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REGULAR ARTICLE

IMPACT OF ROW-PLANTING ADOPTION ON PRODUCTIVITY OF RICE FARMING IN NORTHERN GHANA

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ABSTRACT

This paper employed the endogenous switching regression and propensity score matching methods to analyse the impact of row-planting technology on rice productivity using 470 rice farms in Northern Ghana. The empirical findings showed that the adoption of row-planting technology exerted greater positive impact on rice yields of smallholder farmers. In addition, rice yields of adopters and non-adopters are driven by farm inputs, socioeconomic, institutional and technological factors. We suggest that achieving self-sufficiency in rice and rural economic transformation in sub-Saharan Africa requires promotion of agricultural technologies including row-planting. Different specific policy interventions are also required to promote rice yields for adopters and non-adopters.

Keywords: Rice productivity, row-planting technology, PSM, endogenous switching regression
JEL: Q1, Q16 Q12

INTRODUCTION

Achieving sustainable global food security has attracted discussion among various stakeholders and international organisations. One of the major crop commodities that has been targeted to address global food security related issues is rice. Rice is gradually emerging as an important staple food in sub-Saharan Africa, including Ghana where it contributes to 9 % of the food requirements (**GSS, 2012**). However, in Ghana, the local rice supply is unable to meet the high national demand. The local rice producers, who are poorly endowed in resources, are only able to supply 33 % of the national demand of 1.8 million tonnes. This shows that there is a wide deficit of 67 % (1.2 million tonnes), which is accounted for through importation at an estimated expenditure of US$ 450 million annually (**SRID, 2013**).

Moreover, this poor performance of the rice sector is attributed to a number of factors including inadequate input supplies, inappropriate farm technologies, reliance on unpredictable rainfall, low output and productivity growth, low incomes and inability to generate savings for investment (**Breisinger et al., 2008**). **Ackah and Kutsoati (2008)** argued that sustainable agricultural development and transformation requires green revolution type of investments, inter alia, promoting of improved farm technologies including row-planting. This suggests that for smallholder farmers to produce enough to meet the ever increasing food demand, they need to be innovative in their production process by adopting improved farm technologies such as row-planting technology. Row-planting confers a planting technique in which crops like rice are grown in lines with specific planting space. Row-planting enhances the application of agrochemicals and reduces competition among crops for nutrients, light and water. It is therefore expected that the adoption of row-planting improves the productivity of rice farms in the sub-Saharan countries including Ghana.

However, empirical studies (for example **Ragasa et al., 2013**) show that the rate of adoption of row-planting technology is low, and most farmers are still using the traditional planting method. Part of the reason for the low adoption is attributed to the lack of empirical studies that clearly establish the impact of row-planting on crop yields. Therefore, agricultural extension agents find it difficult to convince farmers to adopt row-planting in the absence of a proof. The present paper raises the following pertinent research questions: What factors influence the adoption of row-planting technology? What is the impact of adoption of row-planting technology on rice productivity? What factors influence the productivity of rice farming among adopters and non-adopters of row-planting?

LITERATURE REVIEW

The contribution of rice to global food security has attracted extensive empirical studies on improving the productivity and efficiency of rice farming. These empirical studies identify diverse factors, including institutional factors (extension contact, access to credit), farmers' socioeconomic characteristics (age, household size, education) and technological factors (fertiliser and pesticide application, improved seed varieties), that significantly influence productivity levels among rice farms. **Abdulai and Huffman (2000)** and **Islam et al. (2012)** found that a farmer's age exerted a negative effect on the profit efficiency of rice production, showing that young farmers are less risk averse and more likely to adopt improved technologies that promote efficiency of rice production. Contrary to these findings, **Khan et al. (2010)** showed that older farmers are more technically efficient in rice farming because older farmers are assumed to have more experience in rice cultivation than young farmers. This suggests that the effect of a farmer's age on efficiency is indeterminate and varies from one region to another.

Empirical studies have also shown a significant positive relationship between a farmer's education and productivity of rice farms (**Abdulai and Huffman, 2000; Khan et al., 2010; Islam et al., 2012**). **Abdulai and Huffman (2000)** and **Islam et al. (2012)** found a significantly negative relationship between credit access and inefficiency of rice production, indicating that credit access is essential to promote rice production. On the other hand, **Donkor and Owusu (2014)** did not observe any significant effect of credit on the technical efficiency of rice farms. We observe that these studies on efficiency and productivity of rice farming did not include row-planting technology and its effect on rice farming in their analyses.

The growing body of literature (**Coelli et al., 2002; Rahman, 2003; Fuwa et al., 2007; ; Kijima et al., 2008; Rahman et al., 2009; Bashir and Yasir, 2010; Aung, 2011; Hoang and Mitsuyasu, 2011; Rodney et al., 2011; Stefan et al., 2011; Rahman et al., 2012; Kijima et al., 2012; Pradyot and Ulrike, 2012**) in Africa and Asia, where rice production is very intensive, have also failed to estimate the effect of adopting row-planting technology on the productivity of rice production. This has therefore resulted in a dearth of information available on the effect of row-planting technology adoption on rice productivity. Such information has a potential to influence policy related to the development of the rice industry in Africa. This current study therefore contributes to closing this knowledge gap by providing a rigorous empirical analysis on the impact of row-planting technology adoption on rice productivity in Ghana, using endogenous switching regression and propensity score matching methods.

METHODS and DATA

Theoretical framework

This study follows the theory of innovation proposed by **Rogers (2003)**. Rogers defines innovation as an idea or practice which is regarded as new by an individual. The newness of innovation is expressed in terms of knowledge, persuasion or a decision to adopt. The innovation decision process shows the process by which an individual or other decision-making unit passes from first knowledge of an innovation, to forming an attitude toward the innovation, to a decision to reject or to implement the new idea, and then to confirmation of this decision. Rogers conceptualised this process into five main steps, namely knowledge, persuasion, decision, implementation and confirmation.

Over the years, rural farmers in Africa have been planting crop seeds using the broadcasting method, which usually resulted in overcrowding of crops on the field with intense competition for sun light, water and nutrients. This method of planting is associated with low yield. However, recent findings by the Ministry of Food and Agriculture, in collaboration with Council for Scientific and Industrial Research, have shown that planting in rows results in higher yields, as compared with the broadcasting method, in sub-Saharan Africa. Hence, adoption of row-planting technology has emerged as one of the strategies to increase crop yields, and reduce poverty and food insecurity in the African region. Based on this conception, we assume that a farmer's choice of row-planting technology over broadcasting hinges on the net benefit derived from the technology, given the socioeconomic and institutional characteristics related to the farmer. In this study, two estimation approaches, namely endogenous switching regression (ESR) and propensity score matching (PSM), are employed to estimate the impact of row-planting technology on rice yields.

Implementation of endogenous switching regression (ESR)

ESR is a parametric method that uses two different estimation equations for adoption decision (i.e. whether to adopt or not) while taking into account the selection process by including an inverse Mills ratio that is calculated from the selection equation. We assume that rational farmers will choose row-planting technology if the net benefit (U_{RPT}) derived from it, is greater than that of broadcasting technology (U_{BCT}). This can be expressed as $U_{RPT} > U_{BCT}$. It is important to note that crop yield is used as a proxy for the net benefit. We further express the two scenarios empirically (Eq. 1, Eq. 2).

$$U_{iRPT} = \mathbf{X}_i \partial_{RPT} + \xi_{iRPT} \tag{1}$$

$$U_{iBCT} = \mathbf{X}_i \partial_{BCT} + \xi_{iBCT} \tag{2}$$

where $\mathbf{X}_i$ is a vector of socioeconomic, institutional and technological characteristics related to the farmers under the two regimes. It must be emphasized that credit access and fertiliser adoption were treated strictly as endogenous variables because previous studies have found these factors to be endogenous (**Abdoulaye and Sanders, 2005; Matsumoto and Yamano, 2011**). Therefore, Smith and Blundell (1986) approach was used to address this endogeneity problem. According to Smith and Blundell, two separate binary models are estimated for fertiliser and credit constraints. ∂_{RPT} and ∂_{BCT} are vectors of parameters to be estimated. ξ_{iRPT} and ξ_{iBCT} are error terms. Prior to the research, the perceived net benefits associated with row-planting technology adoption are unknown. However, the researcher observes the $\mathbf{X}_i$ vector characteristics during the field survey. We denote the net benefit derived from adopting row-planting technology by a latent variable ϑ_i^*, which is unobservable. ϑ_i^* is expressed as a function of the observable characteristics and attributes represented by W_i in a latent variable model presented in Eq. 3.

$$\vartheta_i = \begin{cases} \vartheta_i^* = \mathbf{W}_i\boldsymbol{\eta} + \varepsilon_i, \text{ if } \vartheta_i^* > 0 \\ 0, \qquad\qquad \text{otherwise} \end{cases} \tag{3}$$

where ϑ_i denotes adoption of row-planting (ϑ_i = 1 if a farmer adopts the row-planting technology and 0 otherwise), $\boldsymbol{\eta}$ is a vector of parameters to be estimated. ε_i denotes the error term with mean zero and variance σ_ε^2 captures measurement errors and unobserved factors. It is worthwhile to note that ξ_{iRPT}, ξ_{iBCT} and $\boldsymbol{\eta}$ are assumed to have a trivariate normal distribution with mean zero and non-singular covariance matrix (**Johnson and Kotz, 1970**) (Eq. 4).

$$\operatorname{cov}(\xi_{RPT}, \xi_{BCT}, \varepsilon) = \begin{bmatrix} \sigma_{RPT}^2 & \sigma_{RPTBCT} & \sigma_{RPT\varepsilon} \\ \sigma_{RPTBCT} & \sigma_{BCT}^2 & \sigma_{BCT\varepsilon} \\ \sigma_{RPT\varepsilon} & \sigma_{BCT\varepsilon} & \sigma_\varepsilon^2 \end{bmatrix} \tag{4}$$

where $\operatorname{var}(\xi_{RPT}) = \sigma_{RPT}^2$, $\operatorname{var}(\xi_{BCT}) = \sigma_{BCT}^2$, $\operatorname{var}(\varepsilon) = \sigma_\varepsilon^2$, $\operatorname{cov}(\xi_{RPT}, \xi_{BCT}) = \sigma_{RPTBCT}$, $\operatorname{cov}(\xi_{BCT}, \varepsilon) = \sigma_{BCT\varepsilon}$ and $\operatorname{cov}(\xi_{RPT}, \varepsilon) = \sigma_{RPT\varepsilon}$. The expected values of the truncated error terms are expressed as (**Johnson and Kotz, 1970**) Eq. 5.

$$E(\xi_{BCT} \mid \vartheta = 0) = E(\xi_{BCT} \mid \varepsilon \le -\mathbf{W}'\boldsymbol{\eta}) = \sigma_{BCT\varepsilon}\frac{\Phi(\mathbf{W}'\boldsymbol{\eta})}{1-\Omega(\mathbf{W}'\boldsymbol{\eta})} = \sigma_{BCT\varepsilon}\lambda_{BCT} \tag{5}$$

and

$$E(\xi_{RPT} \mid \vartheta = 1) = E(\xi_{RPT} \mid \varepsilon > -\mathbf{W}'\boldsymbol{\eta}) = \sigma_{RPT\varepsilon}\frac{\Phi(\mathbf{W}'\boldsymbol{\eta})}{\Omega(\mathbf{W}'\boldsymbol{\eta})} = \sigma_{RPT\varepsilon}\lambda_{RPT} \tag{6}$$

where Φ and Ω denote the probability density and cumulative distribution function of the standard normal distribution, respectively. The covariates between the error terms for the non-adopters and adopters equations are denoted by σ_{BCT} and σ_{RPT}. λ_{RPT} and λ_{BCT} are termed as the inverse Mills ratio (IMR) evaluated at $\mathbf{W}'\boldsymbol{\eta}$ (**Greene, 2003**). The inverse Mills ratios are included in equations (1) and (2) to account for selection bias in a two-step estimation procedure (**Maddala, 1986**).

The first stage involves a probit regression to estimate the probability of adoption. Thus, estimation of the parameter $\boldsymbol{\eta}$ is provided in equation (3). These estimates are then employed to compute the selectivity terms (λ_{RPT} and λ_{BCT}) as expressed in equations (5) and (6). The shortcoming of this two-stage procedure is that it creates heteroskedastic residuals that cannot be used to derive consistent standard errors without cumbersome adjustments (**Maddala, 1986**). The full information maximum likelihood (FIML) method is employed to overcome this shortcoming by estimating the adoption and outcome equations simultaneously. FIML also generates $\rho_{RPT} = \sigma_{RPT\varepsilon} / \sigma_{RPT}\sigma_\varepsilon$ and $\rho_{BCT} = \sigma_{BCT\varepsilon} / \sigma_{RPT}\sigma_\varepsilon$ which are estimates of the correlation coefficients between the error terms in the outcome and adoption equations. **Lokshin and Sajaia (2004)** explained that to ensure that the estimated ρ_{RPT} and ρ_{BCT} are bounded between -1 and 1, and the estimated σ_{RPT} and σ_{BCT} are always positive, the maximum likelihood directly computes $\ln\sigma_{RPT}$, $\ln\sigma_{BCT}$ and $\operatorname{atanh}\rho_j$. $\operatorname{atanh}\rho_j$ is estimated (Eq. 7).

$$\operatorname{atanh}\rho_j = \frac{1}{2}\left(\frac{1+\rho_j}{1-\rho_j}\right) \tag{7}$$

The signs and significance levels of ρ_{RPT} and ρ_{BCT} have economic implications (**Lokshin and Sajaia, 2004**). If either ρ_{RPT} or ρ_{BCT} is non-zero, then there is endogenous switching that would result in selection bias, if not addressed. If $\rho_{RPT} < 0$, it indicates a positive selection bias, suggesting that farmers with above-average rice yields tend to adopt the row-planting technology. On the contrary, if $\rho_{RPT} > 1$, this implies a negative selection bias which indicates that farmers with below-average rice yields are more likely to adopt the row-planting technology (**Abdulai and Huffman, 2014**). The effect of row-planting adoption on rice yield is determined by predicting the expected values of the outcomes for adopters and non-adopters. Thus, the change in rice yield resulting from row-planting adoption is the difference between the predicted outcomes of adopters and non-adopters. The difference is referred to as treatment effect on the treated (ATT) (**Maddala, 1983; Maddala, 1986**) which is expressed as Eq. 8.

$$ATT_{ESR} = E[Yield_{RPT} \mid \vartheta = 1] - E[Yield_{BCT} \mid \vartheta = 1] = \mathbf{X}(\partial_{RPT} - \partial_{BCT}) + \lambda_{RPT}(\sigma_{RPT\varepsilon} - \sigma_{BCT\varepsilon}) \tag{8}$$

A propensity score matching method (PSM) is also employed as a robust check to complement the ESR approach. According **Mare and Winship (1978)** and **Lokshin and Sajaia (2004**), ESR accounts for both observable and unobservable factors, while PSM only addresses observable factors (**Rosenbaum and Rubin, 1983**). **Wanglin and Abdulai (2015)** indicated that if at least one of the selectivity correction terms (ρ_{RPT} and ρ_{BCT}) is significant, it implies the existence of selection bias emanating from unobservable factors. In this case, the ESR model is appropriate for estimating the causal effect of the row-planting adoption decision. Conversely, if none of the selectivity correction terms is significant, it suggests the absence of selection bias resulting from unobservable factors. In this scenario, the PSM method is used to determine the causal effect related to the adoption decision.

Implementation of propensity score matching

Propensity score matching indicates the pairing of treatment and control units with similar values on the propensity score and possibly other covariates, while removing all the unmatched units (**Rubin, 2001**). Propensity score matching is employed to evaluate the impact of row-planting adoption on rice productivity. It involves two stages. In the first stage, propensity scores (probability) of adopting row-planting are estimated, using a probit regression model. The propensity score matching can be expressed as (Eq. 9).

$$p(X) = \Pr[\vartheta = 1 | X] = E[\vartheta | X];\ p(X) = \Omega\{h(X_i)\} \quad (9)$$

where Ω {.} is a normal cumulative distribution and *X* is a vector of pre-treatment characteristics. Estimating the treatment effects, based on the propensity score, requires two assumptions. The first is the conditional-independence assumption (CIA) which requires that the common variables that affect treatment assignment and treatment-specific outcomes be observable. The dependence between treatment assignment and treatment-specific outcomes can be removed by conditioning on these observable variables. The second assumption is that the average treatment effect for the treated (ATT) is only defined within the region of common support. This assumption ensures that persons with the same X values have a positive probability of being both participants and non-participants (**Heckman et al., 1998**). The second stage involves the estimation of ATT based on the propensity score (Eq. 10 – Eq. 12).

$$ATT = E\{Yield_{RPT} - Yield_{BCT} | \vartheta = 1\} \quad (10)$$

$$ATT = E[E\{Yield_{RPT} - Yield_{BCT} | \vartheta = 1, p(X)\}] \quad (11)$$

$$ATT = E[E\{Yield_{RPT} | \vartheta = 1, p(X)\} - E\{Yield_{BCT} | \vartheta = 0, p(X)\} | \vartheta = 1] \quad (12)$$

A number of methods have been suggested in the literature to match similar participants and non-participants. The most commonly used approaches are the nearest neighbour matching (NNM), Kernel-based (KBM) and radius approaches.

Source of data and variable description

The study was conducted in the Upper East region of Ghana. The Upper East region is among the rice producing regions in Ghana, contributing about 25 % of the total rice production of the country (**MoFA, 2013**). The Upper East region of Ghana is located in the north-eastern corner of the country and is bordered to the west by the Upper West region, to the south by the Northern region, and to the north by Burkina Faso. The total land area of Upper East is about 2.7 % (8842 km^2) of Ghana's total land area. The land is relatively flat, with a few hills to the east and southeast, and the soil is shallow and low in fertility and organic matter content, and is coarse textured (**MoFA, 2013**). The Upper East region is divided into eight districts for administrative purposes. These districts are Bawku Municipal, Bawku West, Bolgatanga Municipal, Bongo, Builsa, Garu-Tempane, Kassena Nankana East, and Talensi-Nabdam. A multi-stage stratified sampling technique was used to select the respondents. The first stage involved purposive selection of two predominant rice producing districts. The districts were Kassena Nankana East and Bawku districts. The second stage involved the random selection of three hundred and fifty (350) rice farmers from Kassena Nankana East and 120 rice farmers from Bawku using the districts farmers' population.

A survey questionnaire was employed to solicit relevant information regarding rice output, farm inputs, and socioeconomic and institutional variables related to the farmers. The output data include rice output measured in kilograms and the input data include the quantity of fertiliser in kilograms, amount of labour in man-days and quantity of seeds in kilograms. Other information on rice producers, such as socioeconomic and institutional variables, was also captured in the survey questionnaire. The socioeconomic variables include gender, education and experience, while the institutional factors include extension contact, credit access and distance to market. Fertiliser and pesticides application are regarded as technological variables in this study.

Table 1 presents the socioeconomic, institutional and technological characteristics that are related to the adopters and non-adopters of row-planting technology. Mean differences, together with the t-values, are also provided in Table 1. The results indicate that 40 % of the rice farmers have adopted the row-planting technology, while the majority (60 %) have not adopted the technology. This indicates that the adoption of the technology is generally low in Northern Ghana. The rice producers asserted that row-planting technology makes the application of agrochemicals and other farming practices very easy. Adopters of row-planting technology are associated with higher productivity, with a rice yield of 1287.1894 kg/ha, compared with 1111.794 kg/ha for non-adopters. This result gives a clear indication that row-planting can significantly influence rice yield by increasing efficiency. The mean difference is 175.395 kg/ha, which is statistically significant at 1 % level. Adopters have higher resource endowments in terms of chemical fertiliser and land while non-adopters used higher labour and seed.

There are significant differences between adopters and non-adopters in terms of farm input usage (seed, fertiliser and farm size). This result is supported by the finding of Abdulai and Huffman (2014) who indicated that adopters of bundle technology have greater farm land areas. There is also a significant difference between adopters and non-adopters in terms of access to extension. Forty per cent (40 %) of adopters had access to agricultural extension services, while 30 % of the non-adopters had contacted extension agents for agricultural information. In terms of application of pesticides and fertiliser, the mean differences for adopters and non-adopters are statistically different from zero. The residuals of credit access and fertilizer adoption among adopters are not statistically different from that of non-adopters.

The number of adopters who applied fertiliser is higher than that of non-adopters. Although the discussion of the comparisons indicates some significant differences between adopters and non-adopters in terms of productivity, the average knowledge of the differences is insufficient to explain the adoption decisions among the selected rice farmers, since they do not account for the effect of other characteristics of farmers. Empirical estimates of the adoption decision process, as well as its impact on rice yield, are therefore presented and discussed in the next section.

RESULTS AND DISCUSSION

The estimates of the adoption of row-planting technology and its impact on rice yields are presented in Table 2. As mentioned earlier, the full information maximum likelihood approach was used to jointly estimate the adoption and the outcome equations.

The selection equation represents the determinants of row-planting adoption. In addition, two different sets of rice yield functions are specified for adopters and non-adopters due to differences in technology adoption. The coefficients of the adoption equation are interpreted as normal probit coefficients. Then the predicted residuals (*ResidC* and *ResidF*) from the binary models for credit constraint and fertiliser adoption models are included in the selection model.

Table 1. Summary statistics of variables included in the empirical analysis.

Variable	Description	Adopters N= 187 (40%)	Non-adopters N=283 (60%)	Mean difference	t-value
Rice yield	Quantity of rice harvested in kg/ha	1287.1894 (475.337)	1111.794 (375.047)	175.395***	4.455
Farm inputs					
Seed	Quantity of seed planted in kg/ha	43.573 (15.340)	52.0556 (16.016)	-8.482***	-5.714
Labour	Quantity of man-days per ha	72.405 (59.759)	73.301 (32.1890)	-0.895	-0.210
Fertiliser	Total quantity of fertiliser applied in kg/ha	85.371 (96.645)	23.339 (45.918)	62.031***	9.325
ResidF	Predicted residuals for fertilizer adoption	0.69 (0.321)	0.43 (0.130)	0.261	1.643
Farm size	Land area under cultivation of rice in hectares	1.646 (1.274)	1.167 (0.709)	0.479	5.219
Socioeconomic characteristics					
Gender	1 if farmer is a male and 0 otherwise	0.48 (0.501)	0.54 (0.500)	-0.061	-1.298
Kassena	1 if farmer is located at Kassena Nankana district and 0 otherwise	0.730 (0.444)	0.75 (0.432)	-0.020	-.487
Education	Number of years of formal schooling	2.96 (4.473)	2.52 (4.131)	0.434	1.079
Experience	Number of years farmer has been cultivating rice	7.29	8.577	0.953	1.260
Household size	Number of people in the household	5.22 (2.885)	5.54 (2.894)	-0.318	-1.167
Land ownership	1 if farmer owns the farmland	0.78 (0.415)	0.74 (0.438)	0.039	0.957
Institutional variables					
Extension	1 if farmer contact extension agent for information and 0 otherwise	0.41 (0.492)	0.35 (0.479)	0.053	1.163
Credit	1 if farmer has access to credit and 0 otherwise	0.97 (0.177)	0.97 (0.166)	-0.01	-0.238
ResidC	Predicted residuals for credit access	0.38 (0.171)	0.32 (0.112)	0.06	0.432
Market	Distance from house to the nearest market centre in kilometre	6.86 (5.105)	7.89 (6.496)	-0.004	-1.828
Technological variables					
Fertuse	1 if farmer applied fertiliser and 0 otherwise	0.66 (0.25)	0.25 (0.436)	0.403***	9.461

*’**’*** denote 10%, 5% and 1% significant levels respectively.

The empirical results indicate that the predicted residuals for credit access (*ResidC*) and fertilizer adoption *ResidF*) are not significant at even a conventional level of 10 %, suggesting that any potential endogeneity issues that might have arisen from credit constraint and fertiliser adoption are corrected.

The statistically significant covariance term for the adopters ($\rho_{RPT} = -0.428$) in Table 2 imply self-selection into adoption of row-planting technology by the rice farmers in the Northern regions of Ghana. This also implies that adoption of row-planting may impact differently on non-adopters, should they decide to adopt the technology. The negative sign of the covariance term also suggests the existence of positive selection bias and that the rice farmers whose yields are above average are more likely to adopt row-planting technology.

The coefficient of labour is positive and significant at 1% pointing out that adoption of row-planting technology increases with labour availability. *HOUSEHOLDSIZE* shows a positive significant impact on adoption of row-planting, which suggests that large households are more likely to adopt row-planting. Large rural households are able to provide family labour needed to implement row-planting technology (**Donkor and Owusu, 2014**). Our finding is consistent with that of **Kijima et al. (2008)** who observed that large households had adopted the improved rice variety, NERICA. Contrary to these findings, **Mariano et al. (2012)** established a negative significant relationship between adoption of certified rice seeds and household size. Large rice farms are also associated with a higher probability to adopt the row-planting technology. According to **Acheampong and Owusu (2015)**, a large farm provides enough space for farmers to experiment with the technology, and hence their adoption behaviour is enhanced. Similarly, **Devi and Ponnarasi (2009)** showed that large rice farms had a higher probability of adopting systems of rice intensification technology. The variable – *GENDER* has significant negative effect on adoption of row-planting. This result implies that male farmers are less likely to plant their seeds in rows as compared to females. This is not surprising since in the Northern Ghana, planting of seeds is regarded as female activity. Farmers located in the Kassena Nankana district are less likely to adopt row-planting as compared to farmers in Bawku.

Table 2. Endogenous Switching results for adoption and impact of adoption of row-planting technology on rice yield.

Variable	Selection (N = 470)	Rice Yields Non-adopters (N = 283)	Adopters (N = 187)
Farm inputs			
LABOUR	0.004** (0.002)	0.027 (0.605)	1.661*** (0.477)
SEED		5.713*** (1.266)	3.657** (1.841)
FERTILISER		5.713*** (0.510)	3.299*** (0.278)
FARMSIZE	0.595*** (0.087)		
Socioeconomic characteristics			
GENDER	-0.245* (0.144)	-12.787 (39.467)	-105.327** (53.448)
HOUSEHOLD SIZE	0.039* (0.023)	16.317** (6.662)	-0.545 (9.362)
EDUCATION	0.019 (0.015)	2.057 (4.671)	1.778 (5.909)
EXPERIENCE	0.0138 (0.009)	6.072** (2.554)	5.421* (3.088)
KASSENA	-0.424*** (0.159)	46.110 (44.561)	43.979 (62.214)
LAND_OWNERSHIP	0.099 (0.155)	82.504* (44.647)	34.523 (62.418)
Institutional variables			
EXTENSION	0.235 (0.148)	132.0567*** (43.003)	172.369** (60.984)
CREDIT CONSTRAINT	5.160 (3.458)	131.668 (117.294)	-176.695 (150.452)
RESIDC	-5.554 (3.471)		
MARKET	-0.014 (0.011)	-1.005 (2.998)	-2.421 (5.278)
Technological variables			
FERTUSE	1.126*** (0.152)		
RESIDF	0.095 (0.145)		
CONSTANT	-6.397*** (3.383)	652.101*** (157.153)	677.560*** (200.128)
Diagnostic statistics			
ρ_{BCT}		0.553 (0.339)	
$\ln\sigma_{BCT}$		5.790*** (0.059)	5.884*** (0.067)
ρ_{RPT}			-0.428** (0.180)
$\ln\sigma_{RPT}$			
LR test of independent equations	10.17***		
Wald Chi-square	141.46***		
Log likelihood	-3613.7965		

Note: ***'**'* denote 1%, 5% and 10% significant levels respectively. Values in brackets are standard error

The coefficient representing *FERTUSE* is positive and significantly different from zero, indicating that farmers who apply chemical fertiliser have a higher probability of planting their rice seeds in rows. The possible reason is that the row-planting method makes the application of agrochemicals easier, since row-spaces are left for an applicator to freely walk through the farm, unlike with random planting.

The results on rice yield functions for adopters and non-adopters are provided in the third and fourth columns of Table 2. The estimates generally indicate the effects of farm inputs, and socioeconomic and technological characteristics on rice farm productivity for non-adopters and adopters.

Application of farm productive inputs such as seed, chemical fertiliser and labour are important to promote rice production in Africa. However, our empirical results indicate that the quantity of seed and chemical fertiliser exert significant positive effects on rice yields for both adopters and non-adopters. Labour input shows significant positive effect on rice yield of adopters but is not significant for non-adopters. The implication of this result is that increasing quantity of seed, fertiliser and labour increases rice yields. Our findings are consistent with those of **Donkor and Owusu (2014)** who indicated that seed, fertiliser and labour increased rice yield.

Institutional variables play important role in the day-to-day operations of farm businesses. Access to extension services significantly promotes rice yield for adopters and non-adopters. However, the impact of extension on adopters is higher than that of non-adopters. Agricultural extension is the system of learning and building human capital of farmers through the provision of information and demonstrations, exposing farmers to technologies which can increase agricultural productivity and, in turn, raise income and welfare of the farmers (**Acheampong and Owusu, 2015 and Nyuor et al., 2016**). The coefficients of CREDIT CONSTRAINT AND MARKET did not show any significant effect on rice yields of non-adopters and adopters.

Our findings further indicate that female adopters obtain higher yields, as compared with the male adopters. As indicated in the empirical results on “Selection”, males are associated with low adoption rate. In addition, non-adopters with large households produce higher rice yields. It is also observed that adopters and non-adopters who are more experienced in rice production do harvest greater rice yields. This result is consistent with the theory of learning-by-doing. Non-adopters who owned their farm lands are associated with higher productivity. The possible reason is that land tenure security is guaranteed and that they are more likely to benefit from long-term land improvement investments.

Estimates of ATT from ESR and PSM

The results of PSM and ESR estimates on the impact of row-planting adoption on rice yield are presented in Table 3. The results of average treatment effect on the treated (ATT) from the endogenous switching regression (ESR) estimation in Table 3 generally reveal positive significant impacts of row-planting adoption on rice yield. The causal effect of row-planting adoption is an increase in rice yield by 390.333kg per hectare. In terms of percentage, the results suggest that the adoption of row-planting results in about 43.52 % increase in rice yield. The findings suggest that farmers’ adoption of row-planting technology could improve rice productivity.

Given that there is no selection bias arising from unobservable factors but from observable characteristics, the propensity score matching (PSM) technique was employed to estimate the average treatment effect on the treated (ATT) of row-planting adoption on rice yield. Nearest neighbour (NNM), Kernel-based (KBM) and radius (RM) matching methods were used. The results from the Kernel-based (KBM) and radius (RM) matching algorithms indicate that the adoption of row-planting has significantly positive impact on rice yield. Specifically, adoption of row-planting technology significantly increase rice yield by 10.96% from the Kernel-based matching (KBM) algorithm and 15.73% from radius matching. We observed that the estimated ATT from NNM is lower than from the other three methods (KBM and radius). For the nearest neighbour matching (NNM) algorithm, adopters obtain 36.175 kg/ha higher than non-adopters and is statistically insignificant at even 10 % level. Adopters obtain 127.126 kg/ha greater than non-adopters from Kernel-based matching (KBM) and is statistically significant at 1 % level. From radius matching (RM) approach, adopters obtained 174.998 kg/ha of rice higher than non-adopters and is statistically significant at 1 % level. The findings thus reveal that without accounting for selection bias arising from both observable and unobservable factors, the impacts of row-planting adoption on farmers’ yield will be underestimated.

Based on our average treatment effect on the treated (ATT) from the endogenous switching regression (ESR) estimation, we conclude that adopters of row-planting are more productive in rice farming than non-adopters. Our empirical findings coincide with a study by **Kijima et al. (2008)** who found that improved crop variety significantly increased farmers’ income in Uganda. We observe that when rice seeds are planted in rows, there is proper aeration and less competition for water and nutrients. The application of agrochemicals such as fertiliser, as well as harvesting, becomes quite easier. The results from the study generally show that agricultural technologies are needed to promote agricultural productivity to achieve sustainable global food security.

Statistical tests to evaluate matching

The matching process is checked to test whether it balances the distribution of the relevant covariates in both the treated and control groups. The results are shown in Table 4. The propensity score test indicates a significant reduction in bias after matching. There are no significant differences in matched adopters and non-adopters for any of the covariates (Table 4).

Table 5 further shows statistical tests to evaluate the matching process. The propensity test suggests that there is a substantial reduction in bias after matching. The percentage reductions are 51.36 %, 40.66 % and 45.55 % for NNM, KBM and RM methods, respectively.

Table 3. Estimates of the average treatment effect on treated (ATT)

Outcome variable	Matching algorithm	Treated	Controls	ATT	t-value	% change
Rice Yield (kg/ha)	Nearest neighbour	1287.189	1251.015	36.175	0.44	2.89
	Kernel based	1287.189	1160.072	127.126***	2.79	10.96
	Radius	1287.189	1112.191	174.998***	4.70	15.73
	ESR	1287.189	896.872	390.333***	16.59	43.52

** and *** denote 5% and 1% significant levels respectively.

The results also show that the percentage reduction in bias by both the two matching methods is greater than 20 %. This percentage reduction is a value recommended by **Rosenbaum and Rubin (1983)** as a substantial reduction in bias. This indicates that the matching tremendously reduced the selection bias. Similarly, the pseudo R^2 of the estimated probit model was high before matching, and after matching, it reduced significantly. After matching, the p-values of LR were not statistically significant for NNM and KBM matching methods, suggesting that there is no systematic difference in the distribution of the covariates between adopters and non-adopters.

CONCLUSIONS AND POLICY RECOMMENDATIONS

Proper understanding of the adoption and impact of the row-planting technology on productivity of rice farms is crucial for ensuring food security and poverty reduction in Africa. The row-planting method is an improved planting technology. Despite its potential to increase yield, there is low adoption of the technology. A number of studies have been conducted on productivity of the rice sector worldwide, but there is a dearth of literature addressing the impact of row-planting technology on productivity. Our study, therefore, has determined the impact of row-planting on productivity of rice farms, using 470 rice farmers from Northern Ghana. The study employed endogenous switching regression and PSM in the empirical analysis. The endogenous switching regression was used to address the issue of selection bias and endogeneity of row-planting, while PSM was employed as a robust check.

The empirical results showed that socioeconomic characteristics (gender, location differential, household size), and technological variable (chemical fertiliser application), significantly stimulate adoption of row-planting technology. Furthermore, quantity of fertiliser and seed significantly promote rice yield for both adopters and non-adopters while labour input has significant positive effect on only adopters. Access to extension services and farming experience exert significant positive impact on adopters and non-adopters. Moreover, large household size and land ownership increase rice yield for non-adopters. On the other hand, Male adopters are associated with lower rice productivity, as compared with their female counterparts.

Our conclusion drawn from these results is that specific production information and policy recommendations are required for adopters and non-adopters of row-planting technology. Empirically, we conclude that combining endogenous switching regression and PSM for analysing the impact of improved farming technologies provides efficient and reliable estimates. The findings from the endogenous switching regression reveal the selectivity effect for the adoption of row-planting technology on productivity of rice. The practical implication is that sample selection bias will occur if outcome (yields) of row-planting technology adoption is assessed without considering farmers' adoption decision. Hence, we recommend that future impact analyses of improved farming technologies adopted by farmers in the sub-Saharan region should consider accounting for endogeneity and selection bias by applying such methods in order to capture the real impact of row-planting technology on productivity. An application of such reliable and efficient estimation approach will give a true reflection of the contribution of newly introduced farming technologies.

Table 4. Test of selection bias after matching

Variable	Mean		% Bias	t-value
	Treated	Control		
GENDER	0 .479	0.471	1.8	0.16
HOUSEHOLD SIZE	5.368	5.546	-6.2	-0.59
EXPERIENCE	7.076	7.336	-3.2	-0.29
LABOUR	75.508	72.113	7.1	0.61
FARMSIZE	1.345	1.468	-11.9	-1.38
KASSENA	0 .714	0.709	1.1	0.1
OWNED	0 .772	0.805	-7.8	-0.76
FERTUSE	0 .632	0.614	3.8	0.33
RESIDF	-0.048	-0.032	-3.3	-0.32
EDUCATION	3.018	3.187	-3.9	-0.34
MARKET	6.801	7.613	-13.9	-1.15
EXTENSION	0.386	0.311	15.4	1.45
RESIDC	-0.008	-0.012	2.6	0.22
CREDIT1	0.965	0.958	3.6	0.29

It is also concluded that positive selection bias exists for rice yields from row-planting adoption among rice farmers in Northern Ghana. Adoption of row-planting technology tends to favour farmers who are more productive, compared to below-average farmers, which implies that productive farmers have comparative advantage in terms of row-planting in respect of rice yield.

Table 5. Test of selection bias after matching

Matching Algorithm	Mean bias		% Bias	Pseudo R^2		P -value of LR	
	Before matching	After matching	reduction	Unmatched	Matched	Unmatched	Matched
Nearest neighbour	10.28	5.0	51.36	0.2168	0.017	0.000	0.596
Kernel	10.28	6.1	40.66	0.2168	0.017	0.000	0.936
Radius	10.28	5.6	45.55	0.2168	0.017	0.000	0.895

We further conclude from the empirical evidence that row-planting technology improves rice yield. Therefore, row-planting technology should be promoted through educational campaigns on the impact of the technology on rice productivity. Extension services in the region should be intensified and more qualified extension agents are needed to enhance frequent contact with farmers so as to increase the adoption of improved farming technologies, such as row-planting. Extension officers and other marketing agencies should provide farmers with information regarding closest market outlets. Lastly, policy makers should consider the use of demographic targeting as a feasible strategy to influence a farmer's decision to adopt improved and sustainable farming technologies, since socio-demographic factors significantly influence a farmer's decision to adopt such technologies.

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