Influence of Farmer's Exposure to Development Actors on Intensity of Agricultural Technologies Use in Areas with Commercial Farms

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Abstract

The paper analysed the effect of farmer's exposure on different channels in particular establishment of foreign agricultural investments (FAI) farms that are seen as influential in promoting agricultural technology use among neighbouring farmers. Based on proportionate random sampling strategy in areas with both foreign and domestic commercial farms, the effects of farmer characteristics and different exposure channels for promoting and learning agricultural technologies were fitted and estimated in the general Poisson model. Results show that farmer's age, mobile phones ownership, household poverty, self learning by doing, learning from neighbours, domestic investors, Non-Governmental Organizations (NGOs), National Agricultural Research and Extension Services (NARES) and farmer's location significantly influence agricultural technologies use among farmers living near commercial farms. But age and household poverty were inverse related to the intensity of farmer's agricultural technology use. It implies that old age and poverty negatively affect use of agricultural technologies while exposure to FAI is not effective channel for farmer to use agriculture technologies in areas with commercial farms. It was concluded that presence of FAI farms without formal and informal interactions with neighboring farmers does not influence the use of agricultural technologies among farmers, therefore a mere presence of FAI farms should be considered as private investment and not necessarily as a means for promoting agricultural technology use to neighboring farmers. A selective strategy should be considered to use FAI farms as means of promoting use of agricultural technologies among neighboring smallholder farmers based on crop similarity, location endowments, socio-economic characteristics of farmers, extension services availability and technologies used by FAI farms.

Keywords: Generalized Poisson, farmers, agricultural technology and commercial farms

Introduction

Historically, promotion of agricultural technologies up take to small-scale farmers in developing countries has been an overarching policy and a regional initiative goal in the agriculture sector (Kinuthia and Mabaya, 2017). The focus is on small-scale farming systems which form the backbone of agricultural production for food and cash crops but half of the small-scale farmers live in rural areas where poverty and malnutrition is stubbornly high. The multidimensional head count poverty in rural Tanzania is 60 higher than most Sub-Sahara African countries while 70% are malnourished due to poor knowledge in food preparation (Alphonse, 2017). Therefore, development actors often consider changes in agricultural technology as one of the effective strategy for stimulating productivity gains, spurring commercialization and reducing income and health poverty. In Tanzania and in other developing countries, the agriculture sector is a main source of growth to the economy as it contributes 29.1% to the Gross Domestic Product (GDP), 30% of export earnings and 70% of the rural population derive a livelihood from crop or livestock production (URT, 2017a).

The government of Tanzania collaborates with different development actors in the agriculture sector to improve the use of agriculture technologies. Policies and programs at the national and regional levels emphasized on small-holder farmers among others, purposively to enhance agricultural technology up-take. At the regional level governments had agreed to set 10% of national budget for the agriculture sector (Fontan Sers and Mughal, 2019). The government of Tanzania through the Agricultural Sector Development Program phase I and II has implemented a number of initiatives such National Agricultural Input Voucher Subsidies (NAIVS), Agricultural Marketing Development Program, bulk fertilizer procurement system, and farmer's extension reforms just to name a few to transform the sector from low input-low yields to high input use and high yields (AGRA, 2019; Ariga and Heffernan, 2012). However, agricultural technology use among small-holder farmers is still low, leading to low productivity and limited rural poverty reduction (URT, 2017b).

In the context of neo-liberalization, the government increasingly works with a private investor and non-governmental organizations (NGOs) as a strategy for stimulating wide spread use of agricultural technologies through training, commercialization, market linkage, and employment on commercial farms (German *et al.,* 2016). The government of Tanzania accord political and technical support to the private commercial farms and non-governmental organizations to take the lead in agriculture sector transformation. Establishment of Southern Agricultural Growth Corridor of Tanzania authority after World Economic Forum in 2008 and reforms in Tanzania Investment Center is among the measures in recent years that attest government efforts in support and facilitate private commercial farms (Brüntrup *et al.,* 2016; Cooksey, 2013).

Jayne *et al.,* (2019) reported a rise in the medium to large-scale commercial farms in Tanzania due to strengthening land tenure and rental markets. Government expect rise in investments from the private commercial farm both local and foreign investors leading into wide-spread use of agricultural technology among smallholders. Since, the government accorded policy incentives will lead to increased up-take of agricultural technologies through spillover and employment effects (URT, 1997, 2017a). Furthermore, SACGOT initiative emphasizes engagement of small-holder farmers through different models such as contract farming models, nucleus model, hub and spoke, market linkages and extension services as pathways in which smallholders can learn and use agricultural technologies (Brüntrup *et al.,* 2016). The government also coordinates activities of NGOs and farmer's cooperatives in the agriculture sector to promote modern farming practices. This also includes some NGOs to mention a few such as One Acre Fund in Iringa, Kilimo Endelevu-Sustainable agriculture Organization in Karatu that collaborating with local and foreign investors within a given arrangements for marketing or training activities. In Njombe, Out-growers Services Company Limited (NOSC) link smallholder tea farmers to markets and provide training. Despite multi-strategies and multiple actors' involvement, the use of agricultural technologies among small-holder farmers is still low even in areas with concentrations of commercial farming activities.

Agricultural technology adoption studies point features that impede or facilitate use of agricultural technologies by farmers (Asfaw, *et al.,* 2012; Feyisa, 2020; Mwangi and Kariuki, 2015). While there is no specific grouping of factors due to the study design and nature of technology under investigation, Mwangi and Kariuki (2015) categorized them into technological factors, economic factors, institutional factors, and household specific factors. In the discourse of Foreign land-based Agricultural Investments (FAI), the influence of commercial farms effects on agricultural technology uptake to small-holder farmer attention has been only on the impact of foreign owned farms but silent on other actors (Ali, *et al.,* 2019; Deininger and Xia 2016). Deininger *et al.,* (2015) focused on specific agricultural technologies and Ali *et al.,* (2019) on typical foreign owned commercial farms.

Existing studies analyzed specific channels such as Baumüller (2012) focused on the mobile phone ownership and Foster and Rosenzweig (1995) on the self-learning by doing and from others while Deininger and Xia (2016) detected spillovers of certain types of agricultural technologies by varying distances to FAI. This study contributes into the existing debate focusing on the presence of multiple actors in areas with commercial farms both foreign and local investors, NGOs and the National Agricultural extension system (NARES) in facilitating the agricultural technology up-take to neighboring small-holder farmers. The focus is not on specific agricultural technology but on different combinations of farming practices and technologies which together are measured as intensity of agricultural technology used. The analysis was broadened to include various aspects of possible learning such as if a farmer had contact with neighbors, relatives, and local or foreign investor to discuss or ask about any improved practices or technologies because Bandiera and Rasul (2006) found such informal contact or exchange of information they contribute to the use of agricultural technologies. This differs from previous studies which focused only on demonstration farms or farmer field day or formal training. It also includes self-learning by doing, which, according to Foster and Rosenzweig (1995) facilitates agricultural productivity.

Theoretical framework

According to Rajni (2009) agricultural technologies is an envelope of different techniques and practices that directly affect crop and animal productivity. In this study agricultural technology encompasses various types of agricultural technology innovations from seeds and their varieties, soil improvement and preparation before planting, use of fertilizers, pesticides, herbicides, and production within specific standards, animal husbandry and other best agronomic practices.

The presence of development actors such as foreign and domestic investors undertaking commercial farms activities, NGOs working in agriculture, local agricultural traders and national research and extension staff may positively influence neighboring farmers to use different types of farm practices and other technologies through spillover or employment or demonstrations or contract farming, as well as positive externalities (Deininger and Xia, 2016). The extent to which farmers use agricultural technologies depends on actors and channels that influence farmer's uptake and can happen through training, employment, informal discussions, production agreement or contract. Farmers take one or several agricultural technologies regarding to household poverty, age, their needs and compatibility of technologies to their environment and location. Farmers can learn by doing or others including NGOs or donor project agricultural activities in the area, government extension staff, and having social contact with local or foreign investors in the area (Bandiera and Rasul, 2006; Foster and Rosenzweig 1995). Baumüller (2012) showed ownership of mobile phone among poor farmers facilitate agricultural technology use. Agricultural technology use was measured as a count variable. Farmers were asked if during the last five years they used agronomic practices and techniques for soil improvement and preparation of the soil before planting, use of either new seeds, or a new variety of seeds, tractor, or ex-plough. Also, the use of fertilizers, herbicides, and insecticides was also asked and categorical variables were used to capture farmer's responses.

Methodology

Study areas

The study was conducted in Karatu, Iringa and Njombe districts (Fig. 1). The districts are located in mid to a high altitude and flat plains that are broken up by hills and valleys ranging from 1,000 to 2,400 metres above sea level (asl). The districts have a history of FAI farms during pre and post independence years. FAI farms produce same crops and livestock products similar to locals with the exception of coffee in Karatu. Main crops and products produced in the research locations are maize, beans, day-old-chicks, Irish potato seedlings, maize seeds, vegetables, pigeon pea, processed feeds, and feeder crops with exception of tea, Irish potato seedlings and Irish potato which are widely produced in Iringa and Njombe. FAI farms were fenced (some electric fence other with trees) with security guards and equipped with equipment such as tractors, trailers, knap sprayers, and tractor mounted boom sprayers. Fence and security guards restricted neighboring farmers to enter farm area or visit the farm without permission. Interaction with FAI farms was restricted while interactions with neighbors, NGOs staff, and national investors were not restricted with fence or security guards. Some farms were installed with drip and pivotal irrigation systems. Those few producing barley and wheat in Karatu had combined harvesters. Some of the coffee estate experimented with production of avocado and grapes which are new crops in the area. But avocado is emerging crop that is widely produced in Iringa and Njombe districts. Other farms in Njombe, Iringa and Karatu kept diary cattle's for producing milk, cheese and yoghurt. In one of the coffee estate in Karatu, they organized training to staff for the diary farm enterprise to produce cheese and yogurt. It is common to find tourist coffee lodges on the farms because of tourism activities in Karatu who increase demand for milk while in Njombe and Iringa ASAS limited provides a market for fresh milk to small-scale farmers with dairy cattle.

Fertile land is scarce in Karatu compared to Iringa and Njombe districts. In Karatu fertile land is scarce especially near coffee estates in high altitude. In 2002 Karatu district authority redistributed land from those who owned large uncultivated pieces of land to landless households a minimum of 2 acres for house plot and farming/livestock activities. With the exception of Njombe, bulls are used as draft animal to plough land, providing critical agricultural labor in low land areas where medium to large local investors commercially produce maize, sunflower, pigeon peas and chick peas. Goat, sheep, pigs and chicken are also kept and sold or eaten especially during festivals. There is presence of NGOs activities in Karatu, Iringa and Njombe such as Kilimo Endelevu – Sustainable Agriculture and Selian Agricultural Research Institute in Karatu. In Njombe farmer recognized NOSC while in Iringa, interviewed farmer frequently referred One Acre Fund and foreign investors that provide extension services to livestock keepers, farmers through training and farmer field demonstration on various agronomic practices to restore soil health to increase productivity.

Iringa and Njombe are part of SAGCoT which is dedicated to promoting large-scale agricultural investments to drive agrarian transformation from subsistence to commercial farming through contract farming, market linkage and provision of extension services. Some investors within the Ihemi cluster provide agricultural machinery hiring services to medium and large-scale farmers.

Other commercial farms are specialized on dairy cattle's. Some of the large and medium scale commercial farms were installed with silos of varying capacities.

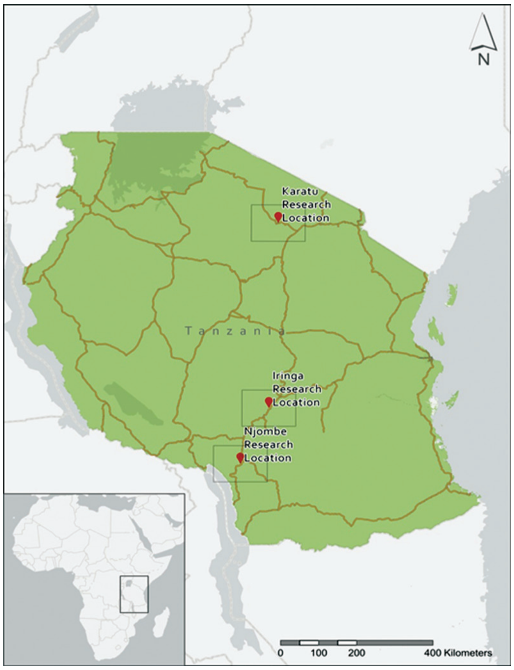

Figure 1: Map Showing Research Locations

Sampling strategy and data collection

Based on Krejcie and Morgan (1970) a predetermined sample size of 400 respondents was aimed to be collected in each research location to have sufficient confidence interval and significance level. First the number of villages in each ward and district was proportionately determined by respective population size. Secondly, sampling frame was obtained by updating Village Population Register to individuals 18 years and above in each selected village within a radius of 50km from point of entry into the research location in each district. Lastly, the number of individuals randomly sampled from each village was determined based on the proportion that the population of the ward constitutes of the total population of the research location. Structured questionnaire was administered to a total sample of 1,203 respondents which constituted 33% of respondents from Karatu district, 34% from Iringa and 33% from Njombe. Sampling and interviews in details are co-authored in Ravnborg *et al.,* (2021).

Table 1: Per cent distribution of farmers by research locations

Research locations	N	%
Karatu	397	33.0
Iringa	405	33.7
Njombe	401	33.3
Total	**1203**	**100**

Data analysis

Descriptive analysis

Characteristics of farmers considered were age, sex, agricultural technologies used and household poverty[1]. Frequencies and percentages were used to describe farmer’s characteristics.

Estimation strategy and analysis

Agricultural technology uptake in this study was captured as a count variable depicting different agricultural technologies used by farmer. Poisson regression is the most basic model opted in such a situation. According to Kumar *et al.,* (2020) the model does not require a strong assumption on aggregating technology counts or the relationship between technologies being investigated. However, the challenge of counting agricultural technologies used among smallholder farmers is heterogeneity as a result there is the possibility of equi-dispersion, over-dispersion or under-dispersion. Therefore the assumption of the equality of the conditional mean and variance within the standard Poisson model do not reflect reality, and the most likely scenario is over-dispersion or excess zeros or under-dispersion. According to Harris *et al.,* (2012); Mahama *et al.,* (2020) measures of the dependent count variable in figure 2 follows a general Poisson distribution.

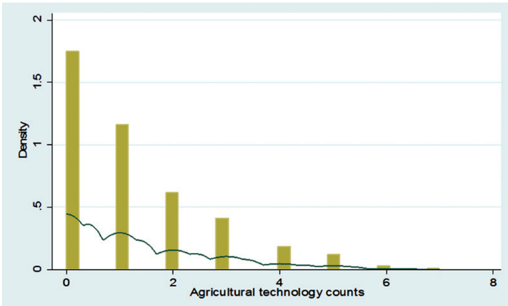

Figure 2: Technology count histogram

Therefore suppose Y_i is count response on agricultural technology uptake by farmer follows a probability mass function (PMF) of Y_i,i=1,2,…,n is specified as

$$f(y_i) = pr(Y_i = y_i) = \left(\frac{\lambda_i}{1+\alpha\lambda_i}\right)^{y_i} \frac{(1+\alpha y_i)^{y^{i-1}}}{y_i^{!}}$$

$$\exp\left[\frac{-\lambda_i(1+\alpha y_i)}{1+\alpha\lambda_i}\right], y_i = 0,1,2,... \qquad (1)$$

The mean and variance of Y_i are mathematically specified as;

$$E(Y_i \mid \chi_i) = \lambda_i, Var(Y_i \mid \chi_i) = \lambda_i(1+\alpha\lambda \qquad (2)$$

When α>0, it is assumed the variance is greater than the mean and in which case, the Generalized Poisson regression model represents count data with over-dispersion. When α<0, the variance is assumed to be less than the mean, it represents a Generalized Poisson regression model with under-dispersion. The dispersion parameter α can be estimated along with the regression parameters in the Generalized Poisson regression model. The maximum likelihood method is used to measure the goodness-of-fit of Generalized Poisson regression. Goodness-of-fit measures the estimates of α and β in the generalized Poisson regression model. Non-parametric tests were used to measure the model’s goodness-of-fit based on the deviance or Pearson test statistic (Harris *et al*., 2012). The test is approximated by the distributional effect of the chi-square when

[1] *Household poverty index was constructed based on local perception of poverty and is explained in detail in Ravnborg et al., (2021)*

μ_i's are large. The command is computationally complex; in this regard, the log-likelihood value is often used. A comparison of Standard Poisson and the Generalized Poisson regression model is often made, and the model with a large log-likelihood value is recommended (Yadav *et al.,* 2021).

The log likelihood (L) for the Generalized Poisson model is specified as:

$$lnL(\beta,\alpha)=\sum_{i=1}^{n}\left[y_i ln\left(\frac{\lambda_i}{1+\alpha\lambda_i}\right)+(y_i-1)ln(1+\alpha y_i)-lny_i^{!}-\frac{\lambda_i(1+\alpha y_i)}{1+\alpha\lambda_i}\right] \quad (3)$$

A test of the hypothesis of adequacy of the General Poisson model over the Standard Poisson model is given by; H_0:α=0 against H_a:a≠0. The test of H_o is an indication of significance of the dispersion parameter. Therefore, when H_o is rejected, the appropriate model to use is the generalized Poisson regression. The test could be conducted by using the asymptotically normal Wald "t" , which is defined as the ratio of the estimate of α to its standard error. Alternatively, the likelihood ratio test statistic could be used for the null hypothesis. This is approximately chi-square distributed and has one degree of freedom when the null hypothesis is true. According to Yadav *et al.,* (2021), one other way of choosing the best count data model based on several likelihood measures is by considering the value of the Akaike Information Criterion (AIC) and Bayesian Schwartz information criteria (BIC). Mathematically the AIC is presented as follows;

AIC=-2 lnL(θ)+2k

Where the L(θ) is defined as the log-likelihood value, and k denotes the number of parameters considered in the model plus the intercept. The smaller the AIC value, the better the model. The BIC is defined as

BIC=-2L+k log(n)

Where, L denotes the log-likelihood, k the number of parameters, including intercept and n the number of rating classes or a number of model observations. The smaller the BIC value the better is the model.

Results and Discussion

Social economic characteristics of farmers

Table 2 presents a summary of socio-economic characteristics of the farmers in vicinity of commercial farms. About 51% of farmers were male and 49% female. Slight differences of the farmer's gender indicate equal representation of the gender. On average age of farmers interviewed was 41 years. The majority (58%) of farmers interviewed were adults aged 36 years and above while youth farmers aged 15 to 35 years were 42%. It shows majority of farmers were within the economically active age to participate in farming activities. Studies show the sex of farmers does not matter, but as long as one has access to household resources and decision, they can decide to take one or several agricultural technologies. Age has been found to positively or negatively influence agricultural technology use. Young farmers are considered both adventures and also with limited resources to try new technologies. Adult farmers are considered experienced, but as one ages older the ability to take a risk on new technologies decreases.

The majority (66%) of farmers had secondary education. Education helps a farmer to absorb, and process different agricultural technology information and increases their ability to practice. It also helps farmers to learn from complex technologies and compromise to suit their needs. It implies most of the interviewed farmers have enough education to learn, absorb and practice agricultural technologies. About 32% of farmers came from the less poor households, 45% from the poor and 23% from the poorest. As the household poverty of farmers increases from less poor to poorest, it decreases the chances for a farmer to use agricultural technology because they have less of everything including land. It implies interviewed farmers are more likely to use agricultural technologies because majority belongs to less poor households. Most farmers (56%) owned radio while few (11%) owned television set. Access to media of communication facilitates the use of agricultural technologies through programs that teach or inspire farmers to modernize crop enterprises (Mwangi and Kariuki, 2015).

Mobile phone ownership in the era of information technology plays a critical role in agricultural technology uptake. About 75% of farmers owned mobile phones for communicating with others and providers of agricultural technologies solutions. Studies e.g.

Table 2: Farmers socio-economic characteristics

Variable	Description	n	Percent
Sex	If a farmer is male = 1	613	51.00
	If a farmer is female = 0	590	49.00
Age categories[1]	15-35 years = 1	502	41.70
	36 years and above = 0	701	58.30
	Average (years)	1203	41 (16)
Secondary education	If any member of a household has secondary education = 1 otherwise = 0	795	66.10
		408	33.90
Household wellbeing	Less poor household	383	31.80
	Poor household	538	44.70
	Poorest household	282	23.40
Own radio	If a farmer own radio = 1, otherwise = 0	678	56.34
		525	43.64
Own TV	If a farmer owns TV = 1, otherwise = 0	130	10.81
		1073	89.19
Own mobile phone	If a farmer owns mobile phone = 1, otherwise = 0	899	74.73
		304	25.27
Self-learning by doing	If a farmer taught him/herself or has been doing it = 1, otherwise = 0	254	21.11
		949	78.89
Neighbors	If a farmer was inspired, exchange ideas with neighbors, relatives or friend = 1 otherwise = 0	488	40.57
		715	59.43
Domestic investor	If farmers exchange ideas or inspired by local investors or traders = 1, otherwise 0	264	21.95
		939	78.05
Foreign investor	If farmers exchange ideas or inspired by foreign investors = 1, otherwise 0	225	18.70
		978	81.30
NGOs working in the area	If a farmer inspired by NGOs staff or trained by NGOs = 1, otherwise 0	59	4.90
		1144	95.10
NARES	If a farmer inspired by government extension staff or research = 1, otherwise 0	92	7.65
		1111	92.35
Worked in commercial farms	If a farmer worked in foreign or domestic owned farm = 1, otherwise 0	363	30.17
		840	69.83
Karatu	If a farmer lives in Karatu = 1, otherwise 0	397	33.00
		806	67.00
Iringa	if a farmer lives in Iringa = 1, otherwise 0	405	33.67
		798	66.33
Njombe	If a farmer lives in Njombe = 1, otherwise 0	401	33.33
		802	66.67

Note: In parentheses is the standard deviation (SD)

[1] *Categories based on Tanzania Bureau of Statistics report on employment and earning survey. Categorization in this report is guided by National Policy on Employment*

Mwangi and Kariuki (2015) have established that mobile phone influences agricultural technology use. Sources of inspiration for agricultural technology use were grouped into self-learning by doing, neighbor or relatives, domestic investors, foreign investors, NGOs, NARES and employment in commercial farms.

Table 3: Intensity of agricultural technologies used by farmers

Technology counts	Frequency	Percent
0	491	40.81
1	326	27.10
2	173	14.38
3	116	9.64
4	52	4.32
5	34	2.83
6	8	0.67
7	3	0.25
Mean	1.22	
Variance	1.99	
Total	**1203**	**100**

It was found 41% of farmers more frequently were inspired by neighbors or relatives; 30% of farmers inspired through employment in commercial farms; 22% of farmers contacted domestic investors and 19% foreign investors; 8% of farmers inspired by NARES and 5% by NGOs working in the area. Armah and Svensson (2010) argued that a word of mouth or person-person communication facilitate use of agricultural technology among farmers. During qualitative interviews farmers in Iringa, Karatu and Njombe reported that fence and security guards in foreign investor's farms prevent frequent informal interactions with foreign investors as opposed to extension staff or domestic investors or NGOs extension staff. Since FAI farms are private investments, they are often secured limiting frequent informal interactions. Furthermore, Bandiera and Rasul (2006); Foster and Rosenzweig (1995) argued that farmers learn more effective to use agricultural technology to sources that they have frequent and informal interactions with. This analysis is carried further in Table 5.

Geographical location of farmers and presence of FAI farms was considered for unobserved location specific effects. Geographical location was included in the model to capture attribution of household technology differences, infrastructures, agriculture production potentials and land resource endowments. The assumption is that in areas where FAI farms produce the same crop with farmers then farmers use of agricultural technologies is positively influenced and vice versa is negative. In Karatu all FAI farms produce coffee and no smallholder farmers in the area produce coffee while in Iringa and Njombe smallholder farmers produce same crops with FAI farms in the respective areas.

Intensity of agricultural technologies used

Table 3 shows the intensity of agricultural technologies uptake by farmers. Overall, it shows technology count had an inverse relation to farmers' use of agricultural technologies. As the number of technology used by farmer's increases, the number of farmers' decreases. It was found the majority of farmers (40%) did not take any agricultural technologies over the last five years. This was followed by 27% who used only one technology, 14% used two technologies, 10% used three technologies, 4% used four technologies, 3% used five technologies, 1% used six technologies and less than one percent used seven technologies. It means few farmers in vicinity of FAI farms use different types of agricultural technologies from farm preparation to planting and majority frequently use low cost agricultural technologies.

Table 4 shows specific agricultural technologies farmer's asked. It was found the majority of farmers, 56% used tractor for ploughing, followed by 32% who used cow dung to improve soil (although it is often confused with increasing productivity), and 30% used ox-plough for ploughing. About 13% used new varieties of seeds and chemical fertilizers, and 12% used new seeds. The rest of the agricultural technologies used were less than 10%, as shown in table 4. Based on frequently used agricultural technologies, farmers use technologies related to soil improvement, ploughing, and seeds, while few farmers use

Table 4: Types of agricultural technologies used by farmers

Agricultural technologies	# of replies	Percent of replies	Percent of Cases
Soil improvement			
• Mulching	46	3.10	6.50
• No till/conservation farming	42	2.90	5.90
• Using green manure crops	25	1.70	3.50
• Avoided burning	63	4.30	8.80
• Using cow dung	227	15.50	31.90
• Live barriers/grass strips	5	0.30	0.70
• Soil barriers	52	3.50	7.30
• Terraces	4	0.30	0.60
• Chemical fertilizers	91	6.20	12.80
Seed			
• New seeds or crops	88	6.00	12.40
• New varieties of seeds or crops	90	6.10	12.60
Farm mechanization			
• Oxen for ploughing	399	27.20	56.00
• Tractor for ploughing	216	14.70	30.30
Soil preparation before planting			
• Used tractor ploughing to prepare the soil	66	4.50	9.30
• No till farming, used herbicides to prepare soil	24	1.60	3.40
• No till farming without the use of herbicides to prepare the soil	29	2.00	4.10
	1467	**100.00**	**206.00**

Note: Multiple response table based on cases

technologies related to soil preparation before planting. It means that farmer frequently use farm preparation agricultural technologies and seeds while very few take care of plant after planting. Employment opportunities from neighboring could explain because Maro, *et al.,* (inpress) found on average farmer work 4 days a week in FAI farms or other investor's farm in the area.

Estimation results of exposure factors influencing intensity of agricultural technologies use in areas with commercial farms

Table 5 indicates the estimation results of exposure factors influencing the intensity of agricultural technology use. Exposure factors were fitted in three models of Poisson and diagnostic tests were performed to determine the appropriate model with consistent results. The estimates from the models are similar with the exception of the age variable under generalized Poisson distribution, which was found significant. The log-likelihood, AIC, and BIC values were used. The log-likelihood values from the Generalized Poisson model were largest compared to values yielded by standard and zero-inflated Poisson models. This indicates General Poisson model results can be used to explain with confidence the exposure factors influencing farmers' intensity of agriculture technologies to use in areas with commercial farms. This is because the test of hypothesis of adequacy of the Generalized Poisson model over the standard Poisson shows that the dispersion factor α is less than zero (-0.068), implying the presence of significant under dispersion of the technology count variable. Therefore the null hypothesis of equi-dispersion is rejected. Furthermore, AIC and BIC showed generalized Poisson model had marginally lower values than other Poisson models tested. This provides a significant justification for the choice of the generalized Poisson model over others.

About 65% of the variables used which is more than half, were statistically significant exposure factors influencing agricultural technology use intensity to farmers in areas with commercial farms. Age, mobile phone ownership, household poverty, sources of inspiration such as own learning by doing, neighbors, domestic investors, NGOs, NARES, and the geographical location of FAI farms were significant factors influencing farmers agricultural technology use. However, it was found that farmer's age and household poverty had an inverse relation to farmer's use of agricultural technologies.

The findings as presented in table 5 indicate that as the farmer's age increases, they are less likely to intensify agricultural technologies use. It shows adult farmers in areas with commercial farms do not intensify agricultural technologies from the wages they receive or by being near to the farm. During qualitative interviews, it was found that youth farmers use wage to purchase agricultural inputs but not adults. However, this finding contradicts Mahama *et al.,* (2020) who found that the desire to purchase agricultural inputs increases as farmers age increases in Ghana. The priori assumption was that age can influence either positive or negative but in this context it was found that age negatively influence use of agricultural technologies as farmer became adult. Mmbando *et al.,* (2021) also found adult in Tanzania from poorest households with meager resources are less likely to invest in new agricultural technologies. Is more likely such farmers do not invest their wage in agricultural technologies but they purchase other household necessities. Furthermore, they are more likely to devote more time in FAI farms employment reducing their labor and more investment in farm technologies.

Household poverty had negative significant influence on intensity of agricultural technologies use. This was anticipated since majority farmers from poorest household have less land and other resources for agricultural production. They are more likely not taking agricultural technologies and frequently seek employment in FAI farms than working on their farms. Own learning by doing was anticipated to have positive influence on intensity of agriculture technology use. It was found own learning has positive statistical significant relation to agricultural technologies use. As farmer increases the ability of own learning by doing, then use of agricultural technologies increases. Learning from neighbor was anticipated to have positive influence on agricultural technology use. It was found that as farmer learns from neighbors it increases uptake of agricultural technologies. Kumar *et al.,* (2020) in Nepal they found adoption of improved practices increased when farmer obtain information from informal sources. Prior sign of exposure to domestic investors influence on agricultural technology use was positive. As expected it was found domestic investors had positive and significant influence on agricultural technology uptake.

NGOs and NARES activities were anticipated to have positive influence on farmer's intensity of agricultural technology use. As expected it was found that NGOs and NARES activities had significant positive influence on farmer's intensity of agricultural technology use. Kumar *et al.,* (2020) they found probability of farmer adoption of improved practice is increased when public and private extension program engage farmers through informal sharing of information's. furthermore Mmbando *et al.,* (2021) found frequent contacts with extension agents increases the intensity of adopting crop specific production technologies. Geographical location of FAI farms and farmers was found to have positive and significant influence on farmer's intensity of agricultural technology use. This was anticipated to have positive in areas where FAI farms produce same crops with farmers and negative if vice versa. It implies there are unobserved location specific effects such as household technology differences, infrastructures, agriculture production potentials

Table 5: Factors influencing intensity of agricultural technologies uptake

Model		Generalized Poisson		Standard Poisson		Zero Inflated Poisson	
Variables		Coefficient	Std Err.	Coefficient	Std Err.	Coefficient	Std Err.
Farmer and household features							
• Sex		(-0.068)	0.05	(-0.052)	0.054	(-0.041)	0.054
• Age categories		(-0.095)*	0.052	(-0.087)	0.057	(-0.092)	0.057
• Secondary education		(-0.035)	0.053	(-0.034)	0.056	(-0.019)	0.057
• Own television		(-0.043)	0.076	(-0.033)	0.081	(-0.049)	0.081
• Own radio		0.059	0.055	0.065	0.059	0.074	0.059
• Own mobile phone		0.202**	0.068	0.189**	0.073	0.192**	0.073
• Household wellbeing		(-0.170) ***	0.04	(-0.176)***		(-0.183)***	0.042
Sources of inspirations							
• Own learning by doing		0.91***	0.051	0.896***	0.055	0.904***	0.055
• Neighbor		1.003***	0.059	1.041***	0.063	1.041***	0.063
• Domestic investors		0.305***	0.062	0.305***	0.067	0.316***	0.068
• Foreign investors		0.002	0.064	0.008	0.069	(-0.009)	0.070
• NGOs working in the area		0.317***	0.084	0.299***	0.091	0.351***	0.092
• NARES		0.56***	0.076	0.57***	0.082	0.562***	0.088
• Commercial farms employment		0.041	0.06	0.04	0.064	0.036	0.064
Location dummies							
• Karatu		0.40***	0.082	0.438**	0.088	0.438	0.088
• Iringa		0.376***	0.072	0.394***	0.078	0.396	0.078
• Njombe		0		0		0	
Constant	(-0.859)***	0.15	(-0.913)***	0.161	(-0.928)***	0.162	
Observations	1203	1203	1203				
Alpha	(-0.068)	0.019	N.A	N.A	N.A	N.A	
LR Chi-square	974.74		1129.56		981.94		
Prob>Chi-square	0.000		0.000		0.000		
Pseudo R^2	0.27		0.3		N.A		
Log likelihood	(-1339.61)		(-1345.17)		(-1342.78)		
Dispersion	(-0.068)		N.A		N.A		
AIC	2715.24		2724.34		2723.57		
BIC	2806.91		2810.92		2820.33		
Vuong test (Pr>z)	N.A		N.A		0.221		
Likelihood-ratio test of delta=0; $chi^2(1)=11.1$ Prob>=$Chi^2=0.0004$				N.A		N.A	

Note:*,**,*** indicate significant at 10%, 5% and 1% levels respectively and land resource endowments (Mmbando *et al.,* 2021). However, it was found positive influence in agricultural technology use in Karatu and Iringa while Njombe was dropped due to multi-collinearity. Furthermore, the positive and significant influence which was found in Karatu suggest cross enterprise agricultural technology learning and uptake since crops produced by FAI farms and smallholder farmers are different. But in Iringa crops produced by farmers were the same produced by investors.

Conclusion

The paper analyzed the influence of farmer's exposure to development actors on intensity of agricultural technologies use in areas with commercial farms. It was concluded that farmer's age, household poverty, mobile phone ownership, sources of inspiration such as learning from neighbors, self learning by doing, presence of domestic investors, NGOs and NARES as well as geographical specific endowments have influence on farmer's intensity of agricultural technology use. This is because farmers had frequent and informal interactions with neighbors, domestic investors, NGOs and NARES staff than with foreign investor. Based on the analysis it is recommended that presence of FAI without frequent interactions with farmers does not influence farmers to use agricultural technologies. But more importantly is that FAI farms established in rural areas should be considered as private investments and not necessarily as a means for promoting use of agricultural technologies to surrounding farmers. A selective strategy should be considered to use FAI as means of promoting use of agricultural technologies among neighboring smallholder farmers based on crop similarity, location endowments, socio-economic characteristics of farmers, extension services availability and technologies used by FAI farms.

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