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Social network effects on mobile money adoption in Uganda

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Abstract

Social networks play a vital role in generating social learning and information exchange that can drive the diffusion of new financial innovations. This is particularly relevant for developing countries where education, extension and financial information services are underprovided. The recent introduction of mobile money in Africa represents a case where imperfect financial markets, weak extension services and information asymmetries limit the ability of rural households to make informed decisions to take advantage of mobile money innovation. This article identifies the role of social networks in the adoption of mobile money in Uganda. Using data from a survey of 477 rural households, a probit model is estimated controlling for household characteristics, correlated effects, and other possible information sources. Results suggest that learning within social networks helps disseminate information about mobile money and has enhanced its adoption. Compared to poor households, non-poor households rely more on social networks for information about mobile money. Mobile money adoption is likely to be enhanced if promotion programs reach more social networks.

Keywords: social networks; mobile money; adoption; Uganda

JEL codes – D14, D83, O33, Q12

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Introduction

Over the last decade mobile money has emerged as an important innovation where individuals, households and businesses conduct financial transactions over mobile phones. According to Donovan (2012), mobile money refers to the provision of financial services through a mobile device. The range of services provided by mobile money include payments (e.g. peer-to-peer transfers, airtime purchase, utility bills and school fees payments), finance (e.g. insurance products), and banking (e.g. account balance inquiries). Mobile money is making an important contribution to financial inclusion in developing countries in many ways. First, it increases access to financial services to a large number of people, who are effectively excluded from banks due to longer travel distances or insufficient funds to meet the minimum deposit required to open a bank account as mobile money attracts modest and proportionate withdrawal fees (Jack et al., 2013; Jack & Suri, 2014; Kirui et al., 2012). With mobile money, households can transfer money on their mobile phones without physically visiting the bank or through mobile money agents (MMA) that are now widespread even in remote villages. This reduces households travel time and costs. In addition, mobile money is associated with fast and timely transfer of money, hence reduces transaction costs associated with accessing financial services. Furthermore, it is now possible to extend the range of financial services offered by mobile money beyond basic payment and withdrawal to other financial products, such as micro insurance, electricity and school fees payments (MTN, 2014; IFC, 2011).

According to Gutierrez & Choi (2014) about 27% of the adult population in Uganda use mobile money and half of these mobile money users have no bank accounts. This means mobile money has not been widely adopted by households in the country. One possible reason for the existence of mobile money adoption gap is information asymmetries that limit households' ability to make informed decisions to take advantage of mobile money innovation. This is particularly true for Uganda and other developing countries where extension and formal financial information services are underprovided. In the absence of formal information institutions, households learn from their social networks about new financial innovations. According to information cost theory (Röper et al., 2009), the use of informal channels, for example social networks potentially lowers search costs and leads to positive outcomes. In Uganda, informal assessments by InterMedia (2012) show that individuals started using mobile money because of recommendation from family members, friends or other acquaintances. However, this study did not provide rigorous econometric evidence to show that information from one's social network leads to mobile money adoption.

Previous research has analysed the adoption of mobile money by households in developing countries (Kirui et al., 2012; Kikulwe et al., 2014; Munyegera & Matsumoto, 2014). Kirui et al. (2012) and Kikulwe et al. (2014) analysed the determinants of mobile money adoption by households in Kenya while Munyegera & Matsumoto (2014) focused on households in Uganda. These studies do not pay particular attention to the role of social networks in mobile money adoption. Social networks play an important role in diffusing financial information. Our paper on mobile money is closely related to recent studies that link social networks to financial decision making by rural households (Okten & Osili, 2004; Wydick et al., 2011; Zhang et al., 2012; Banerjee et al., 2013). In Indonesia, Okten & Osili (2004) found that family and community networks had a larger impact on credit awareness of new credit institutions. In addition, women benefited more from participating in community networks than men and social network effects did not differ by poverty status of the household. Wydick et al. (2011) found that church networks influenced microfinance borrowing by households in Guatemala. Zhang et al. (2012) show that households with larger social networks were more likely to borrow from formal intermediaries than households with smaller networks in

Western China. Banerjee et al. (2013) found that information obtained from neighbours who participated in microfinance positively influences the decision on microfinance participation by households in India.

This study explores the role of social networks in households' adoption of mobile money in Uganda. More specifically, we analyse how learning within social networks and the structure of the social network affect adoption of mobile money. In addition, we assess whether social network effects on mobile money adoption vary with the poverty status of the household. To the best of our knowledge, none of the previous studies have systematically analysed how social networks affect mobile money adoption.

Our results allow drawing some recommendations on whether mobile money innovation could be diffused using social networks in Uganda. While our study focuses on mobile money, the results can be applied to other new innovations in developing countries, where information asymmetries limit household's adoption decisions. The remainder of this article is organised as follows. In the next section we describe mobile money in Uganda, thereafter the conceptual framework and hypotheses. We then discuss the empirical model specification and estimation issues, followed by a description of survey data used for empirical analysis. Empirical results are presented and discussed. The last section concludes and discusses policy implications.

Mobile Money in Uganda

Mobile Telephone Network (MTN) launched the first mobile money (*MTN mobile money*) in Uganda in March 2009. Another provider, Uganda Telecom launched the second mobile money (*M sente*) in 2010. In 2011, Warid Telecom joined the industry and introduced *Warid Pesa* and this was followed by *Airtel Money* from Airtel in 2012. The mobile money industry continued to grow and *Orange money* from Orange Telecom was launched in 2013. In early

2013, Airtel merged with Warid Telecom to offer *Airtel-Warid Pesa*. Currently MTN is the largest mobile phone operator and mobile money service provider in Uganda (InterMedia, 2012; Mobile Money Africa, 2013; MTN, 2014). All mobile money service providers work in partnership with one or more banks[1], making it possible for clients to make banking transactions on their mobile phones without visiting the bank.

Mobile money provides a convenient way to send money to anyone anywhere in Uganda no matter the network or mobile money service provider. Mobile money users have two options of conducting mobile money transfers (sending and receiving) through: a) transfers on their own or on mobile phones of their relatives or friends provided they are connected to the mobile money account, and b) visiting a registered MMA, who conducts the transfers on behalf of the client. The services offered by different mobile money service providers have many similarities: They all allow registered mobile money users (individuals, businesses, institutions etc) to load money into their mobile money accounts or transfer through MMA (cash-in), make transfers to other users (both registered or not), buy airtime and withdraw money (cash-out) (InterMedia, 2012). The mobile money account is an electronic money account which receives electronic value either after the account holder deposits cash via an agent or receives a payment from elsewhere (MTN, 2014; IFC, 2011). Depending on the service provider, a registered user has access to other mobile money functions for example paying utility bills and school fees. Though mobile money registration is free, all transactions have a predetermined fee (InterMedia, 2012; Airtel, 2014; MTN, 2014). The transaction fees are calculated differently for registered and non-registered mobile money users as well as differently when transferring money to the same and different network. For example, in October 2014 a registered sender of Airtel was charged 450 UGX ($0.17)[2] to send between 500 and 5000 UGX ($1.91) to registered Airtel users while sending to unregistered users and

[1] For example *MTN mobile money* partners Stanbic Bank, *M sente* with Standard Chartered Bank and *Orange money* with Pride Microfinance.

[2] The exchange rate was 1USD = 2615UGX in August 2014

other networks attracted a charge of 1000 UGX ($0.38) for the same amount of money (Airtel, 2014). During the same time period, withdrawing 500 to 2500 UGX from an agent attracted a fee of 300 UGX ($0.11) for Airtel and 330 UGX ($0.13) for MTN. Different and comparably lower rates are charged for paying utility bills, goods and services. The maximum amount that can be transacted per day also varies. For example, MTN has a maximum of 4 million UGX ($1530), while Airtel has an upper limit of 5 million UGX ($1912) per day (Airtel, 2014; MTN, 2014). The possibility to send money from one network (e.g. MTN) to the other (e.g. Airtel) increases access to mobile money services. Some households have multiple mobile money accounts from different service providers to take advantage of this flexibility. In addition, MMAs work for more than one mobile money service provider at a time thus bringing a variety of financial services under one roof. When sending mobile money through mobile phone the sender is charged while the recipient is not. On the other hand, if one transfers money through a mobile money agent, the transaction fees are charged upon withdrawal.

From the above discussion, we see there are two options of conducting mobile money transfers: through mobile phone or authorised MMA. Anecdotal information suggests that most households in our sample conduct their transfers through mobile money agents instead of using their own mobile phones. Using own mobile phones requires individuals to have high mobile phone literacy to navigate and use mobile money applications, often written in English. This may partly explain why households prefer to transfer money with the help of mobile money agents. In this study, a household is classified as mobile money adopter if any member of the household used mobile money services in the past 12 months prior to the survey. This classification is consistent with the definition used in literature (InterMedia, 2012; Kikulwe et al., 2014).

The growth in mobile money has been spurred by an increase in penetration and use of mobile phones in rural areas coupled with expansion of mobile money agents. As of 2013, Uganda had about 16,4 million mobile phone users (UBOS, 2013). Mobile money users grew from 1.7 million in 2010 to approximately 12 million by the end of 2013. In contrast, about 7.6 million individuals are estimated to hold bank accounts at a formal financial institution (World Bank, 2014). This shows that mobile money users now exceed the number of customers holding conventional bank accounts. Furthermore, MTN alone had over 20 000 mobile money agents as of 2013, which reflect more points of financial services compared to the combined 900 bank branches and 800 automated teller machines (GSMA, 2013; MTN, 2014; Mobile Money Africa, 2013). The introduction of mobile money has been associated with unprecedented transfers of money among individuals, households and businesses in Uganda. By the end of 2013, the estimated cumulative value of money transferred via mobile money transactions had reached US$4.6 billion (Mobile Money Africa, 2013; World Bank, 2014).

Conceptual framework and hypotheses

Conceptual framework

Following the innovation adoption theory (Rogers, 1995) and previous research on mobile money (Kirui et al., 2012; Kikulwe et al., 2014; Munyegera & Matsumoto, 2014), factors related to the adoption of mobile money can be conceptualised into: household and farm characteristics; wealth and asset ownership; information and education; institutions and location. In developing countries, social networks are an important source of information because formal information institutions are underprovided. According to Maertens & Barrett (2013) and Borgatti et al. (2009), social networks refer to individual members and the links among them through which information, money, goods or services flow. Social networks enhance the adoption of new innovations through many pathways. First, social networks constitute a channel through which households obtain information about new technologies and this helps to reduce information asymmetry and transaction costs for innovation adoption (Maertens & Barrett, 2013). Second, social networks enable households to pool resources together and reduce financial and labour constraints. This is especially important for innovations requiring initial capital investment and intensive labour demands respectively. For mobile money innovation, the information access appears to be the most important pathway. Social networks affect household's financial choices by determining the quantity and quality of information and resources a household can access through social ties. Studies have shown that rural households lack information on finance opportunities and many of them rely on social networks to acquire financial information (Zhang et al., 2012). Zhang et al. (2012) found that households with larger social networks were more likely to borrow credit from formal intermediaries due to information benefits of a larger social network.

Various network theories exist in the literature. Three social network theories that are relevant for our study are: (i) Social learning theory (Foster & Rosenzweig, 1995; Bandiera & Rasul, 2006; Conley & Udry, 2010; Maertens & Barrett, 2013); (ii) Granovetter's strength of weak tie theory (Granovetter, 1973); and (iii) Social resources theory (Lin et al., 1981; Lin, 1999; Lai et al., 1998).

According to social learning theory, social networks should be linked to the exchange of information, material and services (Foster & Rosenzweig, 1995; Bandiera & Rasul, 2006; Conley & Udry, 2010; Borgatti et al., 2009; Maertens & Barrett, 2013). Households may know someone in their social network group, but may not necessarily communicate with them about the use of mobile money. Without information exchange on mobile money, simply knowing a social network member may not produce the learning externality of social networks (Maertens & Barrett, 2013), especially for mobile money which is highly unobservable. Bandiera & Rasul (2006) use the number of adopters among family and friends to capture the impact of social learning on technology adoption in Mozambique. Maertens &

Barrett (2013) use a variety of variables to capture the presence of social learning in India. First, they asked respondents whether they would approach a specified progressive farmer for advice in case of problems with their biotechnology cotton crop. In addition, they asked respondents whether they pass by the social network members' fields when going to their own fields. The assumption is that households will observe the biotechnology cotton crop in the fields of their social network contacts and this will likely influence their adoption decision.

Social network benefits may emanate from the specific type of network connections such as strong and weak ties. The strength of a tie is a combination of the amount of time, emotional intensity and reciprocal services that characterize a relationship (Granovetter, 1973). According to the strength of weak tie theory of Granovetter, tie strength among actors in a network has an impact on the quality of information transferred and shared. New and novel financial information flows to individuals through weak ties rather than strong ties (Granovetter, 1973; Granovetter, 2005). Weak tie contacts know other contacts outside the household's circle of friends and possess diverse and heterogenous information that overlaps less with what one already knows. Although weak ties deliver heterogenous and more diversified financial information, Zhang et al. (2012) stress that the social influence flowing through strong tie contacts may increase the household's capacity to mobilize the actual financial resources possessed by the contacts. In a developing country context, strong ties are often used as referrals when seeking credit from both formal and informal institutions. This serves as a risk mitigating factor as the lenders feel reassured lending money to borrowers referred by a close contact (Granovetter, 2005). Tie strength can be measured by the type of relationship (Granovetter, 1973), the duration of acquaintanceship (Son & Lin, 2012; Fu et al., 2013) and the frequency of contact (Fu et al., 2013). The classification based on the type of relationship considers the number of acquaintances (weak tie contacts) in one's social network relative to close friends and relatives (strong tie contacts). In this study, we define the strength of network ties based on the frequency of contact. Frequent interactions between contacts represent a strong tie whereas infrequent contact captures weak ties. People with strong ties may meet regularly and in several contexts, while people with weak ties often meet irregularly and exchange diverse and often crucial information (Son & Lin, 2012; Fu et al., 2013).

The social resources theory considers the structural factors of social networks. The theory posits that social resources (e.g. wealth, socioeconomic status, power, etc.) embedded in an individual's social network positively influence information access (Lin et al., 1981; Lai et al., 1998; Song & Chang, 2012). For example, Song & Chang (2012) found that education of network members is positively associated with frequency of health information seeking in the U.S. Lai et al. (1998) also show that contact resources positively influence finding a job for men in the U.S. Households with more connections to network members with rich socioeconomic resources are more active in financial information seeking. Song & Chang (2012) identify the mechanisms through which social resources influence the frequency of health information seeking and diversity. Drawing on this analogy, two of the mechanisms can also be applied to financial information seeking: increased exposure to financial information and enhanced seeking abilities. Regarding the first mechanism, people with more socioeconomic resources, in particular education, are more active in seeking financial information and are better informed about financial products from different information sources (Song & Chang, 2012; Röper et al., 2009; Zhang et al., 2012). Hence, when connected to network members with higher socioeconomic status, individuals are more likely to be exposed to financial information and products from their network members, which can motivate them to utilize the respective products (Zhang et al., 2012). The second mechanism relevant in our study context is enhanced seeking abilities. Having ties to social contacts of higher socioeconomic status, individuals are more likely to receive diverse forms of social support, e.g. financial and material support (Song & Chang, 2012), which can enhance individuals' capability of seeking financial information from various sources.

Specific hypotheses

The selection of our network measures for analysing social network effects on adoption is guided by the network theories discussed above. We focus on social capital generated through the number of adopters within the social network with whom the household communicates[3] about mobile money (*exchange adopters within the social network* - hereafter referred to as *exchange adopters*); type of network connections (share of *weak ties*) and social resources embedded in the social network (*network education status*). The last two variables, *weak ties* and *network education status,* capture the structure of the social network.

Number of exchange adopters: Information about new technologies such as mobile money can spread by word of mouth through discussion and persuasion (Foster & Rosenzweig, 1995; Conley & Udry, 2010; Maertens & Barrett, 2013). Using the number of adopters within the social network is not sufficient to capture information exchange. As discussed earlier, for an individual to learn directly from the contact they have to interact and discuss about mobile money (Maertens & Barrett, 2013). In this study, we are interested in social learning generated through information exchange because mobile money is highly unobservable. We use the variable *exchange adopters* to proxy the presence of social learning. The *exchange adopters* refer to the number of mobile money adopters in the household's social network with whom the household communicates and discusses about mobile money. Households with more exchange adopters in their social network are likely to have better access to financial information, and thus to adopt mobile money as well. From this, we develop the following testable hypothesis:

[3] This encompasses all forms of communication e.g. word of mouth, mobile phone communication via sms or voice call and other channels.

H1. Compared to households with fewer exchange adopters in their social network, those with more exchange adopters are more likely to adopt mobile money due to information benefits of a larger network.

Weak ties: In addition to the number of exchange adopters within the social network, household's adoption choices can be influenced by the structure or composition of their network. This is because the structure of the network affects the quantity and diversity of information available to a household (Granovetter, 2005). We therefore argue that when a household's social network contains a larger share of weak ties the household is more likely to access more diversified information about mobile money and other financial information which increases the chances of adopting mobile money (Granovetter, 2005). We expect that:

H2. A larger proportion of weak ties within a household's social network increase the likelihood of adopting mobile money.

Network education status: People with formal education tend to have diverse and extensive financial knowledge (Zhang et al., 2012). Knowledge about mobile money, savings and various forms of financial transfer systems may be correlated with higher probabilities of using mobile money as financial transfer systems. Guided by the social resources theory of Lin et al. (1981), we expect:

H3. Compared to households with less educated social network members, those with well-educated network members are more likely to adopt mobile money due to more and better financial information.

Although the social network is expected to be important for the adoption of mobile money, other factors are likely to influence the household's adoption decision. Previous studies indicate that factors such as age, education, gender, income and the distance to a mobile money agent can affect mobile money adoption by rural households (Kirui et al., 2012; Kikulwe et al., 2014; Munyegera & Matsumoto, 2014). Kirui et al. (2012) and Munyegera &

Matsumoto (2014) reported that the distance to a mobile money agent has an inverse relationship with the adoption of mobile money. Distance to the mobile money agent can thus be considered a proxy for the influence of transaction costs on mobile money adoption. Households living far away from a mobile money agent and in areas with poor mobile network coverage are less likely to adopt mobile money. Wealth and asset ownership are also among the factors that have been found to explain adoption (Abdulai & Huffman, 2014). Generally, households with larger financial capacities are considered to be more prone to technology adoption.

Econometric estimation

The effect of social network variables on the probability of adopting mobile money is estimated using a probit model specification:

$$MM_i = X_i^{'}\beta_1 + D_i\beta_2 + SN_i^{'}\beta_3 + v_i$$

where, MM_i is the observable binary discrete choice of whether or not the household adopted mobile money. $X_i^{'}$ is the vector of variables capturing household and contextual characteristics; including age, sex and education of the household head, household size, distance to mobile money agent, amount of land owned and off-farm income. We also accounted for access to other information sources by including the number of mobile phones owned by the household, contact with a community knowledge worker[4] and ownership of radio and TV. D_i is a vector of dummy variables accounting for unobserved variation across villages that could affect a household's mobile money use decision. The social network effect (number of exchange adopters and network structure) is captured through $SN_i^{'}$. v_i is the error

[4] The Community Knowledge Worker program is a mobile-phone based extension system that uses locally recruited peer farmers. Community knowledge workers are local farmers recruited by Grameen Foundation, and trained to use android smart phones to disseminate agricultural and market information to fellow farmers in their respective villages. Their smart phones have mobile money applications. Therefore households in close contact with community knowledge workers are likely to have higher mobile phone and mobile money literacy.

term, capturing unobserved household and network characteristics that potentially affect the adoption decision, for example motivation and risk attitude.

Bias in the reported number of adopters within the social network could emerge if adopters are systematically better (or less) informed about the prevalence of adoption among the members of their network than non-adopters (Liverpool-Tasie & Winter-Nelson, 2012). This bias may be quite substantial in this application, because mobile money use is not highly visible and households will not automatically be aware of adoption in their network. If a household is unaware of the adoption of mobile money by a network member, the contact is considered inactive and the measure will appropriately exclude the unobserved adopter from the measured social network. We mitigate the bias from misreporting by accounting for particular household characteristics (like age and education) which could affect their ability to properly identify network characteristics. Furthermore, in addition to the reported mobile money adoption status we estimate a model based on actual adoption status in order to check whether misreporting bias is an issue. We discuss this in detail in the data section, where we describe social network measurement.

In any empirical analysis of social networks, identification is always an issue because the individual is also part of the group. Manski (1993) describes this as the *reflection problem* - meaning that the group affects individual behaviour and at the same time individual behaviour contributes to some of the group behaviour. When behavioural effects of a group on an individual, who is a member of the group, are modelled, the results obtained are biased. This problem is usually mitigated through appropriate research designs. To tackle the identification problems associated with social networks, we implemented a random matching within sample sampling approach to collect social network data (Maertens & Barrett, 2013). We randomly matched households to their potential network members and thus do not allow households to select their network member group. Such random assignment ensures that households do not choose network members of similar preferences and thus correlation between observed peer attributes and the error term in the mobile money adoption regression equation is limited by design (Richards et al., 2014).

Apart from the reflection problem, social networks typically have endogeneity problems. Manski (1993) highlights three categories as to why network members behave in a similar fashion: (1) *correlated effects*, which refer to the idea that peers may be similar in mobile money adoption choices because they face a similar environment or because of similar individual and institutional characteristics they self-select into a given social network; (2) *exogenous effects*, which are similarities with respect to the contextual factors such as similar demographics within a social network (e.g. background and cultural conditions), and (3) *endogenous effects*, which explain the existence of herd behaviour, in that members behave like other members in their social network rather than using their information. Wydick et al. (2011) identifies three types of endogenous effects as *pure social, instrumental and informational conformity*. *Pure social conformity* is seen when fashion or social approval dictates behaviour within a particular network. For example, studies have shown that farmers are significantly more likely to adopt organic agriculture, if they think that their neighbours would be approving of their decision (Wollni & Andersson, 2014; Läpple & Kelley, 2013). *Instrumental conformity* refers to a scenario where members in a reference group use mobile money because it makes it easier for each of them to send group subscription fees to the treasurer. Another example would be people in the village using the same type of mobile phone because it makes it easier for each of them to obtain spare parts. *Informational conformity* is based on a member seeing another member in the social network using mobile money. This is assumed to inform her that using mobile money yields a higher level of utility, making her eager to use mobile money. In this study context, *instrumental* and *informational conformity* are likely to be the more relevant endogenous effects.

Failure to control for the correlated, exogenous and endogenous effects of social networks may lead to biased estimates (Manski, 1993; Matuschke & Qaim, 2009). To control for the correlated effects, we estimate a model with village fixed effects by including village dummies (Matuschke & Qaim, 2009; Liverpool-Tasie & Winter-Nelson, 2012) in addition to adjusting for cluster-correlated standard errors. By including village dummies (fixed effects), we are controlling for the average differences across villages in any observable or unobservable predictor, such as differences in mobile network coverage. We use robust standard errors clustered at the village level to account for the fact that standard errors across households within the same village may be correlated. Brock & Durlauf (2007) also demonstrate that peer effects are identified in a discrete choice model, even in the presence of correlated effects with binary choice models as is our case. Furthermore, to control for exogenous effects, we included demographic information (in particular ethnicity and religion) to control for household level characteristics that could be correlated with adoption. Because our social network groups are exogenously determined, there is limited endogenous sorting into groups and thus endogenous effects are minimized due to our research design.

Our approach of estimating a probit model with fixed effects however introduces the incidental parameters problem which leads to biased and inconsistent results (Lancaster, 2000; Greene, 2004; Hahn & Newey, 2004; Fernández-Val, 2009). According to Fernández-Val (2009), this problem occurs because the unobserved individual effects in nonlinear models are replaced by sample estimates. In nonlinear models, the estimation of model parameters cannot be separated from the individual effects, hence the estimation error of the individual effects contaminates the other parameter estimates (Fernández-Val, 2009). There are a variety of econometric approaches to correct incidental parameter bias in static and dynamic panel models. These approaches are based on adjusting the estimator, the moment equation, and the criterion function (Lancaster, 2000; Greene, 2004; Hahn & Newey, 2004;

Fernández-Val, 2009). However, we are not able to find any empirical guidance on an appropriate estimator for probit models estimated using cross-sectional data. In view of this, we estimate two additional models as robustness checks. First, we estimate a linear probability model (LPM) because linear models do not suffer much from incidental parameter bias (Greene, 2004). Furthermore Lewbel et al. (2012) highlight that the marginal effects estimated by probit or LPM estimators are almost the same. Second, we ignore the village correlated effects and estimate a probit model without fixed effects. This model does not suffer from incidental parameter bias. If estimates from probit model with fixed effects are fairly comparable to those of the LPM and probit model without fixed effects, then we can assume that incidental parameter bias do not significantly alter our results.

Data

Household survey

This study uses data collected from rural households in Mukono and Kasese districts in Uganda. We applied a multi-stage stratification approach to draw the sample. In the first stage, we randomly selected approximately 20 villages in each district: 10 villages where a mobile phone-based extension program, namely the Community Knowledge Worker program, is implemented (program villages) and 10 villages not hosting the program (non-program villages). The selection of non-program villages was such that they share similar agro-ecological characteristics and are neighbouring the program villages. In each village, about 12 households were randomly selected for interview. Households were chosen from lists that were compiled in collaboration with the village administration, NGO workers and local extension staff. In total, we interviewed 482 households in 39 villages. For the analysis, we had to drop five households because of inconsistent data on the social network module, resulting in a total sample size of 477 households.

The data were collected through personal interviews using a pre-tested questionnaire during November and December 2013. The questionnaires were administered to the household head and/or the spouse. The data collected includes information on household demographics, crop and livestock production, agricultural marketing, mobile phone ownership and use, mobile money services, household assets and information sources including social networks. From the mobile money module, we are able to distinguish between households using mobile money and those who are not, based on questions related to the use of mobile money services, as well as the frequency and amount of money transferred via mobile money. Our sampling strategy yielded a random sample of 273 mobile money adopters and 204 non-adopters across all program and non-program villages (Table 1).

(Table 1 about here)

Measuring social networks

To collect social network data we used the random matching within sample approach (Maertens & Barrett, 2013). According to Maertens & Barrett (2013), this approach performs better compared to other techniques as it can capture both strong and weak network links. Each household was matched with five other households randomly drawn from the sample (matched households). Interviewed households where first asked whether they know each of the matched households. Conditional on knowing the matched household; we elicited the details of the relationship between the interviewed household and the matched household, whether they discuss about mobile money and the household's knowledge about the matched household's mobile money use. The matched households unknown to the interviewed household were excluded from the household's social network. In this study, the known matched households constitute the household's social network. Based on the household's social network we compute the number of adopters, exchange adopters and variables measuring the structure of social network.

Exchange adopters: For each household this variable was computed as the number of mobile money adopters within the household's social network (i.e. known matched households) with whom the household has communicated and discussed about mobile money over the past 12 months. In line with Maertens & Barrett (2013), our measure captures the presence of information exchange within social networks. The variable *exchange adopter is* based on the reported mobile money adoption status. However, household members are often ill informed about their matched household's behaviour and outcomes. This is especially true for innovations, which are not highly visible, like mobile money. Because of this, Maertens & Barrett (2013) recommend to use information on both the reported and actual behaviour and outcomes of network contacts. Since the households' social network is also part of the sample, we estimated another model based on network members' actual mobile money adoption in addition to the reported adoption status. This serves as a robustness check for misreporting bias.

In order to analyse how the structure of the social network affects the adoption of mobile money, we use two variables; *weak ties* and *education of social network members*:

Weak ties: During the interview, respondents were asked how frequently they talk with social network members (1 = everyday, 2 = at least once a week, 3 = once a month and 4 = less often than once a month)[5]. The frequency of contact was dichotomized by distinguishing between strong relations (0 = combining categories 1 and 2) and weak ties (1 = combining categories 3 and 4). The share of weak ties was calculated as the number of weak ties in a household's social network relative to the total number of social network members.

Network education status: This variable refers to the aggregate mean years of education completed by the household heads of the social network members. This variable serves to examine the effect of network socioeconomic status.

[5] We also tried a different definition of weak ties based on the type of relationship but this did not change the results of our models.

Wealth and poverty measurement

We constructed a wealth index to measure household wealth. The wealth index was constructed using factor analysis based on several variables related to housing quality (material of the main wall, floor, roof and type of cooking fuel), water and sanitation (type of toilet and drinking water source) and household physical and agricultural assets (ownership of motorcycle and/or car, bicycle, radio and/or TV, area cultivated, value of farm equipment and total livestock units (TLU)). Table A1 and A2 in the appendix present the descriptive information of these variables and their factor loadings, respectively. One factor with eigenvalue greater than 1 was extracted explaining 94% of the total variation. Given that all the included variables are closely related to households' wealth status, the first factor explaining 94% of the total variation is assumed to be our measure of wealth (McKenzie, 2005; Sahn & Stifel, 2000). Kaiser–Meyer–Olkin measure of sampling adequacy is 0.7 and Bartlett's test of sphericity has a value of 538.575 (df = 66, $P < .000$) indicating that the model fit is appropriate. Based on our wealth index variable, we categorized households into two poverty groups. Households who are below the 40th percentile of the wealth index are categorized as poor and all others as non-poor. Sahn & Stifel (2000) and Fisher & Kandiwa (2014) also applied the asset poverty approach and used the 40th percentile as a cut off-point for poverty categories. The descriptive statistics for the social network variables as well as the other control variables included in the econometric model are provided in Table 2.

Results and discussion

Results of descriptive analyses

Overall, 57% of the households in our sample adopted mobile money (see Table 2). Table 2 further shows that mobile phone ownership is very common in the research area. Eighty three percent of the households in the sample own a mobile phone, and on the average households own 1.5 mobile phones. Household heads in the sample have relatively low levels of education with an average of 6.4 years of schooling. Low literacy may be associated with difficulties in navigating through mobile phone menus, which are often written in English. Furthermore, 50 percent of the households in our sample have a household member who is engaged in off-farm activities. This variable is of relevance to our study, because most off-farm income activities are conducted outside the village and mobile money is one alternative channel for remitting money back to members in the village.

(Table 2 about here)

Table 3 shows the size of the households' social network. As discussed earlier this is the number of known matched households regardless of mobile money adoption status. Twenty two percent of the households in our sample had only one social network member. About 50% of the households had a social network size of 5. This implies that these households knew all the 5 households that they were randomly matched with.

(Table 3 about here)

Table 4 shows the frequency distribution of adopters and exchange adopters in a household's social network. Seventy eight and eighty four percent of the households reported zero adopters and exchange adopters in their social network, respectively. About 22% of the households in the sample identified at least two mobile money adopters in their network. The number of actual adopters in the household's social network is shown in column 4. The fact that there are many more actual adopters than reported adopters is quite interesting. This confirms that households are indeed not well informed about mobile money use of their contacts. In this article, we use the reported adopters because this is what matters for social learning, i.e. if household does not know contact is using mobile money, obviously the contact will not influence his decision. Furthermore, we control for the effect of reporting bias by estimating different model specifications. Regarding exchange adopters, results indicate that only about 16% of the sampled households communicated and discussed about mobile money with one or more exchange adopters in their social network. This statistic is quite low, possibly because households have limited information about social network members' mobile money use. This is often the case with unobservable technologies such as mobile money.

(Table 4 about here)

Table 5 compares selected characteristics of mobile money adopters and non-adopters, presenting differences in means and t-test results. As evident, there are some notable differences between the two groups. Mobile money adopters have more exchange adopters in their social network than non-adopters. There is however no significant difference in terms of the share of weak-ties between the two groups. On average, mobile money adopters have a more educated social network than non-adopters. Furthermore, mobile money adopters live in closer proximity to mobile money agents compared to non-adopters.

(Table 5 about here)

One important question is how the adoption of mobile money is distributed across poverty levels, which will help us to identify whether the poor use mobile money. Figure 1 shows mobile money adoption differentiated by poverty status. Sixty seven percent of the wealthy households adopted mobile money, compared to only 43% of the poor households. Thus, in comparison to wealthier households, poor households appear to be lagging behind in the adoption of mobile money. Later in our econometric analysis, we split up the sample according to wealth category to identify heterogeneous effects of social network variables across wealth categories.

(Figure 1 about here)

Table 6 compares the social network and information access characteristics of poor and wealthy households, presenting differences in means and t-test results. Wealthy households have more exchange adopters in their social network than poor households. This suggests that wealthy households have better access to mobile money information. On the average, wealthy households also have more educated social network contacts than poor households. Based on the number of exchange adopters and network education status, we can argue that poor households are associated with information-poor networks. This result, taken together with earlier descriptive statistics that poor households are lagging behind in mobile money adoption (see also Figure 1), suggests the importance of improving information access especially for the poor.

(Table 6 about here)

Although the comparisons discussed above show some significant differences by adoption and poverty status, these descriptive statistics are not sufficient to explain adoption decisions across sample households, since they do not account for the effects of other household specific characteristics (Abdulai & Huffman, 2014). In the next section, we use a probit model to estimate the effects of social network variables on adoption decisions controlling for variation in household and village level variables.

Econometric results

Estimation results of our regression analyses on the effects of social networks on the adoption of mobile money are presented in Table 7. We estimate four different probit specifications. In the first specification, we include household characteristics and social network information without controlling for village fixed effects. In the second model, we add village fixed effects and robust cluster-correlated standard errors to control for correlated effects. The third model is similar to the second model, only that the wealth variable is excluded. The wealth variable could potentially be endogenous, if the adoption of mobile money leads to greater efficiency in households' business operations and accordingly to higher profits. We try to minimize the endogeneity of the wealth variable by choosing an asset index to measure wealth, which responds more slowly to changes in income flows (Lindelow, 2006; Howe et al., 2008). In addition, we explore how sensitive our results are to the exclusion of the wealth variable. While models 1 to 3 are based on reported network members' mobile money adoption status, model 4 uses actual network members' mobile money adoption status to control for misreporting bias.

(Table 7 about here)

We first discuss models 1 and 2. We find that in the first specification the number of exchange adopters is positive and significant, which suggests that having more exchange adopters in a households' social network is correlated with a higher adoption probability for this household. In the second specification, the variable exchange adopters is also positive and significant at the 5% level, and the marginal effect increases from 0.113 in the first model to 0.131 when controlling for correlated effects in model 2. The fact that the number of exchange adopters in the social network is positive and significant in both models suggests that controlling for individual characteristics (exogenous effects), correlated effects (village fixed effects), and other possible information sources, social learning based on farmer-to-farmer communication may be effective in disseminating information on mobile money innovation and may therefore promote the adoption of mobile money. The variables capturing social network structure, weak ties and network education status, remain insignificant in both models.

After discussing the results of the first and second models, we now compare results from the second and third models, in both of which we control for correlated effects in social networks. The only difference is that in model 3, we exclude the wealth variable. Results in models 2 and 3 are quite similar in signs, and the magnitudes increase only slightly in model 3, suggesting that results are not sensitive to the exclusion of the wealth variable. Given that the wealth variable is not significant once we control for village fixed effects, we proceed excluding the wealth variable in our specifications.

The third and fourth models are quite similar in that we exclude the wealth variable and control for correlated effects. The only difference is that model 4 is based on the actual mobile money adoption status of network members instead of the reported adoption status used in model 3. Results show that the variable, exchange adopter is positive and significant in both models. The marginal effect increases from 0.134 in model 3 to 0.140 in model 4, and the corresponding significance level changes from 5% to 1% level. The variables "weak ties" and "network education status" remain insignificant in both models. Other control variables, such as the number of mobile phones owned, extension contact, and off-farm income activity are all positive and significant at the 1% level in both models. The results in models 3 and 4 are qualitatively and quantitatively similar implying that misreporting bias is not a major issue in our study. In what follows, we thus interpret results based on the reported behaviour of network members (model 3). As discussed earlier there is no appropriate estimator to correct the incidental parameter bias in model 3. As a robustness check, we estimated a linear probability model and a probit model without fixed effects. Table 8 shows the results of linear probability model and probit model without fixed effects alongside results of probit model with fixed effects (model 3).

(Table 8 about here)

We first compare results from model 3 (Probit with fixed effects) against model 5 (LPM with fixed effects). As a rule of thumb we expect to obtain comparable estimates by multiplying the LPM (OLS) marginal effects by 2.5 (Cameron & Trivedi, 2005). For example, the marginal effect of exchange adopters is 0.056 for the LPM model. Multiplying this by 2.5 yields a marginal effect of 0.14 which is comparable to that of probit model. We now compare results from the two probit models: model 3 with fixed effects and model 6 without fixed effects. The marginal effect of exchange adopters is 0.13 in model 3 and not very different to 0.12 in model 6, and the corresponding significance levels remain unchanged at 5% level. The sign and magnitudes of the other social network variables do not change significantly between these two models. These results together with those of the LPM suggest that the inclusion of fixed effects did not distort our estimation results and in particular the social network variables (our variables of interest). This provides us some comfort and we therefore continue and interpret results from model 3.

The results confirm our first hypothesis that the number of exchange adopters affects mobile money adoption. The number of exchange adopters within a household's social network has a positive and significant effect on the adoption of mobile money with an average marginal effect of 0.134. This implies that, on the average, adding one exchange adopter to the household social network increases the probability of adopting mobile money by 13.4%. This result is plausible and emphasizes the crucial role of social learning for the diffusion of mobile money technology. Social networks increase access to information, so that the marginal costs of accessing information for an individual household decrease. This result is in line with other studies indicating that communication within social networks affects financial choices by improving the quantity of information available to the household (e.g. Zhang et al., 2012). When non-adopters interact and discuss about mobile money with adopters, they are better informed and can make their adoption decisions wisely. This shows the importance of learning by communicating and discussing when the technology choices of network members are unobservable to others.

Furthermore, we hypothesized that a larger proportion of weak ties increases the likelihood of mobile money adoption. However, the results show that a larger proportion of weak ties have no influence on the adoption of mobile money. This is in contrast to Zhang et al. (2012) who found that weak ties improve the diversity of information that a household acquires, which leads to higher flexibility in choosing financial intermediaries. Finally, our last hypothesis that households who have a network with higher average educational status are more likely to adopt mobile money is not confirmed either. Similar results are found by Röper et al. (2009) who report that the socio-economic status of network members did not influence the likelihood of finding a home. Our results are at odds with other studies (e.g. Song & Chang, 2012; Lai et al., 1998). Song & Chang (2012) find that education of network members positively influences the frequency of health information seeking. Furthermore, Lai et al. (1998) conclude in their study that social resources positively influence success in job searches.

Model results suggest that mobile money adoption is influenced by the number of exchange adopters in the social network, but not by the structure of the network. Furthermore, besides social network variables, there are other household and contextual characteristics that influence the adoption of mobile money. For example, results reveal that the number of mobile phones owned and contact with mobile-phone based extension services affect the adoption decision positively. This implies that in addition to social networks, households are informed about the existence of mobile money through other information channels, such as mobile phone communication and extension agents. On the average, an additional mobile phone in the household increases the likelihood of mobile money adoption by 23.6%. The mobile-phone based extension system relies on peer farmers (so called community knowledge workers), who receive technical training on the use of smart phones and reside in the same villages with sample households. Our results show that the contact with mobile-phone based extension agents increases the probability of adopting mobile money by 22.3%.

The education of the household head has a positive, but insignificant effect on mobile money adoption. Off-farm income activity is positive and significant at the 1% level. In particular, households with members engaged in off-farm income activities are 19% more likely to adopt mobile money. This is plausible, as most off-farm income activities are conducted outside the village and mobile money is used as one of the channels for remitting money to household members in the village. The district variable is negative and significant at the 1% level. This implies that households located in Kasese district are more likely to adopt mobile money than their counterparts in Mukono. Differences in distance to the capital city may potentially explain our results. Kasese lies about 300 km south-west of the capital city Kampala, while Mukono is only 30 km away from Kampala. Households residing in Kasese and having members working in Kampala may not afford to travel frequently back to their villages because of longer distances. These members may then rely on mobile money services instead to transfer remittances to other household members.

Social network effects by household poverty status

Chang (2005) highlights that wealthier households rely less on social networks and consult different sources of financial information, e.g. newspapers, internet and radio. The poorer oftentimes depend much stronger on social networks as their sole source of information. Even though social networks may be the sole source of information, they may not have an effect on poor households if they are associated with an information-poor network (Liverpool-Tasie & Winter-Nelson, 2012). To formally test the differential impacts of social networks, we estimate separately probit models with fixed effects for poor and non-poor households. In addition we estimate two separate LPM with fixed effects as a robustness check. The regression results are shown in Table 9. As mentioned earlier, we multiply the estimates of LPM by a factor of 2.5 to make them comparable to probit model estimates (Cameron & Trivedi, 2005). After accounting for the conversion factor, the marginal effect of the variable; exchange adopters in the LPM becomes 0.10 and 0.15 for the poor and non-poor households respectively. These results are fairly comparable to the probit model. In addition, the majority of the variables across the two models and poverty categories have the same sign and significance level. Given that the two models yield fairly similar results, in the next section we only interpret results of the probit model with fixed effects.

(Table 9 about here)

For non-poor households, the number of exchange adopters within a household's social network is positive and significant at the 5% level with a marginal effect of 0.120. In contrast, this variable is insignificant for poor households. Furthermore, results reveal that the share of weak ties is positive and significant at the 10% level for non-poor households only. The other variable capturing network structure, network education status, is insignificant for both poverty categories. Our results show that the effects of exchange adopters and weak ties are stronger in the case of non-poor households, a finding that is not in line with Chang (2005) who studied the influence of social networks on sources of financial information. In our study context, poor households may potentially benefit less from social network effects because they are associated with information-poor networks, as shown earlier in Table 6. This interpretation is in line with the findings of Liverpool-Tasie & Winter-Nelson (2012).

Other control variables, including the number of mobile phones owned, extension contact, off-farm income activity and location, are significant in both categories. Age, household size and ethnicity are only significant in the case of poor households. Household size is negative and significant at the 5% level for poor households, indicating that larger households are less likely to adopt mobile money. Furthermore, ethnicity is significant and positive indicating that for poor households belonging to the major ethnic group is critical for mobile money adoption.

Conclusion and policy implications

This article examines the influence of social networks on the adoption of mobile money among rural households in Uganda. Based on innovation diffusion and social network theories, we model mobile money adoption decisions using a probit specification with village fixed effects. We control for household characteristics, correlated effects, and other possible information sources. Empirical results suggest that communication and learning within social networks helps disseminate information about mobile money and increases its adoption. In contrast, the structure of the social network is found to have no significant influence on the adoption of mobile money. In addition to social network effects, the number of mobile phones owned, contact with mobile phone based extension services and the existence of off-farm income activities positively affect the adoption of mobile money. Our results also show that social network effects, and in particular the number of exchange adopters and the share of weak ties in the social network, appear to be more pronounced for non-poor households.

Study findings have important policy implications for the diffusion of mobile money. In particular, they suggest that social networks and mobile-based extension services help disseminate information about mobile money. The adoption of mobile money is likely to be increased if promotion programs enhancing mobile-phone literacy are strengthened and reach more social networks. Scaling up extension services will have positive multiplier effects on the diffusion of mobile money through social networks. Furthermore, extension services need to reach the poor, because our evidence suggests that the poor may be trapped in information-poor networks and thus multiplier effects will most likely not automatically work in their case. Improving rural household's access to informal information channels is particularly important in developing countries, where formal information institutions are lacking.

Mobile money is a relatively new innovation in developing countries and many research questions remain unexplored. This study adds to the emerging literature on mobile money, and in particular on the influence of social networks on the adoption decision. Here, in addition to the number of adopters in the social network with whom the household communicates about mobile money, we use two variables to measure the structure of the social network. Future studies could enhance the analysis by using additional measures of social network structure.

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Table 1. Survey sample differentiated by mobile money adoption and program status

	Mobile Money Non-Adopters	Mobile Money Adopters	Total
Non-program village	119	119	238
Program village	85	154	239
Total	204	273	**477**

Table 2. Variable names, definitions and descriptive statistics

Variable	Definition	Mean	SD	Min	Max
Dependent variables					
Mobile money adoption	Household adopted mobile money: dummy (0;1)	0.57	0.50	0	1
Independent variables					
Social network					
Exchange adopters	Number of mobile money adopters among known matched households that household communicated and discussed about mobile money	0.32	0.91	0	5
Weak ties	Number of weak ties relative to the total number of social network members	0.52	0.40	0	1
Network education	Average years of schooling of social network members	6.33	2.54	0	19
Group membership	Household member(s) belongs to any group: dummy (0;1)	0.70	0.46	0	1
Access to information					
Mobile phone	Number of mobile phones owned by household	1.5	1.16	0	9
Extension contact	Household accesses information from community knowledge worker: dummy (0;1)	0.50	0.50	0	1
Household characteristics					
Age	Age of household head (years)	49.54	13.59	22	86
Age squared	Squared age of household head (years)	2639.47	1427.81	484	7396
Gender	Gender of household head (1=Male)	0.85	0.36	0	1
Education	Education of household head (number of years of schooling)	6.42	4.36	0	20
Household size	Household size (number)	7.00	2.80	1	18
Religion	Main religion of household (1=Christianity; 0 = Islam)	0.87	0.34	0	1
Ethnicity[6]	Household belongs to main ethnic group of the district: dummy (0;1)	0.77	0.42	0	1
Wealth					
Wealth index	The first principal factor from factor analysis	-1.30e-09	0.83	-1.79	2.75
Off farm income activity	At least one household member engaged in off-farm income activity: dummy (0;1)	0.50	0.50	0	1
Transaction costs and location					
MMA distance	Distance to mobile money agent (MMA) in km	2.76	3.33	0	30
District	Household is located in Mukono district: dummy (0;1)	0.50	0.50	0	1

[6] Baganda and Bakonjo are the main ethnic groups in Mukono and Kasese, respectively. If a household did not belong to any of these, it was recoded into ethnic minority.

Table 3. Size of household's social network

Number	Frequency	Percent
1	22	4.61
2	25	5.24
3	70	14.68
4	122	25.58
5	238	49.90
Total	477	100

Table 4. Frequency distribution of adopters and exchange adopters within a household's social network

Number	Adopters (reported)		Adopters (actual)		Exchange adopters (reported)	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
0	370	77.57	125	26.21	403	84.49
1	-	-	-	-	35	7.34
2	43	9.01	133	27.84	19	3.98
3	21	4.40	125	26.21	4	0.84
4	27	5.66	75	15.72	11	2.31
5	16	3.35	19	3.98	5	1.05
Total	477	100	477	100	477	100

Table 5. Mean of social network variables and distance to mobile money agent by mobile money adoption status

	Mobile money adopters	Mobile money non-adopters	Differences *(Non-adopters less adopters)*
Exchange adopters	0.498	0.088	-0.41^{***}
Weak ties	0.54	0.50	-0.04
Network education	6.560	6.027	-0.53^{**}
Group membership	0.766	0.608	-0.16^{***}
Distance to MMA	2.315	3.366	1.05^{***}
Number of observations	273	204	

Comparisons were made between adopters and non-adopters of mobile money using t-test.
*, **, *** indicates the corresponding differences are significant at the 10%, 5%, and 1% levels, respectively.

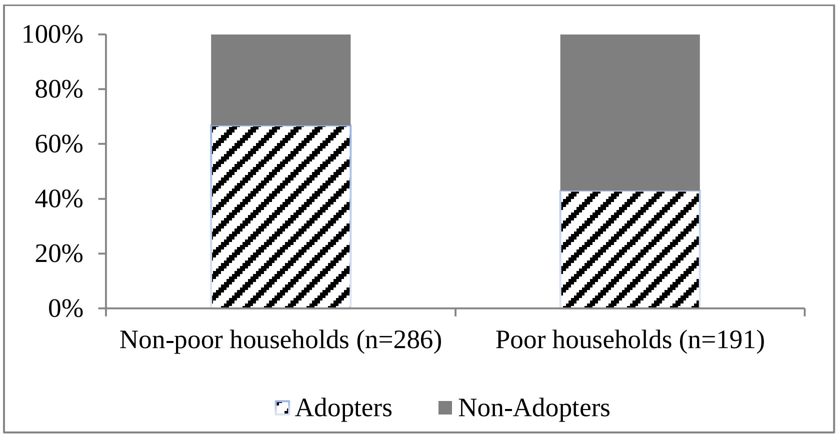

Figure 1. Mobile money adoption differentiated by household poverty levels

Table 6. Mean of social network and information variables by household poverty status

	Poor	Non-poor	Differences *(Non-poor less poor)*
Exchange adopters	0.183	0.416	0.23***
Weak ties	0.492	0.542	0.05
Network education	5.996	6.557	0.56**
Group membership	0.660	0.724	0.06
Mobile phone	1.152	1.755	0.60***
Extension contact	0.445	0.538	0.09**
Distance to MMA	2.755	2.770	0.02
Number of observations	191	286	

Comparisons were made between adopters and non-adopters of mobile money using t-test.
*, **, *** indicates the corresponding differences are significant at the 10%, 5%, and 1% levels, respectively.

Table 7. Determinants of mobile money adoption

	Model 1		Model 2		Model 3		Model 4	
	AME	SE‡	AME	SE‡	AME	SE‡	AME	SE‡
Social network								
Exchange adopters	0.113**	0.055	0.131**	0.058	0.134**	0.058	0.140***	0.052
Weak ties	-0.012	0.063	0.043	0.074	0.036	0.072	0.035	0.072
Network education	0.005	0.010	-0.009	0.015	-0.007	0.015	-0.007	0.015
Group membership	0.042	0.062	0.062	0.075	0.073	0.070	0.077	0.072
Access to information								
Mobile phone	0.231***	0.047	0.230***	0.053	0.236***	0.050	0.237***	0.049
Extension contact	0.103**	0.049	0.220***	0.062	0.223***	0.061	0.224***	0.060
Household characteristics								
Age	0.010	0.013	0.003	0.015	0.004	0.015	0.008	0.016
Age squared	-0.000	0.000	-0.00004	0.0001	-0.00004	0.0001	-0.0001	0.0002
Gender	0.098	0.091	0.144	0.107	0.158	0.104	0.153	0.105
Education	0.011*	0.006	0.010	0.007	0.011	0.007	0.010	0.007
Household size	-0.007	0.012	-0.004	0.014	-0.003	0.014	-0.003	0.014
Religion	0.052	0.079	0.067	0.091	0.068	0.091	0.075	0.089
Ethnicity	0.001	0.062	0.039	0.072	0.048	0.066	0.039	0.066
Wealth								
Wealth index	0.064	0.042	0.054	0.051	-	-	-	-
Off farm income activity	0.158***	0.049	0.185***	0.057	0.190***	0.058	0.193***	0.058
Transaction costs and location								
Distance to MMA	-0.022**	0.009	-0.015	0.010	-0.015	0.010	-0.014	0.010
District	0.151***	0.057	-0.257***	0.080	-0.241***	0.078	-0.226***	0.075
Village control	No		Yes		Yes		Yes	
N	*477*		*465†*		*465†*		*465†*	
Pseudo R^2	*0.311*		*0.351*		*0.349*		*0.343*	
Wald chi2(19)	*163.72****		-		-		-	
Log likelihood	*-224.52*		*-206.93*		*-207.72*		*-209.45*	

Notes: 1.*, **, *** indicates the corresponding marginal effects (AME) are significant at the 10%, 5%, and 1% levels, respectively. Marginal effects and standard errors obtained using the *margins* command in Stata. 2. ‡ Robust cluster-correlated standard errors are reported. 3. Marginal effects of dummy variables reported as discrete change from 0 to 1. 4. †One village is automatically dropped by the probit estimation when village controls are included because all households in that village use mobile money, so the village dummy predicts the adoption outcome perfectly and therefore it returns likelihood either 0 or 1. Log(0) is undefined and log(1) equals to 1 which does not add anything to the total log likelihood. So dropping these observations does not affect the estimation.

Table 8. Determinants of mobile money adoption with robustness checks

	Model 3: same as in Table 7		Model 5: LPM with fixed effects		Model 6: Probit without fixed effects	
	AME	SE‡	AME	SE‡	AME	SE‡
Social network						
Exchange adopters	0.134**	0.058	0.056***	0.017	0.117**	0.054
Weak ties	0.036	0.072	0.025	0.043	-0.020	0.060
Network education	-0.007	0.015	-0.003	0.010	0.008	0.010
Group membership	0.073	0.070	0.050	0.054	0.052	0.061
Access to information						
Mobile phone	0.236***	0.050	0.154***	0.026	0.241***	0.044
Extension contact	0.223***	0.061	-0.077	0.055	0.107**	0.048
Household characteristics						
Age	0.004	0.015	0.005	0.011	0.011	0.013
Age squared	-0.00004	0.0001	-0.000	0.000	-0.000	0.000
Gender	0.158	0.104	0.127*	0.074	0.110	0.089
Education	0.011	0.007	0.009*	0.005	0.013**	0.006
Household size	-0.003	0.014	0.000	0.010	-0.006	0.012
Religion	0.068	0.091	0.021	0.066	0.049	0.079
Ethnicity	0.048	0.066	0.059	0.049	0.007	0.060
Wealth						
Wealth index	-	-	-	-	-	-
Off farm income activity	0.190***	0.058	0.135***	0.040	0.163***	0.050
Transaction costs and location						
Distance to MMA	-0.015	0.010	-0.008	0.006	-0.022***	0.008
District	-0.241***	0.078	0.111***	0.036	0.187***	0.053
Village control	Yes		Yes		No	
N	*465†*		*477*		*477*	
Pseudo R^2/Adjust R^2	*0.349*		*0.314*		-	
Wald chi2(16)	-				*124.37****	
Log likelihood	*-207.72*				*-225.90*	

Notes: 1.*, **, *** indicates the corresponding marginal effects (AME) are significant at the 10%, 5%, and 1% levels, respectively. Marginal effects and standard errors obtained using the *margins* command in Stata. 2. ‡ Robust cluster-correlated standard errors are reported. 3. Marginal effects of dummy variables reported as discrete change from 0 to 1. 4. †One village is automatically dropped by the probit estimation when village controls are included because all households in that village use mobile money, so the village dummy predicts the adoption outcome perfectly and therefore it returns likelihood either 0 or 1. Log(0) is undefined and log(1) equals to 1 which does not add anything to the total log likelihood. So dropping these observations does not affect the estimation.

Table 9. Social network effects differentiated by household poverty status

	Probit with fixed effects				LPM with fixed effects			
	Poor households		Non-poor households		Poor households		Non-poor households	
	AME	SE‡	AME	SE‡	AME	SE‡	AME	SE‡
Exchange adopters	0.126	0.133	0.120**	0.058	0.040	0.052	0.060**	0.024
Weak ties	-0.115	0.187	0.166*	0.097	-0.041	0.106	0.123*	0.067
Network education	-0.013	0.025	-0.023	0.019	0.001	0.019	-0.015	0.013
Group membership	0.167	0.135	0.066	0.082	0.084	0.093	0.049	0.072
Mobile phone	0.374***	0.092	0.161***	0.057	0.207***	0.044	0.117***	0.036
Extension contact	0.729***	0.169	0.207**	0.082	0.119	0.183	0.163**	0.071
Age	0.065*	0.038	-0.009	0.018	0.027*	0.014	-0.003	0.015
Age squared	-0.001	0.0003	0.0001	0.0002	-0.000*	0.000	0.000	0.000
Gender	0.168	0.130	0.127	0.151	0.108	0.090	0.122	0.110
Education	0.006	0.017	0.011	0.009	0.010	0.009	0.009	0.007
Household size	-0.050**	0.020	0.004	0.015	-0.019	0.013	0.007	0.013
Religion	-0.042	0.148	0.226**	0.111	-0.062	0.090	0.121	0.084
Ethnicity	0.338***	0.103	-0.057	0.098	0.224*	0.116	-0.009	0.087
Off farm activity	0.371**	0.155	0.200***	0.073	0.212**	0.092	0.122**	0.056
Distance to MMA	-0.063*	0.035	-0.001	0.009	-0.009	0.012	-0.003	0.009
District	-0.486***	0.123	-0.254**	0.109	-0.304***	0.108	-0.174*	0.091
Village controls	Yes		Yes		Yes		Yes	
N	*179†*		*271†*		*191*		*286*	
Log likelihood	*-58.85*		*-115.29*		*-62.09*		*-124.02*	

Notes: 1.*, **, *** indicates the corresponding marginal effects (AME) and coefficients are significant at the 10%, 5%, and 1% levels, respectively. Marginal effects and standard errors obtained using the *margins* command in Stata. 2. ‡Robust cluster-correlated standard errors are reported. 3. Marginal effects of dummy variables reported as discrete change from 0 to 1.4. † Some villages are automatically dropped by the probit estimation when village controls are included. As explained before, dropping these observations does not affect the estimation.

Appendix

Variables used in constructing wealth index

Table A1. Variables used in constructing wealth index

Dimension	Variable	Definition	Mean	SD	Min	Max
Housing quality	Wall	Main house wall (mud, wood = 0; brick, stone = 1)	0.72	0.45	0	1
	Floor	Main house floor (mud, wood = 0; cement, tiles = 1)	0.49	0.50	0	1
	Roof	Main house roof (grass = 0; iron, tiles = 1)	0.90	0.30	0	1
	Light	Main source of lighting (paraffin, candle = 0; electricity, solar, generator, gas = 1)	0.18	0.39	0	1
Water and sanitation	Toilet	Toilet system (bush = 0; flush, pit, ventilated latrine = 1)	0.99	0.11	0	1
	Water	Source of drinking water (unprotected well = 0; tap, borehole, protected well = 1)	0.71	0.45	0	1
Physical assets	Motor/car	Own motorcycle and or car (no = 0; yes = 1)	0.14	0.35	0	1
	Bicycle	Own a bicycle (no = 0; yes = 1)	0.60	0.49	0	1
	Radio/TV	Household has radio and or TV (no = 0; yes = 1)	0.84	0.36	0	1
	Land	Size of land cultivated (acres)	3.78	3.12	0	20
	Farmequip	Log value of farm equipment	10.75	1.21	7.82	15.41
	TLU	Total livestock units	1.00	1.95	0	21.80

Wealth index factor loadings

Table A2. Wealth index factor loadings

Variable	Factor loading
Wall	0.5447
Floor	0.5888
Roof	0.1218
Light	0.2735
Toilet	0.1018
Water	0.1093
Motor/car	0.3758
Bicycle	0.3581
Radio/TV	0.3210
Land	0.4316
Farmequip	0.4530
TLU	0.4065