Ind. Jn. of Agri. Econ.
Vol.73, No.4, Oct.-Dec. 2018

ARTICLES

What Influences Adoption and Use Intensity of Artificial Insemination Technology among Smallholder Dairy Farmers in Assam? A Double Hurdle Approach

Baban Bayan and Mrinal Kanti Dutta*

ABSTRACT

Using cross-section data from 245 smallholder dairy farmers from three districts of Assam, the present study attempts to identify various factors influencing adoption decision of artificial insemination (AI) technology and extent of adoption at farm level with the help of Double-Hurdle Model. Various farm, farmer, physical, environmental and perception factors such as education and experience of the household head, awareness about AI technology, government support, distance to AI centre, all-weather road and market and herd-size are found to significantly influence the decision to adopt AI technology; while, factors such as experience of the farmer, access to credit and local breeding bull, herd size and perceived risk associated with AI adoption are found to have significant influence on intensity of adoption of AI technology.

Keywords: Adoption, Artificial insemination, Double-hurdle model, Assam.

JEL: O33, Q12, Q16.

I

INTRODUCTION

Crossbreeding of bovine stock using artificial insemination (AI) is an important strategy for enhancing dairy productivity in India (Udo *et al.*, 2011; Chandel and Malhotra, 2006). The increase in productivity due to AI has resulted in significant increase in milk production in the country reflected in the huge increase in the milk production from 17 million tonnes at the beginning of the first Five Year Plan (1951) to 132.43 million tonnes during the Twelve Five Year Plan. The milk production of the country now accounts for more than 15 per cent of the global milk production (Deshetti *et al.* 2017). Introduction of AI in the crossbreeding system is an important and economically viable technique of the 20th century. However, its diffusion in the developing countries is still very limited compared to the developed countries where more than 70 per cent animals are bred using AI (Kaaya *et al.*, 2005). It is also observed that regional disparity in the diffusion of AI is acute in developing country like India with some states performing quite well in milk production while some are

* Department of Humanities and Social Sciences, Indian Institute of Technology Guwahati, Assam - 781 039.
The study is part of Ph.D. thesis of the first author submitted to the Department of Humanities and Social Sciences, Indian Institute of Technology, Guwahati, Assam on July 24, 2017.

lagging far behind. In the north-eastern state of Assam, the proportion of crossbred cattle in total cattle population was only 3.84 per cent in 2012-13 which may be attributed to low diffusion of AI in the state. It can be mentioned that albeit AI programme in Assam was started in the field condition way back in 1970s through Intensive Cattle Development Project (ICDP), the AI coverage of breedable cattle population in the state was less than 9 per cent in 2012-13 and the same may be attributed to various socio-economic characteristics affecting the rate of adoption of AI at field level. Given that the state is predominantly cattle based in the composition of bovine population (94 per cent) and there is lack of recognised indigenous breed for conservation purpose, adequate diffusion of AI for wider coverage of breedable cattle population may contribute significantly in increasing the proportion of high yielding crossbred cattle population in Assam and thereby in increasing milk production. However, crossbreeding is also viewed in terms of its probable negative consequences of milk loss due to disease susceptibility of crossbred cattle and aggravation of the problem of feed scarcity because of their higher feed and fodder requirements (Rao *et al*. 1995; Kluszezynska, 2012). Nevertheless, economic merits of crossbreeding are well documented. Available theoretical studies on adoption of agricultural technology point out that there are various socio-economic, environmental and perception factors affecting adoption and use intensity of agricultural technology at farm household level (Doss, 2006; Feder *et al.*, 1985; Feder and Umali, 1993). New agricultural technology like AI may be treated along similar lines and important factors influencing its adoption by the farmers of Assam may be identified. It may be mentioned that to our knowledge there is lack of studies on crossbreeding of bovine stock in Assam. The study, therefore, is an attempt to identify the factors affecting adoption and use-intensity of AI technology in the state and suggest policy measures for pursuing and disseminating the technology. In the process, the finding of the study may be expected to contribute to the existing literature on agricultural technology adoption as well.

The study is organised in four sections including the introduction. Section two presents the materials and methods used in the study. Section three discusses the key results of the study; while the final section concludes the paper with a set of policy recommendations.

II

MATERIALS AND METHODS

Data and Sampling Design

The study is based on primary data collected from cattle rearing farmers spread over three districts of Assam. The study has used multi-stage sampling techniques for selection of survey households. In the first stage, using the secondary data available at Assam Livestock Development Agency (ALDA) for TE 2013-14, all 27 districts are divided into high, medium and low strata based on AI coverage of breedable cattle population. Then from each stratum one district is randomly selected. Thus, Barpeta, Sonitpur and Karbi Anglong districts are chosen from high, medium and low stratum respectively. In the second stage, two community development blocks (CDBs) are selected purposively from each district considering that one block has higher concentration of crossbred cattle with high AI coverage and the other with relatively lesser concentration and low AI coverage. The selection of the blocks is done in consultation with the senior officials of ALDA, District Veterinary officer (DVO) and the Veterinary Doctor of the Block Veterinary Dispensary. In the third stage, three villages are selected from each of these development blocks. The villages are selected on the understanding that both adopters of AI and non-adopters were sufficiently present in each village along with the consideration that the villages are not contiguous to each other. In the last stage, dairy farm households are selected in two categories: adopter and non-adopter of AI technology. Since there is lack of concrete information about the list of farmers (of adopter and non-adopter of AI) available with the AI centre and/or veterinary dispensary, a list is prepared in consultation with the village headman, veterinary surgeon and the veterinary field assistant engaged in the AI service of the village. Approximately, 20 to 30 per cent of sample farmers are selected from the list of farmers from each village. Thus, a total of 245 respondents (137AI adopters and 108 non-adopters) are interviewed using systematically designed and pre-tested questionnaire for generating primary data to fulfil the objective of the study.

Empirical Model

When the dependent variable is binary, normal density function (Probit) or logistic function (Logit) is used to see factors that drive the adoption decision. In order to identify the factors that drive the adoption and extent of adoption Tobit model is frequently used following Tobin (1958) under the assumption that the two decisions (adoption and extent of adoption) are affected jointly by the same set of factors. Thus, Tobit model is appropriate when the adoption and extent of adoption are affected by the same set of factors, estimated through right or left censoring of the dependent variable (Green, 2007). Some previous research undertook this method to identify the factors responsible for extent of adoption (Kaaya *et al.*, 2005; Mazvimavi and Twomlow, 2009). However, in corner solution application, an important limitation of the standard Tobit model is its reliance on single mechanism that determines adoption and extent of adoption decision (Cragg, 1971; Wooldridge, 2010; Burke, 2010). Given this limitation of the Tobit model, a Double-Hurdle or two-tiered model was proposed originally by Cragg (1971) and later implemented by several technology adoption studies (Tefera *et al.*, 2014; Hazarika *et al.*, 2016; Beshir, 2014; Beshir *et al.*, 2012; Gebremedhin and Swinton, 2003). The basic assumption in the Double-Hurdle model is that the decision to adopt precedes the extent of adoption decision and the factors that may affect the two decisions are likely to be different (Gebremedhin and Swinton, 2003; Tefera *et al.*, 2014).This may be due to the fact that resource endowments, constraints, perception on risk and other socio-economic factors tend to be heterogeneous across individuals (Hazarika *et al.*, 2016). The Double-Hurdle model is parametric generalisation of the Tobit model, where two different stochastic processes explain the decision to adopt and the intensity of adoption of the technology (Green, 2007; Gebremedhin and Swinton, 2003; Tefera *et al.*, 2014). The model allows for the possibility that the two decisions are affected by the different set of variables with a varied level of impacts.

In the present study, Cragg's (1971) double-hurdle model is used to identify the factors influencing the probability of adoption and intensity of use of AI technology. The two decision process is conditioned by the various explanatory factors mentioned in Table 1. The double-hurdle model has an adoption (D) decision with the following equation:

$$\begin{aligned} &D_i = 1 \ldots \text{if} \ldots\ D_i^* > 0 \ldots \text{and} \\ &D_i = 0 \ldots \text{if} \ldots D_i^* \leq 0 \\ &D_i^* = \alpha' Z_i + \varepsilon_i \end{aligned} \qquad \ldots.(1)$$

where D_i^* is a latent variable that takes the value 1 if the farmer adopts AI technology and 0 otherwise, Zi is a vector of household characteristics and α is vector of parameters. ε_i refers to standard error term. The second hurdle of the Double-Hurdle model involves truncated model which considers all the non-zero (positive) observations of the first hurdle. The truncated model is expressed as:

$$\begin{aligned} &Y_i = Y_i^* \text{ if } Y_i^* > 0 \text{ and } D_i^* > 0 \\ &Y_i = 0 \text{ otherwise} \\ &Y_i^* = \beta' x_i + v_i \end{aligned} \qquad \ldots.(2)$$

where, Y_i^* is the observed response on the proportion of calf born using AI technology during 12 months preceding the survey, x_i is a vector of explanatory factors, β is a vector of parameter and v_i is the standard error term.
The error terms are distributed as:

$$\begin{cases} \varepsilon i \sim N(0,1) \\ vi \sim N(0, \sigma 2) \end{cases} \qquad \ldots.(3)$$

The error terms ε_i and v_i are usually assumed to be independently and normally distributed. It is assumed that for each respondent the decision whether to adopt the technology and the decision of what proportion to adopt are made independently.
Finally the observed variable in a Double-Hurdle model is:

$$Y_i = Di^* Y_i^* \qquad \ldots.(4)$$

The log likelihood function for the Double-Hurdle model is

$$LogL = \sum_0 ln\left[1 - \Phi\alpha z_i\left(\frac{\beta X_i'}{\sigma}\right)\right] + \sum_+ ln\left[\Phi\alpha z_i \frac{1}{\sigma}\phi\left(\frac{Y_i - \beta X_i'}{\sigma}\right)\right] \quad \text{....(5)}$$

Under the assumption of independency between the error terms ε_i and v_i the Double-Hurdle model is equivalent to univariate Probit model (equation 1) and the truncated regression model (equation 2). The "Φ" denotes the standard normal CDF and "ϕ" is the univariate standard normal PDF.

A likelihood ratio test is carried out between Tobit and the Double-Hurdle model to determine the appropriateness of the model. The likelihood ratio statistics is computed using the following formula

$$\Gamma = -2\left[lnL_t - \left(lnL_p + lnL_{TR}\right)\right] \sim \chi_k^2 \quad \text{....(6)}$$

where, L_t,$L_p$and $L_{TR}$are the likelihood for Tobit, Probit and Truncated regression model respectively and κ is the number of independent variables in both the equations.

The test hypothesis is written as:

$$H_0: \lambda = \frac{\beta}{\sigma} \; and \; H_1: \lambda \neq \frac{\beta}{\sigma}$$

H_0 will be rejected on a pre-specified significance level, if $\Gamma > \chi_k^2$

III

RESULTS AND DISCUSSION

Measurement and Definition of Variables

The literature on technology adoption identifies various factors which are hypothesised to have a combined influence on the decision whether to adopt AI technology or not and to what extent it is adopted. These factors may include household characteristics, socio-economic characteristics and the physical environment in which the farmer operates. The variables identified to influence adoption decision and intensity of adoption in the present case are - age and education of the household head, family size, land size, area under fodder cultivation, access to credit, membership of dairy co-operative society, whether beneficiary of any government dairy development programme, number of years since starting the dairy farm, herd size, number of years since first came to know about the technology (a proxy for access to extension services), distance to market, AI centre and all weather road, access to grazing land and access to local breeding bull in the locality. The model has also incorporated a subjective variable (farmer's self-assessment regarding riskiness of the AI technology) to see if that has an influence on uptake of AI technology. These explanatory variables in the context of Assam have been identified following various technology adoption literatures; such as Doss (2006); Feder *et al.*, (1985); Feder and Umali (1993); Kaaya *et al.* (2005); Tefera *et al.*

(2014); Rehman *et al.* (2007); Awotide *et al.* (2014); Beshir *et al.* (2012). Variables along with their description and hypothesised relationship with adoption and extent of adoption of AI technology are presented in Table 1.

TABLE 1. DESCRIPTION OF VARIABLESAND THEIR HYPOTHESISED RELATION WITH ADOPTION OF AI TECHNOLOGY

Factors (1)	Description (2)	Measure (3)	Hypothesised relation (4)
Dependent variable			
AI adoption	Decision to adopt AI or Not	1 for those who have gone for use of AI, 0 otherwise	
Proportion of cattle bred using AI	Number of calves born using AI out of total calves	Ratio	
Independent variable			
Age	Age of the household head in years	Years	+/-
Education	Number of years spent in school	years	+
family size	Number of family member living together	Number	+
Land size	Land owned by the household (in hectare)	Number	+
Fodder cultivation	Amount of land used by the farmer for fodder cultivation (in hectare)	Number	+
Access to credit	Access to formal or informal sources of credit	1 if farming household have access to credit, 0 otherwise	+
Membership of DCS	Farming household having membership to Dairy cooperative Society	1 if farming household have membership to DCS, 0 otherwise	+
Distance to market	Distance to the nearest market	Kilometer	-
Distance to all weather road	Distance to the nearest all weather road	Meter	-
Grazing land	Easy access to grazing land	1 if farming household has access to grazing land, 0 otherwise	-
Beneficiary of Government Dairy Development programme	Farming household has ever availed the benefit of any dairy development programme	1 if household is a beneficiary, 0 otherwise	+
Years of starting the dairy farm	Number of years since first established the dairy farm	Years	+
Distance to AI Centre	Distance to nearest AI centre	Kilometer	-
Access to local breeding bull	Easy availability of local breeding bull in the locality of the farming household	1 if farmer has access to local breeding bull, 0 otherwise	-
Herd size	Number of cattle owned by the farming household	Number	-
Number of years since first knew about AI	Number of years since the head of household first heard about AI	Years	+
Farmers self-assessing AI as risky	Farmer's self-assessment or perception in inherent riskiness of going for AI technology	1 if the household head considers AI to be risky, 0 otherwise	-

'+' indicates the expected positive relation, and '-' indicates the negative relations of independent variable on the dependent variables.

Description of Explanatory Variables of the Empirical Model

Table 2 presents the descriptive statistics of the continuous explanatory variables with mean difference test across adopters and non-adopters group of AI technology. It is evident that among the continuous explanatory factors the mean education of the household head, land size owned by the household, land size used for fodder cultivation, distance to all weather road and number of years since first knew about AI are found to be statistically different between the two categories of respondents and significant at 1 per cent probability level. The mean herd size is significantly different between the two groups at 5 per cent probability level. The mean age of the household head of the adopter group is relatively higher compared to the non-adopter group but statistically not significant. Mean years of schooling is more than 7 years for respondents adopting AI technology against 4.7 years for non-adopter group. The reason may be that during the survey it was observed that respondents from the Nepali community engaged in the dairy activity had higher mean years of schooling and their proportion in the total sample size of the adopter group was also relatively high (37 per cent). Education being crucial for technology adoption, a lower level of education limits the information dissemination and thus hampers the process of technology adoption-diffusion (Hazarika *et al.*, 2016). Non-adopters have relatively

TABLE 2. DESCRIPTIVE STATISTICS OF EXPLANATORY VARIABLES (CONTINUOUS) BY FARMERS' GROUP IN THE AI TECHNOLOGY ADOPTION MODEL (MEAN)

Variables (1)	Adopter (N=137) (2)	Non-Adopter (N=108) (3)	t-test (two tailed) (4)
Age	50.672	49.778	0.893
	(1.101)	(1.167)	(1.6159)
Education	7.489	4.676	2.813***
	(0.404)	(0.413)	(0.5845)
family size	5.723	6.083	-0.361
	(0.203)	(0.263)	(0.3268)
Land size	0.1943	0.1277	0.067***
	(0.117)	(0.060	(0.0191)
Fodder cultivation	0.0985	0.0117	0.087***
	(0.114)	(0.031)	(0.0176)
Distance to market	2.8525	4.0648	-1.212
	(0.137))	(0.911)	(0.8227)
Distance to all weather road	350.0007	471.7685	-121.767**
	(33.283)	(35.902)	(49.208)
Years of starting the dairy farm	27.5401	27.083	0.457
	(1.274)	(1.411)	(1.905)
Distance to AI centre	2.5080	2.3865	0.121
	(0.117)	(0.130)	(0.175)
Herd size	7.16058	5.3889	1.772**
	(0.736)	(0.358)	(0.888)
Number of years since first knew about AI	13.459	7.852	5.608***
	(0.747)	(0.570)	(0.982)

Source: The authors' estimation based on field survey data.

** and *** denote significance level at 5 and 1 per cent respectively. Figures in parentheses represent standard error.

higher family size compared to the adopter category but the difference between the two categories is not statistically significant. The mean land size owned by the adopter group is higher by 0.067 hectare against the non-adopter group. Similarly, the amount of land allotted by the AI technology adopting respondents for fodder cultivation is higher by 0.087 hectare compared to non-adopting respondents. The mean distance to the nearest market from the non-adopter households is almost 4 kilometers, while it is 2.9 kilometers for the adopters of AI technology. There is a notable difference observed in the mean distance to all-weather road from the respondent's house between the two categories. Other important factors among the continuous variables incorporated in the model that may exert significant causal relation in the adoption of AI technology are the herd size and awareness about AI. The mean herd size of the AI adopting respondents is 7 cattle heads against almost 5 of non-adopting respondents. A sizeable difference is also observed with respect to number of years since first heard about AI where the mean years of first knowing about AI for the adopter category is more than 13 years against close to 8 years for the non-adopters of AI (See Table 2). This indicates that the adopters have relatively better information access about AI and may also be active participant in the awareness programme carried out by the concerned government department. Among the dummy explanatory factors incorporated in the model statistically significant differences in the two categories of respondents is observed for all the variables except grazing land (See Table 3).

TABLE 3. DISTRIBUTION OF SAMPLE HOUSEHOLDS BY EXPLANATORY VARIABLES (CATEGORICAL)

Factors (1)	Character (2)	Non-Adopter (N=108 (3)	Adopter (N=137) (4)	Total (N=245) (5)	Pearson chi^{2}test (6)
Access to credit	No	96	108	204	4.383**
	Yes	12	29	41	
Membership of DCS	No	96	74	170	34.5789***
	Yes	12	63	75	
Grazing land	No	67	94	161	1.1592
	Yes	41	43	84	
Beneficiary of Government Dairy Development programme	No	106	2	198	37.422***
	Yes	92	45	47	
Access to local breeding bull	No	2	33	35	24.3852***
	Yes	106	104	210	
Farmers' self-assessment of AI as risky	No	39	108	147	45.925***
	Yes	69	29	98	

Source: Authors' estimation based on field survey data.
*, ** and *** denote significance level at 10, 5 and 1 per cent respectively.

Diagnostic Tests

The results of the likelihood ratio test between the Tobit and the two step modeling (using Probit and Truncated regressions) show that the Double-Hurdle model is superior to Tobit model since the Γ=237.42 which exceeds the critical χ^2

value with 17 degree of freedom [$\chi 2(17)=34.41$] and significant at 1 per cent probability level (Table 4). For the robustness of model specification, Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) are included. Model with lowest AIC and BIC is always preferred. This also indicate a better fit of the Double-Hurdle model over Tobit model and suggest that decision to adopt AI technology and use intensity are governed by two independent processes (refer to supplementary file).

TABLE 4. TEST STATISTICS OF DOUBLE HURDLE MODEL

Type of statistics (1)	Probit, D (2)	Truncated, Y (Y>0) (3)
Wald χ^2	97.76	62.95
Prob> χ^2	0.000***	0.000***
LOG-L	- 80.90	35.31
AIC	197.80	-32.61
BIC	260.825	22.87
χ^2-Test Double Hurdle versus Tobit	$\acute{\Gamma}=237.42> \chi^2(17)=34.41$	

Note: ***denote significance at 1 per cent level.

Factors of Adoption and Intensity of Adoption of AI Technology

As the adoption and intensity of Adoption of AI technology is a two-step decision process and explanatory variables affect both the decisions at varying degree, the marginal effects are used for interpretation purpose of the variables. As presented in Table 5, both the first and second hurdle of the Double-Hurdle model are statistically significant (p=0.000) with Wald chi^2 value of 97.76 and 62.95 respectively indicating a good fit of the model.

Table 5 shows that education of the household head positively and significantly ($p<0.01$) affects adoption of AI technology. The value of marginal effect (0.0194) shows that with one year increase in schooling, the probability of adoption of AI technology increases by 1.94 per cent. But to what extent the technology will be adopted is not significantly explained by the formal years of schooling of the head of household in the present study. The finding is consistent with the findings of the previous literatures (Ghimire *et al.*, 2014; Asfaw *et al.*, 2012; Kassie *et al.*, 2011; Abdulai and Huffman, 2005). The amount of land used for fodder cultivation has a positive and statistically significant effect on adoption of AI technology by the farming households. Marginal effect of 3.52 indicates that one extra hectare of land brought under fodder cultivation may increase 352 per cent chance of AI technology adoption by the dairy farm households. It may be argued that domestically available inputs facilitate acceptance of a new technology. However, the same variable is found insignificant on the extent of adoption of AI technology indicating that after adoption of the technology farm households may gradually become commercialised and may later become indifferent to own input supply.

TABLE 5. DOUBLE-HURDLE ESTIMATES OF VARIABLES INFLUENCING ADOPTION AND INTENSITY OF ADOPTION OF AI TECHNOLOGY

Factors	Probit			Truncated regression		
	Coefficient	Robust Std. Err.	Marginal effect	Coefficient	Robust Std. Err.	Marginal effect
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	0.1179	0.109	0.0036	0.0024	0.0015	0.00235
Education	0.632***	0.24287	0.0194	0.0065	0.0040	0.00653
family size	-0.119	0.0441	- 0.0037	0.0064	0.0059	0.00642
Land size	1.9857	1.2869	0.6080	0.0952	0.0732	0.0952
Fodder cultivation	11.511***	3.1483	3.5244	0.0095	0.0107	0.0714
Access to credit	0.1519	0.345	0.0465	0.084**	0.0384	0.0840
Membership of DCS	0.2037	0.2881	0.0624	0.0281	0.0366	0.0282
Distance to market	-0.359***	0.940	- 0.1098	0.0006	0.0142	0.0006
Distance to all weather road	-0.0054*	0.0003	- 0.00016	0.00003	0.0000	0.00003
Grazing land	0.5164*	0.2981	0.0158	-0.0161	0.0410	-0.0161
Beneficiary of Government Dairy Development programme	0.8062*	0.4773	0.0247	0.0374	0.0365	0.0374
Years of starting the dairy farm	-0.0222**	0.0105	- 0.0068	-0.0022*	0.0013	-0.0022
Distance to AI centre	0.37931***	0.1123	0.1161	0.0059	0.0150	0.0059
Access to local breeding bull	-1.759***	0.0274	- 0.5385	-0.1547***	0.0339	-0.1547
Herd size	0.8246***	0.02741	0.0252	-0.0126***	0.0037	-0.0126
Number of years since first knew about AI	0.0714***	0.0204	0.2187	0.0064***	0.0020	0.0064
Farmer's self-assessment of riskiness of going for AI	-0.0102***	0.7683	- 0.2892	-0.0869*	0.0486	-0.0869
Constant	0.1021	0.7683		0.7604***	0.0969	
Test statistics						
	Wald χ^2***(17) = 97.76			Wald χ^2***(17) = 62.95		
	Log-L = -80.90			Log-L = 35.31		
	Pseudo R^2 = 0.52					
	No of Observation = 245			No of Observation = 137		

*,** and ***denote significance level at 10, 5 and 1 per cent respectively.

Access to institutional credit can play an important role in the adoption intensity of AI technology in Assam. The study has shown that there is a positive and significant (p<0.5) relation between the use intensity of AI technology and access to credit. The marginal effect of 0.0840 shows that having access to credit by a farm household leads to 8.4 per cent increase in the probability of AI technology intensification. The finding is consistent with Islam *et al*. (2015) and Lapple *et al.* (2015). Distance to market has negative and statistically significant influence on the adoption of AI. Farm households that are away from the market are constrained by higher transportation cost and information access about a new technology and thus have lower adoption rate. The present study has found that 1 kilometer increase in the distance from farm house to the nearest market results in 10.98 per cent decrease in the probability of AI technology adoption (p<0.01). However, there is no significant influence of the same on intensity of adoption of AI technology. The finding is consistent with the finding in some other studies (Hazarika *et al.*, 2016; Abdulai and Huffman, 2005).

The variable 'distance to all-weather road' is negatively and significantly related with the decision to adopt AI ($p<0.10$). Higher the distance to the nearest all weather road higher is the opportunity cost of labour and thus adoption decision of AI technology is negatively affected. However the variable is not found to be significant on the extent of adoption. The possible explanation may be that as farmers go for intensification of AI by increasing the number of crossbred cattle they may ensure higher earnings of the family labourers by working in their own farm getting the opportunity cost reduced. Those farmers who find grazing land easily in the locality, their input cost will decline and they may find rearing indigenous breed economical and hence may unlikely to adopt AI technology (crossbreds are reared in stall-fed condition). The finding in Table 5 counters this hypothesised relation and a significant ($p<0.10$) positive relationship is observed in the adoption of AI technology and availability of grazing land. It is found that farmers having easy access to grazing land are 1.58 per cent more likely to adopt AI technology. The possible explanation is that farmers are initially indifferent about the input cost and may decide to try the technology. However, there is a negative though not significant relation is observed between availability of grazing land and extent of AI technology adoption. Gradual reliance on stall fed rearing of crossbred cattle is likely to make them indifferent to availability of grazing land nearby.

The value of marginal effects for variable 'years of starting dairy farm' shows that with one additional year older dairy farm, the probability of adoption and intensity of adoption go down by 0.6 per cent and 0.02 per cent respectively. The justification in support of the finding may be that farmers starting with a new farm may be aspiring to increase the profitability through adoption of more innovative technology. It may also be the case that the old farmers being risk averse may always like to stick to the traditional technology and may not want change. A new farm started by a new dairy farmer may have the intent to generate higher income and thus may be less risk averse. Adoption rate will increase when the distance to necessary equipments/inputs/technicians is less and vice-versa. However, the finding of the present study goes against the negative hypothesised relation between distance to AI centre and adoption of AI technology. It is found that one kilometer increase in the distance to AI centre leads to 11.6 per cent increase in the probability of adoption of AI technology by the farm households. The justification in support of the positive relation may be given based on the explanations given by the respondents. During the course of the survey it was found that only 10.22 per cent of the farm households had inseminated their cattle at AI centre. Most of the inseminators use their two wheelers to visit the farm households and they consider inseminating farms located at far-off places from the AI centre more profitable. The higher charge than usual the inseminators can charge for fuel and transportation cost may encourage them to prefer relatively longer destination for AI insemination purpose.

It is found in the study that increase in herd size significantly and positively affects adoption of AI technology ($p<0.01$). However, increase in herd size significantly lowers intensity of AI technology adoption. One cattle head increase in the herd size leads to 2.5 per cent increase in the probability of adoption and 1.26 per cent decrease in the probability of extent of adoption of AI technology. This implies that increase in the number of cattle heads to a certain extent may encourage farmer to accept more innovative AI technology because he is gaining confidence to rear high yielding crossbred cows. However, it may happen that with further increase in the herd size with more crossbred cattle his capacity in cattle herd management and individual monitoring of stages of heat of each of the cows are constrained resulting in decrease in AI adoption intensity.

Number of years since first knew about AI is taken as proxy to access to extension support. Farmers who heard about AI much before had better extension contact compared to the one who had recently known about AI. The relation of this variable to the likelihood and intensity of adoption is consistent with the hypothesised sign. There is significant increase ($p<0.01$) in the adoption and extent of adoption of AI technology with increasing number of years since first heard about AI. It is found that with one additional year increase in the period between first knowing about AI and its adoption increases the probability of adoption and use intensity by 21.8 per cent and 0.6 per cent respectively. Thus, access to information about AI is very crucial for adoption decision of AI technology.

Perception on probable risk embedded in a new technology is very important determinant in the adoption literature. Farmers who feel new technology to be risky are very much unlikely to adopt it. The finding of the study is in line with the hypothesised relation. There is significant ($p<0.01$) decrease in the likelihood of adoption of AI technology when farmers self-assess a new technology to be risky. The marginal effects show that there is 28.9 per cent decrease in the probability of his/her adoption of AI when he/she feels adoption of AI to be risky. Similarly, there may be 8.69 per cent decrease in the probability of use intensity of AI when the farmer considers that adoption of AI technology is risky.

IV

CONCLUSIONS AND POLICY RECOMMENDATIONS

Using Double-Hurdle model the present study tries to identify factors influencing adoption and use intensity of AI for 245 smallholder dairy farmers in three districts of Assam. The study has found education of the household head and area under fodder cultivation as positive and significant. These suggest that expansion of education and encouraging fodder cultivation for lowering input costs may have stronger implications on diffusion of AI technology. There is a positive and significant relation between credit access and extent of AI technology adoption which calls for facilitating AI adopting farmers with better access to credit services. Physical environment characteristics in which farmers operate such as distance from farm household to market and all-weather road affect adoption of AI technology negatively implying that market linkages and expansion of rural roads can go a long way in increasing the rate of adoption of AI technology. The study has also found 'availability of grazing land' and 'beneficiary of existing dairy development programmes' as positive and significant factors for AI adoption. These, again, suggest laying emphasis on conservation of the grazing land and continuation of the existing government dairy development programmes (subsidised fodder seed/concentrate feed distribution under RKVY). Relatively new farms are found to be influenced more towards adoption and extent of adoption of AI technology necessitating policy priorities for targeting these farms for diffusion of AI technology. The study has shown that distance to AI centre is positive and significant implying that more than the spread of AI centre, deployment of technicians is important as AI services are mostly carried out at the farmers' door step. It is also found that access to local breeding bull negatively influences adoption and extent of adoption of AI due to risk-averse farmer's knack for sticking to lower return traditional technology. Therefore, the study suggests that intensifying the existing programme of scrub bull castration may be significant for diffusion of AI among the farmers. Finally, the study recommends that providing extension services and conducting awareness programme are important for influencing the adoption and extent of adoption positively as these may reverse the negative perception (embodied riskiness of the technology) of the farmers about AI.

Received February 2018. *Accepted November 2018.*

REFERENCES

Abdulai, A., and W.E. Huffman (2005), "The Diffusion of New Agricultural Technologies: The Case of Crossbred Cow Technology in Tanzania", *American Journal of Agricultural Economics,*Vol.83, No.3, pp.645-659.

Asfaw, S., B. Shiferraw, F. Simtowe and L. Lipper (2012), "Impact of Modern Agricultural Technologies on Smallholder Welfare: Evidence from Tanzania and Ethiopia", *Food Policy,* Vol.37, No.3, pp.283-295.

Awotide, B.A., T. Abdoulaye, A. Alene and V.M. Manyong (2014), "Assessing the Extent and Determinants of Adoption of Improved Cassava Varieties in South-Western Nigeria", *Journal of Development and Agricultural Economics,* Vol.6, No.9, pp.376-385.

Beshir, H. (2014), "Factors Affecting the Adoption and Intensity of Use of Improved Forages in North East Highlands of Ethiopia", *American Journal of Experimental Agriculture,* Vol. 4, No.1, pp.12-27.

Beshir, H., B. Emana, B. Kassa and J. Haji (2012), "Determinants of Chemical Fertilizer Technology Adoption in North Eastern Highlands of Ethiopia: The Double Hurdle Approach", *Journal of Research in Economics and International Finance,* Vol.1, No.2, pp.39-49

Burke, W.J. (2010), "Fitting and Interpreting Cragg's Tobit Alternative Using Stata", *Stata Journal,* Vol.9, No.4, pp.584-592.

Chandel, B.S. and R. Malhotra (2006), "Livestock Systems and their Performance in Poor Endowment Regions of India", *Agricultural Economics Research Review,* Vol.19, pp.311-326.

Cragg, J.G. (1971), "Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods", *Econometrica,* Vol.39, No.5, pp.829-844.

Deshetti, M.B., M.Y. Teggi and S.V. Hosamani (2017), "Milk Production and Resource Use Efficiency of Dairy Farming Under Stall-Fed Condition in Karnataka", *Indian Journal of Dairy Science*, Vol.70, No.4, pp.466-470.

Doss, C.R. (2006), "Analyzing Technology Adoption Using Microstudies: Limitations, Challenges, and Opportunities for Improvement", *Agricultural Economics*, Vol.34, No. 3, pp.207-219.

Feder, G. and D. Umali (1993), "The Adoption of Agricultural Innovation: A review", *Technological Forecasting and Social Change*, Vol.43, pp.215-239.

Feder, G.L., R.E. Just and D. Zilberman (1985), "Adoption of Agricultural Innovation in Developing Countries: A Survey", *Economic Development and Cultural Change*, Vol.32, No.2, pp.255-298.

Gebremedhin, B. and S.M. Swinton (2003), "Investment in Soil Conservation in Northern Ethiopia: The Role of Land Tenure Security and Public Programs", *Agricultural Economics*, Vol. 29, No.1, pp.69-84.

Ghimire, R., H. Wen-chi and R.B. Shrestha (2014), "Factors Affecting Adoption of Improved Rice Varieties among Rural Farm Households in Central Nepal", *Rice Science*, Vol.22, No.1, pp.35-43.

Green, W.H. (2007), "Econometric Analysis", Sixth Edition, Mcmillan, New York, U.S.A.

Hazarika, B., M.P. Bezbaruah and K. Goswami (2016), "Adoption of Modern Weaving Technology in the Handloom Micro-enterprises in Assam: A Double Hurdle Approach", *Technological Forecasting and Social Change*, Vol.102, pp.344-356.

Islam, A.H. Md.S., B.K. Barman and K. Murshed-e-Jahan (2015), "Adoption and Impact of Integrated Rice-fish Farming System in Bangladesh", *Aquaculture*, Vol.447, pp.76-85.

Kaaya, H., B. Bashasha and D. Mutetikka (2005), "Determinants of Utilization of Artificial Insemination (AI) among Ugandan Dairy Farmers", African Crop Science Conference Proceedings, Vol.7, pp.561-567.

Kassie, M., B. Shiferaw and G. Muricho (2011), "Agricultural Technology, Crop Income, and Poverty Alleviation in Uganda", *World Development*, Vol.39, No.10, pp.1784-1795

Kluszezynska, M. (2012), "Crossbreeding Strategies for Dairy Cattle: Introduction, Development and Impact on Smallholder Farms in North Gondar, Ethiopia", A Master Thesis submitted to University of Natural Resources and Life Sciences, Vienna.

Lapple, D., A. Renwick and F. Thorne (2015), "Measuring and Understanding the Drivers of Agricultural Innovation: Evidence from Ireland", *Food Policy*, Vol.51, pp.1-8.

Mazvimavi, K. and S. Twomlow (2009), "Socioeconomic and Institutional Factors Influencing Adoption of Conservation Farming by Vulnerable Households in Zimbabwe", *Agricultural System*, Vol.101, No.1-2, pp.20-29.

Rao, S.V.N., V. Venkatasubramaniun and J.D. Wit (1995), Consequences of Crossbreeding Programme in India", *Economic and Political Weekly*, Vol.30, No.39, 30 September, pp.A112-A116.

Rehman, T., K. McKemey, C.M. Yates, R.J. Cooke, C.J. Garforth, R.B. Tranter, J.R. Park and P.T. Dorward (2007), "Identifying and Understanding Factors Influencing the Uptake of New Technology on Dairy Farms in SW England Using the Theory of Reasoned Action", *Agricultural Systems*, Vol.94, pp.281-293.

Tefera, S.S., J.K. Lagat and H.K. Bett (2014), "Determinants of Artificial Insemination Use by Smallholder Dairy Farmers in Lemu-Bilbilo District, Ethiopia", *International Journal of African and Asian Studies*, Vol.4.

Tobin, J. (1958), "Estimation of Relationship for Limited Dependant Variables", *Econometrica*, Vol.26, pp. 24-36.

Udo, H.M.J., H.A. Alkilu, L.T. Phong, R.H. Bosma, I.G.S. Budisatria, B.R. Patil, T. Samdup and B.O. Bebe (2011), "Impact of Intensification of Different Types of Livestock Production in Smallholder Crop-Livestock Systems", *Livestock Science*, Vol.139 No.1, pp.22-29.

Wooldridge, J.M. (2010), *Econometric Analysis of Cross Section and Panel Data*, Second Edition, MIT Press, Massachusetts, London, England.