

Economic analysis of the adoption of inorganic fertilisers and improved maize seeds in Tanzania

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Abstract

The adoption of improved agricultural technologies is very low in Tanzania, which has led to both low crop productivity and low production. This paper therefore analyses the factors that influence the adoption of improved seeds, inorganic fertilisers and a package of technologies by smallholder maize farmers in Tanzania using the national panel survey (NPS) data collected in three waves: 2008/2009, 2010/2011 and 2012/2013, with a sample size of 1 551 maize-farming households used for analysis. A probit model was used to estimate the likelihood of household adoption of agricultural technologies. The findings reveal that the adoption rates of the package of technologies, improved maize seeds and inorganic fertilisers are low, at 17%, 21% and 28% respectively. The key findings further indicate that the accessibility of extension services, ICT services, agricultural inputs on credit and education level are significant in influencing smallholder maize farmers to adopt these improved agricultural technologies, as has been reported in previous studies that used cross-sectional data. Therefore, the policy options that promote rural extension services, education services, access to ICT services and credit input markets are pertinent in order to enhance the adoption of improved agricultural technologies by smallholder farmers in Tanzania.

Key words: improved agricultural technologies; smallholder maize farmers; adoption decision; panel data; Tanzania

1. Introduction

The agricultural sector acts as a crucial, significant and strategic sector in the process of economic development in both developed and developing countries. The significance of agriculture has attracted maximum attention from both researchers and policymakers within and across the borders of the African continent due to its importance to the economy. Agriculture is a part of the economic development process that facilitates economic growth, since it acts as the main source of employment, food and income for the world population. Globally, the share of the agricultural population is about 67%, of which agriculture contributes 39.4% of the GDP, while exports of agricultural goods account for 43% of world total exports (FAOSTAT 2013). The World Bank (2016) indicates that agriculture accounts for 65% of the African continent's employment and 75% of its domestic trade, of which small-scale farmers account for 75% of the regional agricultural production, although with variations in productivity.

Majid (2004) postulates that there are similarities and differences in global agricultural productivity across regions. Globally, the estimated agricultural output increased from 8.2% in 2016 to 10% in 2018, while the population engaged in agricultural activities increased from 39.2% to 40% in the

same period (Shikuku *et al.* 2019). However, the growth in the trends in agricultural productivity varies across the regions, as there was much improvement in agricultural activity in Asia, especially in China, but there was less improvement in Africa, especially in Sub-Saharan Africa (SSA). Thus, to encourage and improve economic growth across Africa and tackle problems such as hunger and poverty, an agriculture-led development programme, known as the New Partnership for Africa's Development (NEPAD), was established by African leaders in 2001 with the major aim to promote sustainable agricultural production and food security. Later, in 2003, the leaders of African regional economic organisations and other multilateral organisations founded the Comprehensive Africa Agriculture Development Programme (CAADP) with the major aim of increasing the performance of agricultural productivity on the continent. In order to sufficiently emphasise agricultural productivity, African leaders suggested during the African Union Agriculture and Food Security Summit in 2006 that each member country should allocate at least 10% of its national budget to promote agricultural and rural development within five years (Bumb & Gregory 2006).

According to the International Fund for Agricultural Development (IFAD 2017), the rural poor are estimated to be close to 75% of the world's poor, and the majority of them are living in developing regions such as Sub-Saharan Africa, South Asia and East Asia. IFAD further states that one of the similar features in developing regions is the existence of small-scale subsistence farming, which is most common in rural areas. It is estimated that 85% of small-scale farmers in Tanzania occupy 91% of the agricultural land but account for about 75% of total agricultural production,¹ and that the agricultural sector contributes around 25% of the GDP (AFDB 2009; United Republic of Tanzania [URT] 2013; Townsend 2015; URT 2016). Moreover, 67% of the total population of Tanzania lives in rural areas and engages in agricultural activities. Therefore, an improvement in the agricultural sector will have a significant impact on the standard of living in rural areas, and contribute greatly to the reduction of poverty, particularly in the rural areas. However, the agricultural sector has been performing poorly over the past decades compared to other sectors, such as the service sector. For example, the contribution of agricultural production accounted for as much as 45.95%, 33.45%, 24.95% and 31.41% in 1990, 2000, 2010 and 2016 respectively, while the value added of the service sector accounted for 36.39%, 47.33%, 46.34% and 41.21% of GDP in the same periods (National Bureau of Statistics [NBS] 2017). The performance of the agriculture sector shows a declining trend, and thus much effort is needed from the public and private sectors to improve the sector. There are several factors that have been contributing to this decline in agricultural performance, but one of them is the lack of investment in agro-technology, which includes the use of inorganic fertiliser and improved seeds in the agricultural sector in the economy (URT 2013; Khonje *et al.* 2015; Selejio *et al.* 2018). Therefore, there is a need for the stakeholders in the agricultural sector to understand the importance of agro-technology, which includes the use of inorganic fertilisers and improved seeds in order to boost agricultural production in the economy.

Despite the existence of agricultural policies that have been initiated to encourage the adoption of agricultural technologies in order to boost agricultural productivity, there is still a low rate of adoption of improved seeds and inorganic fertilisers among small-scale farmers in Tanzania. For example, the percentage rate of adoption of agricultural technologies among smallholder farmers in maize production in Tanzania, using both inorganic fertiliser and improved seeds, is 5.7% (URT 2016). Benson *et al.* (2012)² note that the adoption of improved agricultural technologies is a useful tool to boost productivity in the agricultural sector, since small-scale farmers who use agricultural technologies produce much more output of a higher quality compared to those who do not use

¹ Medium and large-scale farmers account for 10% and 5% of total agricultural production respectively.

² The adoption of a new technology is a choice between traditional and new technology. It is often believed that modern varieties of seeds lead to higher yields than the traditional varieties. For econometric analysis, the definition of adoption depends on whether the adopter is a discrete state, with a binary variable (use or not), or a continuous measure (e.g. proportion of land allocated to technologies as measure of adoption), as explained by Doss (2003) and Benson *et al.* (2012).

improved agricultural technologies. Many of the existing studies have concentrated on explaining the adoption of one improved agricultural technology at a time – either inorganic fertiliser or improved seeds across Africa and in developing countries in Asia (see Bisanda *et al.* 1998; Alene *et al.* 2000; Zavale *et al.* 2005; Adeoti 2009; Lopes 2010; Tura *et al.* 2010; Rutaiwa 2017). These studies found that extension services are a significant factor encouraging farmers to adopt improved agricultural technologies. However, these studies were not able to investigate the factors affecting the adoption of both improved agricultural technologies among small-scale farmers. In this regard, most of the literature that has concentrated on the adoption of multiple improved agricultural technologies or a package of technologies in developing countries use cross-sectional data (Khonje *et al.* 2018; Aurangozeb 2019; Barnes *et al.* 2019; Donkoh *et al.* 2019; Shikuku 2019). Notably, cross-sectional studies are likely to suffer from endogeneity problems, which make it difficult to control for unobserved heterogeneity and examine what happens to the adoption over time (Gujarati 2004; Wooldridge 2019). Thus, this paper has taken this advantage of panel data in the analysis for better and more informative results. As a result, there is a need to put more effort into investigating the factors that affect the adoption of improved seeds, inorganic fertilisers and a package of technologies among small-scale farmers in all agro-ecological zones in Tanzania. This can be done by using panel data and models that control for the problems of endogeneity that leads to the estimates being biased. Therefore, the aim of this paper was to estimate the rates of non-adoption and adoption of inorganic fertilisers, improved seeds and a package of technologies among smallholders' farmers. Lastly, the aim was also to examine the factors affecting smallholder farmers' adoption decisions relating to individual and a package of technologies, i.e. both improved maize seeds and inorganic fertilisers. Furthermore, the findings of this paper reveal that the adoption rates of the package of technologies, improved maize seeds and inorganic fertilisers are low, at 17%, 21% and 28% respectively. The key findings further indicated that the accessibility of extension services; ICT services; education level; and agricultural inputs on credit are significant in their influence on maize smallholder farmers deciding to adopt these improved agricultural technologies.

2. Theoretical framework

This paper is grounded in three different theoretical perspectives on the adoption of improved agricultural technologies that have been used in recent studies: innovation diffusion theory; economic constraints; and adopter perceptions perspectives (Aurangozeb 2019; Barnes *et al.* 2019). The accessibility of information that is disseminated is a core subject of innovation diffusion theory, which includes factors such as the accessibility of extension services, education level, and access to phones or TVs – aspects that have been used in this paper. In the case of adopter perception perspectives, these are observed as a series of linear stages, from knowledge acquisition, decision and implementation, which are embedded in several factors, such as farm size, gender, distance from farm to market, household size, and so on. The theoretical perspective on economic constraints states that adoption is influenced by the accessibility of economic resources and specifies that limited accessibility of these resources affects technology adoption, for instance the accessibility of credits. Therefore, this paper integrates the three theories to develop a conceptual understanding of the research problem.

Shikuku (2019) states that the decision to adopt or not to adopt improved agricultural technologies is a function of farmers' perceptions on improved technologies and the decisions they take. Mottaleb *et al.* (2018) documented that there are several reasons why farmers may adopt improved agricultural technologies. Some farmers may be rational in their decision behaviour, and their perceptions may be influenced by their field production information, institutional factors, and socio-demographic characteristics. Recent literature (Khonje *et al.* 2018; Mottaleb *et al.* 2018; Ntshangase *et al.* 2018; Aurangozeb 2019; Barnes *et al.* 2019; Shikuku 2019) has identified several variables as determining the adoption level of improved agricultural technologies. These include credit

constraints, gender, distance, extension services, education level, land tenure, accessibility of information devices such as radios and TVs, labour availability, risk, and input supply. Understanding these variables and how they influence the adoption level are significant in developing policies and strategies to encourage farmers to adopt improved agricultural technologies.

In this paper, the probit regression model is used to empirically analyse the factors influencing the adoption of improved agricultural technologies among smallholder maize farmers in Tanzania. The endogenous variable in this paper takes the values of 0 and 1, which categorically means that it takes 1 if a household adopted agricultural technologies in three consecutive waves of the agricultural National Panel Survey data, and 0 otherwise. In estimating the qualitative response of dummy dependent variables, several models are used, such as the logit model, the linear probability model and the probit model. The linear probability model has some setbacks, such as the non-normality of the error term, and also that the given probabilities can exceed 1 or be lower than 0. Thus, these limitations of the linear probability model can be solved by the probit or logit model, which are grounded in normal cumulative distribution functions (CDF). Moreover, these models have special characteristics to solve the setbacks of the linear probability at which the probability of the dependent variable ($P_i = (Y = 1|X)$) can be examined in relation to the increase or decrease in the series for the independent variables (X_i). Thus, the probability of adoption ($P_i = (Y = 1|X)$) increases or decreases only in an interval of 0 to 1. Also, the association between X_i and P_i is nonlinear (Wooldridge 2019). In addition, as the independent variables (X_i) approach a negative value, the probability of adopting agricultural technologies approaches 0, and 1 otherwise. The probit and logit models have similar features; however, the logistical distribution has slightly flatter tails. Consequently, the conditional probability approaches 0 or 1 at a more sluggish rate in the logit than in the probit model. Therefore, this is the reason for using the probit model in this paper, since it involves a binary dependent variable and allows the error term to be normally distributed.

2.1 Conceptual analysis of the model

The conceptual analysis of the model used in this paper is parallel to the model adopted by Ntshangase *et al.* (2018) to estimate the adoption of improved agricultural technologies among households. The utility maximisation model acts as a basis underlying the decision-making by households in the probit model. The decision of a household either to adopt (inorganic fertiliser or improved maize seeds) or not depends on the utility latent index y^* , which is determined by other factors. This means that, the higher the value rate of the utility latent index y^* , the higher the rate of the household's adoption of agricultural technologies.

The latent utility index is articulated as follows:

$$y^* = X'\beta + \varepsilon \quad (1)$$

The $X'\beta$ index is a function and ε is IID, with mean 0 and unit variance.

$$y = 1 \text{ if } y^* > 0 \quad (2)$$

$$y = 0 \text{ if } y^* \leq 0, \quad (3)$$

where 0 is the threshold level or critical level of the index y^* .

Green (2008) and Wooldridge, (2019) provide an explanation of household choices to adopt the random utility model. According to them, U_{i1} is the i^{th} household's indirect utility linked to the rate

of adoption of advanced technology, and U_{i0} is the i^{th} household's indirect utility linked to no adoption of technology.

Then,

$$U_{i1} = X_i' \beta_1 + \varepsilon_{i1} \text{ stands for the adoption of the improved agricultural technology} \quad (4)$$

$$U_{i0} = X_i' \beta_0 + \varepsilon_{i0} \text{ stands for non-adoption of the improved agricultural technology} \quad (5)$$

Since the level of utility is random, then the i^{th} household will choose to adopt inorganic fertiliser/ improved maize seeds if and only if $U_{i1} > U_{i0}$. Then, for farmer i , the probability of adoption is calculated as follows:

$$P(Y_i = 1|X) = P(U_{i1} > U_{i0}) \quad (6)$$

$$= P(X_i' \beta_1 + \varepsilon_{i1} > X_i' \beta_0 + \varepsilon_{i0}) \quad (7)$$

$$= P(\varepsilon_{i0} - \varepsilon_{i1} < X_i' \beta_1 - X_i' \beta_0) \quad (8)$$

$$= P(\varepsilon_{i0} - \varepsilon_{i1} < X_i' (\beta_1 - \beta_0)) \quad (9)$$

$$= P(\varepsilon_i < X_i' \beta) \quad (10)$$

$$= \phi(X_i' \beta), \quad (11)$$

where $\phi(\cdot)$ signifies the cumulative distribution function (CDF) of the standard normal distribution, X' stands for vector of independent variables THAT describe the adoption of agricultural technology, and β is a vector of parameters.

The model that is used in estimating the adoption of improved technology by a farmer can be described as follows:

$$P(Y_i = 1|X) = \phi(X_i' \beta) = \int_{-\infty}^{X_i' \beta} \frac{1}{\sqrt{2\pi}} \exp\left(-Z^2/2\right) dz, \quad (12)$$

where P stands for the probability that the i^{th} farmer adopted agricultural technologies (improved maize seeds or inorganic fertiliser), and 0 otherwise. Thus, this paper is based on the binary dependent variable, which is defined as whether or not a household adopted agricultural technology in the agricultural seasons of 2008/2009, 2010/2011 and 2012/2013. Three waves are used in this paper, instead of the four available waves, because the fourth wave (2014/2015) is based on data from new households that were not available in the previous three waves.

2.2 Model specification

The probit regression model empirically explains the factors affecting the adoption decisions regarding the improved agricultural technologies among the farm households. The probit regression model is set out as follows:

$$P(TECH = 1) = \beta_0 + \beta_1 HH_Sex + \beta_2 Farm_Size + \beta_3 HH_Age + \beta_4 Acc_Extn + \beta_5 Acc_Crdt + \beta_6 Acc_ICT + \beta_7 HH_Size + \beta_8 Dist_Mark1 + \beta_9 Dist_Mark2 + \beta_{10} HH_Educ1 + \beta_{11} HH_Educ2 + \beta_{12} HH_Educ3 + \varepsilon, \quad (13)$$

where *TECH* signifies the adoption of the following agricultural technologies: inorganic fertilisers (*Adopt_inorganicfert*) or improved maize seeds (*Adopt_imaizeseeds*) or the adoption of both technologies altogether (*UsePackage*). β_0 signifies the intercept, β_1 to β_{12} stand for the coefficients of the various explanatory variables, and ε signifies the error term.

2.3 Description of variables

In this paper, the variables used are classified into two classes: (i) dependent variables and (ii) independent variables. The choice of these variables is based mainly on the nature of the study area (Tanzania), and is also influenced by other literature reviews (Bisanda & Mwangi 1996; Kaliba *et al.* 2000; Chirwa 2005; Adeoti 2009; Akudugu *et al.* 2012, Khonje *et al.* 2015). The independent variables in the probit regression models are categorised into three categories: (i) field production information, (ii) institutional factors and (iii) farmers' socio-demographic characteristics.

The category of field production information includes size of the farm (*Farm_Size*). Institutional factors are access to extension services (*Acc_Extn*), distance from the plot to the market (*Dist_Mark1*) and (*Dist_Mark2*), accessibility of inputs on credit (*Acc_Crdt*), and household possession of ICT devices such as mobile phones or TVs (*Acc_ICT*). Farmers' socio-demographic characteristics are household size (*HH_Size*), level of education of household (*HH_Educ1*), (*HH_Educ2*) and (*HH_Educ3*), age of household head (*HH_Age*) and gender of the head of the household (*HH_Sex*).

2.3.1 Dependent variable

There are three dependent variables in this probit adoption model: *Adopt_imaizeseeds*; *Adopt_inorganicfert*; and *UsePackage*, which are all dummy variables taking the value of 1 or 0. They take the value of 1 if a farmer adopted improved maize seeds, inorganic fertilisers or both agricultural technologies within a period of the Agriculture National Panel Survey (2008/2009, 2010/2011 and 2012/2013), and 0 otherwise. Thus, the household's probability of adoption of improved maize seeds, inorganic fertiliser or both is described and estimated by the sign, the statistical significance, and the magnitude of the parameter estimates in the probit adoption model.

2.3.2 Independent variables

The independent variables are postulated to facilitate the decisions of the households either to adopt improved maize seeds and inorganic fertiliser, or not.

Farm_Size is grouped as a continuous variable that points towards the land utilised by the members of the household during the 2008/2009, 2010/2011 and 2012/2013 agricultural seasons. Farm size encompasses areas with certificate of ownership, that are held under customary law, borrowed, bought, rented and share-cropped from others, and specific areas that are under various forms of tenure. Normally it is assumed that the households that own larger farms have higher agricultural adoption probabilities of improved maize seeds and inorganic fertiliser, unlike households with smaller farms. The motive to favour this variable is that households with larger farms can dedicate large parts of their farmlands to adopting new technologies, such as improved maize seeds and inorganic fertiliser, so as to boost their agricultural production. On the other hand, some technologies need a fairly large investment in cash, therefore these become a barrier, especially in the case of large farms.

Acc_Extn is a dummy variable that takes the value of 1 if the household obtained extension advice for crop production during the 2008/2009, 2010/2011 and 2012/2013 agricultural seasons, and 0

otherwise. Extension advice includes services and education that are given to farmers by rural agricultural agents on how to grow and manage crops in a professional way. The access to an extension service in this variable includes receiving advice on the use of improved maize seeds and inorganic fertilisers. Access to extension services is expected to have a positive effect on the adoption of agricultural technology.

Acc_ICT is a dummy variable with a value of 1 if the household has access to ICT devices such as mobile phones, radios or TVs for access to information, and a value of 0 otherwise. If the household owns a telephone (mobile or landline), radio and/or television (TV), it is considered as having access to information. This variable is introduced in the paper because information technology influences the adoption of agricultural technology, as indicated by several authors (see Bisanda *et al.* 1998; Alene *et al.* 2000; Zavale *et al.* 2005; Adeoti 2009; Lopes 2010; Tura *et al.* 2010; Rutaihwa 2017). For example, there are agricultural programmes that are aired on television that provide awareness of agricultural activities and could influence households to adopt these agricultural technologies. Hence, the existence of information technology can have a positive effect on the adoption of agricultural technology.

Dist_Mark1 and *Dist_Mark2* are categorised as continuous variables that specify the distance from the plot to the market in terms of kilometres in short and moderate distances respectively. Long distance (*Dist_Mark3*) acts as a reference category, entailing a long distance from the plot to the market in terms of kilometres. Input and output purchases and sales are encompassed in the market. There is a great deal of literature that shows that the adoption of new agricultural technology can be affected by distance to the market (see Bisanda *et al.* 1998; Alene *et al.* 2000; Zavale *et al.* 2005; Adeoti 2009; Lopes 2010; Tura *et al.* 2010; Rutaihwa 2017). As the distance from the plot to the market increases, the probability of adopting new technology decreases. It therefore is postulated that, if the household's plot is located near to the market, then there is a higher probability that new technology (improved maize seeds and inorganic fertiliser) will be accessed. Shiferaw and Tesfaye (2006) hypothesised that the distance from the household plot to the market is negatively associated with the probability of adoption of new technology (improved maize seeds and inorganic fertilisers).

HH_Size is a continuous variable that signposts the number of household members, counting direct family living in the household and other persons living together with the family. This variable is a proxy of labour availability in a particular household. It is assumed that the household size has a positive association with the adoption of new agricultural technology, since the members of the household provide labour on the farmlands, particularly if many household members are adults. However, the converse is true if the household has many dependants (children), since their contribution of labour is low on the basis of adult equivalent and may lead to low household saving for the adoption of costly technology (Kassie *et al.* 2015; Ntshangase *et al.* 2018).

HH_Sex is a dummy variable that shows the gender of the head of the household. It entails a value of 0 for females and 1 for males. The reason for including this variable is to test whether the households that are headed by females perform differently from the households headed by males in terms of the adoption of agricultural technology. It is common for this variable to be used in developing countries due to the social-cultural aspects that limit women from making vital decisions. Thus, *HH_Sex* has positive effects on the adoption of agricultural technologies.

Acc_Crdt is a dummy variable that takes the value of 1 if any household member received any improved seeds and/or inorganic fertiliser on credit to be paid later on, and a value of 0 otherwise. This variable is included in the probit technology adoption model in order to test whether the

market for credit³ is vital in adopting new agricultural technology, particular the use of inorganic fertiliser and improved seeds. Thus, *Acc_Crdt* has positive effects on the adoption of agricultural technologies.

HH_Educ1, *HH_Educ2* and *HH_Educ3* are dummy variables that take the value of 1 if the household head received education at a particular level, such as non-formal, primary education or secondary education respectively, and a value of 0 otherwise. *HH_Educ4* stands as a reference category for tertiary education or higher training. The reason to include this variable is to test whether household heads with different levels of education present different behaviour regarding the adoption of agricultural technology through the use of inorganic fertiliser and improved seeds.

HH_Age is a continuous variable that indicates the age of the head of the household in years. It is a proxy for the experience of the head of household. The variable is expected to exhibit different performance in the adoption of agricultural technology, since old farmers may perform contrarily from young farmers due to their different farming experiences, their accumulation of capital, and their knowledge about the advanced agricultural technology. However, the old farmers may not take the risk to invest in new technologies, as risk-taking decreases with age, and they also have less energy to adopt labour-demanding technologies.

2.4 Data

The analysis uses the secondary National Panel Survey (NPS) data that was collected by the National Bureau of Statistics (NBS) of Tanzania with the collaboration of the World Bank. The households used in this paper were interviewed in waves: the first wave was 2008/2009, the second wave in 2010/2011, and the third wave in 2012/2013. Although the information of the recent (fourth) wave was collected in 2014/2015, it was not used for analysis in this paper, since the majority of households in this wave were new, which would give rise to high attrition.

Initially, the dataset contained 3 265, 3 924 and 5 010 households for the first wave (2008/2009), the second wave (2010/2011), and the third wave (2012/2013) respectively. These numbers included all types of different crop farmers. In order to have a balanced panel dataset, data merging, appending and cleaning was done to track only small-scale maize farmers who either had or had not adopted improved maize seeds, inorganic fertilisers or both technologies within a period of the National Panel Survey. Afterwards, the analysis of balanced panel data was based on 1 551 concrete observations, involving a sample of 517 small-scale maize farmers who appeared in the three waves. The purpose of this was to ensure consistent tracking of the same household members in the three waves. The sample of panel data in this paper comprise households on the Tanzania mainland only. Households from Zanzibar were dropped during the sampling procedure, since maize is cultivated only to a very limited extent on the island.

3. Results and discussion

3.1 Descriptive results

The descriptive analysis of statistical variables is vital in helping to understand the features of sample units. Thus, in this descriptive analysis, we present the means, standard deviations, and minimum and maximum values of the variables used in this paper. The analysis of the summary statistics for the dependent and independent variables is presented in Table 1.

³ In this context, the term credit is referred to as finance in the form of cash or in kind, such as contributions through the provision of machinery, inputs and other related materials to boost crop production, and in relation to which the value of the credit must be repaid to the creditor.

This paper includes three important agricultural technologies as dependent variables, viz. adoption of inorganic fertilisers, adoption of improved maize seeds, and the adoption of the package of technologies. The descriptive summary shows that the adoption of inorganic fertilisers was mostly done by households at an adoption rate of 24.8%, followed by the adoption of improved maize seeds, at a 21.7% adoption rate, while the adoption of the package of technologies (UsePackage) was adopted at a rate of 20.5%. The current adoption rates differ from the rates in the country in previous years. For example, Bisanda and Mwangi (1996) and Kaliba *et al.* (2000) reported that the adoption rates of improved seeds were 8.5% and 10% respectively, while those of inorganic fertilisers were 9.6% and 11% respectively. These findings show that the adoption rates of agricultural technologies in Tanzania has improved considerably, probably due to the implementation of the agricultural input voucher system in the years when NPS data was collected. However, Adeoti (2009) documented that the adoption rates of improved maize seeds and inorganic fertilisers were 34% and 38% in Ghana respectively, implying that the adoption rates of agricultural technologies in Tanzania are still low compared to those in other African countries.

The summary statistics for the independent variables in Table 1 shows that the sample mean of the household head's age was 49 years, with a range from 20 years to 90 years. Regarding the gender of the household head, 76.8% of households were headed by a man, while 23.2% were headed by a woman.

Agricultural household heads who received government extension services totalled 10.3% on average. This result agrees with that of Kaliba *et al.* (2000), who found that 17% of households accessed government extension services. This implies that a large number of smallholder farmers do not have access to government extension services.

Table 1: Descriptive statistics for independent panel data variables

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
<i>Dependent variables</i>					
Adopt_inorganicfert	1 551	0.248	0.432	0	1
Adopt_imaizeseeds	1 551	0.217	0.412	0	1
UsePackage	1 551	0.205	0.404	0	1
<i>Independent variables</i>					
HH_Age	1 551	49.65	14.836	20	90
HH_Sex	1 551	0.768	0.371	0	1
HH_Size	1 551	5.946	2.997	1	35
Farm_Size	1 551	7.533	6.943	2	78
Acc_Crdt	1 551	0.021	0.144	0	1
Acc_Extn	1 551	0.103	0.303	0	1
Acc ICT	1 551	0.492	0.521	0	1
Dist_Mark1	1 551	0.415	0.493	0	1
Dist_Mark2	1 551	0.301	0.459	0	1
*Dist_Mark3	1 551	0.284	0.451	0	1
HH_Educ1	1 551	0.216	0.412	0	1
HH_Educ2	1 551	0.742	0.438	0	1
HH_Educ3	1 551	0.039	0.194	0	1
*HH_Educ4	1 551	0.003	0.051	0	1

* signifies that the variable is a reference category

Source: Authors' computation from the Tanzania National Panel Survey Dataset

In this panel survey, the summary statistics show that a large number (74.2%) of household heads had primary education as their highest level of education, followed by household heads who had attained a non-formal education level (21.6%). The results further reveal that 3.9% of household heads had secondary education, while 0.3% had tertiary education (reference category). The results imply that the number of heads of households in the sample with a secondary and tertiary level of education is smaller than the number of household heads with non-formal and primary education.

The low number of household heads with secondary and higher education may be associated with the observed low rate of adoption of improved agricultural technologies (improved seeds and inorganic fertilisers), since education is important for understanding and comprehending agronomic practices and extension services.

Moreover, the mean size of maize-farming households was 5.9, which is slightly higher than the national average of household size of 4.7, as indicated in the 2012 Tanzania Population and Housing Census. The descriptive summary shows that the lowest household size is one member, and the largest household size is 35 members. The households with a large number of household members are found in Kigoma, Mwanza and Shinyanga. This is associated with high fertility and the fact that polygamous families are common in these regions.

Table 1 further indicates that a large number of maize plots (41.5%) are located only a short distance from the market, followed by plots (30%) that are located at a moderate distance, while 28.4% of maize plots are located a long distance from the market (reference category).

The average household farm size during the three years of the panel survey (2008/2009, 2010/2011 and 2012/2013) was 7.5, which is higher compared to the national average, viz. 5.2 acres per household. This difference is attributed to the sample used by the current paper, which focused mainly on households growing maize, which is a dominant crop in the country in terms of land occupied by the crop and consumption, while the national average farm size includes all households and crops. The descriptive summary shows that only 49.2% of the agricultural households had access to information technology in terms of owning a telephone (mobile or landline) and/or a television and/or a radio. Thus, in the panel surveys of 2008/2009, 2010/2011 and 2012/2013, 50.8% of households did not have access to information technology. This is not astonishing, since there is not a great deal of advancement of information technology in rural areas, inasmuch that rural households are unable to have access to ICT devices due to their low purchasing power and inadequate ICT knowledge. In addition, this result agrees with Leyaro and Morrissey (2013), who found that more than 50% of smallholder farmers have no access to information technology.

About 2% of the farming households in the sample had access to agricultural inputs on credit during the three years of the panel surveys of 2008/2009, 2010/2011 and 2012/2013. The result supports the findings of previous studies, such as that of Kibet (2016), who found that smallholder farmers involved in maize growing have lower access (4%) to agricultural inputs on credit in Tanzania compared to smallholder farmers engaging in other cash crops, such as tobacco, coffee and cashew nuts. Most of the agricultural households were not able to access agricultural inputs on credit, since there is a bureaucracy in agricultural schemes that needs many requirements to be fulfilled for smallholder farmers to gain access to agricultural inputs on credit (National Bureau of Statistics [NBS] 2017). Thus, this implies that there is a need for facilitating the smallholder farmers to access agricultural inputs on credit in order to improve their crop production and productivity.

3.2 Adoption rates of improved agricultural technologies in the years of the panel survey

3.2.1 Adoption and non-adoption rates of improved agricultural technologies by the age of the head of household

In this paper, the household head is categorised as a continuous variable in models of agricultural technology adoption. Thus, four groups were created to assess the critical relationship between the adoption of improved agricultural technologies and the ages of the household heads. Table 2 indicates that there is a high frequency of adopters of the package of technologies (159), inorganic fertilisers (293) and improved maize seeds (213) in households with a head in the age group 25 to 54 years. On the other hand, household heads from the age group of younger than 25 years have a

low number of adopters of the package of technologies (1), inorganic fertilisers (3) and improved maize seeds (3).

Table 2: Adoption rates of improved agricultural technologies by age of household head

Age of household head	Package of technologies		Inorganic fertilisers		Improved maize seed	
	No. of adopters	Adoption rate (%)	No. of adopters	Adoption rate (%)	No. of adopters	Adoption rate (%)
< 25	1	5.26%	3	15.79%	3	15.79%
25-54	159	16.34%	293	30.11%	213	21.89%
55-64	72	27.27%	73	27.65%	59	22.35%
≥ 65	45	15.25%	70	23.73%	53	17.97%
Total	277	17.86%	439	28.30%	328	21.15%

Source: Authors' computation from the panel surveyed years (TZNPS dataset)

The highest level of adoption of the package of technologies was 27.27% in the age group 55 to 64 years, while the lowest level of adoption was 5.26% in the age group < 25 years. The findings furthermore indicate that the highest adoption rate for inorganic fertilisers was 30.11% in the age group 25 to 54 years, and the lowest adoption rate was 15.79% in the age group < 25 years. Concerning the aspect of improved maize seeds, the highest adoption rate was 22.35% in the age group 55 to 64 years, and the lowest adoption rate was 15.79% in the age group < 25 years.

These results show that the rate of adoption of improved agricultural technologies is higher among household heads in their early and late middle age, compared to household heads from younger and older groups. The possible reason for these results could be that most of the household heads from the middle-aged group might be pursuing the objective of resource maximisation, and thus might have accumulated enough capital to promote the adoption of improved agricultural technologies, in contrast to the household heads from the younger group, while farmers in the old-age group are risk averse to investing in new technologies. However, the household heads could have other reasons apart from the maximisation of resources. These findings agree with several other studies, such as those by Ntshangase *et al.* (2018) and Donkoh *et al.* (2019). In respect to decisions on the non-adoption of improved agricultural technologies, the results indicate that most of the household heads are from the younger group and from the early middle-aged group, compared to the older and late middle-aged group. The major reason might be that the members in the younger group have no farming experience, or that they have not accumulated enough capital to purchase the improved agricultural technologies, unlike the older and late middle-aged group.

3.2.2 Adoption and non-adoption rates of improved agricultural technologies by the education level of the head of household

The level of education of heads of household was categorised into four categories, namely non-formal level of education, primary level of education, secondary level of education and tertiary level of education. The largest number of heads of household had a primary education level, followed by household heads with non-formal education. However, fewer household heads had a secondary and tertiary level of education (Table 3).

The highest adoption rate of the package of technologies and improved maize seeds was 42.86%, which was observed among the household heads with a tertiary level of education. While the highest level of adoption of inorganic fertilisers was 60.00%, which was observed among the household heads with a secondary level of education, the lowest level of all improved agricultural technologies, viz. improved maize seeds (14.53%), inorganic fertilisers (16.52%) and the package of technologies (13.11%), was observed in the households having no formal education.

Table 3: Adoption rates of improved agricultural technologies by education level of household head

Education level	Package of technologies		Inorganic fertilisers		Improved maize seeds	
	No. of adopters	Adoption rate (%)	No. of adopters	Adoption rate (%)	No. of adopters	Adoption rate (%)
Non-formal	46	13.11%	58	16.52%	51	14.53%
Primary	206	18.26%	340	30.14%	252	22.34%
Secondary	22	33.85%	39	60%	22	33.85%
Tertiary	3	42.86%	2	28.57%	3	42.86%
Total	227	17.86%	439	28.30%	328	21.15%

Source: Authors' computation from the National Panel Survey data

The dissimilarities between the adoption rates of agricultural technologies by household heads and their education levels could be attributed to the fact that the level of education influences a farmer's ability to adopt more improved agricultural technologies. Several studies (Chirwa 2005; Akudugu *et al.* 2012) have found that education has a positive relationship with the adoption of improved technologies.

3.2.3 Adoption and non-adoption rates of improved agricultural technologies by household size

For this paper, an assessment was conducted of how the adoption of agricultural technologies varies across the size of households. The household size was categorised depending on the number of members within a particular household. Four categories were generated – one to four members, five to eight members, nine to 12 members and more than 12 in a particular household (Table 4).

Table 4: Adoption rates of improved agricultural technologies by household size

Household size	Package of technologies		Inorganic fertilisers		Improved maize seeds	
	No. of adopters	Adoption rate (%)	No. of adopters	Adoption rate (%)	No. of adopters	Adoption rate (%)
1 to 4	107	16.59%	171	26.51%	117	18.14%
5 to 8	141	18.15%	241	31.02%	171	22.01%
9 to 12	27	23.68%	25	21.93%	34	29.82%
≥ 13	2	13.33%	2	13.33%	6	40%
Total	277	17.86%	439	28.30%	328	21.15%

Source: Authors' computation from the National Panel Survey data

The highest rate of adoption of the package of technologies was 23.68%, which was found among the households with nine to 12 members, followed by the adoption of improved maize seeds, at an adoption rate of 40.00% by households with 13 members and more. With regard to the adoption of inorganic fertiliser, the highest adoption rate was 31.02% by the group of households containing five to eight members. The lowest adoption rate of the package of technologies and inorganic fertilisers was at 13.33%; both were found in the groups of households with 13 and more members. The lowest adoption of improved maize seeds was 18.14%, found in the group of household with one to four members. This implies that the highest adoption rates of agricultural technologies were found in households with five to eight and up to 13 members, as these particular households have a larger labour force that can participate in cultivation/extensive farming, thus no longer being involved in intensive farming. However, the lowest adoption rates of the package of technologies and inorganic fertilisers were found in households with 13 and more members. This might be due to the fact that a large number of the households' members were inactive in farming activities because they were dependents (sick people, elders and children). The findings agree with Adeoti (2009) and Akudugu *et al.* (2012), who found that the rates of the adoption of agricultural technologies are higher when particular households have a large labour force, unlike households with more dependants, i.e. a lower number of members active as labour in farming activities. The reason

behind this is that, when there are large number of members of an active and productive labour force, the output increases, which uplifts the farm income profit, which can be used to purchase agricultural technologies. Thus, this fundamental factor has a multiplier effect (Donkoh 2019).

3.2.4 Rates of adoption and non-adoption of improved agricultural technologies by gender of household head

The findings indicate that male-headed households had a higher rate of adoption of agricultural technologies, viz. inorganic fertilisers (29.39%), improved maize seeds (22.39%) and the package of technologies (18.84%) compared to female-headed households (Table 5). This is because, in developing countries such as Tanzania, males are endowed with more resources and are exposed to new or improved technologies more so than females (Pender & Gebremedhi 2007; Hepelwa 2013; Palacios-López & López 2014). The findings are consistent with those of Akudugu *et al.* (2012), Manda *et al.* (2015), Thapa (2016) and Shikuku *et al.* (2017), who find that female-headed households are less likely to adopt most of the improved or sustainable agricultural technology packages because of an income that is too low to purchase or acquire the technologies compared with male-headed households.

Table 5: Adoption rates of improved agricultural technologies by gender of household head

Sex of household head	Package of technologies		Inorganic fertilisers		Improved maize seeds	
	No. of adopters	Adoption rate (%)	No. of adopters	Adoption rate (%)	No. of adopters	Adoption rate (%)
Male	218	18.84%	340	29.39%	259	22.39%
Female	59	14.97%	99	25.13%	69	17.51%
Total	227	17.86%	439	28.30%	328	21.15%

Source: Authors' computation from the National Panel Survey data

3.2.5 Adoption and non-adoption rates of improved agricultural technologies in the panel-surveyed years

In this paper, adopters are categorised as household heads that used improved agricultural technologies, i.e. inorganic fertiliser, improved maize seeds or the package of technologies, while non-adopters are categorised as household heads that did not use any improved agricultural technologies during the three years of Agriculture National Panel Surveys (2008/2009, 2010/2011 and 2012/ 2013). There is literature that shows that, once farmers adopt improved agricultural technologies, their output increases, thus there is a positive relationship between improved agricultural technologies and farm output (Suri 2011; Aurangozeb 2019).

The findings show that the highest rates of adoption of agricultural technologies, viz. inorganic fertilisers (29.98%), improved maize seeds (33.85%) and the package of technologies (18.96%), occurred during the 2012/2013 agricultural season (Table 6). The reason for this is that the government had launched a project, the National Agriculture Input Voucher Scheme (NAIVS), in 2009. The main objective of this project was to give farmers a 50% subsidy, particularly for improved maize seeds and inorganic fertiliser. Thus, the rate of adoption of agricultural technologies increased yearly after the NAIVS project was established (URT 2015).

Table 6: Adoption rates of improved agricultural technologies in the panel survey years

Year	Package of technologies		Inorganic fertilisers		Improved maize seeds	
	No. of adopters	Adoption rate (%)	No. of adopters	Adoption rate (%)	No. of adopters	Adoption rate (%)
2008/2009	90	17.41%	137	26.50%	84	16.25%
2010/2011	89	17.21%	147	28.43%	69	13.35%
2012/2013	98	18.96%	155	29.98%	175	33.85%
Total	277	17.86%	439	28.30%	328	21.15%

Source: Authors' computation from the National Panel Survey data

3.3 Probit regression results

The findings of the probit regression models are presented in Table 7, which shows that the Chi-square probability ($\text{Prob} > \chi^2$) is 0.0000 for all models, indicating that the model fit is good.

Table 7 shows the direction of the relationship between the dependent and the explanatory variables. In addition, in order to determine the relative effectiveness of a unit change in the value of an explanatory variable on the probability of adoption, the marginal effects after the probit regression method are computed. These findings are presented in Table 8.

Table 7: Probit regression results for the adoption of agricultural technologies

Variables	Inorganic fertilisers		Improved seeds		Package of technologies	
	Coefficient	Robust std err.	Coefficient	Robust std err.	Coefficient	Robust std err.
HH Age	0.004*	0.003	0.001	0.003	0.006***	0.003
HH Sex	0.012	0.1	0.062	0.105	0.063	0.105
HH Size	0.037***	0.013	0.004	0.012	0.039***	0.012
Farm Size	-0.006*	0.005	0.001	0.005	-0.009**	0.006
Acc Crdt	0.496***	0.283	0.254	0.249	0.225	0.244
Acc Extn	0.544***	0.113	0.205*	0.116	0.327***	0.113
Acc ICT	0.295***	0.075	0.526***	0.076	0.471***	0.077
HH Educ1	-0.434**	0.09	-0.330*	0.694	-0.129**	0.694
HH Educ2	0.097	0.096	0.181*	0.689	0.070*	0.689
HH Educ3	0.763**	0.697	0.707*	0.706	0.166	0.709
Dist Mark1	0.141*	0.691	0.165**	0.092	0.015**	0.093
Dist Mark2	0.126	0.708	0.228*	0.098	0.191	0.097
cons	-0.005	0.708	-0.183	0.708	-0.775	0.711
Prob > χ^2	0.000		0.000		0.000	
Pseudo r-squared	0.085		0.053		0.053	
Log pseudo-likelihood	-795.19428		-767.282		-745.0912	

Source: Authors' own computation from national panel survey data

Notes: * Statistically significant at the 10% level; ** statistically significant at the 5% level; *** statistically significant at the 1% level

Table 8 shows that the probit models for inorganic fertilisers, improved seeds and the package of technologies are specified correctly, at 73%, 65% and 82% respectively since, for the model to be specified correctly, these figures have to be above 50% (Wooldridge 2019). Based on the findings from both Table 7 and 8, the behaviour of the explanatory variables is discussed next.

As hypothesised, the non-formal education level of household head (*HH_Educ1*) is negatively related to the adoption of improved maize seed technology, inorganic fertiliser technology and the package of technologies. Non-formal education level is statistically and negatively significant at the 1% level for inorganic fertiliser and the package of technologies. However, it is statistically and negatively significant at the 5% level for improved seeds. Hence, this shows that the household

heads with non-formal education level their probability to adopt inorganic fertilisers, improved seeds and the package of technologies decreases by 0.1, 0.3, and 0.03 units respectively.

Table 8: The marginal effects after probit regression

Variables	Inorganic fertilisers		Improved seeds		Package of technologies	
	Marginal effect	Std. err	Marginal effect	Std. err	Marginal effect	Std. err
HH Age	0.001155	0.00079	0.0003865	0.0008	0.0017577	0.0007
HH Sex*	0.003811	0.03057	0.0176829	0.0297	0.0172418	0.0287
HH Size	0.0113712	0.00387	0.0011487	0.0035	0.0105455	0.0033
Farm Size	-0.0018881	0.0016	0.0003971	0.0015	-0.002394	0.0017
Acc Crdt*	0.5455606	0.08648	0.0789277	0.0839	0.067117	0.0788
Acc Extn*	0.187995	0.04258	0.0620127	0.0372	0.0992167	0.0374
Acc ICT*	0.0898168	0.02288	0.1492095	0.0213	0.1290268	0.0208
HH Educn1*	-0.1196235	0.17152	-0.2643824	0.0902	-0.0342038	0.1778
HH Educn2*	0.0291147	0.20329	0.3910489	0.2413	0.0187529	0.183
HH Educn3*	0.2774216	0.27971	0.1462697	0.0956	0.0482619	0.2189
Dist Markt1*	0.043247	0.02775	0.0472781	0.0267	0.0041386	0.0254
Dist Markt2*	0.0392614	0.03026	0.0671094	0.0296	0.0540546	0.0282
% specified correctly	0.73		0.65		0.82	

Source: Authors' own computation from TZNPS dataset

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

Primary education level (*HH_Educ2*) is positively related to the adoption of improved seeds and the package of technologies. Primary education level is also positively and statistically significant at the 5% level for improved seeds and the package of technologies. This shows that the probability that household heads with a primary education adopt improved seeds and the package of technologies increases by 0.3 and 0.01 units respectively. In addition, secondary education level (*HH_Educ3*) is positively related to the adoption of inorganic fertilisers and improved seeds. Secondary education level is statistically and positively significant at the 1% and 5% levels for inorganic fertilisers and improved seeds respectively. This implies that the probability that household heads with a secondary education will adopt inorganic fertilisers and improved seeds increases by 0.3 and 0.1 units respectively. Hence, this shows that, as the household head's education level increases, the propensity to adopt agricultural technologies increases compared to non-educated households, if such agricultural technology is more profitable for the farmers. Furthermore, this result agrees with many other studies (Alene *et al.* 2000; Adeoti 2009; Lesseri 2015; Thapa 2016), which have found that the level of a farmer's education influences his or her capacity to adopt agricultural technologies and understand new agricultural practices. These studies conclude that farmers with a low level of education have a low probability to adopt new agricultural technologies, unlike farmers with a higher level of education, who have a high probability of adopting agricultural technologies.

The household size (*HH_Size*) is positively related to the adoption of inorganic fertilisers and the package of technologies. The household size is statistically significant at the 1% level for both inorganic fertilisers and the package of technologies. This shows that, when the household size increases, the propensity to adopt inorganic fertilisers and the package of technologies increases by 0.01 units. This finding is supported by Akudugu *et al.* (2012), and the probable reason for this result is that households containing a large number of members find it easier for them to participate in the adoption of agricultural technology by having many active members engaged in agricultural activities. However, the current findings are contradicted by Rutaiwa (2017), who found that household size is negatively related to the adoption of improved seeds. The probable reason for her result is that households containing a large number of members find it easier for them to participate in extensive/cultivation farming, since members of the household provide enough labour for

clearing and tilling virgin lands, compared to households that have a smaller number of members who may prefer intensive farming.

The accessibility of agricultural inputs on credit to households (**Acc_Crdt**) is statistically significant and positively related to inorganic fertilisers, as was hypothesised. However, it is statistically insignificant in relation to improved maize seeds and the package of technologies. The estimated coefficient for inorganic fertiliser is statistically significant at the 1% level. Thus, households with agricultural inputs on credit, such as ox ploughs and tractors, have a higher probability to adopt inorganic fertiliser – by 0.5 units – compared to households with no access to borrowing agricultural inputs. This finding agrees with Simtowe and Zeller (2006), who found that there is a high probability of farmers adopting the new agricultural technology if they have access to agricultural inputs on credit, unlike other farmers who have no means of access to agricultural inputs on credit.

As hypothesised, access to extension services (**Acc_Extn**) has positive effects on the adoption of inorganic fertilisers, improved maize seeds and the package of technologies. The estimated coefficient for (**Acc_Extn**) is statistically significant at the 1% level for inorganic fertilisers and the package of technologies, and it is statistically significant at the 5% level for improved seeds. This shows that households that get a chance to receive crop extension advice from government agricultural officers have a higher probability to adopt inorganic fertilisers, improved maize seeds and the package of technologies, by 0.2, 0.06 and 0.1 units respectively, compared to households that have no such chance. The extension officers play a major role in reducing the problem of information asymmetry concerning the benefits of adopting agricultural technologies. This finding is supported by Thapa (2016) and Selejio *et al.* (2018), who show that farmers who obtain agricultural advice from government, cooperatives, NGOs or any other sources have a high likelihood of using advanced agricultural technologies compared to farmers with no access of extension services.

As expected, access to ICT devices such as mobile phones, radio or TV (**Acc_ICT**) has a positive and significant effect in relation to all agricultural technologies. The estimated coefficients for inorganic fertilisers, improved seeds and the package of technologies are statistically significant at the 1% level. This means that the household heads with access to ICT devices have a higher probability of adopting inorganic fertilisers, improved seeds and the package of technologies, by 0.09, 0.15 and 0.13 units respectively, compared with the household heads who do not have access to ICT devices. These findings were anticipated, since 68% of the households adopted improved maize seeds and 58% of the households adopted inorganic fertilisers. Therefore, the results suggest that access to ICT devices increases the likelihood of accessing information on improved agricultural technologies. For example, there are several programmes on television that focus on *Kilimo Kwanza* (Agriculture First) and the Participatory Agricultural Development and Empowerment Project (PADEP). Thus, household heads with access to information are much more likely to be influenced to adopt agricultural technologies. In addition, information on the varieties of seeds and fertilisers are usually broadcast on radio, especially during the planting season, and the content of these radio programmes includes information on usage, price, quality and accessibility. This view is strongly supported by Mottaleb *et al.* (2018), who found that farmers who are more well informed concerning their agricultural activities have better access to chances to adopt agricultural technologies than farmers who are relatively less informed.

Farm size (**Farm_Size**) used by the household during the three agricultural years of the panel surveys was found to negatively influence the adoption of inorganic fertilisers and the package of technologies. The estimated coefficient of (**Farm_Size**) is statistically significant at the 5% level with inorganic fertilisers, and 0.1% with the package of technologies. According to these findings, the reason for farm size having a negative association with the adoption of agricultural technologies

is that, when a household head owns a larger farm, it becomes more expensive to purchase agricultural technologies for the whole farm. Thus, this shows that when the household head owns a larger farm the propensity to adopt inorganic fertilisers and the package of technologies decreases by 0.001 and 0.002 units respectively. These findings agree with those of Mottaleb and Mohanty (2015), who found that there is a negative association between farm size and the adoption of inorganic fertilisers. Moreover, there is a great debate among researchers on whether farm size influences the adoption of agricultural technologies or not. Thus, this is a mixed debate; many studies find no consistent patterns of farm size acting as a major influencer of the adoption of agricultural technology. However, other studies, such as those of Chirwa (2005) and Akudugu *et al.* (2012), found that there is a positive correlation between farm size and agricultural technology adoption. In addition, Dixon *et al.* (2006) and Mottaleb (2018) point out that soil quality plays a bigger role than farm size in determining the adoption of agricultural technology, since the probability of adoption is more likely to occur in farmlands with fertile soil, unlike farmlands with unfertile soil.

As hypothesised, the correlation between short (**Dist_Mark1**) and moderate (**Dist_Mark2**) distance from the cultivated maize plot to the market and the adoption of advanced agricultural technologies is positive. A short distance (**Dist_Mark1**) from the cultivated maize plot to the market is positively and statistically significantly associated with the adoption of inorganic fertilisers, at the 5% level and 1% level for both improved seeds and the package of technologies, while a moderate distance (**Dist_Mark2**) from the cultivated maize plot to the market is also positively associated with the adoption of improved maize seeds, and statistically significant at the 5% level. The findings show that households located at a short distance (**Dist_Mark1**) to the market from the cultivated maize plot have a higher probability of adopting inorganic fertilisers, improved seeds and the package of technologies, by 0.043, 0.047 and 0.004 units respectively. Also, households located at a moderate distance (**Dist_Mark2**) to the market from the cultivated maize plot have a higher probability of adopting improved maize seeds, by 0.067 units. The findings agree with Shikuku (2019), who found that farmers who are located at shorter and moderate distances to the market from the cultivated plot have a higher probability of adopting advanced agricultural technologies, since they are exposed to the market and incur low transportation costs, unlike farmers who have to travel far from the cultivated plot to the market.

The age of the head of household (**HH_Age**) is positively associated with the adoption of inorganic fertilisers and the package of technologies, as anticipated. The household head's age is statistically significant in relation to the adoption of inorganic fertilisers, at the 5% level, and at the 1% level to the package of technologies. The positive association agrees with the findings of other analyses, such as those by Adeoti (2009), Lopes (2010) and Shikuku (2019). This indicates that the households headed by older people have a higher probability of adopting the package of agricultural technologies compared to households with younger heads. A increase of a year in the age of the household head increases the likelihood of adopting inorganic fertilisers and the package of agricultural technologies by 0.001 and 0.002 units respectively. The notion behind the findings might be that the households with older heads have more farming experience and have accumulated sufficient capital to enable the adoption of the package of agricultural technologies compared to younger headed households.

This situation reveals that, as the number of adopters decreases from technology to technology, the number of significant variables decreases as well. Thus, the smallness of the number of households that adopt a particular technology within the sample is the likely reason for the non-statistical significance of some variables in the improved maize seeds, inorganic fertiliser and package models.

We have thus observed that, in the model for the adoption of inorganic fertiliser technology, the significant variables are age of the household head (**HH_Age**), household size (**HH_Size**), size of the farm (**Farm_Size**), access to agricultural inputs on credit (**Acc_Crdt**), accessibility of government extension services (**Acc_Extn**), access to ICT devices such as mobile phones, radio or TV (**Acc_ICT**), non-formal education level of household head (**HH_Educ1**), secondary education level of household head (**HH_Educ3**), and short distance from the cultivated maize plot to the market (**Dist_Mark1**).

In the model for the adoption of improved maize, the significant variables are accessibility of ICT devices such as mobile phones, radio or TVs (**Acc_ICT**), accessibility of government extension services (**Acc_Extn**), non-formal education level of household head (**HH_Educ1**), primary education level of household head (**HH_Educ2**), secondary education level of household head (**HH_Educ3**), short distance from the cultivated maize plot to the market (**Dist_Mark1**), and moderate distance from the cultivated maize plot to the market (**Dist_Mark2**).

In the last model, the significant variables influencing the adoption of package of technologies are farm size (**Farm_Size**), age of the household head (**HH_Age**), short distance from the cultivated maize plot to the market (**Dist_Mark1**), non-formal education level of the household head (**HH_Educ1**), primary education level of the household head (**HH_Educ2**), access to ICT devices such as mobile phones, radio or TV (**Acc_ICT**), accessibility of government extension services (**Acc_Extn**) and household size (**HH_Size**).

Therefore, the primary determinants of the adoption of the two technologies, viz. inorganic fertilisers and improved seeds, are accessibility of ICT devices such as mobile phones, radio or TV (**Acc_ICT**), access to government extension services (**Acc_Extn**), short distance from the cultivated maize plot to the market (**Dist_Mark1**), and the level of education of the household head, specifically level of non-formal education (**HH_Educ1**) and secondary education (**HH_Educ3**).

4. Policy implications

The paper has used rich panel data and a rigorous econometric analysis to investigate the possible determinants of the adoption of inorganic fertilisers, improved maize seeds and the package of technologies among smallholder maize farmers in Tanzania. The findings of this paper provide useful information in order to suggest important policies to agricultural stakeholders, especially in the maize sector in Tanzania and other comparable developing countries. The key findings from modelling the adoption of improved agricultural technologies are: accessibility of extension services, ICT services, agricultural inputs on credit, and education level. The results of this paper, which used panel data, do not differ with the results of previous studies that analysed cross-sectional data, and thus they are conclusive. The findings indicate that the first possible policy direction that could influence farmers to adopt improved agricultural technologies would be to promote extension services through field-based training and extension seminars. The second policy direction could be to empower small-scale farmers to have easy access to agricultural inputs on credit, which could solve the liquidity constraint on purchasing these inputs. The third policy option is improving the agricultural education curriculum by including key topics that deal with concepts of good agricultural practices, such as the adoption of improved agricultural technologies. Furthermore, the adoption of these improved agricultural technologies could increase agricultural productivity and assist the government to reach its goal to end hunger and malnutrition by 2030. This therefore could be attained when there is public-private partnership among all agricultural stakeholders.

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