THE DETERMINANTS AND EFFECTS OF JICA RICE TECHNOLOGY ADOPTION IN THE SAGNARIGU DISTRICT OF THE NORTHERN REGION, GHANA

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Abstract

This study analysed the adoption of JICA rice production technologies and its effect on output in Sagnarigu District of the Northern Region. A total of 120 respondents from six communities in the Sagnarigu District were randomly selected and interviewed using semi-structured questionnaires. The logit model was used to determine the factors that influenced the adoption of JICA rice production technologies while the propensity score matching was employed to estimate the effect of treatment (adoption) on rice output. The study found that membership to farmer association and fertilizer subsidy positively and significantly influenced adoption of the rice production technologies whereas farm size, access to agricultural extension, use of other improved seed, and household size negatively affected adoption of the rice production technologies. The adoption of technologies led to a significant improvement in rice output. We recommend that farmers be supported to step up their adoption of the rice technologies through the formation of farmer groups as well as the fertilizer subsidization programme, among others.

Keywords: Adoption, JICA, Propensity Score Matching, Rice, Technology

Introduction

Rice is one of the important food crops in the world and ranks second in terms of area and production (Devi and Ponnarasi, 2009). It is the staple food for about 50 per cent of the population in Asia, where 90 percent of the world's rice is grown and consumed (Devi and Ponnarasi, 2009). In Asia, food security depends largely on irrigated rice fields, which account for more than 75% of the total rice production (Virk *et al.,* 2004). India has the largest area under rice cultivation occupying 29.4% of the global area, but also has the lowest yield in Asia (Devi and Ponnarasi, 2009). It is estimated that the consumption of rice would increase by 501,043 thousand metric tonnes in 2021/2022, given the 2012/2013 consumption of 465,084 thousand metric tonnes in order to assure food security in the rice-consuming countries of the world (Wailes and Chavez, 2012). To meet this demand, the adoption of rice production technologies must be stepped up to boost production. Rice provides 21% of global human per capita food energy and 15% per capita protein (IRRI, 2002). Calories from rice are particularly important in Asia, especially among the poor, where it accounts for 50-80% of the daily caloric intake (IRRI, 2001).

In sub-Saharan Africa (SSA), West Africa is the leading producer and consumer of rice, widely produced in Cote d'Ivoire, the Gambia, Guinea, Guinea Bissau, Liberia, Burkina Faso, Senegal and Sierra Leone (WARDA, 1996; NISER, 2002). Approximately 20 million farmers in SSA grow rice and about 100 million people depend on it for their livelihoods (Nwanze *et al.*, 2006). From 2007-2010, domestic paddy production in SSA grew by 14% (CARD, 2013).

In Ghana, rice is ranked the second most important staple crop after maize (MoFA, 2011). The crop occupies 11% of total land area under cereal cultivation, representing about 5% of the total arable land area (Martey *et al.,* 2013). In 2010, Ghana produced a total of 491,603 metric tonnes of rice (MoFA, 2011). However, Ghana still depends largely on imported rice (400,000 tons/annum) to make up for the deficit in rice supply (Bruce *et al.*, 2014).

Agricultural development depends on a great extent on how successfully knowledge is generated and applied (World Bank, 2007). Despite this, the adoption of improved rice production technologies by farmers is still low, leading to a wide gap between achievable (6.5mt/ha) and actual (2.4mt/ha) yield (MoFA, 2011). It is against this backdrop that JICA in 2009 introduced new rice production technologies under its "Sustainable Development of Rain-fed Lowland Rice Project" in the Ashanti and Northern regions.

Background to Sustainable Development of Rainfed Low-land Rice Production Programme by JICA

The Japanese government has been supporting Ghana since 1962 through technical cooperation, Official Development Assistance (ODA) loans, grants and volunteer work. Japan International Cooperation Agency's (JICA) supports to the Ghana government are in the form of programmes and projects in areas such as infrastructure, agriculture, education, industry and health. The Sustainable Development of Rain-fed Lowland Rice Production project is a joint initiative by the Japanese government through JICA and the Ghana government through the Ministry of Food and Agriculture (MoFA). It was launched in 2009 with a total estimated funding amount of $1.6 million for a five year period to increase the production of rice and farmers' income in selected communities of two regions in Ghana (Mumuni and Oladele (2012). The project was implemented in the Ashanti and Northern regions in which JICA introduced Japanese agricultural techniques to local farmers through the MoFA and Japanese experts. The main aim of the project was improvement in productivity and profitability of rice farming in rain-fed lowlands in project areas. After the launch of the Sustainable Development of Rain-fed Lowland Rice production project, farmers yield increased to an average of 4.3ton/ha and 2.9ton/ha (see Table 3.1 below) for Ashanti and Northern regions respectively (Mumuni and Oladele, 2012).
JICA operates in four districts in the Northern region; Tamale Metropolis, East Gonja, West Mamprusi and Sagnarigu Districts. The goal of JICA in these districts is to contribute to food security as well as improve the livelihood of the rural people.

These new rice production technologies introduced include bund construction, harrowing, farrowing, drilling, plant spacing (20*30cm), seed selection by soaking, fertilizer application (NPK-200kg/ha and Nitrogen Sulphate 170kg/ha) and use of Gbewa rice (Jasmine 85) seed. However, since the introduction of the technologies there has not been any study to evaluate the extent of adoption and the effects on output, to the best of our knowledge, hence this present study to investigate the factors that influence the adoption of the JICA rice production technologies and its effect on rice output in Sagnarigu District of Northern Region of Ghana.

METHODOLOGY

Adoption and Diffusion of Technology

Technology can be defined as an innovation that is perceived as new and helps to increase production. Rogers (2003) described an innovation to be "an idea, practice, or object that is perceived as new by an individual or other units of adoption". The terminologies "adoption" and "diffusion" though interrelated are different, in the sense that adoption is when an individual makes full use of an innovation, while diffusion means the spread of the innovation among a community or even globally (Feder *et al*., 1985). Feder *et al*. (1985) emphasized that "adoption takes place only in a long run equilibrium when the farmer has full information about the technology and its potential."
Rogers (2003) argued that for any innovation, categories of adopters will naturally emerge. These adopter types broadly include the innovators, the early adopters, the early majority adopters, the late majority adopters, and the laggards. He noted how membership to these adoption categories is influenced by one's subjective perceptions of certain attributes of the innovation. He further stated that there are five attributes that impact on a person's decision to adopt an innovation as follows: relative advantage; compatibility; complexity; trialability; and observability. According to Rogers (2003), there is usually a normal distribution of the various adopter categories that forms the shape of a bell curve (see figure 1). Innovators", those who readily adopt an innovation, make up about 2.5% of any population. "Early Adopters" make up approximately 13.5% of the population. Most people will fall into either the Early Majority (34%)

or the Late Majority (34%) categories. "Laggards", those who will resist an innovation until the better end, comprise about 16% of the population. The concept of adopter categories is important because it shows that all innovations go through a natural, predictable, and sometimes lengthy process before becoming widely adopted by an individual or within a society (Rogers, 1995).
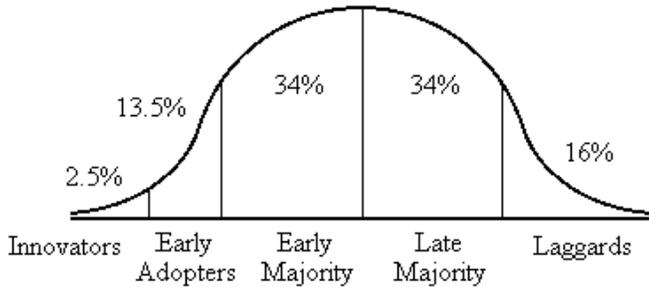
Source: Rogers (1995): Figure 1; Diffusion of Innovation

Rogers (2003) also observed that the adoption of technology progresses overtime through five stages. These are as follows;

i. The target group must learn about the innovation (knowledge);

ii. The target group must be persuaded on the value of the innovation (persuasion);

iii. They must decide to adopt the innovation (decision);

iv. The innovation must be implemented (implementation); and

v. The technology must be reaffirmed or rejected (confirmation).

However, he changed the terminology of the five stages of adoption to awareness, interest, evaluation, trial and adoption. Nonetheless, the descriptions of these stages remain similar.

The Study Area
The Sagnerigu District Assembly is one of the newly created districts in the Northern Region in 2012 (GSS, 2014). It was carved out of the Tamale

Metropolis (Figure 1). The District has 79 communities comprising 20 urban, 6 peri-urban and 53 rural areas. The district covers a total land size of 200.4km² and shares boundaries with the Savelugu - Nanton Municipality to the north, Tamale Metropolis to the south and east, Tolon District to the west and Kumbungu District to the north-west. The district lies between latitudes 9º16' and 9º 34' North and longitudes 0º 36' and 0º 57' West. Like Northern Ghana in general, the Sagnerigu District has a unimodal rainfall pattern that starts from May and ends in October. This period is the farming season. This is followed by a dry season from November to March the following year. The dry season is characterised by dry Harmattan winds. The mean day temperatures range from 28ºC (December - mid-April) to about 38ºC (April - June) while the mean night temperatures range from 18ºC (December) to 25ºC (February, March). The district lacks water bodies, and this is attributed to the high underground table. Dams and dug outs are therefore the sources of water for the people and livestock in the district.

The Sagnarigu District, like many others in the Northern Region, has a single rainy season, usually stretching from May to October, and this period naturally coincides with the farming activities in the district. Annual rainfall average ranges from 600mm to 1100mm, the peak being usually between July and August. The mean day temperatures range from 28ºC (December - mid-April) to about 38ºC (April - June) while the mean night temperatures range from 18ºC (December) to 25ºC (February, March). The dry season (November – March) is characterized by the dry Harmattan winds; the Harmattan season presents two extreme weather conditions, the extreme dry cold temperature of the early dawns and mornings and the very warm afternoons. The district lies within the Savannah Woodland Region characterized by tree savannah vegetation of varying sizes and density. The commonest types of tree in the district include dawadawa, nim, acacia, mahogany and baobab. The main soil types in the district are sandstone, gravel, mudstone and shale that have weathered into different soil grades. As a result of seasonal erosion, soil types emanating from this phenomenon are sand, clay and laterite ochrosols.

Data and sampling method

Semi-structured questionnaires were administered to rice farmers through personal interviews. Twenty (20) respondents, comprising 10 JICA and 10 non-JICA rice farmers were sampled in each community. The total sample size was 120 respondents from six communities in the district. Simple random sampling technique was used to select both the study communities as well as the respondents.
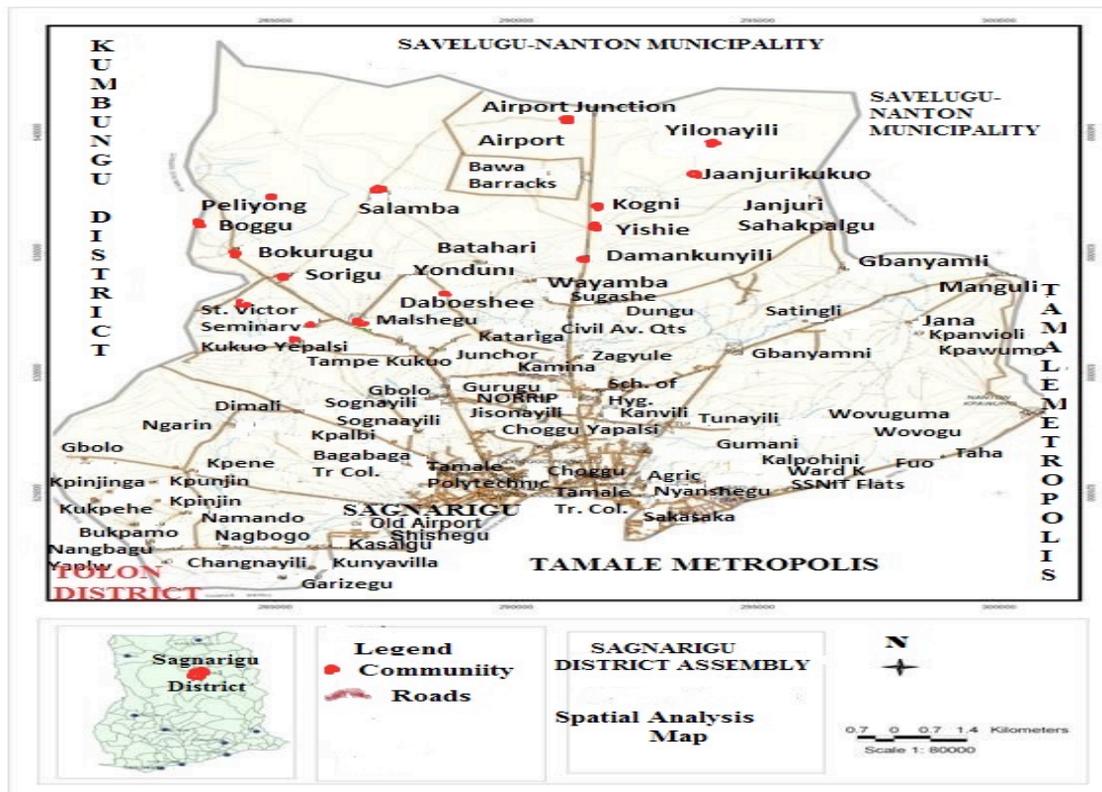

Figure 2: Sagnarigu District Map

Propensity Score Matching

The Propensity Score Matching (PSM) technique, first proposed by Rosenbaum and Rubin (1983), is an econometric approach that is used by researchers to evaluate the effects or impacts of a programme intervention on social or economic outcomes. This approach accounts for sample selectivity bias in programme interventions, since selection of participants into such programmes are often non-random and therefore is subject to sample selection bias. PSM is used in analysis of data from quasi-experiments to balance two nonequivalent groups on observed characteristics to obtain more accurate estimates of the effects of a treatment (e.g. adoption of intervention) on which the two groups differ (Luellen, Shadish & Clark, 2005). The rationale behind the analysis is to eliminate or at least minimize sample selection bias since a treated group (such as participants) and a control (non-participants) in an intervention or training programmes often differ even in absence of

treatment. When the selection bias is eliminated the differences in outcome(s) of the treated (adopters) and the control (non-adopters) group can be attributed to the intervention (Caliendo & Kopeinig, 2008).

In this study, PSM is used to construct a group for comparisons based on probability model of adoption of JICA rice cultivation technologies. Members who adopted the technologies are matched to non-adopters on the basis of the probability [or propensity scores, (PS)]. After matching the individuals with similar characteristics in both the adopter (treatment) and non-adopter (control) groups, the real effect of JICA rice technology adoption can then be calculated as the mean difference in rice output per hectare between the adopters and non-adopters. In addition to assessing the effect of adoption on rice output, the method of PSM allows us to examine the probability of a farmer adopting a technology.

First a binary choice model, usually logit or probit regression, is used to estimate the propensity score

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of each respondent as the probability of the respondent to adopt one or more JICA rice technologies. Propensity scores are estimated using farmer, farm characteristics and the affinity to use agricultural technologies (Deschamps and Jean, 2013; Djido, Adoulaye & Sanders 2013; Godtland et al, 2003).

Denoting the probability of a farmer to adopt JICA rice technology by Y and the set of covariates that influence this decision by X, the propensity score (PS) model of adoption can be specified as follows:

$$PS = \Pr(Y = 1 \mid X)$$
$$= \Pr(b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_7 + b_8X_8 + b_9X_9 + \quad (1)$$
$$b_{10}X_{10} + b_{11}X_{11} + u) > 0.$$

X denotes all variables that determine treatment selection. Specifically, X_1 is a farmer's membership to a farmer group (FBO) (dummy 1, if farmer belonged to an FBO and 0, otherwise); X_2 = Access to fertilizer subsidy (dummy, 1 if farmer had access, and 0, otherwise) ; X_3 = Access to agricultural extension services (dummy; 1 if farmer had access, and 0 otherwise) ; X_4 = Number of people hired to work on the farm. X_5 = use of other improved rice seeds (dummy; 1 if farmer used other improved rice seeds apart from Jasmine 85, and 0 otherwise); X_6 = household size; X_7 = access to production credit (dummy; 1 if farmer has access to production credit, and 0 otherwise); X_8 = age of respondent; X_9 = education (dummy; 1 if farmer has at least attended primary school, and 0 otherwise); X_{10} = farm size in hectares; and X_{11} = number of years of experience in rice cultivation.

The basis of the PSM is that it helps in comparing the observed output of technology adopters to the output of counterfactual non-adopters based on the predicted propensity of adopting at least one technology (Rosenbaum and Rubin, 1983; Heckman *et al.,* 1998; Smith and Todd, 2005; Wooldridge, 2005).

After estimating the propensity scores using the logit or probit model, the next task is to estimate an average treatment effect (ATE) for adoption on rice output. The propensity scores are used to match treated observations (adopters) with untreated observations (non-adopters). The ATE is estimated as the mean difference in rice output between adopters, denoted by Y (1) and matched control group, denoted by Y (0). Symbolically, equation (2) represents the model for estimation of the ATE.

$$ATE = E[Y(1) \ Y(0)] = E[Y(1)] \ E[Y(0)] \quad (2)$$

The ATE model compares the rice output of farmers who adopted one or more technologies with that of non-adopters or control for farmers that are similar in terms of observable characteristics and also partially control for non-random selection of participants in the JICA rice technology adoption programme. The ATE as calculated in equation (2) could be interpreted as the effect of the JICA rice technology adoption on rice output.

Apart from the ATE, an average treatment effect on the treated (ATT or ATET) is also estimated. The ATT model measures the effect of adoption on output for only farmers who actually adopted the JICA rice technology rather than across all rice farmers who could potentially adopt these technologies. ATT is calculated using the expression in equation (3) as follows:

$$ATT = E[Y(1) \ Y(0) \mid D=1] = E[Y(1) \mid D=1] \ E[Y(0) \mid D=1] \quad (3)$$

where G is a dummy or indicator for treatment (D = 1 for adopters, 0 for non-adopters). Again, one could also estimate the average treatment effect on the untreated or control groups (ATC), which measures what the effect of adoption on output would be for farmers who did not adopt the JICA rice technology at all. The model for measuring such a parameter is expressed by equation (4) below.

$$ATC = E[Y(1) \ Y(0) \mid D=0] = E[Y(1) \mid D=0] \ E[Y(0) \mid D=0] \quad (4)$$

Earlier empirical works that use the PSM approach have revealed and stressed that the outcomes depend crucially on the strict specification and the matching methods used (Imbens, 2004; Caliendo & Kopeinig 2008). Therefore, sensitivity analysis is often needed to check the robustness of the approach used for the estimation. In empirical work, many researchers use different specifications and

matching techniques as a robustness check, and the same approach is adopted in this study. The matching techniques commonly used in propensity score matching models are the nearest neighbour matching (NNM) and kernel-based matching (KBM). In this study, we also include the results from regression adjustment method (RAM) in order to compare three different estimation techniques, which may serve as a sensitivity check.

Results and Discussion

Descriptive Analyses of Socio-economic Characteristics of Respondents

The socio-economic characteristics of the respondents including age, educational level, farming experience, household size, and farm size among others, are presented in Table 1. The average household consists of eight (8) members but only three (3) of these members worked on the rice farm. Rice farming has been an occupation in the study area for about 12 years, despite the fact that the average respondent is about 34 years old. This means that the average respondent started cultivating rice only after 22 years of age. The results indicate that most of the respondents are smallholders with an average farm size of 2.52 hectares. This figure is slightly above the average farm holdings of less than 2 hectares in size estimated for Ghana (MoFA, 2011). Generally, the farmers in the study area had very low level of formal education. The highest educated rice farmer had only received 12 years of formal education (approximately, a JHS leaver) while the average rice farmer had received less than two years of formal education. In terms of labour requirement, an average rice farmer employed three (3) people to cultivate the rice farm.

Similarly, the average quantity of fertilizer applied in the rice field was 411.4kg/ha (8.2bags/ha) for the pooled data. Meanwhile, the average quantity of fertilizer used by adopters of JICA rice production technologies was 453.9kg/ha compared with the recommended application rate of 370kg/ha for rice. However, the mean fertilizer used by non-adopters was 368.8kg/ha which is very close to the recommended application rate of 370kg/ha.

Table 1: Average differences in characteristics of adopters and non-adopters of JICA rice technologies

Variable	Adopters	Non-adopters	T-test	Pooled
Household size	8.40	7.93	0.58	8.17
Household labour	3.25	2.52	1.85*	2.88
Age(years)	33.90	32.80	0.64	33.35
Education (years)	1.40	1.65	0.72	1.53
Farm size (hectares)	2.38	2.66	1.00	2.52
Farm experience (years)	11.32	11.75	0.33	11.53
Quantity of fertilizer applied (kg/ha)	453.9	368.8	1.69*	411.4
Rice output(kg/ha)	4306.075	2575.016	3.43***	3440.545

*=10% significant levels; ***=1%significant level*

The average yield of 3.44mt/ha of rice in Sagnarigu district is higher than the national average of 2.4mt/ha. Meanwhile, there was a 1.7mt/ha increase in rice yield for adopters of the JICA rice production technologies. The average yield of adopters was 4.3mt/ha against 2.64mt/ha for non-adopters of the rice production technologies in Sagnarigu district.

Comparing the characteristics of the respondents in the treated (adopters) and untreated (non-adopters) categories, it is observed that in many respects, these respondents are very similar, except labour requirement, rice output and fertilizer use, which obviously are significantly higher for the adopters than non-adopters. The result is also seen in the quantity of rice realized per unit area. But purely based on the observable demographics of the respondents, one could conclude that the respondents are not very much different.

Technology Adoption Levels
The eight rice cultivation technologies recommended by JICA were: Gbewa rice (Jasmine 85) seed; bund construction; harrowing; farrowing; drilling; recommended plant spacing (20cm x 30cm); seed selection by soaking; and recommended fertilizer application rate (NPK: 200kg/ha; Nitrogen Sulphate: 170kg/ha). The adoption of the individual technologies is shown in Table 2. Fertilizer application (NPK: 200kg/ha and Nitrogen Sulphate: 170kg/ha) with a percentage of 73.33% recorded the highest level of adoption followed by drilling (54.17%) and the lowest was seed selection by soaking (44.17%).

Table 2: Adoption of individual Rice Production Technologies by Respondents

Technology	Adopters		Non –adopters	
	Frequency	%	Frequency	%
Fertilizer application (NPK: 80kg/ha Sulphate of Ammonia: 50kg/ha)	88	73.33	32	26.67
Drilling	65	54.17	55	45.83
Use of Jasmine 85 seed	63	52.50	57	47.50
Bund construction	62	51.67	58	48.33
Harrowing	61	50.83	59	49.17
Farrowing	60	50.00	60	50.00
Planting space (20*30cm)	60	50.00	60	50.00
Seed selection (soaking)	53	44.17	67	55.83

The Determinants of Adoption of Rice Production Technologies
As part of the PSM method in measuring the effects of JICA rice technology adoption on output, an attempt was made to study the factors that determine this adoption process. The results in Table 3 indicate that the model was good in fitting the data under discussion. The likelihood ratio chi-square test indicates that at least some (6 out of 11) of the selected explanatory variables for determining adoption contributes to the model. The Pseudo R-squared value of 62.72% indicates a moderate fit of the model in which about 63% of variation in adoption is explained by the associated covariates.
The results highlight that 6 out of the 11 variables significantly influence adoption. More specifically, farmer group membership significantly exerts a positive influence on adoption of the JICA rice technologies in the Sagnarigu district. Farmers who are members of farmer based organizations have probabilities of 0.474 of adopting the technologies compared to non-members. Thus, belonging to farmer associations has greater likelihood of adoption, and this confirms the findings by Abdallah *et al.* (2013), who established that group membership had positive influence on technology adoption. FBOs provide one of the main avenues of social capital where farmers get the opportunities to gain mutual support, knowledge and skills from colleagues and other actors in the agricultural value chain. Social capital formation is an important means of sharing information and also improving productivity. Membership to an FBO is also a

guarantee for assessing most microfinance in recent times. Against the backdrop that farmers generally lack collaterals with which to borrow, financial institutions have resorted to lending to them and using their group membership as guarantee for one another. However, this finding contradicts the work of Martey et al. (2012) that group membership reduces technology adoption.

In addition, access to fertilizer subsidy has positive and significant influence (at 10% significant level) on adoption of the JICA rice technologies in the Sagnarigu district. Thus farmers who had access to

fertilizer subsidy had a 0.254 higher probability of adopting the improved seed. High price of fertilizer affects the purchasing power of farmers, thereby reducing the quantity of fertilizer bought by farmers. The fertilizer subsidy programme enables farmers to buy enough quantity of the fertilizer and apply the right quantity on their rice farms but not every farmer necessarily has access to this. Generally a farmer's access would depend on his/her socioeconomic circumstances such as being an opinion leader or have some form of formal education.

Table 3: Logit estimates of the determinants of JICA rice technology adoption

Variables	Marginal Effect	Standard Error	p- value
Farmer group membership	0.474***	0.130	0.000
Access to fertilizer subsidy	0.254*	0.154	0.101
Access to extension	-0.725**	0.300	0.016
Labour used	0.009	0.017	0.605
Use of improved seed	-0.826***	0.255	0.001
Household size	-0.027**	0.014	0.049
Access to credit	0.041	0.313	0.896
Age	0.002	0.007	0.956
Education	-0.007	0.020	0.717
Farm size	-0.237*	0.132	0.073
Farming experience	-0.016	0.014	0.274

Wald chi-square (11) = 32.2, Prob>Chi-square = 0.0007
Pseudo R-squared = 62.72%, Count R-squared = 90.83%

*, *** and*** represent 10%, 5% and 1% significant levels respectively.

Agricultural extension service is widely known in literature as an important determinant of adoption of improved production technologies (Feder *et al*., 1985). It is the means by which information on better and new production technologies can be disseminated to farmers. More importantly, it also serves as the major link by which research on new ways of farming and other crop cultivation practices get to the farmers. However, in this present study farmers who had access to agricultural extension services rather had a smaller probability (-0.725) of adopting JICA rich technologies, compared with their non-adopting counterparts. This result is in sharp contrast with the findings by Donkoh and Awuni (2011), Ransom et al. (2003) and Doss and Morris (2001), who established that agricultural extension significantly influenced the adoption of improved agricultural technology and practices. Even though the result does not meet our *a priori*

expectations, it is not implausible, since the effect of extension on adoption is technology specific. Depending on the expertise and specialization of the farmer, some technologies might not necessarily need education from extension agents for adoption to take place.

Similarly, farmers who adopted the JICA rice production technologies were given training prior to adoption of the technologies and agricultural extension service work was only a follow-up to remind farmers of the need to apply the technologies to achieve the desired yield. The findings is consistent with the work by Abdallah et al. (2013) who reported a negative influence of agricultural extension services on the adoption of soil and water conservation techniques in Ghana. Similarly, the use of improved varieties had a significant negative effect (p < 0.01). Improved seeds have the potential to improve productivity and

increase output. Therefore, farmers who were already used to planting other improved seeds found it not quite necessary to adopt the JICA technologies compared with those who planted traditional varieties. Farmers who used traditional varieties had 0.83 probability of adopting the technologies. The results also indicate that farmers with larger farm lands and bigger households were less likely to adopt the rice technologies. The effects of farm size on the probability of technology adoption are mixed in the literature; while some studies (Feder et al., 1985; Ayoade, 2012) establish a positive marginal effect, others have found negative effects (Bruce et al., 2014; Donkoh and Awuni, 2011). The former group argues that a large farm size means that the farmer does not only have the means to adopt the technologies, he/she can allocate part of his/her plot to the new technology (Feder et al., 1985; Ayoade, 2012). On the other hand, the latter group argues that the adoption of some technologies, especially SWC technologies is quite laborious and so it cannot be done on a large scale (Bruce et al., 2014; Donkoh and Awuni, 2011). The findings of this present study are consistent with this latter view. It was based on the argument that the adoption of SWC technologies is laborious that we thought that in our study the

labour variable would exert a positive influence on the probability of adoption. The contrary was however the case.

Effect of Technology Adoption on Rice Output
The logit model was first used to estimate the propensity scores for matching farmers who are characteristically similar in both the treated and untreated groups before the real effect of rice technology adoption was calculated. It is always important to verify the performance of PSM in eliminating differences in observed characteristics between adopters and non-adopters. This can be verified by checking the common support condition. In the estimation, the common support condition is imposed by matching in the region of common support. This ensures proper matching of treated and untreated observations. To inspect whether the common support condition is met in estimating the counterfactual, we check the presence of adequate overlap between adopters and non-adopters. The histogram in figure 3 demonstrates graphically the distribution of propensity scores for adopters and non-adopters after matching. There is moderately a balanced match in the common support for the entire sample for adopters and non-adopters, suggesting adequate overlap. This shows that
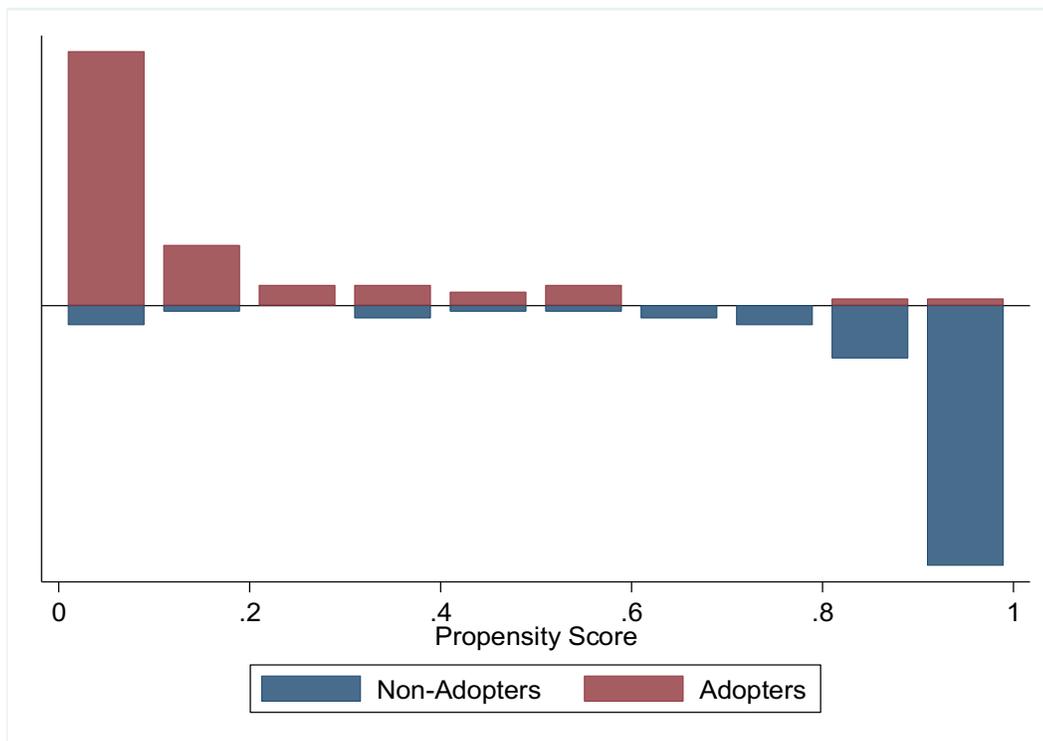
matching has generated counterfactual samples of adopters that are statistically similar to non-adopters in the sample

Figure 3: Propensity score distribution of adopters and non-adopters in the sample

The estimated ATE, ATT and ATC for the three estimation methods are presented in table 4 below. In this study, the most important parameter of interest is the ATE, which measures the average effect of rice technology adoption across the entire sample (adopters and non-adopters). Across all the estimation techniques, the estimated ATE values indicate that JICA rice technology adoption has significant and positive effect on rice output. The ATE of the adoption of the improved rice cultivation techniques led to an increase in rice output that ranges between 649kg to 693kg among rice farmers in the study area. Given the average rice yield per hectare of 3.44mt/ha in the sample, it means that on the average, those who adopted the JICA rice technologies increased output ranging from 47 to 50% , which is very significant.

Table 4: The effect of adoption of cultivation technologies on rice output

	Kernel-based matching		Nearest matching		neighbor Regression adjustments	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
ATE	648.96***	241.0	693.20***	167.9	665.16***	169.4
ATT	674.87***	233.9	717.79***	177.7	585.00***	172.3
ATC	623.04***	277.8	668.60***	184.5	-	-

*** indicates significance at 1%

Similarly, there was a significant increase in rice output by a range of 585 - 718kg for those farmers who adopted (ATT) the rice production technologies within the Sagnarigu district. The average treatment effect of the control (ATC) was equally statistically significant (p < 0.01), which implies that future programmes of this nature are likely to help improve rice output, and hence productivity in the district. So if the programme implementers aim to improve rice output through the use of the technologies, it will be beneficial to carry out all processes that could foster the adoption of these technologies.

Conclusion and recommendations
The adoption of the rice production technologies by farmers in the Sagnarigu district under the JICA programme led to a significant improvement in rice output. On the average, rice output in the district improved by a margin of 47 – 50%. The rice technologies introduced by JICA have the potential to increase productivity, and for that matter, rice output in the district, if interventions are designed to increase adoption. The adoption of JICA rice production technologies is most likely to increase if farmers are supported with fertilizer subsidy and also if they are made to form farmer based organisations. This means that among others, the fertilizer subsidization programme should be re-

introduced if the adoption of rice production technologies is to increase.

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