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RESEARCH ARTICLE

Adoption and dis-adoption of farm mechanization in Bangladesh: Case of rice-wheat thresher

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ABSTRACT

Agricultural mechanization has the potential to greatly increase cropping intensity and production. The identification of factors that influence adoption and dis-adoption will assist policymakers in filling knowledge gaps, allowing for more successful policy implementation in Bangladesh. As a result, this study was carried out to ascertain the factors influencing the adoption and dis-adoption of rice-wheat threshers in Bangladesh. The International Food Policy Research Institute's (IFPRI) Bangladesh Integrated Household Survey (BIHS) data were used in the analysis. A total of 5605 households were selected to fulfill the objectives, and a bivariate probit model was employed. According to the findings, 52.41% households adopted the thresher, with 13.75% abandoning it later. When compared to non-adopters, farmers with larger farm sizes and regular extension contacts were 31% and 33% more likely to adopt. Dis-adoption analysis, on the other hand, revealed that the chance of dis-adoption was 9.3% lower for households that maintained contact with extension officers as compared to their counterparts. Demand-driven extension services have the ability to promote adoption while lowering dis-adoption. Farmer-based groups and technology-based extension initiatives can help to keep adoption going.

Keywords: Bivariate probit; Extension services; Farm mechanization; Rice-wheat farming

INTRODUCTION

Green revolution technologies and high-yielding cultivars have mostly propelled Bangladesh's agricultural progress (Tiwari et al., 2017). However, the agriculture sector is presently facing a number of difficulties, including a labor shortage, diminishing land, natural resource degradation, and vulnerability to climate change. Agriculture must be modernized in order to be more resilient in the face of these challenges. Agricultural mechanization is widely recognized as a critical component in modernizing agriculture across the world. Agricultural mechanization has recently received a lot of attention as a result of increasing production requirements to meet food demand (Adamade and Jackson, 2014). Demand for cereals will have to more than treble by 2050 to achieve global food security (Tilman et al., 2011; Mottaleb et al., 2016). Farm mechanization, which is related with the green movement, plays a significant role in increasing productivity required to fulfill food demand (McNulty and Grace, 2009; Adamade and Jackson, 2014). The mechanization of agricultural processes such as land preparation, irrigation, and harvesting will considerably enhance cropping intensity and productivity (Pingali, 2007)

A considerable push has been made for farm machinery for small holdings in order to increase production and promote long-term agricultural intensification (Kienzle et al., 2013). Mechanization has the ability to cut production costs and drudgery by substituting human labour and old processes with sophisticated machinery (Kienzle et al., 2013; Mahmud et al., 2014). Mechanization in land preparation and irrigation is currently increasingly common in Bangladesh. Other agricultural tasks, such as planting and harvesting, are still mostly unmechanized (Aryal et al., 2019). To boost agricultural productivity, various farm equipment, such as threshers and harvesters, have recently been added into rice-wheat cultivation in Bangladesh (Khalequzzaman and Karim, 2007; Rahman et al., 2011; Hossain, 2017). Because of labour migration

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from rural to urban areas, mechanization of rice-wheat threshing has become critical. Farmers were forced to migrate from conventional to mechanized harvesting due to a labour shortage during the peak harvesting season. Bangladesh currently has 370,000 threshers in service (Mandal, 2017). In rice cultivation, the use of mechanized harvesters will minimize postharvest losses by around 3% per season (Nath et al., 2017). Wheat threshing, on the other hand, is extremely difficult, and there is a severe labour shortage during wheat harvesting seasons, putting wheat cultivation in jeopardy. As a result, farmers need mechanical threshers for both rice and wheat threshing.

Considering the role of thresher, it is important to understand the factors that have an effect on adoption and dis-adoption. Mottaleb et al. (2016) identified the factors affecting the ownership of agricultural machineries such as irrigation pump, thresher, and power tiller in Bangladesh. However, estimates of agricultural machinery adoption based on ownership would vastly understate actual use by farmers because farmers frequently used hiring services (Aryal et al., 2019). A study conducted by Moniruzzaman et al. (2021) suggested that adoption of farm mechanization was affected by education, spouse education, farm size, and training. Takele and Selassie (2018) identified the factors that affect tractor hiring services and found that land ownership, adult female labour endowment and oxen endowment all had a substantial impact on farmers' willingness to use tractor hiring services. Several other studies identified the determinants of farm mechanization around the world (Wang et al., 2016; Gauchan and Shrestha, 2017; Alam and Khan, 2017; Akram et al., 2020). Tractors, power tillers, and irrigation pumps have been used as indicators of mechanization in prior research, which is a fairly common type of mechanization. Most previous research relied on cross-section data gathered from a limited number of sample farms, which may not be representative of the nation as a whole. Furthermore, none of the prior research addressed the issue of dis-adoption.

Taking into account the aforementioned concerns, this study was designed to investigate the determinants influencing thresher adoption and dis-adoption using nationally representative census data. This study contributes to the existing literature in two ways. First, it uses a nationally representative sample to identify the factors influencing rice-wheat thresher adoption, which may be generalized to other developing countries such as Bangladesh. Second, it identified the factors driving the dis-adoption of rice-wheat thresher. The identification of determinants will fill knowledge gaps for policymakers, which may aid in the more successful implementation of policies in Bangladesh.

AGRICULTURAL MECHANIZATION IN BANGLADESH

Agriculture mechanization in Bangladesh has been underway since the early 1950s (Tiwari et al., 2017; NAMP, 2020). Agricultural mechanization in the 1970s was mostly driven by public-sector investment in irrigation. Nonetheless, significant advancements occurred after 1990 as a consequence of private sector participation and machinery market liberalization (Tiwari et al., 2017; Islam, 2020). The private sector's market involvement has been consistent due to ongoing demand for various tillage and threshing machines. The market of agricultural machineries in Bangladesh has grown up to USD 2461.26 million in 2020 from USD 1215.68 million in 2011 (Alam, 2021). Many tasks, including as sowing, crop harvesting, threshing, and so on, have yet to be entirely completed with the assistance of machinery (Mottaleb et al., 2016). The scarcity, inefficiency, and high cost of drought animal power, as well as the availability of associated machineries such as tractors and power tillers, have all led to the adoption of 90% mechanization in tillage activities. According to recent statistics, there are 60 thousand tractors and 700 thousand power tillers in use (Alam, 2021). A shallow or deep tube-well is used to irrigate around 95% of crop land in Bangladesh. Rice-wheat threshers, on the other hand, are still infrequently used. Threshers do approximately 70% of all threshing activity in the country (Alam, 2021). Furthermore, prior to widespread adoption, a modest number of farmers began to abandon the usage of threshers. In agricultural activities, notably threshing, there is lots of opportunity for mechanization. The Government of Bangladesh has adopted the National Agricultural Mechanization Policy 2020 in order to gain the most benefits from effective agricultural mechanization (NAMP, 2020).

METHODOLOGY

Data sources and sampling

The data source for this study is Bangladesh Integrated Household Survey (BIHS) (IFPRI, 2020). The household survey was carried out by International Food Policy Research Institute (IFPRI) in rural areas of Bangladesh during 2018-2019. Data were collected from nationally representative 5605 sample households from 325 primary sampling units (PSUs) or villages. IFPRI followed a stratified sampling in two stages: selection of PSUs and selection of households within each PSU using the sampling frame developed from the community series of the 2001 population census of Bangladesh. The whole sample was divided into three groups: adopter, dis-adopters, and non-adopters of thresher. Farmers in Bangladesh typically utilize

hand or cattle treading, which raises threshing costs and reduces product quality. The usage of a thresher machine, on the other hand, is both cost effective and efficient. There are several types of threshers available in Bangladesh, including pedal threshers, open drum threshers, and close drum power threshers. A household had been classified as adopter if the household adopted any type of thresher ever. Dis-adoption is defined as household adopted thresher, but later abandoned it and currently not using it. Non-adopters did not adopted thresher ever. Out of 5605 households, 2398 households were identified as initial adopters, 2436 were non-adopters and 771 were identified as dis-adopters.

Model specification

Random utility framework was used to analyse the farmer's decision to adopt mechanized practices (Fischer and Qaim, 2012; Abebaw and Haile, 2013). Underlying the theory farmers choose to adopt mechanized practices if the utility gained from adoption is higher than non-adoption. Utility gain can be expressed as a function of several independent variables (X_i) in the following type of latent variable model;

$$Y_i^* = \beta X_i + \varepsilon_i \quad (1)$$

Where, is Y_i the dependent variable (adoption status); β is the parameter to be estimated, and ϵ_i is the error term. Binary logit and probit models were frequently used to assess the adoption or dis-adoption of a technology (Ghimire et al., 2015; Habanyati et al., 2018). However, in this study, households made two decisions: whether to adopt the thresher and, later, whether to abandon it.

In this study, the drivers of initial adoption were modelled in the first stage, and those of dis-adoption were modelled in the second (Figure 1). However, the random error terms of the two equations may be related. The bivariate probit model could be a viable option for accounting for dichotomous decisions and their possible association (Neill and Lee, 2001).

A bivariate probit model was thus used to investigate empirically the variables underlying the decision to adopt or dis-adopt. A correlation term (ϱ) is provided by the bivariate probit model to reflect how the unobserved characteristics that influence utility maximization inferred by the first decision are related to the second. A non-significant correlation term ($\varrho = 0$) means that no correlation exists between the error terms of the two equations and that

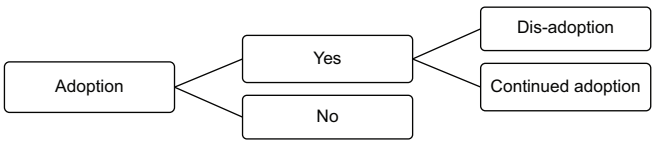

Fig 1. Decision tree related to adoption and dis-adoption of thresher

it can be calculated using different probit/logit model. In the present analysis, $Y_1 = 1$ was allocated to represent thresher's initial adoption and $Y_2 = 1$ to represent thresher's dis-adoption. Positive coefficients in both decisions were associated with an increase in the likelihood of adoption, while negative coefficients were associated with a decrease in the probability. Let Y^*_1 and Y^*_2 are two latent variables.

$$Y_i^* = \beta X_i + \varepsilon_i \quad (1)$$

$$Y_2^* = \beta_i X_{i2} + \varepsilon_2 \quad (2)$$

Where, X_i is the explanatory variables, β_i is the parameters to be estimated, ε_1 and ε_2 are joint normal error terms with means zero, variances one, and correlation $\varrho=0$.

The bivariate probit model specifies the observed outcomes as follows:

$$Y_1 = \begin{cases} 1, & if\ Y_1^* > 0 \\ 0, & Otherwise \end{cases} \quad (3)$$

$$Y_2 = \begin{cases} 1, & if\ Y_2^* > 0 \\ 0, & Otherwise \end{cases} \quad (4)$$

The model can be written as:

$$P(Y_1 = 1, Y_2 = 1) = \Phi(\beta_i X_{i1}, \beta_i X_{i2}, \rho) \quad (5)$$

Explanation of explanatory variables

Farm and socio-demographic features, economic conditions, knowledge transformation processes, and institutional factors all have an effect on the adoption of a technology (Mendola, 2007). The explanatory variables for this study were chosen based on previous studies and expectations. Table 1 contains a summary of the explanatory variables used in our model.

RESULTS

Descriptive statistics

Table 2 provides descriptive statistics for the model's explanatory variables. Table 2 reveals that 2938 (52.41%) of the 5605 households used a rice-wheat thresher. However, around 13.75% of the households that had previously adopted thresher but later abandoned it. There were some variations in selected characteristics between adopters, dis-adopters, and non-adopters. The average age of the three household groups was nearly similar. Approximately 92% of adopter households were headed by a male, whereas 67% of non-adopter households were headed by a male. When compared to adopters, dis-adopters (4.03 years) and non-

adopters (4.22 years) had a longer average schooling year (3.68 years). Agriculture is the primary source of income for 54 % of adopters. Adopters had a higher average yearly income than the other two groups, showing that capital supply may be important in farm mechanization. Adopters also had larger farms and maintained regular communication with agricultural extension officials than the other two groups. These three groups were almost identical in terms of ownership of mobile, television and credit accessibility.

Table 1: Description of explanatory variables

Variable	Description
Age	Age of the household head in years.
Gender	1 if household head is male, otherwise 0.
Education	Total years of schooling completed by the household head.
Spouse education	Total years of schooling completed by the spousal of household head.
Main earning source	1 if main source of earning is agriculture, otherwise 0.
Annual income	Total annual income from agriculture and non-agriculture sources in USD.
Working member	Total number of working members in the household.
Farm size	Total farm size in ha.
Extension contacts	1 if primary farmer maintain communication with extension officer, otherwise 0.
Mobile phone	1 if household has mobile phone, otherwise 0.
Television	1 if household has television, otherwise 0.
Access to credit	1 if household has access to credit, otherwise 0.
Access to electricity	1 if household has access to electricity, otherwise 0.
Distance from market	The distance in kilometers between the respondent's house and local market.

Factors affecting adoption and dis-adoption

The statistically significant value of Wald test indicates that there was a correlation between two equations and thus, cannot be estimated by two separate probit or logit models (Table 3). Thus, justifies the use of bivariate probit model (Rahman, 2020). Before model estimation, multicollinearity was also checked. The variance inflation factor (VIF) for each explanatory variable was observed to be less than 10 (mean VIF = 1.16), indicating no multicollinearity (Maddala, 1992). Gender, main earning source, annual income, number of working members, farm size and extension were six of the fourteen explanatory variables in the adoption equation that affected the probability of adoption. In contrast, annual income, extension contacts, and farm size, on the other hand, had a negative influence on thresher dis-adoption (Table 3).

According to the marginal effect analysis, a one-year increase in the age of the primary farmer reduced the likelihood of adoption by 0.2%. Findings also indicated that a one-year increase in schooling, while other factors remained constant, reduced the likelihood of adoption by 0.6%, which is surprising. Similarly, increasing farm size by 1 ha increases the likelihood of adoption by 31%. Marginal effect study revealed that the likelihood of adoption was around 43% higher for households whose main source of income is agriculture when compared to their peers. Similarly, the likelihood of adoption was 33% higher for household who had maintain regular contact with extension officers compared to their counterparts.

According to dis-adoption analysis, increasing farm size by 1 ha reduces the likelihood of dis-adoption by 5.6%. When compared to their contemporaries, households that

Table 2: Descriptive statistics of explanatory variables

Variable	Adopters		Dis-adopters		Non-adopters	
	Mean	Std.	Mean	Std.	Mean	Std.
Age (years)	47.84	12.92	48.31	14.56	44.80	14.16
Gender (dummy)	0.92	0.27	0.75	0.43	0.67	0.47
Education (years)	3.68	5.33	4.03	4.65	4.22	6.24
Spouse education (years)	3.67	8.90	3.51	9.92	3.01	8.21
Main earning source (dummy)	0.54	0.50	0.12	0.32	0.09	0.28
Annual income (USD)	1,770.96	1,609.91	1372.02	1659.35	1292.35	1468.46
Working member (Number)	4.55	1.76	4.04	1.75	3.96	1.69
Farm size (ha.)	0.47	0.53	0.19	0.38	0.11	0.30
Extension contacts (dummy)	0.30	0.46	0.06	0.23	0.04	0.20
Mobile phone (dummy)	0.90	0.30	0.88	0.33	0.88	0.32
Television (dummy)	0.39	0.49	0.41	0.52	0.40	0.51
Access to credit (dummy)	0.98	0.12	0.99	0.12	0.98	0.15
Access to electricity (dummy)	0.86	0.34	0.88	0.33	0.85	0.36
Distance from market (Km.)	10.42	13.76	9.98	9.77	10.48	23.06
No. of observations	2398		771		2436	

Table 3: Factors affecting adoption and dis-adoption of thresher

Variable	Adoption			Dis-adoption		
	Coefficients	Robust standard error	Marginal effect	Coefficients	Robust standard error	Marginal effect
Constant	-1.1177	0.1829	--	-1.63681	0.21310	--
Age	-0.0044***	0.0015	-0.00205	0.00914***	0.00158	0.00182
Gender	0.4866***	0.0554	0.18933	0.04438	0.05923	0.00851
Education	-0.0175***	0.0049	-0.00694	0.00176	0.00370	0.00036
Spouse education	-0.0047*	0.0026	-0.00195	0.00340	0.00212	0.00068
Main earning source	1.0538***	0.0513	0.43142	-0.53590	0.06935	-0.10693
Annual income	0.0003**	0.0001	0.00001	-0.00001***	0.00002	0.00001
Working member	0.0310**	0.0128	0.01257	-0.01238	0.01387	-0.00247
Farm size	0.7727***	0.1012	0.31256	-0.28139***	0.06225	-0.05628
Extension contacts	0.8241***	0.0664	0.33916	-0.47103***	0.08816	-0.09393
Mobile phone	0.0871	0.0645	0.03369	0.01365	0.07124	0.00266
Television	-0.0738	0.0506	-0.02993	0.02950	0.04553	0.00590
Access to credit	-0.0244	0.1490	-0.01745	0.23284	0.17260	0.04620
Access to electricity	0.0127	0.0562	0.00106	0.11644*	0.06663	0.02309
Distance from market	-0.0011	0.0008	-0.00044	0.00005	0.00093	0.00001
Log pseudolikelihood	-4499					
Wald test (ρ=0)	228***					
Wald Chi-square	1295***					
Number of observations	5605					

*, ** and *** indicates significant at 10%. 5% and 1% level, respectively

maintained contact with extension agents had a 9.3% lower likelihood of dis-adoption. Similarly, the likelihood of dis-adoption was lower in higher-income households than in lower-income households (Table 3). Dis-adoption, on the other hand, increases with the age of the household head and access to electricity.

DISCUSSION

According to descriptive statistics, income, the number of working members in the family, farm size, and extension contact are all higher in adopter group than in the non-adopter and dis-adopter groups. Higher income may enable households to acquire threshing machines. Extension programmes are one way of broadening farmers' knowledge and encouraging them to adopt. Wages of farm labourers in Bangladesh were extremely expensive during harvesting season (Tiwari et al., 2017), and thus the availability of family labour might motivate farmers to use threshers to perform threshing operations in a timely and cost-effective manner.

Adoption analysis revealed that age and education had a negative effect on the likelihood of adoption. The young group are prospective clients for thresher adoption. Young farmers are more interested in new technology and are more willing to accept the challenge of new innovation, which may motivate them to adopt. Takele and Selassie (2018) also stated that young farmers in Ethiopia are more inclined to use tractor rental services. Adoption was impacted negatively by both the education of the household head and the education of the spouse. Several studies (Alene and Manyong, 2007; Moniruzzaman et al., 2021) showed that education encourages adoption by increasing farmers' knowledge and comprehension of new technologies. In our study, however, we found a negative relationship between adoption and schooling. One probable explanation is that more education improves the likelihood of paid jobs, lowering the likelihood of agricultural technology adoption. According to Uematsu and Mishra (2010), formal education increases the tendency of small-scale farmers to work off-farm and decreases the likelihood of technology adoption.

Gender, source of income, working members, farm size, and extension contacts were also found to have a positive and significant influence on adoption. Gender marginal effect analysis shows that male-headed households are more likely to adopt than their female counterparts. However, the adoption of agricultural technology in regard to gender varies depending on the situation (Gebre et al., 2019). Males and females usually have varied access to inputs and, as a result, make distinct decisions about technology adoption. In Bangladesh, the majority of households are headed by men, and men are more active in agriculture than women. Our findings, as shown in Table 2, also revealed that more than 90% of adopters are men. This might explain why there are substantial variations in adoption rates between men and women. Adoption is more likely in households where agriculture is the primary source of income. Farmers that are primarily involved

in agriculture understand the significance of agricultural machinery, which may increase adoption. Farmers with higher incomes had a higher likelihood of adopting than their competitors. This finding is similar with the findings of Awotide et al. (2013), who found that farmers' wealth status influenced adoption positively. Farmers in better financial standing can buy threshers, which may increase adoption. The findings also showed that households with a larger number of members active in farming may be able to relax the labour constraints, which may augment adoption of new technologies.

Adoption analysis also revealed that the likelihood of adoption is higher on larger farms than on small farms. Larger farms produce more and may find it harder to employ the hand threshing technique. Larger farms benefit from economies of scale, which may push them to adopt new technologies (Uematsu and Mishra, 2010). Land is also regarded as a proxy for wealth and it is claimed that better-off households are more inclined to adopt technology (Aryal et al., 2019). Due to Bangladesh's limited and fragmented agricultural land, scale-appropriate mechanization can play an important role in improving output and minimizing post-harvest loss (Paudle et al., 2019). Access to extension services was critical to adoption. Extension personnel are constantly used as intermediaries in the dissemination of knowledge to farmers and in providing feedback to researchers. Extension programmes educate farmers on the benefits of agricultural technologies, which can lead to increased adoption.

According to dis-adoption analysis, older farmers are more likely to be dis-adopted than younger farmers. Older farmers were unwilling to face the obstacles associated with adopting a new technology, and they were also unaware of the benefits of agricultural mechanization, which may have encouraged dis-adoption. The findings also showed that having access to electricity encourages dis-adoption. However, we were unable to pinpoint the specific reasons why access to power encourages dis-adoption. Higher educational levels are related with household access to electricity and higher educated farmers are more likely to engage in off-farm services (Khandker et al. 2012). At the same time, access to electricity allows household members to participate in off-farm income-generating activities, which can increase dis-adoption.

The results of the dis-adoption analysis also indicated that income, farm size, and extension contacts all had a negative and significant influence on dis-adoption. Farmers typically reject any technology due to budgetary limitations (Uematsu and Mishra, 2010). Diversifying agricultural activities and income sources can provide a steady flow of cash that can be used to buy threshers, reducing dis-adoption. Large farmers gain more than small farms from continuing to utilize threshers. They can finish threshing activities on time, which helps to alleviate the issue of a labour shortage at peak periods (Aryal et al., 2019). Farmers who keep frequent contact with extension staff have the opportunity to discuss the necessity and advantages of agricultural mechanization, perhaps discouraging dis-adoption. Efforts by relevant authorities to improve access to agricultural extension are required. This might be accomplished by concentrating on improving extension service delivery channels such as farmer-based organizations.

CONCLUSIONS

Using census data, this study analyzes the factors that influence thresher adoption and dis-adoption. Annual income, farm size, and contact with extension officers all had a significant effect on adoption and dis-adoption. Because everyone's income is varied, the usage of a thresher may not be economical for all farmers. Farmer-based groups can play an important role in this regard. Threshers can be purchased through these groups and made available to farmers with limited financial resources. In developing countries such as Bangladesh, poor extension programme design is linked to poor extension service delivery. The usage of contemporary communication technology to modify the extension strategy will help in wider adoption. SMS (short message service) in the local language, for example, might be beneficial. These technologically based approaches have the ability to increase awareness and, as a result, reduce dis-adoption. Demonstrations may be beneficial when it comes to introducing threshers to farmers. The Department of Agricultural Extension, in collaboration with manufacturing companies, can effectively promote and demonstrate threshers around the country. Because adoption is higher on larger farms, a specific emphasis on small farms is required to bring them inside the mechanized umbrella.

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CONFLICTS OF INTEREST

None.

Authors contribution

Md. Sadique Rahman: Conceptualization, Data analysis, Writing - original draft, review & editing. Md. Hayder

Khan Sujan: Data curation, Writing - review & editing. Md. Sherf-Ul-Alam: Data curation, Writing - review & editing. Muhammad Humayun Kabir: Writing - review & editing.

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