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Adoption of agricultural technologies among rice farmers in Benin

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Abstract

Adoption of agricultural technologies in Benin remains at a very low level. This paper analyzes the factors that determine the adoption of agricultural technologies by rice producers in Benin. It employs a simple probit and Poisson regression models, as well as a multivariate probit model to account for the unobserved interaction between technology adoption decisions. Results reveal that variables such as education, access to extension services, membership of a farmers-based organization, access to credit, media and use of a mobile phone are important in the process of increasing adoption of agricultural technologies. These variables must be taken into consideration in the elaboration of the agricultural modernization policy.

KEYWORDS

adoption, agricultural technologies, Benin, multivariate probit model, rice

JEL CLASSIFICATION

D01; O33; Q12

1 | INTRODUCTION

About 80% of the poorest people in sub-Saharan Africa depend on agriculture for their livelihoods (Food and Agriculture Organization (FAO), 2014). Agriculture in sub-Saharan Africa is constrained by agroecological characteristics, lack of knowledge and inputs, poor access to services, and low levels of investment in infrastructure (FAO, 2014). Furthermore, the high rate of population growth increases pressure on food production and further complicates the issue of food security and poverty reduction (Domenech & Ringler, 2013). In addition, climate change introduces risks and uncertainties in the livelihoods of a population strongly dependent on climate variables (Farid et al., 2015). Increasing adoption of agricultural technologies is vital for improving productivity and achieving Goal 2 (end hunger, achieve food security and improved nutrition and promote sustainable agriculture) of the Sustainable Development Goals. Several studies (Bezu et al., 2014; Burke et al., 2019; Houeninvo et al., 2020; Karanja et al., 2003; Ricker-Gilbert & Jones, 2015; Verkaart et al., 2017) in sub-Saharan Africa have found that adoption of technologies contributes to improving productivity, which increases farm income and food security. Yigezu et al. (2018) argue that the decision whether to adopt a technology is more challenging for smallholder farmers when the new technology involves high initial investment. Procrastination, time-inconsistent preferences, high transaction costs due to poor infrastructure, lack of information and difficulties in learning, and absence of formal insurance are other factors explaining the limited use of technologies and good practices (Emerick et al., 2016; Karlan et al., 2014; Suri, 2011). On the supply side of technology, Emerick et al. (2016) argue that farmers lack technologies that are adapted to local conditions.

Adoption of technologies may be affected by several factors. Traditionally, economic analysis of agricultural technology adoption has focused on imperfect information, risk, uncertainty, institutional constraints, human capital, input availability, and infrastructure as potential drivers for adoption decisions (Feder et al., 1985; Foster & Rosenzweig, 1996; Obayelu et al., 2017; Stoneman, 1981). Other work have advanced the concept of social learning resulting from interactions between producers (Conley & Udry, 2001, 2010; Genius et al., 2013; Koundouri et al., 2006; Marra et al., 2003; Stoneman, 2013; Stoneman & Toivanen, 1997). For these groups of studies the social learning process facilitates dissemination of technologies. Genius et al. (2013) argue that even in the absence of contact with extension agents, farmers can learn from their interactions with other producers. Social learning affects adoption through two channels: improved skills (Ghadim & Pannell, 1999), and uncertainty reduction and improvement of decision-making (Genius et al., 2013; Marra et al., 2003; Wang et al., 2013). The sequence of adoptions is also determined by changes in the supply of the innovated products owing to market price reduction due to imitative entry of competitors or the introduction of incremental innovations that widen the scope of application and use of the product innovation (Chang & Tsai, 2015; Hellegers et al., 2011; Houeninvo et al., 2020). Smallholder farmers respond to the set of price signals for products and inputs used in the production process, given available technology (Chang & Tsai, 2015; Houeninvo et al., 2020). Hellegers et al. (2011) argue that market prices of both outputs and inputs are affected by large-scale adoption of technology, which in return influences adoption decisions and output supply. Empirically, numerous studies have shown that farmer and farm characteristics and institutional variables are exogenous factors that influence the adoption of agricultural technologies. For example, in Benin, Houeninvo et al. (2020) found that farm size, extension services, training in improved seeds, and farmers' location are key variables that affect farmers' decision to adopt improved seeds. In Ethiopia, Tura et al. (2010) found that adult workers, off-farm activity, hiring labor, farm size, membership in a farmer-based organization (FBO), and access to credit strongly affect farmers' decision to adopt improved maize. In Nigeria, contact with extension agents, education, and access to credit significantly affected the decision to adopt improved maize seeds (Idrisa et al., 2012). A study by Ali et al. (2018) in Ghana indicated that the likelihood of fertilizer adoption was influenced by factors such as farmers' engagement in off-farm activities, extension contacts, farm size, hired and family labor, and the value of productive farm assets. From these empirical studies on agricultural technology adoption it can be seen that the factors that encourage adoption of agricultural technologies differ across countries and are location-specific. Therefore, there is a need for specific investigation to support agricultural technology adoption policy in Benin.

Rice is the second most consumed cereal after maize in Benin. It represents 17% of total cereal consumption, behind maize (68%), and ahead of sorghum (9%) and millet (4%). Rice is one of the food crops on which the government is focused to reduce food insecurity and poverty. It is therefore a strategic product for Benin because of its increasing importance in national consumption and trade opportunities with neighboring countries including Niger, Nigeria, and Togo. Rice consumption per capita has increased from 12 kg per year in 2004 to 30 kg per year in 2011 and to 45.7 kg per year in 2017 (MAEP, 2017). Rice production is largely dominated by small family-type farms that produce mainly for domestic consumption. In addition to this family farming, there are landscaped areas where irrigation with partial or total water control is observed. The rice produced on the irrigation schemes is mainly sold. The majority of rice farms are concentrated in the developed or undeveloped lowlands. Statistics show that only 8.64% of rice farmers practice the irrigated system, compared to 22.87% practicing the strict rain system and 13.97% practicing the rain system associated with irrigation. The majority of rice farmers, about 53.92%, practice the floodplain lowland system (MAEP, 2017). The major rice-producing municipalities in Benin are Malanville, Glazoué, Boukoumbé, Banikoara, Dassa-Zoumé, Kandi, and Karimama. These seven municipalities are together responsible for around 64% of national production (MAEP, 2017). The municipality of Malanville is the largest rice-producing municipality in Benin, producing about 27% of national rice production (MAEP, 2017). National rice production in Benin covers only 56.3% of the domestic needs of the population. In addition, the rice yield remains low, decreasing from 3.9 tonnes per hectare in 2011 to 3.1 tonnes per hectare in 2015 (MAEP, 2017). This poor performance of the rice sector in Benin reflects trends in the agricultural sector where the use of agricultural technologies remains very low. According to the World Food Programmme (WFP) report in 2017, about 69.8% of farmers did not use any agricultural inputs, including improved seeds, herbicides, organic fertilizers, chemical fertilizers, and insecticides. Among those who use agricultural inputs, only 52.6% applied chemical fertilizers compared to 21.7% who used organic fertilizers (manure), 40.9% used herbicides, and 26% used insecticides. In addition, only 7.7% of farmers used improved seeds. The same report suggested that the agricultural yield decline in Benin is due to the insufficient use of farm inputs (WFP, 2017); therefore, technology adoption is important for the modernization of agriculture in Benin.

This paper aims to answer the following research question: what factors influence the adoption of agricultural technologies among rice farmers in Benin? It uses the municipality of Malanville as a case study because it is the largest rice-producing area in Benin. Rice is chosen because it is the second most consumed staple food for billions of people around the world. Very little work has so far been done on the issue of technology adoption, and few studies have attempted to explain the low rate of adoption of agricultural technologies in Benin (Allagbe & Biaou, 2013; Dandedjrohoun et al., 2012; Houeninvo et al., 2020; Seye et al., 2016; Sodjinou et al., 2015). In addition these previous studies in Benin have focused on a single agricultural technology. Previous studies have generally treated technologies as independent and independently adopted (see Ali et al., 2018; Banerjee et al., 2008; Dandedjrohoun et al., 2012; Ogada et al., 2010; Rahman & Chima, 2018; Sodjinou et al., 2015; Yigezu et al., 2018). These studies focus on a single technology adoption decision and do not consider agricultural technologies as a package of multiple, complementary technologies. Few studies have attempted to fill this gap. For instance, a study by Nkonya et al. (1997) in northern Tanzania employed a simultaneous equation tobit model to assess factors affecting adoption of improved maize seed and fertilizer. Ogada et al. (2014) in Kenya used a bivariate probit model which captures the interdependence of inorganic fertilizer and improved maize variety adoption decisions. Abay et al. (2018) in Ethiopia focused on three inputs: chemical fertilizers, improved seeds and extensions services. To account for the simultaneity in decision-making, Abay et al. (2018) employed a multivariate probit model. This study adds to these previous studies by focusing on four agricultural technologies, namely, chemical fertilizers, herbicides, improved seeds, and animal traction or tractors.

In terms of methodology, the study provides a rigorous estimate of the determinants of technology adoption. First, the factors that influence the adoption of a single agricultural technology are identified using a simple probit model. Second, a Poisson regression was estimated to identify the factors affecting the number of technologies adopted. Third, the univariate model may suffer from endogeneity and simultaneity problems. To control for these problems, we consider, all the technologies as a unique package. This is in line with the idea that yield-improving technologies involve a package of innovations rather than a single technology (Becerril & Abdulai, 2010). Thus, if farmers adopt only one technology instead of a package, then the yield-improving effect may not be realized (Becerril & Abdulai, 2010; Karanja et al., 2003). The multivariate probit model is then estimated. This model is preferable to the simple and multinomial probit or logit model (Abay et al., 2018; Soglo & Nonvide, 2019). The advantage of the multivariate probit model is that it simultaneously estimates the adoption decisions and allows the unobserved and unmeasured factors (error term) of each equation to be correlated (Abay et al., 2018; Bahinipati & Venkatachalam, 2015; Soglo & Nonvide, 2019). From a policy perspective, this study offers additional insight since it considers the complementarity between agricultural technologies.

The rest of the paper is organized as follows. Section 2 presents the research methods, followed by the empirical results and discussion in section 3, and the final section presents the conclusion and policy implications.

2 | RESEARCH METHODS

2.1 | Study area and data collection

The study was carried out in the municipality of Malanville, Benin. Malanville is bounded to the north by the Republic of Niger, to the south by the municipalities of Kandi and Ségbana, to the west by the commune of Karimama, and to the east by the Federal Republic of Nigeria. The climate is Sudano-Sahelian, with only one rainy season from May to October. The municipality benefits from a low rainfall, varying between 700 mm and 1,000 mm per year. It has a high level of food insecurity (35%) and poverty (42.5%), with the majority of its people engaged in agriculture and other activities such as fishing, livestock, small businesses, trade and crafts (INSAE, 2013). Maize, rice, millet, sorghum, cotton, and vegetables are the main crops.

The municipality of Malanville was chosen for this study because it is the largest area of rice production in Benin. It is located in the Niger River basin, which offers an important opportunity for rice production (Nonvide et al., 2018). The survey covers four districts (Garou, Guene, Malanville, and Tombouctou) out of the five in the municipality of Malanville. District selection was based on the level of production. Using the list of rice farmers, 135 producers were randomly selected from each district. A total of 540 rice farmers were interviewed from April to June 2015.

2.2 | Empirical approach

Two properties determine the adoption of new agricultural technologies. The first is the change in the production function. The adoption of new technologies by the farmer moves the production function to the left. Technically, with the same level of inputs, the level of output may increase due to new technologies. In other words, the same output level can be produced with fewer inputs. Therefore we can conclude that the adoption of new technologies leads to improved agricultural production.

The second property of the adoption of new agricultural technologies is the increase in profitability. Farmers base their adoption decision on the expected utility. In this case, and in line with the neoclassical microeconomic theory, the farmer decides to adopt a technology when it provides him a utility greater than in the case of non-adoption.

2.2.1 | Probit model

Let U_{i1} denote the utility derived from the adoption of agricultural technology and U_{i0} the utility of non-adoption. The difference in utility between adoption and non-adoption is U_i. Farmer i decides to adopt a new agricultural technology if $U_i = U_{i1} - U_{i0} > 0$. Although utility is not directly observable, the actions of economic agents are observed through their choices. Therefore, the decision to adopt a new agricultural technology can be expressed as follows:

$$U_i^* = \beta X_i + \varepsilon \tag{1}$$

with

$$U_i = \begin{cases} 1 \text{ if } U_i^* > 0, \\ 0 \text{ otherwise} \end{cases}$$

where U_i^* is the latent variable representing the probability of farmer i adopting a new agricultural technology. It takes the value 1 if the farmer has adopted the technology and 0 otherwise. X_i is the vector of independent variables influencing the adoption decision, β is the vector of parameters to estimate, and ε is the error term.

The discrete-choice models frequently used in adoption studies are logit and probit. These models differ only in the choice of the cumulative distribution function (F). The probit model assumes a normal functional form and can be used to estimate the likelihood of adoption of agricultural technologies by rice farmers in the municipality of Malanville, Benin. In its specific form, the probit model can be expressed as

$$P_i = P\left(U_i = 1\right) = \int_{-\infty}^{\beta X_i} (2\pi)^{-1/2} e^{-p^2/2} \beta dp. \tag{2}$$

2.2.2 | Multivariate probit model

For a set of agricultural technologies, model (1) can be rewritten as follows:

$$\begin{aligned} U_{i1}^* &= \beta_1 X_{i1} + \varepsilon_{i1} \\ U_{i2}^* &= \beta_2 X_{i2} + \varepsilon_{i2} \\ U_{i3}^* &= \beta_3 X_{i3} + \varepsilon_{i3} \\ U_{i4}^* &= \beta_4 X_{i4} + \varepsilon_{i4} \end{aligned}, \tag{3}$$

with U_{i1}^*, U_{i2}^*, U_{i3}^*, and U_{i4}^* representing the probability that farmer i adopts, respectively, fertilizer, herbicide, improved seed, and animal traction or tractors.

Assuming that the error terms are independent and normally distributed, each of the equations in model (3) can be estimated separately using a probit model. However, the equations estimating the probability of adoption could be correlated, thus increasing the risk of obtaining biased coefficients, since adoption decisions can be made simultaneously. In this case, the unobserved errors terms for the probit model would be correlated (Mittal & Mehar, 2016; Velandia et al., 2009). To account for this unobserved interaction between technology adoption decisions, the multivariate probit model (MPM) was estimated. This allows for the possible contemporaneous correlation in the choice to access the four different sources simultaneously, and provides more efficient estimates because it controls for the selection bias associated with adoption (Abay et al., 2018; Mittal & Mehar, 2016; Soglo & Nonvide, 2019). MPM estimation has already been used in numerous studies analyze factors that affecting the adoption of agricultural technologies (Abay et al., 2018; Gillespie et al., 2004; Lee et al., 2004; Mittal & Mehar, 2016; Soglo & Nonvide, 2019; Velandia et al., 2009). These studies argue that modeling technology adoption decisions using an MPM framework allows for increased efficiency in estimation in the case of simultaneity of adoption.

The general form of the multivariate probit model is

$$U_{ij}^{*} = \beta_j X_{ij} + \varepsilon_{ij}, \tag{4}$$

where U_{ij}^{*} is the probability that farmer i adopts technology j ($j = 1, \ldots, 4$), X_{ij} is the vector of the exogenous variables that affect the adoption decision, and β_j is the vector of parameters to be estimated.

In the multivariate probit model the error terms jointly follow a multivariate normal distribution with zero conditional mean and variance normalized to unity, $(\left(\mu_1, \mu_2, \mu_3, \mu_4\right) \rightarrow MVN\,(0, \Omega)$. The covariance matrix (Ω) is given by

$$\Omega = \begin{pmatrix} 1 & \rho_{12} & \rho_{13} & \rho_{14} \\ \rho_{21} & 1 & \rho_{23} & \rho_{24} \\ \rho_{31} & \rho_{32} & 1 & \rho_{34} \\ \rho_{41} & \rho_{42} & \rho_{43} & 1 \end{pmatrix}, \tag{5}$$

where ρ denotes the pairwise correlation coefficient of the error terms corresponding to any two agricultural technologies. If these correlations in the off-diagonal elements in the covariance matrix become non-zero, then it justifies the use of a multivariate probit instead of a univariate probit for each individual agricultural technology (Aryal et al., 2018). If ρ is significantly positive, then there is a complementary relationship between different agricultural technologies. But if ρ is significantly negative, then there is a substitution relationship between different agricultural technologies.

Equation (4) was estimated by the method of simulated maximum likelihood. The method uses the Geweke–Hajivassiliour–Keane smooth recursive conditioning simulator procedure to evaluate the multivariate normal distribution. The model was estimated using the Stata 13 software.

2.2.3 | Poisson regression model

Considering the total number of technologies adopted by a farmer, a Poisson regression is estimated. Poisson regression is habitually employed when the dependent variable is a count variable, which in this case is the sum of agricultural technologies adopted. The Poisson probability distribution is more appropriate than the normal used in the probit model or the logistic distribution used in the logit model (Carrer et al., 2017). The probability density function can be represented as follows:

$$f\left(y_i/x_i\right) = P\left(Y_i = y_i\right) = \frac{e^{-\lambda}\lambda^y}{y!}, \quad y = 0, 1, 2, 3, \ldots, \tag{6}$$

where y_i is the total number of technologies adopted by the farmer and x_i are the variables that influence the adoption process. The expected mean parameter (λ) of this probability function is defined as:

$$E\left(y_i/x_i\right) = \lambda_i = \exp\left(x_i'\beta\right) = \exp\left(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki}\right) + \varepsilon_i. \tag{7}$$

Equation (7) can be estimated through maximum likelihood procedures.

2.3 | Choice of independent variables

The variables used in the models are those that characterize the socioeconomic and demographic situation of farmers and the institutional variables. These variables have been identified in the literature and assumed to be important in the adoption of agricultural technologies in Benin. Indeed, a producer is considered as adopter when he uses the technology. Table 1 presents the definitions of the variables of the model and the expected signs.

The *age of the farmer* is a continuous variable measured in years. It is expected to have a nonlinear effect on the likelihood of adoption of agricultural technology. The sign of this relationship can be positive or negative (Barry, 2016; Sodjinou et al., 2015). *Gender* is a binary variable that takes the value 1 if the producer is a male, and 0 if female. It is postulated that the adoption of agricultural technologies may be gender-biased because of differences in access to productive resources. Being male increases the probability of adoption of new agricultural technologies (Sodjinou et al., 2015). *Education level* is a binary variable that takes the value 1 if the producer has reached at least the level of primary school and 0 otherwise. The work of Huffman (2001) and Duraisamy (2002) showed that education is positively correlated with the adoption of technologies. Farmers with at least primary education are assumed to have greater capacity and skills to adapt to change. *Access to extension services* takes the value 1 if the producer has access to extension services and 0 otherwise. Regular contact with extension agents positively influences the probability of adoption of agricultural technologies (Allagbe & Biaou, 2013; Nkonya et al., 1997). *Membership of an FBO*

TABLE 1 Explanatory variables and expected signs

Variable	Expected sign
Age of producer (years)	+/–
Gender (male = 1, female = 0)	+
Level of education (none = 0, at least primary = 1)	+
Membership of farmer-based organization (1 = yes, 0 = no)	+
Access to extension services (1 = yes, 0 = no)	+
Access to credit (1 = yes, 0 = no)	+
Access to the media (use of radio or TV = 1, no = 0)	+
Ownership of mobile phone (1 = yes, 0 = no)	+
Farm size (in hectares)	+

is a binary variable taking the value 1 if the producer belongs to an FBO and 0 otherwise. Being a member of a farmers' association can facilitate the sharing of agricultural information and thus increase the probability of adoption of agricultural technologies (Conley & Udry, 2001, 2010; Genius et al., 2013; Seye et al., 2016). *Access to credit* takes the value 1 if the producer has obtained credit and 0 otherwise. Access to credit allows the producer to secure in time other agricultural inputs such as improved seeds, fertilizers and agrochemicals (Mdemu et al., 2016; Nonvide et al., 2018.). Therefore, the expected sign is positive. *Access to media* takes the value 1 if the producer has a radio or television, and 0 otherwise. According to Sangbuapuan (2012), the media can provide the producer with information on different agricultural technologies. The expected sign is therefore positive. *Ownership of a mobile phone* is a binary variable that takes the value 1 if the producer has a mobile phone, and 0 otherwise. The use of telephones by producers facilitates information sharing. This variable is assumed to have a positive effect on the likelihood of adoption of agricultural technologies. *Farm size* is a continuous variable measured in hectares. It is expected to have a positive effect on the likelihood of adoption of agricultural technology. Farmers who have large farms may have a higher propensity to adopt more technology because they can afford to devote more land to the new technology than those with smaller farm sizes (Abay et al., 2018; Houeninvo et al., 2020; Mwangi & Kariuki, 2015).

2.4 | Estimation issues: multicollinearity, correlation of error terms and potential endogeneity

Prior to the estimation of Equation 4, we investigate the problem of multicollinearity among the explanatory variables. A condition index was used to detect correlation (Belsley et al., 1980; Mittal & Mehar, 2016). A value of the condition index less than 30 implies that there is no serious problem of multicollinearity (Aryal et al., 2018; Kennedy, 2003; Mittal & Mehar, 2016). With a condition index (15.87) less than 30, therefore, our data have no serious problem of multicollinearity. A pairwise correlation of the error terms associated with farmers' adoption decision of agricultural technology is also computed and its significance is tested to further justify the use of the multivariate probit model.

Due to possible reverse causality, some explanatory variables could be endogenous in the adoption decision models. In this study, the endogeneity of access to extension services and FBO membership is discussed. These variables are likely to increase the adoption of agricultural technologies, but extension agents and FBOs would maximize their effect by targeting farmers who have already adopted agricultural technologies. Thus, it is important to control for the potential endogeneity of access to extension services and FBO membership in order to avoid biased estimators. Following previous studies (Houeninvo et al., 2020; Lampach et al., 2020; Sinyolo et al., 2017), the endogeneity test follows two steps. First, a probit regression was estimated for FBO membership and access to extension services on the exogenous explanatory variables. Then the generalized residuals were calculated and included in the structural equation for the second step. A *t*-test of the generalized residual tests the null hypothesis of exogeneity (Houeninvo et al., 2020; Lampach et al., 2020; Sinyolo et al., 2017; Wooldridge, 2012). A statistically significant coefficient of the generalized residuals means endogeneity. The result of the endogeneity-corrected model is presented in Table A1 in the Appendix. As the generalized residual terms for the two variables (access to extension services and FBO membership) are not significant in all the models, we present the result of the model without the generalized residual terms.

3 | RESULTS AND DISCUSSIONS

3.1 | Descriptive analysis

The overwhelming majority (98.8%) of the rice producers surveyed in the municipality of Malanville reported that they use fertilizer (Table 2). It can thus be said that the use of fertilizer has become standard practice in rice farming in the municipality of Malanville. This stands in contrast to Benin as a whole, where about 69.8% of farmers did not use any agricultural inputs in 2017 (WFP, 2017). It can be justified by the fact that majority of rice produced in the municipality of Malanville is for commercial purposes rather than subsistence, as sorghum and millet are the main foods consumed in this municipality. Moreover, a thorough analysis shows that about 58% of producers apply a lower dose compared to the standard of 300 kg per hectare in the municipality. About 55% of rice farmers use herbicides (Table 2). The use of improved varieties of rice remains low in the municipality. Less than 50% of producers reported using improved rice varieties. The two types of improved varieties generally grown are NERICA and IR 841. Approximately 90% of producers use animal traction, compared to only 0.55% who have access to tractors. This testifies the fact that, as far as plowing is concerned, human labor is almost completely replaced by animal traction in the municipality of Malanville. However, the level of motorization is still very low. Overall, the adoption rate of agricultural technologies is still low in the municipality of Malanville. As shown in Table 2, about 32% of farmers adopted all agricultural technologies (fertilizers, herbicides, improved seeds, animal traction or tractor).

The analysis of the socioeconomic and institutional variables determining the adoption of agricultural technologies shows that adopters are relatively older than non-adopters (see the last three columns in Table 3). Adopters also have a significantly larger farm size (2.10 ha) compared to non-adopters (1.30 ha). More than half of those who have adopted the different technologies are educated, suggesting that educated farmers are more likely to adopt agricultural technologies compared to non-educated farmers. There is also a significant difference between technology adopters in terms of FBO membership and access to extension services. Compared to non-adopters, those who adopted the technologies have more contact with extension agents and the majority of them are members of FBO. About 75% of farmers who adopted agricultural technologies had access to credit, compared to only 41% of non-adopters. Therefore, credit can facilitate access to agricultural inputs. Table 3 also shows that the majority of producers accessing the media or using their own mobile phone adopted agricultural technologies.

TABLE 2 Agricultural technologies adoption by rice producers in Malanville, Benin

Variables	Adopters (%)
Fertilizer	98.88
Herbicides	55.00
Improved seed	46.66
Animal traction	90.18
Tractor	0.55
Animal traction or tractor	90.55
All	31.85

Source: Field survey, 2015.

TABLE 3 Socioeconomic characteristics of the respondents

	Fertilizer			Herbicide			Improved seed			Animal or tractor			All technologies		
Variables	**Adopt**	**Non-adopt**	***t*-test**	**Adopt**	**Non-adopt**	***t*-test**	**Adopt**	**Non-adopt**	***t*-test**	**Adopt**	**Non-adopt**	***t*-test**	**Adopt**	**Non-adopt**	***t*-test**
Age of farmer (years)	41.96	35.83	−1.65*	43.14	40.37	−3.57***	44.16	39.91	−5.60***	42.41	36.92	−4.19***	44.95	40.47	−5.51***
Farm size (ha)	1.56	1.33	−0.51	1.98	1.04	−10.9***	1.79	1.35	−4.64***	1.61	1.02	−3.74***	2.10	1.30	−8.30***
Gender (% male)	72.47	66.66	0.10	68.01	77.77	6.37**	76.19	69.09	3.38*	71.77	78.43	1.02	76.74	70.38	2.37
Education (yes = 1)	38.01	16.66	1.15	47.81	25.51	28.26***	58.73	19.44	88.24***	40.08	15.68	11.69***	63.37	25.81	70.33***
Membership of FBO (yes = 1)	30.71	16.66	0.55	41.41	17.28	36.67***	44.04	18.75	40.53***	32.10	15.68	5.86**	53.48	19.83	62.55***
Extension services (yes = 1)	45.50	16.66	1.99	49.15	40.32	4.20**	56.74	35.06	25.49***	48.05	17.64	17.24***	64.53	36.14	38.15***
Access to credit (yes = 1)	52.05	33.33	0.83	62.62	38.68	30.68***	63.49	41.66	25.64***	56.44	7.84	43.69***	75.00	41.03	54.17***
Access to the media (yes = 1)	56.92	16.66	0.83	69.36	40.74	30.68***	55.15	57.63	25.64***	58.07	41.17	43.69***	65.69	52.17	54.17***
Ownership of mobile phone (yes = 1)	100	74.90	2.00	84.84	63.37	33.03***	86.11	65.62	30.23***	76.68	60.78	6.26**	88.37	69.02	23.52***

***$p < .01$; **$p < .05$; *$p < .1$.

3.2 | Econometric analysis

This section presents the estimation results on the factors affecting adoption of agricultural technologies. Table 4 presents both the results of the probit model where we consider all technologies together as a package and the results of a Poisson regression model where we consider the total number of technologies adopted as the dependent variable. For the probit model, the dependent variable was set to 1 if the producer adopts the full technological package (fertilizer, herbicide, improved seed, and animal traction or tractor) and 0 otherwise. In addition to estimated parameters, Table 4 also presents the marginal effects which show the variation in the dependent variable as a response to small variations in an independent variable, ceteris paribus. Both models are globally significant, as indicated by the significance of the Wald chi-squared tests. Overall the same variables were significant in both

TABLE 4 Results of probit and Poisson regression models

	Probit model		Poisson regression	
Variables	**Coefficient**	**marginal effects**	**Coefficient**	***dy/dx***
Age	0.058	0.013	0.006	0.019
	(.307)	(.305)	(.425)	(.425)
Age squared	−0.0005	−0.0001	−0.00002	−0.00008
	(.426)	(.424)	(.763)	(.763)
Gender	0.097	0.023	−0.053	−0.155
	(.537)	(.536)	(.340)	(.340)
Education	0.665***	0.158***	0.140***	0.407***
	(.000)	(.000)	(.000)	(.000)
Extension services	0.480***	0.114***	0.058**	0.171**
	(.001)	(.001)	(.022)	(.022)
Membership of FBO	0.514***	0.122***	0.100***	0.294***
	(.001)	(.001)	(.000)	(.000)
Access to credit	0.596***	0.142***	0.104***	0.302***
	(.000)	(.000)	(.000)	(.000)
Access to media	0.530***	0.126***	0.115***	0.336***
	(.000)	(.000)	(.000)	(.000)
Ownership of phone	0.546***	0.130***	0.144***	0.419***
	(.001)	(.001)	(.000)	(.000)
Farm size	0.374***	0.089***	0.063***	0.183***
	(.000)	(.000)	(.000)	(.000)
Constant	−4.473***	–	0.425**	–
	(.001)	–	(.020)	–
	Log likelihood : −229.891		Log likelihood : −837.696	
	Wald $\chi^2(10) = 148.33$		Wald $\chi^2(10) = 373.75$	
	Prob. > χ^2 = .000		Prob. > χ^2 = .000	
	Pseudo R^2: .31		Pseudo R^2: .038	

***$p < .01$; **$p < .05$. Values in parentheses are probabilities.

models, suggesting that the decision to use agricultural technologies and the intensity are governed by the same factors.

The results indicated a positive correlation between education and adoption of technologies, suggesting that producers with at least a primary level of education have a high probability of adopting agricultural technologies. This is because educated farmers are generally more able to cope with changes and new challenges, and thus to adopt new technologies (Adeoti, 2009; Nonvide, 2017). The coefficient of the FBO membership variable is positive and significant, implying a positive correlation between FBO membership and adoption of technologies. Being an FBO member increases the likelihood of adoption of agricultural technologies. Conley and Udry (2001, 2010) have shown that extension services and FBOs provide channels for information sharing among producers. These results are consistent with those obtained by Abdulai et al. (2011), Allagbe and Biaou (2013), Barry (2016), and Seye et al. (2016). A positive relationship was observed between access to credit and the likelihood of adoption of agricultural technologies. Farmers who obtained credit are more likely to adopt agricultural technologies. Mdemu et al. (2016) in Tanzania and Nonvide et al. (2018) in Benin have shown that lack of credit is one of the main constraints in the agricultural sector. They argue that access to credit may facilitate the acquisition of production inputs. The use of information and communication technologies (ICT) increases the probability of adoption of agricultural technologies. Producers who own a radio, television or mobile phone are more likely to adopt agricultural technologies than those who do not. Through ICT, the farmers can access information on different agricultural technologies (Sangbuapuan, 2012).

Table 6 provides the multivariate probit model estimates where it is hypothesized that adoption decisions can be made simultaneously, and then the unobserved errors terms for the probit model for each technology would be correlated. Before this, the pairwise correlation analysis between the four technology adoption equations in the multivariate probit model is presented in Table 5. These coefficients measure the correlation between the decisions of adoption of agricultural technologies after controlling for the effects of the explanatory variables (Greene, 2003; Mittal & Mehar, 2016; Velandia et al., 2009).

Four of the correlation coefficients are significant. This confirms the assumption that the error terms in the technology adoption equations are correlated. Thus, the use of the multivariate probit model is justified. A positive sign on the correlation coefficient indicates that adoption of a particular technology increases the likelihood of adoption of the second technology, suggesting a complementary relationship between the two technologies. On other hand, a negative sign suggests a substitution relationship. For example, the positive coefficient for the adoption of improved seeds and herbicides

TABLE 5 Correlation between the agricultural technology adoption decisions

Adoption variables	Correlation coefficient	Standard error	Probability
Herbicides and fertilizers	.037	0.108	.732
Improved seeds and fertilizers	.290**	0.139	.038
Animal traction/tractor and fertilizer	.275**	0.112	.015
Improved seeds and herbicides	.223***	0.081	.006
Animal traction/tractor and herbicides	.016	0.143	.908
Animal traction/tractor and improved seeds	−.252**	0.099	.011

***$p < .01$; **$p < .05$.

Source: Estimation results.

TABLE 6 Results of the multivariate probit model

Variables	Fertilizer	Herbicides	Improved seed	Animal traction or tractor
Age	0.126	−0.004	−0.010	−0.291**
	(.266)	(.932)	(.829)	(.019)
Age squared	−0.001	−0.0003	0.0003	0.004**
	(.304)	(.950)	(.555)	(.015)
Gender	0.079	−0.483***	0.041	−0.113
	(.797)	(.002)	(.767)	(.592)
Education	0.512	0.516***	0.901***	0.284
	(.191)	(.001)	(.000)	(.198)
Extension services	0.596	0.009	0.341**	0.705***
	(.177)	(.953)	(.017)	(.003)
Membership of FBO	−0.110	0.750***	0.336**	−0.206
	(.846)	(.000)	(.031)	(.430)
Access to credit	0.099	0.311**	0.217*	1.134***
	(.684)	(.029)	(.091)	(.000)
Access to media	0.849*	1.057***	−0.025	0.551***
	(.075)	(.000)	(.837)	(.003)
Ownership of phone	3.841***	0.540***	0.550***	0.315*
	(.000)	(.001)	(.000)	(.090)
Farm size	0.006	0.832***	0.109*	0.301**
	(.56)	(.000)	(.067)	(.029)
Constant	2.298	−3.016***	−1.535	4.840**
	(.317)	(.003)	(.149)	(.031)
	Log likelihood: −664.212			
	Wald $\chi^2(40) = 972.34$			
	Prob. > $\chi^2 = .000$			
	Likelihood ratio test: $\chi^2(6) = 19.953$			
	Prob. > $\chi^2 = .0028$			

***$p < .01$; **$p < .05$; *$p < .1$. Values in parentheses are probabilities.

(Table 5) indicates that rice farmers using improved seeds also tend to use herbicides. The negative coefficient between the use of animal traction or tractors and improved seeds shows that farmers using animal traction or tractors tend not to use improved seeds. This reveals the transitory character of producers' behavior in the adoption process (Mittal & Mehar, 2016), and the fact that farmers are averse to changing farming practices. The negative sign could also perhaps due to the low popularity of improved seed among rice farmers as less than half (46.67%) used improved rice seeds.

The estimates of the multivariate probit model are shown in Table 6. The Wald test indicates that the model is globally significant at 1%. The likelihood ratio test indicated a probability of 0.0028. This confirms once again the correlation assumption of error terms in adoption equations and justifies the use of multivariate probit model. The variables that significantly influence fertilizer use are access to media and use of a mobile phone (Table 6). These variables have a positive effect on the probability of fertilizer use. Thus, radio, television, and mobile phones are channels through which rice producers could collect information (availability, type, price and quantity) on fertilizer.

The results also show that variables such as gender, education, FBO membership, access to credit and media, and mobile phone ownership have a positive correlation with farmers' decision to use herbicide. The coefficient associated with the gender variable was negative and significant, indicating that women use herbicides more than men in rice production. This can be explained by the fact that women, who have very limited access to labor and less time to spend on their own production, may prefer to adopt weeding technologies. With regard to the adoption of improved seeds, variables that are significant include education, access to extension services, FBO membership, access to credit, and use of a mobile phone. These variables increase the likelihood of adopting improved rice varieties in the municipality of Malanville.

The adoption of animal traction or tractors is positively associated with extension services, credit, media, and use of a mobile phone. Age has a nonlinear relationship with the likelihood of adoption of animal traction or tractors. A unit increase in farmer's age decreases the probability of adopting animal traction or tractor up to 35 years, beyond which the likelihood increases. This result implies that older farmers have a higher probability of using animal traction or tractors.

4 | CONCLUSION

Increasing adoption of agricultural technologies is vital for transforming the agricultural sector in developing countries. However, the rate of adoption of agricultural technologies remains low in developing countries, especially Benin. This paper has analyzed the main factors affecting the adoption of agricultural technologies by rice farmers in Benin. It uses the municipality of Malanville and rice producers as a specific case study. Although this is a very specific study, conducted on one small region of Benin and focusing specifically on rice farmers, it raises a general problem in developing countries. The issue of low use of agricultural technologies remains a major concern in developing countries and throughout the agricultural sector. The four technologies considered in this study are fertilizers, herbicides, improved seeds, and animal traction or tractors. First, a simple probit model was estimated by considering all the technologies as a package. Second, a Poisson regression was estimated using the number of technologies adopted. Third, taking into account the potential correlation among different technologies, a multivariate probit model was used. The results revealed that farmers' socioeconomic characteristics and institutional variables are crucial in the adoption process. The variables that explain the adoption of technologies in rice farming in the municipality of Malanville in Benin include education, extension services, FBO membership, access to credit and media, and use of mobile phones. These findings could be used further to design policies to facilitate farmers' adoption of technologies. Using these results, policy-makers can better anticipate which types of policy can help in promoting the adoption of agricultural technologies. Overall, the findings imply the need to facilitate regular access to extension services. In this context an improvement in extension services is necessary. FBOs must also be promoted. Being a member of an FBO can facilitate learning and information sharing about the technologies. It is also important to facilitate access to credit for farmers, but also to provide them with a framework for more efficient credit management. Finally, there is a need to strengthen farmers' capacities for good agricultural practices; this can be done through periodic training.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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APPENDIX

TABLE A1 Multivariate probit model estimates controlling for endogeneity

Variables	Fertilizer	Herbicides	Improved seed	Animal traction or tractor
Age	0.025	−0.078	0.001	−0.249
	(.158)	(.069)	(.070)	(.221)
Age squared	0.0002	0.001	0.0002	0.004
	(.002)	(.0009)	(.0008)	(.003)
Gender	0.275	−0.516***	0.077	0.297
	(.437)	(.197)	(.192)	(.526)
Education	0.208	−0.188	0.902***	0.538
	(.459)	(.243)	(.221)	(.582)
Extension services	−0.003	−2.330***	0.375	3.221**
	(1.027)	(.690)	(.617)	(1.259)
Membership of FBO	3.730	2.916	0.572	3.984
	(5.032)	(2.174)	(1.928)	(8.026)
Access to credit	.297	.541***	.246	1.381***
	(.351)	(.172)	(.159)	(.424)
Access to media	0.873*	0.887***	−0.025	0.567***
	(.512)	(.127)	(.122)	(.182)
Ownership of phone	−4.274***	0.245	0.588***	0.284
	(.612)	(.234)	(.223)	(.754)
Extension services_residuals	−6.445	−3.603	−0.348	−6.670
	(9.075)	(3.716)	(3.288)	(13.369)
Membership of FBO_residuals	1.275	4.464***	−0.142	−5.613**
	(2.160)	(1.357)	(1.261)	(2.553)
Constant	5.613	1.232	−1.689	4.865
	(4.338)	(1.948)	(1.902)	(6.478)
	Log likelihood: −709.850			
	Wald $\chi^2(44) = 1{,}016.73$			
	Prob. > $\chi^2 = .000$			
	Likelihood ratio test: $\chi^2(6) = 23.781$			
	Prob. > $\chi^2 = .0006$			

*** $p < .01$; ** $p < .05$; * $p < .1$. Value in parentheses are standard errors.