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THE EFFECT OF ADOPTION OF IMPROVED VARIETIES ON RICE PRODUCTIVITY IN THE NORTHERN REGION OF GHANA

Clement Y. LAMPTEY [1, 5], *Nashiru SULEMANA* [1], *Samuel A. DONKOH* [2], *Abraham ZAKARIA* * [6], *Shaibu Baanni AZUMAH* [3, 4]

Address:
[1] Department of Agricultural Innovation Communication, University for Development Studies, P. O. Box TL 1350. Tamale, Ghana. Phone: +233-243438678
[2] School of Applied Economics and Management Sciences, University for Development Studies, P. O. Box TL 1350. Tamale, Ghana. Phone: +233-504646915
[3] Asdev Consult. P. O. Box TL 407. Tamale, Ghana. Phone: +233 24 780 6330.
[4] DAAD climapAfrica Postdoctoral fellow. University for Development Studies, P. O. Box TL 1350. Tamale, Ghana. Phone: +233 24 780 6330.
[5] Bagabaga College of Education, P. O. Box ER 35, Tamale
[6] Department of Agricultural and Food Economics, University for Development Studies, P. O. Box TL 1882. Tamale, Ghana. Phone: +233-248609294
* Corresponding author: zackabram@yahoo.com

ABSTRACT

Research background: Adoption of improved rice varieties remain paramount in fighting food and nutrition insecurity across sub-Sahara Africa (SSA). A lot has been done in the space of the adoption of agricultural innovations and food and nutrition insecurity. However, studies on the drivers of improved rice variety adoption and its effect on rice output, considering time and location-specific factors, are limited.
Purpose of the article: This study estimated and examined the drivers and effect of improved rice variety adoption on rice output in the northern region of Ghana.
Methods: A multistage sampling technique was employed to select 404 rice farm households in the northern region of Ghana. Propensity Score Matching (PSM) approach was used to analyse the data.
Findings, Value added & Novelty: This study provides literature on drivers of improved rice variety adoption and its effect on rice output, by jointly considering time and location-specific factors. The empirical results revealed that adoption of improved rice varieties has significant positive effect on rice output of farm households. This could translate into reducing food and nutrition insecurity and the importation of rice into Ghana. Similarly, improved rice varieties adoption is positively and significantly affected by family labour, membership in FBO, farmers' perception of rainfall, awareness of government rice policy, telephone ownership, and closeness to input markets. However, the adoption of improved rice varieties bears a significant negative relationship with the age of a farmer and mechanization. To enhance rice productivity and food security outcomes, the study recommends that the development of enhanced rice varieties responsive to current climatic situation. Dissemination and promotion of the varieties should be given priority among stakeholders in the rice value chain. Farmers should be encouraged to join or form farmer-based organisations (FBOs) and support their farm work with family labour to minimize rice production costs due to external payments. Access to market by farmers should be enhanced by improving rural road networks, especially in the rural areas where rice production takes place. Government policy towards rice production should be well designed and communicated to rice farmers since awareness of government rice policy stimulates improved rice varieties adoption among rice farmers.

Keywords: adoption; improved rice varieties; propensity score matching; logit; Northern Ghana
JEL Codes: R52; R58; H41

INTRODUCTION

The significance of rice for achieving food security and poverty reduction in the world has been acknowledged **(Belayneh & Tekle, 2017)**. The food crop commodity is the second to maize in the area of production and productivity in West Africa, including Ghana **(MoFA, 2016).** The adoption of green agricultural technologies in the rice sector is necessary for the transformation of food systems and economic growth **(Webb & Block, 2012; Dzanku *et al.*, 2020**). However, the adoption of green agricultural technologies in the rice sector in Ghana faces a lot of challenges, resulting in low adoption and rice output. In Northern Ghana, where the food crop contributes substantially to food systems and socio-economic transformation, the rice productivity is found to be below the national average **(Azumah, 2019; MoFA, 2020).** Among the reasons for low rice productivity is the low uptake and utilization of enhanced rice varieties (**Ragasa *et al.*, 2013)**. Therefore, there is the need to update the status of improved rice varieties adoption and its contribution to rice output towards achieving food security and reducing poverty in rural Ghana. Hence, there is a need for this study.

Demand for rice is increasing as a result of rapid growth in population and changes in diet patterns. More than 90 percent of rice produced in the world is from South and East Asia with China being the leading producing country. For instance, about 501,201 thousand metric tons of rice produced globally in 2020/2021 is from South and East Asia. In Africa, 19,613 thousand metric tons of rice were produced in the 2020/2021 cropping season **(FAO, 2021)**. That is, Africa contributes approximately 4 percent to the global rice basket, meaning that Africa contributes abysmally to the world rice market. The reason is that there are poor marketing opportunities for rice producers in Africa, which leads to poor adoption decisions of improved rice varieties coupled with other agronomic practices among farm households. This makes Africa the net importer of rice from developed countries. High importation of rice to Africa increases governments' debt stock, which slows down economic growth and socio-economic transformation in the rural economy. There is therefore the need to boost rice production in Africa, particularly Ghana, to minimize rice importation through the adoption of improved rice production varieties.

The agricultural sector in Ghana is one of the pillars for sustainable economic growth and development. The sector has benefited from several interventions, particularly in the rice sector, to improve productivity, reduce poverty, and increase the incomes of farm households **(Ragasa *et al.*, 2013; GRA, 2020)**. Rice farm households in Ghana have been introduced to enhanced rice varieties in addition to other agronomic practices **(Langyintuo & Dogbe, 2005; Martey *et al.*, 2013)**. The aim of promoting green technologies such as high-yielding rice varieties is to increase rice production to meet domestic demand and also create market opportunities for farm households and other rice value chain actors. Increasing rice production and market opportunities have a positive impact on sustainable job creation in rural areas. However, rice production in Ghana is dominated by smallholder farmers who still largely depend on traditional rice varieties and agronomic practices for rice production. Smallholder farmers also depend on rainfall for rice production. These adversely affect rice production and productivity, which therefore lowers market opportunities for all rice value chain actors. In support of Ghana's dedication to enhance and sustain agricultural productivity, food security and facilitate the growth of the agricultural sector, the government of Ghana, has partnered with non-profit making organizations in promoting and disseminating improved rice varieties to farm households in order to enhance rice production and productivity **(McNamara *et al.*, 2014)**. The improved rice varieties disseminated to farm households in Ghana, particularly in northern Ghana, include Jasmine, AGRA, TOX, GR-18, Nerica, Mande, Digan, Afife, among others. Despite the dissemination of these improved rice varieties to farm households, rice farmers are still operating at low levels of productivity **(Langyintuo & Dogbe, 2005)** due to poor observation and usage of green revolution farming methods and technologies **(Azumah, 2019).** Rice projects mostly introduce improved rice varieties to farm households with high access to farm inputs and market opportunities. With these incentives, when improved rice variety is first released to farm households through a project, the adoption rate is high. When the rice projects end, rice farm households cease to have access to farm inputs and markets as well as other incentives. This leads to poor adoption and/or dis-adoption of improved rice varieties **(Lamptey, 2018)**. Most studies investigate the adoption of improved rice production technologies status when the projects are still ongoing or immediately the end of the project **(Lamptey, 2018; Obayelu, Dontsop, & Adeoti, 2016)**. This research sought to analyze the determinants of improved rice varieties adoption coupled with its contribution to rice output among farm households in the northern region of Ghana, by considering rice projects which have ended for over five years. The outcomes of this study would give policy directions to policymakers, along the rice value chain, to enhance rice productivity and incomes. The subsequent sections of this paper are organized into the literature review, methodologies, data collection and analysis, results and discussions, as well as conclusions and policy recommendations.

LITERATURE REVIEW

The term *adoption* refers to the full acceptance, use, and continuous use of a new idea or technology to enhance productivity **(Doss, 2006; Rogers, 2005).** It can also be defined as a unified, unique, and general phenomenon that is multifaceted with many inputs, actors, and consequences to improve productivity**.** In this study, adoption is considered as the degree of a rice farm household's usage of improved rice varieties, techniques, or phenomena to increase rice production and output. Farm households are inclined to adopt innovations that have positive effects on their rice production, income, and welfare as well as access to farm inputs and markets. Non-adoption of improved rice varieties among farm households is high when farmers have inadequate opportunities to access farm inputs and markets. Non-adoption of improved rice varieties can also occur when farmers feel that their traditional rice varieties perform better than the improved rice varieties.

Many studies have been conducted in the space of rice production technologies adoption and its impact on productivity (**Uaiene *et al.*, 2009; Muzari *et al.*, 2012; Bruce *et al.*, 2014; Wiredu *et al.*, 2014, 2010; Kasirye, 2013; Zakaria *et al.*, 2016; Abdulai *et al.*, 2018).** For instance, **Muzari *et al*. (2012)** reviewed studies on the impacts of innovation adoption among small-scale farmers in SSA. The authors' findings showed that adoption did not result in higher income of farmers as a result of land degradation, higher costs of fertilizers, production credit constraints, among others. However, **Kasirye (2013)** conducted a study on the bottlenecks to enhanced agricultural innovation usage in Uganda. The study found that the adoption of agricultural innovations has led to higher income and reduction of poverty among farm households. Similarly, the study revealed that adoption of enhanced agricultural innovations increased nutritional outcomes, reduced prices of consumable foods, and promoted job opportunities for rural Uganda. In Southern Ethiopia, assessing the adoption of numerous sustainable agricultural mechanisms and their effects on farm household earning was conducted by **Mohammed *et al.* (2015)**. The study demonstrated that the adoption of multiple sustainable agricultural mechanisms enhanced farm household income status. However, the study further revealed that multiple adoptions of sustainable agricultural mechanisms among farm household increases the cost of production but is relatively low for farm households whose selectively combined alternative mechanisms. In addition, the benefits of modern rice production innovations in smallholder farms have been well examined in Nigeria. It was found that about 98.6% and 91.5% of the smallholders achieved higher rice output and acquired new rice production skills respectively, due to the adoption of improved rice production technologies. It was also reported about 85.5% increase in rice income among rice farmers **(Adisa *et al.*, 2019)**. This demonstrates that the adoption of enhanced rice production technologies contributes positively to households' welfare and food security.

In Ghana, **Azumah *et al.* (2017**) studied the productivity effect of an innovation called urea deep placement among irrigation rice growers. The study found that the use of the urea deep placement enhanced rice yield, which would create jobs for rural dwellers. **Bruce *et al.* (2014)** likewise investigated the drivers and effects of enhanced rice variety adoption on rice output among rural farm households in Ghana. The study discovered that the use of improved rice varieties had a positive effect on rice farmers' output. The effect of NERICA rice variety adoption in Ghana was investigated by **Wiredu *et al.* (2014)**. The NERICA usage greatly enhanced rice income, farm incomes, per-capita income, and total annual incomes among rice farm households. The study recommended that there is a need to intensify NERICA promotion by creating farmers access to the improved rice seed. It also means efforts need to be made to provide markets and road infrastructure to facilitate rice farmers' access to farm resources and market outlets as well as services of extension agents.

The discussions above show that there have been several studies on the effects of adopting improved rice production technologies, to unlock rice production potential. However, these studies could not assess the adoption and effects of improved rice varieties on rice output using rice varieties that have been released to farmers over ten years (between 2009-2019 period). Against this backdrop, the study aimed at examining the determinants of improved rice varieties adoption and its effect on rice output in the northern region of Ghana. This study will add to the existing literature on the effects of the adoption of improved rice varieties and guide policymakers along the rice value chain to enhance rice production.

DATA AND METHODS

Profile of the study area

This study was conducted in the northern region of Ghana. The regional capital is located in the Tamale metropolis. The region is one of the largest regions in Ghana, covering an area of 70,384 square kilometers. The Northern Region is bounded to the North East Region to the north, Ghana-Togo international border to the east, the Oti Region to the south, and the Savannah Region to the west. The Savannah Agricultural Research Institute (SARI) is located in the region. SARI is among the thirteen research stations of the Council for Scientific and Industrial Research (CSIR) of this country. SARI is responsible for breeding improved rice and other crop varieties and disseminating them to farmers for adoption in other to enhance agricultural production in the northern part of Ghana.

The region is among the top first five regions massively into rice production in the country. Yet rice productivity is still below achievable yield due to poor adoption coupled with poor soil conditions, climate change, and high dependence on rain-fed farming **(Azumah, 2019; MoFA, 2016).** The wet season commences partly in April and augments from August to September but gradually secedes between October and November. The average annual precipitation stands between 750mm and 1050 mm, which is about 30 or 40 inches. Average temperatures are between 14 °C (59 °F) and 40 °C (104 °F) at night and day respectively. This is usually associated with a shorter wet season and less precipitation with a corresponding longer dry season and hot weather, which is unfriendly to rain-fed agriculture.

Sampling procedure, sample size, and data collection

Several sampling methods were employed to select the respondents from farming communities in the Northern Region of Ghana. The study area was purposively selected for this study because it is one of the leading rice-growing regions in the country. The region has a good environment that is favourable for rice production. The region alone contributed about 37% of rice output to the national food basket **(MoFA, 2020)**. A simple random sampling strategy, based on the lottery method, was employed to choose four districts in the region. The selected districts include Tolon, Kumbungu, Savelugu, and Nanton. Similarly, the simple random procedure by lottery method was also used to choose the rice-producing communities for the study. The selected rice-growing communities and their respective sample sizes were as follows: Nyankpala (29), Tingoli (29), Tolon (29) and Woribogu (29) in the Tolon District; and Botanga (28), Gbullung (28), Kpachi (28) and Kumbungu (28) in the Kumbungu District. The rest were Libga (30), Diare (30), Nabogu (30), and Savelugu (30) in the Savelugu Municipality while Nyamadu (31) and Nanton (31) were in the Nanton District. The sample size per selected community was derived from a sample frame obtained from the Northern Regional Directorate of MoFA, to form the total sample of 410 rice farmers for this study.

Scientifically, **Smith's (2019)** sample size formula was used to compute the sample size for this research. The formula involves a constant value of 95% confidence level, corresponding to a Z-score of 1.96, to determine the sample size, as shown in Equation 1.

$$Sample\ size\ (n) = (Z - score)^2 * Std\ Dev.* \frac{(1-Std.Dev.)}{(margin\ of\ error)^2} \quad (1)$$

Following Equation (1), the sample size computed for the study was 385 rice farmers. The study then adjusted the sample size to 410 to make room for lapses that might arise in the data collection and transmission process. After data cleaning, 404 questionnaires were found to be consistent and reliable for the analysis. Thus, primary data was mainly gathered using semi-structured questionnaires. The data was collected by 10 trained research assistants (graduates). They were all fluent both in the English language and the local dialects of the participating communities/districts. The data was collected between December 2019 and February 2020.

Analytical Framework: Propensity Score Matching Model

This study aims at examining the effect and determinants of improved rice varieties adoption on rice output in the northern region of Ghana. Since adoption is endogenously determined, examining the effect of improved rice varieties on rice output without addressing selectivity bias would give inconsistent and biased estimates which will lead to wrong policy recommendations. To remedy selectivity biases in data, we opted for the Propensity Score Matching **(**PSM) approach **(Rosenbaum & Rubin, 1983)**. Several stages followed to have robust estimates for the study. As part of the PSM approach, Logistic regression (logit) was first employed to examine the socioeconomic factors affecting improved rice varieties adoption among farm households. In the second step, a histogram was used to check for overlaps and common supports in the propensity score distribution. The third step was carried out to test the propensity score of the variables in the model. The fourth step was an overall quality test of factors before and after matching, while the final step estimated the effect of improved rice varieties adoption on rice output among farmers, using the average treatment effect model.

Propensity Score Matching and average treatment effect models

The PSM approach was first employed by **Rosenbaum & Rubin (1983)** as an econometric model to assess the effects of innovation on socio-economic outcomes. This method handles selectivity bias. This is because the selection of participants into programmes is often non-random and subject to sample selection bias.

PSM is used to analyse quasi-experimental data, to balance two non-equivalent groups on observable features, to get reliable estimates for the effect of improved rice varieties adoption for two groups **(Luellen *et al.*, 2005)**. The purpose of the analysis is to remove or at least reduce sample selection bias because a treated group (adopters) and a control group (non-adopters) in rice dissemination technologies projects are often different without any treatment. With the help of PSM, the selection bias can be removed, which would assist in actually estimating the actual impact of improved rice varieties adoption on rice output for adopters, which can be ascribed to the projects promoting improved rice production in the study area **(Caliendo & Kopeinig, 2008)**.

Against this backdrop, the study employed PSM to form a group for comparisons depending on the likelihood model of adoption or non-adoption of improved rice varieties. Farm households who adopted the improved rice varieties are compared with non-adopters based on chance (propensity scores). The real effect of improved rice varieties adoption is computed as the average difference in rice output per hectare of the adopters and non-adopters. This was achieved after comparing the individuals with similar features for both adopters and non-adopters.

For the empirical estimation, the binary choice logistic regression was first employed to estimate the propensity score of every farm household-head as the tendency to adopt improved rice varieties. Propensity scores were estimated with farm households and farm features using adoption as a dependent variable (**Deschamps & Jean, 2013; Djido *et al.*, 2013)**. The propensity score (PS) model of adoption is represented mathematically with Y as the likelihood of a farm household adopting at least one or more improved rice varieties and X as the set of covariates, which influence adoption decision (Equation 2).

$$PS = P_r\left(\frac{1}{X}\right) = (b_0X_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + \cdots b_{15}X_{15} + \mu) > 0 \quad (2)$$

Where: Xs are socioeconomic variables expecting to be influencing rice farmers' adoption of improved technologies, bs are the logistic coefficients to be estimated and μ denotes the random white noise capturing measurement errors and unobservable factors influencing adoption.

The essence of PSM is to help compare the observed outputs of improved rice variety adopters and non-adopters depending on the predicted chance of adopting at least one variety **(Wooldridge, 2005; Heckman *et al.*, 1998)**. The Average Treatment Effect (ATE) for adoption on rice output is then estimated in consonance with the propensity scores determined with the logit model. The ATE is the average difference in rice output between adopters, which is represented by $[Y(1)]$ and non-adopters, represented by$[\ Y(0)]$. The model for estimation of the ATE is symbolically denoted by Equation (3).

$$ATE = E[Y(1) - Y(0)] = E[Y(1)] - E[Y(0)] \quad (3)$$

The ATE model seeks to compare the rice output of farm households who continue to use at least one improved rice variety, with the output of non-adopters. It serves as a control for farm households with similar noticeable features and partial control for non-random selection of members in the adoption of improved rice varieties. The ATE output is interpreted as the effect of the improved rice variety adoption on rice output. An average treatment effect on the treated (ATT) is likewise estimated, besides the ATE. The ATT model is used to measure the effect of adoption on the output of only actual adopters of the improved rice varieties, and not those of potential adopters, non-adopters, initial adopters, or dis-adopters. The ATT can be computed as Equation (4).

$$ATT = E\left|Y(1)\frac{Y(0)}{D} = 1\right| E\frac{[Y(1)]}{D} = 1\; E\left|\frac{Y(0)}{D} = 1\right| \quad (4)$$

Where: E is a dummy variable or indicator for treatment (D = 1 for adopters, 0 for non-adopters). The average treatment effect on the untreated or control categories (ATC) is estimated to measure the effect of adoption on output for non-adopters of the improved rice varieties. The model for this parameter is measured by Equation (5).

$$ATC = E\left|Y(1)\frac{Y(0)}{D} = 0\right| E\left|\frac{Y(1)}{D} = 0\right|\; E\left|\frac{Y(0)}{D} = 0\right| \quad (5)$$

Previous empirical studies that used the PSM model have shown and emphasized that the outcomes are based essentially on precision and approaches employed for the matching **(Imbens, 2004; Caliendo & Kopeinig, 2008)**. This study employed different specifications and matching approaches to check for robustness in its empirical work. The matching strategies mainly employed in PSM methods include the Kernel-Based Matching (KBM) and the Nearest Neighbour Matching (NNM). Results of the Regression Adjustment Method (RAM) were thus included in this work to compare three different estimation methods, to check for sensitivity.

Definition and measurement of variables and their a-priori expectations

Table 1 illustrates the variable description, measurement of variables, and a-priori expectations. The expected effects of each variable on adoption are also presented in Table 1.

RESULTS AND DISCUSSIONS

Descriptive Statistics of Selected Variables

The results of socio-demographic factors of the rice farm households are presented in Table 2. The study found that about 46% of the rice farm households continued to use the improved rice varieties in the study area. This implies that the majority of rice farmers are not using the improved rice varieties. That could lead to low rice production and productivity, which could worsen food insecurity and poverty among rice farm households.

Table 1: Definition of variables, measurements, and their *a-priori* expectations

Variables	Definitions	Measurements	A-priori expectations
Adoption	If a farmer ever adopted improved rice variety and continues using it.	Dummy: (1) Yes (0) No	N/A
Rice output	Amount of rice harvested per hectare	Kg	N/A
Age	Age of a rice farmer.	Years	+/-
Gender	Sex of a rice farmer.	Dummy: (1) Male (0) Female	+/-
Education	The number of years a farmer attended formal school.	Years	+
Family labour	The total number of family labour used in rice production.	Number	+/-
Electricity	A rice farmer household has access to electricity.	Dummy: (1) Yes (0) No	+/-
FBOs	A rice farmer belongs to the rice farmers' association.	Dummy: (1) Yes (0) No	+
Mobile phone	Rice farmer has his/her phone for communication.	Dummy: (1) Yes (0) No	+
Input market	A rice farmer has access to the input market in the community.	Dummy: (1) Yes (0) No	+
Credit	A rice farmer has access to a production credit.	Dummy: (1) Yes (0)No	+
Extension service	A rice farmer had access to an extension advisory service in the 2019/2020 cropping calendar	Dummy: (1) Yes (0)No	+
Farm area	Rice farm plot area of a farmer.	Hectare	+/-
Rice policy	A rice farmer is aware of any government rice policy in Ghana.	Dummy: (1) Yes (0)No	+
Field Demo	A rice farmer ever participated in a rice production field demonstration	Dummy: (1) Yes (0) No	+
Mechanization	Farmer has access to tractor service and used it for ploughing rice fields.	Dummy: (1) Yes (0)No	+
Rainfall perception	A rice farmer's perception of rainfall pattern.	Dummy: (1) decreased (0) increased	+

The reasons for non-adoption of improved rice varieties include (1) poor access to farm inputs and output market; (2) pests and diseases; (3) lack of access to production credit; (4) taste and aroma of rice varieties; and (4) high demand of labour for adopting rice varieties and its agronomic practices after the end of the rice projects. One of the respondents said: "I wanted to cultivate Jasmine rice variety when it first came to our community. However, I realized that it is less resistant to pests and diseases. These made me not to plant the variety and maintained my local rice varieties".

Another rice farmer argued: "When non-governmental organizations and Ministry of Agriculture are coming to implement improved rice variety adoption projects, the projects come with access to farm inputs and ready markets for outputs. When the projects end, it is difficult for us to access farm inputs and markets for our paddy rice. These discourage us from continuing to use improved rice varieties when the projects end". This confirms the fact that rejection of innovation is possible at any stage of the adoption process (**Rogers, 2003**). The average yield of a rice farmer was found to be 1438.9kg/hectare (1.44mt/ha), equivalent to 14.4 maxi bags (100kg each) of rice per hectare in the study area. This was far below the national average rice yield of 2.96mt/ha reported by MoFA (2019). The low yield could be attributed to poor adoption of rice production technologies among farmers.

Table 2: Descriptive statistics of variables

Variable	Mean	Std. Dev.
Adoption/non-adoption	0.46	0.50
Rice output	1438.90	1775.55
Age	39.69	10.65
Gender	0.90	0.30
Education	0.29	0.46
Electricity	0.80	0.40
Family labour	5.63	8.80
FBOs	0.47	0.50
Mobile phone	0.25	0.43
Field demo	0.62	0.49
Input market	0.85	0.36
Production credit	0.35	0.48
Extension service	0.80	0.40
Farm plot area	1.55	1.53
Government policy	0.87	0.34
Mechanization	0.78	0.41
Rainfall perception	0.92	0.28

Source: Survey Data, 2020: 1bag = 86 kg (MoFA conversion chart)

In addition, the mean age of a rice farmer was approximately 40 years with a corresponding mean formal education being 3 years. This means the rice farmers were predominantly in their youthful years with little education, which could translate into real adoption/usage of improved rice varieties. Meanwhile, formal education among rice farmers was still low, which resulted in the non-adoption of rice production technologies. **Martey *et al.* (2013)** revealed that farmers with formal educational backgrounds are more prone to the adoption of improved agricultural technologies since they tend to co-operate favourably with other farmers' development organizations. The family labour and mean farm size of the rice farmers were approximately 6 people and 0.65 ha respectively. The little higher use of family labour means that rice farmers can rely on family labour to reduce the cost of production when adopting new rice varieties. The low average rice farm size (1.55 hectare) of the farmers confirmed **MoFA (2016)** findings that about 90% of smallholders cultivate less than 2 Ha in Ghana. The study further revealed that about 90% of the respondents were males, meaning that rice is predominantly produced by men in Northern Ghana. The low percentage of female farmers in this study corroborates **Martey *et al.* (2013)** who asserted that females were normally occupied with domestic activities such that they did not have enough time to participate in Rice Development Projects (RDP) compared to their male counterparts. Rice farmers' awareness of government policy about rice production plays a critical role in technology adoption to enhance rice production and productivity. The study demonstrated that about 87% of rice farmers were aware of government policy for the rice sector. This will influence farmers positively, especially the youth, to make rice production a business instead of conventional farming. Also, about 62%, 85%, 80%, and 35% of rice farmers had access to field demonstration, input market, extension services, and production credit respectively. These imply that rice farmers' ability to access agricultural extension services, farm inputs, and participation in rice field demonstrations were high but they had less access to production capital. About 92% of rice farmers perceived a decrease in the rainfall pattern for the past ten years, 75% had access to a good road network, 47% belonged to FBOs, 25% owned mobile phones, and 78% practiced mechanization (used tractor for land ploughing).

Factors affecting improved rice variety adoption

This section discusses socio-demographic factors which influence farm households' decision to adopt improved rice varieties. The results are presented in Table 3. Although the Pseudo R-Squared value was low at 0.1840, the Chi^2 test statistic value (101.38) was highly significant at the 1% level. This is an indication that the logit model (PSM approach) was best fit for the estimation. Eight (8) out of the 15 explanatory variables were significantly influencing farm households' adoption decision of improved rice varieties in the study area. These include age, family labour, membership to FBOs, input market, mobile phone, rainfall perception, mechanization, and government rice policy.

The study found that age had an inverse relationship with improved rice variety adoption, which was averagely significant at a 5% level. The inverse relationship of age to adoption meant that younger rice farm households had a higher propensity to adopt improved rice varieties than older farmers. This is plausible since younger farmers tend to be more innovative than their older counterparts (Rogers, 2005). Older farmers are more risk-averse, sceptical, and conservative when it comes to adopting innovations. These could make older rice farmers not innovative to adopt improved rice varieties, especially when they are not yet tested or tried improved rice varieties. Older farmers may also fail to adopt improved agricultural technologies based on their experience. This finding corroborates **Martey *et al.* (2013)** and **Ragasa & Chapoto (2017)** on the adoption of agricultural technologies in Ghana. However, it contradicts the finding of **Azumah & Zakaria (2019)** that age had a positive effect on farmers' usage of chemical fertilizers in Ghana.

Family labour had a positive effect on farm household adoption behaviour of improved rice varieties and it was statistically significant at a 10% level. This implies that rice farm households who depend on family labour have a high probability to continue using improved rice varieties than those who depend on hired labour. Labour-intensive technologies stand the risk of being non-adopted by rice farm households who depend on hired labour for their adoption. However, labour-intensive agricultural technologies can easily be adopted by farm households with relatively large family labour. **Ehiakpor *et al.* (2019)** found that farmers who used family labour had a higher tendency of adopting the *Zai* farming innovation method in Ghana than those who did not. Similarly, **Azumah & Zakaria (2019)** found a positive effect of family labour on farmers' participation in fertilizer subsidy programmes in Ghana.

Membership to FBOs in the study had a positive effect on the adoption of improved rice varieties, which was significant at a 5% level. This implies that rice farm householders belonging to rice farmers' associations (FBOs) have a high chance to continue using improved rice production technologies compare to those who do not belong to rice farmers' associations. FBOs strengthen social capital, which encourages farmers to continue the use of modern production technologies. Farm households who do not belong to any farmers' association easily reject improved agricultural technologies since there is nobody to motivate them to use the modern production technologies. However, farm householders who join FBOs, assist each other to adopt green revolution technologies to enhance productivity and income. Adoption of labour-intensive technologies by farm households becomes easier when belonging to farmers' associations. It has been argued that FBOs help in linking farmers to input sources and product markets as well as to important resources like extension advisory services alongside farmer field schools, or field demonstrations **(Zakaria *et al.*, 2020).** This suggests that farm householders will be associating themselves with FBOs which have the potential to stimulate their ability to continue using improved rice production technologies. According to **Ojoko *et al.* (2017),** being a member of farmers' associations in a geographical area influences a farmer's access to agricultural technical inputs and markets. These open an opportunity for farmers to enhance farmer-to-farmer-transfer of agricultural technologies, which is the quick way for technology dissemination.

Furthermore, access to the inputs market yielded a positive effect on the adoption of improved rice varieties and it was highly significant at a 1% level. The positive significance implies that rice farmers with access to input markets like fertilizers, weedicides/pesticides, and improved seeds in the community or nearby community are more likely to continue using improved rice production ideas than other farmers. This can also be interpreted to mean that rice farmers having less access to input markets are quite likely to reject rice production ideas. This is probable since the additional cost of traveling to input markets far from their communities serves as a disincentive to the farmers who would genuinely love to use new rice varieties. As result, poor access to inputs markets by farmers makes them resort to the cultivation of the traditional rice varieties that have low input requirements. Making farm inputs accessible to farmers tends to strengthen sustainable adoption of enhanced farming innovations, especially in cereal food crop production. Since agricultural technology adoption is the cornerstone to combat food insecurity and poverty outcomes, access to farm inputs in farmers' communities or nearby communities is critical.

Ownership of mobile phones assists farm households to access agricultural-related information. Mobile phone ownership was found to have a positive effect on the adoption of improved rice varieties. This was statistically significant at a 1% level in the study. That is, a farm household with a cell phone is very likely to continue the use of improved rice varieties and access agricultural information. It has been argued that mobile phone technology assists farmers to access and uptake improved agricultural technologies **(Chimoita *et al.*, 2017; Azumah, Zakaria, & Boateng, 2020).** Perception of rainfall had a positive and significant effect on the adoption of improved rice varieties at a 1% level. This implies that a perceived decrease in rainfall influences rice farmers to enhance their continued use of improved rice varieties. That means farmers who perceived a decrease in the intensity of rainfall in recent years had a higher probability of adopting and/or continued the use of improved rice varieties than those who thought otherwise. This outcome is supported by **Zakaria *et al.* (2020a)** that perception of decreased rainfall positively influenced farmers' decision to adopt climate-smart mechanisms in Ghana.

Mechanization in the study was found to have a negative effect on the adoption of improved rice varieties, which was significant at a 1% level. This explains that rice farm households who do not have access to tractor services are more likely to reject improved rice varieties. Access to tractor service by farm households assists them to practice large-scale rice farming, which also aids farmers' adoption of improved rice varieties, to enhance productivity. Less access to tractors for rice cultivation will force farmers to continue in small-scale farming and non-adoption of improved rice varieties, which they used to practice. In Pakistan, **Ullah *et al.* (2018)** found mechanization to have a positive effect on the adoption of improved agricultural cultivars. The last variable of interest is rice farmers' awareness of government rice policy, which had a positive significant effect on improved rice variety adoption at a 1% level. This implies that farmers who are aware of government policy about rice production are more likely to adopt and/or continue to use improved rice cultivars. Communication of government policy about rice production to farmers through MoFA and other media will boost their decision to adopt new rice cultivars to enhance rice production and productivity. Lack of farmers' awareness of government policy for rice production is a potential threat to the adoption of rice new cultivars and production. Hence, farmers need to be considered when designing and implementing government policy about the rice sector.

Propensity score test of variables in the model

The propensity score test results of variables in the model, consisting of real adopters (treated) and non-adopters (control) rice farm households, using both the matched and unmatched samples are presented in Table 4. The average age of the real adopters (from the treated households) was about 41 years while those of the non-adopters (from the control households) were found to be 39 years. The age difference between the two households is statistically significant. **Zakaria *et al.* (2019)** also found a significant difference between the average age of farmers from livelihood diversified households (40 years) and those from non-livelihood diversified households (39 years). Similarly, **Dagunga *et al.* (2020)** found that adopters and non-adopters of farming innovations in the Northern Region were younger than their fellow farmers who live within the Upper East of Ghana.

About 89% of the adopters were males while 91% of their non-adopter counterparts were also males, corroborating **Ragasa *et al.* (2013)** and **APS (2015)**. About 76% of the adopters in both the matched and unmatched samples had access to electricity while about 72% and 80% of the non-adopters in the matched and unmatched samples respectively had no access to electricity. Farmers' inability to access electricity hinders their adoption of agricultural innovations. The mean level of education of treated and control farm households were both about 3 years, which was very low and in tandem with **Dagunga *et al.* (2020)** and **Mahama *et al.* (2020)**.

In addition, the results have shown that all farmers in the region over-rely on family labour. About 58% of the adopters in both the matched and unmatched samples belonged to FBOs whereas only 54% and 32% of the non-adopters in the matched and unmatched samples respectively belonged to FBOs. There were therefore statistically significant differences between adopters who belonged to FBOs and their non-adopting counterparts. A good number of both the adopters (44%) and non-adopters (41%) in the region had access to credit. Having access to credit enhances the adoption of agricultural innovations but the results of this study showed that more than 50% of the farmers in the region lacked access to credit, because they were risk-averse.

Most of the adopters (85%) in both the matched and unmatched samples are accessible to extension services. Farmers' ability to obtain extension services facilitates their adoption of farm technologies. However, the non-adoption of improved rice varieties in the northern region of Ghana, despite farmers' greater access to extension services, implied that most of the farmers did not take advantage of extension services at their disposal, to harness their adoption potentials. The results further showed that most of the treated farm households (over 85%) had access to input markets in their communities, with an average farm size of about 2 acres. More adopters (36%) had access to telephones than non-adopters (11%), which may explain the rationale for their adoption decisions. More than half of the adopters (53%) attended field demonstrations. Participation in field demonstrations increases farmers' chances of adopting improved rice varieties promoted by agricultural extension officers. **Dagunga *et al.* (2020)** also found that only 26% of adopters attended field demonstrations. Almost all the farm households (about 98%) in Northern Ghana noticed a decrease in the rainfall pattern in the last ten years. It means both adopters and non-adopters suffered the effects of climate change on their rice farming. Similarly, a large number of the farmers (over 74%) had access to mechanization services, meaning mechanization is a necessity in rice farming compared to maize that can be conveniently cultivated under zero tillage. Finally, over 80% of the farmers were aware of government policies aimed at increasing domestic rice production in Ghana. However, more adopters (91%) than non-adopters (81%) were aware of these policies, meaning more efforts should be made to educate all rice farmers on government policies in aid of boosting rice production and enhancing food security in this country.

Overall quality test of factors before and after matching

Table 5 reports the summary statistics of the overall quality test of factors before and after matching. The mean bias of the unmatched (adopters) and matched (non-adopters) were 108.6 and 55.4 respectively. Both means were significant at 10%, meaning there was selection bias of either adopters or non-adopters of improved rice varieties in the region. The percentage reduction of bias in the sample was 48.98%.

Overlapping and common support in the propensity score distribution

Observed dissimilarities in characteristics between adopters and non-adopters of improved rice seed varieties were checked using the PSM approach. The observed differences between treated (adopters) and untreated (non-adopters) were detected using the common support region. The minima and maxima were used to figure out the validity of the common support region (**Smith & Todd, 2005; Caliendo & Kopeinig, 2005**). The matching distribution of the propensity scores after matching for treated and untreated are shown by the histogram in Figure 1. The lower part of the figure shows the propensity score distribution for the non-adopters, and the upper part represents the adopters. The densities of the scores are on the y-axis. A closer look at the figure reveals that the common support region is a well-balanced match for the entire sample. This signifies adequate overlap between the two groups and implies that the matching has produced counterfactuals that are statistically related to the adopters. The findings are consistent with those of **Zakaria *et al.* (2019), Martey *et al.* (2015),** and **Elias *et al.* (2013).**

Table 3: Maximum likelihood estimation of the factors affecting improved rice variety adoption

Variable	Coef.	Std. Err.	Z	Marginal effect	Std. Err.	Z
Age	-0.013**	0.007	-1.960	-0.005**	0.003	-1.960
Gender	-0.220	0.242	-0.910	-0.083	0.088	-0.940
Electricity	-0.198	0.181	-1.090	-0.076	0.068	-1.110
Education	-0.015	0.016	-0.950	-0.006	0.006	-0.950
Family labour	0.049*	0.029	1.680	0.019*	0.011	1.680
FBOs	0.351**	0.157	2.240	0.135**	0.059	2.270
Credit	-0.099	0.140	-0.710	-0.039	0.054	-0.710
Extension	0.263	0.177	1.480	0.103	0.070	1.470
Input market	0.721***	0.223	3.230	0.282***	0.083	3.390
Farm size	0.039	0.024	0.600	0.015	0.009	1.600
Mobile-phone	0.753***	0.193	3.910	0.270***	0.061	4.450
Field Demo	0.244	0.154	1.580	0.094	0.059	1.590
Perception of rainfall	0.747**	0.323	2.310	0.290***	0.116	2.500
Mechanization	-0.424**	0.180	-2.350	-0.158***	0.063	-2.490
Government rice policy	0.481**	0.204	2.360	0.190**	0.080	2.380
cons	-1.021*	0.571	-1.790			
Model diagnosis						
The number of obs.	404					
LR chi^2 (15)	101.38***					
Prob > chi^2	0.0000					
Log likelihood	-224.86849					
Pseudo R2	0.1840					

* represents 10%, ** represents 5%, and *** represents 1% levels of significance.
Source: Survey data, 2020

Table 4: Propensity score test of variables in the model

Variable	Unmatched(U)	Mean				t-test	
	Matched(M)	Treated	Control	% bias	% red. Bias	T	p>t
Age	U	39.263	40.942	-15.800	42.200	-1.570	0.1160
	M	39.263	40.233	-9.100		-0.990	0.323
Gender	U	0.888	0.919	-10.400	43.800	-1.020	0.309
	M	0.888	0.905	-5.800		-0.610	0.543
Electricity	U	0.763	0.797	-8.100	-15.500	-0.800	0.424
	M	0.763	0.724	9.300		0.960	0.340
Education (years)	U	2.578	2.791	-4.500	-419.800	-0.450	0.652
	M	2.578	1.470	23.400		2.850	0.005
Family labour	U	1.987	1.247	27.900	15.000	2.750	0.006
	M	1.987	1.359	23.700		2.590	0.010
FBOs	U	0.578	0.320	53.500	83.300	5.300	0.000
	M	0.578	0.534	9.000		0.930	0.351
Credit	U	0.444	0.453	-1.900	-669.500	-0.190	0.850.
	M	0.444	0.371	14.700		1.610	0.109
Extension	U	0.853	0.721	32.700	74.000	3.310	0.001
	M	0.853	0.888	-8.500		-1.110	0.269
Input market	U	0.888	0.797	25.200	52.900	2.550	0.011
	M	0.888	0.845	11.900		1.360	0.173
Farm size	U	1.780	1.058	26.400	-149.500	2.680	0.008
	M	1.780	3.582	-65.900		-3.080	0.002
Telephone	U	0.362	0.105	63.700	98.300	6.140	0.000
	M	0.362	0.358	1.1		0.100	0.923
Field Demo	U	0.526	0.320	42.600	89.500	4.210	0.000
	M	0.526	0.504	4.4		0.460	0.643
Rainfall perception	U	0.978	0.890	36.300	95.200	3.800	0.000
	M	0.978	0.983	-1.800		-0.340	0.737
Mechanization	U	0.741	0.843	-25.200	91.500	-2.470	0.014
	M	0.741	0.750	-2.100		-0.210	0.832
Government policy	U	0.909	0.814	27.900	72.900	2.830	0.005
	M	0.909	0.884	7.5		0.910	0.361

Source: Survey data, 2020

The effect of improved rice varieties adoption on rice output

Table 6 presents the estimates of the effect of improved rice varieties adoption on rice output among farm households. All the coefficients for ATT, ATE, and ATC for the estimators employed for examining the effect of adoption of improved rice varieties was statistically significant except nearest-neighbour matching for the average treatment effect on the control (ATC). These imply that future projects for rice production are more likely to enhance rice production and productivity. This is plausible, if the prevailing climatic, environmental, and socio-economic factors hindering adoption are removed or held constant. The propensity score matching was significant at 1% for the average treatment effect (ATE), the average treatment effect on the treated (ATT), and the average treatment effect on the control (ATC). This means that other things being equal, farm households' rice output will increase if they adopt improved rice varieties. It confirms that adopters of improved rice varieties are better off than non-adopters. Specifically, the coefficients for NNM, PSM, IPW, and RA for ATE were approximately 4.2, 7.7, 8.2, and 8.8 respectively, which were significant at different levels. These suggest that adopters of improved rice varieties improved from 4.2 kg/ha to 8.8 kg/ha compared to the non-adopters. This implies that adopters' rice output improved by about 52.3%.

The coefficients for the estimators NNM, PSM, IPW, and RA for ATT include 5.3, 8.4, 7.7, and 8.5 respectively and they were all significant at 1% and 5% levels. The ATT estimates the impact of adopters only. The positive significant coefficients for the ATT imply that the adoption of improved rice varieties led to higher rice output. That is, actual adopters' rice output increased from 5.3 kg/ha to 8.5 kg/ha. The ATC measures potential adopters of improved rice varieties. The coefficients for ATC for PSM and NNM were estimated to be approximately 6.8 and 2.6 respectively. This implies that if the non-adopters had adopted they would have had higher rice output compared to their non-adoption condition.

Table 5: Overall quality test of factors before and after matching

Sample	Ps	R2	LR	chi2	p>chi2	Mean Bias	Percentage reduction of bias
Unmatched	0.184	101.380	0.000	26.800	26.400	108.6*	48.98
Matched	0.057	36.350	0.002	13.200	9.00	55.4*	

Source: Survey data, 2020. * indicates significance at 10%

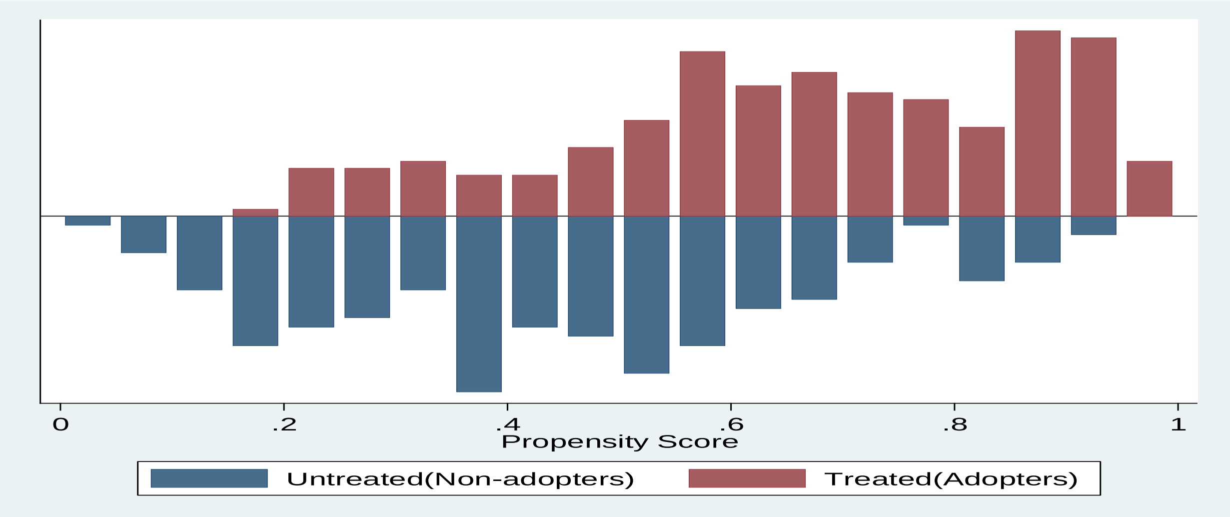

Figure 1: Propensity score distribution
Source: Survey data, 2020

Table 6: Estimated impact of improved rice variety adoption on rice output

Estimator	ATE	Treatment status ATT Coefficient (Std. Err.)	ATC
Propensity score matching (PSM)	7.705*** (1.763)	8.390*** (2.478)	6.782*** (2.549)
Nearest-neighbour matching (NNM)	4.151** (1.805)	5.321** (2.378)	2.573 (1.649)
Inverse-probability weights (IPW)	8.209*** (2.779)	7.710** (3.446)	
Regression adjustment (RA)	8.844*** (2.015)	8.481*** (2.255)	

Source: Survey data, 2020.
*** indicates significance at 1% and ** indicates 5% respectively

The positive significant effects of all the estimators for the ATE, ATT, and ATC demonstrate that adoption of improved rice varieties have a positive impact on productivity. Higher productivity of rice as a result of the adoption of improved rice varieties will increase farm household's income, reduce food insecurity, and poverty among resource-poor farm households in Ghana, as well as the whole of SSA. The findings are in tandem with those of **Martey *et al.* (2015), Abate *et al.* (2013),** and **Elias et al. (2013)**. Generally, the positive impact could be ascribed to the demonstration plots of MoFA on practices relating to the adoption of improved rice varieties and access to input markets, among others, in the region. These benefits served as incentives to improve farm households' adoption of improved rice varieties and their related agronomic practices to maximize output. The result justifies investment in agricultural innovation dissemination projects to increase improved rice variety adoption levels among farm households in Ghana and other parts of SSA to ensure maximum rice output to enhance the welfare of smallholder farmers.

CONCLUSIONS AND RECOMMENDATIONS

This study used the propensity score matching (PSM) model to examine the drivers and effect of improved rice variety adoption on rice output in the northern region of Ghana. Multistage sampling techniques were employed to collect data from 404 rice farm households in the study area. The empirical results reveal that adoption of improved rice varieties by farm households contribute positively to rice output. This could translate into reducing food and nutrition insecurity and the importation of rice into Ghana. The adoption of improved rice varieties is positively affected by family labour, membership in FBO, temperature, awareness of government policy, telephone ownership, and closeness to input markets. However, the adoption of improved rice varieties bears a significant negative relationship with the age of the farmer and mechanization. To enhance rice productivity and food security outcomes, it is recommended that the development of enhanced rice varieties, dissemination, and promotion of the varieties should be given priority among stakeholders along the rice value chain. Farmers should be entreated to join/form FBOs and support their farm work with family labour to maximize rice output. Access to market by farmers should be created or enhanced by improving rural road networks, especially in the rural areas where rice production is eminent. Government policy about rice production should be well designed and communicated to rice farmers since awareness of government rice policy leads to an increase in improved rice variety adoption. Finally, the government of Ghana should subsidize mechanization services for rice farmers to help decrease their costs of production and to maximize output.

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