areas where majority of clients use the service to receive cash remittances from friends and family. These findings therefore indicate priorities for policymakers and the private sector to invest in linking farmers to financial services. They also highlight the importance of improving rural literacy level of the farming communities.

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