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RESEARCH ARTICLE

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# Mobile money adoption, input use, and farm output among smallholder rice farmers in Ghana

Awal Abdul-Rahaman[1,2] | Awudu Abdulai[3]

[1]Department of Agribusiness Management and Finance, Faculty of Agriculture, Food and Consumer Sciences, University for Development Studies, Nyankpala Campus, Tamale, Ghana

[2]Christian-Albrechts-Universität zu Kiel

[3]Department of Food Economics and Consumption Studies, University of Kiel, Kiel, Germany

**Corresponence**
Awal Abdul-Rahaman, Department of Agribusiness Management and Finance, Faculty of Agriculture, Food and Consumer Sciences, P. O. Box, TL 1882, University for Development Studies, Nyankpala Campus, Tamale, Ghana.
Email: awalrahaman@uds.edu.gh

## Abstract

Financial exclusion continues to be a major challenge to smallholder farmers' participation in agricultural value chains in developing countries. Digitizing procurements and other forms of transactions using mobile money technology among value chain actors is essential for ensuring financial inclusion and enhancing agricultural value chain transformation. This study examines the factors influencing the adoption of mobile money technology and the impact of the technology on production input use and farm output, utilizing data from a cross-sectional survey of smallholder rice farmers in northern Ghana. A linear regression with endogenous treatment effects method is employed to account for both observable and unobservable selection bias. The results reveal positive and significant marginal effect of mobile money technology on input use and farm output. Adopters of the technology applied 18% and 13% more fertilizer and herbicides, respectively than nonadopters. The output increased by about 4% for the adopters. The results also show that mobile money technology adoption, input use and farm output are significantly influenced by education, farmer-based organization (FBO) membership, access to credit, input prices, and location fixed effects. Expansion of mobile technology networks, increased investment in education, credit facilities, and FBOs can be quite relevant in promoting the adoption of mobile money technology in Ghana. [EconLit citations: C34, C35, Q12, Q13]

**KEYWORDS**
farm output, input use, mobile money technology, treatment effects model

## 1 | INTRODUCTION

Agricultural value chains continue to transform remarkably in developing countries (Reardon et al., 2009). This transformation stems from rising incomes, urbanization, consumer consciousness for food safety and standards, as well as liberalization of foreign direct investment (Reardon et al., 2009; Wang et al., 2014). The value chain constitutes input dealers, farmers (upstream actors), processors, wholesalers, retailers, and service providers (downstream actors). Despite creating stringent requirements, and generating compliance costs, this transformation has created significant market and income opportunities for smallholder farmers resulting from their participation in these value chains (Badiane & Ulimwengu, 2017). For instance, large agribusinesses procure produce directly from smallholder farmers mostly through contractual arrangements and other forms of vertical and horizontal co-ordination mechanisms in developing countries including Ghana (Abdul-Rahaman & Abdulai, 2020a; Bijman et al., 2006).

However, one significant challenge hindering the efficiency of these value chain relationships is the fact that vast majority of smallholder farmers in developing countries remain unbanked or financially excluded (Global System Mobile Association [GSMA], 2016). They purchase production inputs using cash, and receive cash payments for the sale of their farm produce (GSMA, 2016, 2018). Research has shown that about 71% of the rural folks in sub-Saharan Africa are financially excluded. Notable reasons include lack of sufficient funds and cost of operating an account, lack of documentation, distrust for the financial system, and longer distance to financial institutions among others (World Bank Global Findex, 2017). Financial exclusion has consequences on smallholder farmers. For instance, it can limit farmers' ability to repay outstanding debts, carry out savings, and manage risks effectively (Donovan, 2012).

Previous studies have recognized that digitizing procurements and other forms of transactions amongst value chain actors can be very essential in ensuring financial inclusion and enhancing agricultural value chain transformation and efficiency in the developing world, where majority (53%) of smallholder farmers live (Donovan, 2012; GSMA, 2016; World Bank Global Findex, 2017). One important example of such digital technological innovations is mobile money payments using a mobile phone, which was introduced in some countries of Africa, Asia and Latin America by private telecommunication service providers (Kikulwe et al., 2014; Must & Ludewig, 2010). Mobile money is a digital financial technology that enables receipt, storage and transfer of money by way of simple messaging service, using a mobile phone with connection to a mobile network (Beck et al., 2018; Jack & Suri, 2014; Liébana-Cabanillas et al., 2014; Peruta, 2017). In Africa, the use of mobile money services was first introduced in Kenya, but now very popular in most African countries, especially in sub-Saharan Africa (Jack & Suri, 2014).

Mobile money transactions among value chain actors can provide several benefits and offer significant opportunities for inclusive value chain development. Generally, besides providing opportunities for savings, especially in socially volatile and risky environments (Beck et al., 2018), it allows for a reliable money transfer between value chain actors, reduces transaction costs, and facilitates market exchange (Jack & Suri, 2011; Kikulwe et al., 2014; Shambare, 2011). In particular, mobile money technology presents several advantages for smallholder farmers and agribusiness companies in a typical agricultural value chain. Significant advantages for smallholder farmers include (among others): time and cost savings, convenience, efficient cash management and improved financial identity (transactional records) (GSMA, 2016). On the other hand, agribusiness companies experience lower costs associated with securing and transporting cash, and distributing payments, timely and safer payments to farmers at multiple locations, and mitigating risks (e.g., theft and fraud) associated with handling cash (GSMA, 2016; Liébana-Cabanillas et al., 2014).

Given the increasing significance of mobile money technology in developing countries, many studies have analyzed the implications of this technology over the past decade. Most of these studies have been carried out in East Africa, where mobile money was first introduced. For example, in Kenya, Suri et al. (2012) found that in times of economic shocks, the use of mobile money smoothened household consumption due to remittances received. The study by Mbiti and Weil (2011) revealed that mobile money usage decreased individual ability to use informal savings mechanisms (e.g., ROSCAS), as well as the prices of competing money transfer services (e.g., Western Union), but encouraged financial inclusion of the unbanked and underserved in Kenya. Using a quantitative dynamic general equilibrium model, Beck et al. (2018) found that mobile money technology has significant quantitative implications for macroeconomic development and entrepreneurial growth in Kenya. Other previous studies showed that mobile money adoption contributes to developing the payment ecosystem, promoting financial inclusion and cash-lite economy in Ghana (e.g., Bank of Ghana [BoG], 2017).

Despite this plethora of studies, only a handful of studies focused on the implications of mobile money adoption on farming households in developing countries (e.g., Kikulwe et al., 2014; Kirui et al., 2013; Peprah et al., 2020). In their studies on Kenya, Kirui et al. (2013) and Kikulwe et al. (2014) found significant improvement in household welfare resulting from the adoption of mobile money, while the study by Peprah et al. (2020) revealed that mobile money adoption increases output and welfare of smallholder farmers in Ghana. However, none of these previous studies examined the effects of mobile money adoption on the use of farm inputs such as chemical fertilizer and herbicides used. The present study attempts to fill the gap on the impact of mobile money technology adoption on smallholders' input use and farm output, using cross-sectional data from selected districts in northern Ghana.

Our study focuses on chemical fertilizer and herbicides because they are the production inputs commonly purchased by smallholder farmers in the study area. Smallholder farmers normally use seeds saved from the previous season's harvest, and mostly rely on family labor for farm activities. Specifically, the study contributes to the literature in the following ways. First, the study identifies and analyzes the drivers of smallholder farmers' decisions to adopt mobile money technology for value chain transactions such as input procurement and farm output. Second, this study examines the effects of these adoption drivers on smallholder farmers' input use (chemical fertilizer and herbicides) and farm output. Third, the study evaluates the impact of mobile money technology adoption on smallholder farmers' input use and farm output. Smallholder farmers' adoption of mobile money technology can stimulate the use of purchased farm inputs that are essential for increasing farm output. This is possible especially in situations where inputs may be purchased and payments made at a later date. Such delayed payments can be made via mobile money technology without the farmer having to incur extra transaction costs (transportation) in going to the agro-input dealer's shop again (Kikulwe et al., 2014). Reduced transaction costs could likely stimulate increased investment in farm inputs, which considerably affect farm output.

Our study is among the very few ones that explicitly link mobile money adoption to smallholder input use and farm output in sub-Saharan Africa, and the first in Ghana. The study focuses on the rice sector, which contributes substantially to increasing household income, reducing poverty, and improving food and nutrition security. Moreover, rice is noted to be the second most common cereal staple after maize in Ghana. Mobile money technology could be very important in reducing transaction costs when purchasing farm inputs for production. The promotion of mobile money technology in value chains transactions is already ongoing in Ghana by the government, donors, and private companies via a number of value chain development interventions (e.g., USAID-ADVANCE project etc.). Because farmers' access to mobile money technology is not randomly assigned, this study employs linear regression with endogenous treatment effects model to jointly examine the drivers of the adoption decisions and their related implications on input use and farm output and to account for potential selection bias from both observable and unobservable factors. Our empirical results reveal positive and significant effects of mobile money technology on input use and farm output. The results also show that mobile money technology adoption, input use, and farm output are significantly influenced by education, membership in farmer-based organizations (FBOs), access to credit, and input prices. The findings suggest that expansion of mobile technology networks, increased investment in education, and credit facilities can be quite relevant in promoting the adoption of mobile money technology in Ghana. Thus, the findings from our study can contribute to policy formulation targeted at enhancing smallholder financial inclusion, value chain development and overall economic growth in Ghana.

The remainder of this article proceeds as follows. Section 2 presents an overview of mobile money usage and smallholder interventions in Ghana. The conceptual framework used to guide the empirical analysis is described in Section 3, followed by the empirical method in Section 4. Section 5 presents data and summary statistics of the variables used in the estimations. Results and discussions are presented in Section 6, while conclusions and policy implications are presented in the final section.

## 2 | OVERVIEW OF MOBILE MONEY USE AND SMALLHOLDER INTERVENTIONS IN GHANA

Mobile money technology has been receiving growing attention and gradually becoming the most convenient means of carrying out financial transactions especially for the unbanked and underserved in developing countries (Akomea-Frimpong et al., 2019; BoG, 2017; Markovich & Snyder, 2017). The technology has gained importance with profound implications on agricultural value chain development. The widespread use of mobile money is partly attributed to the penetration and application of mobile phones, especially in rural remote areas. Mobile money is a technology for providing financial services using a mobile phone device, and offers a wide range of services such as government to person payments, peer-to-peer transfers, receiving remittances, and payment for goods and services through an electronic wallet (Donovan, 2012; GSMA Mobile Money Tracker, 2012). The use of mobile money payment system gained much recognition worldwide after the 2008 and 2009 "Mobile Money Summits" held in Cairo, Egypt and Barcelona, Spain, respectively (Gosavi, 2017; Suri & Jack, 2016). Kenya was the first African country to introduce mobile money payment system known as M-PESA, which has gradually spread to other African countries including Ghana.

In Ghana, mobile money technology was first introduced by Mobile Telephone Network (MTN) in 2009 and subsequently by Airtel and Tigo in 2011 (Fintech Africa, 2017). Currently, four communication companies (MTN, Airtel, Vodafone, and Tigo) are involved in rendering mobile money payment services to the public in Ghana: MTN mobile money, Airtel money, Vodafone cash and Tigo Cash (Roberts, 2016). According to the National Communications Authority (NCA) (2015), MTN is the leader in terms of mobile voice subscriber base (46%), followed by Vodafone (27%) and then Tigo (14%). The remaining market share is captured by Airtel, GLO and Expresso with a subscriber base of 12%, 5%, and 1%, respectively (NCA, 2015). Research indicates that about 80% of Ghana's adult populations do not operate bank accounts in accredited financial institutions (e.g., PricewaterhouseCoopers, 2011). Such unbanked population relies on mobile money technology as a means of participating in the formal financial system (Akomea-Frimpong, 2017). Ghana has about 14,700,000 active mobile money users and 235,000 active mobile money agents (BoG, 2020). Mobile money technology can play a significant role in agricultural development through its potential of ensuring smallholder farmers' financial inclusion. Mobile money transaction is usually accomplished via a mobile money vender (agent). Mobile money vendors provide financial services via mobile phone and mobile network by converting cash into an electronic value and vice versa (Donovan, 2012). They charge small commission for the service rendered to customers.

In Ghana, significant efforts have been made by development agencies, government and the private sector to enhance mobile money technology adoption by value chain actors for market transactions. An example of such efforts is the almost 5-year (February 2014 to September 2018) USAID's Agricultural Development and Value Chain Enhancement (ADVANCE) II project implemented by ACDI/VOCA in northern Ghana. It was mainly focused on upscaling agricultural investments to improve the competitiveness of maize, rice, and soybean value chains. The ADVANCE II project was supported by Feed the Future, the U.S. Government's global hunger and food security initiative.

In partnership with Mobile Telephone Network (MTN), the largest telecommunications company in Ghana, the ADVANCE II project identified and built the capacities of a group of nucleus farmers, input dealers, and outgrowers on the use of mobile money services. Nucleus farmers subsequently trained smallholder farmers on the use of the technology, entered into contract with, and provided support to these farmers. Smallholder farmers under the project began purchasing production inputs, and received monies from the sale of their produce using mobile money technology. The technology has been generally recognized as being simple to use, ensures efficient and smooth payment to farmers by produce buyers, as well as offers additional opportunity to access financial services including insurance, savings, and credit. In addition, some of the produce buyers travel from the southern part of Ghana to the rural, agricultural north to purchase produce during harvest period. These buyers normally carry along huge sums of money with them, due to lack of banks especially in the rural areas of the north, which is very risky, as they may be exposed to the threat of theft. Mobile money technology is used in many rural areas to eliminate this threat.

Another important mobile money intervention in Ghana is Rice Mobile Finance (RiMFin), which was piloted from September 2013 to June 2014 by Agribusiness Systems International in partnership with Tigo cash, Open-Revolution, an international firm with the expertise of building mobile money platforms, and Ghana Agriculture Development Company (GADCO), a major rice producer and a miller. The project targeted 5000 outgrowers whose produce was supplied to GADCO, and payment received via Tigo cash. Following the successes and lessons from RiMFin project, the agricultural value chain mobile finance (AgFin) project was also launched in 2015 by same collaborators, with funding from the International Fund for Agricultural Development. The AgFin project was aimed at expanding mobile money technology, and improving financial literacy for about 10,000 smallholder farmers in the cocoa, oil palm, and dried fruits value chains in rural communities of some selected regions in Ghana.

# 3 | CONCEPTUAL FRAMEWORK

## 3.1 | Modeling mobile money technology adoption decisions

Mobile money adoption decision by a smallholder farmer is assumed to be binary, where she/he decides whether to adopt the technology or not. We further assume that farmers are risk neutral, and make adoption decisions by comparing the expected benefits ($M_A^*$) from adoption and the expected benefits ($M_N^*$) from nonadoption. By intuition, a farmer decides to adopt the mobile money technology if the benefits associated with adoption outweigh the benefits from nonadoption, or if the net benefit is positive, that is, $M_i^* = M_A^* - M_N^*$. $M_i^*$ represents unobservable latent variable, which can be expressed as a function of observable characteristics as:

$$M_i^* = \vartheta' Z_i + \mu_i,\ M_i = 1[M_i^* > 0], \tag{1}$$

where $M_i$ is a binary indicator variable that takes on a value of one if a farmer adopts mobile money technology and zero otherwise; $\vartheta$ is a vector of parameters to be estimated; $Z$ is a vector of explanatory variables that influence mobile money adoption decision; and $\mu$ is the error term with mean zero and variance $\sigma^2$. The probability of adopting mobile money technology can be specified as:

$$\Pr(M_i = 1) = \Pr(M_i^* > 0) = \Pr(\mu_i > -Z_i\vartheta) = 1 - F(-Z_i\vartheta), \tag{2}$$

where $F$ is the cumulative distribution function for $\mu_i$. Generally, not all farmers use mobile money technology for their value chain transactions due to the fact that they are heterogeneous. However, adoption of mobile money technology is expected to impact on other farm outcomes such as the input use and farm output. Relating the adoption decision to the outcomes, it is assumed that farmers maximize expected net returns, which may be expressed as (Abdulai & Binder, 2006):

$$\pi_{max} = [PQ(\tau, Z) - D\tau], \tag{3}$$

where $P$ is price of output, $Q$ is the farm output level, $\tau$ is the vector of input quantities, $D$ is the vector of input prices, and $Z$ is a vector of farm and household characteristics. This implies that the net returns can be expressed as a function of the input and output prices, farm and household characteristics and the mobile money technology adoption ($M$), represented by the following relation:

$$\pi = \pi(D, M, P, Z). \tag{4}$$

Assuming any well-specified normalized profit function, directly applying Hoteling Lemma to Equation (3) results in the following respective input use and farm output functions (Abdulai & Binder, 2006):

$$\frac{\partial \pi(P, D)}{\partial D_i} = -\tau_i^* \text{ for all i}, \tag{5}$$

$$\frac{\partial \pi(P, D)}{\partial P_i} = -Q_i^* \text{ for all i}, \tag{6}$$

where $\tau_i^*$ and $Q_i^*$ denote the optimal levels of input use and farm output produced by farmer $i$, respectively, with their corresponding reduced form equations represented by the following relationships:

$$\tau = \tau(D, M, P, Z). \tag{7}$$

$$Q = Q(D, M, P, Z). \tag{8}$$

The specifications in Equations (7) and (8) imply that the input use (chemical fertilizer and herbicides) and optimal supply quantity are influenced by input and output prices, mobile money technology adoption and the farm and household characteristics.

## 3.2 | Impact of mobile money technology adoption on input use and farm output

This section presents an approach for estimating the impact of mobile money technology on input use and farm output. To begin with, we consider a linear relationship between the vector of outcomes and the vector of farm and household characteristics and a mobile money technology adoption dummy, specified as follows:

$$Y_i = X_i\delta + M_i\beta + \varepsilon_{i,} \tag{9}$$

where $Y_i$ is the vector of continuous outcome variables (quantities of fertilizer and herbicides applied and paddy output), $X_i$ is the vector of farm and household characteristics, $M_i$ is the mobile money technology adoption dummy by farmer $i$, $\delta$ and $\beta$ represent vector of parameters to be estimated, and $\varepsilon_i$ is the error term. Mobile money adoption decisions and the outcomes among farmers are likely to be influenced by unobserved heterogeneity, especially as farmers self-select into groups of adopters and nonadopters. This could lead to selection bias, which needs to be addressed to obtain unbiased and consistent estimation of the treatment effects of mobile money technology (Kikulwe et al., 2014). Using standard regression such as ordinary least square method would generate biased estimates. Some previous studies have employed propensity score matching (PSM) and inverse probability-weighted with regression adjustment (IPWRA) methods to control for the bias associated with a binary treatment variable such as the case in hand (e.g., Danso-Abbeam & Baiyegunhi, 2018; Peprah et al., 2020). However, a commonly known limitation of these methods is their inability to account for selection bias caused by unobserved factors. As in previous studies (e.g., Abdul-Rahaman & Abdulai, 2020b; Ma & Abdulai, 2017), this study employs a linear regression with endogenous treatment effects model in the estimations, which accounts for selection bias associated with both observable and unobservable factors.

## 4 | EMPIRICAL METHOD

### 4.1 | Linear regression with endogenous treatment effects model

The concept of the endogenous treatment effects model evolved from the pioneering work of Heckman (1978, 1979). He developed a framework for modeling sample selection, as well as addressing issues of selection bias in nonrandomized studies. The endogenous treatment effects model is similar to the Heckman's model in the sense that it is a two-step sample selection model. However, unlike the Heckman's model, a dummy variable representing the treatment condition (e.g., $M_i = 1$ if mobile money adopter, and $M_i = 0$, otherwise) is included in the outcome equation, and the continuous outcome variables (fertilizer, herbicide, and farm output) are observed for the treated ($M_i = 1$) and untreated ($M_i = 0$) groups (Traore, 2020). Several past studies have employed the linear regression with endogenous treatment effects model in their empirical estimations (e.g., Abdul-Rahaman & Abdulai, 2020b; Ma & Abdulai, 2017; Traore, 2020). Using the model, Ma and Abdulai (2017) examined the economic impacts of co-operatives on smallholder farmers in China, while Traore (2020) investigated the effects of input diversion strategy on maize productivity by farmer organizations in Burkina Faso. Abdul-Rahaman and Abdulai (2020b) assessed the impact of value chain participation and social networks on market performance among rice farmers in Ghana.

This study uses the two-stage linear regression with endogenous treatment effects model to estimate the drivers of farmers' mobile money technology adoption decisions at the first-stage, and the impact of the mobile money technology on continuous outcome variables such as farmers' input use and output in the second-stage. The model is employed due to its advantages over other impact assessment methods such as PSM and IPWRA. First, the direct marginal effect of mobile money technology on input use and farm output can be obtained. Second, the model can reveal the various factors influencing mobile money adoption decisions. Third, the model also accounts for selection bias arising from both observed and unobserved farmer attributes. It is important to mention that all farmers in the sample applied fertilizer and chemicals, as well as generated output, and so we did not encounter zero values of these outcomes in the data set, thus making the linear regression with endogenous treatment effects model appropriate for the analysis. However, zero values of these outcome measures would have called for the use of instrumental variable-based Tobit model.

As stated earlier, the linear regression with endogenous treatment effects model uses the maximum likelihood method to jointly estimate the mobile money technology adoption equation (Equation 1) and the input use and output equation (Equation 9). The error term in Equation 1 ($\mu$) and the error term in Equation 9 ($\varepsilon$) are assumed to follow a bivariate normal distribution with zero mean and covariance matrix. Following Cong and Drukker (2000), the expected outcomes of farmer $i$ conditional on mobile money technology adoption and nonadoption are respectively expressed as:

$$E(Y_i \mid M = 1) = X_i\delta + \vartheta + E(\varepsilon_i \mid M = 1) = X_i\delta + \vartheta + \rho_{\mu\varepsilon}\sigma_{\mu\varepsilon}\frac{\phi(Z_i\vartheta)}{\Phi(Z_i\vartheta)}, \tag{10}$$

$$E(Y_i \mid M = 0) = X_i\delta + E(\varepsilon_i \mid M = 0) = X_i\delta - \rho_{\mu\varepsilon}\sigma_{\mu\varepsilon}\frac{\phi(Z_i\vartheta)}{1 - \Phi(Z_i\vartheta)}, \tag{11}$$

where $\Phi(.)$ represents the standard normal cumulative distribution function and $\phi(.)$ is the standard normal density function. The ratio of $\phi(.)$ and $\Phi(.)$ is referred to as the inverse mills ratio. $\delta$ and $\vartheta$ denote the vectors of parameters to be estimated, $\sigma_{\mu\varepsilon}$ is the covariance between the two error terms, $\mu, \varepsilon; \rho_{\mu\varepsilon}$ is the correlation coefficient that indicates the presence or absence of selection bias due to unobservable factors. A positive and significant $\rho_{\mu\varepsilon}$ indicates the presence of selection bias, and the fact that farmers with above average input use and farm output are more likely to adopt mobile money technology. The average treatment effects (ATEs) of mobile money technology adoption on the input use and farm output for sample $N$ can be estimated as the difference between Equations 10 and 11, expressed as:

$$ATE = \frac{1}{N}\sum_{i=1}^{N}[E(Y_i \mid M = 1) - E(Y_i \mid M = 0)]. \tag{12}$$

It is important to identify the model using a valid instrument. A good instrument variable should significantly influence the selection equation, but not the outcomes of interest (Abdul-Rahaman & Abdulai, 2020b; Ma et al., 2017). The model is identified using distance to mobile money vender as instrument, which significantly influences mobile money technology adoption, but does not have direct effect on input use and farm output. We argue that the farther the distance to a mobile money vender, the less likely farmers would be willing to engage in mobile money transactions. A falsification test reveals the validity of the instrument (see Table A2 in appendix). In conducting the falsification test, the instrument is included in the selection and outcome equations and its significance level tested at each stage of the model estimation. The statistical significance of the instrument in the selection equation and insignificance of the variable in the outcome equation indicates validity of the instrument.

Variables representing access to credit and membership in FBO are argued to be potentially endogenous in farmers' decisions to adopt mobile money technology. Smallholder farmers obtain credit to enhance their investments in inputs (e.g., seeds, fertilizer, chemicals, etc.) for improved productivity. The credit disbursements are sometimes done through farmers' mobile money accounts. Therefore, having a mobile money account could be a precondition for credit acquisition by smallholder farmers. This means that some farmers may decide to adopt mobile money technology to receive credit, making these two decisions jointly determined. In addition, produce buyers normally engage farmers in the form of a group, and as well make payments for produce purchased using mobile money technology. In that regard, farmers can make a joint decision of belonging to the FBO and also adopting the mobile money technology to have access to guaranteed markets. This makes FBO membership potentially endogenous in mobile money technology adoption decision. These potential endogeneities are addressed using the control function approach[1] with suitable instruments to ensure consistent estimation of the endogenous treatment effects model. The control function approach is a two-stage estimation procedure proposed by Wooldridge (2015). In our study, the first-stage involves estimating two separate probit models with FBO membership and access to credit (potential endogenous variables) as dependent variables, and farmer perception of FBO benefits (1 for beneficial, 0 for not beneficial) and distance to credit institution (km) as instruments, respectively (see Table A1 in appendix for the firs-stage estimates). Note that these instruments are expected to significantly influence the potential endogenous variables, but not mobile money technology adoption. In the second-stage, the observed FBO membership and access to credit variables and their respective predicted residuals from the first-stage regression are then included in the endogenous treatment effect model for estimation. The $t$

[1]Details of the control function approach can be found in Wooldridge (2015).

statistics for the significance of the residual coefficients determine the exogeneity of the FBO membership and access to credit variables (Wooldridge, 2015).

## 5 | DATA AND DESCRIPTIVE STATISTICS

This study employs data collected from a recent household survey of five selected districts in northern Ghana from June to August, 2016. These districts include Tolon, Kumbungu, Sagnarigu districts, Savelugu Nanton municipal, and Tamale metropolis. The data was collected with the help of trained research assistants for the doctoral studies of one of the authors. Multistage sampling procedure was used in drawing the sample for the study. Using purposive sampling method in the first stage, the five study districts were selected in consultation with the Ministry of Food and Agriculture and some officials of donor funded projects (e.g., USAID-FtF program, etc.). The selection was based on their geographic accessibility, and the fact that rice is commonly produced in these districts. In the second stage, random sampling was employed to select two to three communities from each study district. In the third stage, a total of 421 smallholder rice farmers comprising 234 adopters and 187 nonadopters were randomly sampled in proportion to the farmer population in each district. The sampled farmers were then interviewed using structured questionnaire. The information gathered includes farm and household characteristics, production, marketing, and other value chain activities.

Table 1 presents the definition and summary statistics of the variables used for the empirical analysis. The data reveal that 55% of farmers in the sample adopted mobile money technology for input procurement and receipt of proceeds from paddy sales, suggesting that the use of this technology is gradually increasing among smallholder farmers in the study area. The remaining 45% of farmers did not adopt the technology. Notable reasons have been linked to farmers' inability to afford a mobile phone device, poor telecommunication networks in some of the rural communities, the risk of losing one's savings to fraudsters, and inability to operate mobile account due to lack of formal education, among others. As shown in Table 1, the average age of a farmer is 37 years with an average of about 2 years of formal education. The data also reveal that on average, a rice farmer cultivates 1.14 ha of land, applies 268.34 and 1.94 kg/ha of nitrogen fertilizer and active ingredient in herbicide, respectively, and generates about 1251.68 kg of output.

The variable mean differences between adopters and nonadopters of mobile money technology, and their associated statistical *t* tests are presented in Table 2. Significant mean differences between adopters and nonadopters with respect to most of the variables have been observed. Adopters of the mobile money technology are more educated, mostly belong to FBOs, and constitute a greater proportion of farmers who have obtained credit for their farming operations, as compared to nonadopters. In addition, adopters cultivate more land, apply higher quantities of fertilizer and chemicals, as well as produce higher output quantities than nonadopters. However, the adopters and nonadopters are similar in terms of variables such as age, motorcycle ownership, distance to the nearest rice market, and distance to input store. These significant mean differences between adopters and nonadopters in terms of input use and farm output cannot be interpreted as impacts because other confounding factors are not accounted for in the computation. The linear regression with endogenous treatment effects model accounts for these confounding factors, and also generates unbiased and consistent mobile money technology impact estimates.

## 6 | EMPIRICAL RESULTS AND DISCUSSION

As indicated earlier, the maximum likelihood method is employed in estimating the two-stage endogenous treatment effects model. The model estimates the drivers of mobile money technology adoption decision and its related impact on input use and farm output among smallholder farmers. The estimation results are presented in Tables 3–5. In particular, the second column of Tables 3–5 reports estimates for the drivers of mobile money technology adoption decision, while the third column presents results for the impact of these factors on input use

**TABLE 1** Variable definition and summary statistics

| Variable | Definition | Mean (SD) |
|---|---|---|
| *Dependent variables* | | |
| Farm output | Quantity of paddy output (kg) | 1251.68 (1702.77) |
| Fertilizer | Quantity of nitrogen fertilizer applied (kg/ha) | 268.34 (366.36) |
| Herbicide | Quantity of active ingredient in herbicide applied (kg/ha) | 1.94 (1.91) |
| *MMT* adoption | 1 if farmer adopts mobile money technology, 0 otherwise | 0.55 (0.49) |
| *Independent variables* | | |
| Age | Age of respondent (years) | 37.78 (11.80) |
| Education | Education of respondent (years) | 2.14 (4.04) |
| Gender | 1 if farmer is male, 0 otherwise | 0.90 (0.30) |
| Farm size | Size of farm (ha) | 1.14 (1.25) |
| Motorcycle | 1 if farmer owns a motorcycle, 0 otherwise | 0.43 (0.49) |
| Credit | 1 if farmer has access to enough credit and not liquidity constraint, 0 otherwise | 0.44 (0.49) |
| Dist. to input store | Distance to input store (km) | 5.31 (4.39) |
| Dist. to paddy market | Dist. to paddy market (km) | 6.46 (4.050) |
| FBO member | 1 if farmer belongs to rice FBO, 0 otherwise | 0.47 (0.49) |
| Fertilizer price | Price of fertilizer per kilogram (Gh¢) | 1.93 (0.32) |
| Herbicide price | Price of herbicides per liter (Gh¢) | 19.50 (18.94) |
| Output price | Price of paddy rice per kilogram (Gh¢) | 1.20 (0.49) |
| Dist. to mobile money vender | Dist. to mobile money vender (km) | 2.84 (4.88) |
| Sagnarigu | 1 if farmer is located in Sagnarigu district, 0 otherwise | 0.13 (0.33) |
| Tolon | 1 if farmer is located in Tolon district, 0 otherwise | 0.23 (0.42) |
| Kumbungu | 1 if farmer is located in Kumbungu district, 0 otherwise | 0.26 (0.43) |
| Savelugu Nanton | 1 if farmer is located in Savelugu Nanton Municipal, 0 otherwise | 0.19 (0.39) |
| Tamale | 1 if farmer is located in Tamale metropolitan area, 0 otherwise | 0.17 (0.38) |

*Note:* GH¢ is Ghanaian currency (US$1 = GH¢ 4.19).
Abbreviations: FBO, farmer-based organization; MMT, mobile money technology.

and farm output. The wald test ($\rho_{\mu\varepsilon}$ = 0) is significantly different from zero, indicating that the null hypothesis that the mobile money technology adoption variable in Equation 9 is exogenous is rejected.

The results also reveal the presence of selection bias arising from unobservable factors as indicated by statistically significant correlation coefficient ($\rho_{\mu\varepsilon}$) for all the specifications. The negative $\rho_{\mu\varepsilon}$ for the farm output and herbicide use specifications indicates negative selection bias, suggesting that farmers with lower than average farm output and herbicide use have a higher probability of adopting mobile money technology. Conversely, the significant and positive sign of $\rho_{\mu\varepsilon}$ in the fertilizer use specification suggests that farmers with above average fertilizer use are more likely to adopt mobile money technology. The significance of the $\rho_{\mu\varepsilon}$ confirms the appropriateness of the linear regression with endogenous treatment effects model in the empirical estimations as it addresses selection bias on unobservable factors, and also generates unbiased estimates. The residual estimates for the potential endogenous variables such as the FBO membership and access to credit are not significantly different from zero, implying that the coefficients of these variables have been consistently estimated (Wooldridge, 2015).

**TABLE 2** Differences in characteristics of farmers by mobile money technology adoption status

| Variable | *MMT* adopters Mean | SD | *MMT* nonadopters Mean | SD | Difference (*t* stat.) |
|---|---|---|---|---|---|
| Age | 37.44 | 11.81 | 38.20 | 11.81 | −0.659 |
| Education | 2.85 | 4.65 | 1.25 | 2.89 | 4.090*** |
| Gender | 0.92 | 0.26 | 0.86 | 0.34 | 2.082** |
| Farm size | 1.27 | 1.54 | 0.98 | 0.71 | 2.391** |
| Motorcycle | 0.43 | 0.49 | 0.43 | 0.49 | 0.056 |
| Credit | 0.50 | 0.50 | 0.36 | 0.48 | 2.883*** |
| Dist. to input store | 5.01 | 4.10 | 5.68 | 4.73 | −1.54 |
| Dist. to paddy market | 6.33 | 3.96 | 6.63 | 4.16 | −0.735 |
| FBO member | 0.57 | 0.49 | 0.34 | 0.47 | 4.704*** |
| Fertilizer price | 1.95 | 0.28 | 1.90 | 0.37 | 1.677* |
| Herbicide price | 17.70 | 9.12 | 21.76 | 26.39 | −2.195** |
| Output price | 1.22 | 0.67 | 1.18 | 0.27 | 0.711 |
| Dist. to mobile money vender | 2.30 | 3.93 | 3.51 | 5.80 | 2.529** |
| Sagnarigu | 0.10 | 0.30 | 0.17 | 0.37 | 2.063** |
| Tolon | 0.22 | 0.42 | 0.24 | 0.43 | −0.260 |
| Kumbungu | 0.29 | 0.45 | 0.21 | 0.41 | 1.757* |
| Savelugu Nanton | 0.20 | 0.40 | 0.16 | 0.37 | 1.132 |
| Tamale | 0.15 | 0.36 | 0.19 | 0.39 | −1.063 |
| Farm output | 1634.07 | 2098.80 | 773.18 | 784.13 | 5.319*** |
| Fertilizer | 346.02 | 463.14 | 171.13 | 131.48 | 5.004*** |
| Herbicide | 2.21 | 2.13 | 1.59 | 1.53 | 3.313*** |
| Sample size | **234** | | **187** | | |

Abbreviation: MMT, mobile money technology.

*, **, and *** represent significance at 10%, 5%, and 1% levels, respectively.

## 6.1 | Drivers of mobile money technology adoption decision

The drivers of mobile money technology adoption decision are presented in the second column of Tables 3–5. As can be observed, the variables with the same name in the various specifications have similar signs and effects on adoption, and therefore are interpreted together as normal probit estimates. The empirical results show that adoption of mobile money technology is significantly influenced by education, farm size, access to credit, FBO membership and location fixed effects. In particular, education is positive and significant at conventional levels in all the specifications, suggesting that farmers with formal education are more likely to adopt mobile money technology. This finding is consistent with the empirical literature that education enables farmers to make informed decisions such as technology adoption. Farm size has a positive and significant effect on mobile money technology adoption decision, implying that farmers with larger farm sizes are more likely to adopt mobile money technology. Similar finding has been revealed by other studies (e.g., Abdulai & Huffman, 2014; Tufa et al., 2019). Farm size is an

**TABLE 3** Determinants of *MMT* adoption and fertilizer use

| Variable | MMT adoption Coefficient | SE | Fertilizer Coefficient | SE |
|---|---|---|---|---|
| Constant | −0.452 | 0.528 | 4.554*** | 0.620 |
| *MMT* adoption | | | 1.583*** | 0.122 |
| Age | −0.004 | 0.006 | 0.005 | 0.006 |
| Education | 0.051*** | 0.018 | 0. 026 | 0.019 |
| Gender | 0.216 | 0.232 | 0.238 | 0.274 |
| Farm size | 0.223*** | 0.049 | 0.369*** | 0.062 |
| Motorcycle | −0.072 | 0.117 | 0.079 | 0.155 |
| Credit | 0.309*** | 0.119 | 0.518*** | 0.153 |
| Dist. to input store | 0.019 | 0.018 | −0.001 | 0.023 |
| Dist. to paddy market | −0.001 | 0.018 | −0.010 | 0.024 |
| FBO member | 0.491*** | 0.124 | 0.826*** | 0.160 |
| Fertilizer price | 0.193 | 0.180 | −0.056** | 0.023 |
| Herbicide price | −0.005 | 0.004 | −0.007* | 0.004 |
| Output (paddy) price | −0.089 | 0.166 | 0.019 | 0.163 |
| Sagnarigu | −0.038 | 0.281 | 0.267 | 0.295 |
| Tolon | 0.431** | 0.216 | 0.472** | 0.249 |
| Kumbungu | 0.351* | 0.205 | 0.571** | 0.236 |
| Savelugu Nanton | 0.202 | 0.196 | 0.262 | 0.254 |
| Dist. to mobile money vender | −0.031*** | 0.009 | | |
| FBO residual | 0.390 | 0.278 | | |
| Credit residual | 0.197 | 0.220 | | |
| ath($\rho_{\varepsilon\mu}$) | 2.280*** | 0.198 | | |
| $\rho_{\varepsilon\mu}$ | 0.979*** | 0.008 | | |
| ln($\sigma$) | 0.418*** | 0.042 | | |
| Wald test ($\rho_{\varepsilon\mu}$ = 0) | 11.43 with Prob > $\chi^2$ = 0.0000 | | | |
| Sample size | 421 | | | |

Abbreviations: FBO, farmer-based organization; MMT, mobile money technology.
*, **, and ***Significance at 10%, 5%, and 1% levels, respectively.

indicator of household wealth, as well as a major production asset. It is expected that wealthier farmers use improved technologies in their farming businesses.

Access to credit also plays an important role in mobile money technology adoption decisions. As shown by the results, the positive and significant coefficient of access to credit suggests that the likelihood of mobile money technology adoption increases with farmers' access to credit. FBO membership also exerts a significant positive effect on mobile money technology adoption. This means that farmers who belong to an FBO have a higher likelihood of adopting a mobile money technology relative to nonmembers, which is in line with previous

**TABLE 4** Determinants of *MMT* adoption and herbicide use

| Variable | MMT adoption | | Herbicides | |
|---|---|---|---|---|
| | Coefficient | SE | Coefficient | SE |
| Constant | −0.791 | 0.661 | 0.189** | 0.196 |
| *MMT* adoption | | | 0.611*** | 0.113 |
| Age | −0.008 | 0.007 | 0.005** | 0.002 |
| Education | 0.061*** | 0.023 | 0.008 | 0.006 |
| Gender | 0.021 | 0.301 | 0.057 | 0.085 |
| Farm size | 0.317*** | 0.091 | 0.148*** | 0.019 |
| Motorcycle | −0.126 | 0.140 | 0.121** | 0.048 |
| Credit | 0.458*** | 0.135 | 0.695*** | 0.150 |
| Distance to input store | −0.029 | 0.023 | −0.003 | 0.007 |
| Distance to paddy market | −0.002 | 0.023 | −0.002 | 0.007 |
| FBO member | 0.603*** | 0.141 | 0.309*** | 0.114 |
| Fertilizer price | 0.238 | 0.207 | −0.032 | 0.072 |
| Herbicide price | −0.005 | 0.004 | −0.076*** | 0.013 |
| Output (paddy) price | −0.164 | 0.203 | 0.046 | 0.051 |
| Sagnarigu | −0.167 | 0.349 | −0.024 | 0.092 |
| Tolon | 0.225 | 0.271 | −0.132* | 0.078 |
| Kumbungu | 0.233 | 0.270 | −0.127* | 0.074 |
| Savelugu Nanton | 0.626** | 0.243 | −0.182** | 0.082 |
| Dist. to mobile money vender | −0.042** | 0.016 | | |
| FBO residual | −0.132 | 0.510 | | |
| Credit residual | −0.070 | 0.479 | | |
| ath($\rho_{\varepsilon\mu}$) | −0.707*** | 0.171 | | |
| $\rho_{\varepsilon\mu}$ | −0.609*** | 0.108 | | |
| ln($\sigma$) | 0.744*** | 0.059 | | |
| Wald test ($\rho_{\varepsilon\mu}$ = 0) | 8.42*** with Prob > $\chi^2$ = 0.0037 | | | |
| Sample size | 421 | | | |

Abbreviations: FBO, farmer-based organization; MMT, mobile money technology.

*, **, and ***Significance at 10%, 5%, and 1% levels, respectively.

technology adoption studies (e.g, Abdulai & Huffman, 2014; Tufa et al., 2019). The estimate for distance to mobile money vender from farmer's house is found to be negative and significant for all the specifications, indicating that farmers with longer distance to a mobile money vender are less likely to adopt mobile money technology. Finally, the role of location fixed effects has also been highlighted in the results. Specifically, relative to Tamale metropolis (reference district), the coefficients of the district dummies exert positive and significant effect on mobile money technology adoption decisions, suggesting that farmers who live and farm in Kumbungu and Savelugu Nanton districts have a higher likelihood of adopting mobile money technology.

**TABLE 5** Determinants of *MMT* adoption and quantity of paddy output

| Variable | *MMT* adoption Coefficient | SE | Paddy output Coefficient | SE |
|---|---|---|---|---|
| Constant | −0.294 | 0.634 | 2.167*** | 0.751 |
| *MMT* adoption | | | 2.122*** | 0.468 |
| Age | −0.001 | 0.007 | 0.007 | 0.007 |
| Education | 0.068*** | 0.023 | 0.048** | 0.024 |
| Gender | 0.240 | 0.304 | 0.235 | 0.327 |
| Farm size | 0.246*** | 0.087 | 0.023 | 0.075 |
| Motorcycle | −0.034 | 0.137 | 0.201 | 0.186 |
| Credit | 0.404*** | 0.136 | 0.391** | 0.193 |
| Dist. to input store | −0.020 | 0.023 | −0.005 | 0.027 |
| Dist. to paddy market | −0.003 | 0.021 | −0.019 | 0.028 |
| FBO member | 0.539*** | 0.140 | 0.403* | 0.215 |
| Fertilizer price | 0.121 | 0.193 | −0.072** | 0.028 |
| Herbicide price | −0.006 | 0.004 | −0.003 | 0.005 |
| Output (paddy) price | −0.131 | 0.195 | 0.172 | 0.196 |
| Sagnarigu | 0.118 | 0.351 | 1.142*** | 0.352 |
| Tolon | 0.386 | 0.272 | 0.725** | 0.299 |
| Kumbungu | 0.495* | 0.268 | 1.032*** | 0.286 |
| Savelugu Nanton | 0.579** | 0.237 | 0.391 | 0.315 |
| Dist. to mobile money vender | −0.063*** | 0.017 | | |
| FBO residual | 0.421 | 0.504 | | |
| Credit residual | 0.096 | 0.467 | | |
| ath($\rho_{\varepsilon\mu}$) | −0.727*** | 0.191 | | |
| $\rho_{\varepsilon\mu}$ | −0.621*** | 0.117 | | |
| ln($\sigma$) | 0.595*** | 0.063 | | |
| Wald test ($\rho_{\varepsilon\mu}$ = 0) | 5.27** with Prob > $\chi^2$ = 0.0217 | | | |
| Sample size | 421 | | | |

Abbreviations: FBO, farmer-based organization; MMT, mobile money technology.

*, **, and ***Significance at 10%, 5%, and 1% levels, respectively.

## 6.2 | Drivers of input use and farm output

The results of the second stage estimation are presented in the third column of Tables 3–5 for fertilizer and herbicide (input) use, as well as quantity of farm output, respectively. At this stage, the drivers of input use and farm output, conditional on mobile money technology adoption, are examined. The results show positive and significant effects of mobile money technology adoption on fertilizer and herbicide use and farm output at the 1% level, suggesting that mobile money technology adoption is associated with higher input use and farm output by smallholder farmers. This is consistent with the finding by Kikulwe et al. (2014) on mobile money use and household welfare in Kenya. As shown in Table 3, farmers with larger farm sizes apply more fertilizer per hectare as indicated by its positive and significant coefficient. Similar results have been reported by Abdulai and Binder (2006) and Kikulwe et al. (2014). However, farm size plays a positive but insignificant role in herbicide use and farm output as indicated in Tables 4 and 5. Access to credit also enhances input use and farm output. In particular, the coefficient of access to credit variable is positive and significant at conventional levels for the input use and farm output specifications. This finding confirms the role of credit in overcoming financial constraints, and ensuring increased investments in farm inputs, as well as enhances farm output.

Membership in FBO increases fertilizer and herbicide use, as well as farm output, as shown by the positive and significant effect on these outcomes. Abdul-Rahaman and Abdulai (2018) also found that FBO membership enhances farm output in northern Ghana. FBOs promote collective action by ensuring collective negotiation for better input and output prices, access to inputs, technology and information, as well as improving market linkages in agricultural value chains. Tables 3–5 reveal that the education variable positively influences farm input use and output, but only significant in the output specification, suggesting that higher number of years of formal education is associated with increased quantities of farm output. As shown in Tables 3–5, farm input prices also play significant role in input use. In particular, fertilizer price exerts negative and significant effect on fertilizer use and farm output at the 5% level, suggesting that an increase in fertilizer price reduces the quantity of fertilizer use by smallholder farmers, which is in line with intuition. Similarly, an increase in herbicide price reduces the quantity of fertilizer and herbicide use as shown by its negative and significant effect on these outcomes at conventional levels. However, the results show that output price plays a positive but minor role in input use and farm output. The location fixed effects are also important in input use and farm output. Farmers who live and farm in Sagnarigu, Tolon and Kumbungu apply more fertilizer and also generate higher quantities of farm output, as compared to farmers in Tamale metropolis (reference district). This finding could be attributed to the widespread use of mobile phones, as well as the presence of mobile money venders around these areas.

## 6.3 | Impact of mobile money technology adoption on input use and farm output

The impact of mobile money technology adoption on input use and farm output is estimated by computing the ATEs. The results are presented in Table 6. Unlike the mean differences in input use and farm output in Table 2, the confounding factors including unobservable selection bias are accounted for in the estimation of the ATEs. As shown in Table 6, the adoption of mobile money technology enhances farm input use, as well as quantity of farm output. In particular, adoption of the technology increases fertilizer and herbicide use and quantity of farm output by about 18%, 13%, and 4%, respectively. These findings are consistent with some past studies, which report that mobile money technology adoption stimulates smallholder farmers' investment in production inputs for improved farm productivity (e.g., Kikulwe et al., 2014; Sekabira & Qaim, 2017). This means that mobile money technology can promote intensive use of fertilizer and herbicides resulting in higher farm output.

## 6.4 | Robustness checks

To check the robustness of the results, the ATEs of mobile money technology on input use and farm output are estimated using PSM and IPWRA methods. The results are presented in Table 7. As stated earlier, the commonly known limitation of these two approaches is that they do not account for selection bias arising from unobservable factors (e.g., farmer's innate skill, motivation, risk preference, etc.). As revealed by the PSM and IPWRA results, adoption of mobile money technology significantly increases input use and farm output. This finding is consistent with the results obtained from the linear regression with endogenous treatment effects model. However, the PSM and IPWRA estimates are slightly higher than that of the endogenous treatment effects model. In particular, Table 7

**TABLE 6** Impact of *MMT* adoption on input use and farm output

| Outcome variables | Mean outcome<br>*MMT* adopters | *MMT* nonadopters | ATE | *t* value | Change (%) |
|---|---|---|---|---|---|
| Farm output | 6.416 | 6.197 | 0.219*** | 22.727 | 3.53 |
| Fertilizer use | 5.594 | 4.725 | 0.869*** | 10.71 | 18.39 |
| Herbicide use | 0.992 | 0.875 | 0.117*** | 36.85 | 13.37 |

*Note:* The dependent variables are the log of outcome variables. ATE calculation is based on log of the predictions.
Abbreviation: MMT, mobile money technology.
***Significance at 1% level.

**TABLE 7** Impact of *MMT* adoption on farm input use and output sold (PSM and IPWRA)

| Outcome variable | ATE<br>ATE (PSM)<br>Coeficient | SE | ATE (IPWRA)<br>Coeficient | SE |
|---|---|---|---|---|
| Farm output | 0.361*** | 0.110 | 0.325** | 0.154 |
| Fertilizer use | 0.869*** | 0.164 | 0.867*** | 0.147 |
| Herbicide use | 0.221*** | 0.050 | 0.141*** | 0.051 |

*Note:* The dependent variables are the log of outcome variables. ATE calculation is based on log of the outcome predictions
Abbreviations: ATE, average treatment effects; IPWRA, inverse probability-weighted with regression adjustment; MMT, mobile money technology; PSM, propensity score matching.
** and ***Significance at 5% and 1% levels, respectively.

reveals PSM ATE estimates of 0.361, 0.869, and 0.221 for farm output, fertilizer, and herbicides use, respectively, while the IPWRA ATE estimates for farm output, fertilizer, and herbicide use are 0.325, 0.867, and 0.141, respectively. These estimates suggest that the impact of mobile money technology on input use and farm output has been overestimated probably due to the fact that unobservable selection bias could not be accounted for by these methods. This finding justifies the use of the linear regression with endogenous treatment effects model in this study, as it addresses selection bias due to both observable and unobservable factors.

## 7 | CONCLUSIONS AND POLICY IMPLICATIONS

This study examined the factors influencing the adoption and impact of mobile money technology on input use and farm output among smallholder rice farmers, using recent farm household survey data gathered from selected districts in northern Ghana. Mobile money adoption among smallholder farmers is increasing in Ghana. 55% of smallholder rice farmers use mobile money technology when purchasing inputs for production. In addition, adopters of the technology apply more production inputs and generate more output than nonadopters, as shown by the simple mean differences. Accounting for unobservable selection bias in mobile money technology adoption decisions is relevant in ensuring unbiased and consistent adoption estimates of the impact of adoption on input use and farm output.

Mobile money plays a very important role in input use and farm output. Relative to nonadopters, adoption of mobile money technology stimulates farmers' use of fertilizer, herbicides, and output by about 18%, 13%, and 4%, respectively. Farmers' use of fertilizer and herbicide, and farm output are positively and significantly influenced by access to credit, FBO membership, input prices, and location fixed effects. As expected, farmers with larger farm sizes apply more fertilizer, while those with more education obtained higher output. Variables such as education, farm size, access to credit, FBO membership positively, and significantly influence farmers' mobile money technology adoption decisions. However, longer distance to mobile money vender decreases the probability of adoption.

We draw some policy implications based on the findings from this study for the development of the rice value chain in Ghana. The important contribution of mobile money adoption in enhancing input use and farm output suggests that policies enhancing the adoption of the technology need to be promoted. For instance, expansion of mobile technology networks and mobile money service centers can probably increase adoption rate of the technology especially in remote areas. In addition, increased investment in education and expansion of credit facilities to smallholder farmers can also enhance mobile money technology adoption. Formation and capacity strengthening of FBOs by stakeholders in value chain interventions could be very relevant in promoting adoption of the technology for enhanced input use and farm output.

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## DATA AVAILABILITY STATEMENT

Data is available upon request.

## ORCID

*Awal Abdul-Rahaman* http://orcid.org/0000-0002-7356-6326

*Awudu Abdulai* http://orcid.org/0000-0003-4618-2789

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**Awal Abdul-Rahaman** is a Senior Lecturer at the Department of Agribusiness Management and Finance, University for Development Studies, Tamale, Ghana. He received his MPhil Agribusiness from the University of Ghana in 2009 and Ph.D. Agricultural Economics from the University of Kiel, Germany. His current research interests include agribusiness and value chain development and agricultural economics.

**Awudu Abdulai** is Professor of Food Economics and Food Policy at the University of Kiel, Germany. He holds an M.Sc. Agricultural Economics from the Swiss Federal Institute of Technology, Zurich (1990) and a Ph.D. Agricultural Economics from Swiss Federal Institute of Technology, Zurich (1994). His current research interests include development economics, consumer economics, environmental and resource economics. He is currently Co-Editor-in-Chief of Agricultural Economics.

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## APPENDIX A

**TABLE A1** First stage regression estimates for addressing potential endogenous variables

| Variables | FBO membership | | Access to credit | |
|---|---|---|---|---|
| | Coefficient | SE | Coefficient | SE |
| Constant | −2.595*** | 0.582 | −0.475 | 0.534 |
| Age | 0.015*** | 0.005 | 0.005 | 0.005 |
| Education | 0.048*** | 0.016 | −0.002 | 0.016 |
| Gender | 0.475** | 0.246 | −0.056 | 0.225 |
| Farm size | 0.093* | 0.059 | 0.084 | 0.053 |
| Motorcycle | 0.001 | 0.136 | 0.091 | 0.131 |
| Distance to input store | 0.019 | 0.020 | 0.041** | 0.019 |
| Distance to paddy market | 0.022 | 0.021 | −0.043** | 0.020 |
| Fertilizer price | 0.334 | 0.203 | −0.108 | 0.195 |
| Herbicide price | 0.001 | 0.003 | −0.002 | 0.003 |
| Output (paddy) price | 0.155 | 0.203 | 0.201 | 0.175 |
| Sagnarigu | 0.480* | 0.256 | 0.501** | 0.250 |
| Tolon | 0.380* | 0.216 | 0.217 | 0.212 |
| Kumbungu | 0.321 | 0.203 | 0.324 | 0.203 |

**TABLE A1** (Continued)

| Variables | FBO membership Coefficient | SE | Access to credit Coefficient | SE |
|---|---|---|---|---|
| Savelugu Nanton | −0.256 | 0.227 | 0.172 | 0.220 |
| Dist. to mobile money vender | −0.042** | 0.019 | 0.016 | 0.16 |
| Perception of FBO benefit | 0.421*** | 0.138 | | |
| FBO member | | | −0.081 | 0.133 |
| Credit | 0.099*** | 0.031 | | |
| Distance to credit institution (km) | | | −0.035** | 0.015 |
| Log likelihood | −256.87 | | −277.96 | |
| Number of observations | 421 | | 421 | |

Abbreviation: FBO, farmer-based organization.

** and ***Significance at 5% and 1% levels, respectively.

**TABLE A2** Instrument validity test (distance to mobile money vender)

| Variable | $\chi^2$ | *p* value |
|---|---|---|
| 1. Mobile Money Technology adoption | 7.09 | 0.0078 |
| Output sold | 1.11 | 0.2680 |
| 2. Mobile Money Technology adoption | 10.81 | 0.0010 |
| Fertilizer use | 2.60 | 0.1066 |
| 3. Mobile Money Technology adoption | 7.56 | 0.0060 |
| Herbicide use | 0.09 | 0.7606 |