agriculture

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The Adoption of Farm Innovations among Rice Producers in Northern Ghana: Implications for Sustainable Rice Supply

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Received: 12 July 2018; Accepted: 30 July 2018; Published: 2 August 2018

Abstract: Achieving a sustainable food supply is crucial to meet the ever-increasing demand emanating from high population growth, rising consumer incomes, and high rates of urbanisation in developing countries including Ghana. The adoption of farm innovations in these countries has proven to be quintessential to the attainment of self-sufficiency in supply food including rice. Nonetheless, the adoption of farm innovations has been challenging. This paper, therefore, analyses the factors that influence the number of farm innovations adopted by rice farmers in two districts of the Upper East Region of Ghana using the Poisson model. The result indicated that the adoption of individual farm innovations was low. The study showed that farm size, labour input, experience in rice farming, access to extension services, and access to credit exerted significant positive effects on the number of farm innovations adopted, whereas farmer age and distance to market tended to decrease the number of farm innovations used by rice farmers. The study concludes that increasing the number of farm innovations adopted tends to promote a sustainable supply of rice output; therefore, food policy should aim at promoting the adoption of different farm innovations in developing countries including Ghana.

Keywords: adoption; farm innovations; Ghana; Poisson model; rice; sustainable food supply

1. Introduction

The global demand for food keeps escalating due to population growth, rising incomes of consumers, and the high rate of urbanisation [1]. The current population of 7.6 billion is expected to grow by 12% in the next 12 years [2]. The African population constitutes 17.17% of this world population [2]. This suggests that food demand will continue to grow accordingly. About 70% of the African population are smallholder farmers who derive their livelihoods from agriculture [3]. These smallholder farmers also supply about 80% of the food demand in Africa, and these small farms tend to provide employment opportunities for many actors in the food supply chain [3,4]. Surprisingly, smallholders are characterised by high poverty rates and malnourishment. In African alone, about 20% of the population is living below the poverty line, $2 a day, and 20.6% are suffering from food insecurity [5]. Moreover, the farm yields of these farmers are far below the potential yield, especially in the context of rice producers in West Africa, notably Ghana. The available statistics indicate that Ghana supplies only 40% of its rice demand while the remaining 60% is met through importation. Ghana's import bills on rice alone amount to over US $600 million annually [6]. This alarming situation tends to drain the foreign reserves of the country. Among other factors, existing studies suggest that the low adoption rate of farm innovations, notably fertiliser, pesticides, improved rice varieties, and row planting technique contribute to the low productivity in rice farming [7–12].

The present study seeks to address the following questions: What are the magnitudes and effects of the factors that influence the number of farm innovations adopted by rice farmers in Northern Ghana. To what extent does the number of farm innovations affect rice yields of the farmers? The main objective of this study is to analyse the factors that influence the number of farm innovations adopted by rice farmers in Northern Ghana. The related specific objective is to estimate the effect of the number of farm innovations on rice yields of farmers.

A study on the adoption of farm innovations in the rice sector of Ghana is relevant for several reasons. First, there is a growing demand for rice in Ghana due to the increasing population, rising income of consumers, and the cooking convenience of rice [6]. This high demand suggests the need to increase the rice yield of farmers by promoting different farm innovations in the rice sector of Ghana. Second, the country is self-insufficient in rice production; therefore, it spends a huge amount of foreign earnings in the importation of rice from Asia and America. This huge expenditure on rice importation tends to drain the national foreign reserves. The financial resources expended on rice importation can be invested in the rice production through the promotion of farm innovations. This will, in turn, create many jobs for rural people thereby transforming the rural economy in rice-producing areas in Ghana.

In a few decades, the adoption of agricultural innovations has attracted scientific research in developing countries including Ghana. A number of studies have been conducted to investigate the determinants of farm innovations in developing countries [7–13]. The literature shows that the adoption of farm innovations is generally influenced by farmer characteristics (e.g., farmer education, age, household size), farm assets/resources (e.g., land size, off-farm income) and institutional factors (e.g., farmer access to extension, access to credit, and distance to market). Noltze et al. [8] found that participation in training programs and availability of household labour enhanced the adoption of the system of rice intensification in Timor-Leste. In the Philippines, Mariano et al. [9] indicated that the adoption of modern rice technologies and management practices was positively influenced by farmer education, machinery ownership, irrigation water supply, access to credit, contact with extension agents, and profit-oriented behaviour of farmers. Ghimire et al. [11] concluded that education, extension, farm size, oxen, and technology-specific characteristics such as yield potential and acceptability encouraged the adoption of improved rice varieties among farming households in Central Nepal. In Africa, specifically Uganda, Kijima et al. [14] showed that experience in rice farming, education, and household size promoted the adoption of the New Rice for Africa (NERICA) variety, whereas lower adoption rate was associated with female farmers. Lambrecht et al. [15] analysed the adoption behaviour of farmers towards mineral fertiliser in Eastern Democratic Republic (DR) of Congo. The study reported that membership in a farmer association and off-farm income tended to increase the adoption of mineral fertiliser among rice producers. In Ghana, a recent study by Donkor et al. [12] demonstrated that the decision of rice farmers to adopt a row-planting technique was positively affected by labour availability, farm size, household size, and fertiliser application. Another study by Donkor et al. [13] revealed that access to extension services, education, farm size, gender, and access to irrigation water positively influenced rice farmers' decision to apply mineral fertiliser, whereas age tended to minimise the adoption of the technology.

It is clear that few studies have rigorously and scientifically focused on the promotion of farm innovations such as mineral fertiliser, improved rice varieties, improved planting techniques, and pesticides use in the rice sector in Ghana. In the few existing studies, the researchers principally focused on the analysis of the factors that influenced the adoption of the individual farm innovations. The researchers, however, did not analyse the factors that influenced the number of farm innovations adopted by farmers in the cropping seasons. The aforementioned farm innovations constitute a package, and they tend to complement each other. The adoption of the package tends to give a better yield rather than individual farm innovations. Therefore, the present study takes the analysis of farm innovations to a different level by rigorously and scientifically analysing the determinants of the number of farm innovations adopted by rice farmers in Northern Ghana using the Poisson regression model. The study further investigates the effects of the number of farm innovations adopted by farmers on rice yields of farmers. It is expected that the findings generated from the present study would be beneficial to policy-makers in the formulation of agricultural policy that aims at promoting different farm innovations to ensure a sustainable supply of rice in Ghana. This will, in turn, minimise the menace of food insecurity and rural poverty in Ghana.

2. Methodology

2.1. Conceptual Framework

The underlying theory for the analysis of the effect of the number of farm innovations adopted by farmers on their rice yield can be explained using the production function theory. The theory establishes a relationship between farm outputs and a bundle of inputs used in agricultural production with a given technology. In this study, rice yield (R_i) is expressed as a function of farm inputs (X_i), human capital (H_i), institutional factors (K_i), and the number of farm innovations used (F_i):

$$R_i = f(X_i, H_i, K_i, F_i) \tag{1}$$

$$R_i = \sum_{j=1}^{J} \Omega_j X_{ij} + \sum_{j=1}^{J} \gamma_j H_i + \sum_{j=1}^{J} \Psi_j K_i + \Phi_j F_i + \varepsilon_i \tag{2}$$

X_i, H_i, K_i are assumed to be exogenous but F_i is regarded as endogenous because the number of farm innovations adopted by a farmer is influenced by a set of factors Z_i. Equation (2) can be estimated with the ordinary least squares (OLS). However, without addressing the potential endogeneity of F_i, the OLS estimates generated tend to be biased. The endogeneity of F_i can be addressed using the estimation procedure proposed by Smith and Blundell [16]. Smith and Blundell's procedure for addressing the endogeneity problem involves two steps.

First, the endogenous variable (F_i) is estimated using an appropriate econometric approach. The endogenous variable F_i, the number of farm innovations adopted by the farmer is a choice problem; therefore, the rational choice theory is applied to explain the adoption decision process. The rational choice theory argues that an economic agent selects a choice that tends to maximise his/her utility subject to some constraints. Based on this theory, the study conceptualises that prior to the adoption of a farm innovation, a farmer first compares the net benefit generated from the adoption of the farm innovation to the expected net benefit from using a conventional practice. It is expected that the farmer tends to adopt the farm innovation if the expected net benefit (U_a) exceeds the expected net benefit (U_n) from non-adoption. Moreover, the farmer tends to adopt more farm innovations within the cropping season if his/she obtains higher benefits than just adopting one innovation. In this case, the adoption decision becomes a multiple choice problem or a counting problem. Our study analyses these multiple problems of the adoption decision of farm innovations using the Poisson regression model. The natural starting point for analysing counts is the Poisson distribution. The univariate Poisson distribution, denoted by Poisson (y/μ) for the number of farm innovations adopted by farmers in the cropping season, has the probability mass function [17,18]:

$$\Pr(Y_i = y) = \frac{e^{-\mu}\mu^y}{y!}, \quad y = 0, 1, 2, \cdots, K \tag{3}$$

where Y_i is the dependent variable, y is an occurrence of an event or a count, and μ is the intensity or rate parameter. The first two moments are $E(Y) = \mu$ and $Var(Y) = \mu$. This shows that the expected mean and variance are equal. In the econometric literature, this property is termed as the equidispersion property of the Poisson distribution [18]. To ensure that the standard mean parameterisation is non-negative and non-zero, thus $\mu > 0$, μ is expressed as:

$$\mu = \exp(X'\Upsilon) \tag{4}$$

where X is a vector of explanatory variables and Υ is the parameter to be estimated. This Poisson model (1) is a non-linear model; therefore, the maximum likelihood estimation (MLE) method is employed to estimate the parameters. The MLE is expressed as:

$$L = \prod_{i=1}^{n}\left(\frac{e^{-\mu}\mu^{y}}{y!}\right) \tag{5}$$

In most empirical data, the equidispersion property of the Poisson distribution is violated. Thus, the expected variance exceeds the expected mean. In this case, overdispersion issue is encountered. This overdispersion problem is accounted for using the negative binomial (NB) distribution.

Once Equation (3) is estimated, the next step is to predict the residuals and include the predicted residuals (F_i^R) in Equation (2). This is expressed as:

$$R_i = \sum_{j=1}^{J}\Omega_j X_{ij} + \sum_{j=1}^{J}\gamma_j H_i + \sum_{j=1}^{J}\Psi_j K_i + \Phi_j F_i + \omega F_i^R + \varepsilon_i \tag{6}$$

Equation (6) is then estimated with the OLS, and if the coefficient (ω) of the predicted residuals is statistically significant, it confirms the endogeneity of F_i. In this case, Equation (3) is re-estimated, and the predicted number of farm innovations adopted ($\hat{F}_i$) is included in Equation (2) instead of the observed (F_i):

$$R_i = \sum_{j=1}^{J}\Omega_j X_{ij} + \sum_{j=1}^{J}\gamma_j H_i + \sum_{j=1}^{J}\Psi_j K_i + \Phi_j \hat{F}_i + \varepsilon_i \tag{7}$$

Once the endogeneity problem is addressed, the parameters in Equation (7) can be estimated using the OLS.

2.2. Empirical Model Specification

Based on the theoretical foundation, the empirical model employed to analyse the effect of the number of farm innovations adopted on rice yield is specified as:

$$R_i = \sum_{j=1}^{J}\Omega_j Farminputs_{ij} + \sum_{j=1}^{J}\gamma_j Hcapital_{ij} + \sum_{j=1}^{J}\Psi_j Institutional_{ij} + \Phi_j NFI_{ij} + \varepsilon_i \tag{8}$$

where R_i denotes rice yield (the quantity of rice output per hectare of land), $Farminputs_{ij}$ is a vector of farm inputs such as rice seed (the quantity of rice seed in kg) and labour input (mandays). $Hcapital_{ij}$ represents a set of human capital: gender, educational level, location, experience, and land ownership. $Gender_i$ indicates 1 if farmer is a male and 0 otherwise, $Householdsize_i$ is the number of people in the farmer's household, $Primary_i$ denotes primary education, 1 if the farmer had primary education and 0 otherwise, $Secondary_i$ indicates secondary education, 1 if the farmer had secondary education and 0 otherwise, $Tertiary_i$ denotes tertiary education, 1 if the farmer had attained tertiary education and 0 otherwise, and no formal education is used the base category, $Location\_Dummy_i$ is denote the location of the farmer, 1 if the farmer was located in the Kassena Nankana district and 0 otherwise, $Experience_i$ denotes the number of years the farmer has been cultivating rice, $Landownership_i$ denotes land ownership, 1 if the farmer cultivated on his/her own land and 0 otherwise.

$Institutional_{ij}$ is a bundle of institutional factors which include access to extension services, access to credit, and market distance. $Extension_i$ denotes access to extension service (1 if farmer received extension service in 2011 and 0 otherwise), $Credit_i$ denotes access to credit (1 if the farmer had access to credit in 2011 and 0 otherwise), $Market_i$ denotes the distance from the farmer's house to the nearest market centre (km).

The empirical model applied to analyse the factors that influence the number of farm innovations adopted by rice farmers is specified as:

$$\begin{aligned} NFI_i = {} & \Upsilon_0 + \Upsilon_1 Gender_i + \Upsilon_2 Age_i + \Upsilon_3 Householdsize_i + \Upsilon_4 Primary_i + \Upsilon_5 Secondary_i + \Upsilon_6 Tertiary_i \\ & + \Upsilon_7 Location\_Dummy_i + \Upsilon_8 Experience_i + \Upsilon_9 Labour_i + \Upsilon_{10} Landownership_i \\ & + \Upsilon_{11} Farmsize_i + \Upsilon_{12} Extension_i + \Upsilon_{13} Credit_i + \Upsilon_{14} Market_i + \varepsilon_i \end{aligned} \tag{9}$$

NIF_i denotes the number of farm innovations adopted by rice farmers in the 2011/2012 cropping season. $Farmsize_i$ denotes the area of land under rice cultivation (hectares), Υ_0 denotes constant term, $\Upsilon_1, \cdots, \Upsilon_{14}$ denotes the coefficients of the explanatory variables and ε_i represents the error term. The parameters ($\Upsilon_1, \cdots, \Upsilon_{14}$) in the model are estimated with the Poisson maximum likelihood approach.

In the estimation of cross-sectional data, the issues of multicollinearity and heteroskedasticity are encountered, and these tend to generate biased results. Therefore, variance inflation factor (VIF) and the Breusch–Pagan/Cook-Weisberg are applied to diagnose the presence of these issues.

2.3. Source of Data

The study was carried out in the Upper East Region of Ghana. Rice is considered to be one of the major agricultural activities for most people in the region. Rice production in the region is characterised as small-scale where the majority of the farmers operate on less than 2 ha of farmland. The region contributes about 25% to the total rice output in Ghana. The total land area of the region is 8,842 km^2 which constitute about 2.7% of the total land area of Ghana. The topography of the region can be characterised as flat with a few hills. The soil has a coarse texture with a low level of organic matter content. The Upper East Region of Ghana has eight districts: 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 a purposive selection of two predominant rice producing districts. The districts included Kassena Nankana East and Bawku districts. The second stage involved a 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 used to collect relevant data from the farmers.

3. Results

3.1. Adoption of Farm Innovations

Table 1 presents the results of the adoption of farm innovations among rice farmers in the study area. The study focused on the adoption of farm innovations such as fertiliser, pesticides, improved rice varieties, and row-planting technique. These farm innovations tend to be complementary. Therefore, the Ministry of Food and Agriculture is encouraging farmers to adopt them as a package. Overall, 68.30% of the farmers adopted at least one farm innovation, whereas the remaining 31.70% did not adopt any of the farm innovations. The evidence suggested that the adoption of farm innovations is gradually improving in the study area. However, a few farmers (38.94%) applied mineral fertiliser on their rice farms whereas the majority did not use fertiliser in their rice production. This result is not a surprise because most farmers were faced with budget constraints and they could hardly afford to purchase the fertiliser input. The results further revealed that 31.28% of the farmers applied pesticides to control diseases and pests in their rice farms. This result indicated that the adoption of pesticides as a farm innovation was low in the Upper East Region of Ghana. The production of rice in the study was associated with disease and pest infestation which could result in total loss. However, a few farmers could buy pesticides to control the diseases and pests on their farms.

Table 1 indicates that 14.26% of the farmers had adopted improved rice varieties. This result demonstrated that the vast majority of the farmers still grew the traditional rice varieties which were associated with low yield and long maturity period. The results in Table 1 also indicated that the 23.62% of the farmers planted their rice in rows while the majority tended to broadcast their rice seeds. A recent study by Donkor et al. [12] suggested that the row-planting technique tended to make the application of agrochemicals and harvesting easier. In addition, row-planting permits the use of machinery to perform most of the farm operations such as the application of agro-inputs, weeding, and harvesting of rice output. The study concluded that the adoption of row-planting increased the yields of rice farmers in Northern Ghana.

Table 1. Adoption of farm innovations.

Variables	Category	Frequency	Percentage (%)
Farm innovations			
Fertiliser	Yes No	183 287	38.94 61.06
Pesticides	Yes No	147 323	31.28 68.72
Improved rice varieties	Yes No	67 403	14.26 85.74
Row-planting	Yes No	111 359	23.62 76.38
Overall adoption of farm innovations	Yes No	321 149	68.30 31.70
Number of farm innovations	0 1 2 3 4	149 182 106 25 8	31.70 38.72 22.55 5.32 1.70
Mean	1.066		
Minimum	0		
Maximum	4		
Standard deviation	0.951		

Source: Authors' computations based on the primary dataset.

Our results revealed that 31.70% had not adopted any of the farm innovations, 38.72 had adopted one, 22.55% adopted two of the farm innovations, 5.32% adopted three of the farm innovations, whereas only a few (1.70%) had adopted all four farm innovations considered in the study. The average number of farm innovations adopted by the farmers was one with a minimum and maximum of 0 and 4, respectively.

3.2. Summary Statistics of the Variables Included in the Model

The means and standard deviations of the relevant variables included in the model are presented in Table 2 according to adopters and non-adopters. The result in Table 2 showed that the proportion of males in the adopter sample was higher than that of the non-adopter sample. Mean difference in gender showed statistical significance at $p > 0.10\%$. The mean age, household size, education, rice farming experience of the adopters and non-adopters of the farm innovations were similar. The mean differences of these variables between the two groups were not statistically different from zero at $p > 0.10\%$. The mean difference of labour input between the two groups was 38.83 man-days which were statistically different from zero at $p > 0.01\%$. This showed that adopters employed higher labour input than non-adopters in the cultivation of rice. The proportion of adopters who cultivated their own farm lands was lower than that of non-adopters. The mean difference was statistically significant at $p > 0.05\%$. The mean farm size of adopters was 1.285 ha, which was larger than that of non-adopters with a mean farm size of 0.845. The mean difference of farm size exhibited statistical significance at $p > 0.01\%$.

Table 2. Means and standard deviations of the explanatory variables included in the model.

Variables	Adopters (A) (n = 321)		Non-Adopters (B) (n = 149)		Mean Difference (A-B)	t-Value
	Mean	Standard Deviation	Mean	Standard Deviation		
Human capital						
Gender	0.505	0.501	0.409	0.497	0.09 *	1.94
Age	33.561	17.168	33.341	16.523	0.22	0.13
Household size	5.489	2.996	5.205	2.511	0.284	1.00
Primary education	0.114	0.321	0.075	0.263	0.039	1.29
Secondary education	0.075	0.263	0.068	0.255	0.007	0.27
Tertiary education	0.034	0.182	0.000	0.000	0.034**	2.28
Location dummy	0.679	0.468	0.977	0.151	−0.298 ***	−7.58
Experience in rice farming	7.273	8.971	6.673	8.201	0.60	0.69
Labour input	95.807	68.855	56.977	43.631	38.83 ***	6.32
Land ownership	0.754	0.431	0.864	0.347	−0.11 **	−2.73
Farm size	1.285	1.020	0.845	0.466	0.44 ***	5.03
Institutional factors						
Extension services	0.424	0.495	0.068	0.255	0.356 ***	8.28
Credit	0.050	0.218	0.000	0.000	0.05***	2.80
Market distance	6.114	5.095	7.455	5.894	−1.34 ***	−2.52

*, ** and *** denote 10%, 5% and 1% statistical significance, respectively. Source: Authors' computation based on the primary dataset.

Moreover, the proportion of adopters who had access to extension services or credit was higher than that of non-adopters. The mean differences of access to extension services or credit were statistically significant at 0.01%. This result implied that adopters had better access to institutional support services, notably extension services and credit. The mean distance to the nearest market for adopters was 6.114 km whereas that of the non-adopters was 7.455 km; the mean difference of −1.34 km was statistically significant at 1%. This indicated that adopters were located in places closer to market centres than non-adopters.

3.3. Determinants of the Number of Farm Innovations Adopted

The Poisson estimates are presented in Table 3. One of the important assumptions regarding the Poisson model is the equidispersion property which suggests that the expected mean and variance of the dependent are equal. The equidispersion property was validated using the expected mean and variance of the number of farm innovations adopted by the farmers in the cropping season. The predicted mean (1.016) and the predicted variance (0.904) are approximately equal, thereby fulfilling the equidispersion property of the Poisson model. The fulfilment of this property justifies the appropriateness of the application of the Poisson model in the empirical analysis. Moreover, the Wald Chi-square value ($\chi^2_{(15)} = 201.44$) was statistically significant at $p > 0.01$, and this suggested that the explanatory variables had a joint effect on the number of farm innovations adopted by the farmers. The constant term showed no statistical significance even at $p > 0.01\%$.

Note that for policy implications, the marginal effects are interpreted instead of the coefficient. The coefficients only provide the direction of the effects of the explanatory variables on the dependent variable, whereas the marginal effects provide both the directions and magnitudes of the effects of the covariates on the dependent variable.

Table 3. Determinants of the number of innovations adopted by rice farmers.

Variables	Parameter	Coefficient	Standard Error	*z*-Value	Marginal Effects	Standard Error	*z*-Value
Constant	Υ_0	0.154	0.111	1.39			
Human capital							
Gender	Υ_1	0.019	0.047	0.41	0.031	0.076	0.41
Age	Υ_2	−0.007 ***	0.002	−3.14	−0.012 ***	0.004	−3.15
Household size	Υ_3	0.005	0.007	0.7	0.008	0.012	0.7
Primary education	Υ_4	0.013	0.070	0.19	0.022	0.113	0.19
Secondary education	Υ_5	0.025	0.085	0.29	0.041	0.137	0.29
Tertiary education	Υ_6	0.069	0.091	0.76	0.111	0.146	0.76
Location dummy	Υ_7	0.391 ***	0.050	7.78	0.631 ***	0.080	7.86
Experience in rice farming	Υ_8	0.017 ***	0.005	3.39	0.028 ***	0.008	3.4
Labour input	Υ_9	0.002 ***	0.000	3.8	0.003 ***	0.001	3.8
Land ownership	Υ_{10}	−0.006	0.051	−0.11	−0.009	0.081	−0.11
Farm size	Υ_{11}	0.055 **	0.026	2.08	0.088 **	0.042	2.09
Institutional factors							
Extension services	Υ_{12}	0.253 ***	0.050	5.08	0.408 ***	0.080	5.1
Credit	Υ_{13}	0.512 ***	0.092	5.53	0.825 ***	0.151	5.48
Market distance	Υ_{14}	−0.008 **	0.004	−2.37	−0.014 **	0.006	−2.37
Diagnostic statistics							
Wald chi-square	$\chi^2{}_{(15)}$	201.44 ***					
Pseudo R-squared	R^2	0.053					
Log pseudolikelihood	LL	−624.275					
Test of over-dispersion	$E(\hat{y}) = Var(\hat{y})$						
	$E(\hat{y})$	1.061					
	$Var(\hat{y})$	0.904					
Observation	N	470					

** and *** denote 5% and 1% statistical significance, respectively. Source: Authors' computation based on the primary dataset.

3.3.1. Human Capital

Out of the 11 human capital factors included in the model, five showed statistical significance at most $p > 0.10\%$. The significant variables were farmer age, location dummy, experience in rice farming, labour input, and farm size. Notably, the marginal effect of farmer age exhibited negative signs which were statistically significant at $p > 0.01\%$. This suggested that as farmers' age increased by a year, they tended to reduce the number of farm innovations adopted by 0.012. The result also showed that farmers located in the Kassena Nankana East District tended to increase the number of farm innovations adopted 0.631 higher than those located in the Bawku Municipal. It was also observed that as farmers became more experienced in rice farming, they were likely to increase farm innovations by 0.028. The labour input variable had a significant positive effect on the number of farm innovation adopted as indicated by the statistical significance of the marginal effect at $p > 0.01\%$. The results indicated that as the farmers increased their labour input by a man-day, they tended to increase their farm innovations by 0.003. The empirical finding further suggested that as the farmers expanded their farm size by a hectare, they tended to increase the number of farm innovations adopted by 0.088.

On the other hand, the results showed that other human capital factors such as farmer gender, education, household size, and land ownership did not exhibit statistical significance even at 10%. This demonstrated that these variables did not influence the farmers' decision on the number of farm innovations they adopted in their rice farming in the Upper East Region of Ghana.

3.3.2. Institutional Factors

The empirical results in Table 3 revealed that all the two institutional factors (i.e., access to extension services and access to credit) incorporated in the empirical analysis had significant positive effects on the number of farm innovations adopted by the farmers. The marginal effects of farmer access to extension services and credit showed statistical significance at $p > 0.01\%$. This result indicated that farmers who had access to agricultural extension services were likely to increase the number of farm innovations adopted in their rice farming by 0.408 higher than those who did not have access to extension services. Access to credit tended to empower farmers to increase their farm innovations by 0.825. The long market distance was found to reduce the farm innovations used by farmers by 0.014.

3.4. Effect of the Number of Farm Innovations Adopted on Rice Output

The diagnostic results showed that the overall mean variance inflation factor (VIF) was far less than 10 which suggested that multicollinearity was not an issue in the model. Also, the Chi-square value (1.67) from the Breusch–Pagan test was not statistically significant, and this indicated the absence of heteroskedasticity in the model. The Smith and Blundell endogeneity test showed that the number of farm innovations adopted by farmers was indeed an endogenous variable; therefore, the predicted values were incorporated in the rice output function instead of the observed values to address the endogeneity problem in the model [19]. These results suggest that the OLS estimates are unbiased.

The F-statistic value (38.07) was statistically significant at $p > 0.01\%$ which indicated that the explanatory variables jointly explained the variation in rice output among the rice producers. This evidence is consistent with the R-square value (0.572) which implied that about 57.3% of the variation in rice output was explained by the independent variables included in the model. The dependent variable (rice output) and all the continuous variables were transformed into a natural logarithm. Hence, the coefficients represent the partial elasticities; a percentage increase in the rice output due to a percent increase in the respective variables.

The empirical result showed that the partial elasticity of the number of farm innovations adopted by farmers was positive and statistically significant at $p > 0.01$. This implied that a 10% increase in the number of farm innovations adopted by farmers tended to raise their rice output by 4.32%. The variable land had the greatest impact on rice output as shown by the partial elasticity of 0.747. This showed that a 10% increase in the land area cultivated by farmers tended to increase their rice output by 7.47%. However, the partial elasticity of labour showed no statistical significance although it exhibited a positive sign. This result suggested that labour input did not affect rice output.

Among the human capital variables, farmer age, secondary education, experience in rice farming, and location dummy exerted significant effects on rice output. The partial elasticity of age was negative and statistically significant at $p > 0.05$. This shows that a 10% increase in farmers' age tended to reduce their output by 2.15%. The positive partial elasticity of secondary education implied that farmers with secondary education had 1.6% of rice output greater than those with no formal education. Experience in rice farming showed a significant positive effect on rice output, and this suggested a 10% increase in farmers' experience in rice farming tended to enhance their rice output by 1.19%. Farmers in Kassena Nankana East District harvested 4.22% rice output greater than those in Bawku Municipal. The result also showed that the partial elasticities of farmer gender, household size, primary education, tertiary education, and land ownership showed not statistical significance even at $p > 0.10\%$, which indicated that these variables had no effects on rice output.

With the exception of farmer access to extension services, all the institutional variables showed significant effects on rice yield at $p > 0.01$. Increasing farmers' access to credit tends to raise their rice output by 3.79%, whereas a 10% increase in the distance from farmers' community to the nearest market decreases their rice output by 0.10%.

4. Discussion

4.1. Determinants of Farm Innovations

The empirical findings clearly showed that human capital (i.e., farmer age, location, experience, labour, and farm size) and institutional factors (i.e., access to extension services, access to credit, and market distance) were the key determinants of the number of farm innovations adopted by rice farmers in Northern Ghana. Farmer age exhibited a negative influence on the number of farm innovations adopted within the cropping season. There is a general observation in the literature that when farmers get older, they tend to be more conservative in their conventional farming practices [7,12].

Moreover, studies have argued that older farmers are risk-averse; therefore, they may prefer to stick to a technology they are using rather than adopting more farm innovations [13,20]. The reverse is true for young farmers. Our empirical findings are consistent with previous studies which had established a strong negative relationship between farmer age and their adoption behaviour or decision [7,12,13,20]. Another important determinant of the number of farm innovations adopted by farmers was farmers' experience in rice cultivation. The study established a positive association between experience in rice farming and the number of farm innovations adopted farmers. The reason is that more experienced farmers are able to evaluate the benefits of using different farm innovations based on the accumulated knowledge gained over the years compared to those with less experience in rice farming. This observation collaborates empirical finding from Kijima et al. [14]. On the contrary, other studies found no significant effect of farming experience on farmers' adoption behaviour [11–13,15]. The finding further revealed that farmers located in Kassena Nankana tended to adopt more farm innovations than those in Bawku Municipal. Farmers in Kassena Nankana had better access to support services such as extension services, credit, and good road networks. The availability and easy access to these support services in Kassena tend to encourage farmers to adopt more farm innovations in their rice farming. The availability of cheap labour input tends to stimulate farmers' decision to adopt more farm innovations. The adoption of farm innovations such as fertiliser, pesticides, and row-planting requires more labour; therefore, farmers with cheap labour source are more likely to adopt more farm innovations. This evidence agrees with the finding of Kijima et al. [14] and Noltze et al. [8]. The result further indicated that farmers with large farms tended to adopt more farm innovations than those with small farms. In the northern region of Ghana, wealthy farmers have large farms; therefore, they can afford to adopt more farm innovations, especially the capital-intensive innovations. Our finding is consistent with previous empirical studies that established a positive relationship between farm size and adoption of the decision of farmers [11–13].

Institutional support services such as extension services and credit are important to positively influence farmers' adoption behaviour. More specifically, extension services create more awareness of farm innovations available to farmers. The extension agents understand the essence of adopting more than one farm innovations; they tend to encourage farmers to use different farm innovations to obtain higher yields. Therefore, farmers who had access to extension services were more convinced to adopt more farm innovations. In developing countries, particularly Africa, extension services have proven to be an important driving force behind the promotion and adoption of farm innovations [9,11,13]. Another important factor that is necessary to promote the adoption of farm innovations is the market. The result showed that an increase in the distance between farmers' community and the nearest market tends to discourage them from adopting more farm innovations. Long market distance increases the costs of transporting productive inputs such as fertiliser, improved rice and pesticides from the market to their homes or farms. Based on the farmers' landholdings, one can infer that most of the farmers are smallholders who face budget constraints. It is acknowledged that financial capital is needed to acquire the farm innovations, notably improved rice seed, pesticides and fertiliser. Therefore, farmers' access to credit enables them to purchase these productive farm inputs. This finding collaborates with an empirical evidence of Mariano et al. [9].

4.2. Effects of Farm Innovations, Farm Inputs, Human Capital and Institutional Factors on Rice Output

The result in Table 4 suggested that the adoption of more farm innovations tends to increase rice yield. The farm innovations, viz., fertiliser, pesticides, row-planting and improved rice seed tend to be complementary. For instance, weeds in rice farms may compete with rice plants for the nutrients supplied by mineral fertilisers. However, if weeds are effectively controlled through the application of approved pesticides, nutrients from the fertiliser inputs can become more available to rice plants. Similarly, combining the productive agro-inputs with improved rice seeds and row-planting technique tend to generate better yields. However, the result showed that few farmers were using more than one farm innovations; therefore, the farmers had not yet achieved the potential yield. This suggests that holistic and rigorous measures are required to ensure that farmers adopt the full package of the farm innovations. It is acknowledged that the use of agro-inputs, notably chemical fertilisers and pesticides could be harmful to the agro-ecological environment and human. Therefore, a careful education and supervision is required to ensure that the farmers apply them with caution. Besides farm innovations, the empirical findings showed that farm inputs such as land tended to increase rice output. Studies have shown that an expansion in area land is one of the key drivers of agricultural output among smallholder farmers in Africa [7,20,21]. In rice farming, some studies have established a positive relationship between rice output and land area [7,12,21].

Table 4. Determinants of rice yield.

Variables	Coefficient	Standard Error	*t*-Value
Constant	5.991	0.435	13.76 ***
Farm inputs			
Number of farm innovations	0.432	0.101	4.28 ***
lnLand	0.747	0.065	11.55 ***
LnLabour	0.029	0.053	0.56
Human capital			
Gender	−0.045	0.055	−0.83
lnAge	−0.215	0.106	−2.04 **
lnHousehold size	0.031	0.045	0.68
Primary education	0.050	0.069	0.72
Secondary education	0.168	0.097	1.74 *
Tertiary education	0.023	0.081	0.29
lnExperience	0.119	0.044	2.74 ***
Location dummy	0.422	0.101	4.19 ***
Land ownership	−0.021	0.052	−0.40
Institutional factors			
Extension services	0.420	0.261	1.61
Credit	0.379	0.169	2.24 ***
lnMarket_distance	−0.012	0.004	−2.68 ***
Diagnostic statistics			
F-statistic	38.07 ***		
R-squared	0.573		
Breusch/Pagan heteroskedasticity test Chi-square	1.67		
Mean VIF	2.28		
Endogeneity test: Coefficient of residual of the number of farm innovations adopted	−0.403	0.101	−4.01 ***
Observation	470		

*, **, *** denote 10%, 5% and 1% statistical significance. ln denotes natural logarithm.

Human capital such as farmer age showed a negative effect on rice output. As farmers become older, their labour productivity tends to decline; this consequently reduces their total rice output. This result supports the previous finding of Abdulai and Binder [7], Donkor and Owusu [20] and Owusu et al. [21] that attributed the low agricultural productivity in Africa to the ageing population of farmers. Secondary education was found to increase rice output of farmers. Formal education, particularly, secondary level, helps to improve the cognitive and managerial skills of farmers. This enables farmers to combine effectively farm inputs that generate a higher rice output. Experience in rice farming tends to improve rice output of farmers. More experienced farmers have accumulated adequate knowledge regarding the relevant farm innovations and practices which enhance rice output. Also, farmers located in Kassena Nankana obtain a higher rice output than those in Bawku Municipal. As noted earlier on, farmers in Kassena adopted different farm innovations; therefore, it not surprising that they obtained a higher rice output. More importantly, soils in Kassena are characterised as the Savannah ochrosols which are porous, well-drained, loamy, and mildly acidic and interspersed with patches of black or dark-grey clay soils. This soil type is suitable for crop production including rice. Kassena has water bodies including an irrigation dam (Tono irrigation project dam), one of the large irrigation dams in the Upper East Region, which supply water for many smallholder farmers, notably rice producers. The aforementioned suitable environmental conditions tend to contribute to the higher rice output of the farmers in the Kassena-Nankana East District of the Upper East Region.

Access to credit and distant to market were the institutional factors that affected rice output of farmers. Access to credit enables farmers to overcome the issue of budget constraints; they can purchase productive inputs such as land, labour, fertiliser and pesticides which empower them to increase their rice output. On the other hand, long distance to nearest market centres reduces rice output of farmers. In most farming communities in Northern Ghana, farmers travel to nearby peri-urban centres to purchase farm inputs. A long distance tends to discourage farms to intensify the use of productive inputs since they are costly to acquire considering the associated transportation costs.

5. Concluding Remarks

The adoption of improved farm innovations is required to ensure a constant supply of food to meet the ever-increasing demand both globally and locally. The present study has analysed the factors that influenced the adoption of the number of farm innovations adopted by rice farmers in the cropping season. The study drew on a primary dataset from 470 rice farmers from two districts in the Upper East Region of Ghana. The Poisson regression model was employed in the empirical analysis. The study concluded that the overall adoption of the farm innovations was encouraging. However, the adoption of the individual farm innovations remained low in the study area. The key factors that influenced the number of farm innovations adopted were generally classified into human capital and institutional. Among the human capital factors, labour input, experience in rice farming, farm size, and location-specific tended to positively influence farmers' decision to increase the number of farm innovations adopted in the cropping season whereas farmer age decreased the number of farm innovations adopted. Institutional factors, notably farmer access to extension services and credit tended to encourage farmers to adopt more farm innovations. Market distance tended to reduce the number of farm innovations adopted. These findings suggest that there is the need to pay particular attention to institutional and context specific variables rather than focusing on micro variables such as education, household size, land ownership, and gender.

The study also concluded that adopting different farm innovations, particularly, the whole package (fertiliser, row-planting, improved rice variety, and pesticides) are required to sustainably increase the rice yields to meet the ever-increasing domestic rice demand. Achieving this goal demands that a holistic policy framework that ensures an effective delivery of extension services by empowering the agricultural extension directorate with adequate mobility infrastructure such as vehicle and motorbikes, relevant training as well as recruiting new extension agents. We advise that the extension agents should intensify the education of farmers on the effective use of the agro-inputs, notably fertilisers and pesticides, to ensure that they are not misused to become harmful to the agro-ecological environment and human survival. It is acknowledged that adequate capital is requisite to the adoption of the farm innovations; therefore, it is recommended that affordable credit with flexible terms of payment should be provided to the farmers. Moreover, it is important to get innovative farm inputs such as fertiliser, pesticides, and improved rice variety closer to farmers. This may require the establishment of farm input market outlets in farming communities to enable farmers to have easy access to the inputs. Policy should also intensify education on adopting the farm innovations as a package, particularly among older farmers. It is expected that the appreciation and effective implementation of these policies will encourage farmers to increase the number of farm innovations adopted so as to ensure sustainable supply of rice.

Author Contributions: E.D. contributed to the designing, analysis of the data and writing of the first draft. V.O. offered assistance in the methodology. E.O.-S. and A.A.O. edited and proofread the paper.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

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