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# Social network effects on mobile money adoption in Uganda

Conrad Murendo[a]*, Meike Wollni[a], Alan de Brauw[b] and Nicholas Mugabi[c]

*[a]Department of Agricultural Economics and Rural Development, Georg-August-University of Goettingen, 37073, Goettingen, Germany*

*[b]International Food Policy Research Institute (IFPRI), Washington, DC 20006-1002, USA*

*[c]Grameen Foundation, Kampala, Uganda*

** Corresponding author; phone: +49-551-3920212, fax: +49-551-3920203, e-mail: conrad.murendo@agr.uni-goettingen.de*

***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. This article identifies the effect of social networks on the adoption of mobile money by households in Uganda. Using data from a household survey, conditional logistic regression is estimated controlling for correlated effects and other information sources. Results show that mobile money adoption is positively influenced by the size of social network members exchanging information, and the effect is more pronounced for non-poor households. The structure of social network however has no effect. The findings show that information exchange through social networks is crucial for adoption of 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, D85, O33, Q12

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## 1. Introduction

Mobile money refers to the use of mobile phones to perform financial and banking functions and includes among others remittance transfers, airtime purchase, utility bills and school fees payments, savings and mobile banking (Donovan, 2012; IFC, 2011). 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 (MMA). Since 2009, there are now over 100 million active mobile money users worldwide (GSMA, 2015). In most developing countries there are now more mobile money accounts than bank accounts. According to GSMA (2015), there are currently over 2.3 million mobile money outlets globally and these outnumber the traditional financial and remittance service networks. As of 2013, Uganda had 16.4 million mobile money users[1] compared to 7.6 million individuals who hold bank accounts at financial institutions (InterMedia, 2012; World Bank, 2015). This shows that mobile money users now exceed the number of customers holding conventional bank accounts. Furthermore, there are over 50 000 mobile money agents in Uganda, which reflect more points of financial services compared to the combined 900 bank branches and 800 automated teller machines (GSMA, 2014).

Over the last years, mobile money has emerged as an important innovation with a potential to increase financial inclusion in developing countries in many ways. Mobile money is increasing 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 (Jack et al., 2013; Kikulwe et al., 2014). With mobile money, households can transfer money on their mobile phones without physically visiting the bank or through mobile money agents that are now widespread even in remote villages. This reduces households travel time and costs. Furthermore, mobile money is relatively cheap as it attracts modest and proportionate withdrawal fees (Jack et al., 2013). In addition, mobile money is associated with fast and timely transfer of money, hence reduces transaction costs associated with accessing financial services. Again, mobile money is now being used to facilitate access to insurance, credit and savings even for poor households in remote areas (IFC, 2011).

[1] This includes individuals, households and institutions.

Despite its potential benefits, mobile money has not been widely adopted by rural households in developing countries. According to World Bank (2015), about 35% of the adult population in Uganda is using mobile money, which implies that the technology has not been widely adopted. 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 technology. This is particularly true for developing countries where extension and formal financial information services are underprovided. Social networks constitute an important channel through which households obtain information about new financial innovations and this helps to reduce information asymmetry and transaction costs for innovation adoption (Röper et al., 2009; Zhang et al., 2012). A growing number of recent studies link social networks to financial decision making by rural households (Banerjee et al., 2013; Wydick et al., 2011; Zhang et al., 2012). For example, 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. In Uganda, informal assessments by InterMedia (2012) show that individuals started using mobile money because of recommendations 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 (Kikulwe et al., 2014; Munyegera and Matsumoto, 2014), and adoption of electronic commerce and mobile banking (Drouard, 2011; Gikandi and Bloor, 2010; Goh and Sun, 2014; Goldfarb and Prince, 2008; Narayanasamy et al., 2011; Schierz et al., 2010). Munyegera and Matsumoto (2014) analysed the determinants of mobile money adoption by households in Uganda. Kikulwe et al. (2014) proxied neighbourhood effects by the percentage of households owning a mobile phone at the village level and found a positive effect on mobile money use in Kenya. However, this study fails to capture the presence of information exchange explicitly. Empirical studies analysing the effects of social networks on mobile money adoption are hardly available. Therefore an important research question to answer is: What is the effect of social networks on mobile money adoption?

This essay explores the role of social networks on households' adoption of mobile money in Uganda. More specifically, we use unique social interactions dataset to analyse how information exchange within social networks affect the adoption of mobile money. In addition, we assess whether social network effects vary with poverty status of household. To the best of our knowledge, this has not been systematically analysed in previous studies.

Our results allow drawing some recommendations on whether mobile money technology could be diffused using social networks in Uganda. While our study focuses on mobile money, the results can be applied to other new technologies in developing countries, where information asymmetries limit household's adoption decisions. The remainder of this essay is organised as follows. In the next section we describe 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.

## 2. How mobile money works

Mobile money provides a convenient way to send money to anyone anywhere no matter the network or mobile money service provider. Mobile money service providers work in partnership with one or more banks, making it possible for clients to make banking transactions on their mobile phones without visiting the bank. Mobile money users have two options of conducting mobile money transfers: a) through transfers on their own or on mobile phones of their relatives or friends provided they have activated the mobile money account, and b) visiting a registered MMA, who conducts the transfers on behalf of the client. The mobile money account is an electronic money account which receives electronic value either after the account holder deposits cash through an agent or receives a payment from elsewhere (IFC, 2011).

The services offered by different mobile money service providers have many similarities: They all allow registered mobile money users (individuals, businesses, institutions and so forth) 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). Though mobile money registration is free, all transactions have a predetermined fee (InterMedia, 2012; 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. 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.

For Uganda, Mobile Telephone Network (MTN) launched the first mobile money (*MTN mobile money*) 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*.

## 3. Conceptual framework and hypotheses

In developing countries, social networks are an important source of information because formal information institutions are underprovided. According to Maertens and 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. Our conceptual framework is guided by the social learning theory (Conley and Udry, 2010; Maertens and Barrett, 2013; Van den Broeck and Dercon, 2011). Within this, we identify three social network theories that are relevant for our study: (i) Network size; (ii) Granovetter's strength of weak tie theory (Granovetter, 1973); and (iii) Social resources theory (Lai et al., 1998; Lin et al., 1981; Lin, 1999). The size of network contacts affects the quantity and quality of financial information a household can acquire (Zhang et al., 2012). Households may know someone in their social network 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 and Barrett, 2013), especially for mobile money which is highly unobservable. Hence, we use the size or number of adopters within the social network with whom the household communicates[2] about mobile money (hereafter called *exchange adopters*) to capture information exchange. 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:

[2] This encompasses all forms of communication, for example word of mouth, sms or voice calls and so forth.

**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.

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). Tie strength can be measured by the type of relationship (Granovetter, 1973), the duration of acquaintanceship (Fu et al., 2013; Son and Lin, 2012) 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). 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 (Fu et al., 2013; Son and Lin, 2012). The tie strength among households in a network has an impact on the quality of information transferred and shared. New financial information flows to individuals through weak ties rather than strong ties (Granovetter, 2005; Granovetter, 1973). 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. 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.

The social resources theory considers the structural factors of social networks. The theory posits that social resources (for example wealth, socio-economic status and so forth.) embedded in an individual's social network positively influence information access (Lai et al., 1998; Lin et al., 1981; Song and Chang, 2012). For example, Song and Chang (2012) found that education of network members is positively associated with frequency of health information seeking in USA. Households with more connections to network members with rich socio-economic resources are more active in financial information seeking. People with more socio-economic resources, in particular education, are more active in seeking financial information and are better informed about financial products from different information sources (Röper et al., 2009; Song and Chang, 2012; Zhang et al., 2012). Hence, when connected to network members with higher socio-economic 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). Using network education status and 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 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 (Kikulwe et al., 2014; Munyegera and Matsumoto, 2014). Munyegera and Matsumoto (2014) reported that distance to a mobile money agent had an inverse relationship with the adoption of mobile money. Wealth and asset ownership are also among the factors that have been found to explain adoption (Kikulwe et al., 2014). Generally, households with larger financial capacities are considered to be more prone to technology adoption.

## 4. Econometric estimation

The effect of social network variables on the likelihood of adopting mobile money is estimated using conditional (fixed-effects) logistic regression. The approach of estimating a probit model with village dummies to control for the correlated effects (Liverpool-Tasie and Winter-Nelson, 2012; Matuschke and Qaim, 2009) may be inappropriate in our case. The approach introduces the incidental parameters problem which leads to biased and inconsistent results because the unobserved individual effects are replaced by sample estimates (Fernández-Val, 2009; Lancaster, 2000). We therefore use conditional logistic regression which does not suffer from incidental parameter bias (Allison and Waterman, 2002; Greene, 2012). The conditional logistic regression model for a specified group (village), $k$, is expressed as (Greene, 2012; Yau Fu et al., 2005):

$$\pi_k(x) = \frac{\exp(\beta_{0k}+\beta_x^{'})}{1+\exp(\beta_{0k}+\beta_x^{'})} \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where, k is $1, 2, 3, \ldots, K$. $\pi_k(x)$ is the likelihood that household adopt mobile money. $\beta_{0k}$ is a nuisance or incidental (village specific) parameter, with constant contribution within the $k^{th}$

village. The village-specific parameters $\beta_{0k}$ $(k = 1,2, \dots, K)$ are eliminated from the likelihood by conditioning on the number of positive outcomes in each village. For details on the conditional likelihood and log likelihood see Yau Fu et al. (2005) and Heinze and Puhr (2010). $\beta' = (\beta_1, \beta_2, \beta_3, \dots, \beta_N)$ are coefficients with respect to covariates, $x = (X_1, X_2, X_3, \dots, X_N)$. The covariates of interest are the size of exchange adopters and structure of social network. The other covariates include household and contextual characteristics. We also accounted for access to other information sources by including the number of mobile phones owned by the household and contact with extension (community knowledge worker[3]).

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 and 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 and Barrett, 2013). We randomly

[3] Community knowledge workers are locally recruited peer farmers who are trained by Grameen Foundation to use android smart phones to disseminate agricultural and market information to fellow farmers in their respective villages.

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 (for example 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. The two types of endogenous effects relevant for our context are *instrumental and informational conformity* (Au and Kauffman, 2008; Wydick et al., 2011). *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. *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. 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.

## 5. Methodology

### 5.1. 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. The selection of villages was such that they share similar agro-ecological characteristics. 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. From the mobile money module, we are able to distinguish between households using mobile money and those who are not, based on questions pertaining to the use of mobile money services. Our analysis is therefore based on a random sample of 273 mobile money adopters and 204 non-adopters across the two districts as shown in Table 1.

*(Table 1 about here)*

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, food and non-food consumption, income, mobile phone ownership and use, mobile money services, household assets and information sources including social networks. In this study, a household is classified as mobile money adopter (user)[4] 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 (Kikulwe et al., 2014).

### 5.2. Measuring social networks

We used the random matching within sample approach to collect social network data (Maertens and Barrett, 2013). According to Maertens and 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

[4] Mobile money user and adopter are used interchangeably.

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*: As earlier discussed, this was computed as the number of mobile money adopters within the household's social network with whom the household communicated about mobile money over the past 12 months. In line with Maertens and Barrett (2013), our measure captures the presence of information exchange within social networks. This variable 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 and 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 *network education status*:

*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 socio-economic status.

## 5.3. 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

[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.

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 2 present the descriptive information of variables used to construct the wealth index and their factor loadings. 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 and 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 40$^{th}$ percentile of the wealth index are categorized as poor and all others as non-poor. Sahn and Stifel (2000) also applied the asset poverty approach and used the 40$^{th}$ percentile as a cut off-point for poverty categories.

*(Table 2 about here)*

## 6. Results and discussion

### 6.1. Results of descriptive analyses

Overall, 57% of the households in our sample adopted mobile money (Table 3). Eighty three percent of the households in the sample own a mobile phone and on average, households own 2 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 3 about here)*

Table 4 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 4 about here)*

Table 5 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 that is 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 5 about here)*

Table 6 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 6 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 social network effects.

*(Figure 1 about here)*

Table 7 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. The descriptive statistics suggest that poor households are lagging behind in mobile money adoption highlighting the importance of improving information access especially for the poor.

*(Table 7 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. In the next section, we use econometric techniques to estimate social network effects.

## 6.2. Econometric results

### 6.2.1. Effect of social network on mobile money adoption

Estimation results of the effects of social networks on adoption of mobile money are presented in Table 8. We estimate four different model specifications. In all models, we report the exponentiated coefficients (odds-ratios), which may be interpreted as the estimated odds of change in mobile money adoption as a result of a unit change in the independent variable (Gould, 2000). In the first specification, we estimate an ordinary logistic regression without controlling for correlated effects. In the second model, we estimate conditional logistic regression with 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 (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 8 about here)*

In models 1 and 2 the size of exchange adopters is positive and significant at the 5% level. The exponentiated coefficient decreases from 1.80 in first model to 1.75 when controlling for correlated effects in model 2. The variables capturing social network structure, weak ties and network education status, remain insignificant in both models. Therefore the size of exchange adopters in the social network positively influences the adoption of mobile money. In the second and third models 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 size of exchange adopters is positive and significant in both models. The exponentiated coefficient decreases from 1.77 in model 3 to 1.70 in model 4, and the corresponding significance level changes from 5% to 10% 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 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).

The results confirm our first hypothesis that the size of exchange adopters affects mobile money adoption. The size of exchange adopters within a household's social network has a positive and significant effect on the adoption of mobile money with an exponentiated coefficient of 1.77. This implies that adding one exchange adopter to the household social network increases the odds of adopting mobile money by 77%. 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 (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 that social learning may be effective in disseminating information on mobile money technology and may therefore promote the adoption of mobile money.

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 financial information that a household acquires. 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 (Lai et al., 1998; Lin, 1999; Song and Chang, 2012). For example, Song and Chang (2012) find that education of network members positively influences the frequency of health information seeking. Model results suggest that mobile money adoption is influenced by the size of exchange adopters in the social network and not by the structure of social network. Therefore the effects of social network structure depend upon the type of technology under study and should not be generalized.

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 gender of head 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. Mobile phone is positive and highly significant with an odds ratio of 3, which means that the odds of adopting mobile money are 3 times higher for households with more mobile phones. This is expected as households can transact mobile money on their own mobile phones as long as the mobile money account is registered. Our results show that male headed households have a higher likelihood of adopting mobile money compared to female headed households. Off-farm income activity is positive and significant at the 1% level. In particular, households with members engaged in off-farm income activities have a 2-fold greater odds of adopting mobile money compared to those with no off-farm income. 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.

### 6.2.2. 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, for example 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 and Winter-Nelson, 2012). To formally test the differential impacts of social networks, we estimate conditional logistic regression models separately for poor and non-poor households. The regression results are shown in Table 9.

*(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 an exponentiated coefficient of 1.8. In contrast, this variable is insignificant for poor households. The other variables capturing network structure: weak ties and network education status are insignificant for both poverty categories. Our results show that the effects of size of exchange adopters is 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 7. This interpretation is in line with the findings of Liverpool-Tasie and Winter-Nelson (2012).

Other control variables, including the number of mobile phones owned and off-farm income activity are positive and significant in both categories. Ethnicity is positive and significant only in the case of poor households indicating that for poor households belonging to the major ethnic group is critical for mobile money adoption. On the other hand, religion is positive and highly significant for non-poor households.

## 7. Conclusion and policy implications

This article examines the influence of social networks on the adoption of mobile money among rural households in Uganda. We estimate conditional logistic regression to control for household characteristics, correlated effects, and other possible information sources without introducing the incidental parameter bias. Empirical results show that the size of exchange adopters positively influence the adoption of mobile money. This suggests that information exchange 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 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 size of exchange adopters appear to be more pronounced for non-poor households.

Study findings have important policy implications for the diffusion of mobile money in developing countries, where formal information institutions are lacking. They suggest that exchange within social networks help disseminate information about mobile money. The adoption of mobile money is likely to be increased if promotion programs reach more social networks. Furthermore, mobile money promotion programs need to reach the poor, because our evidence suggests that the poor may be trapped in information-poor networks and thus social network multiplier effects will most likely not automatically work in their case. Therefore, there is need to target mobile money promotion programs to reach the poor. One possible promotion strategy is the provision of mobile money education and awareness campaigns in rural areas. Making rural households more aware about mobile money, its use and advantages is likely to improve adoption. In particular, mobile money service providers should be at the forefront of rolling out mobile money promotion programs because they stand to benefit financially if more households adopt mobile money. From a policy perspective, there is a need for policy makers, mobile money service providers and extension to strengthen and utilize informal institutions to disseminate information about mobile money.

Mobile money is a relatively new technology 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. The study has limitations that are worth mentioning. We use only two variables to measure the structure of the social network. Future studies could enhance the analysis by using additional measures of social network structure, for example difference in educational attainment level, age and distance of network members relative to interviewed household. In addition, other drivers of adoption, for example: consumer protection, perception of fraud and security associated with mobile money are not accounted in this study. Our study uses cross-section data which is static and relates to current effect. Such a static analysis fails to account for the dynamic nature of social networks. Further research might need to build on panel data to explore the effects of social networks over time.

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**Table 1.** Sample differentiated by mobile money adoption status

| | Non-Adopters | Adopters | Total |
|---|---|---|---|
| Mukono | 92 | 147 | 239 |
| Kasese | 112 | 126 | 238 |
| Total | 204 | 273 | **477** |

**Table 2.** Variables used in constructing wealth index and their factor loadings

| Dimension | Variable | Definition | Mean | SD | Factor loading |
|---|---|---|---|---|---|
| Housing quality | Wall | Main house wall (mud, wood = 0; brick, stone = 1) | 0.72 | 0.45 | 0.5447 |
| | Floor | Main house floor (mud, wood = 0; cement, tiles = 1) | 0.49 | 0.50 | 0.5888 |
| | Roof | Main house roof (grass = 0; iron, tiles = 1) | 0.90 | 0.30 | 0.1218 |
| | Light | Source of lighting (paraffin, candle = 0; electricity, solar, generator, gas = 1) | 0.18 | 0.39 | 0.2735 |
| Water and sanitation | Toilet | Toilet system (bush = 0; flush, pit, ventilated latrine = 1) | 0.99 | 0.11 | 0.1018 |
| | Water | Source of drinking water (unprotected well = 0; tap, borehole, protected well = 1) | 0.71 | 0.45 | 0.1093 |
| Physical assets | Motor/car | Own motorcycle and or car (no = 0; yes = 1) | 0.14 | 0.35 | 0.3758 |
| | Bicycle | Own a bicycle (no = 0; yes = 1) | 0.60 | 0.49 | 0.3581 |
| | Radio/TV | Household has radio and or TV (no = 0; yes = 1) | 0.84 | 0.36 | 0.3210 |
| | Land | Size of land cultivated (acres) | 3.78 | 3.12 | 0.4316 |
| | Farmequip | Log value of farm equipment | 10.75 | 1.21 | 0.4530 |
| | TLU | Total livestock units | 1.00 | 1.95 | 0.4065 |

**Table 3.** Variable names, definitions and descriptive statistics

| Variable | Definition | Mean | SD |
|---|---|---|---|
| *Dependent variables* | | | |
| Mobile money adoption | Household adopted mobile money: dummy (0;1) | 0.57 | 0.50 |
| *Independent variables* | | | |
| *Social network* | | | |
| Exchange adopters | Number of mobile money adopters household communicated about mobile money | 0.32 | 0.91 |
| Weak ties | Number of weak ties relative to total number of social network members | 0.52 | 0.40 |
| Network education | Years of schooling of social network members | 6.33 | 2.54 |
| Group membership | Household member(s) belongs to any group: dummy (0;1) | 0.70 | 0.46 |
| *Access to information* | | | |
| Mobile phone | Number of mobile phones owned by household | 1.5 | 1.16 |
| Extension contact | Household accesses information from community knowledge worker: dummy (0;1) | 0.50 | 0.50 |
| *Household characteristics* | | | |
| Age | Age of household head (years) | 49.54 | 13.59 |
| Age squared | Squared age of household head (years) | 2639.47 | 1427.81 |
| Gender | Gender of household head (1=Male) | 0.85 | 0.36 |
| Education | Education of household head (years of schooling) | 6.42 | 4.36 |
| Household size | Household size (number) | 7.00 | 2.80 |
| Religion | Main religion of household (1=Christianity; 0 = Islam) | 0.87 | 0.34 |
| Ethnicity[6] | Household belongs to main ethnic group: dummy (0;1) | 0.77 | 0.42 |
| *Wealth* | | | |
| Wealth index | The first principal factor | -1.30e-09 | 0.83 |
| Off farm income | Household member engaged in off-farm income : dummy (0;1) | 0.50 | 0.50 |
| *Location* | | | |
| MMA distance | Distance to mobile money agent (MMA) in km | 2.76 | 3.33 |
| District | Household located in Mukono district: dummy (0;1) | 0.50 | 0.50 |

[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 4.** 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 5.** Frequency distribution of 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 6.** Social network variables by adoption status

| | Adopters | Non-adopters | Differences |
|---|---|---|---|
| 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*** |
| *Observations* | 273 | 204 | |

*, **, *** indicates the corresponding differences are significant at the 10%, 5%, and 1% levels, respectively (t-test).

**Table 7.** Social network and information variables by poverty status

| | Poor | Non-poor | Differences |
|---|---|---|---|
| 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 |
| *Observations* | 191 | 286 | |

*, **, *** indicates the corresponding differences are significant at the 10%, 5%, and 1% levels, respectively (t-test).

**Table 8.** Determinants of mobile money adoption: Conditional logistic regression

| | Model 1: logit | | Model 2 | | Model 3 | | Model 4 | |
|---|---|---|---|---|---|---|---|---|
| | EC | Std. err.‡ | EC | Std. err.‡ | EC | Std. err.‡ | EC | Std. err.‡ |
| *Social network* | | | | | | | | |
| Exchange adopters | 1.800** | 0.444 | 1.752** | 0.396 | 1.773** | 0.402 | 1.704* | 0.472 |
| Weak ties | 0.876 | 0.231 | 1.114 | 0.375 | 1.075 | 0.359 | 1.066 | 0.354 |
| Network education | 1.015 | 0.045 | 0.964 | 0.068 | 0.969 | 0.068 | 0.973 | 0.068 |
| Group membership | 1.215 | 0.344 | 1.329 | 0.398 | 1.404 | 0.415 | 1.432 | 0.421 |
| *Access to information* | | | | | | | | |
| Mobile phone | 3.407*** | 0.810 | 2.944*** | 0.512 | 3.029*** | 0.522 | 3.054*** | 0.523 |
| Extension contact | 1.475* | 0.325 | | | | | | |
| *Household characteristics* | | | | | | | | |
| Age | 1.052 | 0.062 | 1.009 | 0.064 | 1.010 | 0.064 | 1.026 | 0.065 |
| Age squared | 1.000 | 0.001 | 1.000 | 0.001 | 1.000 | 0.001 | 1.000 | 0.001 |
| Gender | 1.549 | 0.619 | 1.743 | 0.632 | 1.831* | 0.658 | 1.791 | 0.640 |
| Education | 1.037 | 0.029 | 1.030 | 0.033 | 1.035 | 0.033 | 1.034 | 0.033 |
| Household size | 0.976 | 0.050 | 0.993 | 0.050 | 0.997 | 0.050 | 0.993 | 0.049 |
| Religion | 1.295 | 0.454 | 1.434 | 0.511 | 1.451 | 0.516 | 1.482 | 0.526 |
| Ethnicity | 0.999 | 0.274 | 1.237 | 0.412 | 1.288 | 0.425 | 1.238 | 0.406 |
| *Wealth* | | | | | | | | |
| Wealth index | 1.289 | 0.240 | 1.222 | 0.225 | | | | |
| Off farm income | 2.007*** | 0.472 | 2.007*** | 0.536 | 2.045*** | 0.545 | 2.064*** | 0.549 |
| *Location* | | | | | | | | |
| Distance to MMA | 0.905*** | 0.034 | 0.934 | 0.047 | 0.937 | 0.048 | 0.941 | 0.048 |
| District | 1.964*** | 0.489 | | | | | | |
| *Observations* | *477* | | *465†* | | *465†* | | *465†* | |
| *Pseudo $R^2$* | *0.324* | | *0.317* | | *0.314* | | *0.307* | |
| *Wald chi2(17)/LR chi2(15)* | *135.51**** | | *146.10**** | | *144.91**** | | *141.47**** | |
| *Log likelihood* | -220.14 | | *-157.50* | | -158.10 | | -159.82 | |

Notes: *, **, *** indicates the corresponding exponentiated coefficients (EC) are significant at the 10%, 5%, and 1% levels, respectively. ‡ Cluster-correlated standard errors are reported to account for the fact that standard errors across households within the same village may be correlated. †One village is automatically dropped by the estimation because all households in that village use mobile money. From model 2 onwards, Extension contact and District variables have constant within-group effect and are omitted during estimation. This does not affect the estimation results (Gould, 2000).

**Table 9.** Social network effects differentiated by poverty status

| | Poor households | | Non-poor households | |
|---|---|---|---|---|
| | EC | Std. err. | EC | Std. err. |
| Exchange adopters | 1.677 | 0.856 | 1.802** | 0.477 |
| Weak ties | 0.678 | 0.456 | 1.856 | 0.870 |
| Network education | 0.949 | 0.118 | 0.902 | 0.091 |
| Group membership | 1.882 | 1.143 | 1.233 | 0.493 |
| Mobile phone | 3.851*** | 1.393 | 2.316*** | 0.498 |
| Age | 1.257 | 0.189 | 0.961 | 0.087 |
| Age squared | 0.998 | 0.001 | 1.000 | 0.001 |
| Gender | 1.679 | 1.293 | 1.672 | 0.883 |
| Education | 1.014 | 0.067 | 1.051 | 0.048 |
| Household size | 0.847 | 0.086 | 1.032 | 0.067 |
| Religion | 0.884 | 0.651 | 2.619** | 1.250 |
| Ethnicity | 4.823* | 3.942 | 0.838 | 0.387 |
| Off farm income | 3.993** | 2.245 | 2.370** | 0.910 |
| Distance to MMA | 0.798 | 0.114 | 0.995 | 0.052 |
| *Observations* | *179* | | *271* | |
| *Pseudo $R^2$* | *0.478* | | *0.298* | |
| *LR chi2(14)* | *69.96**** | | *67.63**** | |
| *Log likelihood* | *-38.19* | | *-79.68* | |

*, **, *** indicates the corresponding exponentiated coefficients (EC) are significant at the 10%, 5%, and 1% levels, respectively.

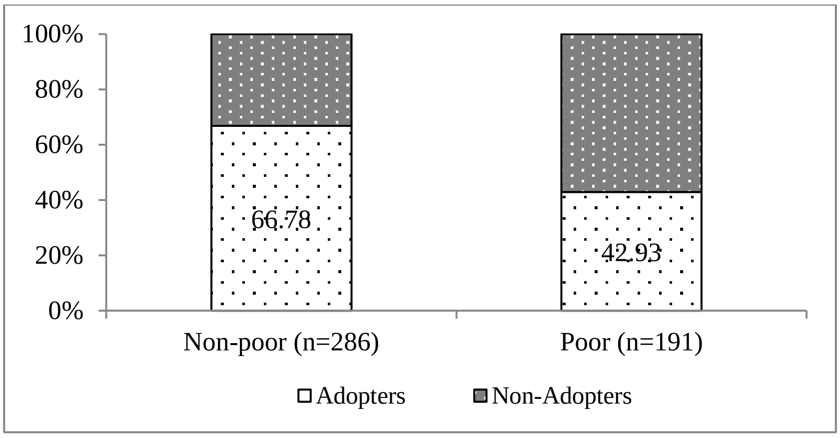


**Figure 1.** Mobile money adoption differentiated by household poverty