# Adoption and Profitability of Breeding Technologies on United States Dairy Farms

Aditya R. Khanal* and Jeffrey M. Gillespie**

*Department of Agricultural and Applied Economics
Virginia Polytechnic Institute and State University,
Blacksburg, VA 24061

**Department of Agricultural Economics and Agribusiness
Louisiana State University Agricultural Center
Baton Rouge, LA 70803

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*Adoption decisions and profitability of advanced breeding technologies are analyzed for U.S. dairy farms. The bivariate probit with selection model is used. Results show that specialized, younger, more educated farmers with longer planning horizons are more likely to adopt the technologies, with positive impacts on profitability and negative influences on cost of production.*

*Key Words: breeding technologies, dairy, profitability, bivariate probit, selection, artificial insemination, sexed semen, embryo transfer*

## Introduction

Productivity of U.S. dairy farms has increased rapidly over the past 50 years: from 1959 to 2009, milk produced per cow increased 302%, according to USDA-SRS (1965) and USDA-NASS (2010). Increased productivity is attributed to improved genetics, advanced technology, and better management practices, including the use of advanced breeding innovations. Modern breeding technologies such as artificial insemination (AI), embryo transplants (ET), and sexed semen (SS) are increasingly replacing conventional natural breeding. Breeding technology affects herd genetics and reproductive performance, influencing farm economics and productivity. In this study, we examine the type of producer most likely to adopt AI, ET, and SS, and evaluate the impact associated with the adoption of these technologies on farm profitability.

Artificial insemination is the most widely used breeding technology on U.S. dairy farms. Introduced in the 1940s, AI experienced rapid initial diffusion (Johnson and Ruttan, 1997) and allowed farmers to forgo keeping potentially temperamental dairy bulls on their farms. The 2005 U.S. adoption rate of AI was 81.4% (Khanal et al., 2010). Other modern breeding technologies, ET and SS, are newer, still-diffusing technologies on U.S. dairy farms. Embryo transplant technology was first used at the farm level after the development of non-surgical methods in the 1970s. Studies suggested that ET application could yield substantial genetic improvement and increase the reproductive rate of females (De-Boer and Arendonk, 1994; Arendonk and Bijma, 2003). Its use reduces the number of dams needed to select for the next generation. However, embryo-based technologies have lower uptake rates in dairy (Smeaton et al., 2003), as a structured ET operation requires significant capital investment in facilities (Funk, 2006).

Farm use of SS is increasing. Since SS application requires sorting of semen by sex, it allows the dairy farmer to increase the supply of replacement heifers, resulting in lower heifer purchase costs. Slow sorting speed in sperm sexing and a lower conception rate associated with SS have been limitations (Weigel, 2004), but SS is expected to have wider adoption and impact in the near future (Weigel, 2004; De Vries et al., 2008). The percentage of U.S. dairy farms adopting ET and/or SS was 10.4% in 2005 (Khanal et al., 2010).

Previous studies have shown advanced breeding technologies to have significant economic value in dairy performance. The economic value of AI (Hillers et al., 1982; Barber, 1983), ET (Seidel, 1984), and SS (De Vries et al., 2008) have been discussed. Past literature provides technical description of these technologies and their application. However, we are aware of no recent studies assessing factors influencing the adoption of these technologies in dairy, as well as their farm-level impacts on profitability.

Breeding technologies are often described as information and knowledge-intensive (Johnson and Ruttan, 1997), whose adoption is affected by both biological and monetary factors (Barber, 1983). Studies have examined technology adoption in the U.S. dairy industry (El-Osta and Johnson, 1998; El-Osta and Morehart, 2000; Foltz and Chang, 2002; McBride et al., 2004; Tauer, 2009). Several have cited challenges associated with determining the impact of one, separate from other technologies (El-Osta and Johnson, 1998; Foltz and Chang, 2002; McBride et al., 2004). Since there are likely to be a number of factors affecting profitability, the effects of other technologies need to be controlled for to assess the technology of major interest.

For the present study, first, an adoption decision model assessing the factors affecting the adoption of breeding technologies is estimated, accounting for the probable correlation of the adoption of breeding technologies. The influences of adoption decisions on farm profit and costs per cwt milk produced are then estimated in impact models.

## Modeling the Adoption and Impact of Dairy Breeding Technologies

### *Adoption Decision Model*

Farmers' technology adoption decisions are generally affected by demographic and socioeconomic factors. Farmers adopt a technology if the utility associated with its adoption is greater than the utility associated with the existing technology. Letting $U_O$ and $U_N$ represent the utility of old and new breeding technologies, respectively, the dairy farmer adopts the new technology if $U_N{*}= U_N - U_O > 0$. Net benefit due to adoption of the new breeding technology, $U_N*$, which is latent to farmers, is assumed to be a function of farm and farmer attributes, as well as management considerations. If $F$ represents farm and farmer attributes and $M$ the management considerations associated with the technology and farm, $U_N * = f\,(F, M)$. If $X$ is the vector containing all of the variables in $F$ and $M$, and $\alpha$ the coefficient vector of $X$, then the equation with normally distributed error term assumption would be: $U_N * = X\alpha + \varepsilon$. So, the observable choice $D$ to adopt new breeding technologies is: $D_N = 1$ if $U_N* > 0$; $D_N = 0$ otherwise.

Let $AI*$ be the latent net benefits associated with AI adoption and $ETSS*$ be those associated with adoption of ET and/or SS[1] technologies. Then, $AI*$ and $ETSS*$ depend on

[1]Creating the variable "ETSS" is in accordance with the ARMS 2005 question regarding breeding technology: "Did this operation adopt embryo transplants and/or sexed semen as a part of genetic selection?" Thus, in this study, we have considered the "ETSS" as an indicator of modern and more recently introduced breeding technologies other than AI.

variables (whose vectors are $X_1$ and $X_2$, respectively, with $\beta_a$ and $\beta_b$ the respective coefficients) such that: $ETSS^* = X_1\beta_a + \varepsilon_1$ and $AI^* = X_2\beta_b + \varepsilon_2$. Then, $ETSS = 1$ if $ETSS^* > 0$ and $AI = 1$ if $AI^* > 0$. Variable AI =1 for adoption and 0 for non-adoption, and ETSS likewise.

Given AI and ETSS are adopted as breeding technologies, their adoption decisions are assumed to be related, implying the correlation of $\varepsilon_1$ and $\varepsilon_2$. An "older" technology, AI has been considered a successful, farmer-friendly technology. On the other hand, ET and SS are newer, still-diffusing technologies. There is the involvement of semen collected by artificial means in the use of both ET and SS. For practical purposes, ET and/or SS adopters are a subset of AI adopters since there would be few cases where ET or SS were used by farmers who did not practice AI. Thus, we assume that AI-adopting farms select to either use or not use ETSS. We adopt bivariate probit with selection to model this adoption pattern. This type of estimator was proposed by Van De Ven and Van Praag (1981) and has been used by Boyes et al., 1989; Kaplan and Venezky, 1994; and Mohanty, 2002. In the bivariate probit with selection setting, $y_{i1}$ is not observed unless $y_{i2}$ =1. So, there would be three observed outcomes with log likelihood:

$$LogL = \sum_{y2=1,y1=1} log\,\Phi_2[\beta_1,\, X'_{i2}\beta_2, \rho] + \sum_{y2=1,y1=0} log\,\Phi_2(-X'_{i1}\beta_1,\, X'_{i2}\beta_2, -\rho) - \sum_{y2=0} log\,\Phi(X'_{i2}\beta_2)$$ (Greene 2009).

*Adoption Impact Model*

A farm impact model assesses the impact of the adoption of breeding technologies (AI and ET and/or SS) on farm profitability. If $Prof_i$ is an indicator of farm profitability, then it is a function of vectors of explanatory variables ($Z_i$) indicating farm size and specialization and farmer demographics, and there are dummy variables for the adoption of breeding technologies (AI and ETSS). Other technologies may also influence profitability. So, if $T'$ is a vector of other technologies, management practices, and production systems on the farm, we can write the impact model as:

$$Prof_i = Z_i'\alpha + \gamma_1 AI_i + \gamma_2 ETSS_i + T_i'\omega + e_i,$$

where $\alpha$ is the vector of parameters for vector $Z_i$; AI and ETSS are dummy variables with $\gamma_1$ and $\gamma_2$ as respective parameters; and $\omega$ is the coefficient vector for other technologies. Estimate $e_i$ is the random error term. This equation can be estimated using Ordinary Least Squares (OLS) regression. However, estimators computed using OLS regression may be biased and inconsistent in the presence of correlation between the explanatory variables and $e_i$. Explanatory variables that are correlated with $e_i$ are endogenous and the OLS estimator fails to estimate accurately (Hill et al., 2008). We suspect AI and ETSS to be endogenous. If so, ETSS and AI are replaced with appropriate instrumental variables (Greene, 2008). Predicted probabilities from probit adoption decision models can be used as instrumental variables in profit equations (Fernandez-Cornejo et al., 2002; Fernandez-Cornejo and McBride, 2002; Foltz and Chang, 2002). Replacing actual with predicted, our equation would be:

$$Prod_i = Z_i'\alpha + \gamma_1 \widehat{AI}_i + \gamma_2 \widehat{ETSS}_i + T_i'\omega + e_i,$$

where $\widehat{AI}_i$ and $\widehat{ETSS}_i$, predicted probabilities from the bivariate probit equation, are used as instruments.

We have not assigned farmers as adopters or non-adopters; they have chosen themselves as such. If the potential for self-selection bias were ignored in estimating the impact on profit, inconsistent estimates would result. In this case, Heckman's (1979) procedure is applicable. From the bivariate probit with selection equation in the adoption decision model, selection terms, or inverse Mills ratios ($\lambda$), are estimated and used as variables in the impact equations. Two selection variables ($\widehat{\lambda^a}$and $\widehat{\lambda^b}$) are obtained from the bivariate probit model for AI and ETSS, respectively. So, the final farm impact model correcting for endogeneity and self-selection is:

$$Prod_i = Z_i'\alpha + \gamma_1 \widehat{AI_i} + \gamma_2 \widehat{ETSS_i} + T_i'\omega + \theta^a \hat{\lambda}_i^a + \theta^b \hat{\lambda}_i^b + e_i$$

Endogeneity and self-selection were tested and corrected for if detected. Based on suggestions by Wooldridge (2006) for testing endogeneity, predicted values $\widehat{AI}$ and $\widehat{ETSS}$ obtained from the bivariate probit adoption decision model were added as independent variables into the profitability equations and regressed to check for significance. Predicted values were included if either was significant; otherwise actual values were included.

*Data*

We use data from the 2005 Agricultural Resource Management Survey (ARMS), dairy version, conducted by the Economic Research Service and National Agricultural Statistical Service (NASS) of the U.S. Department of Agriculture (USDA). The dataset includes 1,814 observations from 24 states representing 90% of U.S. dairy production. Sample dairy farms were selected from the list of farms maintained by USDA-NASS. Data on agricultural production, land use, revenue, expenses, and input usage are covered by ARMS. The survey also includes information on farm operator and financial characteristics, size, commodities produced, and technology use. Each farm is weighted based on dairy production and region.

*Independent Variables: Adoption Decision Model*

Table 1 shows descriptive statistics of all variables used in the adoption decision and impact models. Farm size and specialization, farm characteristics, and demographic characteristics are included as independent variables in the adoption decision model. Artificial insemination may be considered as scale-neutral, but ET is expected to have associated scale economies, as additional investment in facilities will be required in some cases (Funk, 2006).

Degree of specialization in dairy is expected to impact managerial conditions, *M.* El-Osta and Morehart (2000) found the likelihood of being a top dairy producer to increase with specialization. We use the ratio of dairy enterprise revenues to total farm revenues, SPECIALIZE, to indicate degree of dairy enterprise specialization. A second dimension of specialization is the farmer's off-farm employment. The lower the off-farm income, the greater has been the adoption of managerially-intensive technologies such as precision farming (Fernendez-Cornejo, 2007). On the other hand, adoption of herbicide tolerant soybean, a management-reducing innovation, was positively related with off-farm income (Fernendez-Cornejo et al., 2005). In this study, dummy variable OFFFARM, which indicates whether the principal operator or spouse worked off-farm for wages or salary, is included.

Two location variables are included. WESTUS includes observations in AZ, CA, ID, NM, OR, TX, and WA. SOUTHUS includes observations in FL, GA, KY, TN, and VA. The base is the northern region that includes IL, IN, ME, MI, MN, MO, NY, OH, PA, VT, and WI.

Since having a parlor milking system was the most common factor associated with adoption of most of the other technologies, management practices and production systems on dairy farms (Khanal et al., 2010), PARLOR is included as a dummy variable in the adoption decision model as a production system indicator.

Farmer demographics included in the adoption model are AGE, education (COLLEGE), and planning horizon (TENYEARS). Younger farmers are expected to more likely adopt new technology. More educated farmers are expected to more likely adopt new technologies, as found by McBride et al. (2004) with recombinant bovine somatotropin (rbST) and Gillespie et al. (2004) with AI in the hog industry. Farmers with longer planning horizons may be more willing to invest in development of human or other capital that supports AI and/or ETSS adoption.

*Dependent Variables: Adoption Impact Model*

Profit and cost are analyzed in the adoption impact models. Net return over total costs per cwt milk produced (NETTOTCWT) and net return over operating costs per cwt milk produced (NETOPCWT) are measures of dairy enterprise profitability. These measures have been used in previous dairy profitability studies: NETTOTCWT (Gillespie et al., 2009), NETOPCWT (McBride et al., 2004), and both (Short, 2000; Short, 2004). In constructing these measures, gross returns include the value of milk sold, revenues from cull cattle sales, the implicit fertilizer value of manure produced, and other dairy income. Operating costs include feed (including the implicit value of homegrown feed), veterinary and medical, bedding, marketing, custom services, fuel, lube, electricity, repairs, other operating costs and interest on operating costs. Allocated overhead costs include hired labor, the opportunity cost of unpaid labor, capital recovery of machinery and equipment, the opportunity cost of land (rental rate), taxes and insurance, and general farm overhead. Total costs per cwt of milk produced (TOTALCWT) and its components, operating costs per cwt of milk produced (OPERCWT) and allocated costs per cwt of milk produced (ALLOCWT), are included as cost measures.

*Independent Variables: Adoption Impact Models*

Farm size has been positively related with dairy profit in previous studies (Foltz and Chang, 2002; McBride et al., 2004). Assuming dairy economies of size (Tauer and Mishra, 2006; MacDonald et al., 2007), profitability (cost) is expected to increase (decrease) with COWS. A squared term on the number of milk cows is also included. More specialized dairy farms (SPECIALIZE) are expected to yield greater enterprise net returns. Purdy et al. (1997) and El-Osta and Morehart (2000) found more specialized operations to be the better financial performers. OFFFARM is also included.

Previous studies have included technologies other than those of primary interest in profit equations to isolate the impacts of the technology of interest (Foltz and Chang, 2002; McBride et al., 2004). We include dummy variables for three production systems: PARLOR, whether animals received ≥50% of their total forage ration from pasture during the grazing season (GRAZE), and whether animals were milked three times per day (M3TIMES). Variable SUMTECH is a summation of the adoption of eight dairy technologies and management practices, measuring the intensity of technology adoption. For detailed descriptions of each of eight technologies and management practices, see Khanal et al. (2010). As discussed earlier, AI and ETSS or their predicted values, as well as the inverse Mills ratios, if applicable, are included. It is expected that AI will have positive influences on profitability (Hillers et al., 1982; Barber, 1983). The impact of ETSS is explored.

Demographic and regional variables (WESTUS and SOUTHUS) are included. COLLEGE is expected to positively influence profitability (Foltz and Chang, 2002). AGE is expected to negatively influence profitability (Foltz and Chang, 2002; Gillespie et al., 2009).

## Results

*Breeding Technology Adoption*

Table 2 shows estimates of the bivariate probit with selection adoption decision model. Though separate probit equations were also estimated, the Likelihood Ratio test indicated rejection of the null hypothesis of no correlation, suggesting the bivariate probit with selection.

Marginal effects in the bivariate probit setting may have originated from different sources. Total effects are the sum of both direct and indirect effects. Table 2 shows total marginal effects of the respective variables (partial effects for $E[y1|y2 = 1]$ with respect to the vector of characteristics). The mean estimate of $E[y1|y2 = 1]$, which is *Prob* [*ETSS=1*, *AI=1*] / *Prob*[*AI=1*], is 0.105.

Positive, significant coefficients for COWS and SPECIALIZE in the AI equation suggest larger, more specialized operations were more likely to be AI adopters. An off-farm job held by the operator and/or spouse had negative effects on both AI and ETSS adoption. The principal operator and/or spouse's holding of an off-farm job reduced the probabilities of adoption of ETSS, given AI had been adopted, by 0.033. Southern and Western U.S. dairy farmers were less likely than Midwestern and Northeastern U.S. farmers to adopt AI.

AGE and TENYEARS were negatively and positively associated, respectively, with ETSS adoption. A one year increase in the farmer's age decreased the probability of ETSS adoption, given AI had been adopted, by 0.0018. Dairy operators planning to continue operating their farms for the next ten years or more had probabilities of ETSS adoption, given AI had been adopted, that were 8.5 points higher than those not planning to continue operating for the next 10 years. COLLEGE was positively associated with the adoption of both technologies: holding a college degree increased the probability of adoption of the breeding technologies by 0.187.

*Profitability Measures*

Table 3 presents parameter estimates of the profitability measures. The adoption of both AI and ETSS positively impacted profit, with increases in net returns over both total and operating costs per cwt milk produced with both. Significant, negative coefficients of the λs in both equations were found, suggesting that self-selection would have led to biased estimates had we not corrected for it. Large influences of AI and ETSS on profit are actually larger than what would have been estimated using simple OLS regression without correcting for selection.

Other results of the profitability equations are also noteworthy. Larger farms had higher net returns over total costs per cwt milk produced, and the COWSSQU variable was negative and significant, as expected. More specialized dairy operations experienced higher profit, indicated by results for SPECIALIZE. The coefficients of GRAZE and M3TIMES were negative for NRTOTCWT. Positive SUMTECH (for NRTOTCWT) and PARLOR (for both) coefficients suggested adoption of modern dairy technologies were associated with higher profitability per cwt milk produced. Older farmers had lower NRTOTCWT, while COLLEGE led to higher net returns over both total costs and operating costs per cwt milk produced.

*Cost Measures*

To investigate the contributors to profitability, the impacts of AI and ETSS on cost are examined (Table 4). Negative, significant coefficients of AI in the three cost equations suggest that farmers can reduce both operating and allocated costs by adopting AI. Despite the higher profitability associated with ETSS adoption (relative to non-adoption), higher allocated costs per cwt milk were shown with ETSS adoption, consistent with significant associated facilities costs as discussed by Foote (2006). For OPERCWT, the $\lambda$s were significant, suggesting selection bias was corrected for. Positive signs suggest that, had we not corrected for selection bias, the influence of AI on OPERCWT would have been smaller, a result that is consistent with those found with the profit equations. Furthermore, for ALLOCWT, instrumental variables for AI and ETSS corrected for endogeneity.

Other notable results are that larger, more specialized farms had significantly lower allocated and operating costs per cwt milk produced than their counterparts. Pasture-based operations and those milking 3 times daily had higher allocated costs per cwt milk produced. The SUMTECH coefficient suggests adoption of dairy technologies reduced allocated costs.

Southern dairy farms had relatively higher operating costs per cwt milk produced. Operations with younger operators had lower allocated and operating costs per cwt milk produced than their counterparts. Operators with college degrees had higher allocated costs.

## Conclusions

For the past 70 years, advanced breeding technologies have been among the important components of structural change in the U.S. dairy industry, as their adoption can have rapid effects on genetics and reproductive performance. Previous studies have shown AI to be a widely adopted, farmer-friendly technology and ET and SS technologies to be relatively newer, still-diffusing technologies. Embryo transplant and SS technologies have been suggested to have potentially wider adoption in the near future. According to Khanal et al. (2010), in 2005, AI had an adoption rate of 81.4%, while ET and/or SS were adopted by 10.4% of dairy farms.

This study accounts for the correlation of adoption decisions of breeding technologies. The adoption of breeding technologies in the U.S. has been influenced by farm characteristics, operator characteristics, adoption of other technologies, and regional differences. Artificial insemination and ET and/or SS adopting farms are, in general, run by relatively younger and more educated farmers who do not work off-farm and plan to continue farming for at least 10 years into the future. They also produce more milk per cow than non-adopters.

Our results suggest higher net returns over both total and operating costs associated with both AI and ETSS adoption. Adopters of AI were lower-cost on both operating and allocated cost bases. However, higher allocated costs were found with ETSS, reflecting higher capital costs. Corrections for self selection bias led to increased estimates in profit associated with advanced breeding technologies and lower estimates of operating costs per cwt milk produced.

As with other studies, our findings show that larger and more specialized dairy farms are more profitable, suggesting that dairy farms can increase in size to capture the higher net returns per cwt milk. The adoption of SS may be complementary with an increase in the number of milk cows by increasing the supply of replacement heifers. For ET, significant allocated (fixed) costs should be considered. Since some part of the costs involved in the adoption of either ET or SS may be for conducting AI, larger farms that had already adopted AI may consider adoption of one or both of these technologies. Farm adoption decisions, however, would be based on the added advantages of adoption versus the additional costs of adopting these.

One of the limitations of this study is the inseparability of ET and SS adopters. In accordance with a combined question for those in 2005 ARMS dairy survey, we considered the technology, "ETSS." Though adopters of these technologies may have similar traits, the results and implications when they are treated separately may be different. Sexed semen technology is expanding and is expected to have wider adoption in near future. The actual impact of the SS technology, once it becomes more diffused, would be of further interest. We suggest further study to investigate the complementary heat synchronization techniques used on farms because its adoption may also affect breeding technology adoption decisions. Since farmer's perceptions about the profitability of the technology may also affect the adoption decision, inclusion of perception questions could also lead to greater insight.

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**Table 1: Weighted Descriptive Statistics of Variables Used in the Study**

| Variable name | Description | Mean | Standard Deviation |
|---|---|---|---|
| AGE | Principal operator's age in years | 51.467 | 11.194 |
| COLLEGE | Principal operator's education level; 1 if principal operator is college graduate or beyond | 0.209 | 0.407 |
| OFFFARM | Operator's off-farm job; 1 if principal operator or spouse work off-farm for wages or salary, else 0 | 0.475 | 0.499 |
| TENYEARS | Continuation of farm operation; 1 if operator plans to continue the operation for next 10 years or more, else 0 | 0.605 | 0.488 |
| COWS | Continuous variable; number of milk cows in the farm/1000 | 0.322 | 0.609 |
| SPECIALIZE | Farm specialization; contribution of the dairy to the total farm value of production | 0.849 | 0.170 |
| WESTUS | Regional dummy; 1 if farm is located in western US (CA, OR, WA, AZ, ID, NM or TX), else 0 | 0.212 | 0.409 |
| SOUTHUS | Regional dummy; 1 if farm is located in southern US (FL, GA, KY, TN, VA), else 0 | 0.173 | 0.378 |
| PARLOR | If parlor is adopted in the farm; 1 if adopted, else 0 | 0.685 | 0.465 |
| GRAZE | Grazing pattern,1 if farm is pasture based (those that obtain 50-100% of the total forage ration for milk cows from pasture during the grazing season), else 0 | 0.223 | 0.416 |
| M3TIMES | Milking frequency, 1 if cows are milked 3 times/day; else 0 | 0.149 | 0.357 |
| SUMTECH | Sum of the eight dummy variables for 8 different technologies or management practices of dairy (value 0 to 8) | 2.91 | 1.88 |
| AI | Whether artificial insemination is adopted on the dairy farm; 1 if adopted, else 0 | 0.789 | 0.415 |
| ETSS | Whether embryo transplant and/or sexed semen is adopted on the farm; 1 if adopted, else 0 | 0.113 | 0.317 |
| NRTOTCWT | Net return over total cost per cwt of milk produced, dollars | -9.92 | 12.87 |
| NROPCWT | Net return over operating cost per cwt of milk produced, dollars | 5.02 | 5.10 |
| TOTALCWT | Total costs per cwt of milk produced | 27.87 | 13.72 |
| OPERCWT | Operating costs per cwt of milk produced | 12.93 | 4.83 |
| ALLOCWT | Allocated costs per cwt of milk produced | 14.94 | 10.66 |

**Table 2: Adoption Decision Model: Bivariate Probit with Selection**

| Variables | ETSS Estimates | AI Estimates | Total Marginal Effects | Mean of X |
|---|---|---|---|---|
| Constant | -1.4538** | 0.1951 | | |
| | (0.6492) | (0.1951) | | |
| COWS | 0.0221 | 0.4383*** | -0.0060 | 0.147 |
| | (0.1672) | (0.0962) | (0.0254) | |
| SPECIALIZE | 0.4246 | 1.3947*** | 0.0469 | 0.847 |
| | (0.6331) | (0.1906) | (0.0696) | |
| OFFFARM | -0.2105* | -0.2633*** | -0.0333* | 0.508 |
| | (0.1075) | (0.0801) | (0.0173) | |
| WESTUS | -0.0709 | -0.6930*** | 0.0075 | 0.112 |
| | (0.2761) | (0.1162) | (0.0275) | |
| SOUTHUS | -0.0256 | -0.8652*** | 0.0255 | 0.046 |
| | (0.4435) | (0.1373) | (0.0396) | |
| PARLOR | 0.0934 | 0.0387 | 0.0185 | 0.420 |
| | (0.0983) | (0.0824) | (0.0182) | |
| AGE | -0.0104** | -0.004 | -0.0018*** | 50.920 |
| | (0.0041) | (0.0036) | (0.0007) | |
| TENYEARS | 0.4556*** | 0.0161 | 0.0852*** | 0.497 |
| | (0.1179) | (0.0818) | (0.0182) | |
| COLLEGE | 0.8008*** | 0.4088*** | 0.1870*** | 0.171 |
| | (0.1017) | (0.1151) | (0.0294) | |
| Rho (1, 2) | 0.44 | | (Selection model based on AI) | |
| Log Likelihood function -1235.97 | | | | |
| Mean estimate $E[y1 \vert y2 = 1]$= 0.105 | | | | |

***= Significant at 1%, **= Significant at 5%, * = Significant at 10%

**Table 3: Dairy Enterprise Profit Measures**

| Variables | NRTOTCWT | NROPCWT |
|---|---|---|
| Constant | -38.66** | -12.09* |
| | (6.72) | (4.93) |
| COWS | 7.01** | 0.60 |
| | (1.55) | (0.86) |
| COWSSQ | -1.16** | -0.11 |
| | (0.38) | (0.20) |
| SPECIALIZE | 19.44** | 7.83** |
| | (3.42) | (2.57) |
| OFFFARM | -0.02 | -0.17 |
| | (0.55) | (0.25) |
| PARLOR | 4.27** | 1.67** |
| | (0.67) | (0.36) |
| GRAZE | -3.76** | -0.26 |
| | (0.84) | (0.32) |
| M3TIMES | -2.20** | -0.43 |
| | (0.76) | (0.42) |
| SUMTECH | 1.99** | 0.08 |
| | (0.18) | (0.09) |
| WESTUS | -1.05 | -1.93** |
| | (0.90) | (0.37) |
| SOUTHUS | -4.76** | -3.92** |
| | (1.58) | (1.14) |
| AGE | -0.11** | 0.01 |
| | (0.02) | (0.01) |
| COLLEGE | 2.94** | 4.11** |
| | (1.29) | (0.97) |
| AI | 12.58** | 8.54** |
| | (3.20) | (2.14) |
| ETSS | 5.82* | 6.86** |
| | (2.82) | (2.10) |
| LAMDAAI | -5.24** | -5.15** |
| | (1.65) | (1.35) |
| LAMDAETSS | -4.52* | -5.27** |
| | (1.82) | (1.43) |
| Adjusted $R^2$ | 0.27 | 0.08 |

**= Significant at 1%, *= Significant at 5%.

**Table 4: Dairy Enterprise Cost Measures**

| Variables | TOTALCWT | OPERCWT | ALLOCWT |
|---|---|---|---|
| Constant | 43.15** | 25.54** | 23.56** |
| | (2.55) | (2.96) | (1.73) |
| COWS | -8.41** | -0.89** | -6.67** |
| | (1.75) | (0.53) | (1.15) |
| COWSSQ | 1.27** | 0.10 | 1.08** |
| | (0.15) | (0.09) | (0.28) |
| SPECIALIZE | -16.31** | -8.51** | -11.23** |
| | (2.26) | (1.67) | (1.72) |
| OFFFARM | -0.17 | -0.23 | -0.02 |
| | (0.55) | (0.23) | (0.41) |
| PARLOR | -3.87** | -1.71** | -2.50** |
| | (0.78) | (0.30) | (0.47) |
| GRAZE | 4.06** | 0.45 | 3.57** |
| | (0.88) | (0.31) | (0.67) |
| M3TIMES | 1.89** | 0.31 | 1.54** |
| | (0.54) | (0.34) | (0.49) |
| SUMTECH | -2.03** | -0.13 | -1.94** |
| | (0.20) | (0.08) | (0.13) |
| WESTUS | 0.21 | 0.50 | -0.39 |
| | (0.65) | (0.32) | (0.69) |
| SOUTHUS | 2.35 | 2.78** | 0.78 |
| | (0.80) | (0.75) | (1.04) |
| AGE | 0.15** | 0.002 | 0.13** |
| | (0.02) | (0.01) | (0.02) |
| COLLEGE | 1.56* | -1.33 | 1.38** |
| | (0.68) | (0.57) | (0.51) |
| AI | -4.34** | -4.71** | |
| | (0.88) | (1.23) | |
| ETSS | 0.36 | -1.69 | |
| | (0.70) | (1.16) | |
| PREDAI | | | -1.29** |
| | | | (0.33) |
| PREDETSS | | | 1.37* |
| | | | (0.83) |
| LAMDAAI | | 2.12** | |
| | | (0.73) | |
| LAMDAETSS | | 1.92* | |
| | | (0.77) | |
| Adjusted $R^2$ | 0.29 | 0.09 | 0.37 |

**= Significant at 1%, *= Significant at 5%.