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The Role of Rural Credit in Agricultural Technology Adoption: The Case of Boro Rice Farming in Bangladesh

Shah Johir Rayhan [1,2], Md. Sadique Rahman [2] and Kaiyu Lyu [1,*]

[1] Institute of Agricultural Economics and Development, Chinese Academy of Agricultural Sciences (CAAS), 12 Zhongguancun South St., Haidian District, Beijing 100081, China; sohagag@gmail.com
[2] Department of Management and Finance, Sher-e-Bangla Agricultural University, Sher-e-Bangla Nagar, Dhaka 1207, Bangladesh; saadrhmn@yahoo.com
* Correspondence: lyukaiyu@caas.cn; Tel.: +86-158-1128-1808

Abstract: Rice agriculture provides millions of households with a steady source of income and employment. However, for small and marginal farmers, the exorbitant cost of production inputs presents a formidable obstacle in their pursuit of acquiring it. Credit constraints are a significant impediment to the adoption of agricultural technologies. Therefore, this paper identifies the determinant of access to rural credit and its impact on Boro rice production technology adoption in Bangladesh using cross-sectional data. The study employed probit regression, propensity score matching (PSM), inverse probability weighting (IPW), and inverse probability weighted regression adjustment (IPWRA) techniques. The findings indicate that age, family size, working members, and involvement in safety net programs negatively and significantly influence access to rural credit, while earning persons in the family, literacy, rice farming experience, remittance, and total income positively influence access to rural credit. The positive and significant ATT values suggested that access to rural credit has a positive and significant effect on technology adoption and the level of technology use. It was also found that access to rural credit has a heterogeneous effect. In particular, non-government organization (NGO) credit has a more significant impact on technology adoption than formal bank credit. Access to credit and the adoption of agricultural technologies can be greatly improved with the help of a location-specific rural credit policy and strong monitoring from the formal banking sector.

Keywords: rural credit; technology adoption; rice; propensity score matching

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1. Introduction

Agriculture supports the economies of over 60% of countries in Sub-Saharan Africa, South Asia, and the Pacific, in contrast to 18% in Latin America and 4% in other high-income economies [1]. Bangladesh possesses a primarily agrarian economy and ranks among the most densely populated nations globally, with it experiencing an annual population growth rate of 1.4% [2]. Agriculture holds paramount significance in Bangladesh, contributing 13.61% to the nation's gross domestic product (GDP). The rice sub-sector alone constitutes more than 70% of the overall agricultural GDP [3]. Agriculture is critical for economic development in Bangladesh since it ensures food security, generates jobs, and helps alleviate hunger and poverty [4]. Rice is Bangladesh's primary staple food, with it accounting for two-thirds of daily calorie requirements and half of total protein consumption. Rice is also one of the most important cash crops in Bangladesh [5]. Bangladesh ranks fourth among the world's thirteen largest rice producers, with average annual rice production of 37 million tons, or 6.3% of global production [6], and is the world's third-largest rice-consuming country [7]. Almost half of the country's labor force works in rice farming [8]. Rice agriculture provides a stable source of work and income for millions of households [9].

The rice-growing seasons in Bangladesh are pre-monsoon (mid-March to mid-July), monsoon (mid-July to mid-December), and winter (mid-December to May). About 42%

of farmers typically cultivate winter season rice (hereafter Boro rice), and it contributes to around 57% of total rice production in Bangladesh [10]. When compared to other rice types, Boro has the highest production (4.03 t/ha), although it is significantly lower than that of other Asian countries, such as Japan, Indonesia, Vietnam, China, and the Republic of Korea [2]. To raise productivity and ensure food security, it is critical to understand how to use resources efficiently and technology adoption to design a new production process that minimizes costs and maximizes resource usage [11–15]. However, rice production in the country is limited due to various constraints, including the insufficient distribution of quality seeds to farmers, a lack of sophisticated production equipment, and insect or pest attacks [11,16–19]. As the population continues to grow, the demand for rice is also steadily increasing [20–22]. Furthermore, the exorbitant cost of production inputs poses a significant challenge for small and marginal farmers in procuring them. These problems can be solved if the government pays attention to financial issues, controls the prices of farm inputs, and makes good policies and rules.

In recent years, the relevance of smallholder farmers in developing nations adopting contemporary technologies in agriculture has garnered considerable attention [23]. Several studies have suggested that agricultural production in developing countries remains poor, owing mostly to a lack of acceptance of widely accessible contemporary technology such as new seeds, chemical fertilizers, and automated irrigation [24–28]. Therefore, the adoption of innovative agricultural technologies lays the framework for sustainable agricultural expansion and increased food security in the long run [23]. Enhancing agricultural productivity via the adoption and dissemination of new agricultural technology and practices has long been regarded as a feasible strategy for economic growth and agricultural transformation [29–32]. However, in order to adopt agricultural technologies, an adequate amount of capital supply is necessary.

A study conducted by Nakano and Magezi [33] revealed that access to credit can enhance the utilization of agricultural technology, specifically in the context of fertilizer application. The existing literature [34,35] has posited that farmers' access to finance along with environmental and socioeconomic factors influences farmers' performance in different ways, increases the adoption of technology, and may increase productivity. Furthermore, Ouattara et al. [35] suggested that policymakers must promptly implement measures to enhance rice farmers' access to credit and subsidized fertilizers. Several other studies have suggested credit constraints as a barrier to agricultural technology adoption in developing countries [36,37]. Several studies have suggested capital availability as a crucial element in the adoption of agricultural technology, which consequently boosts productivity and rural development [38–44]. According to Foster and Rosenzweig [44], credit constraints play a significant role in delaying the adoption of new technologies and limiting the levels of inputs required to exploit these new technologies.

The above discussion indicates the existence of multiple studies regarding the impact of credit on the adoption of agricultural technology. However, the majority of the studies focused exclusively on a single technology, specifically the use of fertilizers. Prior research did not make a distinction between formal credit (provided by banks) and semi-formal credit (provided by NGOs). This study addresses these research gaps by taking into account various agricultural technologies. In addition, this study also examines the influence of formal and semi-formal sources of credit on agricultural technology adoption individually. The results will assist policymakers in developing a suitable rural credit policy that will enhance productivity and consequently promote rural development.

2. Materials and Methods

2.1. Rural Credit Sources in Bangladesh

Like other developing countries, the financial sector in Bangladesh is divided into three subsectors: formal, semi-formal, and informal. In Bangladesh, formal credit comes from different bank and non-bank financial institutions, semi-formal credit comes from different non-government organizations (NGOs) and informal credit comes from indi-

vidual money lenders. In addition to commercial banks, the formal sector also includes two specialized banks, namely Bangladesh Krishi Bank and Rajshahi Krishi Unnayan Bank, which provide loans to rural farmers. The rural credit market in Bangladesh is highly imperfect due to the lack of knowledge by farmers, insufficient collateral, misinformation, the restriction of credit volume, classified or non-performing loans, and private money lenders [41]. In addition, farmers are required to submit various legal documents to formal sector lenders in order to obtain a loan. This process can sometimes create an unfavorable credit environment, which in turn may lead to limited adoption of agricultural technology and low productivity. Capital availability is limited for farmers in Bangladesh. Thus, it is necessary for them to have capital, preferably in the form of rural credit, to promptly acquire different types of agricultural technologies [41].

2.2. Study Areas, Sampling Procedure, and Data Sources

This study collected ex-post data from a sample of rural credit recipients and non-recipients. The study's empirical data come from farmers in five districts (administrative units) in Bangladesh. These are Dinajpur, Naogaon, Lalmonithat, Faridpur, and Mymensingh. These districts were selected due to the large area for Boro rice production and the availability of farmers who received credit from banks and NGOs.

For this study, a multi-stage sampling procedure was used. In the first stage, five districts were purposefully selected based on the presence of rural credit borrowers and a large area allocated to Boro rice cultivation [45]. Second, one upazila (sub-district) was randomly selected from each district. Third, the sample was drawn from 10 villages in 5 upazila of Bangladesh (2 villages from each upazila). To collect the data, a list of credit recipients was generated across the selected districts in consultation with the managers of selected banks and NGOs. The generated list contained 1984 credit recipients in five districts—Dinajpur (387), Naogaon (395), Lalmonithat (405), Faridpur (389), and Mymensingh (408). Farmers who primarily received loans from July 2018 to June 2019 were taken into consideration. Following the probability proportional to size (PPS) sampling procedure, 250 credit recipients (50 from each upazila) were randomly selected from the generated list of credit recipients. Out of 250 credit recipients, 125 credit recipients belonged to the formal sector (banks), while an equal number of 125 credit recipients belonged to the semi-formal sector (NGOs). Furthermore, to select non-recipient farmers, a complete list of households was collected from the local administration. Following the PPS sampling protocol, 250 (50 from each upazila) credit non-recipients were randomly selected. Hence, the total sample size for this study was 500. The sample distribution is presented in Table 1.

Table 1. Distribution of the sample.

Location	Farmers Group			Total
	Credit Recipient		Credit Non-Recipient	
	Bank	NGO		
Dinajpur	25	25	50	100
Naogan	25	25	50	100
Lalmonirhat	25	25	50	100
Faridpur	25	25	50	100
Mymensingh	25	25	50	100
Total	250		250	500

To collect the data, four data collectors were selected and trained. An interview schedule was developed by the research team. A pre-test of the interview schedule was conducted in a village in the Mymensingh district with 20 rice growers. The responses of those 20 rice growers were excluded from the final analysis. Based on the rice growers' feedback and suggestions, additional orientation was given to finalize the interview schedule. The final survey was carried out using a paper-based interview schedule written in English.

The enumerators asked questions in the local language, and the farmers' responses were written in English by the enumerators. A face-to-face interview with each respondent was conducted between September to December 2019.

2.3. Variables' Definition and Measurement

2.3.1. Treatment Variable

Access to rural credit is the treatment variable. The treatment variable is classified into two groups, i.e., the treatment group and the control group. The farmers in the treatment group are those who live in villages with access to formal or semi-formal sources of credit and received rural credit in the production year of 2018–2019. The control group, on the other hand, comprises farmers living in the village without having any access to credit.

2.3.2. Outcome Variables

The most two important variables for technology adoption are high-yielding variety (HYV) seeds and fertilizer. We also classified the fertilizer into three fertilizers, i.e., urea, TSP fertilizer, and MoP fertilizer. Farmers make decisions on adopting technology based on two levels [46–49]. At the first level, whether to adopt the technology (initial adoption decision), and second, to determine how much input to use in its cultivation (level of adoption). Thus, the impact of rural credit was assessed based on both initial adoption and the level of adoption.

2.3.3. Explanatory Variables

Determination of rural credit and technology adoption is influenced by different factors, such as socio-demographic characteristics and economic factors. For this study, the choice of explanatory variables was guided by the previous literature, a priori expectations, and theoretical and empirical works on determinants of access to rural credit and its impact [50–54]. In order to identify potential multicollinearity, we calculated the variance inflation factor (VIF) for all of the explanatory variables. The range of the VIF (1.04 to 3.57) was found under the conventional threshold level of 10, and the mean value was 1.77. To check the heteroscedasticity problem, the Breusch–Pagan (BP) test was used and could not reject the null hypothesis of homoscedasticity. A description of the treatment, outcome, and explanatory variables used in the models is given in Table 2. The same set of explanatory variables was used in all models.

Table 2. Definition of variables and measurement.

Variable	Type	Definition and Measurement
Treatment variables		
Access to rural credit	Dummy	Equal to 1 if the farmer has access to rural credit from banks or NGOs and received credit during the 2018–2019 production year
Outcome variables		
HYV seed adoption	Dummy	Equal to 1 if HYV seeds have been adopted, 0 otherwise
Volume of HYV seeds	Continuous	Volume of HYV seeds used per hectare (in kilograms)
Urea fertilizer per hectare	Continuous	Volume of urea fertilizer applied per hectare (in kilograms)
TSP fertilizer per hectare	Continuous	Volume of TSP fertilizer applied per hectare (in kilograms)
MoP fertilizer per hectare	Continuous	Volume of MoP fertilizer applied per hectare (in kilograms)
Explanatory variables		
Age	Continuous	Age of household head in years
Family size	Continuous	Number of household members
Earning members in the family	Continuous	Number of household members who have earning sources
Working family members	Continuous	Number of family members working on the rice farm
Literacy	Dummy	Equal to 1 if the household head went to school, otherwise 0
Distance to bank	Continuous	Distance from home to the nearest commercial bank (in kilometers)
Distance to NGO	Continuous	Distance from home to the nearest NGO (in kilometers)
Distance to road	Continuous	Distance from home to the main road (in kilometer)

Table 2. *Cont.*

Variable	Type	Definition and Measurement
Rice farming experience	Continuous	Experience of rice farming of the household head (in years)
Farm size	Continuous	Farm size in decimals
Remittance	Dummy	Equal to 1 if the household has received any remittance, 0 otherwise
Off-farm income	Dummy	Equal to 1 if the household generates off-farm income, 0 otherwise
Television ownership	Dummy	Equal to 1 if the household has a television, 0 otherwise
Safety net	Dummy	Equal to 1 if the household participates in a safety net program, 0 otherwise
Total income	Continuous	Total annual income of the household
Extension	Dummy	Equal to 1 if the household receives advice from agricultural extension services, 0 otherwise
Farmer training center	Dummy	Equal to 1 if there is a farmer training center in the village where the household resides, 0 otherwise
Dinajpur	Dummy	Equal to 1 if the farmer is located in Dinajpur, 0 otherwise
Naogaon	Dummy	Equal to 1 if the farmer is located in Naogaon, 0 otherwise
Mymensingh	Dummy	Equal to 1 if the farmer is located in Mymensingh, 0 otherwise
Lalmonirhat	Dummy	Equal to 1 if the farmer is located in Lalmonirhat, 0 otherwise

2.4. Analytical Techniques

Both descriptive statistics and an econometric model were used to achieve the objectives of the present study.

2.4.1. Determinants of Farmers' Access to Rural Credit

The probability of access to rural credit was analyzed by applying random utility theory. It was assumed that, given the socio-economic and technological characteristics, farmers would prefer to receive rural credit and continue it if the utility gain from credit received is higher compared to the credit not received [32,50]. The utility gain, ($U_i^{cr} - U_i^{cnr}$) of rural credit can be expressed as a function of observed characteristics (X_i) in the latent variable as follows:

$$Y_i^* = Y_i^{cr} - Y_i^{cnr} > 0 = a + zX_i + u_i, \text{ where, } u_i \sim N(0, 1), i = 1, 2, \ldots\ldots n \quad (1)$$

$$Y = 1 \text{ if } Y_i^* > 0, \text{ Otherwise } 0$$

where Y_i^* is the latent variable indicating the probability of the farmers' decision to receive rural credit. Y_i^{cr} and Y_i^{cnr} represent the rural credit recipient and non-recipient, respectively. X_i represents explanatory variables, and z is the vector of parameters to be estimated.

Two models of binary choice, i.e., logit and probit, are widely used in the study of household access to credit in various studies [51–59]. Both probit and logit models provide reliable, efficient, and asymptotically normal estimates, and the results for empirical research are very similar. In this study, we used the probit regression model to identify the determinants that firmly influence households' access to rural credit. The probit model has advantages in effectively measuring the coefficients with an asymptotic error distribution by using the maximum likelihood measure [60]. The probit model uses the normal cumulative distribution function, which is highly useful for the study of dichotomous variables [61].

2.4.2. Impact Evaluation

There are many strong theoretical reasons to support the relationship between access to rural credit and agricultural technology adoption. In a randomized experiment, the mean effect of a treatment can be measured by calculation of the difference between mean values for the result variable of interest for treatment and control groups. However, this method cannot be implemented in the current situation, as access to rural credit is not random and the counterfactuals are always missing. Another problem for estimating the causal effects of rural credit on technology adoption is selection bias. The true measurement

of impacts requires controlling for sample selection bias through random assignment of individuals into treatments. There are both parametric and nonparametric estimation methods that can be applied to overcome problems of non-randomized data and selection bias. Some past studies have suggested either an endogenous switching regression model or instrumental variable regression as a parametric model-based regression approach to assess the causal impact in the absence of baseline data and to solve the selection bias problem that arises when farmers who received rural credit (treatments) are not chosen randomly [32,62–66]. However, we could not use these methods in our analysis due to a lack of suitable instruments. In the absence of proper instruments and baseline information, a suitable quasi-experimental method may also be used for an impact evaluation [67,68]. Therefore, in this study, the propensity score match (PSM) method was applied to determine the causal effects [69,70]. Previous studies have also used PSM to estimate the average treatment on treated (ATT) [31,50,52,71–73]. PSM can reduce the dimensionality of the covariates, making it simpler to achieve balance between the treatment (credit recipients) and control (credit non-recipients) groups. PSM helps construct a counterfactual from the control group based on observed characteristics, but the validity depends on conditional independence (CI) and common support (CS) assumption in propensity scores (PSs) across the credit recipient and credit non-recipient farmers. Under the CI and CS, the ATT was computed as:

$$ATT = (Y_1 - Y_0 \mid X, T = 1) = (Y_1 \mid X, T = 1) - (Y_0 \mid X, T = 1) \quad (2)$$

where T indicates whether a farmer received rural credit or not (credit received = 1; otherwise = 0), X is the observed characteristics, $(Y_1 \mid X, T = 1)$ is the mean outcome of the treatment group conditioned on X in the treated situation, and $(Y_0 \mid X, T = 1)$ is the mean outcome of the control group conditioned on X in the treated situation. To estimate the ATT, the following steps were followed: firstly, a binary probit model was used to estimate the PS. After the probit regression, the region of the CS was selected and a balancing test was performed. Using the estimated PSs, credit receiver, and non-receiver fatteners were matched, and the mean difference of outcome was considered as the treatment effect of rural credit. Two matching procedures (nearest neighbor and kernel matching) were used to estimate the treatment effect.

However, the ATT from PSM can still generate biased results in the presence of misspecification in the model [74,75]. To check the robustness of PSM, we also used inverse probability weighting (IPW) and a doubly robust estimator known as inverse probability weighted regression adjustment (IPWRA). The IPW method does not match and compare with credit recipients and non-recipients directly but uses the inverse of the propensity score as a weight while calculating the average value of the outcome variable [76,77]. On the other hand, IPWRA provides consistent results in the presence of misspecification in the treatment or outcome model, but not both. IPWRA calculates the ATT on the basis of observed characteristics and balancing property need to be satisfied. A covariate test (balancing property test) was conducted to check the validity of the balancing property. The ATT in the IPWRA model was estimated in two steps. In the first step, the probit model was used to estimate the propensity scores, and in the second step, linear regression was used to estimate the ATT [69].

Since PSM results heavily rely on the assumption of conditional independence, we took several measures to address the problem. First, we included several independent variables for propensity score specification to minimize omitted variable bias [67,78]. Second, matching was implemented on the region on the CS to minimize selection bias. Third, to check the robustness of the results, we employed IPW and IPWRA.

3. Results and Discussion

3.1. Descriptive Statistics of the Variables Used in the Models

Differences in the selected characteristics of credit recipients and credit non-recipients are presented in Table 3. The mean differences suggested that there are some differences

between credit recipients and credit non-recipients in terms of the selected characteristics. HYV seed adoption was significantly different between rural credit recipients (82%) and credit non-recipients (73%). Group differences for the volume of HYV seeds, urea, TSP, and MP were also significant. The credit recipients have a considerably smaller family size and lower age than the credit non-recipients. Farmers who receive credit were more likely to possess higher levels of literacy and also receive remittances. A greater proportion of farmers who do not have access to credit engage in safety net programs. Additionally, the findings indicated that farmers who have access to rural credit have a higher average income. The descriptive statistical results are consistent with the literature concerning access to determinants of rural credit [3,8,32,35,38]. Furthermore, these variations in selected characteristics suggest that these two groups are not directly comparable. Thus, this justifies the use of PSM, which matches rural credit recipients with non-recipients that have akin likelihoods of adopting technology based on the observed characteristics [50,73,79].

Table 3. Summary statistics of sample households for the selected variables.

Variable	Credit Recipient (n = 250)		Credit Non-Recipient (n = 250)		Mean Difference Test * (p-Value)
	Mean	Standard Deviation	Mean	Standard Deviation	
HYV seed adoption	0.82	0.39	0.73	0.45	0.011
Volume of HYV seeds (kg/ha)	49.12	14.53	39.70	12.00	0.003
Volume of urea fertilizer use (kg/ha)	214.74	58.73	179.52	63.29	0.000
Volume of TSP fertilizer use (kg/ha)	148.99	45.65	121.72	37.87	0.000
Volume of MP fertilizer use (kg/ha)	138.21	47.36	123.69	48.86	0.001
Age	44.04	10.06	46.99	11.16	0.002
Family size	5.09	1.67	5.68	2.31	0.001
Earning persons in the family	1.47	0.68	1.55	0.91	0.245
Working family members	1.23	0.52	1.45	0.86	0.001
Literacy	0.64	0.48	0.44	0.50	0.000
Distance to bank	3.24	2.12	3.29	1.82	0.778
Distance to NGO	2.90	1.89	2.86	1.54	0.805
Distance to road	1.30	1.15	1.35	1.11	0.625
Rice farming experience	27.66	10.84	28.67	11.08	0.306
Farm size	227.72	162.74	237.07	176.89	0.539
Remittance	0.16	0.37	0.09	0.28	0.015
Off-farm income	0.69	0.46	0.69	0.46	1.000
Television ownership	0.70	0.46	0.65	0.48	0.254
Safety net	0.02	0.14	0.06	0.23	0.035
Total income	155,228.00	94,214.99	137,677.20	77,560.07	0.023
Extension	0.89	0.31	0.86	0.35	0.279
Training center	0.16	0.37	0.23	0.42	0.055

Source: Field survey data, 2019; * a t-test and a chi-squared test were applied for continuous and categorical variables, respectively.

3.2. Determinants of Access to Rural Credit

It is shown in Table 4 that the estimated probit model is statistically significant at the 1% level. The probit model also correctly predicts 70.02% from the entire sample observations. The results of the probit model indicate that age, family size, family members working, and safety net negatively and significantly influenced access to credit, while having earning persons in the family, literacy, rice farming experience, remittance, and total income positively significantly influenced access to rural credit. The marginal effect of age indicates that the likelihood of access to rural credit decreases by 1.30% with every one-year increase in the age of the farmer. The findings indicate that younger farmers are more interested in rural credit compared to older farmers. This possibly means that elderly people are settled and less likely to pursue new measures that demand money. Younger people should be more actively interested in collecting knowledge on credit sources, agricultural technology, and markets. The negative association of age may imply that older farmers lack access to rural credit due to their comparatively lower level of agricultural activity [80–82].

Table 4. Probit estimation of determinants of farmers' access to rural credit.

Variable	Coefficient	Standard Error	Marginal Effect
Age	−0.039 ***	0.009	−0.013
Family size	−0.135 ***	0.043	−0.047
Earning persons in the family	0.186 *	0.110	0.065
Working family members	−0.300 **	0.116	−0.104
Literacy	0.548 ***	0.126	0.191
Distance to bank	−0.033	0.055	−0.011
Distance to NGO	0.065	0.066	0.022
Distance to road	−0.083	0.057	0.029
Rice farming experience	0.029 ***	0.009	0.010
Farm size	0.000	0.000	0.000
Remittance	0.577 ***	0.202	0.201
Off-farm income	−0.108	0.146	−0.037
Television ownership	−0.0104	0.137	−0.004
Safety net	−0.612 *	0.336	−0.213
Total Income	0.000 *	0.000	0.000
Extension	0.264	0.194	0.092
Training center	−0.179	0.165	−0.062
Dinajpur	−0.238	0.207	−0.083
Naogaon	−0.318	0.219	−0.110
Mymensingh	−0.259	0.210	−0.091
Lalmonirhat	−0.082	0.208	−0.028
Constant	1.430 ***	0.473	
Log-likelihood	−304.89		
Pseudo R2	0.1203		
LR chi2(18)	83.36 ***		
Prob > chi-square	0.000		
% predicted correctly	70.02		
Number of obs	500		

Source: Field survey data, 2019; *** significant at 1%, ** significant at 5%, and * significant at 10%.

There is a significant but negative association between the availability of rural credit and the number of family members in the household, indicating a lower likelihood of larger households borrowing rural credit, and the marginal effect of family size indicates that the likelihood of access to rural credit decreases by 4.70% with every incremental increase in the number of household members. A few studies have suggested that the likelihood of access to credit increases with the size of the household [83,84]. However, we found the opposite result [85–87]. This is probably because bigger households tend to have a low payout capacity, which reduces the probability of borrowing, resulting from the lower future expected per capita income. The results are consistent with the results of a previous study [51].

The negative and significant coefficient of the marginal effect of working family members indicates that one additional working member in the family decreases the probability of obtaining a loan by 10.40%. The result suggests that larger farming families are less likely to receive credit. Families can substitute labor with inputs from cash, such as pesticides and/or sell additional family labor, and use off-farm income, as an alternative, to buy cash input and thus decrease the need for loans. The result is consistent with the finding of [28].

Marginal effect analysis of literacy indicated that literate farmers were 19.10% more likely to borrow compared to illiterate farmers, which is consistent with the findings of [51,54,85]. This is expected because farmers with formal education may be more exposed to the outside environment, including more risks and skills.

The findings also indicate that there is a positive and significant relationship between rice farming experience and access to rural credit. This means that a unit increase in rice farmers' experience will increase the likelihood of obtaining rural credit. A similar finding was found by [86,87]. The marginal effect of an earning person in the family indicates that an additional earning person will increase the probability of obtaining a

loan by 6.50%. This is because more earning members in a family increases the family's total income, which improves the creditworthiness of a farmer and also creates demand to expand rice production. This result is consistent with the result of [53,88]. Additionally, the results suggest that financial institutions are more inclined to extend credit to farmers who possess higher incomes, thereby mitigating credit risk. Consequently, suitable measures are necessary to expand the access of small-scale farmers with lower incomes.

Remittance also has a positive and significant effect on access to rural credit. A household that receives remittance has a 20% higher probability of obtaining a loan than those who do not receive remittance. This is mainly due to the perception that farmers with high incomes will also be more diligent in paying back loans if they take loans [51,87]. The findings also suggest that there is a location-specific variation in terms of access to credit. Consequently, location-specific rural credit policies need to be implemented in consideration of the socioeconomic status of the farmers in that particular area.

3.3. Average Treatment Effect on the Treated

Table 5 shows the treatment effect of rural credit on agricultural technology adoption and the level of adoption using different estimation techniques. In general, all the ATT values indicate that rural credit has a positive and statistically significant impact on adoption and the level of adoption. The ATT values from various matching and weighting techniques range from 8.50–11.20% for HYV seed adoption, indicating that farmers who receive rural credit are 8.50−11.20% more likely to adopt HYV seeds compared to those who do not receive rural credit. Similarly, rural credit increases the use of HYV seeds. A previous study also found that rural credit has a positive and significant effect on agricultural technology adoption and the level of adoption [50]. In Bangladesh, all farmers use different fertilizers in their Boro rice fields but their rate of use is statistically significantly different between the two groups. Farmers who obtain rural credit use (32–35) kg/ha more urea fertilizer, (24–27) kg/ha more TSP fertilizer, and (9–13) kg/ha MP fertilizer in their rice fields. The results are also consistent with previous studies [89,90] that have shown that there is a significant positive impact of access to credit on technology adoption.

Table 5. Impact of rural credit on agricultural technology adoption and volume of adoption.

Outcome Variables	ATT Values			
	PSM		IPW	IPWRA
	Nearest Neighbor	Kernel		
HYV seed adoption	0.112 *	0.119 *	0.095 **	0.085 **
	(0.082)	(0.064)	(0.042)	(0.039)
Volume of HYV seeds (kg/ha)	9.296 ***	10.505 ***	8.656 ***	10.069 ***
	(2.289)	(1.158)	(2.625)	(1.292)
Volume of urea fertilizer (kg/ha)	33.095 ***	35.637 ***	34.981 ***	32.758 ***
	(3.631)	(7.602)	(7.867)	(7.185)
Volume of TSP fertilizer (kg/ha)	24.841 ***	27.196 ***	27.024 ***	26.49 ***
	(5.563)	(3.213)	(4.147)	(3.891)
Volume of MP fertilizer (kg/ha)	9.709 *	13.469 ***	13.353 ***	11.837 **
	(8.479)	(3.519)	(4.726)	(4.687)

Source: Field survey data, 2019. Note: The figure in parenthesis indicates the standard error, which is estimated based on a bootstrap with 5 replications. The number of control (non-recipients) samples: the nearest neighbor produces 120 and 92 sample for HYV seed adoption and the volume of HYV seeds, respectively, for the volume of urea, TSP fertilizer, and MP fertilizer, the nearest neighbor produces 120, 120, and 101 samples, respectively. Kernel matching produces 246 samples. ATT = average treatment effect on the treated. *** significant at 1%, ** significant at 5%, and * significant at 10%.

3.4. Balancing Test for the Treatment and Control Groups

The reliability of the estimated results of propensity score matching depends on the good quality of matching. To evaluate the reliability of our estimated results, we carried out several tests to ensure that there was no significant difference between the control and treatment groups. The covariate balancing test is presented in Table 6. Table 6 shows that rural credit recipients and non-recipients had statistically similar characteristics after

matching in contrast to the unmatched samples. In particular, the balancing test for the treatment control group after matching shows that there is no statistically significant difference between rural credit receivers and non-receivers. The standardized difference (% bias) for the mean value of almost all covariates between rural credit receivers and non-receivers is below 20%. The overall covariate propensity score matching quality test (Table 7) shows that the mean standardized bias decreased from 12.5 before matching to 10.3 after matching. The pseudo-R^2 dropped significantly from 0.068 after matching to 0.143 before matching (Table 7). The findings indicate that propensity matching is successful in terms of balancing the distribution between rural credit receivers and non-receivers.

Table 6. Test of matching quality.

Variable	Mean		% Bias	% Reduction (Bias)	*p*-Value for the Quality of the Mean
	Recipient	Non-Recipient			
Age	44.882	43.225	16.5	25.5	0.123
Family size	5.1834	5.2899	−6.0	72.3	0.542
Earning persons in the family	1.5089	1.3432	21.6	−192.4	0.029
Family members working	1.2012	1.1775	3.8	86.5	0.663
Literacy	0.63905	0.70414	−13.3	68.8	0.204
Distance to bank	3.058	3.0917	−2.1	63.7	0.853
Distance to NGO	2.7219	2.8432	−7.9	34.2	0.472
Distance to road	1.3314	1.2393	8.0	−2150.5	0.451
Rice farming experience	28.172	25.911	21.0	−190.3	0.047
Farm size	233.73	227.47	3.8	−67.8	0.739
Remittance	0.16568	0.10651	18.3	40.6	0.113
Off-farm income	0.68047	0.62722	11.8	29.3	0.305
Television ownership	0.72189	0.73964	−3.9	58.4	0.714
Safety net	0.02367	0.02367	0.0	100.0	1.00
Total income	1.6×10^5	1.5×10^5	13.4	−20.1	0.24
Extension	0.89349	0.95266	−17.9	−64.5	0.041
Training center	0.14793	0.1716	−6.9	−22.0	0.554
Dinajpur	0.28994	0.19527	20.2	−77.3	0.042
Naogaon	0.08876	0.07692	4.1	−198.6	0.694
Mymensingh	0.2071	0.30769	−24.6	−1361.3	0.034
Lalmonirhat	0.18343	0.2071	−6.8	68.8	0.584
Faridpur	0.23077	0.21302	4.2	−51.4	0.696

Table 7. Propensity score matching quality test.

Test	Before Matching	After Matching
Pseudo-R^2	0.143	0.068
LR chi2 (*p*-value)	61.27 ($p > \chi^2 = 0.000$)	31.70 ($p > \chi^2 = 0.083$)
Mean standardized bias	12.5	10.3

The distribution of PS for rural credit recipients and non-recipients is presented in (Figure 1). There is substantial overlap in the PS distribution between the treatment and control groups, and also, a common support condition is satisfied. To check the overlapping assumption, a kernel density of PS distribution was also used (Figure 2). This indicates that all of the estimated densities have most of their respective masses in the regions in which they overlap each other.

3.5. Heterogeneity Impact

To find out whether or not the impact of rural credit varies with respect to the financial institution, the study employed heterogeneity analysis. This is important because of the substantial distinction in the conditions of the lending organization (bank vs. NGO). The results in Tables 8 and 9 show that NGOs have a higher influence on HYV seed adoption and the level of adoption, which is robust in three specifications. Farmers with NGO credit are more likely to adopt HYV seeds compared to those receiving bank credit. Similarly, bank credit recipients use 38 kg/ha more urea fertilizer compared to non-recipients, while NGO credit recipients use 40 kg/ha more urea fertilizer compared to non-recipients. These

results are in line with previous research suggesting that the effect of credit on the adoption of agricultural technology varies across financial institutions [50]. There are some probable explanations for this type of finding. The NGOs' more coordinated rural credit management strategies enable their recipients to make more efficient use of the funds received and to increase the economic strength of the participants. The most important reason for the greater adoption and use of HYV seeds for NGO rural credit receivers was that NGO authorities strictly monitor and ensure the final use of the loan that is designated for use for assigned purposes. The majority of NGO clients have limited asset capital, which poses a significantly greater risk for NGOs than for conventional bank borrowers who advocate for increased monitoring and, consequently, adoption [91].

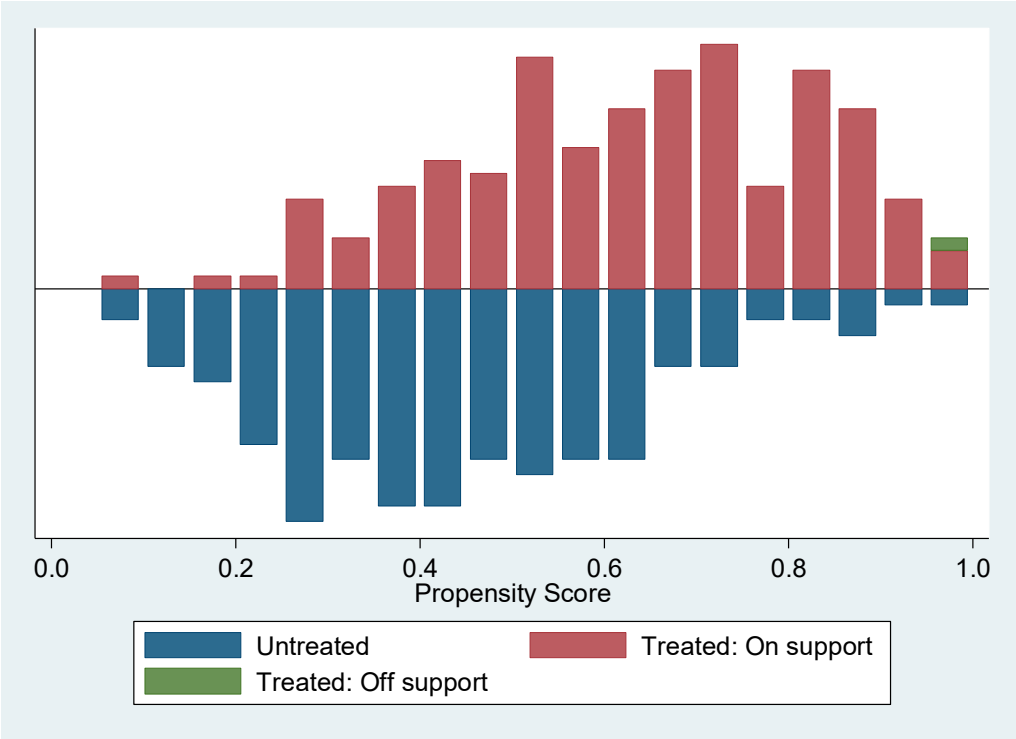


Figure 1. Distribution of propensity score and common support.

Table 8. Impact of rural credit provided by banks on agricultural technology adoption and the volume of adoption.

Outcome Variables	ATT Values			
	PSM		IPW	IPWRA
	Nearest Neighbor	Kernel		
HYV seed adoption	−0.032	0.085 *	0.0848 *	0.0751 *
	(0.029)	(0.071)	(0.047)	(0.046)
Volume of HYV seeds (kg/ha)	10.150 ***	8.328 ***	8.252 ***	8.326 ***
	(1.495)	(1.362)	(2.020)	(1.670)
Volume of urea fertilizer (kg/ha)	33.433 ***	38.389 ***	38.750 ***	37.960 ***
	(7.825)	(10.176)	(7.807)	(7.733)
Volume of TSP fertilizer (kg/ha)	30.805 ***	32.086 ***	32.345 ***	32.118 ***
	(6.065)	(3.171)	(4.927)	(4.879)
Volume of MP fertilizer (kg/ha)	6.630	12.819 *	13.0146 **	12.736 **
	(9.984)	(6.566)	(5.322)	(5.359)

Source: Field survey data, 2019. The figure in parenthesis indicates the standard error which is estimated based on a bootstrap with 5 replications. *** significant at 1%, ** significant at 5%, and * significant at 10%.

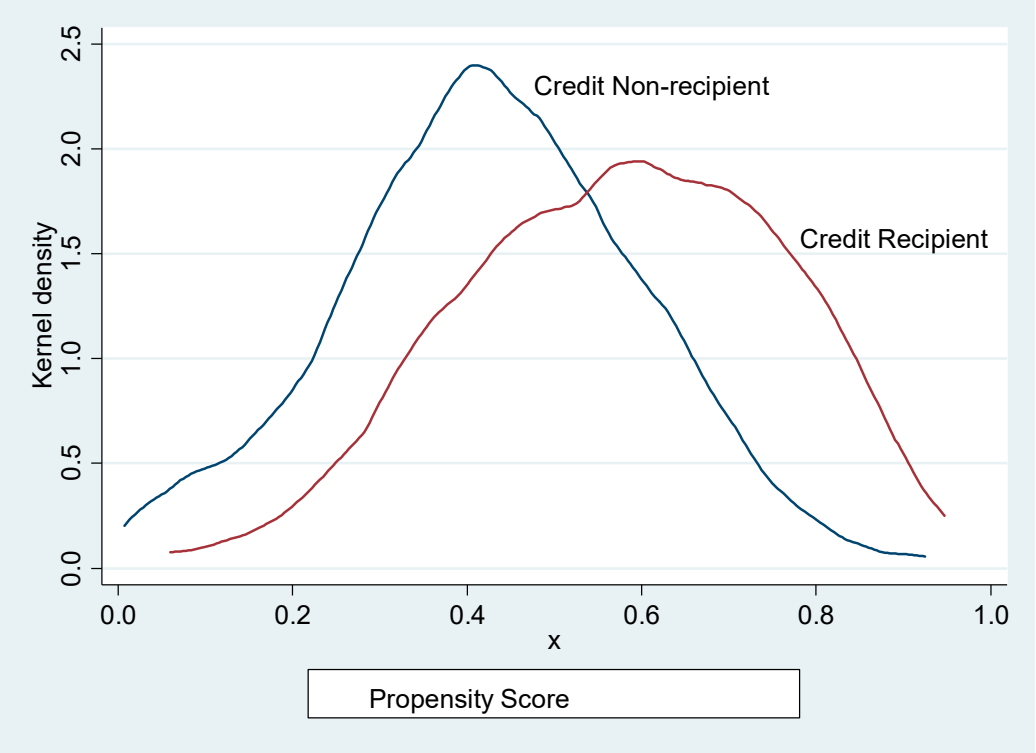


Figure 2. Overlap of propensity scores between rural credit receivers and non-receivers.

Table 9. Impact of rural credit provided by NGOs on agricultural technology adoption and the volume of adoption.

Outcome Variables	ATT Values			
	PSM		IPW	IPWRA
	Nearest Neighbor	Kernel		
HYV seed adoption	0.216 *	0.146 *	0.1050 **	0.0974 **
	(0.088)	(0.061)	(0.053)	(0.049)
Volume of HYV seeds (kg/ha)	11.033 ***	12.031 ***	8.303 *	11.792 ***
	(2.845)	(1.605)	(4.319)	(1.547)
Volume of urea fertilizer (kg/ha)	40.458 ***	29.801 ***	29.516 ***	26.111 ***
	(8.842)	(6.969)	(10.305)	(8.303)
Volume of TSP fertilizer (kg/ha)	18.145 ***	21.117 ***	20.750 ***	20.046 ***
	(3.989)	(2.348)	(5.025)	(4.738)
Volume of MP fertilizer (kg/ha)	6.494	13.632 *	13.003 **	10.468 *
	(13.770)	(6.398)	(6.091)	(5.700)

Source: Field survey data, 2019. The figure in parenthesis indicates the standard error which is estimated based on a bootstrap with 5 replications. *** significant at 1%, ** significant at 5%, and * significant at 10%.

4. Conclusions and Policy Implications

Using cross-sectional data collected from Boro rice farmers in Bangladesh, this study examined the determinants of access to rural credit and its impact on agricultural technology adoption. Both descriptive and empirical methods were used to analyze the data. The findings suggested that age, family size, family members working, and safety net negatively and significantly influence rural credit access, while earning persons in the family, literacy, rice farming experience, remittance, and total income positively influence access to rural credit. The location of the farmer also plays a significant role in credit access. It is possible that a location-specific rural credit policy could significantly increase small farmers' access to rural credit. Appropriate measures are required to increase the quantity of credit available to low-income, small-scale farmers. The results of the impact evaluation revealed that credit through banks and NGOs has had a positive and significant impact on initial adoption as well as the level of adoption of agricultural technologies. The results suggest

that increased access and utilization of financial services have the potential to stimulate productivity growth and accelerate the implementation and utilization of contemporary agricultural technologies in Bangladesh. However, recipients of rural credit from NGOs were able to apply a wider range of technologies, including HYV seeds and fertilizers, than those who received rural credit from banks. Banks can enhance their impact by integrating certain characteristics of NGOs. Strong monitoring is causing the credit of NGOs to perform better than that of banks. By enhancing their monitoring capabilities, the formal banking sector can mitigate credit risk. The banking sector's stringent legal document requirements may impede the ability of small farmers to obtain bank credit; therefore, appropriate measures need to be taken to reduce these legal document requirements. Therefore, future studies should objectively investigate the factors that explain why NGO credit performs better than credit from banks in Bangladesh in terms of agricultural technology adoption. Furthermore, care must be taken in interpreting the findings, as this study considered only a small number of Boro rice farmers. A large-scale survey may be useful to develop a complete picture of the impacts of rural credit on agricultural technology adoption.

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