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Abstract

Innovative financial technologies are becoming a pathway to inclusive economic participation for individuals and firms. This paper presents evidence on how individuals' decisions to adopt such technology, particularly mobile money, relate to the adoption choices of their network of family and friends. Using the Uganda Financial Inclusion Insights (FII) Tracker Survey for 2013, we find that mobile money adoption decisions are closely linked to the network of an individual's family and friends. Networks are defined in two ways: by the source of information on mobile money services and by the average number of adoptions in one's neighbourhood. Like many other studies, we find a positive correlation between mobile money adoption and the adoption decisions of one's network. The correlation persists across the different measures of networks and even when we control for unobservable (neighbourhood fixed effects) characteristics. However, the magnitude of the point estimates decreases as the model becomes saturated. Despite having more mobile money users than adopters in our sample, we do not find evidence that networks can stifle technology adoption due to the possibility of piggybacking on early adopters within the network.

Keyword: Social Ties, Information Network, Mobile Money Adoption, Uganda

1. Introduction

The limitations of providing conventional banking and financial services such limited availability and affordability, have paved the way for mobile money technology which facilitates transactions using a cellular telephone in many developing countries. This new branchless banking technology is a key route out of informal banking for many in the developing world. It reaches farther and deeper into historically marginalised and unbanked communities, thus addressing some of the challenges (traveling to and queuing at distant branches) associated with using the conventional banking system. However, while mobile money (MM) technology has the potential to serve the 1.7 billion financially excluded individuals in developing countries (Demirguc-Kunt et al, 2018), its adoption has been slow in many societies, as some aspects of the adoption process are still poorly understood. This might compromise the scaling up of mobile money and thus its role in enhancing financial inclusion.

Several studies have shown that individual characteristics are important determinants of the adoption of mobile money technologies (Abdinoor and Mbamba, 2017; Khan and Blumenstock, 2017; Afawubo et al., 2017; Gichuki and Mulu-Mutuku, 2018). It is evident that perceived trust significantly influences consumer behaviour towards the adoption of electronic commerce transactions, including mobile money (Mallat, 2007; Tobbin and Kuwornu, 2011). This suggests that the source of awareness or social ties could be an important determinant of mobile money adoption. While social ties and peer effects have been shown to significantly influence most individual and economic outcomes (Maertens and Barrett, 2012; Dahl et al., 2014; Angrist, 2014; Mukong, 2017), little is known about their effect on mobile money technology adoption. Economists suggest that many individual decisions, including labour market decisions (Burns et al., 2010; Angrist, 2014), education attainment (Burke and Sass, 2013), welfare participation (Bertrand et al., 2000; Dahl et al., 2014), health and health care use (Deri, 2005; Fortin and Yazbeck, 2015; Mukong and Burns, 2015), substance use (McVicar and Polanski, 2014; Mukong, 2017), internet adoption (Lu et al., 2005) and agricultural technology adoption (Bandiera and Rasul, 2006; Maertens and Barrett, 2012) are positively correlated with the behaviour of the social group the individual belongs to. This paper contributes to this literature by investigating the effect of social networks on mobile money technology adoption.

Insights from long-standing sociology literature on social networks, have been fruitfully applied by economists in several important areas of economic research including the aforementioned. According to Bertrand et al., (2000), networks work through information sharing among contacts (awareness depends on how knowledgeable one's friends or neighbours are) and norms (preferences influenced through taste or social pressure). However, very few datasets contain information on one's actual social contacts, making the empirical evaluation of network effects extremely problematic [3] . Some measure of spatial ethnic concentration has been commonly used as a proxy for network availability. The underlying assumption is

[3] In practice, it is empirically difficult to verify the effects peers exert on each other's behaviour (Devillanova, 2008). The difficulty stems from the problem of separating the impact of peer behaviour on own behaviour (endogenous effects), from the impact of peer characteristics (contextual or exogenous effects) and/or correlated unobservable factors (correlated effects) on own behaviour (Manski, 1993; Manski et al., 2000).

that individuals from the same ethnic group in a given geographical area are more likely to spend time together and obtain information from each other. This approach has been used to study the take-up of welfare programs (Bertrand et al., 2000; Aizer and Currie, 2004; Deri, 2005; Aslund and Fredriksson, 2009; Dahl et al., 2014). However, the positive correlation between an individual's outcomes and the average behaviour of his/her reference group only provides a potential network effect and a valid identification strategy is required to carefully address the reflection problem highlighted by Manski (1993), that is, how the individual's behaviour influences the network he/she is a member of.

We test the hypotheses as to whether and how the different sources of information (family/friends and media) available to individuals separately affect their decision to adopt mobile money technology. Unlike many of the existing literature, this approach allows us to escape the reflection problem. The paper utilises the 2013 Financial Inclusion Insights (FII) Tracker Survey for Uganda. The richness of the data allows us to address, to a greater extent, many of the identification issues characterising non-experimental studies[4]. This study contributes to the body of literature in the following ways. First, very few studies have quantified the effect of social networks on mobile money technology adoption (Murendo et al., 2018; Okello et al., 2018; Kiconco et al., 2020). However, existing studies focus on a small group of individuals and are hence likely to suffer from external validity. The current study uses a nationally representative sample to explore network effects under the actual contact availability measure rather than the endogenous potential contact availability measure that has dominated the social network literature. The estimation strategy, besides avoiding the endogenous network measure, controls for the possible preference heterogeneity of individuals by evaluating the effects of social networks across social groups. The social groups are differentiated by income, education, gender and bank account ownership. Social networks are thus captured by the source of information. Three sources are identified: media, mobile money field agents/promoters and family/relatives and friends. Mobile money technology use and adoption is captured by a self-reported use of mobile money and ownership of an active mobile money account. We use a probit and a linear probability model to estimate the effect of social networks on the probability of adoption and use of mobile money technology.

Results show that the network of family and friends, as well as other sources of information such as media and mobile money field agents, increases the probability of adoption and use of mobile money technology in Uganda. On average, there are more users than adopters as it is possible for individuals to send and

[4] Devillanova (2008) noted that this is the best way to quantitatively address the identification (reflection) problem highlighted in Manski (1993) and Manski et al. (2000). He further noted that even if information network is imperfectly captured by the proposed measure, the attenuation bias applies and the estimated network effects are biased towards zero.

receive money through an agent or a friend's account. Subsequently, the probability of owning and using mobile money technology increases by 0.57 and 0.38 respectively if the source of information is a mobile money field promoter/agent. On the other hand, these probabilities increase by 0.47 and 0.32 if the individual receives information from the media, while family and friends increase the probability by 0.46 and 0.28 for use and technology adoption respectively. The network effects are generally higher among the unbanked, women, the less educated and high-income individuals. These results suggest that a possible way of scaling up mobile money technology adoption is by leveraging the existing agent infrastructure, including providing them with more information. Mobile money service providers would most likely invest in media, yet these results show that mobile money agents might offer a more effective channel of information sharing on mobile money technology adoption.

The rest of the paper is organised as follows. The next section provides an overview of the development of the mobile money technology. This is followed by a review of the theoretical and empirical perspectives in Section 3. The empirical approach is discussed in Section 4 and results are reported and discussed in Section 5. Section 6 concludes.

2. The Development of Mobile Money Technology

In recent decades, there has been a surge in mobile phone ownership in the developing world (GSMA, 2017). For instance, 50% of Africans have mobile phones and penetration is expanding rapidly[5]. This rapid uptake of mobile telephony has been accompanied by many wireless applications that are of relevance in addressing the needs of individuals and the emergence of small business enterprises. One notable application is the use of mobile phones for financial transactions. Individuals can use their mobile phones for mobile banking or for mobile money transactions. In the former, users are required to have a bank account. They can then download a banking application onto their cellular phones, which allows them to transact without going to the bank, allowing for shorter transaction time. Mobile banking can also take the form of bank officials using movable units to service clients in remote areas where banks do not have physical infrastructure. Mobile money, on the other hand, does not require the user to open a bank account. This technology not only saves time, it also allows individuals at the lower end of the income spectrum to transact with minimal costs. Funds can change hands instantaneously and agents are often in the same location as users.

[5] See "2010 Global Mobile Communications - Key Trends and Growth in a Challenging Environment - BuddeComm". www.budde.com.au

Over one billion of the “unbanked” individuals have access to mobile phones and can be financially included through mobile money technology adoption (GSMA, 2017). Originating from Kenya in East Africa, mobile money has become one of the cheapest, fastest, more reliable, flexible and easily accessible methods of financial transacting compared to other systems it substituted in nearly 90 countries worldwide (GSMA, 2017). The greatest share of mobile money transactions presumably takes place between household members, relatives and friends. Thus, the utility from (and ultimately the benefits of) having a mobile money account is expected to increase when other household members, friends and relatives own mobile money accounts or if they subscribe to the same mobile money platform. Therefore, social ties and information spill-over (networks) between household members, relatives and friends are expected to significantly increase the probability of mobile money technology adoption.

By 2017, Sub-Saharan Africa (SSA) was leading with over 49.1 percent of the globally registered MM customers (GSMA, 2017). Within Africa, the East African Community (EAC) is at the forefront with over 56.4 percent registered MM customers (GSMA, 2017). Relative to Kenya, other East African countries are lagging with lower subscription rates. This could in part, be a function of the number of platforms, with implication for the level of competition among the mobile network operators (MNOs). However, Uganda has unique characteristics that distinguish its mobile money market from the other major markets (Kenya and Tanzania) in the region. It has the highest number of mobile money platforms in the region. The country has also witnessed a high level of entry and exit of MNOs, which has implications for trust and the probability of mobile money account holding as a result of the marketing strategy of new MNOs. This suggests that social ties and the source of information are likely to play an important role in mobile money adoption in such an economy.

3. Theoretical and Empirical Perspective.

There exists sizeable differences in the utilisation of welfare programs and technology adoption between ethnic groups. These differences tend to persist across generations and overtime, posing important policy challenges (Duggan and Kearney, 2005). For instance, Currie (2006) documents that take-up rates of social programs in the United Kingdom and the United States vary substantially across ethnic groups. This implies that social programs may not be fully successful in reaching the targeted groups (Devillanova, 2008). In most cases, those at the bottom of the economic pyramid (the poor) are more likely to be eligible for welfare programs and their take-up rates increase with awareness and accessibility. The mechanisms through which welfare cultures and technology adoption are transmitted across individuals and generations is known as social networks. This paper uses one of these mechanisms (information network) to show the effect of social ties on mobile money adoption.

Sociologists have long emphasized the importance of networks in shaping an individual's behaviour (Portes and Sensenbrenner, 1993; Portes, 1995). In recent decades, insights from this literature have attracted considerable interest from economists who have applied it in several areas of economic research (Bertrand et al., 2000; Topa, 2001; Deri, 2005; Devillanova, 2008). Social networks can provide information to individuals on availability of services, their location, eligibility criteria, procedures of application and other relevant details (information channel) and can equally create peer pressure and alter service utilisation (norm channel). The information channel is relatively more important for policies aimed at increasing technology adoption. The information channel can be formal through media and newspapers, and informal through household members, friends and relatives (Devillanova, 2008).

Quantifying the effects of networks on individual and economic outcomes can be challenging, mainly due to data limitation. Consequently, the network effects literature highly overlaps with the neighbourhood effects and ethnic or language enclave literature, as empirical evidence often uses spatial concentration of ethnic groups as a proxy for contact availability. The crucial assumption of this approach is that individuals mainly interact with geographically close people of the same ethnic group. The setbacks of this approach, however, come from the fact that a positive correlation between an individual's outcome and the average behaviour of his\her reference group does not provide conclusive evidence of network effects, especially when the well understood reflection problem is not properly handled[6].

Many researchers have fruitfully used this approach to study the take-up of welfare programs (Bertrand et al., 2000; Aizer and Currie, 2004; Deri, 2005) and labour market outcomes (Oreopoulos, 2003; Munshi, 2003; Burns et al., 2010). To reduce some of the biases resulting from the reflection problem, the quantity of networks (number of people in one's geographical area who speak the same language) is interacted with the quality of networks (average welfare use of the language group). These studies provide evidence that networks are essential in shaping the take-up of publicly provided welfare programs. Using a natural experiment, Aslund and Fredriksson (2009) show that only the quality of contacts matters in welfare

[6] Manski (1993); Manski et al. (2000) highlighted that causal statements between social networks and individual outcomes cannot be established due to two related omitted variable biases. First, omitted individual characteristics could be correlated with average group outcome. For instance, individuals residing where the incidence of mobile money adoption is low may be less motivated to demand mobile money services. Second, omitted neighbourhood characteristics may be correlated with mean incidence of non-use of mobile money services in that locality. For instance, urban areas may have abundant mobile money agents that increase accessibility and may increase the probability of adoption. Finally, individuals select their contacts and those with many contacts may be qualitatively different from those with few contacts. Estimates derived in this manner may suffer from omitted variable bias.

participation. This indicates the need to understand the role of actual rather than potential contacts on welfare program participation and technology adoption.

However, these studies are limited as they say little or nothing about how networks actually work. Specifically, it is not trivial to ascertain the relative importance of both channels (information and norms) through which social contacts may affect an individual's behaviour. Devillanova (2008) shows that reliance on a strong social tie reduces the delay to seek care by 30 percent and the effects are stable across specifications. In addition, Daponte et al. (1999) and Heckman and Smith (2004) find that racial differences in welfare program participation are determined by whether the individuals are aware of the program or not. Using a randomized experiment, Duflo and Saez (2003) show that the decision to enrol in a retirement plan is a result of information that increases through social interaction. It should be noted that with the exception of studies that use an experimental approach, many rely on potential rather than actual contacts as a measure of information spill-over. Besides the endogeneity problem associated with the use of potential contacts, the literature generally ignores the possibility of preference heterogeneity between social groups.

There is vast evidence on the determinants of mobile money, electronic commerce and mobile banking adoption in developing countries (Drouard, 2011; Narayanasamy *et al.,* 2011; Goh and Sun, 2014; Munyegera and Matsumoto, 2016). These studies identify the important constraints and drivers of mobile money adoption, but fail to account for the effects of social networks. However, recent literature argues that the information asymmetries gap is one possible reason for households' or individuals' limited ability to make informed decisions about the uptake of mobile money in developing countries (Murendo *et al.,* 2018; Okello *et al.,* 2018). Information networks help reduce information asymmetries and transaction costs for financial innovation adoption (Zhang *et al.,* 2012). A number of studies have shown that social network is an important determinant of financial decision-making (Banerjee *et al.,* 2013; Zhang *et al.,* 2012; Wydick *et al.,* 2011) and mobile money adoption among rural households (Murendo *et al.,* 2018; Okello *et al.,* 2018; Kiconco *et al.,* 2020). Informal assessments by InterMedia (2012) show that individuals started adopting mobile money because of recommendations from friends, family members or other acquaintances. While this study did not provide rigorous econometric evidence, Murendo *et al.,* (2018) use rigorous econometric techniques and further confirm that mobile money adoption is positively influenced by the size of the social network with which information is exchanged. The effect was particularly pronounced for non-poor households. Kiconco *et al.,* (2020) compared network effects between a rural and an urban region and concluded that network effects are more substantial in the rural than the urban region.

While these studies focus on a small group of individuals, the current study uses a nationally representative sample to explore network effects under the actual contact availability measure rather than the endogenous potential contact availability measure that has dominated the literature. The paper attempts to contribute to this existing literature by using a novel dataset and research design to quantify the impact of strong social ties on mobile money technology adoption controlling for the possibility of preference heterogeneity between individuals. The data was collected by InterMedia and the Bill and Melinda Gates Foundation, and it provides strategic information for the analysis of mobile money adoption. The data provides several features which are discussed in detail in Section 4.1.

4. Research Methodology

4.1 Model Specification

We investigate the effect of social networks as a determinant of the use and adoption of mobile money technology. We posit that individual i adopts mobile money technology if the present value of expected utility from adopting exceeds the present value of expected utility from choosing other available financial transaction mechanisms. However, *i's* likelihood of adoption also depends on the precision of his/her beliefs on the new technology and the information he/she receives from his/her network. We measure the information available to individual i by first focusing on the major source of information such as family/friends, media and mobile money field agents/promoters. It is important to note that these sources of information are mutually exclusive as the question focuses on individual's first source of information on mobile money. The second measure of networks we consider is the adoption rate in individual *i's* district as a ratio of the national average. Because the network variable is individual specific and defined within a given district, we use district fixed effects to control for district determinants such as service quality and distance to the nearest mobile money agents. Finally, we control for individual characteristics to capture the precision of their beliefs about the new technology. We estimate the following specification:

$$y_i = \alpha + \gamma n_i + \beta x_i + \mu_i \qquad (1)$$

Where y_i is a discrete choice variable measuring the adoption decision of individual i, n_i is the social network variable, x_i is a vector of individual characteristics and μ_i is the random term. In social interaction literature, social networks aim to identify the effect of group behaviour on the behaviour of individuals that belong to the group. This then requires that y_i be estimated as a function of individual *i's* characteristics and the characteristics of the group i belongs to as argued by Manski (1993). The inability to control for group characteristics implies that the assumption of uncorrelated errors is inappropriate. Simultaneity and correlated unobservables pose an identification challenge to the estimation of social network effects. However, Bandiera and Rasul (2006) argued that this depends on the context of the study.

Unless data sets are typically collected for the study of social network effects, this requirement remains very stringent, and the identification of social network effects remains confounded with the correlated unobservable problem. In the absence of such rich data, simplifications have been made. One of these is the use of geographical and cultural proximity as a proxy for social group (Bertrand et al., 2000; Burns et al., 2010; Mukong, 2017). The assumption is that the behaviour of individual i is a function of the average behaviour of his/her neighbours $\bar{n}_i$[7] (using fixed effects to control for neighbourhood unobservable characteristics). In short, much of the literature has estimated the following type of specification;

$$y_i = \alpha + \gamma \bar{n}_i + \beta x_i + \mu_i \tag{2}$$

From this specification, we cannot disentangle endogenous from exogenous social effects, in addition to the correlated unobservable problem. For this reason, a positive effect of γ cannot simply be interpreted as evidence of social network effects. In our data, individuals were specifically asked about their social network. Thus, we can identify the sources of information or the composition of the social network a *priori* and do not need to make assumptions about one's social group definition. In other words, the actual rather than the potential network is identified in our data. This helps us to make some improvements over many of the current studies of social interaction and to escape the reflection problem. We estimate equation 1 using a probit model and equation 2 using the linear probability model (LPM). The social network variable in equation 2 is calculated at district level and requires the use of district fixed effects to control for correlated unobserved district specific covariates. Unlike the discrete choice models, the LPM allows for the use of district fixed effects without biasing other coefficients.

We estimate robust standard error to correct for heteroscedasticity and determine the percentage of probabilities that lie outside the unit interval to identify the severity of this drawback to the LPM estimates. We caution, however, that the estimated γ does not identify the causal effect of the adoption choices of the network on $i's$ adoption decision because they also capture the endogenous effect of $i's$ choice on network

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[7] $\bar{n}_i = V_{jk} * \bar{\bar{use}}_{\bar{k}}$ where V_{jk} represents the density of age-educational attainment group k residing in area j, a measure of the potential number of contacts available to an individual (quantity), $\bar{\bar{use}}_{\bar{k}}$ is the mean frequency of mobile money adoption from age-educational attainment group k in the sample. This provides a measure of the level of mobile money adoption and use in one's network (quality). Based on Bertrand *et al.* (2000), V_{jk} is the proportion of individuals in area j that are in age-educational attainment cohort k as a ratio of the proportion of individuals from the sample in that group. The available measure for contact is therefore $ln\left(\frac{V_{jk}/A_j}{L_k/T}\right)$, where A_j is the number of individuals who reside in area j; L_k is the total number of individuals in the sample belonging to the same age-educational attainment group and T is the total sample. It is the case that small groups will have few available contacts even if there is full concentration, and the fact that individuals self-segregate could be misleading. Using proportions resolves these problems and prevents the underweighting of small age-educational attainment groups (Bertrand *et al.* 2000).

members, but rather that our results are informative of whether adoption decision are correlated within social networks.

4.2 Data Type and Sources

The data for this study come from the Uganda Financial Inclusion Insights (FII) Tracker Survey for 2013. The FII Tracker Survey in Uganda is an annual, nationally representative survey of 3,000 Ugandan individuals aged 15 years and older. The first survey was conducted from September to November 2013 in 10 regions of Uganda. InterMedia and the Ugandan Bureau of Statistics (UBoS) worked together to draw a sample of 300 enumeration areas (EAs) using the 2002 census as a sampling frame. A combination of random-walk and Kish-grid approaches was used to select 10 individuals in each EA. There are currently five cross-sections available, but we focus on the 2013 cross-section because it contains information on social ties, which is not available in recent surveys. This allows us to conduct the analysis of network effects on mobile money technology adoption and use. Bandiera and Rasul (2006) noted that new technology becomes common knowledge over time and social ties no longer play a crucial role in adoption decisions. Thus, the 2013 data is more appropriate in examining the effect of social networks on mobile adoption in Uganda. One would expect that mobile money availability is common knowledge in Uganda now than it was in 2013 and information network may no longer be an important determinant of adoption decisions. While validating such a claim could be important, it is unfortunately not possible since recent surveys do not have data on information network.

The Survey provides in-depth information on the demand side of digital financial services, including mobile money adoption. The data includes information on specific aspects of access and use of mobile money platforms and the drivers and barriers to the use of mobile money services. The empirical strategy detailed above analyses the effect of information network on mobile money adoption and exploits the variation between different social groups and individuals in the same geographical space. We control for individual, household and community level factors that are correlated with adoption choices of individuals.

5. Results and Discussion

Mobile money adoption

The analysis focuses on social network as a determinant of mobile money adoption and usage. The key dependent variable is ownership of an active mobile money account. Mobile money adoption is a discrete choice variable equal to one if the individual has a registered or an active mobile money account and zero otherwise. While nearly half of Ugandans have used mobile money services (44%), only 29% had a registered mobile money account and only 26% had active accounts in 2013 (see Table 1). This implies that about 14% rely on other people's accounts including family members, friends and agents for mobile money transactions. This suggests that the network of family and friends have the potential to reduce the level of mobile money adoption. There is also enough variation in the dependent variable which allows us to identify the effects of information networks among other factors.

Table 1 also highlights reasons why individuals adopted or did not adopt mobile money services. Among the adopters, about 60% cited sending money and paying bills, 79% cited receiving money, 12% cited recommendation from friends, relatives and agents as the main reasons they adopted mobile money services. On the other hand, for non-adopters, 21% cited unsuccessful registration, 17% cited the lack of an agent, 11% cited the lack of an identity card (ID) and registration fees, 8% cited the lack of a SIM card and 19% indicated getting mobile money services from others/agents as the main reason for not having subscribed to mobile money services.

Table 1: Main Reasons for Adoption or Non-Adoption

Variable	Mean	Std. Dev.
(a) Mobile money adoption and use		
Ever used mobile money	0.435	(0.496)
Have a registered MM account	0.293	(0.455)
Have a registered active account	0.263	(0.440)
(b) Why non adopters did not adopt		
Registration not successful	0.214	(0.411)
No agent where I live or work	0.173	(0.375)
Get services via agent/someone's account	0.188	(0.391)
Do not have an ID for registration	0.031	(0.173)
Do not have SIM card of MM provider	0.077	(0.267)
No money for registration/transaction cost	0.077	(0.267)
Others	0.240	(0.427)
(c) Why adopters adopted		
Send money and pay bills	0.597	(0.491)
Receive money	0.786	(0.410)
Someone/agent recommended	0.124	(0.330)
Others	0.114	(0.318)

Notes: The first column reports the average number of individuals for each reason of adoption or non-adaptation of mobile money and the second column reports the standard deviation. There are 880 adopters (individuals with registered accounts) and 388 non adopters (individuals who have never tried to sign up for a mobile money account). Respondents were asked to choose from a list of reasons why they adopted, or did not adopt.

Social Networks

This paper uses the source of information on mobile money technologies available to individuals as a measure of social networks. The mean deviation of a group's level of adoption relative to that of the entire sample is the measure of information network commonly used in economic literature (Aizer and Currie, 2004; Deri, 2005; Burns et al., 2010; Bertrand et al., 2000). This is a potential measure of social networks and requires an identification strategy that is not readily available in many data sets such as the one used in this study. Thus, we supplement the measure with an alternative measure that overcomes this identification problem. In contrast to many studies, we observe the availability of one's contacts (source of information available to each individual) and this allows us to overcome the identification issues of many of the previous studies discussed in Section 2.

We exploit a specific question from the data. All individuals were asked if they were aware of any mobile money technologies. For those who were aware, they were asked how they learnt about the mobile money technologies (source of information). This measure is more appropriate because it provides information on the exact source of information for each individual. It also links individuals to their close contacts (strong social ties) from whom information was obtained. In the social network literature, strong social ties are denoted by friends and relatives. The network variable is categorised as 0 if the individual is not aware of mobile money technologies, 1 if the source of awareness is a friend/relative; 2 if the source is media (including radio/television, billboards or newspapers) and 3 for other sources such as field agents/promoters. For the econometric exercise, this variable is then converted into dummy variables representing each category.

Table 2 highlights the mean values for the different sources of information influencing the uptake of mobile money services. On average, 82% of those that are aware of mobile money service providers learnt about them through social media (radio, television (TV), newspapers, and bill boards). Relatives, friends and neighbours make up the second largest source of information (12%) while very few (6%) learned about mobile money through field agents/other banking institutions. Individuals also highlighted the sources that convinced them to adopt mobile money technology. The majority of adopters (59%) were convinced by their family members, 20% by friends and neighbours and 21% by other sources including mobile money field agents/promoters. This indicates that strong social ties are highly correlated with mobile money adoption.

Table 2: Direct Evidence on Network effects

Variable	Mean	Std. Dev.
(a) Source of information on MM services		
Media sources	0.818	(0.386)
Relatives/friends	0.116	(0.320)
Field agents of mobile money	0.058	(0.234)
(b) Source that convinced adoption		
Was convinced by a friend	0.202	(0.402)
Was convinced by a business partner/other	0.207	(0.328)
Was convinced by a family member	0.591	(0.492)
Was convinced by an agent	0.085	(0.280)

Source: Authors' compilation from the FII survey of Uganda for 2013

Other observable characteristics

In Table 3, we present information on the mean values of other determinants by mobile money adoption. The average age of individuals in the sample is 34 years with adopters significantly more likely to be older than non-adopters. Over 53% of the individuals are married but adopters and non-adopters have the same proportion of married people. There are fewer males (46%) than females in the sample, but adopters, on average, are more likely to be males (51%). Only 16% of the sample are from urban areas, but adopters are more likely to be residing in urban areas. While over 83% are employed, only 34% are employed in the service sector and over 70% of the population are below the poverty line. However, the proportion with registered and active accounts is significantly more likely to be employed or above the poverty line.

Table 3: Descriptive Statistics Adoption Status

Variable		Registered MM		Active MM	
	All	Adopt	Not Adopt	Adopt	Not Adopt
Age (years)	34	35	33**	35	33**
	(0.134)	(0.441)	(0.319)	(0.468)	(0.310)
Married	0.537	0.553	0.53	0.559	0.529
	(0.499)	(0.017)	(0.011)	(0.018)	(0.011)
Male	0.455	0.509	0.433**	0.503	0.438**
	(0.498)	(0.017)	(0.110)	(0.018)	(0.011)
Urban residence	0.163	0.297	0.108**	0.311	0.111**
	(0.373)	(0.015)	(0.007)	(0.016)	(0.007)
Employed	0.833	0.873	0.817**	0.874	0.818**
	(0.373)	(0.011)	(0.008)	(0.012)	(0.008)

Above poverty line	0.296	0.485	0.218**	0.497	0.225**
	(0.457)	(0.016)	(0.009)	(0.018)	(0.009)
Own a mobile phone	0.625	0.966	0.483**	0.97	0.502**
	(0.484)	(0.006)	(0.011)	(0.006)	(0.011)
Own active SIM card	0.647	0.977	0.510**	0.978	0.529**
	(0.478)	(0.005)	(0.011)	(0.005)	(0.011)
Registered bank account	0.119	0.272	0.055**	0.278	0.062**
	(0.323)	(0.015)	(0.005)	(0.016)	(0.005)
Secondary education	0.362	0.585	0.269**	0.602	0.276**
	(0.481)	(0.017)	(0.010)	(0.017)	(0.010)

Notes: Standard deviations are in brackets. ***p<0.01, **p<0.05, *p<0.1.

T-test of equality of the characteristics of adopters and non-adopters. For all tests of means or proportions, the null hypothesis is that the proportions/means are equal between adopters and non-adopters.

There are more people with SIM cards (65%) than with mobile phone (63%). This suggests ownership of multiple SIM cards or the possibility of individuals sharing a mobile phone with separate SIM cards or mobile money accounts. However, over 97% of the individuals with a registered account and 98% with active accounts respectively have access to a mobile phone and a SIM card. Only 36% of the sample have completed secondary education. The proportion of registered and active accounts is significantly higher among individuals with some secondary education. The average number of individuals with registered and active accounts is significantly higher among those with registered bank accounts.

5.1 Baseline Regression

Table 4 presents estimates of the marginal effect of social networks on the three different measures of mobile money technology usage and adoption. First, whether or not the individual has ever used mobile money services (Columns 1 and 2). Second, whether or not he/she has a registered mobile money account (Columns 3 and 4). Third, whether or not the registered account is active (Columns 5 and 6). In Columns 1, 3 and 5, we regress the adoption decision of each individual on the different sources of information available. Interestingly, results from all specifications indicate that adoption decisions are positive and significantly associated with information networks. This is in line with the theory and empirical evidence of information network and many economic outcomes. In the context of new technology adoption, a number of studies have found a positive relationship between information network and mobile money adoption (Murendo et al., 2018; Okello et al., 2018; Kiconco et al., 2020). Bandiera and Rasul, (2006) show that farmers' adoption of new crops was more correlated with the adoption decision of family and friends and less correlated with religion-based networks. Information networks have also been shown to positively affect healthcare utilisation decisions of individuals (Mukong and Burns, 2020; Devillanova, 2008; Deri, 2005). For ease of exposition, only the coefficients of information networks are reported, but observable individual characteristics are controlled for.

Table 4: Marginal effect of social networks on mobile money adoption and use

	Ever used MM		Have registered MM		Have active MM	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Family/relatives and friends	0.712***	0.462***	0.509***	0.283***	0.451***	0.242***
	(0.071)	(0.068)	(0.073)	(0.073)	(0.070)	(0.071)
Social media	0.782***	0.465***	0.616***	0.324***	0.557***	0.284***
	(0.066)	(0.064)	(0.068)	(0.069)	(0.065)	(0.067)
Field agents/promoters	0.948***	0.557***	0.720***	0.365***	0.651***	0.319***
	(0.072)	(0.070)	(0.073)	(0.073)	(0.070)	(0.072)
Individual/household factors	No	Yes	No	Yes	No	Yes
Observations	3,000	2,675	3,000	2,675	3,000	2,675

Note: Robust standard errors are in brackets. ***p<0.01, **p<0.05, *p<0.1.
The social network variable is measured by the source of information about mobile money services. The dependent variables are coded one if the individual has used mobile money services before, has a registered mobile money account, has an active mobile money account and zero otherwise. The base category for information networks is no knowledge about mobile money services. Results in Column 2, 4 and 6 control for individual characteristics including the quadratic of age, employment, marital status, residential type, gender, phone/sim card ownership, income level and education attainment.

Factors that may cause adoption decisions to differ between individuals are included in the remaining specifications (Columns 2, 4 and 6). While network effects remain positive and significant, the magnitude of the estimates varies with the different sources of information and with the inclusion of individual level characteristics. These results suggest that getting information from a mobile money field agent/promoter increases the probability of using mobile money services by 0.56 and adopting mobile money technology by 0.37, while getting information from the media increases the propensity by 0.47 and 0.32 respectively. On the other hand, information from family and friends increases the likelihood to use by 0.46 and to adopt by 0.28. The probability of having an active mobile money account increases by 0.32 if an agent is the main source of information, by 0.28 if from social media and 0.24 if from family and friends. We acknowledge that maintaining an active mobile money account goes beyond network influence and may depend mainly on other economic factors. The results suggest that mobile money service providers need to invest more in empowering their field agents/promoters with as much information as possible.

5.2 Heterogeneous effects

If social learning is important for adoption, then the relationship between the adoption choice of an individual and his network depends on the precision of the individual's own initial belief about the parameters of the new technology. The adoption decision of individuals with more precise information could be less sensitive to the adoption decision of the network. This follows from the fact that an adoption decision could be less sensitive to the adoption decision of the network when individuals have trust issues with the new technology or when they are able to use the accounts of their network members.

To observe if this hypothesis finds support in our data, we allow the effect of the network to vary according to individual characteristics. The characteristics are considered to proxy for the precision of individual initial beliefs on mobile money adoption. We are interested in establishing whether the marginal effects of the network differ across different socioeconomic statuses, including bank account ownership, gender, education attainment and income level.

Results in Table 5 indicate that the marginal effects of information networks on use and adoption is positive and significant for both the banked and unbanked sub-samples, but the estimates are lower for the unbanked sub-sample. This is not surprising as those with bank accounts are more likely to be familiar with related technologies like mobile money than those with no bank accounts. The marginal effects of information networks on use and adoption for the gender, education and income are presented in the appendix in Tables A7, A8 and A9 respectively. The marginal effects are positive and significant across the different sub-samples. For instance, estimates are generally lower for the male sub-sample, those with less than secondary education and those below the poverty line. Specifically, the results indicate that the unbanked and men are generally less sensitive to the adoption choices of their network members. Those with less than secondary education and those below the poverty line are less sensitive to the adoption decisions of their network members compared to their respective counterparts.

Table 5: Marginal effect of social networks on mobile money adoption and use by bank account ownership

	Ever used MM		Have registered MM		Have active MM	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Family/relatives and friends	0.216***	0.610***	0.056**	0.436***	0.043*	0.340**
	(0.029)	(0.146)	(0.025)	(0.156)	(0.024)	(0.158)
Social media	0.219***	0.653***	0.090***	0.580***	0.072***	0.569***
	(0.019)	(0.089)	(0.015)	(0.088)	(0.014)	(0.094)
Field agents/promoters	0.343***	0.620***	0.146***	0.555***	0.111***	0.598***
	(0.042)	(0.120)	(0.042)	(0.121)	(0.041)	(0.129)
Individual/household factors	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,404	271	2,404	271	2,404	271

Note: Robust standard error in brackets. ***p<0.01, **p<0.05, *p<0.1
The base category for information networks is no knowledge about mobile money services. Results control for individual characteristics including the quadratic of age, employment, gender, marital status residential type, phone/sim card ownership, income level and education attainment. Results of individuals with no formal bank account are presented in Columns 1, 3 and 5 and for those with bank accounts in Columns 2, 4 and 6.

5.3 *Robustness Check*

As noted in the descriptive statistics section, there are more users than account holders in the sample, suggesting that individuals can use the accounts of their network members and hence, a possibility of negative network effects on mobile money adoption. However, this cannot be checked with the network measure used so far. It is evident that social networks can be categorized in dimensions of race, ethnicity, age, education and religion (Albeck & Kaydar, 2002). Consequently, Arai (2007) and Mukong (2017) showed that besides relatives, other forms of socialization, including education attainment, are important determinants of fertility and substance abuse respectively. We use age-educational attainment and geography (district of residence) to construct a continuous variable as a measure of network (see footnote 7). We then estimate a linear probability model to test for the possibility of an inverse U-shaped relationship between number of adopters in the network and the propensity to adopt.

As shown in Table 6, we find no evidence of an inverted-U shaped relationship between the number of adopters in the network and the propensity to adopt. Contrarily, Bandiera & Rasul (2006) found an inverse-U shape between social networks and the decision of farmers to adopt new crops, suggesting that social effects are positive when there are few adopters in the network and negative when there are many. Such evidence is missing in the mobile money technology adoption, as our study did not find any inverse-U shape. This is not surprising given that mobile money technologies are continuously being revised – suggesting that learning about this technology is a continuous process. However, the network effect on use and adoption are positive and highly significant (consistent with evidence presented in Table 4). Network size is inversely associated with use and adoption, suggesting that the quality of a network (number of adopters in one's network) and not the quantity of network (number of people in one's network) is an important driver of use and adoption of mobile money services. The obvious drawback of the linear probability model is that it does not take into account that the dependent variable is either zero or one. In this case, it can yield predicted values outside the unit interval of 0 – 1. The problem is particularly serious when the mean of the dependent variable is close to either zero or one (Maddala 1983). In our sample, adoption and use are 29% and 46% respectively and the predicted values that lie outside the unit interval are between 3% and 5%. This suggests that the linear probability model still yields good estimates (Wooldridge, 2002; Bandiera & Rasul, 2006).

Table 6: Estimates of networks effect on mobile money adoption

Variables	(1)	(2)	(3)
Network size	-0.228***	-0.196***	-0.158***
	(0.024)	(0.021)	(0.041)

Social network	0.324***	0.327***	0.137***
	(0.033)	(0.032)	(0.044)
Social network squared	0.098***	0.081***	0.056***
	(0.012)	(0.011)	(0.013)
Age-education fixed effects	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes
Constant	-0.129	-0.238	-0.066
	(0.150)	(0.146)	(0.163)
Observations	2,675	2,675	2,675
R-squared	0.421	0.413	0.413

Note: Robust standard errors are in brackets. ***p<0.01, **p<0.05, *p<0.1.
The social network variable is measured by interacting quality and quantity of networks. Results control for individual characteristics including the quadratic of age, employment, residential type, phone/sim card ownership, income level, marital status and gender.

6. Conclusions

In this paper, we deepen the empirical analysis of social networks and technology adoption by assessing how the decision to use or adopt a new financial technology depends on one's information network, using individual data from the Uganda Financial Inclusion Insights (FII) Tracker Survey collected in 2013. Many researchers have used geographical and cultural proximity as a proxy for social networks in technology adoption studies. This is a potential measure of social networks and does not disentangle endogenous from exogenous network effects. In our data, since we can identify both the potential and actual sources of information and the composition of the social network a *priori,* we do not need to make assumptions about one's social group. The richness of the data allows us to make some improvements over many of the current studies of social interaction and technology adoption and to escape the reflection problem.

The data use reports whether an individual has become aware of mobile money technology opportunities through a friend or a relative, a mobile money agent or through social media. This allows us to focus on the information channels involved in strong social ties. The results show that relying on friends and relatives in order to get information on the opportunities of mobile money services significantly accelerates mobile money adoption. The effect of the networks is robust to a series of alternative sources of information and across the different dimensions of social networks. This is consistent with arguments and evidence of social networks and mobile money adoption in Uganda (Murendo *et al.,* 2018; Kiconco *et al.,* 2020). In the context of Uganda, such results are expected. For example, evidence suggests that in both rural and urban Uganda, learning of mobile money skills is better explained by social network characteristics compared to attributes of the individual (Kiconco *et al.,* 2020). This implies, individuals' profit from people in their network if those network connections are skilful, regardless of how skilled the learner is and learning happens at an accelerated rate in networks that consist of skilled people. We test for the possibility of an inverse U-shaped relationship between social networks and mobile money adoption. We find no evidence of an inverted-U shaped relationship between social networks and mobile money adoption.

Like many others, we find evidence that the adoption of new technology is highly correlated with the source of information and the adoption decisions of group members. These correlations persist when we control for many of the observable individual characteristics. Our results from all specifications indicate that adoption decisions are positively and significantly associated with information networks. However, the magnitudes varies with the different sources of information. Considering preference heterogeneity, the network effects are generally higher among the unbanked, women, the less educated and high-income individuals.

It is important to bear in mind that the present analysis is subject to a few caveats. First, we acknowledge that the effectiveness of social networks is contingent on differences in the characteristics of individuals, the characteristics of their contacts and/or their relationships with their contacts. This paper does not ascertain the various channels through which the effectiveness of networks is contingent on, but simply illustrates the actuality of the network effects for respective sources of information and social clusters. Justification of the effectiveness and pathways of operation of social network effects require more detailed information on the relationship between individuals and their social clusters. Also, we currently have little systematic data on supply side factors. Such information could help us to understand group and location differences in the propensity to use or adopt mobile money. However, the use of district fixed effects reduces the possible bias emanating from the option of these variables. Thus, such analysis can be expanded once data becomes available.

The findings from this study can have direct policy implications. That is, policies aimed at increasing the level of financial inclusion especially among the financially disadvantaged groups can exploit the multiplier effect of information networks. For example, the importance of financial inclusion (mobile money adoption) should continuously be advertised in meeting areas and newspapers, providing the related information in different ethnic languages. In general, knowledge of the working of social networks could help in addressing ethnic differences in the take-up of mobile money services, coping with ethnic segregation and the vicious cycle of financial exclusion.

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Appendix

Table A7: Marginal effect of social networks on mobile money adoption and use by gender

	Ever used MM		Have registered MM		Have active MM	
Variables	Female	Male	Female	Male	Female	Male
Family/relatives and friends	0.449***	0.461***	0.321***	0.224**	0.280***	0.184*
	(0.088)	(0.108)	(0.098)	(0.107)	(0.096)	(0.104)
Social media	0.459***	0.446***	0.349***	0.287***	0.311***	0.245***
	(0.085)	(0.101)	(0.094)	(0.098)	(0.092)	(0.094)
Field agents/promoters	0.558***	0.527***	0.420***	0.293***	0.360***	0.264***
	(0.095)	(0.109)	(0.101)	(0.106)	(0.099)	(0.102)
Individual/household factors	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,416	1,259	1,416	1,259	1,416	1,259

Note: Robust standard error in brackets. ***p<0.01, **p<0.05, *p<0.1.
The base category for information network is no knowledge about mobile money services. Results control for individual characteristics including quadratic of age, employment, residential type, phone/sim card ownership, marital status, education attainment, income level and bank account ownership.

Table A8: Marginal effect of social networks on mobile money adoption and use by education attainment

	Ever used MM		Have registered MM		Have active MM	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Family/relatives and friends	0.443***	0.552***	0.246***	0.353**	0.209***	0.307*
	(0.076)	(0.154)	(0.069)	(0.171)	(0.065)	(0.172)
Social media	0.443***	0.560***	0.272***	0.424***	0.236***	0.382**
	(0.072)	(0.149)	(0.065)	(0.164)	(0.061)	(0.166)
Field agents/promoters	0.503***	0.694***	0.311***	0.464***	0.275***	0.414**
	(0.082)	(0.156)	(0.072)	(0.172)	(0.068)	(0.174)
Individual/household factors	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,648	1,027	1,648	1,027	1,648	1,027

Note: Robust standard error in brackets. ***p<0.01, **p<0.05, *p<0.1.
The base category for information network is no knowledge about mobile money services. Results control for individual characteristics including quadratic of age, employment, residential type, phone/sim card ownership, marital status, gender, income level and bank account ownership. Results of individuals with less than secondary education are presented in Column 1, 3 and 5. For those with at least secondary education in Column 2, 4 and 6.

Table A9: Marginal effect of social networks on mobile money adoption and use by income level

	Ever used MM		Have registered MM		Have active MM	
Variables	Below	Above	Below	Above	Below	Above
Family/relatives and friends	0.468***	0.457***	0.263***	0.329**	0.236***	0.240
	(0.077)	(0.139)	(0.074)	(0.162)	(0.071)	(0.164)
Social media	0.439***	0.536***	0.293***	0.398**	0.253***	0.343**
	(0.074)	(0.134)	(0.070)	(0.155)	(0.066)	(0.157)
Field agents/promoters	0.518***	0.657***	0.336***	0.432***	0.282***	0.395**
	(0.083)	(0.144)	(0.076)	(0.164)	(0.073)	(0.166)
Individual/household factors	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,849	826	1,849	826	1,849	826

Note: Robust standard errors are in brackets. ***p<0.01, **p<0.05, *p<0.1.
The social network variable is measured by the source of information about mobile money services. The dependent variables are coded one if the individual has ever used mobile money services, have a registered mobile money account, have an active mobile money account and zero otherwise. The base category for information network is no knowledge about mobile money services. Results control for individual characteristics including quadratic of age, employment, residential type, phone/sim card ownership, income level and education attainment.

Table A10: The interaction effect of social networks and bank account ownership on mobile money adoption and use

Variables	Ever used MM	Have registered MM	Have active MM
Family/relatives and friends	0.217***	0.087***	0.069***
	(0.019)	(0.015)	(0.015)
Social media	0.215***	0.054**	0.040*
	(0.029)	(0.025)	(0.024)
Field agents/promoters	0.340***	0.141***	0.107***
	(0.042)	(0.042)	(0.041)
active bank account	-0.309***	-0.288***	-0.264***
	(0.054)	(0.035)	(0.035)
Family/relatives and friends #active bank account	0.399***	0.464***	0.426***
	(0.060)	(0.047)	(0.047)
Social media # active bank account	0.370***	0.344**	0.220*
	(0.131)	(0.137)	(0.129)
Field agents/promoters # active bank account	0.257**	0.402***	0.436***
	(0.101)	(0.101)	(0.100)
Constant	-0.292***	-0.280***	-0.291***
	(0.060)	(0.056)	(0.054)
Observations	2,675	2,675	2,675

Note: Robust standard error in brackets. ***p<0.01, **p<0.05, *p<0.1
The base category for information networks is no knowledge about mobile money services. Results control for individual characteristics including the quadratic of age, employment, gender, marital status residential type, phone/sim card ownership, income level and education attainment.

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