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Working or not Working in Commercial Farms and Uptake of Agricultural Technologies in Rural Tanzania

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Abstract
Commercial farms investment plays important role in agricultural technology spillovers but less is known on specific channels influencing neighboring farmer's uptake of agricultural technologies. This study analyzed the effect of farmer's working in commercial farms on agricultural technologies uptake intensity. Multiphased study design was used to randomly and proportionately to collect a sample of 1,203 farmers from three independent samples in Karatu, Iringa and Njombe. Nearest neighbor matching estimator was used to estimate the effect of working in commercial farms after testing for a balanced matching and control samples. In Karatu the intensity of agricultural technology uptake of farmer worked in commercial farm was 0.28 larger but not statistically significant. But if the farmer had not worked uptake intensity is reduced to 0.27 which was statistically significant at 5% p-value. In Iringa the intensity of agricultural technology uptake to farmer working in commercial farm on average is 0.45(P< 0.05) significantly large. In Njombe, on average agricultural uptake intensity is 0.20 not statistically significant compared to uptake intensity of 0.23 which is statistically significant at 5% p-value had he/she not worked in commercial farms. It implies in areas where commercial farm producing different crops to neighboring farmers uptake of technologies is more on soil conservation than growing new crop or seed varieties. But in areas without landscarcity and investor's crop being similar to crops produced by small-holder farmer, it was found farmers grow new crops or new seed varieties, use soil conservation practices, tractor and ox-plough. It was concluded that commercial farms should be promoted while considering crops produced by neighboring smallholder farms and land availability to farmers, if uptake of agricultural technologies to neighboring farmers is the policy expectation.
Keywords: employment, commercial farms, uptake of agricultural technology, matching estimation
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1. Introduction

Since 2000 foreign investments in developing countries particularly those targeted Sub-Saharan agriculture sector is rising yet its implication on technology spillovers to neighboring farmers through employment is sparsely explored (Byerlee and Deininger, 2013; Deininger, 2013). Not only foreigners are attracted to the opportunity but increasingly local elites in politics, government and business invest in commercial farming projects in rural areas by establishing new farms or purchasing existing farms (Jayne *et al.,* 2019; World Bank, 2019). Perception and expectations of development practitioners in international organization, Non-government organization (NGOs) and governments on large-scale commercial farms acquisition of uncultivated land or purchasing existing farms is divided. Some view it as threat to developing countries in particular vulnerable rural poor but others view it as an opportunity for contributing into a larger national development agenda and meeting sustainable development goals (SDGs) through employment opportunities and transfer of agricultural technologies (World Bank, 2014).

To a developing country like Tanzania, re-establishment of previously defunct or underperforming commercial farms or establishment of new large-scale commercial farms[1] is an indispensable opportunity to create employment to over 70% of the population of which youth constitute a larger proportion of unemployed. Agriculture contributes 29.1% of the Gross Domestic Product (GDP) and 30% of export earnings (URT, 2017). Commercial farms are promoted to drive the sector's contribution in meeting national as well as SDGs goals of reducing poverty, unemployment and increasing use of environmental friendly agricultural technologies. However, 65% of the farmers are poor smallholders with limited use of agricultural technologies causing low productivities for both food and cash crops (URT, 2021). The average yield of smallholders for main food crops such as maize is 1.5tons/ha; paddy 2.3tons/ha while global average is 5.82ton/ha and 4.7ton/ha respectively. Area cultivated by tractor is 11% of the total cultivated area while inorganic fertilizer use in Tanzania is only

[1] Large commercial farm in this study is an economic unit of agriculture production operating on at least 20 acres for cereal crops/ or keep at least 50 heads of cattle or 100 goats/sheep or 1,000 chickens/ducks/turkeys. But for flowers is at least 1acres. The greatest part of produce should go to the market and operations of the farm are continuous with application of machineries and at least one permanent employee.

10kg per hectare which is low compared to 175kg per hectare in Brazil or 165kg per hectare in India (Michelson, *et al.,*, 2018; URT, 2021).

Large-scale commercial farms have potential in contributing to technology spillover to surrounding smallholders but empirically the discussion is inconclusive on types of technology and channel which neighbouring smallholder farmer benefit from presence of such farms (Adewumi, Jimoh, & Omotesho, 2013; Ali, Deininger, & Harris, 2019; Deininger, Ali, & Harris, 2016; Deininger & Xia, 2016). Large-scale commercials farms have different characteristics to smallholder farmers in terms of organization, size, profit motivations, installed technologies and use of agricultural inputs and agronomic practices. Some commercial farms produce different crops to those produced by nearby smallholders. Commercial farms which are foreign owned usually are fenced probably with electrical wires, but they hire surrounding farmers, others provide training and learning facilities. Fundamentally, large-commercial farms either local or foreign have features which might positively influence uptake of agricultural technologies but also some features might negatively influence uptake of agricultural technologies. The focus of this paper in the discourse is to enhance positive features of commercial farms and reducing negative effects to local development (Seufert, 2013; World Bank, 2014b).

1.1 Commercial farms and agricultural technology spillover

Theoretically, presence of large commercial farms is assumed to benefit neighboring farmers through spillover effect. Spillover is a term used in all fields and it is important concept in development. There are different types of spillovers such as spatial or locational, direct or indirect, internal or external, positive or negative or policy induced spillovers. In economics spillover or externalities means economic impacts on economic actors (society, business, and government) who are not directly undertaking the activity. But in this paper a general definition of technology spillover is used and it refers to adoption of new technological knowledge or practices to improve agricultural production. Earlier studies i.e. Adewumi *et al.,* (2013) attempted to understand indirectly the effect of foreign farmers from Zambia on agricultural technology spillovers to neighboring farmers in two villages of Nigeria one being a control. This was a case study based on input use and output data collected from farmers from the same local government authority before and after arrival of foreign farmers. Despite of spillover effect on increased production efficiency among smallholders due to uptake of agricultural inputs by neighboring smallholder farmers, results suffers potential bias and inconsistency estimation because of confounders such as presence of other local or foreign investors, local extension officers or presence of other NGOs projects which were not controlled in the estimation.

Deininger *et al.,* (2015) improved on Adewumi *et al.,* (2013) by combining case study and a two years survey-based evidence to systematically detect patterns of agricultural technology spillover from large-commercial farms to smallholders in Mozambique. In the model they controlled for distance and year a large-commercial farms was established. They detected pattern of technology spillover within 25 to 50km large-commercial farms like increased use of improved agricultural practices, animal traction, and inputs use. Ali *et al.,* (2019) also used the same approach but with a ten years data from Ethiopia. However, they found establishing commercial farms did not lead to increased employment opportunities and very modest technology benefits to stallholder farmers. Despite of conflicting conclusions, they did not show which channel farmer learn agricultural technologies and to what extent. Furthermore use of national surveys according to Eckert *et al.,* (2016) do not provide meaningful conclusions about the phenomena. Rather an approach that target contexts that vary within a country, the more detailed the analysis to draw implication about a phenomenon.

This paper analyzes farmer's commercial farm employment as a possible direct channel for learning and uptake of agricultural technologies. It look on generic agricultural technologies without specifying crops as Deininger *et al.,* (2016) to move beyond case study in order to generalize employment effects on uptake of agricultural technologies from 20 geographically stratified villages from each of the three independent samples. Since according to Eckert *et al.,* (2016) the more target contexts vary at lowest administrative level within district the more in-depth the analysis and feasibility for generalizing conclusion is higher. Based on field interviews and data collected, commercial farms hire and train farmer on different tasks which to a rational farmer allow learning by doing. Tasks hired for are relating to use of machinery, chemical and non-chemical inputs, good agronomic practices and other commercial farm practice conservation farming under certification programs. Farmers on average work two to four days a week in commercial farms to perform various tasks. It is hypothesized that working in commercial farms do not have effect on intensity of agricultural technologies uptake. This study take into consideration that a farmer may also be inspired to use agricultural technologies by extension agents, donor projects implemented in the area, non-governmental organization activities and traders. The analysis was done by matching farmer's gender, age and household poverty as priori covariates anchored on the assumption of selection based on observables (Imbens, 2014; Nannicini, 2007). Since commercial farms established provide equal employment opportunities for both sex, age and regardless of household poverty status. The analysis is based on the data collected from Karatu, Iringa and Njombe districts.

1.2 Theoretical framework

Study is based on participatory and social learning theory and actor-oriented theory. Participatory and social learning theory emphasize that technology involves the practices and collective actions of many social actors such as farmers, researcher, entrepreneurs, companies, investors, extension officers, donors who are portrayed as agents interacting to produce and disseminate technological innovations (Glover*et al.,* 2019). Actor-oriented theory of technology uptake assumes encounters and exchanges between actors inhibiting different level of knowledge and practice (*ibid*). These theories put emphasis to a rational agency participation in observing, learning and modifying learned agricultural technologies. The theories recognize that technology uptake happens as one observes in one area and inspired to transfer or modifying and use in another area as a rational agency. However, the socio-economic characteristics, biophysical contexts help rational actors to improvise learned technology to specific local configurations when practicing the technologies.

Using theories above, a theoretical framework to analyze commercial farm direct employment effects on uptake of agricultural technologies to farmers is presented. Potential outcome analytical framework is used due to absence of baseline data before establishment of commercial farms. Commercial farms hire farmers to work on various tasks such as operating machines, irrigation system, weeding, harvesting, applying chemical fertilizers, applying pesticides, insecticides or herbicides; applying animal manure, and applying biological insecticides. Hired farmer receive training and instructions on how to perform their tasks which allow them to interact with trainers, farm supervisors and professional farm managers. Some of the commercial farms use conservation agriculture practices and certified by Rainforest alliance. Farmer as agency is postulated to observe, learn and could be inspired to uptake agricultural technologies from commercial farms to their farms. However, uptake of agricultural technologies is random based on socio-economic characteristics and biophysical context. Farmer as a rational agency is assumed to uptake technologies or modifies or improvises such technologies to benefit from them. Uptake of agricultural technologies by farmer was random and as such there was no consideration for one type of technology to be superior to the other or attempting to measure utility of one technology over another.

2.0 Methodology

2.1 Study areas

Study was conducted in Karatu, Iringa and Njombe districts. The research center in each district was systematically selected based on the presence of land-based agricultural investments which is described in details in Ravnborg et al., (2021). All research locations have history of commercial farms operations before and after independence. Some of commercial farms are new others were re-established after being defunct or sold to new owners (Brüntrup, Absmayr, Dylla, Eckhard, and Remke, 2016; Maganga, Askew, Odgaard, and Stein, 2016; Pallotti, 2008). Karatu has high population density compared to Iringa and Njombe research location as result fertile land for agricultural activities is scarce. Iringa rural district and Njombe Town Council are located in Southern highland of Tanzania within the Southern Agricultural Growth Corridor of Tanzania (SAGCoT). SAGCoT is dedicated to promote large-scale agricultural investments to drive agricultural transformation from subsistence to commercial farming through engagement of smallholder farmers.

Iringa has medium concentration of large commercial farms with mixed products that are also produced by smallholder farmers. Main crops and products produced are maize, day-old-chicks, Irish potato seedlings, maize seeds, processed feeds, and feeder crops. Other commercial farms are specialized on diary cattles. Some of the large and medium scale commercial farms were installed with silos of varying capacities. Some had contract with local traders to aggregate maize which is used in processing feeds. Large commercial farms contracted smallholder farmers through Agricultural Marketing Cooperative Societies (AMCOS) to a special variety of soya beans which is also used in processing feeds. During qualitative interview farmers reported training activities by NGOs on maize production linking with input credit arrangement. Farmers also reported being trained on poultry keeping and participated in a project that introduced improved hybrid of chicken. Farmers also keep other livestock such as cattle, goats, and sheep for own consumption and as source of income.

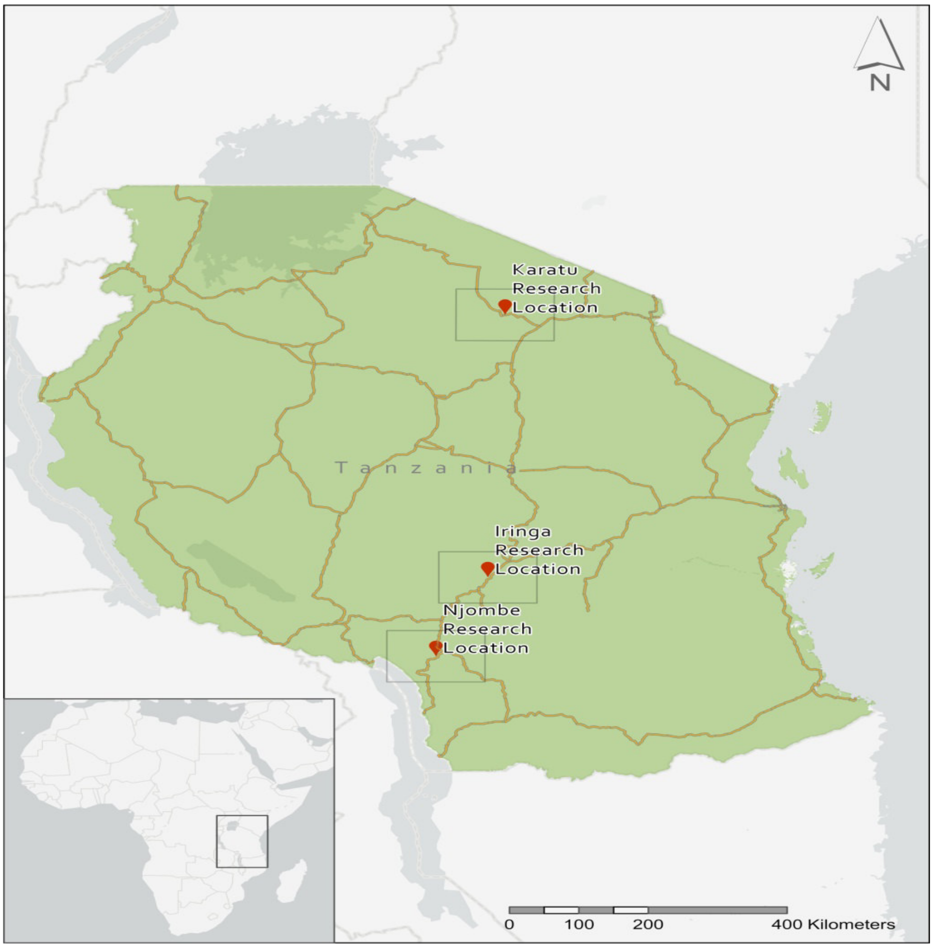

Figure 1: Map showing research locations

Njombe has low concentration of large scale commercial farms, mostly produce tea and emerging avocado production while medium scale commercial farms produce cut flowers. Local investors with medium to small scale farm produce avocado, tea, coffee, maize, Irish potatoes and timber trees. Level of mechanization is low compared to Iringa and Karatu. Human labor is largely used for various farm operations due to hilly topography. Use of improved inputs is moderate compared to Iringa. Smallholder farmers also produce maize, beans, pigeon peas, sunflowers, Irish potatoes, avocado and tea. Maize and beans are produced as cash crops but surplus is sold in local markets. Irish potatoes and pigeon peas are also important cash crops. Not all smallholder farmers keep livestock such as cattle, and chicken.

2.2 Sampling procedures 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. 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 1,203 individuals from February to June 2019, of whom 397 from Karatu, 405 from Iringa and 401 in Njombe were interviewed. Qualitative interviews were also conducted before and after structured interviews for study design and in-depth follow-up based on preliminary data analysis respectively. Enumerators recruited in respective research locations were trained prior data collection. The process is explained in detailed and co-authored in Ravnborg et al., (2021).

2.3 Analytical framework

This study used potential outcome framework for causal inference in observational studies with missing baseline data using nearest neighbor matching (NNM) estimator as suggested by Abadie and Imbens (2006, 2011). The NMM was tested by Becker and Ichino (2002) and found efficient with non-experimental data and Nannicini (2007) provided Stata command for the estimation a. The potential outcome Y_i in this analysis is technology uptake intensity measured as the number of agricultural technologies used by farmer i. Since zero means no technology used. The outcome is measured as count variable as 0, 1 or >1 on a sample of N farmers, indexed by $i = 1, \dots \dots, N,$ of a random sample. $Y_i(0)$ Indicate no any agricultural technology used by farmer i and $Y_i(1\ or > 1)$ indicating 1 or more agricultural technologies used by farmer i. NNM permits only two levels of treatments status for observation which is either farmer i worked $T = 1$ or not worked $T = 0$ in commercial farms but not both. It means for each farmer i, we observe $Y_i = Y_{0i} + T_i(Y_{1i} - Y_{0i})$. NNM estimators uses an average of the individuals with a vector of covariates $X_i = x_{i,1}, x_{i,2}, \dots . x_{i,p}$ that are most similar using Mahalanobis matrix, to get the other treatment level, to predict the unobserved potential outcome y_0 (Abadie and Imbens, 2012). The covariates are based on the prior assumption that large-scale commercial farms provide equal opportunity for working regardless of age, sex, and household poverty. The household poverty is an index which place households as either less poor or poor or poorest. The index is based on individual and other members of the household characteristics in terms of secondary education, land access and ownership, housing characteristics and ownership, ability to hire farm labors, food diversity and feeding frequency, and health. NNM provides the estimator for the average intensity of agricultural technologies uptake in the population of farmer working in commercial farms (ATE) and intensity of agricultural technologies farmer uptake had the farmer not worked in commercial farms (ATET). Formally, ATE is given by $\tau_1 = E(y_1 - y_0)$ and the ATET is $\delta_1 = E(y_1 - y_0 | t = 1)$. Note that y_1 and y_0 are unobserved potential number of agricultural technologies when farmer worked and not worked respectively in commercial farm employment.

Identification and estimation of unobserved potential intensity of agricultural technology used is under the assumptions of un-confoundedness it means the potential intensity of agricultural technologies used $Y_0\ or\ Y_1$ by farmers worked and farmers who not worked in commercial farms are independent from employment status once we condition on employment status T, priori covariates $X_i = x_{i,1}, x_{i,2}, \dots . x_{i,p}$ like age, sex and household poverty given as $(Y_0, Y_1) \perp\!\!\!\perp T|X$. The common support assumption for farmer with any level of covariates X, there is a positive probability of working or not working in commercial farms given as $0 < prob(T = 1|X) < 1$. The combination of these two assumptions according to Imbens (2014) is referred as strong ignorability assumption and average employment spillover effects can be estimated by adjusting for the differences on agricultural technologies uptake in covariates between farmer worked and not worked in commercial farms. NNM uses the estimator ATE or ATET of a model that links the mean intensity of the agricultural technology to covariates given as $\frac{1}{\sum_{i=1}^{n} T_i} \sum_{i=1}^{n} T_i[\mu_1(X_i) - \mu_0(X_i)]$. This can be rewritten as $\mu_1(X_i) = E[Y_i(1)|T_i = 1, X_i] = g(\propto + \beta + X_i\gamma),$ and $\mu_0(X_i) = E[Y_i(0)|T_i = 0, X_i] = g(\propto + X_i\gamma)$. g is a function of the vector of covariates X and unknown parameter vector β. Since this is non-experimental matching $X_i\gamma$ is dropped and β was estimated with Poisson distribution adjusted to covariates X to obtain predicted value of ATE and ATET. Before estimation of the effect of farmer worked or not in commercial farms, balance was checked between control or untreated and treated farmers and biased was controlled based on categorical covariates (Abadie and Imbens, 2011; Imbens, 2014).

3.0 Results and Discussion

3.1 Descriptive analysis

Table 1 show the average age of farmer worked in commercial farms is 39 years much younger compared to farmer who did not work which is 42 years. The same was observed in Iringa and Njombe but in Karatu on average the age of farmer worked in commercial farm was 41 years and 43 Years for farmers not worked. However, there was no statistically significant difference on the distribution of sex with respect to commercial farm employment as measured using chi-square test. Implying that sex distribution of farmers working or not in commercial farms with respect to research locations was similar. Table 2 shows overall farmer who did not work in commercial farms own or access 5 acres while farmer who worked in commercial farms own slightly less at average of 4acres.The mean difference between farmer who worked and not worked in commercial farms is not statistically significant at 5% level. Therefore, on average farmer who worked and not worked own or have access to the equal land size. The same was also observed on sex between male and female farmers who worked or not worked in commercial farms, although the proportion of male farmer who worked in commercial farms was 32% more than 29% of female. The difference was very small hence it was as not statistically significant at 5% level.

Table 1 indicates farmer's household poverty index with respect to commercial farm employment. The index is based on individual's household score based on land ownership and access, housing ownership and their characteristics, secondary education, hiring labor, health, food adequacy, diversity and feeding frequency. The higher the score the better the wellbeing level and vice versa. The cut-off point was obtained using quartile. Computation details of the household poverty index is co-authored in (Ravnborg et al., 2021).

Overall, the household poverty associates significantly with respective research locations. Interestingly, farmers worked in commercial farms from poorest household were 53% compared to 47% of farmers from poor household. Among the farmers from poor households who worked in commercial farms majority were in Njombe (79%) followed by 50% in Karatu and 39% in Iringa. Of the 14% farmers from less poor household who worked in commercial farms in the sample, those from Njombe were 22% more than 9% from Iringa and 5% from Karatu. It was also found that farmers from poor household in Njombe constituted the majority compared to Karatu and Iringa. Therefore, farmers who worked in commercial farms frequently came from poorest households and less frequently from less poor households.

Table 1: Per cent distribution of farmer's characteristics with respect to commercial farm employment by research locations

Characteristics	Statistic	Karatu (n=397)		Iringa (n=405)		Njombe (n=401)		All (N=1203)	
		Worked	Not worked	Worked	Not worked	Worked	Not worked	Worked	Not worked
Age	Mean (SD)	41.08 (13.32)	42.90 (17.70)	36.29 (11.55)	41.88 (17.67)	38.63 (13.67)	42.23 (15.29)	38.87 (13.19)	42.32 (17.04)
Land access (acres)	Mean (SD)	1.79 (1.58)	3.09 (2.66)	5.04 (5.7)	5.21 (8.17)	4.6 (3.58)	6.88 (14.74)	3.82 (398)	4.95 (9.48)
Sex	Male (%)	30.40	69.60	22.7	77.30	41.60	58.40	31.60	68.40
	Female (%)	26.10	73.90	17.50	82.50	42.70	57.30	28.60	71.40
Farmer's Household poverty	Less poor (%)	5.20	94.80	8.90	91.1	22.10	77.90	13.60	86.40
	Poor (%)	22.00	78.00	19.70	80.30	48.30	51.70	29.90	70.10
	Poorest (%)	50.00	50.00	39.20	60.80	79.30	20.70	53.20	46.80

Note:In parentheses is standard deviation; χ^2 Chi-square test.ns=Not statistically significant at p<.05
Age in parentheses is standard deviation; χ^2 Chi-square test.ns=Not statistically significant at p<.05;
Age Iringa t(403)=2.71*; Njombe t(399)=2.44*,;All t=(1201)=3.44**;
Land access karatu t(395)=4.88**; Njombe t(397)=1.96*; All t(1199)=2.19*;
Household poverty karatu χ^2(2, N=397)=63.13,p>0.001; Iringa χ^2(2, N=405)=26.44***; Njombe χ^2(2, N=401)=62.58***; All χ^2(2, N=1203)=121***.

3.2 Agricultural technologies and agronomic practices used by farmers

In Karatu, Njombe and Iringa commercial farms had different levels of technologies and infrastructures. Some of the large commercial farms in Iringa had pivotal irrigation system which is most advanced than drip irrigation.

Table 2: Percent distribution of farmer on agricultural technologies uptake intensity with respect to commercial farm employment

Intensity of agricultural technology uptake	Karatu (n=397)			Iringa (n=405)			Njombe (n=401)			All (N=1203)		
	n	Worked (%)	Not Worked (%)	n	Worked (%)	Not Worked (%)	n	Worked (%)	Not Worked (%)	n	Worked (%)	Not Worked (%)
0	122	33.60	66.40	129	13.20	86.80	240	40.40	59.60	491	31.60	68.40
1	123	22.00	78.00	131	20.60	79.40	72	55.60	44.40	326	28.80	71.20
2	83	31.30	68.70	44	36.40	63.60	46	21.70	78.30	173	30.10	69.90
3	44	25.00	75.00	48	16.70	83.30	24	45.80	54.20	116	25.90	74.10
4	16	37.50	62.50	30	23.30	76.70	6	83.30	16.70	52	34.60	65.40
5	5	20.00	80.00	18	27.80	72.20	11	45.50	54.50	34	32.40	67.60
6	3	33.30	66.70	3	0.00	100.00	2	50.00	50.00	8	25.00	75.00
7	1	0.00	100.00	2	50.00	50.00				3	33.30	66.70
a	69.27			68.15			40.15			59.19		
b		1.30 (1.32)	1.37 (1.40)		1.77 (1.57)	1.42 (1.54)		0.85 (1.33)	0.78 (1.23)		1.20 (1.43)	1.23 (1.40)
c		-0.07 (0.15)			0.34 (0.19)			0.06 (0.13)			-0.03 (0.09)	

Note: ***a***= % of farmers used at least one technologies; ***b***=Mean intensity of technologies; ***c***=Mean differences intensity

Largest silos with maximum storage capacity of 30,000ton for storage in Iringa were the largest among all surveyed commercial farms. Some of commercial farms were Rainforest alliance certified[1]in particular commercial farms owned by foreign investors growing coffee, flowers, and feeder crops. Conservation agriculture technologies relating to soil conservation and improvement were used in coffee estates and feeder crops farms to comply with certification companies. It was observed that all commercial farms used inorganic fertilizers and sprayers for insecticides, pesticides, herbicides. Table 2 shows the intensity of agricultural technologies used by farmer with respect to commercial farm employment. In Karatu 69% of farmers used at least one agricultural technology while in Iringa it was 68% and Njombe it was 40%. On average overall intensity of farmer worked in commercial farm is 1.2 slightly less compared to 1.23 of farmer worked in commercial farms. In Karatu intensity for farmer who worked in commercial farm is 1.3 while for farmers not worked is 1.37. In Iringa average intensity was 1.77 for farmer worked in commercial farms large than intensity of farmers not worked and also larger than farmers from other research locations. However, in Njombe intensity was small than in other research locations.

3.2.1 Soil improvement measures used

Figure 2 shows soil improvement measures used by farmers with respect to commercial farm employment. It shows farmers frequently used cow dung followed by soil barriers, mulching, avoiding burning, using green manure crops, chemical fertilizers, no till/conservation farming, grass strips and terraces. There are variations on soil improvement measures used by farmers who have worked in commercial farms and those who have not. It shows farmers who have not worked frequently used cow dung, soil barriers and mulching while farmers worked in commercial farms used it less frequently. Qualitative interviews with farmer in Iringa who worked in commercial farms reported to use wages earned to purchase fertilizers and improved seeds. In Njombe, farmers who worked in commercial farms frequently used soil barriers, mulching, and avoided burning. Other measures have small variations between farmers worked or not worked in commercial farms with respect to research areas.

[1] A certification program emphasizing commitment to continuous improvement, sustainability training and clear benefits to farmers focusing on the following themes; forests-promote best practices for protecting standing forests, preventing expansion of cropland into forests; fostering the health of trees, soils, and waterways. Climate-promoting responsible land management methods that increase carbon storage while avoiding deforestation. Human rights-assessing and addressing child labor, forced labor, poor working conditions, low wages, gender inequality and violation of indigenous land rights.

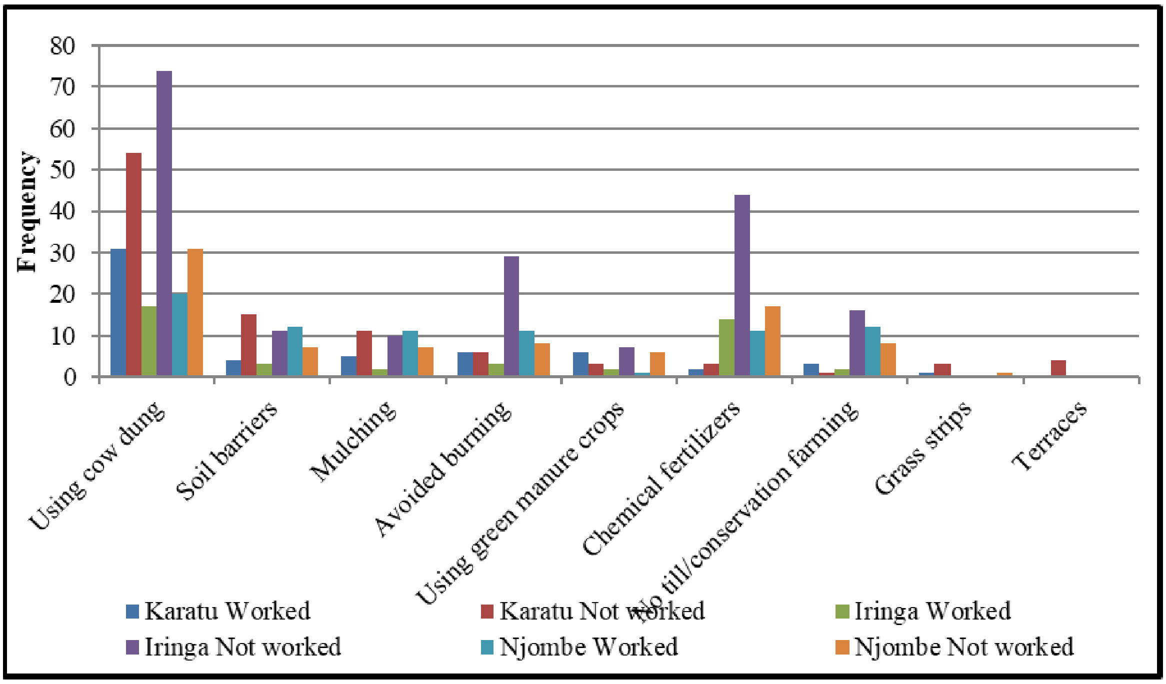

Figure 2: Soil improvement measures used with respect to commercial farm employment by research locations

3.2.2 Soil preparation techniques used before planting

Farmers were asked which soil preparation technique they used before planting. Figure 3 shows in Karatu, farmers who worked in commercial farms used tractor ploughing followed by no till without use of herbicides. Similarly farmer who did not work in commercial farms also used tractor ploughing frequently than no till without use of herbicides. In Iringa, very few farmers used tractor ploughing to prepare the soil before planting but they frequently used not till with herbicides. Those farmers who did not work in commercial farms frequently used tractor ploughing, no till with herbicides and few used no till without herbicides. In Njombe, it was found that farmers who worked in commercial farms frequently used no till without herbicides, followed with no till with herbicides and very few used tractor to plough. The same pattern was also observed to farmers who did not work in commercial farms.

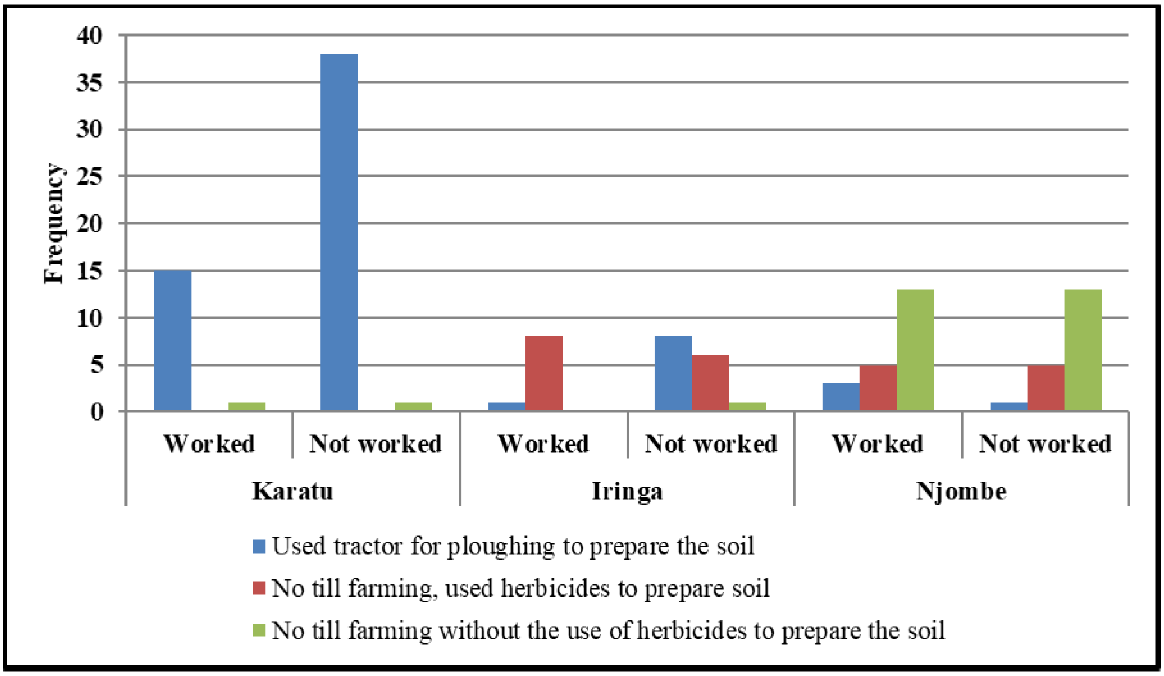

Figure 3: Soil preparation techniques used before planting by farmers with respect to commercial farm employment and research locations

3.2.3 Ox-plough ownership

Table 3 shows ownership of the ox-plough used by farmers with respect to research locations. In overall, it shows with marked statistical significant differences in ownership of ox-plough $\chi^2(3, N=395)=8.45, p>0.04$, in which the ox-plough used by farmers worked in commercial farms were hired (55%), 20% were borrowed or owned and only 6% were partly owned or hired. Ox-plough used by farmers used was hired (46%), 35% owned, 14% borrowed and 4% partly owned or hired. It shows in Karatu, with a marked statistical significant differences $\chi^2(3, N=159)=8.49, p>0.04$, ox-plough used by farmer worked in commercial farms frequently hired (48%), 23% borrowed, 15% owned and 15% partly, owned or hired. On the other hand ox-plough used by farmers not worked in commercial farms frequently owned (40%), 32% hired, 19% borrowed and only 9% partly owned or hired.

Table 3 indicate that in Iringa, ox-plough used by farmer worked in commercial farms were frequently hired (65%), followed by 19% owned, and 16% borrowed. Ox-plough used by farmer not worked in commercial farms frequently hired 65%, 25% owned, 10% borrowed and 1% partly owned or hired. However, the differences were not statistically significant $\chi^2(3, N=179)=2.21, p>0.53$. In Njombe, ox-plough used by farmer worked in commercial farms frequently hired (47%), 32% owned, and 21% borrowed. Ox-plough used by farmer not worked in commercial farms frequently owned (55%), 26% hired, 16% borrowed, and 3% partly hired or borrowed. However, differences were not statistically significant different $\chi^2(3, N=57)=3.88, p>0.27$.

Table 3: Percent ownership of the ox-plough farmer's used with respect to commercial farm employment by research locations

Research locations	Commercial farm employment	n	To whom ox-plough belong (%)				Total (%)
			Owned	Borrowed	Hired	Partly, owned or hired	
Karatu[a]	Worked	40	15.00	22.50	47.50	15.00	100
	Not worked	119	39.50	19.30	31.90	9.20	100
Iringa[b]	Worked	43	18.60	16.30	65.10	0.00	100
	Not worked	136	25.00	9.60	64.70	0.70	100
Njombe[c]	Worked	19	31.60	21.10	47.40	0.00	100
	Not worked	38	55.30	15.80	26.30	2.60	100
All[d]	Worked	102	19.60	19.60	54.90	5.90	100
	Not worked	293	34.80	14.30	46.40	4.40	100
	All	**395**	**30.90**	**15.70**	**48.60**	**4.80**	**100**

Note. *P<.05
a1cells(12.5%) have expected count less than 5.
b3cells(37.5%) have expected count less than 5.
c3cells(37.5%) have expected count less than 5.
d1cells (12.5%) have expected count less than 5.

3.2.4 Tractor ownership

Farmers were asked from whom a hired tractor was obtained? Table 5 shows tractors used by farmer in Karatu who had worked in commercial farms were more frequently hired (90%) than borrowed (7%) or owned (3%). The same pattern was observed among farmers who did not work in commercial farms, in which 76% hired, 17% borrowed and 7% owned. However, the differences in proportions were not statistically significant. In Iringa, it was slightly a different pattern, but hired tractors still retain a large proportion than owned (8%) and there was no tractor which was borrowed among farmers who had work in commercial farms. It was also found that farmer who did not work in commercial farms that hired tractors were 93% more than 6% who borrowed or 2% who owned tractors. In Njombe, there was no farmer either worked or not worked in commercial farms that owned or borrowed tractor for farming activities. Farmers either worked or not worked in commercial farms that used tractor for farming activities they hired. No statistical significant differences were found in Karatu $\chi^2,(2,N=146)=3.16, p>0.05$, Iringa $\chi^2,(2,N=65)=3.16, p>0.05$or and Njombe no statistics computed.

Table 5: Percent tractor ownership with respect commercial farm employment by research locations

Research location	Commercial farm employment	n	Tractor ownership (%)			Total
			Owned	Borrowed	Hired	
Karatu[a]	Worked	31	3.20	6.50	90.30	100
	Not worked	115	7.00	17.40	75.70	100
Iringa[b]	Worked	12	8.30	0.00	91.70	100
	Not worked	53	1.90	5.70	92.50	100
Njombe	Worked	3	-	-	100.00	100
	Not worked	1	-	-	100.00	100
All[c]	Worked	46	4.30	4.30	91.30	100
	Not worked	169	5.30	13.60	81.10	100
	All	**215**	**5.10**	**11.60**	**83.30**	**100**

Note.missing n=988
a2cells*33.3%) have expected count less than 5.
b4cells(66.7%) have expected count less than 5.
c1cells(16.7%) have expected count less than 5.

3.2.5 Source of inspiration to uptake agricultural technologies

Farmers were asked sources of inspiration in uptake for each agricultural technology. Farmers were asked if they had contacts or from whom they learned the agricultural technologies they used. Figure 4 indicates own initiative, neighbor or relative, commercial farms and NARES. It shows for farmer who worked in commercial farms is important as NARES followed by own initiatives.

3.3 Farmer's working status and agricultural technology uptake intensity

Table 6 shows results from two types of models after test for a balanced matching (see annex-1). The first is pooled model comprising of all farmers in the sample (N=1203) and second is the model is with respect to each research locations. In both models farmer's working in commercial farm as a treatment is estimated with first the intensity of agricultural technologies uptake difference by farmers in the population (ATE) and second the difference on average intensity of agricultural technologies uptake by farmers had they not been worked in commercial farms (ATET) with exact match one on one and adjusting for farmer's age, sex, source of inspiration for agricultural technologies uptake and household poverty. Matching results adjusted by sources of inspiration on average intensity of agricultural technology uptake were insignificant for ATE and ATET estimators hence not included in the final table 6.

Estimation results from the pooled model as well as with respect to research locations when matching is adjusted for sex and age had no significant difference on the average intensity of agricultural technologies uptake. Furthermore, it was also found that matching by adjusting with different covariates combinations in other words by considering different farmer's characteristics have effect on intensity of agricultural technologies uptake. Matching adjusting by household wellbeing it was found on overall the average population the difference in intensity of agricultural technology uptake was 0.24 statistically significant at 5% p-value. Average intensity of agricultural technology uptake had the farmer not worked in commercial farm was 0.26 which was significant at 1% p-value. It implies commercial farm employment on average increase agricultural technology uptake intensity but had they not worked in commercial farms intensity of uptake could have been slightly more.

In Karatu, on average in the population the difference on agricultural technology uptake intensity between farmer worked or not worked in commercial farms was 0.28 but not statistically significant at 5%. It was found average difference intensity of agricultural technology uptake had the farmer not worked in commercial farm was 0.27 statistically significant at 5% p-value. This suggests that in Karatu, farmer working in commercial farms uptake intensity of agricultural technology is low compared to farmer not working in commercial farms. In Iringa, the average difference on uptake intensity of agricultural of employees in the population was 0.48 statistically significant at 5% p-value. It was also found that the average difference intensity of agricultural technology uptake was 0.43 which was statistically significant at 5% had the farmer not worked in commercial farm.

Furthermore uptake intensity of agricultural technologies in Iringa increases when adjusting matching by sex and household poverty. It increases to an average of 0.50 which was statistically significant at 5% of p-value among farmer worked in commercial farms in the population but the intensity of agricultural technology uptake decreases to 0.41 which is statistically significant at 5% level of p-value had the farmer not worked in commercial farms. Therefore, commercial farm employment had effect on the intensity of agricultural technology uptake to farmers in Iringa. In Njombe, the average difference in intensity of agricultural technology uptake for farmers worked in commercial farms in the population was 0.20 which is large than average difference of the population uptake intensity of 0.06 but not statistically significant at 5% p-value level. However, the average number of agricultural technologies uptake of employees had they not been employed when controlled for household poverty was 0.23 which was statistically significant at 5% p-value level.

The average difference intensity of agricultural technology uptake of farmers worked in commercial farm in the population was 0.24 which was statistically significant at 5% when matching is adjusted by age and household poverty. Had the employee not worked in commercial farms the average difference in intensity of agricultural technology uptake increased to 0.25 and it was statistically significant at 5% level. However, when matching was adjusted by sex and household poverty not significant results obtained despite of showing a larger difference compared to the population average intensity. Therefore, commercial farm employment increases uptake intensity of agricultural technologies to farmers in Njombe.

Results shows commercial farm employment had effect on number of agricultural technology uptake to farmers who worked in commercial farms. This was found in pooled model and model with respect to research areas and farmers characteristics. In a pooled model it shows had the farmer not worked in commercial farms intensity of agricultural technology uptake is large than farmer worked in commercial farms. Farmers who worked in commercial farms frequently uptake agricultural technologies relating to changing soil preparation practices before planting but farmer not worked majority frequently used ox-plough and tractor. It shows commercial farms had influenced on specific agricultural technologies to farmers. In particular to agricultural technologies associated with learning or own doing such as practices related to soil changing before planting than agricultural technologies that require money to uptake such as use of ox-plough, tractor, seed or new varieties of seeds. Up take of agricultural technologies also depends on land availability and typology. Land in Iringa is flat which allow uptake of tractors or ox-plough as opposed to Njombe.

Table 6: Matching estimation on commercial farm employment effects on intensity of agricultural technologies uptake

Estimator	Matched Covariates	Model Coefficient			
		All	Karatu	Iringa	Njombe
ATE	Sex	0.11	0.13	0.27	0.10
ATET		0.11	0.13	0.24	0.10
ATE	Age	0.12	0.13	0.29	0.11
ATET		0.12	0.12	0.25	0.13
ATE	Household poverty	0.24**	0.28	0.45**	0.20
ATET		0.26***	0.27**	0.43**	0.23**
ATE	Source of inspiration	0.06	*Ns*	*ns*	*ns*
ATET		0.07	*Ns*	*ns*	*ns*
ATE	Age, Sex	0.11	0.11	*a*	*a*
ATET		0.11	0.11	*a*	*a*
ATE	Age, household poverty	0.253**	*A*	0.48**	0.24**
ATET		0.26***	*A*	0.43**	0.25**
ATE	Sex, household poverty	0.23**	*A*	0.50**	0.19
ATET		0.25***	*A*	0.41**	0.22
ATE	Age,sex, household poverty	0.24**	*A*	*a*	*a*
ATET		0.26***	*A*	*a*	*a*

Note: treatment was worked in commercial farm=1 and not worked as control =0. **P<.05; ***P<.001

In Karatu the average number of agricultural technologies uptake to farmers had they not been employed was significant only to soil improvement practices that frequently used by farmer worked in commercial farms and less frequently used tractor or ox-plough. This is due to coffee which is produced by majority of commercial farms on highland areas while neighboring smallholder farmers do not. This means cross enterprise farm technology learning was only in soil improvement practices from commercial farm to neighboring farmers. This finding is contrary to Deininger and Harris (2016) who found in Ethiopia that technology spillovers to neighboring farmers were limited to the same crops grown by commercial farms. In Iringa, commercial farm employment influenced majority of farmer uptake of new crops or seed varieties and changing soil preparations before planting practices because crops grown by farmers in Iringa were also grown in commercial farms. Employment facilitated use of new seed varieties and new crops. One of the commercial farms worked with farmers through AMCOS to produce special variety of soya beans through contract farming. Farmer received training, seed and market. During qualitative interviews farmer reported using new varieties of Irish potatoes because the seedlings were produced by large investor farm in the area. Others reported keeping Sasso chicken breed which is also produced by large poultry farm in the area. This was further confirmed by farmers during qualitative interviews who reported to use wage for buying agricultural inputs. Similar findings were also reported by Adewumi and Omotesho, (2013); Deininger *et al.,* (2015) that employment in commercial farm had spillover effects on fertilizer application and use of improved seeds.

4.0 Conclusion

The paper analysed the effect of farmer's working in commercial farms on the agricultural technologies uptake. The null hypothesis was rejected implying working in commercial farm increases uptake of agricultural technologies but with respect to characteristics of the area. In Karatu where land is scarce and crops produced by commercial farms are not the same with neighboring farmers, uptake intensity of agricultural technology is low compared to farmer not working in commercial farms. However in Njombe and Iringa with no scarcity of land and crops produced by commercial farms is the same with what neighboring smallholder farmer's produce, working in commercial farm increases uptake intensity of agricultural technologies to farmers. It was found in these areas more frequently farmers' started growing new crops or seed varieties, and changing soil preparations before planting practices. Therefore, it was concluded that commercial farms should be strategically promoted if the policy expectation is to contribute in uptake of agricultural technologies to neighboring farmers through employment. This is because characteristics of the commercial farms investments such as the location and crops produced is vital in influencing the type of agricultural technology farmer can learn and use.

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Annex 1-Balanced matching tests results
Pooled model balanced matching test

Statistic	Covariates	Observations		Treated		Control		Matched requested	
		Raw	Matched	Raw	Matched	Raw	Matched	Min	Max
ATE	Sex	1203	2406	363	1203	840	1203	169	421
ATET		1203	726	363	363	840	363	169	421
ATE	Age	1203	2406	363	1203	840	1203	159	497
ATET		1203	726	363	363	840	363	159	497
ATE	Household poverty	1203	2406	363	1203	840	1203	52	377
ATET		1203	726	363	363	840	363	52	377
ATE	Age, Sex	1203	2406	363	1203	840	1203	75	252
ATET		1203	726	363	363	840	363	75	252
ATE	Age, Household poverty	1203	2406	363	1203	840	1203	25	205
ATET		1203	726	363	363	840	363	25	205
ATE	Sex, Household wellbeing	1203	2406	363	1203	840	1203	19	199
ATET		1203	726	363	363	840	363	19	199
ATE	Age, Sex, Household poverty	1203	2406	363	1203	840	1203	8	121
ATET		1203	726	363	363	840	363	8	121

Karatu sample balanced matching test

Statistic	Covariates	Observations		Treated		Control		Matched requested	
		Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched
ATE	Sex	397	794	113	397	284	397	47	151
ATET		397	226	113	113	284	113	47	151
ATE	Age	397	794	113	397	284	397	35	179
ATET		397	226	113	113	284	113	35	179
ATE	Household poverty	397	794	113	397	284	397	5	117
ATET		397	226	113	113	284	113	5	117
ATE	Age, Sex	397	794	113	397	284	397	16	95
ATET		397	226	113	113	284	113	16	95

Statistic	Covariates	Observations		Treated		Control		Matched requested	
		Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched
ATE	Sex	405	810	81	405	324	405	1	37
ATET		405	162	81	81	324	81	37	174
ATE	Age	405	810	81	405	324	405	35	179
ATET		405	162	81	81	324	81	1	35
ATE	Household poverty	405	810	81	405	324	405	11	167
ATET		405	162	81	81	324	81	11	167
ATE	Sex, Household poverty	405	810	81	405	324	405	3	85
ATET		405	162	81	81	324	81	3	85
ATE	Age, Household poverty	405	810	81	405	324	405	4	90
ATET		405	162	81	81	324	81	4	90

Iringa sample balanced matching test

Njombe sample balanced matching test

Statistic	Covariates	Observations		Treated		Control		Matched requested	
		Raw	Matched	Raw	Matched	Raw	Matched	Raw	Matched
ATE	Sex	401	802	169	401	231	401	84	118
ATET		401	338	169	169	232	169	84	118
ATE	Age	401	802	169	401	232	401	78	139
ATET		401	338	169	169	232	169	78	139
ATE	Household poverty	401	802	169	401	232	401	12	127
ATET		401	338	169	169	232	169	12	127
ATE	Sex, Household poverty	401	802	169	401	232	401	4	78
ATET		401	338	169	169	232	169	4	78
ATE	Age, Household poverty	401	802	169	401	232	401	3	81
ATET		401	338	169	169	232	169	3	81