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Adoption and Productivity of Breeding Technologies: Evidence from US Dairy Farms

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Adoption and associated profitability of advanced breeding technologies are analyzed for US dairy farms. We account for correlation and selection associated with breeding technology adoption decisions. The bivariate probit model with selection is used to model adoption decisions and least squares with extended correction terms is used for profit, productivity, and cost equations. Results show that more specialized farms with younger, more educated operators having longer planning horizons are more likely to adopt advanced breeding technologies. Artificial insemination positively impacted farm profit and negatively impacted cost of milk production, while advanced breeding technologies positively impacted milk produced per cow.

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

Introduction

Productivity of US dairy farms has increased rapidly over the past 50 years: from 1961 to 2011, milk produced per cow increased 296%, according to US Department of Agriculture (USDA) Statistical Reporting Service (SRS; 1964) and USDA National Agricultural Statistics Service (NASS; 2012) statistics. This increased productivity is attributed to improved genetics, advanced technology, and better management practices, including advanced breeding innovations. Modern breeding technologies such as artificial insemination (AI), embryo transplants (ET), and sexed semen (SS) have been replacing conventional natural breeding for a number of years: Khanal, Gillespie, and MacDonald (2010) estimate that US dairy farms using genetic selection and breeding programs such as ET and AI increased from 64.3% in 2000 to 81.5% in 2005. Breeding technology affects herd genetics and reproductive performance, influencing farm economics and productivity. Johnson and Ruttan (1997) suggested breeding technologies were the most significant factor contributing to farm livestock productivity since the 1940s. The dairy sector was the first to extensively adopt AI for commercial production in the livestock sector. In this study, we examine the type of producer most likely to adopt AI, ET, and SS and evaluate the impact of these technologies on farm productivity and profitability. In this article, factors influencing the adoption of AI, ET and/or SS are examined, and the impacts of these technologies on farm costs, profitability, and milk cow productivity are shown.

Artificial insemination is the most widely used advanced breeding technology on US dairy farms. After its introduction to the United States from Denmark in 1938 (Shumway, Blake, R.W., Leatham, & Tomaszewski, 1987), AI experienced rapid initial diffusion (Johnson & Ruttan, 1997). It was considered as a solution to the needs for genetic improvement and elimination of costly venereal diseases (Foote, 1996) and allowed farmers to forgo keeping potentially temperamental and dangerous dairy bulls on their farms. It is likely to be particularly beneficial if it improves reproductive success measured by calving interval, days open, and other measures. Hogeland (1990) estimated that 70% of the US dairy herd was bred via AI in 1990. Approximately 81.4% of US dairy farms had adopted AI by 2005; these farms produced 88.9% of the US milk produced (Khanal et al., 2010). Results of the National Animal Health Monitoring Study (NAHMS) survey, conducted in 2007 by the USDA Animal Plant Health Inspection Service (APHIS), showed that 88.4% of US dairy operations had used AI in 2007, with approximately 72.5% of the pregnancies resulting from AI (USDA APHIS, 2009). Statistics from the 2010 USDA Agricultural Resource Management Survey (ARMS) dairy version, conducted by USDA NASS and Economic Research Service (ERS), suggest that 80.1% of US dairy farms used AI in 2010, with these farms producing 90.5% of the nation's milk. Clearly, AI dominates the use of natural service on US dairy farms. There are various protocols that can be followed with AI use, with adoption rates of various protocols shown and discussed in a report by USDA APHIS (2009) and an economic analysis of several AI protocols conducted by Olynk and Wolf (2009).

Other modern breeding technologies, ET and SS, are newer technologies on US 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 (Arendonk, Van, & Bijma, 2003). Its use reduces the number of dams needed to select for the next generation. As discussed in a USDA APHIS report (2009), ET usage has resulted in higher pregnancy rates for cows under heat stress than AI alone. However, embryo-based technologies have lower uptake rates in dairy (Smeaton, Harris, Xu, & Vivanco, 2003), as they require significant investment in facilities (Funk, 2006). Results of the 2007 NAHMS survey suggest that about 11.5% of US dairy operations had used ET during the past year, with 9.9% having pregnancies conceived by ET during that year (USDA APHIS, 2009).

Farm use of SS technology is increasing, as indicated by Dairy Herd Improvement Association herd records, which show respective SS breeding increases from 2006 to 2008 of 1.4% to 17.8% for heifers and 0.1% to 0.4% for cows (Norman, Hutchison, & Miller, 2010). It was first made commercially available in 2003 (Olynk & Wolf, 2007). Since SS application requires sorting of semen by sex, it allows the dairy farmer to increase the supply of replacement heifers (though it might also be used to increase the supply of male calves). Slow sorting speed in sperm sexing and a lower conception rate associated with SS have been the main limitations (Weigel, 2004). Sexed semen technology is expected to have wider adoption and impact in the near future (DeVries et al., 2008;Weigel, 2004). The 2007 NAHMS survey results show that, of the 88.4% of operations where pregnancies were conceived by AI, 11.4% of the heifers had been inseminated with SS, compared with 3.5% of the cows (USDA APHIS, 2009). The greater use of SS with heifers is likely due to the greater fertility of heifers, the lower counts of viable sperm per straw with SS, and thus the recommendation that SS be used only with virgin heifers (USDA APHIS, 2009). DeVries (2013) discussed the increased supply of heifers resulting from use of SS, estimating 722,000 additional heifers over the period of 2008-2012.

Approximately 10.4% of US dairy farms had adopted ET and/or SS in 2005; these farms produced 15.7% of the milk produced in the United States (Khanal et al., 2010). By 2010, USDA ARMS data suggested that 17.8% of US dairy farms had adopted ET and/or SS in 2010, with those farms producing 26.9% of the milk produced in the United States.

Previous studies have shown advanced breeding technologies to have significant economic value in dairy performance. The economic value of AI (Barber, 1983; Hillers, Thonney, & Gaskins, 1982), ET (Seidel, 1984), and SS (DeVries et al., 2008; Olynk & Wolf, 2007) have been discussed. Olynk and Wolf (2007) found that SS use—as opposed to conventional AI—yielded lower net present value in all but the best-case scenario, where SS provided 90% of the conception rate of conventional AI. Past literature provides ample technical descriptions of these technologies and experimental results but limited analysis of adoption rates or farm economic impact. For instance, with no dairy industry population estimates having been made until recently by Khanal et al. (2010), Butler and Wolf (2010) correctly suggested adoption rates of AI to be > 60% of dairy cows and adoption rates of ET to be < 20% of dairy farms. Understanding the adoption of technology and the influences of technology on profitability is of particular importance in an era of rapid structural change. Determination of who are the adopters of technology, their relative successes, and the impacts of the technology on profitability is of importance to non-adopters who are currently considering adoption, as well as industry leaders who seek greater understanding of overall industry structure, conduct, and performance.

Extensive literature has addressed technology adoption on farms—much of the literature in the developing country context (Feder, Just, & Zilberman, 1985) and some with respect to the adoption of dairy breeding stock (Abdulai & Huffman, 2005; Abdulai, Monnin, & Gerber, 2008). Breeding technologies are often described as information and knowledge-intensive technologies (Johnson & Ruttan, 1997) whose adoption is affected by both biological and monetary factors (Barber, 1983). Numerous studies have examined technology adoption in the US dairy industry (e.g., El-Osta & Johnson, 1998; El-Osta & Morehart, 2000; Foltz & Chang, 2002; McBride, Short, & El-Osta, 2004; Tauer, 2009). Several of these have cited challenges associated with determining the impact of a particular technology, separate from other technologies (El-Osta & Johnson, 1998; Foltz & Chang, 2002; McBride et al., 2004). Since there are likely to be a number of factors affecting profitability, the effects of other technologies must 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 decision of breeding technologies is estimated, accounting for the probable correlation of the adoption of breeding technologies. The influences of adoption decisions on farm profit, costs, and milk production per cow are then estimated in impact models. Results can assist producers in making adoption decisions and industry leaders and extension personnel in helping producers to decide whether the technologies can be profitable for their operations.

Modeling the Adoption and Impact of Dairy Breeding Technologies

Adoption Decision Model

Farmers' technology adoption decisions are generally affected by a number of demographic and socioeconomic factors. In an economic sense, farmers adopt a new technology if the utility associated with new technology adoption is greater than the utility associated with the old technology. Let U_O and U_N represent the utility associated with old (traditional) breeding technologies and new breeding technologies, respectively. The dairy farmer adopts a new breeding technology if $U_N^* = U_N - U_O > 0$. The net benefit of 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. Thus,

$$U_N^* = f(F, M), \tag{1}$$

where F indicates farm and farmer attributes and M represents management considerations associated with the technology and farm. If $\boldsymbol{X}$ is the vector containing all of the variables in F and M, and $\boldsymbol{\alpha}$ the coefficient vector of $\boldsymbol{X}$, then

$$U_N^* = \boldsymbol{X}\boldsymbol{\alpha} + \varepsilon, \tag{2}$$

where ε is assumed to be a normally distributed random error term. So, the observable choice D to adopt new breeding technologies will be: $D_N = 1$ 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 several variables (whose vectors are $\boldsymbol{X}_1$ and $\boldsymbol{X}_2$, respectively, with b_1 and b_2 the respective coefficients) such that

$$ETSS^* = \boldsymbol{X}_1\beta_1 + \varepsilon_1 \tag{3}$$

$$AI^* = \boldsymbol{X}_2\beta_2 + \varepsilon_2\,. \tag{4}$$

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.

Since both AI and ETSS are adopted as breeding technologies, their adoption decisions may be related, implying the correlation of ε_1 and ε_2. If so, their joint probability should be considered, suggesting a bivariate probit model rather than separate probit models for each. Using the bivariate probit, the covariance of $[\varepsilon_1, \varepsilon_2]$ equals a constant ρ rather than zero, as is assumed using individual probit models. An "older" technology, AI has long been considered a successful, farmer-friendly technology. On the other hand, ET and SS are newer technologies. There is the involvement of semen collected by artificial means in the use of both ET and SS. Though it is not necessary for an ET adopter to also use AI, for practical purposes, ET and/or SS adopters are a subset of AI adopters since there would seldom be a case where either would be used by a farmer without AI. Thus, we assume that AI-adopting farms select to either use or not use ETSS. If ETSS is adopted only on farms where AI is adopted, there is no difference in observability in the adoption pattern of the sets (ETSS = 0 ∩ AI = 0) and (ETSS = 1 ∩ AI = 0), suggesting the bivariate probit with selection, where ETSS data would be observed only if AI = 1. This type of estimator was proposed by Van De Ven and Van Praag (1981) and has been used in other studies (Boyes, Hoffman, & Low, 1989; Kaplan & Venezky, 1994; Mohanty, 2002).

For the bivariate probit with selection model, $\varepsilon_{i1}, \varepsilon_{i2} \sim$ bivariate normal $(0, 0, 1, 1, \rho)$. The appropriate conditional probability for this case would be

$$Prob[ETSS_i = 1 \mid AI_i = 1] = \frac{\Phi_2\,(X'_{i1}\beta_1, X'_{i2}\beta_2, \rho)}{\Phi_2\,(X'_{i2}\beta_2)}\,,$$

where Φ represents the univariate cumulative distribution function and Φ_2 the bivariate cumulative distribution function. Since $ETSS_i$ is not observed unless $AI_i = 1$, there would be three observed outcomes in this selection model. Their unconditional means are

$$\begin{aligned}
&AI_i = 0\colon Prob(AI_i = 0 \mid X_{i1}, X_{i2}) = 1 - \Phi(X'_{i2}\beta_2)\\
&ETSS_i = 0, AI_i = 1\colon Prob(ETSS_i = 0, AI_i = 1 \mid X_{i1}, X_{i2})\\
&\qquad = \Phi_2\,(-X'_{i1}\beta_1\,, X'_{i2}\beta_2 - \rho)\\
&ETSS_i = 1, AI_{i2} = 1\colon Prob(ETSS_i = 1, AI_i = 1 \mid X_{i1}, X_{i2})\\
&\qquad = \Phi_2\,(X'_{i1}\beta_1\,, X'_{i2}\beta_2\,, \rho).
\end{aligned} \tag{5}$$

1. *We created variable "ETSS" 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?" We have considered the "ETSS" as an indicator of modern and more recently introduced breeding technologies other than AI.*

As shown in Greene (2009), the log likelihood for the bivariate probit model with selection is

$$LogL = \sum_{AI=1,ETSS=1} log\ \Phi_2\ [\beta_1\ , X'_{i2}\beta_2\ , \rho] \\ + \sum_{AI=1,ETSS=0} log\ \Phi_2\ (-X'_{i1}\beta_1\ , X'_{i2}\beta_2 - \rho) \quad (6) \\ - \sum_{AI=0} log\ \Phi\ (X'_{i2}\beta_2)\ .$$

Adoption Impact Model

A farm impact model assesses the impact of the adoption of AI and ET and/or SS on farm productivity and profitability. If $Prod_i$ is an indicator of farm productivity, then it is a function of vectors of explanatory variables ($\boldsymbol{Z_i}$) indicating farm size and specialization and farmer demographics, as well as dummy variables AI and ETSS for the adoption of breeding technologies.

$$Prod_i = \boldsymbol{Z'_i\alpha} + \gamma_1 AI_i + \gamma_2 ETSS_i + e_i\ , \quad (7)$$

where $\boldsymbol{\alpha}$ is the vector of parameters for vector $\boldsymbol{Z_i}$, *AI* and *ETSS* are dummy variables indicating adoption/non-adoption with γ_1 and γ_2 as respective parameters, and e_i is the random error term.

Other adopted technologies may also influence productivity and profitability. So, if $\boldsymbol{T'}$ is a vector of other technologies, management practices, and production systems on the farm, we can rewrite our impact model as

$$Prod_i = \boldsymbol{Z_i'\alpha} + \gamma_1 AI_i + \gamma_2 ETSS_i + \boldsymbol{T_i'\omega} + e_i\ , \quad (8)$$

where $\boldsymbol{\omega}$ is the coefficient vector for other technologies and $\boldsymbol{Z}$ includes all other independent variables besides the technologies. Equation 8 can be estimated using Ordinary Least Squares (OLS) regression. However, estimators computed using simple OLS regression may be biased and inconsistent in the presence of correlation between the explanatory variables and e_i. If there is potential for this problem, it should be tested and, if found, corrected to reduce bias and obtain consistent estimates. Explanatory variables that are correlated with e_i are endogenous and the OLS estimator fails to estimate accurately (Hill, Griffiths, & Lim, 2008). With regard to productivity and profitability, we initially suspected AI and ETSS to be endogenous since farmers self-select into the adoption of AI and ETSS. In the case of endogeneity, ETSS and AI should be replaced with appropriate instrumental variables (Greene, 2008). Previous studies (Fernandez-Cornejo, Klotz-Ingram, & Jans, 2002; Fernandez-Cornejo & McBride 2002; Foltz & Chang, 2002) have used predicted probabilities from probit adoption decision models as instrumental variables in profit equations. Replacing AI and ETSS variables with their predicted probabilities, our equation would be

$$Prod_i = Z'_i\,\alpha + \gamma_1\,\widehat{AI_i} + \gamma_2\,\widehat{ETSS_i} + T_i'\omega + e_i\ , \quad (9)$$

where $\widehat{AI_i}$ and $\widehat{ETSS_i}$ are predicted probabilities from the bivariate probit equation, used as instruments. Alternative methods for dealing with self-selection issues have included Heckman's two-stage and switching regression models. The Heckit model was tried for this analysis, with results providing less plausible estimates that the authors suspected overestimated the impacts of AI and ETSS. With three potential outcomes, AI only, AI and ETSS, and neither, the switching regression model would result in three equations. These issues and our model's ability to adequately consider self-selectivity were the principal bases for our model selection.

In the impact models, endogeneity was tested and corrected for if detected. Based on suggestions by Wooldridge (2006) for testing endogeneity, predicted values of and $\widehat{AI}$ and $\widehat{ETSS}$ obtained from the bivariate probit adoption decision model were added as independent variables into the structural (productivity) equations and regressed to check for their significance. If either were significant, both were included; otherwise actual values for AI and ETSS were used.

Also of concern is identification of the model. For the bivariate probit model with selection, due to non-linearity of the model, the parameters are identified in cases where both equations have the same independent variables. However, such models can present estimation difficulties and weak identification (Hotchkiss, 2004; Jones, 2007). As such, this model is fully identified if one variable is included in the selection equation (AI) that is not in the ETSS equation. In our case, *Grazer* indicates the farm was a pasture-based operation in the AI equation, but is not included in the ETSS equation. (A full discussion of all independent variables is found in the next section.) Of further concern for identification using instrumental variables estimation, a variable is required in the first-stage estimation that is not correlated with the error term in the second stage (profit/productivity) equations. We include two variables, *Ten More Years* and *Off-farm Job*, as identifying instruments in the first-stage bivariate probit adoption model to examine the effect of a longer planning horizon for the dairy enterprise and holding off-farm employment on the adoption of management- and capital-intensive (in the case of ETSS) technology, but not in the second-stage profitability equations, as planning horizon and off-farm employment are not considered as key variables in determining dairy enterprise profitability. (Indeed, when *Ten More Years* and *Off-farm Job* were included in the profitability equations, significant estimates for these variables were not found.) Several variables are also included in second-stage equations that are not included in the first-stage adoption equations, including other technologies that could impact farm productivity and a variable to examine farm size non-linearities and profitability. The inclusion of these additional variables is consistent with previous studies of similar structure, such as Foltz and Chang (2002) and McBride et al. (2004). Since we have two suspected endogeneous variables and two instruments, the model is "just identified," so there is no value in testing for overidentification (Wooldridge, 2006, p. 535), as would be done via the Sargan Test. Further discussion about regressors in the model is included in the *Independent Variables* sections later in the article.

Data

We utilize data from the 2005 Agricultural Resource Management Survey (ARMS), dairy version, conducted by the ERS and NASS of the USDA. Altogether, the dataset includes 1,814 observations from 24 states that represent 90% of US 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 detailed information on input usage are covered by ARMS. The survey also includes information on farm operator and financial characteristics, size, commodities produced, and technology use. Dairy farm profitability and productivity varies among years, so the use of one year of data is a limitation of the study.

Each data unit (farm) in the ARMS is weighted based on farm size, region, and production system (i.e., organic versus non-organic). Making the total number of observations equal to the sample size; for our study, weights were adjusted for each observation as

$$Wts_j = \frac{wt_j}{\Sigma_{j=1}^{N} wt_j} * N, \tag{10}$$

where Wts_j is the weight for farm j, wt_j is the weight variable (scalar) for the j^{th} farm assigned in the ARMS data, and N is the number of observations. Each data unit used in this analysis is weighted and corrected for potential heteroskedasticity. Mishra and El-Osta (2008) used the Huber-White sandwich robust variance estimator using ARMS data with logistic distributions. To correct for heteroskedasticity, we use this estimator for the bivariate probit adoption decision model and the corrected White estimator for the adoption impact OLS equations.

Independent Variables: Adoption Decision Model

Table 1 shows descriptive statistics of 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. Previous technology adoption studies in dairy have included herd size as the indicator of farm size (Foltz & Chang, 2002; McBride et al., 2004). Larger farms have been the greater adopters of dairy technologies (El-Osta & Morehart, 2000; Khanal et al., 2010). Artificial insemination may be considered as scale-neutral, but ET is expected to have associated scale economies, as additional facility investment will be required in some cases (Funk, 2006). The number of milk cows on the farm, *Cows*, is included as an explanatory variable in the adoption decision model.

Degree of specialization in dairy is expected to impact managerial conditions—*M* in Equation 1. 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, *Specialized*, to indicate degree of dairy enterprise specialization. A second dimension of specialization is the farmer's off-farm work. The lower the off-farm income, the greater has been the adoption of managerially-intensive technologies such as precision farming (Fernandez-Cornejo, 2007). Adoption of herbicide-tolerant soybean, on the other hand, was positively related with off-farm income (Fernandez-Cornejo, Hendrix, & Mishra, 2005), as this innovation was management-reducing. As breeding technologies demand greater management consideration through closer attention to animals' biological processes, an off-farm job may adversely affect their adoption. In this study, dummy variable *Off-farm Job*, which indicates whether the principal operator or spouse worked off-farm for wages or salary, is included.

To consider regional differences, three variables are included. *West* includes observations in Arizona, California, Idaho, New Mexico, Oregon, Texas, and Wash-

Table 1. Weighted means of variables used in the study.

Variable name	Description	Mean
Age	Principal operator's age in years	51.467
College	Principal operator's education level: 1 if principal operator is college graduate or beyond	0.209
Off-farm job	Operator's off-farm job: 1 if principal operator or spouse work off-farm for wages or salary	0.475
Ten more years	Continuation of farm operation: 1 if operator plans to continue the operation for next 10 years or more, otherwise 0	0.605
Cows	Continuous variable: Number of milk cows in the farm/1000	0.322
Specialized	Farm specialization, contribution of the dairy total farm value of production (Dairy/VPRODTOT)	0.849
West	Regional dummy: 1 if farm is located in Western United States (CA, OR, WA, AZ, ID, NM, or TX), otherwise 0	0.212
South	Regional dummy: 1 if farm is located in Southern United States (Appalachia—KY,TN, VA; or Southeast—FL, GA)	0.173
Northeast	Regional dummy: 1 if farm is located in Northeastern United States (ME, NY, PA, VT)	0.260
Parlor	1 if parlor is adopted in the farm, otherwise 0	0.685
Grazer	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), otherwise 0	0.223
Milk 3 times	Milking frequency: 1 if cows are milked 3 times per day, 0 if two times or less	0.149
Sum of technologies	Sum of the eight dummy variables for eight different technologies or management practices of dairy (value 0 to 8)	2.91
AI	Whether artificial insemination is adopted in the dairy farm in 2005: 1 if adopted, 0 if not	0.789
ETSS	Whether embryo transplant and/or sexed semen is adopted in the farm in 2005: 1 if adopted, 0 if not	0.113
Return over total cost	Net returns over total cost per cwt of milk produced (in dollars)	-9.92
Return over operating cost	Net returns over operating cost per cwt of milk produced (dollars)	5.02
Milk per cow	Annual milk yield per cow (cwt)	165.96
Total cost	Total costs per cwt of milk produced	27.87
Operating cost	Operating cost per cwt of milk produced	12.93
Allocated cost	Allocated costs per cwt of milk produced	14.94

ington; *South* includes Florida, Georgia, Kentucky, Tennessee, and Virginia; and *Northeast* includes Maine, New York, Pennsylvania, and Vermont. The base region includes Illinois, Indiana, Michigan, Minnesota, Missouri, Ohio, and Wisconsin.

Studies addressing the adoption of dairy technologies (Foltz & Chang, 2002; McBride et al., 2004) have accounted for other technologies in the adoption equation. Khanal et al. (2010) found complementary relationships between dairy technologies, management practices and/or production systems. 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. As discussed earlier, *Grazer*, indicating whether the farm was pasture-based (animals received ≥ 50% of forage needs from pasture during the grazing season) was included in the AI equation, but not in the ETSS equation. Given that pasture-based operations are generally lower-input, as shown by Khanal et al. (2010), the relevant question was whether they were adopters of AI, rather than ETSS, and *Graze* in only the selection equation ensured identification in the bivariate probit.

Farmer demographics are expected to be associated with technology adoption. Younger farmers are generally expected to be the greater adopters of advanced technologies (Feder et al., 1985; Massey et al., 2004), so farmer *Age* is included. Dairy producers with longer planning horizons may be more interested in investing in the development of human or other capital that supports AI and/or ETSS adoption. In this study, *Ten More Years* is a dummy variable indicating the operator plans to continue farming for the next 10 years. Farmer education has been consistently used in adoption studies. 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, Davis, and Rahelizatovo (2004) with AI in the hog industry—as education generally increases managerial ability. Thus, a dummy variable indicating the principal operator's holding of a four-year college degree, *College*, is included.

Dependent Variables: Adoption Impact Model

Milk yield, profit, and cost are analyzed in the adoption impact models. First, productivity is measured as hundredweight (cwt) of milk produced per cow (*Milk per Cow*). Net returns over total costs per cwt milk produced (*Return over Total Cost*) and net returns over operating costs per cwt milk produced (*Return over Operating Cost*) are measures of dairy enterprise profitability. These measures have been used in previous studies as indicators of dairy farm profitability: *Return over Total Cost* (Gillespie, Nehring, Hallahan, & Sandretto, 2009), *Return over Operating Cost* (McBride et al., 2004), and both (Short, 2000, 2004). In constructing these measures, gross returns include the value of milk sold, revenues from sales of culled cattle, the implicit fertilizer value of manure produced, and other income from the dairy. 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 (*Total Costs*), operating costs per cwt of milk produced (*Operating Cost*), and allocated costs per cwt of milk produced (*Allocated Cost*) are included as cost measures. *Total Cost* is the sum of *Operating Cost* and *Allocated Cost*. It is recognized that breeding technologies can be used to alter herd productivity over a number of years. Therefore, ideally, this analysis could examine the impact of these technologies based upon the time period over which they were implemented. This opens up the opportunity for further research that considers length of time over which these technologies have been used.

Independent Variables: Adoption Impact Models

Previous adoption studies show that farm productivity and profitability are influenced by farm size and specialization, technology, and demographic characteristics. Farm size has been positively related with dairy profit in previous studies (Foltz & Chang, 2002; McBride et al., 2004). Assuming economies of size involved in dairy, as shown by Tauer and Mishra (2006) and MacDonald et al. (2007), profitability (cost) is expected to increase (decrease) with *Cows*. A squared term on the number of milk cows considers relationship non-linearities between farm size and productivity. More specialized dairy farms (*Specialized*) are expected to yield greater enterprise net returns. Purdy, Langemeier, and Featherstone (1997) and El-Osta and Morehart (2000) found more specialized operations to be the better financial performers.

Previous studies have included technologies other than those of primary interest in profit and productivity equations to isolate the impacts of the technology of interest (Foltz & Chang, 2002; McBride et al., 2004). To isolate the effect of breeding technologies, we included dummy variables for three production systems: PARLOR, whether animals received ≥ 50% of their total forage ration from pasture during the grazing season (*Grazer*), and whether animals were milked three times per day (*Milk 3 Times*). *Sum of Technologies* is a summation of the adoption of eight dairy technologies and management practices, providing a measure of the intensity of technology adoption: (1) holding pen with udder washer, (2) milking units with automatic takeoffs, (3) computerized milking system, (4) computerized feeding system, (5) use of rbST, (6) Dairy Herd Improvement Association membership, (7) use of a nutritionist to purchase or formulate feed, and (8) accessing the internet for dairy information. For descriptions of each of these technologies and management practices, see Khanal et al. (2010). As discussed earlier, AI and ETSS or their predicted value instruments (if endogeneity is found) are included. It is expected that AI will positively influence profitability and productivity (Barber, 1983; Hillers et al., 1982). The impact of ETSS is explored.

West, *South*, and *Northeast* are included in impact models, as are demographic variables. *College* is expected to have positive influences on productivity (McBride et al., 2004) and profitability (Foltz & Chang, 2002), though McBride et al. (2004) found a negative association with profitability. *Age* is included. Previous studies have found it to be negatively related to profitability (Foltz & Chang, 2002; Gillespie et al., 2009).

Results

Breeding Technology Adoption

Table 2 shows estimates of the bivariate probit with selection adoption decision model. Separate probit equations were also estimated but are not reported. The likelihood ratio test was used to test the null hypothesis of no correlation between the adoption of the two technologies. Log likelihood ratio statistics are given by *LR-statistic* = 2 [$ln\ L_{bivariate} - (ln\ L1 + ln\ L2)$]. Log likelihood functions of the two separate probits are ($lnL1$ and $lnL2$). The LR-statistic of 63.90, greater than the critical value of $\chi^2_{0.05,1} = 3.84$, indicates rejection of the null hypothesis of no correlation, supporting choosing the bivariate probit with selection.

Bivariate probit marginal effects may have originated from different sources. Total effects are the sum of both direct and indirect effects. Direct effects are the marginal effects of the variables that appear in the first equation, while indirect effects are the effects from the second set (Greene, 2009). Table 2 shows the total marginal effects of the respective variables (partial effects for $E\ [y1 \mid y2 = 1]$ with respect to the vector of characteristics). The mean estimate of $E\ [y1 \mid y2 = 1]$, which is $Prob\ [ETSS{=}1, AI{=}1]\ /\ Prob[AI{=}1]$, is 0.105.

Positive and significant coefficients of *Cows* and *Specialized* in the AI equation suggest larger, more specialized operations were more likely to be AI adopters. The result for farm size is generally consistent with results from USDA APHIS (2009), where farms with ≥ 100 cows were numerically more likely to have cattle pregnancies conceived by AI than those with < 100 cows (though farms with ≥ 500 cows had numerically lower percentages than those with 100-499 cows to have had cattle pregnancies conceived by AI). An off-farm job held by the operator and/or spouse had negative effects on AI and ETSS adoption, reducing the probability of ETSS adoption given AI had been adopted by 0.033. An off-farm job may be associated with several factors, one being less time available for farm management. Southern and Western US dairy farmers were less likely than Midwestern US farmers to adopt AI, while Northeastern US dairy farmers were more likely to adopt it. USDA APHIS (2009) divided farms into only two regions, West and East, and did not find differences in percentage of cattle pregnancies conceived via AI by region. Farmers whose cows received > 50% of forage needs from pasture during the grazing season were less likely to adopt AI.

Table 2. Adoption decision model: Bivariate probit with selection.

Variables	ETSS estimates	AI estimates	Total marginal effects
Constant	-1.3801** (0.5823)	0.2734 (0.2718)	
Cows	0.0089 (0.1603)	0.3885*** (0.1006)	-0.0042 (0.0247)
Specialized	0.3451 (0.5785)	1.3814*** (0.1945)	0.0427 (0.0653)
Off-farm job	-0.2014* (0.1114)	-0.2470*** (0.0811)	-0.0333* (0.0173)
West	-0.0330 (0.2491)	-0.6348*** (0.1190)	0.0035 (0.0273)
South	0.0342 (0.3518)	-0.7967*** (0.1382)	0.0183 (0.0385)
Northeast	0.0225 (0.1130)	0.2444** (0.1014)	0.0005 (0.0226)
Parlor	0.0983 (0.0995)	-0.0397 (0.0842)	0.0187 (0.0182)
Graze		-0.3381*** (0.0900)	0.0051 (0.0157)
Age	-0.0105** (0.0042)	-0.0045 (0.0036)	-0.0019** (0.0008)
Ten more years	0.4635*** (0.1114)	-0.0199 (0.0826)	0.0856*** (0.0180)
College	0.7944*** (0.1182)	0.3830*** (0.1171)	0.1404*** (0.0188)
Rho (1, 2)	0.26	(Selection model based on AI)	
Log likelihood function		-1227.09	
Mean estimate		$E[y1 \mid y2{=}1]{=}0.105$	

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

Age and *Ten More Years* were negatively and positively associated, respectively, with ETSS adoption. A one-year increase in *Age* decreased the probability of ETSS adoption, given AI had been adopted, by 0.0019. Dairy operators planning to continue operating their farms for ≥ 10 years had probabilities of ETSS adoption, given AI had been adopted, that were 8.6 percentage points higher than those planning to continue operating for < 10 years. Holding a college degree increased the probability of ETSS adoption, given AI had been adopted, by 0.140.

Profitability and Productivity Measures

A brief examination of weighted means for productivity and profitability measures is provided for three categories of farmers: (1) ETSS and AI adopters, (2) AI-only adopters, and (3) adopters of neither ETSS nor AI, providing a starting point for analyzing profit and productivity. Weighted means for *Return over Total Cost* for the three groups were -$5.16, -$8.42, and -$14.99, respectively, providing initial evidence of differences in profitability. It is noted that these are highly negative, suggesting these farms had high opportunity costs associated with unpaid labor, capital, and land. Weighted means for *Return over Operating Cost* were $4.67, $4.98, and $4.88, respectively, suggesting any differences in net returns over operating costs among the groups were less pronounced than with *Return over Total Cost*. Finally, weighted means for *Milk per Cow* were 209.95 cwt/cow, 177.14 cwt/cow, and 133.02 cwt/cow, suggesting that adopters of AI and ETSS together produced 58% more milk per cow than adopters of neither. Statistical significance of differences in these means is not highlighted since they are not analyzed in a multivariate framework that considers the influences of other technologies, simultaneity of adoption, and self-selectivity issues.

Table 3 presents parameter estimates of the profitability and productivity measures. Artificial insemination positively impacted profit, with increases in returns over total costs per cwt milk produced of $1.20. Adoption of ETSS was not found to impact profit. For both profit measures per cwt milk produced, ETSS and AI were found to be endogeneous; thus, instrumental variables were used to correct for endogeneity. From examining the raw means where differences in *Return over Total Cost* were found, but not for *Return over Operating Cost*, these results are not surprising—the differences are much less pronounced than for the weighted means, as the impacts of self-selection and the adoption of complementary technologies are considered. A limitation of this type of analysis stems from the possibility of partial technology adoption. Some dairies, for instance, may use a "clean-up bull" to breed females unsuccessfully bred by AI. Likewise, ET and/or SS may be used on subsets of animals. In fact, USDA APHIS (2009) shows that 54.9% of US dairy operations had pregnancies conceived via natural service and, considering their estimate of 88.4% and 9.9% of operations having pregnancies resulting from AI and ET, respectively, it appears that most operations were partial adopters. Given this, AI and ETSS estimates for profitability, productivity, and cost are likely to be underestimates of the impacts resulting from 100% adoption. This is a common problem facing researchers in studies addressing technology impacts on productivity and profitability when data indicate only adoption/non-adoption (Gillespie, Nehring, Hallahan, Sandretto, & Tauer, 2010; McBride et al., 2004; Tauer, 2009).

Table 3. Dairy enterprise profit and productivity measures.

Variables	Return over total cost/cwt	Return over operating cost/cwt	Milk per cow
Constant	-16.53*** (2.25)	7.00*** (1.45)	133.47*** (7.72)
Cows	8.87*** (1.38)	2.16*** (0.61)	-0.84 (6.42)
Cows squared	-1.33*** (0.29)	-0.25*** (0.08)	-0.63 (1.24)
Specialized	10.06*** (2.21)	-0.73 (1.36)	48.45*** (6.73)
Parlor	3.20*** (0.59)	0.51* (0.28)	-0.62 (2.51)
Grazer	-3.77*** (0.90)	-0.02 (0.35)	-7.23*** (2.77)
Milk 3 times	-1.82** (0.73)	-0.13 (0.39)	23.16*** (4.09)
Sum of technologies	1.99*** (0.18)	0.05 (0.09)	12.76*** (0.79)
West	-1.47* (0.88)	-2.24*** (0.35)	-4.58 (3.36)
South	-1.43 (1.26)	-1.00* (0.59)	-7.79* (4.55)
Northeast	-0.04 (0.73)	-1.86*** (0.33)	1.28 (2.50)
Age	-0.16*** (0.02)	-0.02** (0.01)	-0.77*** (0.09)
College	-1.01 (0.65)	0.56* (0.30)	-3.58 (2.82)
Predicted AI	1.20*** (0.42)	-0.09 (0.18)	7.17*** (1.14)
Predicted ETSS	0.54 (1.41)	0.86 (0.18)	15.03** (6.79)
Adjusted R^2	0.26	0.04	0.38

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

Other profitability results are also noteworthy. Larger farms had higher returns over total costs per cwt milk produced and returns over operating costs per cwt milk produced, and *Cows Squared* was negative and significant in both, as expected. More specialized dairies had higher returns over total costs per cwt milk produced. The coefficients of *Graze* and *Milk 3 Times* were negative for *Return over Total Cost*. Positive *Sum of Technologies* (for *Return over Total Cost*) and *Parlor* (for both) coefficients suggested adoption of dairy technologies was associated with higher profitability per cwt milk produced. Southern and Northeastern US farmers had lower returns over operating costs per cwt milk produced. Western United States and older farmers had lower profitability under both measures. Similar

Table 4. Dairy enterprise cost measures.

Variables	*Total cost/ cwt*	*Operating cost/cwt*	*Allocated cost/cwt*
Constant	40.28*** (2.50)	16.75*** (1.07)	23.53*** (1.75)
Cows	-8.38*** (1.36)	-1.67*** (0.48)	-6.71*** (1.15)
Cows squared	1.26*** (0.29)	0.18** (0.07)	1.08*** (0.28)
Specialized	-16.09*** (2.52)	-5.30*** (1.03)	-10.79*** (1.77)
Parlor	-3.75*** (0.65)	-1.07*** (0.27)	-2.68*** (0.48)
Grazer	3.93*** (0.92)	0.18 (0.33)	3.75*** (0.69)
Milk 3 times	1.78*** (0.69)	0.08 (0.32)	1.69*** (0.51)
Sum of technologies	-2.02*** (0.19)	-0.08 (0.09)	-1.94*** (0.14)
West	0.43 (0.80)	1.21*** (0.32)	-0.77 (0.71)
South	2.40* (1.43)	1.96*** (0.55)	0.43 (1.07)
Northeast	0.80 (0.74)	2.29*** (0.32)	-1.48*** (0.52)
Age	0.15*** (0.02)	0.01 (0.01)	0.13*** (0.02)
College	1.68** (0.68)	0.11 (0.28)	1.57*** (0.52)
Predicted AI	-1.70*** (0.44)	-0.42*** (0.15)	-1.28*** (0.33)
Predicted ETSS	-0.70 (1.15)	-1.01 (0.67)	0.31 (0.95)
Adjusted R^2	0.30	0.11	0.34

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

regional profitability signs have been found examining the impact of recombinant bovine somatotropin on *Return over Operating Cost* using ARMS dairy data from 2000 (McBride et al., 2004) and 2005 (Gillespie et al., 2010). College-educated farmers had higher returns over operating costs per cwt milk produced.

The use of AI and ET and/or SS positively impacted *Milk per Cow*; adopters produced 7.17 (AI only) and 15.03 (ETSS only) cwt more milk per cow, respectively, than non-adopters. Instrumental variables for AI and ETSS were used to correct for endogeneity. Other *Milk per Cow* results are also notable. Dairy enterprise specialization resulted in greater milk per cow. *Milk 3 Times* and *Sum of Technologies* were positively and *Grazer* was negatively associated with *Milk per Cow*. Older farmers and those in the Southern United States produced less milk per cow.

Cost Measures

To investigate contributors to profitability, the impacts of AI and ETSS on cost are examined (Table 4). Similar to the profit and *Milk per Cow* equations, predicted values for AI and ETSS (instrumental variables) were used. Negative, significant coefficients of AI in the three cost equations suggest that farmers can reduce both operating and allocated costs by adopting AI. Reductions in operating and allocated costs by $0.42 and $1.28, respectively, were associated with AI adoption, for a total of $1.70. Thus, the major contributor to lower cost was in allocated costs, with fewer bulls and associated costs required.

Other notable results are that larger, more specialized farms had lower total, allocated, and operating costs per cwt milk produced than their counterparts, and in all three cases, *Cows Squared* was also significant. Specialized operations had lower costs for all three measures. Pasture-based operations and those milking three times daily had higher total and allocated costs per cwt milk produced. *Sum of Technologies* results suggest adoption of dairy technologies reduced total and allocated costs, while *Parlor* reduced all three cost measures. Southern, Western, and Northeastern dairy farms had relatively higher operating costs per cwt milk produced than Midwestern farms, though Northeastern dairy farms had lower allocated costs per cwt milk produced. Younger operators had lower total and allocated costs per cwt milk produced than their counterparts; college degree holders had higher total and allocated costs.

Conclusions

For the past 70 years, advanced breeding technologies have been important components of structural change in the US dairy industry, as adoption can have rapid effects on genetics and reproductive performance. Artificial insemination has been a widely adopted technology, and ET and SS technologies are newer, still-diffusing technologies. Embryo transplant and SS technologies have been suggested to have potentially wider adoption in the near future.

This study accounts for the correlation of adoption decisions of breeding technologies. The adoption of breeding technologies in the United States 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 total costs associated with AI adoption. The differences are rather striking. Examining only the weighted means, farmers using AI realized $6.57 higher net returns over total costs per cwt milk than those not using it. From the adoption impact model, the impact of AI was $1.20 per cwt milk produced. Though a comparison of raw means showed adopters of ETSS and AI to have returns over total costs per cwt milk produced of $3.26 higher than AI-only adopters, the impact of ETSS was non-significant when placed in a multivariate regression framework including other technologies and farmer characteristics. Adopters of AI were lower-cost on total, operating, and allocated cost bases, but differences in cost structure with ETSS were not found. These results are consistent with what might be expected, given the high adoption rate of AI and the lower adoption rates of ET and SS, the latter of which is a relatively newly introduced technology to the industry and did not result in increased net present value in the Olynk and Wolf (2007) study unless the SS conception rate was 90% or better than that of conventional AI. Despite this finding, significant adoption diffusion of SS appears to be occurring. The bottom line here is that AI-adopting farms were more profitable than non-adopting farms, but the adoption of the newer technologies, ET and/or SS, which could not be separated, did not result in greater profit for the "average" farm.

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. Depending upon the measure used, costs decline up to 3,327-4,320 cows, beyond which there is little data from which to draw inference. The adoption of SS may be associated with an increase in the number of milk cows or at least an increased productivity of milk cows by increasing the supply of replacement heifers. Since some part of the costs involved in either ET or SS adoption 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.

There are at least three additional issues to be considered. First, one of the limitations of this study is the inseparability of ET and SS adopters in the ARMS dairy survey, which disallows analysis of SS and ET alone. Though adopters of these technologies may have similar traits, the results and implications when they are treated separately may be different. Sexed semen technology adoption is rapidly expanding and is expected to have wider adoption in the near future. The actual impact of SS, once it becomes more diffused, would be of further interest. We acknowledge that our study provides insights on adoption factors at an earlier stage of adoption of SS and, as newer SS-specific economic data become available, further analysis will be warranted; the economic environment associated with a new technology usually changes significantly, particularly in the early stages of diffusion. The current study was conducted prior to the 2010 ARMS dairy survey data availability, but the 2010 data do not separate ET and SS either. Furthermore, more research on the conditions under which SS can be expected to lead to greater profitability would be warranted. Second, some farmers use these breeding technologies for only a subset of animals; for instance, they may use bulls for animals that do not breed back. Our analysis cannot account for partial adoption since the data are unavailable on a national basis for economic analysis purposes, but there may be state-level datasets that can address these issues. Thirdly, since farmers' 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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