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Mobile money, market transactions, and household income in rural Kenya

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Summary. Mobile phone based money services have spread rapidly in many developing countries. We analyze micro level impacts using panel data from smallholder farmers in Kenya. Mobile money use has a large positive net impact on household income. One important pathway is through remittances, which contribute to income directly but also help to reduce risk and liquidity constraints, thus promoting agricultural commercialization. Mobile money users apply more purchased inputs, market a larger proportion of their output, and have higher farm profits. These results suggest that mobile money can help to overcome some of the important market access constraints of smallholder farmers.

Key words: mobile banking; remittances; market transactions; agriculture; Africa; Kenya

JEL codes: D13, O13, O16, O33, Q12

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1. INTRODUCTION

During the last decade, mobile phone technology has spread rapidly in many developing countries. Several studies showed that mobile phones can cause significant benefits for rural households through improved access to information, lower marketing costs, and thus higher profits and incomes (Abraham, 2007; Jensen, 2007; Aker, 2008; Muto & Yamano, 2009; Aker, 2010). However, in addition to such direct effects, mobile phones are an enabling technology for other innovations. One important example are mobile phone based money transfers, which could be very relevant for rural households that are often underserved by the formal banking system. So far, relatively little is known about the impact of mobile money on the livelihoods of the rural poor.

Mobile money services were introduced by private telecommunication providers in several countries of Africa, Asia, and Latin America (Must and Ludewig, 2010). The concrete design of these services may differ, but the general idea is to enable cheap and reliable money transfers between people that have access to a mobile phone. This is especially relevant for sending and receiving remittances, which is much more expensive and sometimes risky through traditional formal and informal mechanisms (Morawczynski & Pickens 2009; Mas, 2009). In addition, mobile money facilitates transfers between business partners (Pickens, 2009; Mbiti & Weil 2011; Dermish et al. 2011), reducing transaction costs and promoting market integration and exchange. Finally, mobile money services provide secure opportunities for saving, even in remote rural areas (Shambare 2011; Jack & Suri, 2011).

While these potential effects of mobile money were identified in principle, there are only a few studies that have analyzed impacts on household welfare empirically. Several studies were initiated by telecommunication providers to demonstrate the viability of their business model; these results are not always representative (Duncombe & Boateng, 2009). Moreover, existing studies are often qualitative in nature (e.g., Morawczynski & Pickens 2009; Mas & Morawczynski, 2009; Plyler et al. 2010). One exception is Suri et al. (2012), who used representative household panel data to analyze the impact on risk sharing in Kenya; they showed that mobile money users could smooth their consumption due to remittances received in times of economic shocks. In another quantitative study, Mbiti & Weil (2011) used aggregate data to show that mobile money use has positive effects on different economic indicators, including employment. Both studies did not analyze the impact on household income. The only study that analyzed income effects of mobile money is Kirui et al. (2013). Kirui et al. (2013) used cross-section data from Kenya and a propensity score matching approach to estimate impacts on agricultural incomes of farm households. We add to this literature by analyzing effects on total household income, which is a more comprehensive welfare measure than agricultural income, and by using panel regression models that can better control for potential selection bias. We also examine potential impact pathways of mobile money in terms of remittances received, the intensity of transactions in input and output markets, and farm profits.

The empirical analysis concentrates on farm households in Kenya, where mobile money services have spread very rapidly in recent years (Dermish et al. 2011; Kirui et al., 2013). In 2007, Safaricom, Kenya's largest mobile service provider, launched a mobile money program called M-Pesa.[1] According to the company, M-Pesa now has around 17 million customers and

[1] The letter "M" refers to mobile, and Pesa means money in Swahili.

over 65 thousand agents nationwide; every day, 33.5 million US$ of payments are transferred between customers (Safaricom, 2013). Since 2009, a few other companies have launched similar programs in Kenya under different names. Yet, due to its early success, M-Pesa has almost become the generic term for mobile money among Kenyans. The rapid growth of mobile money services in Kenya is attributed to their promptness, cost effectiveness, reliability, and safety (Morawczynski, 2009; Morawczynski & Pickens, 2009; Jack & Suri, 2011).

The rest of this article is structured as follows. In the next section, we develop a conceptual framework, discussing how mobile money can affect the income of farm households that otherwise have limited access to formal financial services. This is followed by a description of the survey data and the empirical strategy to estimate impacts. Subsequently, the estimation results are presented and discussed. The last section concludes.

2. CONCEPTUAL FRAMEWORK

Availability and use of mobile money services can affect household income through multiple pathways, as shown in Figure 1. The effects could be especially important for poor people in rural areas for whom traditional banks and related financial services are often inaccessible. The first possible pathway is through remittances received, often from relatives and friends who migrated to urban areas. Many studies show that remittances constitute an important component of rural households' incomes and are used for different productive and consumptive purposes (Woodruff & Zenteno 2007; Yang, 2008; Adams & Cuecuecha, 2013). Without access to mobile money services, remittances can be sent through banks. However, the financial system is often underdeveloped in rural areas, so that bank services are not available everywhere (De Brauw et al., 2013). Moreover, hefty fees are often charged, especially when the recipient does not have a bank account. Alternatively, cash is sometimes sent through persons traveling to the destination, such as bus or truck drivers, but such informal mechanisms are also associated with high transaction costs and they are not always safe. Mobile money services reduce the transaction costs considerably, because money can be transferred by sending a simple text message to the recipient's mobile phone. Due to its cheapness, safety and reliability, mobile money is now the main avenue for sending and receiving remittances in Kenya (Morawczynski, 2009; Morawczynski & Pickens, 2009; Jack & Suri, 2011). Studies show that rural households are more likely to receive remittances from their distant relatives and friends through mobile money technology. Likewise, urban households with relatives in rural areas were found to use mobile money services more frequently. Interestingly, for M-Pesa in particular the senders are mostly men in urban areas, while the recipients are mainly women in rural areas (Morawczynski & Pickens, 2009). Similar effects of mobile money services on remittances were also revealed in other countries, such as Uganda, Tanzania, and the Philippines (Mirzoyants, 2012; 2013; Pickens, 2009).

[Figure 1]

A second possible pathway of how mobile money can affect household income is through more intensive use of purchased agricultural inputs and technologies, including fertilizers, pesticides, and hired labor, among others. Market participation by smallholder farmers is often relatively low, due to high transaction costs, liquidity constraints, and risk aversion (Renkow et al., 2004; Barrett, 2008; Poulton et al., 2010; Chamberlin & Jayne, 2013). Mobile money is unlikely to solve all these constraints, but it may still improve the situation for farm households. For instance, inputs may be purchased but paid at a later date without the farmer having to go to the input shop again. Similarly, wages for hired farm laborers can be paid more easily and flexibly, without having to keep large amounts of cash. More savings and higher remittances received may also help to ease liquidity constraints and risk (Must & Ludewig, 2010; Shambare, 2011). Suri et al. (2012) showed that remittances sent through mobile money tend to reduce the impact of negative economic shocks for households, thus providing a form of insurance. Mbiti & Weil (2011) found that mobile money services decreased the propensity to use informal savings and insurance mechanisms. Such informal savings and insurance mechanisms were shown to affect investment behavior and reduce economic efficiency in some situations (Jakiela & Ozier, 2012; Di Falco & Bulte, 2013). Hence, access to mobile money services is expected to increase farmers' willingness and ability to invest in agricultural inputs, which may increase productivity, profits, and thus household income.

A third and related pathway is through higher degrees of commercialization on the output side. Higher input use and productivity through mobile money may contribute to more marketable surplus. In addition, access to mobile money may facilitate farmers' integration into higher-value markets. In a recent study in Kenya, Rao & Qaim (2011) showed that sales to supermarkets are often associated with payments that are delayed by several days. In such situations, a cheap and reliable system to transfer money can reduce market entry barriers. Higher sales volumes and potentially also better prices may contribute to higher farm profits and thus higher incomes.

The relevance of these pathways will be tested empirically below for the example of farm households in Kenya. There are potentially other pathways that may also play a role, such as through increased employment, which is also shown in Figure 1. Mbiti & Weil (2011) found that mobile money services tend to increase rural employment. While we do not analyze possible income effects of increased employment in non-agricultural sectors, we look at agricultural employment effects through analyzing farmers' use of hired labor.

3. DATA AND EMPIRICAL STRATEGY

(a) *Household panel survey*

The empirical research builds on a panel survey of farm households that we conducted recently in Central and Eastern Provinces of Kenya. As this survey was part of a project to analyze socioeconomic conditions and innovations in the Kenyan banana sector, the sampling framework focused on the main banana-growing areas. Within Central and Eastern Provinces, the districts of Meru, Embu, Kirinyaga, Kiambu, Murang'a, and Thika were selected. In each district, banana-growing villages (sub-locations) were purposively sampled. Complete village listings were used to randomly select households to be interviewed. The first round of data collection was carried out between September and December 2009, referring to agricultural production and income in 2009. The second round of the survey with the same households was implemented between December 2010 and January 2011, referring to production and income in 2010. The balanced panel comprises 640 observations from 320 households that were interviewed in both survey rounds.

All sample households are diversified smallholders, most of them with farm sizes of less than 5 acres. In addition to banana, sample farms grow maize and different horticultural crops. Many also have some livestock activities such as raising chicken and small ruminants, and some grow cash crops such as coffee on a small scale. The sample is representative of smallholder banana growers in Central and Eastern Kenya. For the survey, household heads were interviewed using a structured questionnaire. The questionnaire was pretested prior to formal data collection to ensure content validity and clarity. Interviews were carried out in the local language by trained enumerators, who were supervised by the researchers. We collected data on household human capital and demographic characteristics, banana production and other farm enterprises, as well as off-farm economic activities. One special section of the questionnaire focused on mobile phone ownership and use of mobile money services. Sample descriptive statistics are provided below.

(b) *Econometric models*

The main focus of this study is to analyze impacts of mobile money use among smallholder farm households. As mentioned, mobile money services have spread rapidly in Kenya during the last few years. Nonetheless, not all households use mobile money, so that a first question of interest is as to what factors influence the adoption of this innovation. This is analyzed with a probit model:

$$MM_{it} = \alpha + \beta X_{it} + \delta T_t + \varepsilon_{it} \tag{1}$$

where the dependent variable MM_{it} is a dummy that takes a value of one if household i has used mobile money services in year t, and zero otherwise. X_{it} is a vector of farm, household, and contextual characteristics that may influence the decision to use mobile money; some of these characteristics may vary over time, while others are time-invariant. T_t is a year dummy to control for time fixed effects, and ε_{it} is a random error term with a standardized normal distribution.

To analyze impacts we use a different set of panel models:

$$Y_{it} = \theta + \gamma MM_{it} + \varphi Z_{it} + \rho T_t + \mu_{it} \tag{2}$$

where Y_{it} is the continuous outcome variable of interest (e.g., income, remittances received; see below for further details). In these models, we use MM_{it} as treatment dummy. A positive and significant estimate for the coefficient γ would indicate that mobile money use increases the value of the outcome variable, while controlling for other factors. Z_{it} is a vector of relevant covariates, which may include both time-variant and time-invariant factors. Again, we include a year dummy T_t to control for time fixed effects. μ_{it} is the random error, which includes unobserved individual effects that may be constant or also time-variant.

Equation (2) can be estimated with a random effects (RE) estimator. However, MM_{it} may potentially be correlated with the error term due to unobserved heterogeneity between mobile money users and non-users. Such heterogeneity is not unlikely, as households self-select into the group of users. If not controlled for, this could lead to selection bias in the estimated treatment effects. A common way to reduce the issue of selection bias is to use a household fixed effects (FE) estimator (Wooldridge, 2002; Greene, 2008). The FE estimator builds on a differencing approach within households, so that all time-invariant factors cancel out, even when they are unobserved. Efficient FE estimates require within-group variability with respect to the treatment variable. That is, there needs to be a sufficient number of households who used mobile money services in one year of the survey, but not in the other year. Such variability is given in our data, because we surveyed during a time when mobile money services were spreading fast in rural Kenya. We estimate all models with both RE and FE estimators, and use a Hausman test to compare the results (Greene, 2008). However, recent studies have shown that a significant Hausman test statistic is neither a necessary nor a sufficient condition to detect unobserved heterogeneity (Snijders, 2005). Hence, we will show both results, but prefer the FE estimates for interpretation of the mobile money treatment effects.

All outcome variables are continuous, but some of them are censored at zero. For instance, households that did not receive any transfers from relatives or friends in a particular year reported zero remittances. Using the common linear specification for models with a censored dependent variable may potentially lead to biased estimates (Wooldridge, 2002). Hence, for outcome variables where this is relevant we additionally use a Tobit estimator. As Tobit panel models cannot be estimated with household fixed effects, we only show the RE Tobit estimates for comparison as a robustness check.

(c) *Dependent and independent variables*

For the impact models, the main outcome variable of interest is total household income, which is calculated as the sum of all net earnings from on-farm and off-farm sources. Remittances are included as one off-farm income source in the total household income calculations. In addition, a separate model uses remittances as outcome variable, including all transfers from relatives and friends not residing in the household. The treatment variable of interest is mobile money use, which is captured as a dummy.

To estimate the impact of mobile money on the use of agricultural inputs and output sales we concentrate on the banana crop. Obviously, mobile money can also affect other agricultural enterprises, but there are two particular reasons why we decided to take this partial perspective. First, concentrating on one crop allowed us to collect more detailed and disaggregated data on the use of different purchased inputs. Second, banana is a typical semi-subsistence crop in Kenya, which is often cultivated primarily for home consumption with relatively low amounts of purchased inputs (Kabunga et al., 2012). Hence, the effects of mobile money services may be more pronounced than for typical cash crops that are grown with higher input intensities anyway. We will concentrate on the use of hired labor, purchased organic and mineral fertilizer, and chemical pesticides. The use of each of these inputs is expressed in monetary terms per acre and used as dependent variable in separate model specifications. To assess the impacts of mobile money on output commercialization, we use the proportion of bananas sold in the market relative to total banana production as dependent variable. Most farmers sell their bananas as bunches at the farm gate to local traders. Some of the farmers are organized in groups, selling bananas during collective marketing days to wholesalers coming to the region from Nairobi and other urban centers (Fischer & Qaim, 2012). To estimate potential mobile money impacts on profits, we use banana profit per acre as dependent variable; this is calculated as the market value of output (including home-consumed quantities valued at market prices) minus the cost of all purchased inputs.

As covariates in the different models, we include farm and household characteristics such as farm size (area owned), household size, and gender, age, and education of the household head. These variables may influence income, agricultural decisions, and also the decision whether or not to use mobile money services. In addition, we include contextual variables, such as the distance of the household to markets and roads, as well as agro-ecological conditions, which may also affect input use and degree of commercialization. Agro-ecological conditions are captured through a 'high-potential area' dummy, which takes a value of one for regions with more fertile soils and higher amounts of rainfall, and zero otherwise. High-potential areas especially comprise the slopes of Mount Kenya, including the districts of Embu, Meru and the northern half of Kirinyaga. Finally, for the probit model to explain the use of mobile money services, we include a variable measuring the percentage of households using mobile phones at the village level to capture neighborhood effects. It is expected that a wider use of mobile phones in the community increases the likelihood of individual households to also use mobile phones and related services.

4. RESULTS AND DISCUSSION

(a) *Patterns of mobile money use*

Table 1 shows how mobile phone and mobile money use developed over the 2009-2010 period covered by the panel survey. In 2010, 93% of all sample households owned at least one mobile phone, which was up from 86% in 2009. The difference between the two survey rounds was much stronger for the use of mobile money services, which increased from 60% in 2009 to 91% in 2010. We also asked farmers for the distance to the nearest shop offering mobile money services, such as withdrawing or depositing money on the mobile account. In 2010, the average distance was only 2 km, which underlines the wide coverage of these services in rural areas.

[Table 1]

Figure 2 shows for what concrete activities sample households used mobile money services in 2010. Around 60% of the households stated that they withdraw money from their mobile account, which may be money from remittances, payments by traders, or also from previous own saving deposits. Indeed, over 40% of the households stated that they use their mobile money accounts as a savings tool. But the households do not only receive remittances; about 50% stated that they also transferred money to other relatives and friends. Thirty-five percent used mobile services to transfer money to business partners, such as input dealers or farm laborers, while 32% stated that they transferred mobile money to pay for regular water or electricity bills. More than 40% of the households use mobile money to buy airtime for their mobile phone. Interestingly, about 27% also used mobile money services as a means of transferring money to their formal bank account, which is possible when the mobile provider has a special agreement with the respective bank. While the concrete numbers vary, the overall use patterns are similar to those reported in earlier research in Kenya (e.g., Mbiti & Weil, 2011; Jack

& Suri, 2011). Especially the payment of bills and the transfer of money to business partners through mobile money services seems to have increased over time.

[Figure 2]

(b) *Descriptive statistics*

Table 2 shows descriptive statistics for the variables used in the econometric models. For comparison, we differentiate between users and non-users of mobile money services. The upper part of the table shows the outcome variables for the impact assessment models. The columns for the pooled sample, which covers both survey rounds, reveal that mobile money users had significantly higher household incomes than non-users. Users had an annual mean income of around 283 thousand Kenyan shillings (Ksh), which is equivalent to 3435 US$ per household, or around 735 US$ per capita. Non-users had an annual income of 153 thousand Ksh, equivalent to 1854 US$ per household, or 458 US$ per capita. Users of mobile money also had higher profits from banana production and sold a larger proportion of their harvest. As expected, they used significantly higher amounts of purchased inputs per acre of banana production.

The disaggregation by survey round reveals relatively large differences for most variables between 2009 and 2010. The reason is that 2009 was a drought year with below average amounts of rainfall in Central and Eastern Kenya. Hence, input use, profits and incomes were lower in 2009 than in 2010, when rainfall was more favorable. For remittances, the pattern is different: especially for users of mobile money, remittances received were significantly higher in 2009 than in 2010. This suggests that mobile money transfers sent by relatives and friends can help to reduce risk and liquidity constraints in times of negative economic shocks, as was also shown by Suri et al. (2012).

[Table 2]

The lower part of Table 2 shows descriptive statistics of the explanatory variables used in the econometric models. Most of the mean values are not significantly different between users and non-users of mobile money services. However, a few differences can be observed. Households that use mobile money are more likely to be male-headed. The disaggregated data for the two survey rounds also shows that larger households and those with better educated household heads are more likely to use mobile money.

(c) *Determinants of mobile money use*

Estimation results from the probit model explained in equation (1) above are shown in Table 3. Several variables turn out to be significant determinants of mobile money use. While age does not play a significant role, the education level of the household affects mobile money use in a positive way. Each additional year of schooling increases the probability of using mobile money services by 1.7 percentage points. Household size also plays a significant role; households with more members are more likely to use mobile money, which is as expected. Further, the results suggest that wealth proxied by farm size influences the household decision. Each additional acre of owned land increases the probability of mobile money use by 2.3 percentage points. The negative square term indicates that this effect diminishes at larger farm sizes. The market access variables, including distance to the nearest banana market and to road infrastructure, are not significant. Nor do agro-ecological conditions, proxied by the high-potential area dummy, seem to play a role. These are a welcome findings, because they indicate that households in remoter and less favorable areas are able to use mobile money services, too. As supposed, due to the wide coverage and network of shops set up by private telecom providers in rural areas, mobile applications can help to overcome some of typical market access constraints of smallholder farm households.

[Table 3]

The percentage of households owning a mobile phone at the village level has a positive effect on mobile money use of the individual household. As we control for other location related variables, we conclude that neighborhood effects are significant. A large percentage of households with a mobile phone indicates that many in the community are likely to be familiar with mobile applications. Recent research shows that social networks and related knowledge transfer can play an important role for innovation adoption (Maertens & Barrett, 2013). The 2010 year dummy is also highly significant, showing that – independent of other variables included in the model – the use of mobile money services has increased rapidly in Kenya. As mentioned above, in 2010 already 91% of the sample households used mobile money.

(d) *Impact of mobile money on household income*

The factors influencing household income are presented in Table 4. These estimates are based on equation (2), using total annual household income as dependent variable. The results in column (1) are based on the FE estimator, while column (2) shows results with the RE estimator. As explained above, for interpretation of the mobile money impact we prefer the FE results, as these account for unobserved heterogeneity between mobile money users and non-users. Results in column (1) suggest that mobile money use has increased household income by 61,470 Ksh (745 US$). Compared to the mean income in the pooled sample of non-users, this implies a net income increase of 40% through mobile money, which is a very sizeable effect. The year dummy for 2010 is also large and significant, implying that household incomes were higher in 2010 than in 2009. This is expected, because 2010 was a year with more favorable rainfall.

[Table 4]

In the FE model, all other covariates were dropped, as these are time-invariant.[2] Nonetheless, it is interesting to see what role these other factors play for household income, which is shown in the RE results in column (2) of Table 4. Education of the household head has a positive effect on income; each additional year of schooling increases annual income by 9400 Ksh. Likewise farm size and household size have a positive effect on income. The latter should not surprise because the dependent variable is total income per household, not per capita. Somewhat unexpected is the positive effect for distance to the next all-weather road, which is significant at the 10% level. Probably distance alone is not a very comprehensive measure of market access constraints, as was also pointed out by Chamberlin & Jayne (2013).

One aspect that deserves further discussion in terms of mobile money impacts is the potential influence of unobserved factors that are time-variant. The FE specification controls for time-invariant heterogeneity, but not for time-variant factors that may be correlated with mobile money use. For instance, households that use mobile money may be more innovative and may also adopt other technologies more rapidly, which could lead to an overestimated treatment effect for mobile money. Since the time period between our two survey rounds was only one year, the risk that the adoption of other innovations would cause a significant bias is low. Yet, Table 1 showed that the proportion of households owning a mobile phone was still increasing between 2009 and 2010. Therefore, we ran household income models where we included a dummy for mobile phone ownership as an additional time-variant factor. Results of these robustness checks are shown in Table A1 in the Appendix. The mobile phone dummy is insignificant in the FE and RE specifications, while the mobile money effect remains significant and even slightly increases

[2] Age of the household head was also dropped, although this is time-variant. The reason for dropping age is the close correlation with the 2010 dummy. Household heads were one year older in 2010 than they were in 2009, unless the person heading the household changed during this time period.

in magnitude.[3] We conclude that the finding of a sizeable positive impact of mobile money on household income is robust.

(e) *Impact of mobile money on remittances*

Table 5 presents results for the remittances models, again with FE and RE specifications shown in columns (1) and (2), respectively. Mobile money use has a positive and significant effect. It increases annual remittances received by 12,697 Ksh (154 US$), which implies an increase of 66% compared to the mean remittances received by non-users of mobile money. The negative and significant coefficient of the 2010 dummy indicates that remittances received were lower in 2010 than in 2009. Given the drought in 2009, this result emphasizes the risk-reducing nature of money transfers from relatives and friends. Column (2) shows that larger households and those with older household heads received higher remittances on average.

[Table 5]

Since not all sample households had received remittances, the dependent variable is censored at zero. We therefore additionally estimated a RE Tobit model, results of which are shown in column (3) of Table 5. The signs and significance levels of the main variables of interest remain unaffected, but most of the coefficients increase in magnitude. Hence, while the exact numerical results should be interpreted with some caution, this additional model further underlines the significance of the mobile money treatment effect. The Tobit results also produce a few significant coefficients that were insignificant in the linear specifications. For instance, male-headed households received significantly lower remittances than female-headed households.

[3] For the other outcome variables discussed below, we carried out the same robustness tests with similar results. Details of these other tests are not reported here but can be obtained from the authors upon request.

(f) *Impact of mobile money on input use*

In section 2, we hypothesized that mobile money services may increase the use of agricultural inputs through various channels. We test this hypothesis for hired labor, organic and mineral fertilizers, and chemical pesticides, which are used by many sample farmers in their banana crop. The estimation results are shown in Table 6. The FE specifications confirm that mobile money has a positive and significant effect for all of these inputs, except for mineral fertilizer. Mobile money increases the spending for hired labor by 4100 Ksh (50 US$), for organic fertilizer by 2500 Ksh (30 US$), and for chemical pesticides by 1200 Ksh (15 US$) per acre of banana. These are sizeable effects, suggesting that mobile money services contribute to farm intensification through reducing transaction costs, risk, and liquidity constraints. For all inputs, use intensities were higher in 2010, due to more favorable rainfall.

[Table 6]

The RE specifications in Table 6 show that larger farms use more fertilizers and pesticides per acre. The same holds true for male-headed households, which is according to expectations. Female-headed households are often more constrained in their access to modern inputs and other productive resources. As some of the households do not use certain inputs, Tobit specifications of all input models are shown in Table A2 in the Appendix. Most of the estimated coefficients increase in magnitude, suggesting that the linear model results are probably conservative estimates.

(g) *Impact of mobile money on banana sales and profit*

Results of the banana sales and profit models are shown in Table 7. Column (1) reveals that mobile money use increases the proportion of banana sales (relative to total banana production) by 10.4 percentage points. Given that non-users have sold 56% of their harvest in the market, the mobile money treatment effect implies a 19% increase in the degree of output commercialization. This confirms that mobile money services tend to increase market transactions also on the output side. Unsurprisingly, sold proportions were higher in 2010, due to better rainfall and larger quantities harvested. The RE specification in column (2) further shows that larger farmers and those located in high-potential areas market a larger proportion of their harvest. This is according to expectations, as these farmers also produce higher overall output.

[Table 7]

The profit model results are shown in columns (3) and (4) of Table 7. The FE specification suggests that mobile money use increases banana profits by 30,112 Ksh per acre (365 US$), implying a 35% gain over non-users. To some extent, the higher profits may be due to more intensive input use and higher banana yields. Besides, reduced transaction costs in output markets may also play a role. The RE specification reveals that farmers in high-potential areas have higher profits. In contrast, profits per acre are somewhat lower on larger farms, indicating decreasing returns to scale in these smallholder banana systems.

5. CONCLUSION

Previous research had documented the rapid spread of mobile phone based money services in developing countries. Existing studies also suggest that this may have positive effects especially for poor people in rural areas who are often underserved by the traditional banking system. In this article, we have contributed to the literature by analyzing the impacts of mobile money use on the income of smallholder farm households, which had not been done previously. Furthermore, we have examined possible impact pathways by looking at the influence on remittances received, transactions in agricultural input and output markets, and farm profits. The empirical analysis has concentrated on banana-growing households in Kenya, where mobile money services have spread widely in recent years. Panel survey data was collected and used for the analysis. Econometric models with household fixed effects were estimated to control for possible unobserved heterogeneity between users and non-users of mobile money services.

The results show that mobile money use has a positive and large net impact on household welfare, increasing total income by 40% on average. One important impact pathway seems to be through remittances, which have increased by 66%. In comparison to traditional formal and informal mechanisms of transferring money between relatives and friends, mobile money services reduce the transaction costs substantially. They also provide new incentives for saving. And, mobile money contributes to more commercially-oriented farming. Our results reveal that mobile money users apply significantly more purchased inputs – such as fertilizer, pesticides, and hired labor – and sell a larger proportion of their harvest in the market. On the one hand, this is related to lower transaction costs in terms of paying and receiving money from business partners. On the other hand, more remittances and savings seem to reduce risk and liquidity constraints, which also contributes to higher market participation. Mobile money users have 35% higher profits per acre of banana production.

Our results confirm the idea that mobile money services can be welfare-enhancing for poor people in rural areas. In Kenya, mobile money also seems to be widely accessible. While wealthier and better educated households were among the first to adopt this innovation, within only a few years more than 90% of all households in our sample were using mobile money services. Mobile money can help to overcome some of the important market access constraints of smallholder farm households. It is noteworthy to stress that the wide spread of mobile services in Kenya is entirely driven by private sector incentives, underlining that the private sector has an important role to play for rural development. Through sensible regulations the public sector needs to ensure that the emerging markets are competitive.

Our study has focused on banana growers in two provinces of Kenya, so the concrete numerical results should not be generalized too widely. Follow-up research should analyze the access to mobile money and the wider implications under diverse conditions to gain a more comprehensive picture of potentials and limitations. Also the analysis of impact pathways and broader social ramifications deserves further attention. One interesting question is how mobile money services affect informal savings and insurance mechanisms at the local level.

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Table 1. Use of mobile phones and mobile money among sample households

	2009		2010	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Proportion of mobile phone owners	0.86	0.35	0.93***	0.26
Proportion of mobile money users	0.60	0.49	0.91***	0.28
Years owning a mobile phone	3.78	2.92	4.71***	3.02
Years using mobile money	0.94	0.94	1.85***	1.07

*** mean value between 2009 and 2010 is significantly different at the 1% level.

Table 2. Descriptive statistics for variables used in econometric models

	Pooled sample				2009				2010			
Variable	MM users	SD	Non-users	SD	MM users	SD	Non-users	SD	MM users	SD	Non-users	SD
Outcome variables												
Household income (000 Ksh)	283.35***	228.59	152.98	142.70	250.17***	243.14	138.09	116.30	305.05*	216.23	221.56	218.18
Remittances (000 Ksh)	10.91	48.92	6.67	21.71	19.52**	74.00	6.27	22.05	5.28	17.55	8.46	20.36
Banana profit (000 Ksh/acre)	110.94**	124.03	85.65	99.71	92.51*	94.87	76.05	68.12	122.99	138.69	129.87	181.50
Proportion of banana sales	0.69***	0.38	0.56	0.27	0.63***	0.25	0.55	0.27	0.74	0.43	0.61	0.27
Hired labor (000 Ksh/acre)	6.36***	12.31	2.95	13.31	2.37	5.47	1.51	4.28	8.97	14.64	9.60	29.69
Organic fertilizer (000 Ksh/acre)	3.54***	8.34	0.94	3.84	1.63	6.69	0.73	4.01	4.78*	9.06	1.90	2.84
Mineral fertilizer (000 Ksh/acre)	4.46***	8.29	1.23	5.42	0.79	3.68	0.98	5.85	6.47**	9.51	2.39	2.45
Pesticides (000 Ksh/acre)	2.08***	4.71	0.33	1.47	0.28	1.36	0.24	1.49	3.26**	5.66	0.71	1.31
Explanatory variables												
Land owned (acres)	3.43	2.96	3.06	3.09	3.50	2.86	3.11	3.18	3.39	3.03	2.86	2.67
Age of household head (years)	58.14	13.30	61.04	14.45	58.45	13.45	59.45	13.97	57.94***	13.22	68.36	14.63
Education (years)	8.99	3.88	6.78	4.10	9.21***	3.95	7.31	3.93	8.84***	3.83	4.30	4.00
Household size (members)	4.67	2.07	4.05	2.07	4.75**	1.97	4.29	2.07	4.63***	2.13	2.93	1.74
Male household head (dummy)	0.84**	0.36	0.77	0.42	0.85	0.36	0.79	0.41	0.84**	0.37	0.68	0.48
Distance to banana market (km)	4.26	3.59	4.24	3.62	4.28	3.62	4.21	3.57	4.24	3.57	4.35	3.90
Distance to all-weather road (km)	3.62	3.79	3.50	3.84	3.63	3.74	3.53	3.92	3.62	3.64	3.32	3.51
High-potential area (dummy)	0.55	0.50	0.56	0.50	0.54	0.50	0.58	0.50	0.56	0.50	0.50	0.51

Notes: MM means mobile money; SD means standard deviation.

*,**,*** mean value between MM users and non-users in the same period is significantly different at the 10%, 5%, and 1% level, respectively.

Table 3. Determinants of mobile money use (probit estimates)

Variable	Marginal effects	Std. Err.
Age of household head	0.008	0.007
Age squared	-6.8E-05	5.8E-05
Education of household head	0.017***	0.004
Male household head	0.027	0.037
Household size	0.017**	0.008
Land owned	0.023**	0.010
Land squared	-0.001**	4.572E-04
Distance to banana market	0.001	0.004
Distance to all-weather road	0.003	0.004
High-potential area	-0.008	0.029
Percentage of village households with mobile phone	0.008***	0.001
2010 dummy	0.317***	0.028
Model statistics		
Pseudo R^2	0.283	
LR/Wald χ^2	139.49***	
Log likelihood	-393.29	

,* significant at the 5% and 1% level, respectively.

Table 4. Determinants of household income

Variable	(1) FE	(2) RE
Mobile money	61.470* (32.704)	70.694*** (21.312)
2010 dummy	73.343*** (18.373)	71.458*** (16.516)
Age of household head		0.540 (0.732)
Education of household head		9.408*** (2.510)
Male household head		-13.430 (23.772)
Household size		11.729*** (4.141)
Land owned		6.648** (3.034)
Distance to banana market		0.326 (0.514)
Distance to all-weather road		4.090* (2.291)
High-potential area		0.721 (17.533)
Intercept	168.307*** (22.283)	-7.290 (63.957)
Model statistics		
LR/Wald χ^2		96.93***
F value	20.38***	
Hausman test, χ^2	0.37	

Notes: Estimates are based on balanced panel regressions with 640 observations and 320 groups. The dependent variable in both models is total household income (000 Ksh/year). Coefficient estimates can be interpreted as marginal effects; standard errors are shown in parentheses.
*,**,*** significant at the 10%, 5%, and 1% level, respectively.

Table 5. Determinants of remittances received

Variable	(1) FE	(2) RE	(3) Tobit RE
Mobile money	12.697** (6.461)	12.435*** (4.378)	23.722** (11.300)
2010 dummy	-12.625*** (3.630)	-12.543*** (3.303)	-33.947*** (9.573)
Age of household head		0.616*** (0.154)	2.831*** (0.423)
Education of household head		-0.390 (0.530)	-0.379 (1.256)
Male household head		-15.984 (13.603)	-33.102*** (11.568)
Household size		1.819* (0.932)	1.917 (2.178)
Land owned		-0.191 (0.641)	-0.566 (1.470)
Distance to banana market		-0.586 (0.518)	-0.496 (1.288)
Distance to all-weather road		-0.249 (0.490)	-2.468* (1.361)
High-potential area		-2.663 (3.737)	-5.249 (9.111)
Intercept	6.661 (4.402)	-15.984 (13.603)	-159.158*** (36.511)
Model statistics			
LR/Wald χ^2		55.66***	93.60***
F value	6.05***		
Hausman test, χ^2	0.00		
Log likelihood			-2545.30

Notes: Estimates are based on balanced panel regressions with 640 observations and 320 groups. The dependent variable in both models is remittances received per household (000 Ksh/year). Coefficient estimates can be interpreted as marginal effects; standard errors are shown in parentheses.
*,**,*** significant at the 10%, 5%, and 1% level, respectively.

Table 6. Determinants of input use in banana production

Variable	Hired labor (1) FE	Hired labor (2) RE	Organic fertilizer (3) FE	Organic fertilizer (4) RE	Mineral fertilizer (5) FE	Mineral fertilizer (6) RE	Pesticides (7) FE	Pesticides (8) RE
Mobile money	4.122** (1.978)	0.810 (1.278)	2.502** (1.235)	1.267* (0.760)	-1.640 (1.147)	0.503 (0.737)	1.212* (0.628)	0.482 (0.403)
2010 dummy	5.706*** (1.111)	6.751*** (1.005)	2.471*** (0.694)	2.861*** (0.622)	6.118*** (0.644)	5.442*** (0.583)	2.388*** (0.353)	2.618*** (0.319)
Age		-3.0E-04 (0.043)		-0.024 (0.024)		-0.016 (0.024)		-0.029** (0.013)
Education		-0.017 (0.147)		-0.017 (0.086)		-0.051 (0.085)		-0.035 (0.047)
Male head		1.308 (1.390)		0.759 (0.813)		1.590** (0.809)		1.087** (0.442)
Household size		-0.230 (0.258)		-0.063 (0.150)		0.079 (0.150)		1.E-04 (0.082)
Land owned		-0. 004 (0.177)		0. 188* (0.104)		0.510*** (0.103)		0. 305*** (0.056)
Distance to market		-0.033 (0.143)		-0.112 (0.084)		0.058 (0.083)		-0.022 (0.046)
Distance to road		-0.010 (0. 136)		0.167** (0.079)		0.105 (0. 079)		0.054 (0. 043)
High-potential area		0.467 (1.034)		0.731 (0.604)		1.449** (0.602)		0.436 (0.329)
Intercept	-0.442	-1.595 (3.771)	-0.223	-0.587 (2.206)	1.846** (0.781)	-2.880 (2.194)	-0.460 (0.992)	-0.276 (1.198)
Model statistics								
LR/Wald χ^2		59.97***		48.34***		149.99***		133.91***
F value	31.20***		18.18***		56.23 ***		46.86***	
Hausman, χ^2	4.76*		1.61		5.59*		2.29	

Notes: Estimates are based on balanced panel regressions with 640 observations and 320 groups. All dependent variables are measured in thousand Ksh per acre. Coefficient estimates can be interpreted as marginal effects; standard errors are shown in parentheses.
*,**,*** significant at the 10%, 5%, and 1% level, respectively.

Table 7. Determinants of banana sales and profits

Variable	Proportion of banana sales (1) FE	(2) RE	Banana profits (000 Ksh/acre) (3) FE	(4) RE
Mobile money	0.104* (0.059)	0.084** (0.036)	30.112* (17.954)	17.486 (12.171)
2010 dummy	0.092*** (0.033)	0.098*** (0.030)	28.211*** (10.087)	32.004*** (9.198)
Age		-0.001 (0.001)		-0.258 (0.428)
Education		-0.002 (0.004)		-0.566 (1.467)
Male head		0.024 (0.038)		-5.307 (13.908)
Household size		0.001 (0.007)		-2.200 (2.384)
Land owned		0.014*** (0.005)		-3.657** (1.775)
Distance to market		2.5E-04 (0.001)		0.021 (0.301)
Distance to road		-0.003 (0.004)		-0.584 (1.341)
High-potential area		0.049* (0.028)		25.415** (10.259)
Intercept	0.537*** (0.040)	0.505*** (0.104)	7.901*** (12.233)	120.052*** (37.516)
Model statistics				
LR/Wald χ^2		40.60***		34.62***
F value	11.81***		11.62***	
Hausman test, χ^2	0.17		0.20	

Notes: Estimates are based on balanced panel regressions with 640 observations and 320 groups. Coefficient estimates can be interpreted as marginal effects; standard errors are shown in parentheses.
*,**,*** significant at the 10%, 5%, and 1% level, respectively.

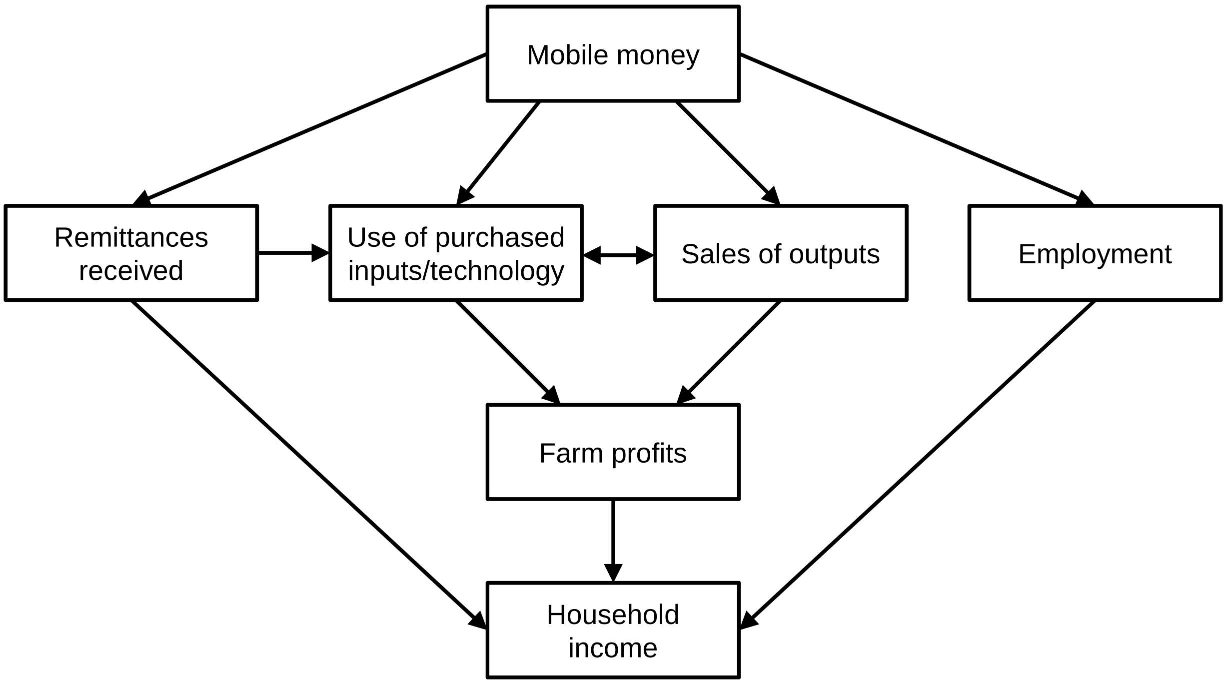

Figure 1. Impact pathways of mobile money

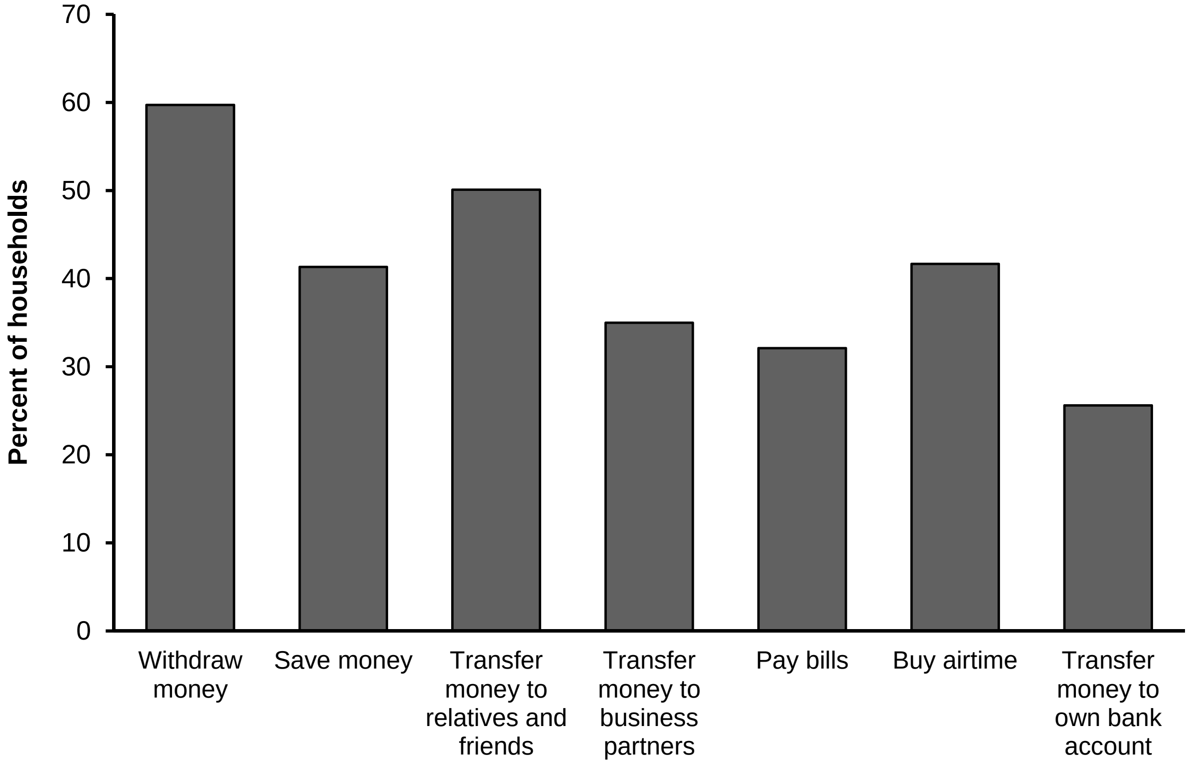

Figure 2. Types of activities performed with mobile money among sample households

Appendix

Table A1. Impact of mobile money on income with mobile phone as additional covariate

Variable	FE	RE
Mobile money	69.546** (34.233)	76.228*** (24.789)
Mobile phone	-50.494 (62.879)	-11.703 (33.822)
2010 dummy	74.265*** (18.419)	69.489*** (16.665)
Model statistics		
LR/Wald χ^2		96.93***
F value	13.79***	

Notes: The models are the same as those shown in Table 4, but additionally including a dummy for mobile phone ownership as a time-variant factor. Intercept and other covariates are not shown to save space. **,*** significant at the 5% and 1% level, respectively.

Table A2. Determinants of input use in banana production (Tobit estimates)

Variable	Hired labor	Organic fertilizer	Mineral fertilizer	Pesticides
Mobile money	3.625 (2.373)	3.881*** (1.583)	0.814 (1.473)	2.373** (1.121)
2010 dummy	12.751*** (1.891)	14.975*** (1.329)	17.346*** (1.295)	10.854*** (0.941)
Age	-0.011 (0.074)	-0.073* (0.044)	-0.031 (0.043)	-0.068 (0.029)
Education	0.101 (0.252)	-0.009 (0.150)	-6.0E-04 (0.143)	-0.017 (0.100)
Male head	0.337 (2.385)	1.413 (1.447)	2.523* (1.398)	3.083*** (1.020)
Household size	-0.486 (0.449)	-0.027 (0.266)	0.127 (0.260)	0.030 (0.179)
Land owned	0.500* (0.296)	0.479*** (0.172)	0.895*** (0.165)	0.659*** (0.112)
Distance to market	0.090 (0.243)	-0.123 (0.145)	0.130 (0.14	-0.006 (0.096)
Distance to road	-0.264 (0. 241)	0.211 (0. 136)	0.105 (0. 134)	0.147 (0. 090)
High-potential area	2.833 (1.779)	2.137** (1.067)	4.290*** (1.044)	2.153*** (0.719)
Intercept	-13.630** (6.594)	-14.190*** (4.074)	-19.651*** (3.930)	-14.130*** (2.781)
Model statistics				
LR/Wald χ^2	72.75***	245.74***	317.30***	285.55***
Log likelihood	-3763.74	-3671.48	-3553.05	-2625.99

*,**,*** significant at the 10%, 5%, and 1% level, respectively.