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Transformation of Global Agri-Food Systems:
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Georg-August-University of Göttingen

GlobalFood Discussion Papers

No. 76

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January 2016

RTG 1666 GlobalFood · Heinrich Düker Weg 12 · 37073 Göttingen · Germany
www.uni-goettingen.de/globalfood

ISSN (2192-3248)

Mobile money and household food security in Uganda

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Abstract.

Despite the fact that the use of mobile money technology has been spreading rapidly in developing countries, empirical studies on the broader welfare effects of the technology on rural households are still limited. Using household survey data, we analyse the effect of mobile money on household food security in Uganda. Unlike previous studies that rely on a single measure of food security, we measure food security using two indicators – a food insecurity index and food expenditures. To account for selection bias in mobile money use, we estimate treatment effects and instrumental variables regressions. Our results indicate that the use of mobile money per se as well as the volumes transferred are associated with a reduction in food insecurity. Furthermore, the use, frequency of use, and volumes of mobile money transferred are associated with increases in food expenditures. Policy interventions and strategies aiming to improve household food security should consider the promotion of mobile money among rural households in Uganda and other developing countries as a promising instrument.

Keywords: mobile money; food security; households; Uganda

JEL codes – G29, I31, O16, O33

Acknowledgement

The authors acknowledge financial support from German Research Foundation (DFG) and German Academic Exchange Service (DAAD). We are also grateful to Grameen Foundation for support in fieldwork coordination. The authors take responsibility for all remaining errors.

1. Introduction

Mobile money, the use of mobile phones to perform financial and banking functions, is spreading rapidly in developing countries (Donovan, 2012; IFC, 2011). Mobile money offers various benefits, which are especially useful in developing countries where financial access is limited (Donovan, 2012; Kikulwe et al., 2014). One key benefit is improving access to financial services for the poor and those with no formal bank accounts. Mobile money facilitates financial transactions through affordable payment systems, which is of particular importance in developing countries where households rely on remittances from family members (Donovan, 2012; IFC, 2011; Jack et al., 2013). The affordability of mobile money also emanates from modest and proportionate withdrawal fees, which are usually not a barrier to poor households transacting in small amounts. Other benefits are associated with reduced security risk of moving around with cash and faster transfer of money into rural areas (Kikulwe et al., 2014). Savings and insurance products are also now being offered through mobile money. This is particularly valuable for poor households as it offers the possibility for protection against vulnerabilities such as illness and to smooth consumption (Jack and Suri, 2014).

A growing number of studies document the positive effect of financial access on savings behaviour (Karlan et al., 2014), consumption, and productive investment (Adams and Cuecuecha, 2013; Dupas and Robinson, 2013). Mobile money is an innovation that has the potential to improve financial access especially for rural households with no access to formal bank accounts. Rural households could gain from using mobile money through faster transfer of money from various sources (e.g. remittances, payment from traders, wage etc), lower financial transaction costs and availability of other financial instruments for example savings and insurance. Mobile money is expected to bridge the financial access gap, thus allowing for food security and broader welfare improvements especially among the financially excluded rural communities in developing countries. To date there are only few studies that have analysed the welfare effects of mobile money on rural households in developing countries (Jack et al., 2013; Jack and Suri, 2014; Kikulwe et al., 2014; Munyegera and Matsumoto, 2014). Most of these studies find positive effects of mobile money on household income (Kikulwe et al., 2014), consumption smoothing (Jack and Suri, 2014) and per capita consumption (Munyegera and Matsumoto, 2014).

The above-mentioned studies provide important empirical evidence of the broader welfare effects of mobile money. However, little is known about the effects of mobile money on food security of the rural poor. This article fills this gap by analysing the effect of mobile money on household food security in Uganda, where the use of mobile money has grown rapidly in recent years. Our paper contributes to the emerging literature on mobile money in several ways. First, to the best of our knowledge this is the first paper that analyses the effects of mobile money on food security in a developing country context. Second, unlike studies that use one measure of food security, we take the multidimensional nature of food security into account (Maxwell et al., 2014) and use two distinct measures. In addition to food expenditures (an objective and monetary measure), we use a subjective and non-monetary measure: the Household Food Insecurity Access Scale (HFIAS). The advantage of the HFIAS is that it includes many facets of food security and also captures subjectively perceived risks of food insecurity. In addition, measurement errors are minimal, in particular in comparison to consumption indicators (Kabunga et al., 2014). The use of two distinct and complementary measures allows us to address the robustness of our results to choosing different outcome variables. Our study is also unique in that we use alternative specifications of the treatment variable; namely mobile money use, frequency of use and volumes transferred via mobile money services.

The remainder of this article is organised as follows. In the next section we describe the conceptual framework. Section three presents the methodology, including the description of survey data and food security measures used in the empirical analysis. Section four describes the estimation strategy employed. Empirical results are presented and discussed in section five and the last section concludes and derives policy implications.

2. Conceptual framework

In our framework, we follow Munyegera and Matsumoto (2014) and consider the same rural household in two scenarios: with and without the introduction of mobile money (Figure 1). The rural household is located in a remote village where financial institutions are not available. This household receives money from various sources (e.g. remittances, payments from traders, wages or pensions) in both scenarios. The only difference is the money transfer or payment method, which affects the overall disposable income. In scenario one, cash is transferred physically through slow and insecure informal methods (e.g by person, bus, taxi) between the sender working in an urban area and the receiver in the rural village (Kikulwe et al., 2014; Munyegera and Matsumoto, 2014). In addition, household members have to travel to distant business centres to receive payments for their agricultural produce from traders as well as access other financial services, for example their pension. This is associated with high costs of accessing capital both in terms of the transport fare and the opportunity cost of travel time between the two locations. The high transaction costs reduce household disposable income and investment in food, health, education and agricultural inputs. Consequently, overall household welfare is reduced.

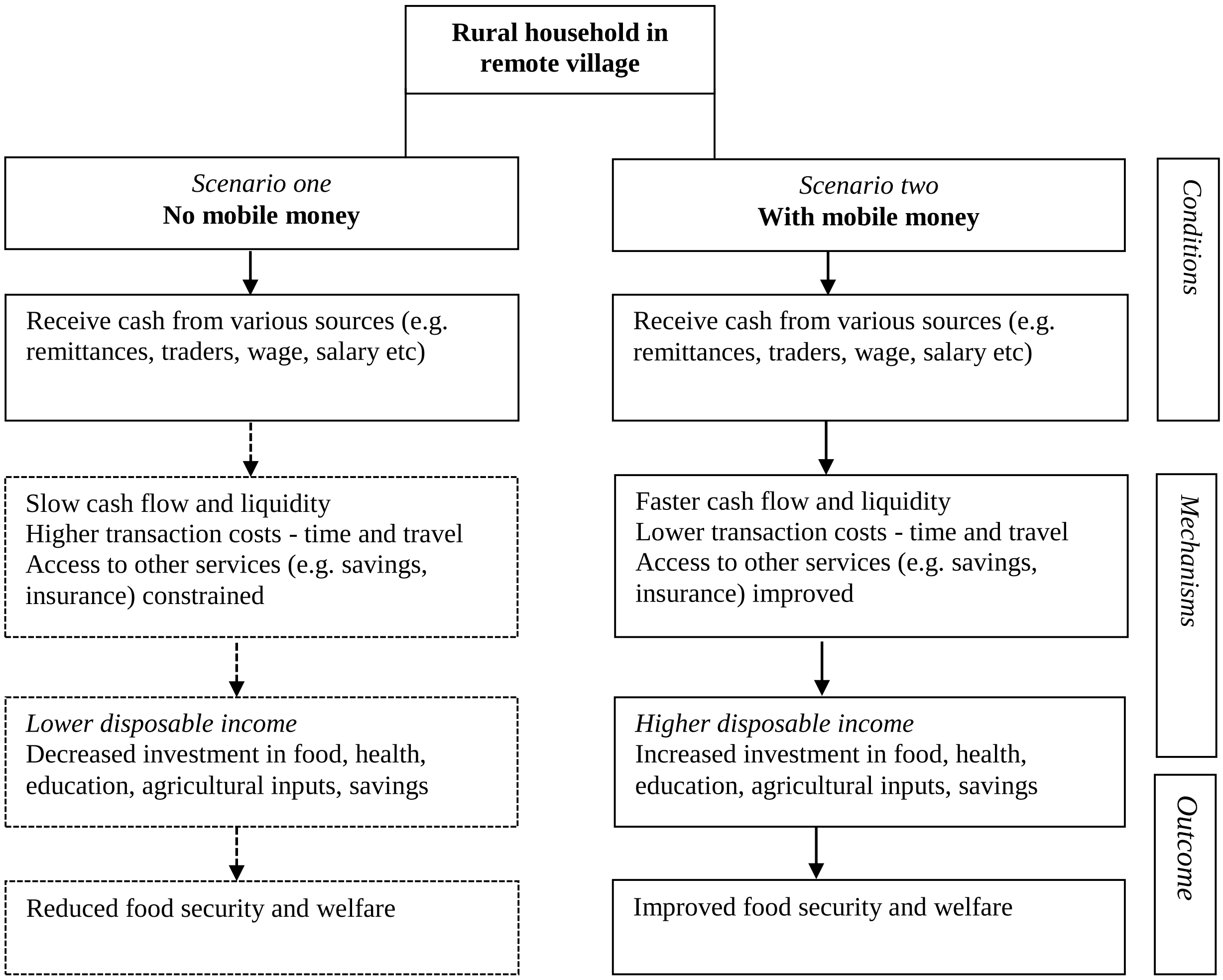

Figure 1. Pathways through which mobile money may affect household food security

In scenario two, mobile money is introduced facilitating access of rural households in remote areas to monetary transfers, such as remittances, payments and pensions. In scenario two, we will likely observe an increased flow of cash into rural households because of the introduction of a relatively faster and safer financial service innovation. The benefits realized through using mobile money have the potential to contribute to household disposable income and food security through at least three pathways. First, the household is able to receive cash faster and more immediately from various sources (e.g. remittances, payments from traders, wages or pension payments). This will result in greater liquidity, which can be used for household productive and consumptive purposes (Adams and Cuecuecha, 2013).

The second pathway through which mobile money can affect household welfare and poverty is through lower transaction costs. Mobile money can be an accessible, convenient and cheap medium for the delivery of financial services and more reliable than traditional and informal methods (Kikulwe et al., 2014). In many countries, mobile money is a relatively cheaper means of money transfer than other alternatives (Donovan, 2012) and users benefit from the reduced time and monetary costs of accessing financial services. The lower transaction costs associated with sending money via mobile money services can directly translate into more money available to households for various consumption expenditures, including food, health, and education, as well as productive investment in agriculture or alternative income-generating activities.

Third, it is now possible to extend the range of financial services offered by mobile money beyond basic payment and withdrawal to other financial products, for example savings and insurance (IFC, 2011). With access to savings or insurance services, households can efficiently manage risks and invest in improving agricultural production.

Some evidence in support of these impact pathways can be found in the literature. Jack et al. (2013) show for example that the introduction of mobile money positively increased the volumes of internal remittances in Kenya. Similarly, Kikulwe et al. (2014) and Munyegera and Matsumoto (2014) show that mobile money is associated with higher remittances received by households. Jack and Suri (2014) found that remittances received via mobile money enabled households in Kenya to smooth consumption, thus offering a form of risk insurance. In this section, we discussed that mobile money potentially lowers the transaction and opportunity costs of transferring money and enhances liquidity through faster transfer of cash. Through these pathways, we therefore hypothesize that mobile money improves food security and welfare among rural households.

3. Methodology

3.1. Data

This article uses data collected from rural households in Mukono and Kasese districts in Uganda. We applied a multi-stage approach to draw the sample. In the first stage, we randomly selected approximately 20 villages in each of the two districts. In the second stage, we randomly selected about 12 households in each village for the interviews. 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 six households because of inconsistent data on consumption and expenditures. The survey instrument contained a mobile money module, based on which we can distinguish between households using mobile money services and those who are not. Our analysis is based on 273 mobile money users and 203 non-users as shown in Table 1.

Table 1. Sample differentiated by mobile money adoption status

	Non-Adopters	Adopters	Total
Mukono	92	147	239
Kasese	111	126	237
Total	203	273	**476**

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. Data on socioeconomic characteristics, including food consumption and expenditures, were collected at the household level. Details on food consumption were collected using a 7-day recall period for food, beverages and tobacco. A 30-day recall period was used to capture purchases of more durable goods and services that are undertaken by households less frequently (Deaton and Zaidi, 2002). The HFIAS module consisted of nine questions, representing different experiences of food insecurity over the last 30 days (Coates et al., 2007).

A household is defined as a mobile money user if any member of the household used mobile money services in the past 12 months prior to the survey (Kikulwe et al., 2014). We measure the frequency of using mobile money as the number of times a household sent or received money via mobile phone in the past 12 months, with zero values indicating that mobile money has not been used. This is similar to the approach used by Kirui et al. (2012). The volume of mobile money transferred is measured as the sum of money sent and received during the past twelve months, with zero values indicating that no money has been transferred through mobile phones.

3.2. Food security measurement

According to the World Food Summit in 1996, food security exists when all people, at all times, have physical and economic access to sufficient safe and nutritious food to meet their dietary needs and food preferences for a healthy and active life (FAO, 1996). Food security is multidimensional and this makes its measurement particularly complex. Several indicators have been used to measure food security. Barrett (2010) gives an overview of objective measures of food security, e.g. dietary intake, expenditures, and health indicators, as well as subjective measures, e.g. perceived adequacy of consumption, exposure to risk, and the cultural acceptability of foods. A drawback of most of the approaches based on dietary intake and anthropometric indicators is that they are expensive and data intensive (de Haen et al., 2011). Maxwell et al. (2014) provide a review of subjective indicators commonly used by agencies working on food security, such as the World Food Program. These include: a) dietary diversity and food frequency, e.g. Household Dietary Diversity Score and Food Consumption Score; b) consumption behaviours, e.g. Coping Strategies Index; c) experiential measures, e.g. the Household Food Insecurity Access Scale and the Household Hunger Scale; and d) self-assessment measures. These subjective measures are simple and easy to use, but their main disadvantage is that they focus only on measuring food access and do not account for food intake and availability. Maxwell et al. (2014) highlight that food security is a multidimensional livelihood outcome and thus should ideally be measured by multiple indicators. In this paper, we use food expenditures as an objective measure and the Household Food Insecurity Access Scale (HFIAS) as a subjective measure of food security. We describe each of these measures separately in the next subsections.

3.2.1. Food Expenditure

We used a 7-day recall period to elicit expenditures on food, beverages and tobacco and a 30-day recall period in the case of household expenditures on less frequently purchased food items. We collected expenditure data on an item-by-item basis. Conversion factors were used to change food consumption expenditures to a 30-day monthly basis. Subsequently, all expenditures were aggregated to derive total food consumption expenditures at household level. Consumption of home-produced food was valued at local market prices. Finally, per capita food consumption expenditures were calculated based on monthly per adult equivalents (AE). We use the OECD adult equivalent scale which is given by: $1 + 0.7(\mathrm{A} - 1) + 0.5\mathrm{C}$, where A and C represent the number of adults and children in a household, respectively (Deaton and Zaidi, 2002). For the econometric analysis, the monthly food expenditure per AE was normalized by log transformation.

3.2.2. Household Food Insecurity Access Scale (HFIAS)

The HFIAS measures the degree of food (access) insecurity (Coates et al., 2007). According to Coates et al. (2007) and Maxwell et al. (2014), the HFIAS is a simple, cost effective and scientifically valid indicator, which captures household experiences in terms of insufficient quality, quantity and uncertainty over insecure food access. The HFIAS is widely used in international contexts and its recent applications to Sub-Saharan Africa include Cock et al. (2013) for South Africa, Kabunga et al. (2014) and Keino et al. (2014) for Kenya, and Maxwell et al. (2014) for Ethiopia.

The HFIAS consists of asking household heads to respond to nine questions, which represent universal domains of the experience of insecure access to food. The nine questions (sub-domains) are grouped into three main domains (Coates et al., 2007; Cock et al., 2013; Kabunga et al., 2014; Keino et al., 2014). The details of the domains and sub-domains are shown in Table 2. Domain I represents anxiety and uncertainty about household food supply. Domain II represents insufficient food quality, while domain III represents insufficient food quantity intake and physical consequences. Respondents answered each sub-domain using a score from 0 to 3, depending on whether the particular problem described occurred: never (non-occurrence), rarely (1–2 times), sometimes (3–10 times), or often (more than 10 times) over the last 30 days. For each individual household, the HFIAS score is computed by aggregating the sub-domain scores, and ranges from 0 to 27. The higher the score, the greater the food insecurity the household experienced; whereas a lower score represents a more food-secure household (Coates et al., 2007).

3.2.2.1. Food insecurity index (FIN)

Creating the dependent variable by summing up the HFIAS scores (Cock et al., 2013; Keino et al., 2014) has the disadvantage of assigning equal weight to each item, regardless of its value or utility. For impact analysis this may not be informative because the sub-domains capture different aspects of food insecurity (Kabunga et al., 2014). One approach to address this weakness involves using factor analysis to create composite scores that capture the common patterns in the data (Kabunga et al., 2014). We therefore created a Food Insecurity Index (FIN) based on the HFIAS using weights obtained from the factor analysis. Kabunga et al. (2014) highlight that the food insecurity index computed from factor analysis represents relative food insecurity within the sample and is suitable for impact evaluations because it compares the extent to which one household differs from the other. Factor analysis determines and assigns weights to capture the relative importance of multiple indicators and maximize the variance explained by the linear composites. The use of factor analysis in this context is a well-established method that has been applied in numerous studies (McKenzie, 2005; Sahn and Stifel, 2000).

In this study, factor analysis was applied to the nine sub-domains of the HFIAS to determine the combination yielding the best accuracy performance for the FIN. In our analysis, eight subdomains loaded highly on the first principal factor. The first factor, which explains 77% of the variation, is considered our measure of food insecurity (Sahn and Stifel, 2000). The factor loadings are shown in Table 2. Positive factor loadings indicate a positive correlation of the variable with relative food insecurity and vice versa. Higher values of the index reflect higher levels of food insecurity.

The appropriateness of the application of factor analysis to our data was confirmed by the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett test of sphericity. The KMO yielded a value of 0.85 and Field (2013) recommends accepting KMO values above 0.6. The Bartlett test of sphericity tests the null hypothesis that the original correlation matrix is an identity matrix. The Bartlett test yielded χ^2 = 2896.03 (p = 0.000); hence, we reject the null hypothesis and conclude that there are significant relationships between the variables used for the index. While the KMO and Bartlett test indicate the data's adequacy for factor analysis, the scale reliability is expressed via the Cronbach's alpha statistic. The corresponding statistic of 0.88 shows that the scale reaches the advisable minimum of 0.7 and therefore consistently reflects the construct that it is measuring (Field, 2013; Keino et al., 2014). The scale's consistency was assessed by correlating the individual sub-domains with the total scale score. The sub-domains are highly correlated with the total score, a reflection of internal consistency.

3.2.2.2. Binary food insecurity

We also used a binary food insecurity indicator as an alternative to the food insecurity index. This approach allows us to define discrete food insecurity levels. To determine the cut-off for these food insecurity levels, we used the Household Food Insecurity Access Prevalence (HFIAP) developed by Coates et al. (2007), which uses the same questions as the HFIAS to categorize households into four levels of food insecurity. The four categories of food insecurity are: 1 = food secure, 2 = mildly food insecure, 3 = moderately food insecure and 4 = severely food insecure. Households are categorized as increasingly food insecure as they respond affirmatively to more severe conditions and/or experience those conditions more frequently (Coates et al., 2007). In our analysis, we merge categories 1 and 2 into food-secure households, and categories 3 and 4 into food-insecure households (Kassie et al., 2014b).

4. Estimation strategy

As discussed in the conceptual framework, mobile money is expected to have positive effects on food security. Econometrically, we examine the effect of mobile money on food security using the following specification:

$$FS = \beta \boldsymbol{X} + \delta MM + \varepsilon \qquad (1)$$

Where FS is one of the food security related outcome variables (food expenditures, food insecurity index, and binary food insecurity); $\boldsymbol{X}$ is a vector of regressors influencing the outcome variable; and MM is the treatment variable (specified as dummy variable for the use of mobile money services, or as continuous variable in the case of frequency of use or volume transferred). Furthermore, β is a vector of parameters to be estimated, and δ, which is also estimated by the model, measures the effect of mobile money on food (in-) security. Finally, ε is an i.i.d. random error term.

When analysing food security, mobile money might be subject to selection bias resulting from unobservable factors influencing not only household's use of mobile money services, but also their food security. For example, mobile money users may be more technically literate and more likely to have family members in the capital city or abroad sending remittances. As a result, mobile money users are more likely to have higher average levels of income and human capital and consequently lower average levels of food insecurity. Due to such potential selection bias, mobile money users and non-users are not directly comparable, which implies that an estimation method needs to be chosen that corrects for this bias in order to obtain unbiased estimates of the effect of mobile money on food security. We therefore use endogenous treatment effects models (in the case of binary treatment variable specification) and instrumental variables regressions (in the case of continuous treatment variable specification) to control for observed and unobserved heterogeneity when estimating the effect of mobile money on food expenditure and food insecurity.

In this study, we use two different instruments: household-specific mobile phone network connectivity and the size of the information exchange network of the household. Regarding mobile phone network connectivity, we asked the household how many network bars are displayed on the mobile phone at the homestead ranging from 0 to 4 (0 equals no network and 4 excellent network connectivity). We classified 0 to 2 network bars into “poor network connectivity” and 3 to 4 network bars into “good network connectivity”. While in principle poor network connectivity at home can be overcome by using network services elsewhere, we expect a positive correlation between network availability at home and the (frequency and extent of) use of mobile phone based financial services. The second instrument – the size of the information exchange network – is based on social network data that was obtained using random matching within sample (Maertens and Barrett, 2013). For this purpose, each interviewed household was matched with five other households randomly drawn from the sample. Conditional on knowing the matched household, the interviewee was asked whether they have ever talked about mobile money. Based on this data, our instrument contains the number of matched households with which information on mobile money services has been exchanged. It is thus a measure for information access and accordingly hypothesized to be positively correlated with the household’s use of mobile money services. While both instruments are strongly correlated with mobile money use, they are unlikely to affect household food security directly. Beyond the instruments described here, we tested other potential instruments, for example, the proportion of households using mobile money and owning a mobile phone in the village (Kikulwe et al., 2014). However, these variables did not qualify as good instruments in our case study.

The choice of the control variables used in the estimations is guided by the emerging literature on mobile money use (Jack and Suri, 2014; Kikulwe et al., 2014; Kirui et al., 2013) and the broader literature on technology adoption and food security (Kabunga et al., 2014; Kassie et al., 2014b; Shiferaw et al., 2014). All variables are described in Table 3 below. Besides household demographic and socio-economic control variables, we included a number of variables related to information access. Firstly, we include the variable "number of mobile phones owned" as a proxy for information access. Controlling for the number of mobile phones owned also allows us to make sure that our variable of interest "mobile money" is not confounded with other more general benefits of mobile phone ownership. Secondly, we included the variable "extension contact" measuring whether a household had accessed information from extension service. In particular, in the research area an extension program had been implemented that uses locally recruited farmers known as community knowledge workers to disseminate mobile-phone based extension. Community knowledge workers are trained by an NGO to use smart phones to access agricultural and market information and provide this information to fellow farmers in their respective villages. Thirdly, we include the variable "group membership" as a proxy for access to information. In general, improved access to agricultural and market information is expected to improve agricultural productivity, incomes, and thus food security.

5. Results and discussion

5.1. Use of mobile money

Overall, 57% of the households in the sample use mobile money. On the average, mobile money was used seven times during the past 12 months, ranging from a minimum of one to a maximum of ten times. Figure 2 shows the activities for which households use mobile money services. Around 96% of the mobile money users stated that they withdraw money from their mobile account. This money may come from various sources (e.g. remittances or payments from traders) and is used for a variety of household activities – for example purchases of food or agricultural inputs among others. Fifty seven percent of the mobile money users stated that they use their mobile money accounts as savings account. About 53% of the households stated that they also transfer money to relatives and friends, and 25% of the households use mobile money to buy airtime for their mobile phones. Eighteen percent used mobile services to transfer money to business partners and a similar proportion (18%) used mobile services to pay school fees.

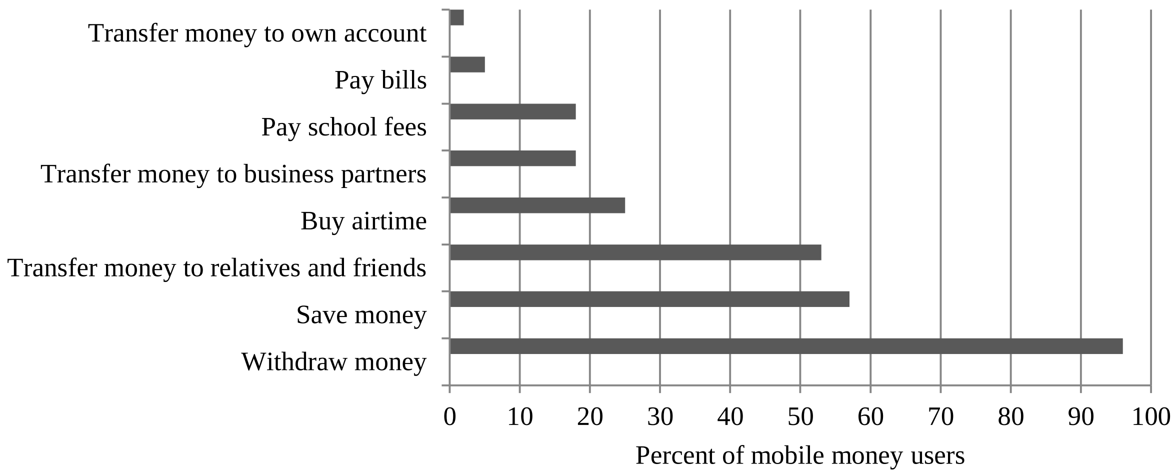

Figure 2. Activities performed with mobile money services

5.2. Results of descriptive analysis

The sample statistics for the HFIAS sub-domains are shown in Table 2. The proportion of households responding ‘never’ in the first sub-domain is about 48%, implying that 52% of the sampled households were anxious and uncertain about their food supply. In domain II, the average proportion of ‘never’ responses is 35%. This means that roughly 65% of the households have insufficient food quality. Lastly, in domain III, the average proportion of ‘never’ responses is 79%, implying that about 21% have insufficient food quantity intake due to physical unavailability.

Table 2. Sample statistics for the HFIAS sub-domains (Percentage response on occurrences in the last 30 days)

	Never (0 times)	Rarely (1-2 times)	Sometimes (3-10 times)	Often (>10 times)	Factor loadings
Domain I. Anxiety and uncertainty about household food supply					
1. Did you worry that your household would not have enough food? *(Anxiety)*	47.90	16.39	27.10	8.61	0.778
Domain II. Insufficient quality (includes food variety and preferences)					
2. Were you or any household member not able to eat the kinds of foods you preferred because of a lack of resources? *(Kinds)*	34.66	12.18	38.87	14.29	0.825
3. Did you or any household member have to eat a limited variety of foods due to a lack of resources? *(Variety)*	37.61	11.76	36.76	13.87	0.817
4. Did you or any household member have to eat some foods that you really did not want to eat because of a lack of resources to obtain other types of food? *(Not want)*	33.61	12.61	39.08	14.71	0.779
Domain III. Insufficient food intake and physical consequences					
5. Did you or any household member have to eat a smaller meal than you felt you needed because there was not enough food? *(Smaller)*	57.37	10.71	27.52	4.41	0.786
6. Did you or any household member have to eat fewer meals in a day because there was not enough food? *(Fewer)*	61.34	7.98	25.63	5.04	0.767
7. Was there ever no food to eat of any kind in your household because of a lack of resources to get food? *(No Food)*	86.76	3.15	9.03	1.05	0.525
8. Did you or any household member go to sleep at night hungry because there was not enough food? *(Sleep)*	92.02	2.31	5.46	0.21	0.465
9. Did you or any household member go a whole day and night without eating anything because there was not enough food? *(Whole day)*	95.80	2.31	1.89	0.00	0.306

Figure 3 shows the food insecurity categories based on the HFIAP classification. The proportions of food secure and mildly food insecure households are higher among mobile money users, while the proportions of moderately and severely food-insecure households are higher among non-users.

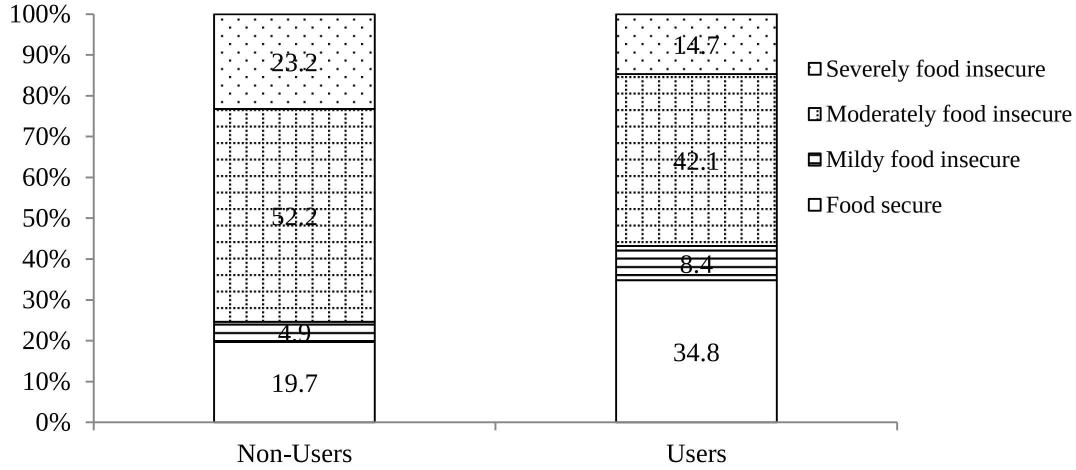

Figure 3. Food insecurity categories

Similarly, mobile money users have an average food insecurity index score of -0.20, which is significantly lower compared to the index score of 0.27 for non-users. The mean difference of 0.47 is statistically significant at the 1% level based on t-test results. Similarly, the monthly food expenditure per AE of users (82861 UGX[1]) is higher than that of non-users (76479 UGX), which is significant at the 10% level. These results suggest that users are more likely to be food secure than non-users. While these descriptive differences cannot be interpreted as causal impacts, they provide an indication that there may be structural differences in food security and expenditures between mobile money users and non-users. In the following sections, we use econometric techniques to identify the effect of mobile money.

Table 3 presents the descriptive statistics of potential explanatory variables included in the econometric models differentiated by mobile money use. For some of these variables, we observe significant differences between users and non-users. On average, mobile money users have better

[1] The exchange rate was 2500 Uganda Shillings (UGX) =1USD at the time of survey.

access to information, as captured by the variables *group membership* and *number of mobile phones owned*.

There are also significant differences with respect to education levels, land holdings and livestock ownership. Better educated mobile money users and those with larger land holdings are more likely to have higher agricultural productivity and to be food secure. Users are more likely to be involved in off-farm income activities, suggesting that household members engaged in off-farm activities may possibly send remittances using mobile money. Off-farm income activities increase household cash, which might be used either to purchase sufficient food or invest in agriculture to increase agricultural productivity and production to meet household food security needs. Earlier studies show the importance of off-farm income for food security (Mabiso et al., 2014; Sinyolo et al., 2014). Considering land, assets, off-farm income activity and livestock as proxies for wealth, results suggest that mobile money users are wealthier than non-users. Significantly more of the mobile money users also have their own means of transportation. This gives them an advantage in mobility and access to agricultural input and output markets.

Table 3. Differences between mobile money users and non-users

		Users		Non-users	
Variable	*Description*	*Mean*	*Std*	*Mean*	*Std*
Treatment variables					
Frequency	Number of times household used mobile money	7.22	2.77	-	-
Volume transferred	Volume of mobile money transferred (log)	12.16	1.42	-	-
Control variables					
Group membership	Household member(s) belong to any group (dummy)	0.766***	0.42	0.606	0.49
Mobile phones	Number of mobile phones owned by household	2.018***	1.06	0.842	0.93
Extension contact	Household accessed information from extension service (dummy)	0.564***	0.50	0.419	0.50
Age	Age of household head (years)	49.377	12.85	49.897	14.48
Gender	Gender of household head (dummy, 1=male)	0.897***	0.30	0.788	0.41
Education	Education of household head (years)	7.414***	4.46	5.064	3.85
Household size	Household size (number)	7.326***	2.64	6.596	2.93
Dependency ratio	Ratio of dependents (15 & below, 65 plus) to workforce (16-64)	1.362	1.10	1.499	1.26
Adult equivalent	Adult equivalent	4.603***	1.51	4.165	1.67
Land size	Size of land owned in acres	5.153***	5.43	3.619	3.25
Ln(Farm equipment)	Value of farm equipment (log)	10.943***	1.26	10.502	1.09
Off farm income	Household member(s) engaged in off-farm income activity (dummy)	0.619***	0.49	0.355	0.48
Access to credit	Household accessed credit (dummy)	0.546***	0.50	0.345	0.48
TLU	Total livestock units[2]	1.242***	2.21	0.671	1.50
Means of transport	Household owns motorcycle and/or car (dummy)	0.201***	0.40	0.059	0.24
Output market	Distance to output market (km)	3.758	4.69	4.252	6.52
District	Household is located in Mukono district (dummy)	0.538	0.50	0.453	0.50
Instruments					
Size of exchange social network	Number of network members household communicates with about mobile money	0.498***	1.13	0.089	0.39
Connectivity	Mobile phone network connectivity (dummy, 1=good connectivity, 0=poor connectivity)	0.780***	0.41	0.507	0.50
Observations		273		203	

*** indicates the corresponding mean differences are significant at the 1% level (t-tests).

[2] TLU is calculated using the numbers of livestock owned by the household using the Storck (1991) conversion factors: cows, oxen, bulls = 1; heifers = 0.75; calves = 0.25; donkey = 0.5; goat, sheep = 0.1; pig = 0.2; chickens = 0.01.

5.3. Econometric results

In this section, we present the econometric results of the effects of mobile money use on food security. As described above, we measure food security using the food insecurity index, binary food insecurity, and food expenditure. The effects of mobile money on these outcome variables are discussed separately in the next sub-sections.

5.3.1. Effect of mobile money on food expenditure

The results from the endogenous treatment effects model on the effect of mobile money use on food expenditure are shown in column 2 of Table 4. The size of the exchange social network and mobile phone network connectivity are used as instruments in the endogenous treatment effects model. The Wald test of independent equations is insignificant, indicating that there is no selection on unobservables. We therefore rely on OLS regression for estimation. The results of the OLS model show that mobile money use is positive and significant at the 10% level. The estimated coefficient indicates that the adoption of mobile money leads to a nine-percentage point increase in monthly food expenditure per adult equivalent.

A number of other covariates are significant. The number of mobile phones owned by the household has a negative and significant effect on food expenditure per AE. Households having many mobile phones may incur higher costs associated with airtime, charging costs, repair and maintenance, which may reduce the food expenditure budget. Furthermore, larger households are associated with lower levels of food expenditures per adult equivalent. An additional member in the household reduces food expenditure per adult equivalent by 4.4 percentage points. This estimate is in line with results based on per capita food consumption reported by Shiferaw et al. (2014). The variables land size, value of farm equipment, and TLU are positive and highly significant. An additional acre of land results in 0.7 percentage points increase in food consumption per AE. A one percent increase in the value of farm equipment is associated with a 5-percentage point increase in food expenditure per AE. An increase in TLU by one unit increases food consumption by 2.3 percentage points. Again, these results are in line with Shiferaw et al. (2014) who found for the case of Ethiopia that livestock ownership increases per capita consumption expenditure. Finally, owning a means of transport has a positive effect that is significant at the 10% level.

Table 4 also presents the results for the alternative specifications of the treatment variable: column 6 shows the estimated treatment effects of the frequency of using mobile money; column 8 shows the estimated treatment effects of the volumes transferred through mobile money. For both specifications, we first estimated IV regressions. The Hausman (endogeneity) test reported at the bottom of the table is insignificant for both specifications highlighting absence of selection bias. We therefore interpret the results of the OLS estimations. The OLS results reveal that the frequency of using mobile money has a significant effect on food expenditures. If the number of times mobile money is used is increased by one, food expenditures per AE increase by 1.9 percentage points. Similarly, the volumes transferred through mobile money are positively and significantly associated with food expenditures. A one-percentage point increase in the volumes transferred increases food expenditure per AE by 1 percentage point. The signs and magnitudes of the estimated coefficients of other covariates are consistent across the different model specifications.

Table 4. Estimated effects of mobile money on monthly food expenditure per AE (log) (n= 476)

Dependent variable: food expenditure per AE	Use (dummy)				Frequency				Volume transferred			
	Treatment effects		OLS		IV		OLS		IV		OLS	
	Coeff	SE‡	Coeff	SE‡	Coeff	SE	Coeff	SE‡	Coeff	SE	Coeff	SE‡
Mobile money	0.225*	0.125	0.091*	0.048	0.057	0.036	0.019***	0.006	0.034*	0.020	0.010***	0.004
Extension contact	0.027	0.042	0.026	0.042	-0.021	0.054	0.014	0.043	0.002	0.046	0.023	0.042
Group membership	0.053	0.052	0.054	0.053	0.058	0.052	0.058	0.053	0.044	0.053	0.053	0.053
Mobile phones	-0.041*	0.021	-0.036*	0.021	-0.095*	0.051	-0.046**	0.021	-0.087**	0.044	-0.041**	0.021
Age	0.001	0.002	0.001	0.002	0.002	0.002	0.002	0.002	0.001	0.002	0.001	0.002
Gender	0.029	0.063	0.025	0.064	0.016	0.063	0.027	0.064	-0.002	0.065	0.022	0.064
Education	0.007	0.005	0.008	0.005	-0.001	0.008	0.005	0.005	0.005	0.006	0.008	0.005
Household size	-0.044***	0.008	-0.044***	0.009	-0.042***	0.009	-0.044***	0.009	-0.043***	0.009	-0.044***	0.009
Dependency ratio	0.025	0.017	0.025	0.018	0.031	0.020	0.026	0.018	0.032	0.020	0.026	0.018
Land size	0.007*	0.004	0.007*	0.004	0.003	0.006	0.006	0.004	0.005	0.005	0.007	0.004
Ln(Farm equipment)	0.049**	0.020	0.050**	0.020	0.039*	0.021	0.046**	0.020	0.043**	0.020	0.048**	0.020
Off farm income	-0.012	0.046	-0.011	0.047	-0.047	0.055	-0.014	0.047	-0.060	0.058	-0.017	0.047
Access to credit	0.021	0.044	0.023	0.045	-0.005	0.052	0.019	0.045	-0.011	0.052	0.018	0.045
TLU	0.023**	0.011	0.023**	0.011	0.026**	0.013	0.024**	0.011	0.025**	0.013	0.023**	0.011
Means of transport	0.103*	0.054	0.104*	0.055	0.045	0.078	0.090	0.055	0.071	0.069	0.099*	0.055
Output market	0.005	0.003	0.005	0.004	0.007	0.004	0.005	0.003	0.007	0.004	0.005	0.004
District	0.022	0.052	0.018	0.053	-0.023	0.062	0.014	0.053	-0.038	0.065	0.011	0.052
Constant	10.561***	0.241	10.636***	0.237	10.747***	0.232	10.668***	0.236	10.707***	0.224	10.653***	0.236
$ath(\rho)$	*-0.201*	*0.177*										
Wald test of independent equations (p-value)	*0.255*											
Wald statistic/F statistic	*98.90****		*6.02****		*4.388****		*6.36****		*4.39****		*6.17****	
Anderson LM statistic					*15.17****				*21.90****			

Cragg-Donald Wald F statistic	*7.52*	*11.02*
Sargan statistic(p-value)	*0.40*	*0.69*
Endogeneity test (p-value)	*0.27*	*0.20*

*, **, *** indicates coefficients are significant at 10%, 5%, and 1% levels. ‡ Robust standard errors are reported. [/a] Dummy variable used in frequency and volumes specifications. Only second stage IV estimates are shown.

5.3.2. Effect of mobile money on food insecurity

5.3.2.1. Effect of mobile money on the food insecurity index

Table 5 presents the estimation results on the effects of mobile money use, frequency of use, and volumes transferred on the food insecurity index. To test for potential selection bias, we estimate an endogenous treatment effects model (in the case of mobile money use) and instrumental variables regressions (in the case of frequency of use and volumes transferred) using the size of the exchange social network and mobile phone network connectivity as instruments. In the endogenous treatment effects model the Wald test of independent equations is statistically significant; we thus reject the null hypothesis that ρ equals zero. The parameter ρ reflects the correlation between the error terms of the selection and outcome equations (Miyata et al., 2009; StataCorp, 2013). A significant ρ indicates that selection bias is present, and thus the endogenous treatment model results are preferred over the OLS results. Given that our outcome variable is food insecurity, the positive sign of ρ indicates a negative selection bias, i.e. the OLS estimates presented in column two of Table 5 underestimate the effect of mobile money on food insecurity. Negative selection bias in our case implies that households with lower food insecurity scores (i.e. more food secure households) are more likely to adopt mobile money. This correlation can be a result of unobserved factors that determine food insecurity and at the same time increase the likelihood of mobile money use, such as innate ability or motivation.

The results of the endogenous treatment effects model controlling for selection bias are presented in column four of Table 5. For the interpretation of the results it is important to keep in mind that the dependent variable is food insecurity; therefore, a negative coefficient implies a reduction in food insecurity and thus an increase in food security. First and foremost, we find that the use of mobile money significantly reduces household food insecurity. The use of mobile money is associated with a decrease in the food insecurity index by 0.20 index points. To put this number into perspective, consider that the food insecurity index is normalized and thus has zero mean and standard deviation one. The average treatment effect of mobile money use thus corresponds to one fifth of the standard deviation.

Table 5 columns 6 and 10 report the results from the IV regressions estimating the effect of frequency of use and volumes transferred on food insecurity, respectively. The Hausman (endogeneity) tests shown at the bottom of the table have p-values of 0.30 and 0.25, respectively. Thus, there is no evidence for selection bias in these specifications. We therefore interpret the results from the OLS models (columns 8 and 12). The incremental effect of the frequency of using mobile money is small and not statistically significant. The volume of money transferred has a significant effect. A one-percentage point increase in the volume transferred via mobile phone is associated with a reduction in food insecurity of 0.007 index points.

The coefficients of the other covariates are similar in sign and magnitude across the different model specifications. In what follows, we discuss results based on the endogenous treatment effects model (Table 5, column 4). We find that land size and ownership of a means of transport have a significant and negative effect on food insecurity. This implies that households with larger land holdings and who possess means of transport are more food secure. One additional acre of land reduces food insecurity by 0.01 index points. Ownership of a means of transport is associated with a 0.09 index point reduction in food insecurity – a result that is in line with the findings of Kassie et al. (2014b) in Kenya. Our results further show that household characteristics, such as education, do not seem to have significant effects on reducing food insecurity. These results are in contrast to findings from earlier studies that have shown that human capital is an important determinant of food security (Cock et al., 2013; Kabunga et al., 2014). Yet, they are in line e.g. with Kassie et al. (2014b), who also find education to be insignificant in their study in Kenya.

Table 5. Estimated effects of mobile money on food insecurity index

Dependent variable: food insecurity index	Use (dummy)				Frequency				Volume transferred			
	OLS		Treatment effects		IV		OLS		IV		OLS	
	Coeff	SE	Coeff	SE‡	Coeff	SE	Coeff	SE‡	Coeff	SE‡	Coeff	SE‡
Mobile money	-0.063**	0.026	-0.201***	0.074	-0.023	0.019	-0.004	0.003	-0.018*	0.010	-0.007***	0.002
Extension contact	-0.063**	0.026	0.006	0.022	0.026	0.028	0.009	0.022	0.020	0.024	0.011	0.022
Group membership	0.009	0.022	-0.037	0.026	-0.040	0.027	-0.039	0.027	-0.032	0.027	-0.036	0.026
Mobile phones	-0.037	0.027	0.001	0.010	0.016	0.027	-0.009	0.012	0.021	0.023	-0.001	0.011
Age	-0.004	0.011	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Gender	0.001	0.001	-0.012	0.032	-0.005	0.033	-0.011	0.033	0.006	0.034	-0.005	0.033
Education	-0.007	0.033	-0.002	0.003	0.000	0.004	-0.003	0.003	-0.002	0.003	-0.003	0.003
Household size	-0.003	0.003	0.008*	0.004	0.007	0.005	0.008*	0.005	0.007*	0.004	0.008*	0.004
Dependency ratio	0.008*	0.005	0.006	0.010	0.004	0.010	0.006	0.011	0.003	0.010	0.005	0.011
Land size	0.006	0.011	-0.008***	0.002	-0.007**	0.003	-0.008***	0.002	-0.007**	0.003	-0.008***	0.002
Ln(Farm equipment)	-0.008***	0.002	-0.012	0.009	-0.008	0.011	-0.012	0.010	-0.009	0.010	-0.012	0.010
Off farm income	-0.013	0.009	-0.037	0.024	-0.027	0.029	-0.043*	0.024	-0.014	0.030	-0.034	0.024
Access to credit	-0.038	0.024	-0.016	0.023	-0.010	0.027	-0.022	0.023	-0.002	0.027	-0.016	0.023
TLU	-0.019	0.023	-0.004	0.005	-0.005	0.007	-0.004	0.005	-0.005	0.006	-0.004	0.005
Means of transport	-0.004	0.005	-0.092***	0.029	-0.070*	0.041	-0.092***	0.030	-0.076**	0.036	-0.089***	0.029
Output market	-0.092***	0.030	0.001	0.002	0.001	0.002	0.001	0.002	0.000	0.002	0.001	0.002
District	0.001	0.002	0.011	0.026	0.028	0.033	0.010	0.027	0.042	0.034	0.020	0.027
Constant	0.016	0.027	0.557***	0.114	0.438***	0.122	0.477***	0.110	0.445***	0.116	0.470***	0.109
Observations	*476*		*476*		*476*		*476*		*476*		*476*	
$ath(\rho)$			*0.400***	*0.204*								
Wald test of independent equations (p-value)			*0.050*									
Wald/F statistic	6.31***		84.93***		4.34***		5.69***		4.57***			
Anderson LM statistic					15.17***				21.90***			

Cragg-Donald Wald F statistic	*7.52*	*11.02*
Sargan statistic (p-value)	*0.03*	*0.07*
Endogeneity test (p-value)	*0.30*	*0.25*

*, **, *** indicates coefficients are significant at the 10%, 5%, and 1% levels. ‡ Robust standard errors are reported. Only second stage IV estimates are shown.

5.3.2.2. Effect of mobile money on binary food insecurity

Last but not least, we estimated a number of probit and IV probit models to obtain the effects of different specifications of the treatment variable on binary food insecurity. The results are shown in Table 6. In the IV probit specifications, we used the size of the exchange social network and mobile phone network connectivity as instruments. The Wald tests of independent equations are insignificant in all IV probit specifications indicating the absence of selection bias. We therefore interpret probit estimates shown in columns 2, 6 and 10.

In line with the estimation in the previous section, we find that the use of mobile money has a significant and negative effect. The adoption of mobile money reduces the likelihood of being food insecure by ten percentage points (column 2). Also in line with previous estimation results, the frequency of using mobile money does not have a significant effect on food insecurity. Finally, the volume of money transferred is associated with a negative and significant effect. A one-unit increase in the volume of money transferred via mobile phone reduces the probability of food insecurity by 1.2 percentage points. The other control variables are consistent across the different specifications of the treatment variable. Group membership has a negative and significant effect on binary food insecurity, reducing the likelihood to be food insecure by about twelve percentage points across all specifications. The variables land size and means of transport are negative and significant, suggesting that larger land holdings and the ownership of a means of transport reduce the likelihood of being food insecure. These findings are also consistent with the models on the food insecurity index presented in the previous section.

Table 6. Estimated effects of mobile money on binary food insecurity

	Use (dummy)				Frequency				Volume transferred			
	Probit		IV probit		Probit		IV probit		Probit		IV probit	
	AME	SE‡	Coef	SE	AME	SE‡	Coef	SE	AME	SE‡	Coef	SE
Mobile money	-0.104*	0.055	-0.679	0.784	-0.002	0.007	-0.015	0.114	-0.012**	0.005	-0.028	0.061
Extension contact	0.054	0.046	0.170	0.133	0.049	0.047	0.143	0.163	0.058	0.047	0.156	0.138
Group membership	-0.116**	0.053	-0.309*	0.164	-0.116**	0.053	-0.328**	0.158	-0.117**	0.053	-0.332**	0.160
Mobile phones	0.001	0.024	0.067	0.144	-0.013	0.024	-0.023	0.160	0.007	0.024	0.012	0.133
Age	0.000	0.002	0.000	0.005	0.000	0.002	0.001	0.005	0.000	0.002	0.001	0.005
Gender	-0.028	0.068	-0.044	0.200	-0.036	0.067	-0.096	0.192	-0.025	0.069	-0.072	0.198
Education	-0.003	0.006	-0.004	0.018	-0.004	0.006	-0.008	0.026	-0.003	0.006	-0.008	0.017
Household size	0.012	0.010	0.032	0.026	0.013	0.010	0.034	0.026	0.012	0.010	0.034	0.026
Dependency ratio	0.001	0.023	-0.002	0.059	0.002	0.023	0.004	0.060	-0.000	0.023	0.000	0.060
Land size	-0.011*	0.006	-0.027*	0.016	-0.011**	0.006	-0.030	0.018	-0.010*	0.006	-0.029*	0.016
Ln(Farm equipment)	-0.027	0.020	-0.069	0.057	-0.026	0.020	-0.070	0.062	-0.025	0.020	-0.070	0.058
Off farm income	-0.075	0.049	-0.149	0.181	-0.087*	0.049	-0.229	0.169	-0.069	0.050	-0.196	0.174
Access to credit	0.001	0.050	0.038	0.151	-0.007	0.050	-0.013	0.153	0.007	0.050	0.013	0.155
TLU	-0.031**	0.013	-0.087**	0.039	-0.031**	0.013	-0.084**	0.040	-0.032**	0.013	-0.087**	0.040
Means of transport	-0.216***	0.073	-0.520**	0.210	-0.224***	0.073	-0.567**	0.236	-0.211***	0.073	-0.555***	0.201
Output market	0.004	0.005	0.008	0.013	0.005	0.005	0.013	0.013	0.004	0.005	0.011	0.013
District	0.078	0.055	0.272	0.193	0.061	0.055	0.178	0.190	0.086	0.055	0.227	0.199
Observations	*476*				*476*				*476*			
Wald statistic	*70.11****		*63.89****		*63.47****		*58.92****		*73.02****		*59.64****	
Pseudo R-square	*0.111*				*0.11*				*0.12*			
Wald test of exogeneity (Prob > chi2)			*0.62*				*0.93*				*0.95*	

*, **, *** indicates the corresponding average marginal effects are significant at 10%, 5%, and 1% levels, respectively. ‡ Robust standard errors are reported. Marginal effects are for discrete change of dummy variable from 0 to 1. Only second stage IV probit estimates are shown.

6. Conclusion and policy implications

Our present study complements and adds to the limited literature on the broader welfare effects of mobile money on households in developing countries. Using original household survey data, we analysed the effect of mobile money on food security among rural households in Uganda. Endogenous treatment effects and instrumental variables regressions are employed to control for potential selection bias. We estimate several specifications of the treatment variable (use of mobile money, frequency of use, volume transferred) as well as of the outcome variable (food expenditures, food insecurity index, binary food insecurity). Our results are largely consistent across the different model specifications indicating that the use of mobile money technology positively contributes to enhancing household food security.

Regarding food expenditures per AE, we find that the use of mobile money, the frequency of use and the volumes transferred are associated with increases in food expenditures. Furthermore, the use of mobile money and the volumes transferred reduce subjectively perceived food insecurity, both measured on a continuous scale as well as on a binary scale. The use of mobile money increases food expenditures per AE by nine percentage points and reduces the food insecurity index by 0.20 index points (one fifth of the standard deviation). The incremental effect of the frequency of use is less important in the context of the subjective perception of food insecurity, but increases food expenditures per AE: a one-unit increase in frequency is associated with a 1.9 percentage point increase in food expenditures per AE. Furthermore, a one-percentage point increase in the volumes transferred via mobile phone increases food expenditures per AE by one percentage point and reduces perceived food insecurity by about 0.007 index points.

These results have important food policy implications, in particular that mobile money services can play a role in improving food security among rural households in developing countries. Providing households with access to cheap and easily available banking functions can have positive liquidity effects and thus increase food expenditures and perceived food security. Against this background, policy interventions to improve household food security should also consider the promotion of mobile money and financial access among rural households in developing countries as a promising strategy.

Besides mobile money, other covariates were found to be significantly associated with improved food security. In particular, land size and ownership of a means of transport are consistently significant across the different food expenditure and food insecurity specifications. These findings have important policy implications as well. Due to land scarcity in Uganda, land area expansion is not a feasible strategy. Instead, policy makers should focus on promoting the adoption of sustainable intensification practices among rural households in Uganda. Sustainable intensification practices that aim to increase output per unit of input resource while conserving the natural resource base include for example modern high-yielding varieties, crop rotation, and soil and water conservation practices (Smith, 2013; The Montpellier Panel, 2013). Finally, the positive effect of ownership of a means of transport on food security is likely due to lower transaction costs and enhanced access to input and output markets. In particular, in rural areas in Uganda (and other developing countries) road infrastructure and public transport are poorly developed. Against this background, public investments in the improvement of transport networks is likely to have positive "side" effects on food security in rural areas.

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