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Determinants of Small-Scale Mechanization for Potato Farming: A Case from Bangladesh

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ABSTRACT

Identifying the determinants of farm mechanization can play a crucial role in the agriculture sector's development. The present study identifies the determinants of potato farm mechanization employing the ordered probit model. A total of 150 potato farmers were interviewed to achieve the objectives. The findings indicate that only around 13% of the respondents were high adopters. The adoption of potato farm mechanization was influenced by education, spouse education, farm size, and training. Marginal effect analysis suggested that farm size and training decrease the likelihood of being in the low adopter's category, respectively, by 13.2% and 10%, while increases the likelihood of being in the high adopter's category by 7.5% and 5.7%. Policy implications included more investment in extension facilities such as training from public agencies to sustain and increase adoption. Modifying the existing extension strategy by targeting not only primary farmers but also members of their families would help with the widespread adoption of farm mechanization.

Keywords: Adoption, farm mechanization, ordered probit model, potato

सारांश

कृषि यान्त्रीकरणका अवयवहरुको पहिचानले कृषि क्षेत्रको विकासको लागि महत्वपूर्ण भूमिका खेल्दछ । यो अध्ययनले आलुखेतीमा यान्त्रीकरणका लागि प्रयोग भइरहेको अर्डर प्रोविट मोडेलका अवयवहरुको पहिचान गर्दछ । अध्ययनको उद्देश्य पूरा गर्न १५० जना आलु उत्पादक किसानहरुसँग अन्तरवार्ता लिइएको थियो । अध्ययनको नतिजाले के देखाउँछ भने जम्मा उत्तरदाताहरुमध्ये १३% मात्र उच्च ग्रहणकर्ता थिए । आलुमा कृषि यान्त्रीकरणलाई ग्रहण गर्नको लागि ग्रहणकर्ताको शिक्षा, पति/पत्निको शिक्षा, फार्मको साइज र तालिमहरुले प्रभाव पारेको पाइयो । सिमान्तकृत असर विश्लेषण गर्दा फार्म साइज र तालिमको कारणले न्यून ग्रहणकर्ताको वर्ग क्रमश: १३.२% र १०% ले घटेको पाइयो । जवकि उच्च ग्रहणकर्ताको वर्ग क्रमश: ७.५% र ५.७% ले बढेको पाइयो । यान्त्रीकरणको ग्रहणलाई बढाउन र यसको दीगोपनाको लागि नीतिगत तहबाटै सार्वजनिक निकायको माध्यमबाट तालिम जस्ता कृषि प्रसारका सुविधाहरुमा लगानी अझ बढाउन पर्ने देखिन्छ। विद्यमान कृषि प्रसारको रणनीतिलाई रुपान्तरण गरी मुख्य किसानहरुका अलवा उनीहरुका परिवारका सदस्यहरुलाई पनि लक्षित गरी कार्यक्रम बनाउँदा कृषि यान्त्रीकरणको प्रयोग किसानस्तरमा व्यापक रुपमा बढ्न सक्छ ।

INTRODUCTION

Bangladesh's agriculture is characterized by relatively small holdings and persistent fragmentation of land. Farm mechanization associated with the green revolution has affirmed the increase in production required to fulfill the food requirements (Adamade and Jackson 2014, McNulty and Grace 2009). Mechanization reduces peak season labour supply pressures, costs of production, and making farming attractive to youth people (Biggs and Justice 2015; Baudron et al 2015). Mechanization of agricultural operations such as land preparation, irrigation, and harvesting can greatly contribute to increase cropping intensity and production (Pingali 2007). Over time, various studies around the world have shown that farm mechanization plays a key role in increasing productivity, income, and the efficiency of agricultural practices (Aurangzeb et al 2007, Rahman et al 2011, Kienzle et al 2013, Benin 2015, Vortia et al 2019). Nowadays mechanization in land preparation and irrigation is very common in Bangladesh. However, mechanization in other agricultural operations such as planting and harvesting is still very low (Aryal et al 2019). Recently, various farm machinery, such as seed planter, thresher, harvester, etc., have been introduced into agricultural farming, special in potato farming, to enhance farm productivity in Bangladesh (Khalequzzaman and Karim 2007, Rahman et al 2011).

Potato (*Solanum tuberosum* L.), Bangladesh's third-largest food crop, has been grown as a cash crop across the country (Haque et al 2012, Sujan et al 2017). Adoption of mechanization in the growing cycle and harvesting can play a significant role in increasing the productivity of potatoes. Promotion of mechanization could be the effective means of reducing costs and alleviating labour shortages during potato planting and harvesting. Although two-wheeler tractor (power tiller) for land preparation and shallow tube-well for irrigation is well adopted in Bangladesh, the adoption of potato seeder and harvester lag behind its potential. Recently, the Farm Machinery and Postharvest Process Engineering (FMPE) division of Bangladesh Agricultural Research Institute (BARI) has developed potato seeder, and harvester to speed up the planting, and harvesting, reduce production costs and minimize labour shortage. The BARI potato planter machine can reduce planting costs by 67% and can be used effectively in small-scale areas (Anonymous 2017). In the manual potato harvesting system, potato beds must first be opened by an indigenous plough, then he/she uncovered potatoes picked up by hands, requiring labour and the costs. The BARI mechanized potato harvester can reduce labour costs by 70% and ensure maximum collection of potatoes from the field (Anonymous 2017). Out-migration of labours traditionally engaged in agriculture, due to better prospect in non-agricultural sectors, has also increased the need for mechanization (Biggs and Justice 2015).

Considering the role of mechanization in potato farming, it is important to understand the factors that affect adoption. A study conducted by Mottaleb et al (2016) identified the factors affecting the ownership of agricultural mercenaries such as irrigation pump, thresher, and power tiller in Bangladesh. However, estimates of the adoption of agricultural machinery based on ownership would largely underestimate actual use by farmers. Because most of the small farmers used hiring services to access agricultural machinery (Mottaleb et al 2017, Aryal et al 2019). Several other studies have been conducted to identify the determinants of farm mechanization around the world (Wang et al 2016, Gauchan and Shrestha 2017, Khondoker et al 2016, Alam and Khan 2017, Mandal 2017, Takele and Selassie 2018). But, failing to take into account the fact that mechanization is essentially a mixed package. Different operations and crops allow for specific mechanization alternatives. Crop specific farm mechanization strategies should be placed in place to boost the overall agricultural productivity and efficiency of Bangladesh (Rahman et al 2011). Most of the earlier studies consider power tiller and irrigation pump as an indicator of mechanization. This study contributes to the literature by taking into account all types of mechanization practices required for potato farming and classifying potato farmers based on these mechanized activities. Without defining the characteristics of adopters, extension activities will need more time and resources to reach the potato farmers. Identification of determinants also fills the gaps in knowledge for policymakers that may augment the further effective development of policies in Bangladesh. The research question, therefore, to understand this, is what are the factors that influence the adoption of mechanization in potato farming.

MATERIALS AND METHODS

Data sources

Three districts: Rajshahi, Rangpur, and Dinajpur were selected based on the highest contributors to potato production in Bangladesh. The list of potato farmers was collected from the local agricultural extension office, which serves as the sampling framework for the present study. Then, for each district, 50 potato farmers were randomly selected from that list. Thus, a total of 150 potato farmers were interviewed to achieve the objectives. The sample was classified into three groups: low adopters, medium adopters, and high adopters, based on the farm mechanization practices adopted. Potato farmers have generally adopted four types of mechanized practices: power tiller for land preparation, shallow tube-well for irrigation, potato seeder for planting, and potato harvester. A potato grower has been assigned to the low adopter category if he adopted power tiller and shallow tube-well because these two practices are available and well adopted in Bangladesh. A farmer who has adopted either a seeder or a harvester and all the practices of low adopter category has been considered as a medium adopter, whereas a farmer has been assigned into high adopter category if he has adopted all the four mechanized practices. Data was collected through a face-to-face interview in 2015. Interview schedule consisting of questions on the socio-demographic profile of respondents, income, cost, and return of potato farming. To analyze the data, STATA was used.

Model specification

The study used a random utility framework to analyze the farmer's decision to adopt mechanized practices (Fischer and Qaim 2012, Abebaw and Haile 2013). According to this framework, farmers choose to adopt mechanized practices if the utility gained from adoption is higher than non-adoption. This utility gain can be expressed as a function of various explanatory variables (X_i) in the following type of latent variable model;

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

Where, Y_i^* is the dependent variable (adoption categories); β is the parameter to be estimated, and ϵ_i is the error term. Several studies (Ghose 2010, Ghimire et al 2015, Takele and Selassie 2018) used binary probit or logit model to find out the determinants of adoption ignoring the fact that farmers may exhibit a different level of adoption decision. A probit or logit model, with values of 0 or 1, is not appropriate when the dependent variable has more than two values. Mechanization is not a single measure where the farmer just decides whether to adopt or not. Rather, mechanization is a package of different practices. Therefore, it is not suitable to label two farmers just as adopters when they might exhibit a different level of adoption. Thus, to overcome the problem of binary probit or logit model, in this study we used the ordered probit model, which allows the dependent variable to take more than two discrete values (Abdel-Aty 2001, Boz and Akbay 2005, Teklewold et al 2013, Hasan 2017). In this study, the dependent variable represents ordered responses depending on the types of the mechanized practices adopted by a potato farmer. The sign of the parameter estimates readily tells us whether an independent variable has a positive or a negative effect on the probability of adoption. The dependent variable was coded as 1 =low adopters, 2 = medium adopters, and 3 = high adopters. The log-likelihood function was estimated as:

$$L = \sum_{j=1}^{j} \sum_{y_i=j} \log\left(\Phi(\mu_j - \beta_i X_i) - \Phi(\mu_1 - \beta_i X_i)\right) \quad (2)$$

Where j is the group category (0-3), μ is the threshold values, Φ is the cumulative standard function of a standard normal distribution.

Explanation of the explanatory variables

The adoption of new technology is generally influenced by different factors, such as farm and socio-demographic characteristics, economic factors, information transformation mechanisms, and institutional factors (Mendola 2007, Awotide et al 2014). The selection of the explanatory variables for this study was based on the previous literature and prior expectations (Rahman et al 2011, Aryal et al 2019). Description of the explanatory variables used in our model is given in **Table** 1.

Table 1. Description of the explanatory variables

Variable	Description	Expected sign
Experience (yrs)	Farming experience in years of the primary farmer.	+/-
Education (yrs)	Total years of schooling of the primary farmer.	+
Spouse education (yrs)	Total years of schooling of the primary farmer's spouse.	+
Farm size (hectare)	Total farm size in a hectare.	+/-
Training (days)	The total number of days spends on training during the last 12 months.	+
Societal membership (dummy)	One, if the primary farmer is involved in any societal organization, otherwise 0.	+
Distance from highway (km)	Distance of farm from the highway in kilometers, used as a proxy of market accessibility.	-
Income (000 Tk.)	Total annual income from agricultural and non-agricultural sources.	+
Credit access (dummy)	One, if the primary farmer has credit access to any formal institution, otherwise 0.	+
Field day participation (dummy)	One, if the primary farmer participated in field days during the last 12 months, otherwise 0.	+

RESULTS

Descriptive statistics of the selected variables

Table 2 gives a summary of the descriptive statistics of the socio-economic characteristics of the respondents. Out of 150 potato farmers, only 20 farmers were high adopters. About 67% of the farmers were in the low adopter category. The findings indicate that there are variations in the selected characteristics. High adopters were more experienced than the other two groups of potato farmers. The average schooling year was much higher for the high adopter's group (8.75) compared to the low adopters (4.68). Farm size was also higher for high adopters, indicating that large potato farms were more mechanized. Medium and high adopters spend more days in training relative to low adopter's group, which can augment their adoption decision. The high adopter's group was also significantly distinguishable in terms of credit access.

Table 2. Descriptive statistics of the variables

Variables	Low adopters (n = 100)		Medium adopters (n = 30)		High adopters (n = 20)	
	Mean	SE	Mean	SE	Mean	SE
Experience (yrs)	16.00	8.06	15.49	5.57	18.30	4.97
Education (yrs)	4.68	4.03	8.20	2.88	8.75	2.05
Spouse education (yrs)	2.69	3.59	4.00	3.94	5.25	4.53
Farm size (ha.)	1.03	0.45	1.26	0.60	1.89	1.10
Training (days)	0.61	0.98	2.11	1.18	2.00	1.12
Societal membership (dummy)	0.35	0.48	0.37	0.49	0.45	0.51
Distance from highway (km)	2.52	1.77	2.19	0.94	1.88	1.17
Income (000 Tk.)	268.38	116.52	324.95	123.79	231.91	72.83
Access to credit (dummy)	0.21	0.41	0.43	0.50	0.45	0.51
Field day participation (dummy)	0.19	0.39	0.29	0.46	0.25	0.44

SE indicates standard error.

Determinants of adoption

The results in **Table** 3 represent the ordered probit model analysis used to estimate the determinants of adoption. The model χ^2 is statistically significant at the 1% level. The estimated cutoff values are positive and statistically significant, suggesting that there is a natural ordering between the groups. Of the 11 explanatory variables, 5 have had a positive influence on the adoption decision. Education, spouse education, farm size, and training are significant at 1% level.

The marginal effects for all explanatory variables are presented in Table 4. The marginal effect of experience indicates that 1-year increase in farming experience decreases the likelihood of being in low adopter’s category by 0.7%. However, 1-year increase in farming experience increases the likelihood of being in the medium adopter’s category by 0.3%. The marginal effect of education indicates that 1-year increase in education would decrease the likelihood of being in the low adopter’s category by 3.6%. On the other hand, 1-year increase in education increases the likelihood of being in the medium and high adopter’s category by 1.6%, and 2.1%, respectively. Similarly, the marginal effect of spouse education indicates that 1-year increase in spouse education increases the likelihood of being in high adopter’s category by 1.2%. The marginal effect analysis of farm size indicates that 1-hectare increase in farm size decreases the likelihood of being in low adopter’s category by 13.2%, whereas 1-hectare increase in the farm size increases the likelihood of being in medium and high adopter’s category, respectively, by 5.6%, and 7.5%. Findings also indicate that 1 more day spends in training increases the likelihood of being in the high adopter category by 5.7%, whereas 1 more day in training in the low adopter category decreases the likelihood of being in the low adopter category by 10%.

Table 3. Factors affecting adoption of potato farm mechanization

Variable	Coefficient	Robust SE
Experience (yrs)	0.027*	0.016
Education (yrs)	0.150***	0.036
Spouse education (yrs)	0.090***	0.033
Farm size (ha.)	0.544***	0.187
Training (days)	0.414***	0.105
Societal membership (dummy)	-0.066	0.263
Distance from highway (km)	-0.125	0.092
Income (000 Tk.)	0.001	0.001
Access to credit (dummy)	0.386	0.257
Field day participation (dummy)	-0.055	0.259
Threshold 1	2.99***	0.57
Threshold 2	4.35***	0.65
Log likelihood	-83	
LR chi square	59***	
Pseudo R^2	0.33	

Note: *, and *** indicate significant at 10%, and 1% level, respectively.

Table 4. Marginal effect of factors affecting adoption

Variables	Marginal effect		
	Low adopters	Medium adopters	High adopters
Experience (yrs)	-0.007*	0.003*	0.004
Education (yrs)	-0.036***	0.016***	0.021***
Spouse education (yrs)	-0.022***	0.009***	0.012***
Farm size (ha.)	-0.132***	0.056***	0.075***
Training (days)	-0.100***	0.043***	0.057***
Societal membership (dummy)	0.016	-0.007	-0.009
Distance from highway (km)	0.030	-0.013	-0.017
Income (000 Tk.)	-0.000	0.000	0.001
Access to credit (dummy)	-0.093	0.040	0.053
Field day participation (dummy)	0.013	-0.006	-0.008

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

DISCUSSION

Findings indicate that the overall adoption of various mechanized practices for potato farming in Bangladesh is low. Most of the farmers had adopted only power tiller and shallow tube-well. This may be because mechanized practices such as potato seeder and harvester are not available in the farmer's field. The economic conditions of the farmers can also prevent them from investing in such mechanized practices.

A significant and positive coefficient of experience indicates that experienced farmers are more likely to be high adopters. Similarly, positive and significant coefficients of education, spouse education, farm size, and training indicate that these variables have a positive influence on the likelihood of being in the high adopter's category. Education helps farmers to understand the benefits of new technology (Alene and Manyong 2007). The positive and significant influenced of spouse education is consistent with the findings of Aryal et al (2019). Respondents who have an educated spouse can consult with them on the benefits and limitations of new technology that can increase adoption. A positive and significant coefficient of farm size indicates that farm mechanization is more prevalent among large farmers, confirms the findings of Ghosh (2010) and Mottaleb et al (2016). The findings indicate that enlargement of farm size as an important aspect of farm mechanization. The farmers who have larger farms benefit more compared to small farmers due to the need for timely farming operations to prevent labour crisis during peak times (Aryal et al 2019). The lands are generally small and fragmented in Bangladesh, which restricts the farmers to use a larger size of farm machinery (Islam 2018). However, smallholder farmers are willing to adopt mechanized technologies when the technology is scale-appropriate (Paudle et al 2019a, Paudle et al 2019b). A significant and positive coefficient of training is consistent with the findings of other studies (Kabir and Rainis 2015, Aryal et al 2019) indicated that farmers with more days in training are more likely to adopt agricultural technologies. Training is one of the ways of empowering farmers with knowledge, which is a prerequisite for better farming performance. Training helps farmers to diversify their knowledge and encourage farmers to adopt more.

CONCLUSIONS

The present study identifies the determinants of mechanization in potato farming using cross-sectional data collected through a face-to-face interview. The results of the study suggested that only about 13% of the respondents were high adopters. Experience, education, spouse education, and training have played a significant role in adoption. Investment in extension services, such as training, field visits, and demonstrations, is needed to increase the awareness and thus, the adoption. Modification of the existing extension approach by targeting the family members, special spouse of the potato farmers, may help the widespread adoption of farm mechanization. More visits to the villages by the extension staffs may ease the process of adoption. Our findings indicate that the farm size has had a positive influence on adoption. Since farmers in Bangladesh are smallholders, the emphasis should be given on small-scale machinery for widespread adoption. Nonetheless, this study has limitations. Only a small number of potato farmers were considered in this study. A large-scale survey can be useful in developing a complete scenario for mechanization in Bangladesh.

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