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Modeling Multiple Adoption Decisions on Agricultural Technologies in Tanzania: A Multinomial Probit Analysis

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Abstract

This paper examines the determinants of adoption of improved agricultural technologies among smallholder maize farmers in Tanzania. Specifically, it reports the findings of a study that employed a sample size of 1,839 smallholder maize farming households that participated in three consecutive waves of 2008 - 2009, 2010 - 2011, and 2012 - 2013 of the National Panel Survey (NPS). Multinomial probit model was used to examine the factors that influence maize producers to adopt inorganic fertilisers, improved seeds, and herbicides. Results show that extension services, information technology, gender, education level, soil quality, age and household size influenced smallholder maize farmer's choice of what agricultural technologies to adopt. Based on the findings, the paper recommends policymakers and other development partners to take these factors on board when promoting and supporting the adoption of agricultural technologies for improved productivity and food security.

Keywords*:* adoption decision, agricultural technologies, smallholder maize farmers, multinomial probit model, Tanzania.

JEL Codes*: Q12; Q16; and Q18*

1. Introduction

The world population is set to increase to 9.1bn by 2050, with a projected concomitant food production growth, chiefly in staple crops, particularly for the 821m people who still face chronic food deprivation (WHO, 2018). Consequently, there is a need to improve agricultural productivity, especially in developing countries. WFP (2018) documents indicate that agricultural production must increase by 60 percent by 2050 to fulfil global consumption demand. This means that smallholder farmers play a crucial role as they dominate over 60 percent of the global agricultural production (FAO, 2016). As a result, policymakers and academicians suggest that increasing agricultural production and productivity requires encouraging smallholder farmers to adopt improved agricultural technologies to eliminate the challenge of food insecurity (Kassie et al., 2015; Tsinigo & Behrman, 2017; Tessema et al., 2018; Selejio & Lasway, 2019).

Food insecurity is a major challenge that affects around 28 percent of the global population, and more than 40m people in Africa, particularly in the Sub-Saharan

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African (SSA) region (WFP, 2018). In recent years, there has been significant emphasis on curbing the problem of food insecurity in SSA region through efforts such as the Alliance for a Green Revolution in Africa (AGRA), and the Comprehensive Africa Agriculture Development Program (CAADP). Amongst the emphasized solutions is promoting agricultural technologies to smallholder farmers, which could enhance agricultural growth to alleviate food insecurity (Agneman et al., 2020). Agricultural growth through higher productivity and production is widely viewed as one of SSA's main path to long-term economic development because about 70 percent of its population are smallholder farmers who depend on agriculture for livelihood (Diao et al., 2010; Ngowi & Selejio, 2019; Lasway et al., 2020). Among the crucial drivers of agricultural productivity, is the adoption of agricultural technologies. This is because agricultural technologies are developed to increase agricultural yields, improve the quality of farm produce, increase farmers' income, and ensure food security (Rutasitara & Selejio, 2008).

In Tanzania, the significance of agro-technology in the agricultural sector in the economy cannot be ignored as agriculture contributes 66.9 percent to employment, 65 percent inputs to the industrial sector, 30 percent of exports, and 23 percent to the Gross Domestic Product (GDP) (URT, 2016). The sector is highly dominated by smallholder farmers (about 75 percent), and most of them use non-improved agricultural technologies (URT, 2015). The overall adoption of agricultural technologies in the country stands at 23 percent (NBS, 2017).

One of the major foods and cash crops in Tanzania is maize, which is highly produced within the country. The crop covers about 26 percent of the arable land, and more than 70 percent of cereals planted area; and is grown by more than 65 percent of agricultural households (URT, 2016). Major producers of the crop are smallholder farmers who account for 85 percent of the total production in the country (URT, 2015; URT, 2016). However, the BoT (2019) documents that since 2016 production in the maize sector in the economy has been increasing yearly by 4 percent due to expansion of cultivated area, but declining in productivity by 2.7 percent.[1] This suggests that there is a negative relationship between maize production and productivity in the economy. Notably, one of the crucial reasons for the low maize productivity is the non-adoption of improved agricultural technologies, which limits the revenues of small-scale farmers, and leads to food insecurity and poverty (Kassie et al., 2015; Lasway et al., 2020). Thus, the big question is: What factors influence the decisions of small-scale farmers to adopt agricultural technologies that enhance improved multiple-productivity?

Moreover, many previous studies have been focusing on the measurement of small-scale farmers' adoption choice of a single improved agricultural technology such as inorganic fertilisers or improved seeds (Shiferaw & Tesfaye, 2006; Lyimo et al.,

[1]For instance, the maize production shows an increasing trend, i.e., 4,733,070 metric tons (MT), 6,737,197MT and 7,437,197MT in 2014, 2016 and 2018 respectively, whereas maize yield productivity stood at 1,625kg/ha, 1,458kg/ha and 1,390kg/ha for the same period (BoT, 2019).

2014; Ghimirea et al., 2015; Simtowe et al., 2016; Mwalupaso et al., 2019; Nchinda et al., 2020), and only a few have concentrated on double agricultural technologies (Mittal & Mehar, 2016; Abay et al., 2016; Shee, 2020). These studies have used cross-sectional data that are likely to suffer from the endogeneity problem, hence making it difficult to control for unobserved heterogeneity. As such, the few studies mentioned above on the adoption of single or double-improved agricultural technologies are unable to apply a systematic approach in investigating factors that influence small-scale farmers' decisions on the adoption of multiple productivity-enhancing technologies. Most significantly, to the best of our knowledge, no single study has rigorously explored the modelling of multiple adoption decisions on agricultural technologies among small-scale farmers using a case of panel data in developing countries such as Tanzania.

This paper attempts to fill this gap by analysing distinctive household-level panel data from Tanzania using the multinomial probit model, which is the appropriate method in modelling multivariate decisions. In doing so, it uses an econometric method to control broader household-level characteristics likely to affect small-scale farmers' decision to adopt more than two agricultural technologies.

The paper is grounded on three technologies: improved maize seeds, inorganic fertilizers, and herbicides. These improved agricultural technologies are not much adopted by small-scale maize farmers in Tanzania, but are crucial in improving agricultural productivity (URT, 2015). The paper, therefore, examines factors influencing small-scale farmers' adoption of all the three improved agricultural technologies. The key findings show that extension services, information technology, education level, and soil quality significantly influence decisions of smallholder maize farmers' adoption of agricultural technologies.

The rest of this paper is organized as follows. The next section covers the conceptual framework, followed by a look at methodology, before discussing the empirical findings. The final section presents conclusion and policy implications.

2. Conceptual Framework

In this paper, small-scale maize farmers' adoption of agricultural technologies for enhancing productivity is grounded in the theory of expected utility (Selejio & Lasway, 2019). This theory works on the assumption that small-scale farmers choose between technological bundles based on comparing their expected utility values. This means that a small-scale farmer adopts a certain agricultural technology when the expected utility for adopting that technology is greater than another technology. Thus, a small-scale farmer chooses a certain technology that satisfies his/her expected utility. For instance, a small-scale farmer $(i = 1,2,3, \dots, n)$ chooses to adopt or not to adopt some, or all, enhancing productivity technologies (j) available, i.e., $(j = 1,2,3, \dots, n)$. The expected utility of a small-scale farmer is denoted by $U = (j_i, K)$; at which j_i signifies agricultural productivity technology bundle, and K represents small-scale maize farmer's environmental features such as extension services, credit accessibility, education, age, off-farm income, etc.

This paper used the multinomial probit model (MNP) to predict small-scale maize farmers' adoption decisions, which is the appropriate method for modelling multivariate decisions (Wooldridge, 2019). The paper uses 1, 2 and 3 improved agricultural productivity technologies to denote inorganic fertilizers, improved maize seeds, and herbicides, respectively. Inorganic fertiliser is chosen as a base category (Option 1). In doing so, the utilities of other improved agricultural productivity technologies (improved maize seeds and herbicides) are compared to that of the base category. A small-scale maize farmer's decision is grounded on the utility derived from other agricultural productivity technologies, and the base category (inorganic fertilizers). This is denoted as $Y_{ij}^{*} - U_{ij} - U_{1j}$, where Y_{ij}^{*} signifies unobservable choice made. $Y_i = j$ if a small-scale farmer i chooses a choice j. $Y_{ij}^{*} < 0$ for $j = 1, \ldots, j$ when a small-scale farmer i chooses the option of the base category (inorganic fertilizers); and $Y_i = 1$. Otherwise, a small-scale farmer i adopts a choice which earns higher value for Y_{ij}^{*} and $Y_{ij} = j$. Assuming that each small-scale farmer i is facing identical j alternatives, based on utilities linear parameters, an MNP is formulated as follows:

$$U_{ij} = K_{ij}\beta + \varepsilon_{ij}, \varepsilon_{ij} \sim N(0, \Sigma) \qquad (1)$$

$$Y_{ij} = 1 \; if \; U_{i1} \leq U_{ij} \; for \; i = 1,2,3,..,n\,; J = 1,2,3,..,n \text{ and } 0 = \text{ Otherwise} \qquad (2)$$

Y_{ij} signifies the choice made by a small-scale maize farmer i of adopting certain technology(ies). U_{ij} represents unobservable alternative utility j as observed by a small-scale maize farmer i. K_{ij} signifies a vector of independent variables featuring both i and j. β refers to coefficient estimates of the regressed variables. Whereas the error term (ε_{ij}) obeys the following characteristics:

$$\text{Cov}(\varepsilon_i) = \begin{matrix} \partial_{11} & \partial_{12} & \partial_{13} \\ \partial_{21} & \partial_{22} & \partial_{23} \\ \partial_{31} & \partial_{32} & \partial_{33} \end{matrix} \qquad \text{with } \partial_{jj} > 0, \forall\, j (\text{positive definitess})$$

The anticipated probability of a small-scale maize farmer for choosing any of the agricultural productivity technologies is illustrated thus:

$$\text{P}(Y_i = 1) = P(U_{i1} + \varepsilon_{i1} > U_{i2} + \varepsilon_{i2} \; and \; U_{i1} + \varepsilon_{i1} > U_{i3} + \varepsilon_{i3}) \qquad (3)$$

$$\text{P}(Y_i = 2) = P(U_{i2} + \varepsilon_{i2} > U_{i1} + \varepsilon_{i1} \; and \; U_{i2} + \varepsilon_{i2} > U_{i3} + \varepsilon_{i3}) \qquad (4)$$

$$\text{P}(Y_i = 3) = P(U_{i3} + \varepsilon_{i3} > U_{i1} + \varepsilon_{i1} \; and \; U_{i3} + \varepsilon_{i3} > U_{i2} + \varepsilon_{i2}) \qquad (5)$$

Assuming these categories are mutually exclusive, then $\Sigma_{j-1}^{j} P_{ij} = 1$. Hence, for each i the probabilities add up to one for each small-scale maize farmer, and we get $j - 1$. This notion indicates that equations (3 + 4 + 5 = 1) are reformulated as follows:

$$\text{P}(Y_i = 1) + \text{P}(Y_i = 2) + \text{P}(Y_i = 3) = 1 \qquad (6)$$

Oftentimes, in the aspect of discrete choice modelling, the MNP is adopted to avoid the limitations of the multinomial logit model (MNL) – the independence from the Irrelevant Alternatives (IRR) (Wooldridge, 2019). This aspect of MNL stems from the assumption based on the components' stochastic of utilities that are identical and independently distributed. For many cases, it is genuine to assume that some of the alternatives are further identical to each other for a small-scale maize farmer's decision-making pertaining to the adoption of a certain technology, as documented in several studies (Dorfman, 1996; Dow & Endersby, 2004). Moreover, the MNP does not enforce limitations on the covariance matrix of the components' stochastic of utilities that are unrecognised (Wooldridge, 2019). In fact, the utility functions in any random utility model are only recognised up to location and scale, which is likely to detect parameters in the co-variance matrix of the utilities that are normalised. These parameters are elements originating from the covariance matrix. Additionally, they are floppy for behavioural and economic analysis (Wooldridge, 2019). Once more, when the choices are enormous, correlations can be large and MNP is suitable for estimating these correlations. This is the notion behind the use MNP only if the number of alternatives is reasonably minor (Wooldridge, 2019).

3. Methodology

3.1 Data Source and Sampling Procedure

The data used in this study originated from the Tanzania National Panel Survey (TZNPS) collected by the National Bureau of Statistics (NBS) in collaboration with the World Bank (WB). The analysis of the study is balanced panel data and used data from small-scale maize farming households that were interviewed in three panel waves: the first wave in 2008–2009; second wave in 2010–2011; and the third wave in 2012–2013. However, the study did not use data from fourth wave (2014–2015) period as the wave covers new households that are not available in the previous waves (NBS, 2017) that led to high attrition.

Thus, the balanced panel data analysis was grounded on actual 1,839 observations, including 613 households from each of the three consecutive waves 2008–2009, 2010–2011, and 2012–2013. The goal of this was to ensure consistent traction of the same household in three panel waves. The sample does not include households from Zanzibar because maize crop production is very low and not a priority cash crop in that area.

3.2 Model Specification

In this paper, small-scale farmers' adoption of improved agricultural technologies is modelled through the MNP since adoption decisions include more than two choices. Scientifically, they have proved to increase quantity and quality of agricultural crops (URT, 2016). Thus, enhancing the quality and quantity of maize production requires the use these technologies, which is the focus of this paper.

Empirically, the MNP model is presented as:

$$
\begin{aligned}
Y_{ij} &= \beta_0 + \beta_1 Farm\_Size_i + \beta_2 Acc\_Credit_i + \beta_3\, Soil\_Quality_i \\
&\quad + \beta_4 Acc\_Extension_i + \beta_5 Gender_i + \beta_6 Age_i + \beta_7 Education_i \\
&\quad + \beta_8 Household\_Size_i + \beta_9 Acc\_ICT_i + \varepsilon_{ij} \qquad (7)
\end{aligned}
$$

Where Y_{ij} $(j = 1,2, and\ 3\ \ i = 1, \ldots. n)$ represent the improved agricultural adoption technology bundle or choice. The agricultural productivity technology bundles are: 1 if a small-scale maize farmer uses inorganic fertilisers; 2 if the farmer uses improved maize seeds; and 3 if the farmer uses herbicides. The intersect is signified by β_0, and the coefficients of the independent variables are represented by $\beta_1 - \beta_9$. The disturbance error term is signified by ε_{ij}.

$Farm\_Size_i$ signifies size of the maize plot cultivated, which is a continuous variable measured in acres. Acc_Credit_i refers to accessibility of credit services: 1 if a small-scale maize farmer access credit services, and 0 otherwise. $Soil\_Quality_i$ represents soil quality: 1 if a small-scale maize farmer's plot farm has a good soil quality, and 0 otherwise. $Acc\_Extension_i$ indicates accessibility of extension services: 1 if a small-scale maize farmer is accessible to extension services, and 0 otherwise. $Gender_i$ represents a gender of a subsistence or peasant maize farmer: 1 if a small-scale maize farmer was a male, and 0 otherwise. Age_i symbolises the age of the head of household (small-scale or subsistence maize farmer) measured in the number of years. $Education_i$ signifies educational level measured by the number of years of schooling. $Household\_Size_i$ represents the household size, it is a continuous variable, which is a proxy of labour availability within the household. Acc_ICT_i specifies accessibility of information and communication technology (ICT): 1 if a small-scale maize farmer is accessible to ICT, and 0 otherwise.

4. Empirical Findings and Discussion

4.1 Descriptive Results

The summary of descriptive statistics results is presented in Table 1. The results indicate that the study sample mean for a small-scale maize farmer's adoption choices is 1.6 units at which a farmer can decide whether to use inorganic fertilisers, improved maize seeds, or herbicides/pesticides. The descriptive results indicate that the sample mean of maize farmers' adoption choices is slightly higher than the national average of agricultural technologies adoption rate (1.5 units) as documented by the NBS (2017) due to improvement of the agricultural voucher system during the years when the study's data were collected.

The average farm size during the three of panel survey of 2008–2009, 2010–2011, and 2012–2013 was 5.8 acres, which is slightly higher than the national mean of 5.2 acres per household. This slight difference occurred since the study sample mainly focused only on small-scale or subsistence maize farmers, which is a staple crop in Tanzania; whereas the national mean farm size include both small- and large-scale farmers growing different crops. Additionally, the descriptive summary indicates that a maize farmer cultivated an area of between 0.9 and 42 acres. Furthermore, only about 1.3 percent of small-scale maize farmers in the study had an access to

Table 1: Descriptive Statistics for Panel Data Variables

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Farmers'_Choices	1839	1.671	.796	1	3
Farm_Size	1839	5.844	5.348	.9	42
Acc_Credit	1839	.013	.147	0	1
Soil_Quality	1839	.874	.251	0	1
Acc_Extension	1839	.171	.217	0	1
Gender	1839	.796	.39	0	1
Age	1839	46.409	17.48	21	87
Education	1571	7.14	2.346	0	19
Household_Size	1839	5.6307	3.619	1	38
Acc_ICT	1142	.36	.491	0	1

Source: Authors' computation from TZNPS Dataset

credit services during the three years of panel survey. This shows that most of the maize small-scale farmers lack access to credit in Tanzania. The findings are consistent with several literatures such as Kassie et al. (2015), Selejio and Lasway (2019) and Lasway et al. (2020), who found that less than 4 percent of small-scale farmers had access to credits. The two major reasons are, first, distrust by banks of most small-scale maize farmers for lacking collaterals to acquire loans; and, second, bureaucracy in the banking system in accessing credits (URT, 2015).

The descriptive findings indicate that about 87 percent of the study sample households cultivated their maize plots on fertile soil during the years surveyed. In other words, most of the small-scale maize farmers surveyed were cultivating on plots with good soils. This findings disagree with Kassie et al. (2015), whose study documented that most small-scale farmers in Sub-Saharan Africa (SSA) practise farming activities on infertile or exhausted soils. During the panel survey years there was an effective programme called *Kilimo Kwanza* ('Agriculture First'), which reached most small-scale farmers with subsidized improved inputs (seeds, inorganic fertilizers, and pesticides) under a national agricultural input voucher system (NAIVS) that motivated farmers to use and conserve soils for positive results of the inputs (NBS, 2017). This development appears to explain why they all seemed to till fertile lands in the survey areas.

The results in Table 1 further shows that 17 percent of agricultural household heads received agricultural extension services from the government. This implies that most of the small-scale farmers were not receiving agricultural extension service. The study's findings also concur with Shee et al. (2020), who found that agricultural households that receive agricultural extension services from the government accounted for 15 percent. Major reason behind this rather restricted coverage was limited number of government extension officers in the field. The descriptive statistics also indicates that the average age of the household head was 46 years, with a range of 21 - 87 years. In addition, male-headed households accounted for 79.6 percent, whereas female-headed households comprised of 20.4 percent.

Furthermore, the average household size of small-scale maize household was 5.6, which is marginally higher than the national mean of 4.7 reported by the 2012 Tanzania Population and Housing Census. The findings further reveal that the least household size is 1 member, and the largest household had 38 members (Table 1). A large household size is associated with the existence of polygamous family systems. The summary statistics indicates that the average of schooling years is 7.14, with 0 and 19 as the minimum and maximum number of schooling years, respectively; implying that a majority of small-scale farmers had primary school education.

Moreover, the descriptive statistics indicates that only 36 percent of the study sample of small-scale maize farmers had access to information technology by owning radio and/or television, and/or a telephone (landline or mobile). This implies that during the panel survey years, a majority (64 percent) of the study sample of small-scale maize farmers had no access to information technology. This is not surprising since most small-scale maize farmers live in rural areas where access to information technology devices and services is limited. The findings concur with Mittal and Mehar (2016) who found that 67 percent of small-scale farmers in India, particularly in rural areas, have no access to information technology devices.

4.2 Econometric Analysis

4.2.1 Multinomial Probit Regression Results

The multinomial regression model was used in modelling maize farmers' adoption decisions in Tanzania using the three wave panel data, i.e., 2008–2009, 2010–2011, and 2012–2013. The results of the MNP are presented in Table 2. In these findings, the convergence emerged after 4 iterations in modelling the farmers' technology adoption decisions, implying that the log-likelihood function was maximised after 4 iterations. Table 2 indicates that the Chi-square probability (Prob > chi2) is 0.0000, which signals a good model fit. Inorganic fertiliser was used as a base outcome for the MNP analysis.

Table 2 further demonstrates the relationship between dependent and explanatory variables. Additionally, to determine the relative effectiveness of a unit change in the value of an explanatory variable in the adoption probability, the marginal effects after MNP regression were computed. The findings are presented in Table 3.

Among the variables fitted in the model, only four (4) significantly influenced the probability that a small-scale maize farmer would decide to adopt improved maize seeds. These variables include extension services, gender, education, and information technology. In addition, five (5) variables were found to significantly influence the probability of a small-scale maize farmer deciding to adopt herbicides. These include soil quality, extension, age, household size, and information technology. These findings demonstrate that extension services and information technology have a significant effect on the probability of a small-scale maize farmer deciding to adopt both technologies: i.e., improved maize seeds, and herbicides/pesticides.

Table 2: Multinomial Probit Regression Results

Farmers'_Choices	Coef.	St. Err	t-value	p-value	Sig.
Inorganic Fertilisers (Base outcome)					
Improved Maize Seeds					
Farm_Size	-0.017	0.091	-0.81	0.615	
Acc_Credit	0.371	0.271	0.36	0.822	
Soil_Quality	-0.359	0.612	-1.46	0.365	
Acc_Extension	0.216	0.222	1.81	0.071	*
Gender	0.619	0.192	1.74	0.061	*
Age	0.041	0.007	2.72	0.018	**
Education	0.043	0.061	3.01	0.000	***
Household_Size	0.045	0.036	1.25	0.733	
Acc_ICT	0.517	0.291	6.11	0.000	***
_cons	-3.816	0.913	-5.22	0.001	***
Herbicides					
Farm_Size	0.071	0.084	0.39	0.748	
Acc_Credit	0.529	0.139	0.81	0.743	
Soil_Quality	-0.851	0.187	-3.74	0.000	***
Acc_Extension	-0.611	0.653	-4.52	0.000	***
Gender	-0.052	0.633	-0.12	0.643	
Age	0.026	0.001	2.73	0.002	***
Education	0.076	0.073	1.22	0.175	
Household_Size	0.021	0.026	2.13	0.034	**
Acc_ICT	0.813	0.642	4.45	0.001	***
_cons	-0.731	0.152	-1.51	0.277	

Mean dependent var	1.812	SD dependent var	0.824
Number of obs	947.000	Chi-square	124.712
Prob> chi2	0.000	Akaike crit. (AIC)	1920.047

*** p<0.01, ** p<0.05, p<0.05, *p<0.1

Legend: *Statistically significant at 10% level; ** statistically significant at 5% level; *** Statistically significant at 1% level.

Source: Authors' computation from TZNPS data.

The results in Table 2 further show that the accessibility of extension services from the government was found to be statistically significant and positive at 1 percent level in terms of influencing a smallholder farmer to adopt agricultural technologies, particularly of improved maize seeds. This means that small-scale maize farmers who received extension services had higher probability to adopt improved maize seeds by 14.6 percent than those who had not received such services. This finding is supported by Tessema et al. (2018) and Nchinda et al. (2020) who found that farmers who benefited from extension services from governmental and non-governmental organisations had a higher likelihood to adopt agricultural technologies than ones with no such access.

However, for herbicides, the findings show that extension services were statistically significant at 1 percent; and negatively correlated with the small-scale maize farmers' probability of adopting herbicides. In this regard, the findings demonstrate that a smallholder maize farmer who received extension services from the government had a lower likelihood to adopt herbicides technology by 23.5 percent. The results agree with Mwalupaso et al. (2019), who contended that most agricultural officers tend to educate farmers who use herbicides, particularly on its negative human health impacts that might cause respiratory diseases when not used correctly. This might be the key reason behind the small-scale maize farmers who received extension services showing lower adoption of herbicides by 23.5 percent.

Table 3: Marginal Effects After MNP Regression Results

	Improved Maize Seeds			Herbicides		
Variables	***Marginal Effect***	***Std. Err***	***P-Value***	***Marginal Effect***	***Std. Err***	***P-Value***
Farm_Size	-.006449	.00436	0.323	.0079612	.00537	0.389
Acc_Credit*	.0436382	.06483	0.636	.0548202	.03362	0.747
Soil_Quality*	.0083382	.07721	0.322	-.282856	.05272	0.002
Acc_Extension*	.1467472	.02746	0.000	-.235649	.03656	0.000
Gender*	.0784129	.02649	0.024	-.047927	.03812	0.361
Age	.0024762	.00671	0.349	.0062425	.00647	0.016
Education	.0260728	.00381	0.001	.0063203	.00646	0.728
Household_Size	.0054634	.00183	0.648	.0542231	.00748	0.023
Acc_ICT*	.1349648	.03647	0.000	.0659383	.02646	0.011

Legend: (*) dy/dx is for a discrete change of dummy variable from 0 to 1.

Source: Authors' own computation from TZNPS Dataset.

Information technology generally has a positive and significant relationship with improved maize seeds and herbicides adoption. In fact, the estimated coefficients for improved maize seeds and herbicides are both statistically significant at 1 per cent level. The findings imply that small-scale maize farmers with access to agricultural information through TVs, radio, mobile phones or the internet have a higher probability of adopting improved maize seeds and herbicides by 13.4 percent and 6.5 percent, respectively, than small-scale maize farmers who had no such access. These results imply that most small-scale maize farmers who had access to information technology received education on applying these agricultural technologies. For example, varieties of improved maize seeds and herbicides are usually promoted on TVs and radios, especially during planting seasons. The specific contents of such promotions includes quality, price, usage, and accessibility. Moreover, numerous agricultural programmes—such as the Participatory Agricultural Development and Empowerment Project (PADEP) and *Kilimo Kwanza*—are promoted on the radio, TV, and sometimes on the Internet, to influence smallholder maize farmers to adopt these technologies. Thus, small-scale farmers with access to such information technologies are likely to adopt them. These results are strongly supported by Mittal and Mehar (2016) who found that well-informed farmers on their agricultural activities have higher likelihood to adopt agricultural technologies than the less-informed ones.

Moreover, the study found the gender variable influences positively the adoption of improved maize seeds. This variable is statistically significant at 5 percent. This result implies that female small-scale maize farmers are likely to adopt improved maize seeds by 7.8 percent than male smallholder maize farmers. This finding is supported by Selejio et al. (2018) and Lasway et al. (2020), who noted that females are more engaged in farming activities than their male counterparts, particularly in African countries as farming is largely a female endeavour at the cultural level, which makes them adopt agricultural technologies unlike their male counterparts.

Furthermore, the study found education level to be positively related to the adoption of improved maize seeds. This variable was found to be statistically significant at 1 percent. This implies that a unit increase of education level of a smallholder farmer increases the likelihood of his/her adopting improved maize seeds by 2.6 percent. Thus, more years of schooling (higher education levels) of smallholder farmers increase the propensity to adopt agricultural technologies compared to smallholder farmers with few years of schooling (lower education levels). Additionally, these results are congruent with several studies such as Simtowe et al. (2016) and Nchinda et al. (2020) who found that farmers' education level influences their decision to adopt agricultural technologies: they have higher capacity to grasp new agricultural practices than those with lower education levels.

On the other hand, soil quality was found to negatively relate with the adoption of herbicides. This variable was statistically significant at 1 percent. The results indicate that smallholder maize farmers, who farmed on fertile soils, had a lower probability of adopting herbicides by 28.2 percent than those who did not. The results align with Kassie et al. (2015) and Lasway et al. (2020) who documented that farmers tilling fertile or quality-enhanced land had lower probability to adopt agricultural technologies than those who farmed on less nutrient-rich or exhausted soils. This implies that farmers working on soils in the latter situation ought to adopt agricultural technologies aimed to revive soil quality and increase their agricultural production, compared to those in the former situation—those already tilling fertile or nutrient-rich soils.

Also, the age of a smallholder maize farmer was found to be positively related to the adoption of herbicides, and was statistically significant at 5 percent. This positive relationship is consistent with the results of studies such as Abay et al. (2016), and Tsinigo and Behrman (2017) whose findings indicated that an increase in the age of smallholder maize farmers increases the likelihood of adopting herbicides by 0.6 percent. Implicitly, older smallholder farmers have more farming experiences and accumulated adequate capital to enable them adopt herbicides technology than younger farmers.

The study also found that household size is positively associated with the adoption of herbicide. This variable was statistically significant at 5 percent. The findings indicate that when a household size increases, the propensity to adopt herbicides technology also increases by 0.7 percent. This finding is supported by Selejio and Lasway (2019) who found that large-sized households found it much easier to participate in the adoption of agricultural technologies than small-sized families as the former can actively engage members in agricultural activities.

Figure 1 shows that the likelihood predictive mean effect of smallholder farmers to adopt inorganic fertilizers is increasing by 0.46 units, with a 95 percent confidence interval of the effect ranging from 0.43 to 0.49. The likelihood predictive mean of a smallholder farmer to adopt improved maize seeds increases by 0.14 units with a 95 percent confidence interval of the effect ranging from 0.12 to 0.16. Furthermore, a smallholder farmer's likelihood predictive mean effect on adopting herbicides also increased by 0.39 units with a 95 percent confidence interval of the effect being 0.36 to 0.42. This implies that smallholder maize farmers had positive decisions when it comes to adopting improved agricultural technologies, i.e., inorganic fertilisers, improved maize seeds, and herbicides, but at different predictive means.

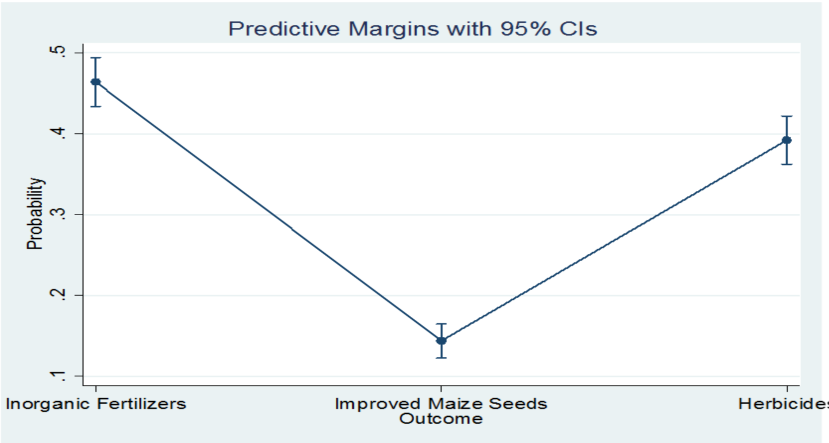

Figure 1: ***Results of Predictive Margins on Adoption of Agricultural Technologies***

Source: Authors' computation from TZNPS Dataset using STATA 14.2 Software.

5. Conclusion and Policy Implications

This study has modelled small-scale maize farmers' adoption decisions in Tanzania using panel data collected from 1,839 observations involving 613 households during three consecutive waves in 2008–2009, 2010–2011, and 2012–2013. The empirical results indicate that adoption decisions were influenced by extension services, information technology, gender, education level, soil quality, age, and household size. Specifically, factors such as extension services, information technology, gender, and education level were significantly found to influence farmers' decisions to adopt improved maize seeds. In addition, soil quality, extension services, information technology, age and household size significantly influenced farmers' adoption of herbicides in the study area.

Overall, this study provides some lessons on what can be done comprehensively to improve agricultural technologies adoption and boost productivity. First, the empirical results indicate that the education level of maize farmers significantly influences adoption. Formal education to maize farmers is required through aggressive infrastructural and human development to impact the knowledge to maize farmers that agriculture is a business, and not 'a way of life'. Formal education to smallholder farmers can be serviced through public education on farm management practices; education that can be offered through mobile phone services, radio, TV programmes, and available platform by the Ministry of Agriculture (MoA) to reinforce maize farmers' knowledge on the adoption of appropriate agricultural technologies. Secondly, strengthening of extension services in rural areas, where most of the agricultural activities occur, can enable the promotion of the adoption of agricultural technologies. Also, more encouragement should be given to credible organisations such as NGOs to impact farmers' technical abilities and enhance farmer-farmer extension services and knowledge-sharing.

Also, the theory of utility maximization explains that price and income are the main determinants of an individual adopting certain improved agricultural technologies. These variables and others—such as harvest value and agro-ecological zones—were not included in this paper because the NPS dataset had many missing values in the variables. This is the limitation of this paper. However, including variables with many missing values in this paper could lead to biasness in econometric results as suggested by Wooldridge, (2019).

More importantly, improved agricultural technologies are not limited to improved seeds, herbicides, and inorganic fertilizers only. Therefore, there is a room for other studies to research on improved agricultural technologies such as erosion control, and fungicides/insecticides; and on other cash crops apart from maize, such as cassava, rice, cashew nuts, etc.

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