Determinants of Artificial Insemination Use by Smallholder Dairy Farmers in Lemu-Bilbilo District, Ethiopia

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Abstract
Despite Ethiopia possessing the highest number of livestock in Africa, its benefit to the country and smallholder farmers is small as more than 99% of the cattle are indigenous breeds with low yield. Though the government introduced Artificial Insemination (AI) technology to improve this condition, the adoption rate by smallholder farmers is still low. The objectives of the study were to determine factors affecting adoption and the extent of adoption of among smallholder dairy farmers in Lemu-Bilbilo district of Ethiopia. Data from 196 smallholder dairy farmers was collected using semi-structured questionnaire. The study utilized double-hurdle model for analysis where the two stages were run separately as Probit and truncated regression, respectively. Contacts with extension agents, access to credit, income from milk sales, feeding concentrate to cows and family size influenced the probability of adoption without affecting the extent of adoption. While membership in dairy cooperatives and off-farm income positively affected the probability and extent of AI adoption, distance from AI station and access to crossbred bull services influenced both variables negatively. Education level and efficiency of AI service had positive impact on the extent of AI use; whereas experience in keeping cross-breeds and years of using AI had negative influence on same. Much work should be done to improve the accessibility of AI service by expanding AI stations throughout the district, by training more AI technicians and by encouraging private involvement. Adult education and education in farmers training centres can be the way forward to improve educational status of farmers. Bureau of Agriculture must work to improve access to credit and extension services; established dairy cooperatives have to be strengthened and more need to be established.
Keywords: adoption, artificial insemination, double hurdle model

1. Introduction

With its 49.33 million heads of cattle, Ethiopia is the leading country in cattle population in Africa and ninth on the world (CSA, 2008). The contribution of livestock and livestock products to the agricultural GDP of Ethiopia accounts for 40 percent, excluding the values of draught power, transport and manure (Kedija *et al*., 2008). Unlike other African countries such as the neighbour Kenya, the large cattle population of Ethiopia has relatively limited numbers of exotic dairy cattle and their crosses. More than 99 percent of Ethiopia's cattle have been reported to be indigenous breeds and small Zebu types that are poor in major economically important traits. Consequently, productivity and production have remained low. According to reports, total annual milk production from about 10 million milking cows is estimated at about 3.2 billion litres, which is translated into 1.54 litres per cow per day (Kedija *et al*., 2008; CSA, 2008). This contributes to low milk consumption (19kg per year) and high infant mortality due to malnutrition. Reports also showed that there is increasing trend in import of milk and dairy products and a considerable amount of foreign exchange is spent on the import of dairy products (Land O'Lakes, 2010).

In order to improve the low productivity of the indigenous Zebu cattle, selection of the most promising breeds and crossbreeding of these indigenous breeds with high producing exotic cattle has been considered as a practical solution (Mekonnen *et al*., 2010). Artificial insemination is the single most important technique ever devised for genetic improvement of animals in all aspects including milk and beef production. The development and use of Artificial Insemination technique has revolutionized cattle production and genetic improvement, particularly in the dairy sector in developed countries (Kaaya *et al*., 2005).

While more than 70 percent of animals are bred using AI in the developed world, the technology is almost practically not available in some countries of Africa (Kaaya *et al*., 2005). In Ethiopia, AI technology was introduced about five decades ago through Chilalo Agricultural Development Unit (CADU) project which was importing semen. But later on, National Artificial Insemination Centre (NAIC) was established in Addis Ababa in the year 1981 (ESAP, 2008). Artificial insemination was started in Lemu-Bilbilo district in 1971. Despite the dominance of low yielding local breeds and the government's effort to provide AI at low price, the utilization rate of artificial insemination technology in Ethiopia in general and in Lemu-Bilbilo district in particular is low. Although there have been several technology adoption studies undertaken in Ethiopia, none of them were carried out on artificial insemination. The objective of this study was to identify the determinants of AI adoption and the extent of adoption in Lemu-Bilbilo district, Arsi zone, Ethiopia.

2. Methodology

2.1 Description of the Study Area

This study was carried out in Lemu-Bilbilo district of Arsi zone, which is located between 7°10'14"- 7°40'20"N latitudes and 39°4'59"- 39°38'56"E longitudes. Lemu-Bilbilo district with its capital at Bekoji town is situated 235km southeast of the capital Addis Ababa. The district has a total area of 1212.5km^2 and is divided in to 25 *kebeles*. The altitude of the district ranges from 1500 meters above sea level around Wabe-Shebelle River to 4195 meters above sea level at mount Kaka. The area receives an average annual rainfall of about 1100mm and has an average annual temperature ranging from 6 to 26°C. Mixed farming system is the main economic activity practiced in Lemu-Bilbilo district.

2.2 Sampling Procedure

Multi-stage sampling procedure was used. First, Arsi zone was purposively selected because AI was initially introduced in Ethiopia to this zone. Second, Lemu-Bilbilo district was purposively selected because of its cattle population and because of the livestock extension activities that have been carried out since the advent of CADU and ARDU projects. Then, four *kebeles* (Bekoji-Negesso, China-Mikael, Dawa-Bursa and Tamegn-Aware) were purposively selected based on the availability and access to the AI technology. Each *kebele* was stratified in to two groups of farmers: adopters of AI and non-adopters. The list of adopters of AI was obtained from the records at the district animal health and artificial insemination office; whereas the list of non-adopters was obtained from *kebele* administration office. From the two groups (adopters and non-adopters), simple random sampling was applied to select 98 adopters and 98 non-adopters of AI to give a total sample size of 196.

2.3 Empirical Models

In adopting new agricultural technologies, the farmer is assumed to maximize expected utility from using a new technology subject to some constraints (Feder *et al*., 1985). Adoption of new technologies normally involves two stages: the decision to either adopt or not and how much of the new technology to adopt (extent of adoption) (Mercer and Pattanayak, 2003). Tobit model has been used to identify factors influencing adoption and the extent of technology adoption under the assumption that the two decisions (adoption and extent of adoption) are affected by the same set of factors (Greene, 2007). However, in principle, the decisions on whether to adopt and how much to adopt can be made jointly or separately. When the decisions are made jointly, the Tobit model is appropriate for analyzing the factors affecting the joint decision (Greene, 2007; Teklewold *et al*., 2006). This assumption has been the norm in previous research into the determinants of the intensity of technology adoption (Pender and Kerr, 1998; Kaaya *et al*., 2005).

The decision to adopt may precede the decision on the intensity of use, and the factors affecting each decision may be different (Gebremedhin and Swinton, 2003), as assumed in this research. In this case, it is more suitable to apply a 'double-hurdle' model in which a Probit regression on adoption (using all observations) is followed by a truncated regression on the non-zero observations (Cragg, 1971). The other weakness of the Tobit model is that it attributes the censoring to a standard corner solution thereby imposing the assumption that non-adoption is attributable to economic factors alone (Cragg, 1971).

The double-hurdle model is a parametric generalization of the Tobit model, in which two separate stochastic processes determine the decision to adopt and the level of adoption of the technology (Greene, 2007; Gebremedhin and Swinton, 2003). The double-hurdle model is applied in such a way that, both hurdles (the decision for adoption and extent of adoption) have equations associated with them, incorporating the effects of farmer's characteristics and circumstances. Such explanatory variables may appear in both equations or in either of one. Most importantly, a variable appearing in both equations may have opposite effects in the two equations (Moffat, 2005). The double-hurdle model allows for the possibility that the two decisions are affected by a different set of variables.

The double-hurdle, originally by Cragg (1971), assumes that households make two sequential decisions with regard to adopting and extent of use of a technology. Each hurdle is conditioned by the household's socio-economic characteristics. In the double-hurdle model, a different latent variable is used to model each decision process. The first hurdle is an adoption equation estimated with a Probit model given as:

$$\left.\begin{array}{l} \mathrm{D_i} = 1 \text{ if } \mathrm{D_i^*} > 0, \\ \mathrm{D_i} = 0 \text{ if } \mathrm{D_i^*} \leq 0 \end{array}\right\} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (1)$$

$$\mathrm{D_i^*} = \alpha' \mathrm{Z_i} + \mathrm{u_i}$$

Where, D_i^* is the latent variable that takes the value of 1 if the farmer adopts AI technology and 0 otherwise, Z_i is vector of household characteristics, α is vector of parameters and u_i is the standard error term.

The second hurdle of double-hurdle model involves an outcome equation, which uses a truncated model to determine the extent of AI adoption. This second hurdle uses observations only from those respondents who indicated a positive value of use of AI. The truncated model, which closely resembles the Tobit model, is expressed as:

$$\left.\begin{array}{l} \mathrm{Y_i} = \mathrm{Y_i^*} \text{ if } \mathrm{Y_i^*} > 0 \textit{ and } \mathrm{D_i^*} > 0 \\ \mathrm{Y_i} = 0 \ \text{ otherwise} \\ \mathrm{Y_i^*} = \beta' \mathrm{X_i} + \mathrm{v_i} \end{array}\right\} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (2)$$

Where, Y_i is the observed response on the proportion of cattle born using AI technology, X_i is vector of explanatory variables, β is a vector of parameter and v_i is the standard error term.
The error terms, are distributed as follows:

$$\begin{Bmatrix} u_i \backsim N(0,1) \\ v_i \backsim N(0,\sigma^2) \end{Bmatrix} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

The error terms u_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 about the adoption level are made independently.
And, finally, the observed variable in a double-hurdle model is:

$$Y_i = D_i Y_i^* \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

The Log likelihood function for the Double-Hurdle model is given by:

$$\text{Log L} = \sum_0 \ln\left[1 - \Phi\alpha Z_i\left(\frac{\beta X_i'}{\sigma}\right)\right] + \sum_+ \ln\left[\Phi\alpha Z_i \frac{1}{\sigma}\phi\left(\frac{Y_i - \beta X_i'}{\sigma}\right)\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Where **Φ** denotes the standard normal CDF (Univariate or Multivariate) and ϕ is the univariate standard normal PDF. Z_i, X_i, β, α, σ as defined earlier (Moffat, 2005).
Whether a Tobit or a Double-Hurdle model is more appropriate, can be determined by separately running the Tobit and the Double-Hurdle models and then conducting a likelihood ratio test that compares the Tobit with the sum of the log likelihood functions of the Probit and truncated regression models (Greene, 2007). This test has been done by several researchers (Gebremedhin and Swinton, 2003; Moffat, 2005; Teklewold *et al.*, 2006), and the test results revealed the superiority of the Double-hurdle model over the Tobit. Similarly in this study, the likelihood ratio test favoured the double-hurdle model over Tobit (Table 2). Hence, double-hurdle model was used to estimate the decision of farmers to adopt AI technology and the extent of adoption.
Under the assumption of independency between the error terms u_i and v_i, the double hurdle model (as originally proposed by Cragg, 1971) is equivalent to a combination of a univariate Probit model and truncated regression model. The Tobit model arises if $\lambda = \frac{\beta}{\sigma}$ *and* $X = Z$.

$$\Gamma = -2[\ln L_T - (\ln L_P + \ln L_{TR})] \backsim \chi_k^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

Where L_T = likelihood for the Tobit model; L_P = likelihood for the Probit model; L_{TR} = likelihood for the truncated model; and k is the number of independent variables in the equations.
If the test statistics is written as $H_0: \lambda = \frac{\beta}{\sigma}$ and $H_1 \ \lambda \neq \frac{\beta}{\sigma}$. H_0 will be rejected on a specified level of significance level, if $\Gamma > \chi_k^2$.

2.4 Measurement and Definitions of Variables of Adoption

The dependent variable of Probit model has a dichotomous value depending on the farmers' decision either to adopt or not to adopt AI. However, the truncated regression model would have a value between 0 and 1 depending on the proportion of calves born with AI out of total calves born during the years 2011/12 and 2012/13.
Adoption literature provides a long list of factors that may influence the adoption of agricultural technologies. Generally, farmers' decision to use improved agricultural technologies and the intensity of the use in a given period of time are hypothesized to be influenced by a combined effect of various factors such as household characteristics, socio-economic and physical environments in which farmers operate. The explanatory variables included in the empirical models were selected following different literature (Feder *et al.*, 1985; Kaaya *et al.*, 2005; Berhanu and Swinton, 2003) as presented in Table 1.

Table 1: Description of Probit and Truncated regression model variables

Variables	**Measurement of the Variables**	**Expected Sign**
Dependent Variables		
Decision to Adopt AI or not (ADAI)	1 for those who have used AI 0 otherwise	
Proportion of cattle bred with AI (PCAI)	Number of calves born using AI out of total calves	
Independent Variables		
Distance from AI station (DISTAS)	Walking hours from home	-
Access to credit (ACRDT)	1 for those who have access 0 otherwise	+
Extension visits (EXTN)	Number of extension visits per year	+
Age of household head (AGHHH)	Number of years	+/-
Education level of household head (EDUC)	Number of years spent in school	+
Gender of household head (GEND)	1 for male and 0 otherwise	+/-
Family size (FMSZ)	Number of family members living together	+
Experience with exotic/cross breeds (EXPCRS)	Number of years	+
Livestock owned (TLU)	Tropical livestock units	+/-
Land size (LNDS)	Land owned in hectares	+
Feeding concentrate-feeds to cattle (CONCFD)	1 for those who feed concentrates 0 otherwise	+
Income from milk and its product sales (INCMLK)	Monthly income from milk product sales Birr	+
Off-farm income (OFRM)	1 for those with additional income 0 otherwise	+/-
Access to exotic/crossbred bull (ACBUL)	1 for those with access	-
Membership in Dairy Cooperatives (MDCOP)	1 for members 0 otherwise	+
Efficiency of the AI service (AIQLTY)	1 if efficient 0 otherwise	+
Years of using AI (YRADPT)	Number of years since the farmer adopted AI	+

3. Results and Discussion

The first step of the analysis consisted of testing the Tobit model against the alternative of a Probit and a truncated regression model (Table 2). The results of the formal test between the Tobit and the two-step modelling (using a Probit plus a truncated regression) represent evidence of the superiority of the double hurdle model. The LR test results suggest the rejection of the Tobit model since the test statistic Γ=193.44 exceeds the critical value of the χ^2 distribution. For good measure, Akakie's Information Criterion (AIC) is included as a model selection criterion. The model with the lowest AIC is preferred. This confirms the clear superiority of the double-hurdle specification and suggests that the decision to adopt AI and the decision about how much to adopt are governed by different process.

Table 2: Test statistics of double-hurdle model

Type of statistics	Probit,D	Truncated, Y(Y>0)
Wald χ^2	78.21	174.64
Prob> χ^2	0.00***	0.00***
LOG-L	-68.86	29.99
AIC(-LOG-L+k/N)	0.43	-0.13
χ^2-Test Double Hurdle versus Tobit	Γ=193.44> $\chi^2(17)$ = 33.41	

There are farmers who have adopted and not adopted AI technology. These farmers can use the new technology in a different level. Therefore, the probability of adoption was estimated using Probit model whereas the intensity and level of use of the AI was estimated using truncated regression model. Hence double hurdle model was used to estimate the Probability and intensity of adoption of improved agricultural technology. The independent variables were checked for problems of multicollinearity using a technique of variance inflation factor (VIF) for continuous variables and contingency coefficients computed for dummy variables. Robust standard errors were used to avoid the problem of heteroscedasticity.

3.1 Econometric Results

The parameter estimates of the Probit and truncated regression models employed to identify factors influencing farmers' adoption and extent of adoption of AI are presented in Table 3. Results of the analyses revealed that probability of adoption and intensity of adoption of AI were influenced by different factors and at different levels of significance.

Focusing on the effects of explanatory variables, farmers' decision on adoption of AI technology is significantly affected by off-farm income (+), family size (-), feeding concentrates to cows (+), contacts with extension agents (+), credit access (+), distance from AI station (-), income from milk sales (+), membership in dairy cooperative

(+) and access to crossbred bull (-). On the other hand, farmers' decision on level of adoption significantly influenced by education level (+), years of experience in keeping crossbred cattle (-), off-farm income (+), access to crossbred bull (-), distance from AI station (-), membership in dairy cooperative (+), the quality of AI service (+) and the years of using AI (-).

The result contrary to the expectations showed that, households with lesser number of members in the family are more likely to adopt AI technology. But conditional on adoption, family size has no significant effect on AI adoption at 5% significance level. The marginal effect of family size implies that an increase in number of households by one family member is associated with a decrease in the probability of adoption by about 5 percent. The possible explanation is that, due to the subsistence nature of the farmers they would rather spend the little they get on dependants than on new technology. Though the result disagrees with some (Asfaw *et al*., 2011; Idrisa *et al*., 2012), it is consistent with the results of Aksoy *et al*. (2011).

Table 3: Estimated Marginal Effects of AI Adoption

Variables	**Probit, D**		**Truncated regression, Y**	
	Marginal Effects	**Robust Std. Error**	**Marginal Effects**	**Robust Std. Error**
Gender of household head	-0.0237	0.5151	-0.1509	0.1069
Age of household head	-0.0031	0.0118	0.0015	0.0025
Family size	-0.0499	0.0506**	0.0151	0.0086*
Education level	-0.0010	0.0403	0.0193	0.0060***
Total landholding	0.0261	0.0712	0.0050	0.0118
Total livestock owned	-0.0056	0.0253	0.0007	0.0049
Off-farm income	0.3160	0.2960***	0.0917	0.0460**
Experience with crossbred cattle	0.0145	0.0262	-0.0112	0.0038***
Feeding concentrates to cattle	0.3998	0.2605***	-0.0318	0.0531
Extension visits per year	0.0674	0.0792**	0.0212	0.0115*
Distance from AI station	-0.2745	0.1582***	-0.1443	0.0313***
Credit access	0.3410	0.2517***	0.0662	0.0433
Income from milk product sales	0.0002	0.0003**	-0.0000	0.0000
Dairy cooperatives membership	0.2561	0.3284**	0.0947	0.0435**
Access to exotic/crossbred bull	-0.2545	0.3031**	-0.1476	0.0537***
Years of using AI	-	-	-0.0102	0.0044**
Quality of AI technology	-	-	0.1170	0.0528**
Constant		0.7756		0.1759***
/sigma	-			0.0125***
Number of observations		196		98
Log likelihood		-68.859		29.99
Wald chi2(15)		78.21		174.64
Prob >chi2		0.000		0.000

The level of education of the respondents significantly influenced the extent of adoption without affecting the probability of adoption. Conditional on adoption, the extent of use of AI increases by 1.93 percent for an additional year of schooling of a farmer. This implies that farmers educated for more than 4 years are most likely to have more number of calves born with AI. Education increases the capacity of farm households to acquire information and knowledge of improved technologies and promote the decision to use it on own farm. Educated farmers are more likely to be conversant with the associated negative effects of using bull service such as inbreeding and related diseases and therefore are more likely to use AI service. Similar results were reported by Murage and Ilatsia (2011).

Off-farm income appears to be an important factor in both hurdles as it has a significant positive effect on the probability and extent of adoption. Those farmers who have off-farm income had higher likelihood of adoption 31.6%, and conditional on adoption, farmers with off-farm income were associated with increment of proportion of calves born with AI by 9.17%. Theoretically, off-farm income can help to overcome a working capital constraint or may even finance the purchase of a fixed investment type of innovation. Having additional sources of income for smallholders can help them keep more crossbred cows as managing these breeds need more income than keeping local cows. Similar results were also obtained by Mal *et al*. (2012) and Beshir *et al*. (2012) in their studies on Bt cotton in India and fertilizer adoption in Ethiopia, respectively.

Experience of keeping crossbred cattle had negative effect on the extent of adoption of without affecting the first hurdle. The result revealed that, keeping crossbred cattle for one more year is associated with a reduction in the proportion of calves born with AI by 1.12 percent. The implication of the inverse relationship is possibly due to the fact that farmers start to own their own crossbred bulls and hence prefer to use them rather than going for AI. Since the education level and knowledge of most farmers about breeding is limited, they consider the off-springs produced by the crossbred bulls and AI as high grade. Though in many studies experience is associated with the positive use of the technology in question (Idrisa *et al*., 2012; Kaliba *et al*., 2000), there are also findings which support this result (Mal *et al*., 2012; Kaaya *et al*., 2005).

The positive coefficient of concentrate feed in the adoption equation supports the hypothesis that farmers who have already practiced provision of additional concentrate feed are more likely to adopt AI technology. There is a 40% higher predicted probability of AI adoption by farmers who feed their cows with supplementary feeds than those who do not. This variable, however, did not have significant effect on the extent of adoption. Adopting AI technology to get improved dairy breeds and the practice of feeding concentrates together provides synergistic benefits as crossbred cows have larger responses to supplementary feeding. The results are similar with the findings of Kaaya *et al*. (2005) and Teklewold *et al*. (2006).

The variable extension contact shows an effect with expected sign in each model, but is only statistically significant in the case of probability of adoption decision. The marginal effect analysis indicate that for each additional extension visit a farmer received, the probability of using AI was higher by about 6.74 percent. Extension as a source of agricultural information has been reported to increase adoption and use of new agricultural technologies (Feder *et al*., 1985). Extension contact determines the information that farmers obtain on production activities and the procedures of cattle breeding using AI. The result agrees with the findings of adoption studies in Nigeria (Idrisa *et al*., 2012) and Uganda (Kaaya *et al*., 2005).

Distance from AI station had the expected negative sign and significant influence on both the probability and extent of AI adoption. Result in Table 3 revealed that, holding other factors constant, the probability of adopting artificial insemination reduced by 27.45 percent for a walking distance of every hour to the AI station, and its marginal effect on the extent of AI use was -0.144.This implies that farmers who live closer to the source of technology are more likely to adopt the technology and are also more likely to use it intensely compared to farmers who live farther away from the AI station. The possible explanation for such trend is the level of risk which tends to increase with increase in distance to source of technology. That is, as the estrus period in cows lasts only for limited hours, farmers must detect the heat signs and take the cows to the insemination centre on time. However, distance increases the chances of expiry of heat and farmers located at distant places prefer to use bull services. The study result is in agreement with the results of Idrisa *et al*. (2012) and Murage and Ilatsia (2011).

Relative to farmers who face credit constraint; farmers who have access to credit are about 34.1 percent more likely to adopt AI technology. Upgraded off springs from AI would need better management and farmers would need to plant forages, buy concentrate supplements and get more feeds either from crop residues or hay. These activities require funds which force the farmers to take credit. The finding concurs with findings of Feder *et al*. (1985); Teklewold *et al*. (2006); Mal *et al*. (2012) which have shown that the lack of access to credit significantly inhibits the adoption of high yielding varieties even when fixed pecuniary costs are not large.

When all other factors are held constant; an increase in monthly income from milk product sales by 100 Birr is associated with 2 percent higher probability of adoption by dairy farmer in the area. This is plausible as earning income from milk product sales strengthens the financial capacity of the farmers so that they have more disposable income to buy the necessities for the crossbred animals such as supplementary feeds and grass land, and are willing to adopt AI services. Previous studies have also indicated the positive influence of farm income on adoption and use of new agricultural innovations (Feder *et al*., 1985; Kaaya *et al*., 2005).

Being member of dairy cooperative has been found to positively affect both decisions. While member farmers are 25.62 percent more likely to adopt the technology, the result of the second hurdle indicated that member of dairy cooperatives had 9.47 percent more proportion of calves born with AI than non-members. Milk being perishable product; unless there is assured market, farmers do not invest in producing more milk by adopting AI. However, cooperatives make them eager to get the breeds which can produce more milk by adopting AI. Dairy cooperatives besides buying the produce of member farmers, serve to educate farmers about how they can keep and manage their cows and also inform on the marketing of their produces. Membership in dairy cooperatives in the study area mostly assured the market for their produce. A similar observation has been made by Beshir *et al*., 2012.

Access to crossbred bull appears to be an important factor in both models. This variable has a significantly negative influence on the probability of adoption decision and extent of adoption of AI. Dairy farmers who had access to crossbred bull service were 25.45 percent less likely to adopt AI technology than those without access, and conditional on adoption, the extent of AI utilization for farmers who had access to crossbred bull was lower by 14.76 percent than farmers who did not have access. This result is logical because farmers who have access to bull services would prefer bull service over AI because of the low or no cost of bull service, the poor accessibility of the AI technology and low success rates associated with it. In the case of extent of adoption, since the respondents have already adopted the AI, it means they have owned crossbred cattle/bulls. Hence, they prefer using natural mating with their own bulls which is believed to have high success rates and more accessible. Murage and Ilatsia (2011) reported similar results in their study in Kenya.

Contrary to the hypothesis made, the experience of using AI technology was negatively related to the extent of using the technology. The result 4 shows that, for every added year of experience in using AI, the proportion of

calves born with AI reduces by 1.02 percent. The probable reason for this negative relationship is that AI is more likely to be adopted on farms with unimproved cattle. Initially, farmers adopt and use AI for the purpose of improving their dairy cattle productivity and when such herds are improved to the farmers' satisfaction AI is only used for routine breeding. In this case farmers with graded cattle herds were found to be more likely to use the bull instead of AI. This finding contradicts with the results of Kaliba *et al*. (2000) and Teklewold *et al*. (2006).
The results revealed that the quality of the AI service provided influenced the extent of AI use positively and significantly. On average, farmers who rated AI as efficient service were associated with increment of the proportion of calves born using AI by 11.7 percent. While the quality/efficiency of AI service is measured by the number of services per conception; it depends on the ability of inseminators, quality of the semen, and heat detection ability and timing of the farmers. Repeats in insemination lead to delayed conception and calving, longer calving intervals, and loss of money in terms of unrealized sales from milk and in-calf heifers. This explains why the number of cows conceiving at the first service is a crucial variable for extent of use of AI. The result is in line with the findings of Kaaya *et al*. (2005) and Mwangi *et al*. (2004).

Conclusion

The econometric results showed the distinct differences in explanatory variable effects between the two hurdles. Specifically, contacts with extension agents, access to credit, income from milk sales, feeding concentrates to cows and family size influenced the probability of adoption positively (except family size) without affecting the extent of adoption in the second hurdle. Education level of household head whereas had positive impact on the extent of AI use without affecting the probability of adoption.
Membership in dairy cooperatives and income from off-farm activities can be instrumental in AI adoption due to milk market guarantee and the strengthening of financial capacity from off-farm income. It was more preferred for farmers to use crossbred bulls due to distance and the risks associated with efficiency of AI services. However, the longer the experience with crossbred bulls, the less was the AI used.
Access to AI should be improved by expanding AI stations throughout the district along with training more AI technicians. Awareness creation especially on the difference between using AI and bull service must be done. Deploying adequate number of extension workers, educating farmers in farmers' training centres and field day visits can be the way forward. Dairy cooperatives and microfinance institutions must be established and strengthened. Ways of milk marketing at farm-gate should be designed, infrastructural development (especially road) should be considered.

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