

2010

Adoption of breeding technologies in the U.S. dairy industry and their influences on farm profitability

Aditya Raj Khanal

Louisiana State University and Agricultural and Mechanical College

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ADOPTION OF BREEDING TECHNOLOGIES IN THE U.S. DAIRY INDUSTRY AND THEIR INFLUENCES ON FARM PROFITABILITY

A Thesis
Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
in a partial fulfillment of the
requirements for the degree of
Master of Science

in

The Department of Agricultural Economics and Agribusiness

by
Aditya Raj Khanal
B.Sc (Ag.), IAAS, Tribhuvan University, Nepal, 2006
December, 2010

DEDICATION

**To my parents Mr. Gopi Raj Khanal and Mrs. Laxmi Khanal, for their love,
inspiration, and support.....**

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to my major advisor, Dr. Jeffrey M. Gillespie for his thoughtful guidance and endless support throughout my study. I was able to learn a great deal as a protégé under his mentorship. There is no way that I can truly express my thanks to you, Dr. Gillespie.

Appreciation is also extended to my graduate committee members, Dr. Ashok Mishra and Dr. Michael Salassi for their insightful suggestions during my study. I would also like to thank Dr. Krishna Paudel and Dr. Carter Hill for their help and suggestions. Thanks also go to Dr. William Greene for quick response to my e-mails regarding LIMDEP programming.

Thanks to my family for their love and support. Thanks dad for helping me become a person I am today, teaching me to choose right from wrong, and never letting me feel down. Thanks to my loving mom, brothers, and sisters, for wishing my best and providing constant support and encouragement.

I am deeply indebted to all my friends who helped me during my stay and study at LSU. Thanks to my colleagues Arun, Narayan, Abhishek, Gnel, Sachin, Mahesh, Kashi, Deepa and many more for their best wishes and support. I would like to thank the Nepalese community at Baton Rouge for their love and support. I will miss you.

Finally, I am thankful to USDA, LSU AgCenter and Department of Agricultural Economics and Agribusiness for providing me a financial support throughout my study, without which this thesis would not be possible.

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ABSTRACT

Current trends in the U. S. dairy industry show an increase in milk cows per farm and milk production per cow, though the total number of milk cows in the industry is declining. This increase in productivity is attributed to advancements and adoption of modern dairy technologies. Breeding technologies are one of the important components of this structural change. This study analyzed the factors affecting the adoption of modern breeding technologies such as artificial insemination, embryo transplants, and sexed semen, and the impact of these technologies on farm productivity and profitability.

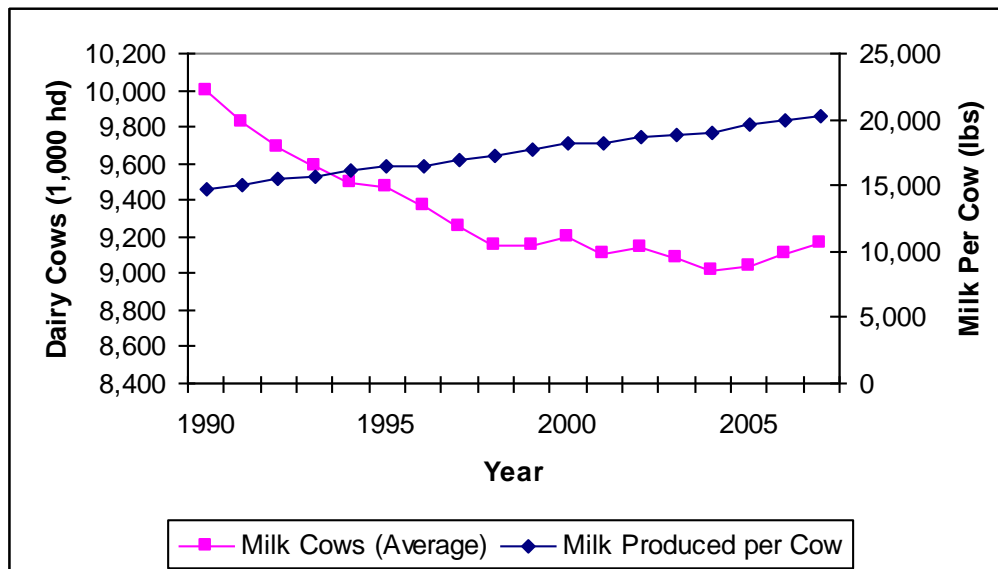
Results of a bivariate probit model with selection showed that the adoption decision is affected by different farm and farmer attributes such as age, education, off-farm work, farm size, and specialization. The embryo transplants and/or sexed semen technology adoption decision was also influenced by the farmer's planning horizon. Farm impact was assessed by estimating net returns and cost measures using ordinary least squares methods. Endogeneity and self-selection bias issues were also tested and corrected for in the impact models. Both artificial insemination (AI) and embryo transplants and/or sexed semen (ETSS) technologies are found to have significant and positive influences on net returns over total and net returns over operating costs per hundredweight of milk produced. Results also suggest that a higher allocated cost is associated with ETSS adoption. Relatively younger, more highly educated farmers and larger and more specialized farms received higher net returns. Since some part of the costs involved in ETSS may be for conducting artificial insemination, larger farms that had already adopted AI may consider ETSS adoption. Adoption decisions on a farm, however, would be based on the added advantages of ETSS adoption versus the additional costs of adopting these.

CHAPTER 1

INTRODUCTION

1.1 Background

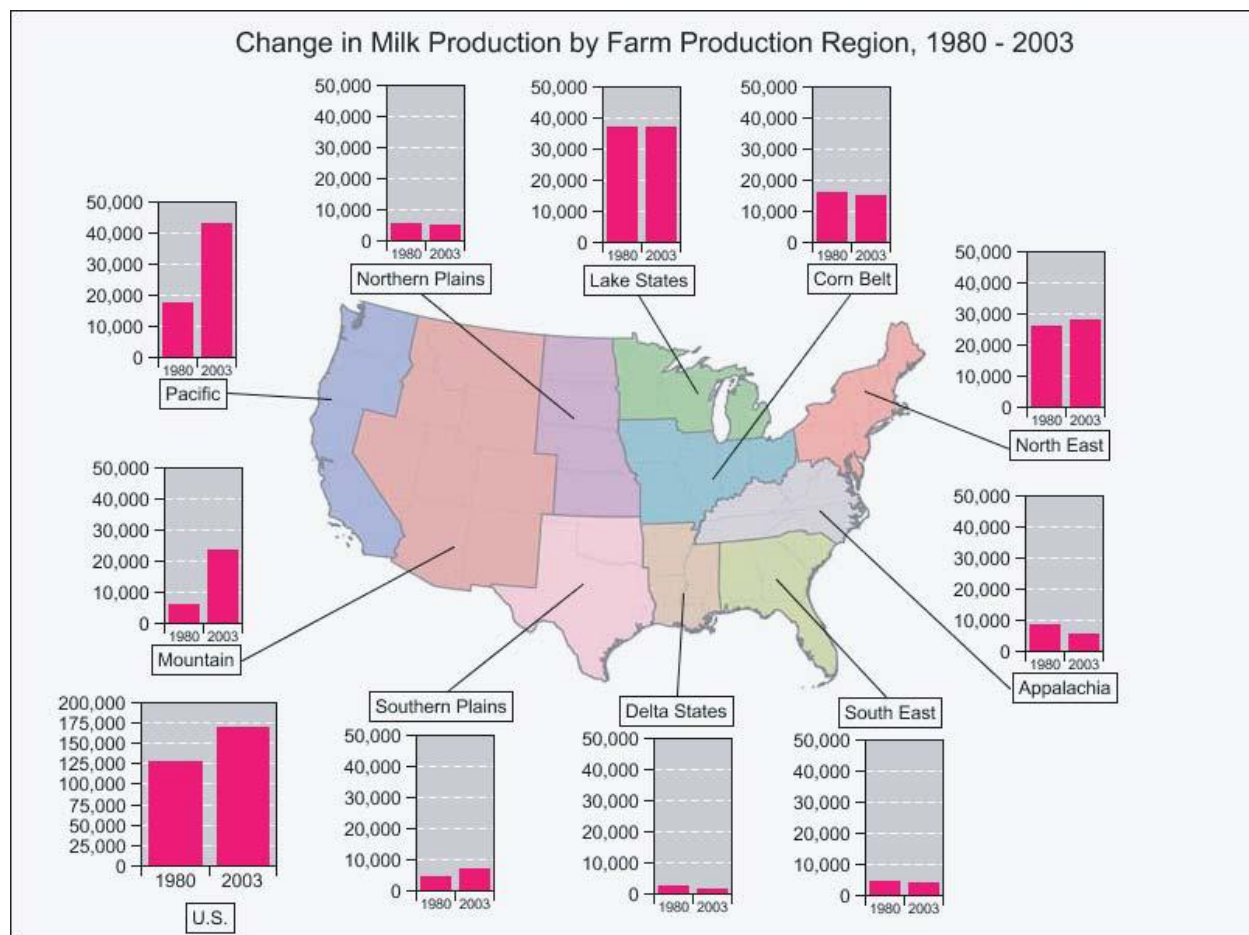
The U.S. dairy industry has experienced significant structural change during the last few decades. Average U.S. herd size was 19 cows in 1970, rising to 120 in 2006 (MacDonald et al., 2007). Over that period, average milk produced per cow doubled and milk produced per farm increased twelvefold (MacDonald et al., 2007). Trends show that the larger, more efficient operations are continually increasing their share of the milk cow inventory and milk production while numbers of smaller operations are declining. The very large operations with 2,000 or more cows doubled in number between 2000 and 2006 (MacDonald et al., 2007). In the industry, farms with more than 1,000 cows are growing (contributing more than one third of the inventory in 2004, but less than 10 percent in 1992). Figure 1.1 shows the increasing trend of milk per cow along with a decline in the cow population over the years.



Source: USDA/ NASS

Figure 1.1: Total U.S. Dairy Cows and Milk per Dairy Cow, 1990-2007

Geographically, milk production has increased in the western United States where herd size is relatively larger. However, traditional dairy states are also rapidly increasing their numbers of larger operations (Short, 2004). Figure 1.2 compares the milk production between 1980 and 2003, showing the changes in milk production across different regions.



Note: Units are millions of pounds of milk. Source: USDA, Report to Congress, July, 2004.

Figure 1.2: Change in Milk Production by Farm Production Region, 1980-2003

Total annual milk production in 2008 is reported at around 180 billion pounds (189,992 million pounds), an increase of 2.3 percent from 2007 (USDA/NASS, 2009). Average milk production per cow in 2008 was 20,396 pounds which is an increase of 501 pounds per cow from 2006 (USDA/NASS, July 2009). The report also shows that the dairy industry generated cash receipts of \$34.8 billion from 189 billion pounds of milk marketed in 2008. Regarding regional

production, the Pacific region (25.63%) was the highest contributor of total U.S. milk production in 2006, followed by Lake States (21.38%) (ERS, USDA, 2009).

Remarkable specialization and mechanization over the years have been key factors associated with structural changes (Short, 2000; Short, 2004; MacDonald et al., 2007). MacDonald et al. (2007) found that the return from large dairy enterprises well exceeds their full costs while smaller dairy farms incur economic losses if capital cost and time contribution of the owners are included. This ongoing structural change of shifting production to larger operations will continue putting downward pressure on dairy prices (MacDonald et al., 2007), forcing smaller operations out of the industry (Short, 2004).

New technology is always a critical element in a changing industry structure. Johnson and Ruttan (1997) found breeding technologies as the most significant factor contributing to farm productivity in the livestock sector since the 1940s. Dairy was the first livestock sector to accept the concept of commercial breeding (Johnson and Ruttan, 1997). The dairy industry has experienced a substantial increase in milk produced per cow, mostly attributed to innovations in breeding and feeding systems (MacDonald et al., 2007).

Breeding technologies are among the important components of structural change in the U.S. dairy industry. Modern dairy cows with higher production potential have been developed through genetic selection. This is consistent with the findings of Short (2004), who indicated a relatively large proportion of farms used genetic selection and breeding programs to improve herd quality. On the other hand, higher yielders require greater management; failing to recognize this fact may result in financial loss (Britt, 1985). There appears to be a direct relationship between herd management and reproductive performance, ultimately influencing farm profit (Britt, 1985). According to Shook (2006), genetics has accounted for about 55% of gains in the yield traits and about one-third of the change in the time interval required to conception. This

can be accomplished through artificial insemination (AI), embryo transplants (ET), sexed semen and/or traditional breeding methods. This thesis addresses adoption rates of AI as well as ET and sexed semen.

Artificial insemination is a breeding process in which sperm collected from the male are processed, stored and artificially introduced into the female. Artificial insemination has become one of the most important techniques for genetic improvement of farm animals. Literature has shown the significant impact of AI in dairy cattle (Barber, 1983; Hillers et al., 1982). Artificial insemination has made maximum use of superior sires, allowing a good economic return (Hillers et al., 1982).

Embryo Transplant is a technique by which embryos are collected from a donor female and are transferred to recipient females. Recipients do not have genetic influence on the embryo. Multiple eggs may be obtained from a cow via hormone administration, even with young heifer calves. These “superovulated,” generally more valuable donor cows are then inseminated and embryos are allowed to grow for 4-5 days prior to their being transferred to relatively less valuable recipient cows (Tyler and Ensminger, 2005). Application of ET results in an increase in the reproductive rate of females. An increase in such rate is an opportunity to reduce the number of dams that need to be selected for the next generation (Arendonk and Bijma, 2003).

Sexed semen technology comprises the separation of sperm into male/Y bearing and female/X bearing sperm cells and then artificially inseminating with the desired sexed-sorted semen. Sexed semen technology lets dairy producers increase the supply of replacement heifers, resulting in lower purchase cost of heifers. Using sexed semen, a calf of specific sex can be produced (De Vries, et al., 2008); however, slower sorting speed and lower conception rate (35 to 40% with sexed semen as compared with 55 to 60% for unsexed semen) are the main limitations (Weigel, 2004).

Artificial insemination, after its introduction in 1940s, gained a rapid initial diffusion (Johnson and Ruttan, 1997). Considering its positive influence on genetic improvement and profitability, AI is one of the farmer-friendly and widely adopted breeding technologies (Johnson and Ruttan, 1997; Hillers et al., 1982; Barber, 1983). Embryo transplants and sexed semen technologies are relatively newer and still diffusing technologies on dairy farms. Embryo transplant technology was used at the farm level after the development of non-surgical methods in 1970s. Studies suggested that the application of ET could produce a substantial genetic improvement and increase in reproductive rate of females (De-Boer and Arendonk, 1994; Arendonk and Bijma, 2003). Use of sexed semen technology on farms is increasing. Application of sexed semen allows sorting the semen and lets dairy farmers increase the supply of replacement heifers, resulting in lower purchase cost of heifers. Sexed semen technology is suggested to have a wider adoption and impact in the near future (Weigel, 2004; De Vries et al., 2008).

Farmers' technology adoption decisions are generally affected by a number of demographic and socioeconomic factors. In an economic sense, farmers adopt technology if the utility associated with adopting it is greater than the utility associated with not adopting. Feder et al. (1985) suggested that changes in parameters affecting farmers' decisions are the result of dynamic processes such as information gathering, learning by doing, or accumulating resources.

Adoption of breeding technologies such as AI, ET, and sexed semen has significant economic value in dairy performance (De Vries et al., 2008; Seidel 1984). Despite their influence on productivity, a number of factors cause the rate of adoption of these technologies to be different across dairy farms. This study uses extensive survey data (Agricultural Resource Management Survey- Dairy Version) of the United States Department of Agriculture (USDA) to

assess factors affecting the adoption of AI, ET, and sexed semen and determine their influence on farm profitability.

This study has two components. First, an adoption decision model explains the factors affecting the adoption decisions of two breeding technologies AI and ET and/or sexed semen. These technologies being breeding technologies, farmers' adoption decisions of the technologies are assumed to be correlated. Thus, there is a need to account for their jointness in adoption. There is involvement of artificially collected semen in ET and /or sexed semen. Basically, AI adopting farms can select for adopting sexed semen and/or ET technologies. A bivariate probit with sample selection model is chosen in this study to model the adoption decision. Second, an impact model includes different indicators of farm productivity and profitability as dependent variables, which are regressed with independent variables to assess the economic impact of these breeding technologies. This study accounts for the potential endogeneity and self-selection issues in impact assessment. Details of the model are explained in the methodology section.

1.2 Problem Definition

Manchester and Blaney (1997) stated that, “technological developments in dairy have changed the assembly, processing, and distribution of milk.” The adoption decision of a particular technology is, however, mainly associated with its impact on productivity. Genetics and reproductive performance of the dairy herd are considered to be among the major farm productivity determinants (Britt, 1985; Shook, 2006; Olynk and Wolf, 2008). The advantage of AI and ET is that they allow dairy farmers to select for specific traits (e.g. milk yield, conformation, reproductive performance, etc.) by increasing the genetic pool dairy farmers have to choose from. Genetic improvement in dairy cattle is driven primarily by the array of bull genetics provided by the AI industry and secondarily by the choices producers make among the available bulls (Shook, 2006).

Adoption of breeding technology is considered as a key element in structural changes in the livestock industry (Johnson and Ruttan, 1997; Gillespie et al., 2004), as it directly affects performance (Olynk and Wolf, 2008). Breeding and feeding technologies are the key for structural changes in the dairy industry (Feder et al., 1985). However, the adoption decision of breeding technology is affected by several things. According to Abdulai and Huffman (2005), the question, especially in the livestock sector, is why seemingly profitable technologies are not adopted. Past literature provides ample technical description of technologies and their methods of operation. However, the factors influencing the adoption decisions associated with these technologies on the farm and their profitability are unclear. For the dairy industry, interesting questions are, Why does the adoption rate of breeding technologies differ among farms?; Are they profitable for farms?, and Who are the early adopters of these technologies? Answers to these questions may provide insight into how to build strategic breeding programs in the dairy sector. Demographic, socioeconomic, and other factors affecting adoption of AI, ET, and sexed semen will give the sketch of linkages between technologies in relation with the factors. How much each factor increases or decreases the likelihood of adopting will be found. The information will be helpful for researchers, policy makers, and farmers aiming to establish a new dairy farm or adjust their current management strategy.

1.3 Research Questions

The following research questions will be addressed in this study:

- (1) What are the factors affecting the adoption of major breeding technologies- AI, ET, and/ or sexed semen on U.S. dairy farms?
- (2) What are the characteristics of dairy farms/farmers who embrace the breeding technologies, AI, ET, and/or sexed semen?

(3) Are these technologies profitable for U.S. dairy farms? What is the impact of adoption of AI and ET and /or sexed semen techniques on U.S. dairy farms?

1.4 Objectives

This thesis research has the following objectives:

- To determine the factors affecting the adoption of breeding technologies on US dairy farms.
- To determine the impact of AI, and ET, and/or sexed semen techniques on the productivity and profitability of U.S. dairy farms.

1.5 Arrangement of the Thesis

Chapter 2 provides a review of literature on adoption of technology. Chapter 3 describes the data, conceptual model, and methodological frameworks used in this study. Chapter 4 presents and discusses the results obtained. Finally, Chapter 5 provides summary and conclusions.

CHAPTER 2

LITERATURE REVIEW

2.1 Technology Adoption

In a general sense, adoption may be viewed as an act of accepting as approval, accepting or choosing or taking something as your own. Rogers (1995) defines adoption of an innovation as the mental process of decision making that begins with hearing about the innovation to its final adoption. Five stages of the adoption process include knowledge, persuasion, decision, implementation and confirmation (Rogers, 1995). Initial adoption is generally followed by diffusion, the spread of the technology within a region (Feder et al., 1985).

Extensive literature can be found regarding technology adoption on farms. Griliches (1957), on the economics of technological change associated with hybrid corn, was one of the early economic studies on adoption and diffusion. Feder et al. (1985) extensively surveyed theoretical and empirical studies regarding the patterns of adoption behavior, focusing on developing countries. They suggested that changes in the parameters that affect farmers' decisions are the result of dynamic processes such as information gathering, learning by doing or accumulating resources. The adoption decision of a farmer is based upon the maximization of expected utility subject to constraints such as limited resources including land, credit, etc. Farmer experience, the information gathered from previous periods, information about indicators (such as yield, profit, revenue) accumulated over periods, and information obtained by other farmers are used in further making the decision about the technology (Feder et al., 1985).

Besley and Case (1993) focused on understanding technology adoption across space and time and developed empirical models for studying technological adoption. Ghosh et al. (1994) studied technology adoption and its relationship with technical efficiency and risk attitude. A

number of factors have been identified as influencing technology adoption. Massey et al. (2004) found that factors relating to the farm business (financial stability, level of debt, etc.); efficiency of the innovation system (presence of extension and consultancy providers, the availability of information, the ease with which individuals can access information, etc.); and individual characteristics (age, education, confidence, and innovation capacity) affect technological learning on the basis of their survey of the New Zealand Dairy industry. Rogers (1995) classified adopters into innovators, early adopters, early majority, late majority and laggards based on the adoption decisions they make. Massey et al. (2004) extensively reviewed the literature regarding early adopters, suggesting that adoption will happen quickly if the individual is better educated, receptive to new ideas, self-confident and younger, and the farm system is large, profitable, endowed with absorptive capacity, able to transplant information, and linked with other farms and networks.

Bandiara and Rasul (2006) studied farmers' adoption choices in relation to their social network. If there were few adopters in a network, the social effect would be positive; the effect, however, is negative with many adopters (Bandiara and Rasul, 2006). Abdulai and Huffman (2005) studied diffusion of cross-bred cows in Tanzania, finding that the effects among farmers are stronger for smaller than for larger areas. Credit availability and contact with extension agents are correlated with adoption (Abdulai and Huffman, 2005). However, in the context of Mozambique, Bandiara and Rasul (2006) wrote, "...giving incentives to adopt early to too many farmers can actually reduce the incentives to adopt for other farmers around them."

Abdulai et al. (2008) examined the decision of dairy farmers to acquire information and adopt technology in the presence of uncertainty in Tanzania. They found that human capital and scale of operation were positive and significant in the adoption decision. Increases in education,

age and herd size, and an expectation of higher profitability from the technology were found to have positive effects on adoption intensity.

2.2 Technology Adoption in the US Dairy Industry

Technology adoption in dairy is an important element of structural change in the industry. Johnson and Ruttan (1997) reviewed the structure of the dairy industry. They revealed that during the 1980s, increased production, slow growth in consumption, and lower government support prices in the dairy sector led farms to increase in size. This also shifted dairy production from the traditional areas where average herd size was 50 to 150 head (Lake States, Northeast) to the Pacific, Mountain and Southern Plain regions (herd sizes of 500 to 1500 cows). Hammond (1994) explains that in traditional dairy states such as Wisconsin and Minnesota, farms with herd sizes of 100 or more increased their herd sizes while smaller farms declined in number. Weersink and Tauer (1991) showed, however, that the direction of casualty appeared to be from herd size to technology; their finding partially supported the view of productivity change as the cause of change in size.

Technological developments in dairy have changed the assembly, processing, and distribution of milk (Manchester and Blayney, 1997). Various studies related to dairy farm cost efficiency have shown that the adoption of production practices or technologies impact profitability. Foltz and Chang (2002), El-Osta and Johnson (1998), and similar studies have found production per cow to be a strong factor associated with dairy farm profitability. Studies have also shown that inferior genetics, low quality feeds, and disease incidence are limiting factors for production per cow. El-Osta and Morehart (2000) showed that the chance of a farmer being in the lowest quartile of production performance is lower with the adoption of capital or management intensive technology. Those farmers who were in the top performance group had milk production costs 53% lower than those in the low-performance group (El-Osta and

Morehart, 2000). These facts demonstrate the importance of improved production practices in dairy production. Early adoption studies in agriculture and more recently Bandiera and Rasul (2006) have shown that agricultural innovations are adopted slowly and some aspects of the agricultural adoption process are yet to be understood. Feder et al. (1985) mentioned that the new technologies have attained only partial success even though new technology often offers an opportunity to increase production and income substantially. Many questions regarding the determinants of technology adoption are not easily answered (Besley and Case, 1993), especially in the livestock sector (Abdulai and Huffman, 2005). This leads to further enthusiasm about the factors affecting technology adoption in the dairy sector.

2.3 Breeding Technologies and Adoption

The application of reproductive and breeding techniques has a major impact on the structure of breeding programs, genetic gain and the dissemination of the genetic gain in livestock production (Arendonk and Bijma, 2003). According to Shook (2006), genetics has accounted for about 55% of gains in the yield traits and about one-third of the change in the time interval required to conception. This can be accomplished through AI, ET, sexed semen and traditional breeding methods.

The dairy sector was the first to adopt improved breeding for commercial production in the livestock sector. Breeding and herd improvement associations had an important role in disseminating information about AI after its introduction in the 1940s (Johnson and Ruttan, 1997). Artificial Insemination was introduced at the local level. The industry experienced a rapid initial diffusion of the technology (Johnson and Ruttan, 1997). In the past 50 years, AI developed as a solution for the need for genetic improvement and elimination of costly venereal diseases (Foote, 1996). Hillers et al. (1982) compared the cost and returns of breeding dairy cows both artificially and naturally. The study clearly showed the economic advantage of using genetically

superior AI bulls in breeding. This study showed that calving intervals with natural service (NS) in excess of 365 days or an initial conception rate of AI greater than 0.5 would make AI economically more favorable compared to NS. In addition, there is the risk of personal injury using NS due to the presence of bulls. Management factors such as accuracy of estrus detection and knowledge of proper insemination techniques are the constraints to even wider use of AI (Hillers et al., 1982). Barber (1983) found both biological and monetary factors affecting the adoption of breeding technologies. For most commercial dairy herds, Barber (1983) outlined the dramatic impact of AI on genetic improvement and profitability. Busem and Bromley (1975) showed the adoption of new breeding technology to be closely linked with stability of farm income. Steady cash flow is their major source of income in intensively managed dairy enterprises. An AI breeding program could be recommended for dairy operations (Barber, 1983). Foltz and Chang (2002), El-Osta and Johnson (1998), and other studies have found production per cow as a strong factor associated with dairy farm profitability.

According to Johnson and Ruttan (1997), “Breeding technologies are highly information intensive. An understanding of the principles of breeding and genetics, as well as performance data collection, management and analysis, are often necessary in order to use the new technologies effectively.” They added, “Increasing knowledge can increase the effectiveness of breeding technologies; however it also favors a large operation over which to spread the costs.” This provides some intuition about the factors affecting the adoption of breeding technologies. There are differences in AI adoption rates and productivity between regions and producers. Shumway (1987) considers the costs involved in effective AI use as one of the explanations for differences in adoption rates and productivity among regions and producers. The farmer’s breeding decision is the key factor in increasing productivity through AI.

Application of ET technologies results in an increase in the reproductive rate of females. An increase in this rate is an opportunity to reduce the number of dams that need to be selected for the next generation (Arendonk and Bijma, 2003). Arendonk and Bijma (2003) referred to research which concluded that Multiple Ovulation and Embryo Transplants (MOET) could produce substantial increases in genetic improvement and its main advantage is faster dissemination of superior genetics using cloned embryos (De Boer and Arendonk, 1994). Arendonk and Bijma (2003) also illustrated that factors such as genetic scheme and genetic merit between available semen and embryos as well as the purchase price of semen and embryos determine a farmer's decision to inseminate a cow with semen from a progeny tested sire or to implant the embryo.

Use of sexed semen will lead to higher genetic merit of the newborn calf (Arendonk and Bijma, 2003). Weigel (2004) revealed that the use of sexed semen has been limited to a few highly marketable animals. However, he also mentioned the keen interest of dairy producers in acquiring sexed semen, which shows the potential high rate of adoption of this technology. De Vries et al. (2008) mentioned that the use of sexed semen is expanding. Due to continued improvement in fertility and sorting capacity of sexed semen, commercial application will be wider (De Vries et al., 2008). With the use of sexed semen and better utilization of genetic markers, cost of progeny testing and ET will be lower (De Vries et al., 2008). According to Weigel (2004), early adopters of this technology capture economic benefits because adopters will get an increased supply of (extra) replacement heifers and the chance to expand rapidly from within a closed herd.

Embryo transplant technology was significantly used after the development of non-surgical methods in the 1970s. The number of registered Holstein calves doubled yearly in 1980s, but the rate slowed after the 1980s (Hasler, 1992). Neither ET nor sexed semen

techniques seem to be perfectly feasible for all types of farms, thus their lack of rapid adoption diffusion. There may be several technical and managerial reasons behind this. Structured ET operations require a great deal of capital to build facilities (Funk, 2006). Smeaton et al. (2003) revealed that embryo technologies have a low uptake rate in New Zealand dairy. They also mentioned that embryo-based reproductive technologies are usually not profitable in the general situation if the offspring obtained by ET does not command a higher price than that from natural mating or AI systems. According to Foote (1996), ET for selected animals was successful partly because the dairy farmers who adopted AI for generations showed their interest in applying new methods of making desired germplasm.

Sexing sperm in a dairy enables producers to predetermine the sex of offspring prior to conception. Seidel (1984) had explained basically two procedures of sexing embryos. The first, 'karyotyping,' requires biopsy and the killing of a number of embryonic cells to examine the chromosomes. The second includes making an antibody to molecules to distinguish male embryos from females with a florescent microscope or by an enzymatic product. Arendonk and Bijma (2003) mentioned that the use of ET or sexed semen help farmers to reduce calving difficulties and improve animal welfare. Medical News Today (2006) in their website (accessed on July, 2009) reports, "Several companies providing artificial insemination to the dairy, beef and swine industries, including some of the world's largest, have signed licensing term sheets with Toronto-based Microbix Biosystems Inc. (TSX:MBX) for distribution of its proprietary Sperm Sexing Technology (SST). Microbix' technology allows breeders to determine the sex of offspring prior to the insemination of cattle or swine." Quoting Willium J. Gastle, the president and CEO of Microbix Company, Medical News Today (2006), "Upon commercialization, this will be the single-greatest breakthrough since the advent of commercial artificial insemination almost 50 years ago and will revolutionize the way animal production takes place. Our market

research indicates within three years of launch of this technology, close to 100 percent of the dairy semen provided will be sexed semen." Microbix (2009) predicts that semen sales in the dairy industry, the largest user of AI, will increase by more than 2-fold with the introduction of sex-specific semen.

Herbst et al. (2009) studied the effects of sexed sorted semen on Southern dairy farms. The study showed that the use of sexed-sorted semen over unsorted semen made available the surplus replacement heifers to sell. The positive results of more heifer calves should compensate the higher cost of sexed-sorted semen to have application of this technology in farms (Herbst et al., 2009).

2.4 Adoption and Impact Studies: Review of Methodology

Assessing the impact of technology is the subject of discussion in some adoption models. Various scholars have discussed and used different statistical methods to assess the actual impact on the farm (Foltz and Chang, 2002; Fernandez-Cornejo and McBride, 2002; Tauer, 2001; Foltz and Lang, 2005; Tauer, 2006). To assess the financial impact of a breeding technology on a farm, we need to control the effects of several other factors that may also affect financial performance. The effects of the other technologies and management practices, size, location and operator characteristics need to be accounted for in order to isolate the effect of a breeding technology on farm financial performance.

Endogeneity and self selection issues and their associated correction methods have been discussed (for e.g., Vella and Verbeek, 1999; Green, 2005; Freedman and Sekhon, 2008). Vella and Verbeek (1999) statistically explained that the popular two procedures in estimating the impact of endogenous treatment effects, instrumental variables and control function procedures, are closely related. Heckman (1978, 1979) suggested a two-step method for taking care of endogeneity. This popular two-step method is used by many scholars in their studies. Freedman

and Sekhon (2008) compared the methods for removing endogeneity bias in regression. They showed that the likelihood methods are superior to the 2SLS method in a probit model. They stated, however, the serious numerical concerns in maximizing the bivariate probit likelihood function by standard software packages. They also referred to the literature where maximum likelihood functions performed rather badly.

Gillespie et al. (2004) studied the adoption of four breeding technologies in the hog industry. They used a multivariate probit technique to estimate the impact of factors affecting adoption. The multinomial probit technique is also possible in this case, but use of multinomial probit becomes more difficult and complicated when more than two technologies are under study (Gillespie et al., 2004).

Burton et al. (1999) used binomial and multinomial logit techniques to study the adoption decision regarding organic techniques. Besides two groups-“adopters” or “non-adopters,” they also categorized “registered-adopters” and “unregistered adopters” within adopters. They used a likelihood ratio test to find significant differences between binomial and multinomial logit techniques. Results suggested that there are differences between “registered” and “unregistered” groups, suggesting that they should not be treated as homogenous.

Caswell and Zilberman (1985) studied the choices of sprinkler or drip irrigation technologies relative to traditional surface irrigation and the factors influencing them. However, Dorfman (1996) commented that the use of the multinomial logit model in Caswell and Zilberman (1985) did not measure the interaction between the two improved technologies. Dorfman (1996) used the multinomial probit model to assess the adoption decision with multiple technologies. According to Dorfman (1996), the multinomial probit model had not been widely used in the past because of some computational difficulties. Now, however, the computation is easier with advances in computing methods, specifically Gibbs sampling and the use of the

numerical Bayesian approach in estimation. The relationship or interaction between two technologies can also be assessed (Dorfman, 1996). Dorfman (1996) used the multinomial probit in an adoption study of two technologies: Integrated Pest Management (IPM) and irrigation, dividing them into four possible technology bundles as four possible adoption decisions.

El- Osta et al. (2007) used the multinomial logit to measure the economic well-being of U.S. farm households among four different wealth categories. They estimated the relative and absolute well-being of households. Using least squares estimates, they also included the probabilities of off-farm work and government payments from the first stage multinomial logit models.

Moreno and Sunding (2003) used a bivariate probit model to estimate the simultaneous nature of technology adoption and land allocation. They included a technology adoption equation as a function of the crop choice decision. A bivariate probit model was estimated by maximum likelihood.

Monero and Sunding (2005) found that technology choice differed for different crops, though technology and crop decisions were taken jointly. So, they estimated technology adoption using a nested logit model of technology adoption and crop choice. They showed a farmer's crop technology choices as a two-level nested choice.

El-Osta and Morehart (2000) used two separate logistic regressions in a first-stage estimation of management and capital intensive technologies. The binomial logits were used to obtain estimated probabilities of adoption. They incorporated the predicted probabilities (technology variables) and selectivity variables from first stage models as exogenous variables in a second stage output frontier model to address simultaneity and self-selectivity concerns.

Abdulai et al. (2008) studied the adoption of technology in the presence of uncertainty among dairy farmers of Tanzania. They jointly estimated the information acquisition and adoption decision. They also estimated the intensity of adoption using the Heckman (1979) procedure using bivariate probit model equations (first step) followed by use of the inverse Mills ratio in the intensity equation. Cooper and Keim (1996) also used a selectivity model with a bivariate probit sample selection in assessment of adoption of water quality protection practices.

Technology adoption and farm financial performance are jointly determined. Thus, there is a simultaneity concern (Zepeda, 1994). Several studies (e.g., Fernandez-Cornejo and McBride, 2002; Foltz and Chang, 2002) have used predicted probabilities from adoption decision models as instrumental variables in second stage impact models. They had randomly assigned farmers as adopters and non-adopters. The farmers had decided themselves to be the adopter or non-adopter. Thus, the adopters and non-adopters in this sense may be systematically different, which may lead to differences in farm performance; thus there is the need to account for self-selectivity (Greene, 1997).

Fernandez-Cornejo and McBride (2002) studied the financial impact of adoption of genetically engineered crops. They included predicted probabilities and an inverse Mills ratio from the first stage adoption decision model (probit) as additional regressors in a second stage regression (impact model) to account for simultaneity and self-selectivity. Fernandez-Cornejo et al. (2002) studied the on-farm impacts of adopting herbicide-tolerant soybean. They used predicted probabilities from first stage probits to account for endogeneity coming from simultaneity and self-selection bias.

CHAPTER 3

DATA AND METHODOLOGY

3.1 Data

This study utilizes data from the 2005 Agricultural Resource Management Survey (ARMS), dairy version, conducted by the Economic Research Service (ERS) and National Agricultural Statistical Service (NASS) of the U.S. Department of Agriculture (USDA). Altogether, the survey includes 1,814 observations from 24 states. States covered include AZ, CA, FL, GA, ID, IL, IN, IA, KY, ME, MI, MN, MO, NM, NY, OH, OR, PA, TN, TX, VT, VA, WA, and WI, shown in Figure 3.1.

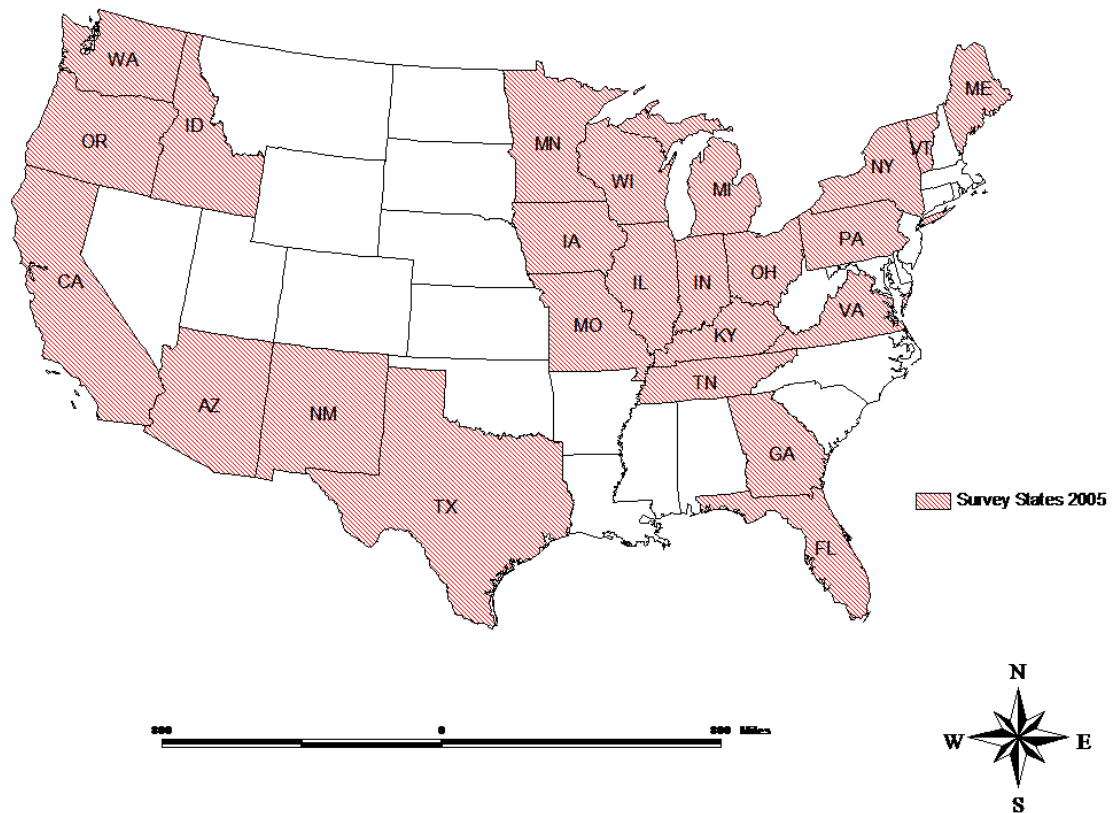


Figure 3.1: U.S. States Covered by ARMS, Dairy Version 2005

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. Sampling is stratified, with sampling probabilities varying by farm size and state. Each sample farm represents a number of like farms in the population, and expansion factors allow for extrapolation to the dairy population of the 24 states where the survey was conducted (90% of the U.S. dairy population).

Each data unit (farm) is weighted based on the difference in dairy production and regions. We included those weights in our study. Making the total number of observations equal to the sample size, weights were adjusted for each observation accordingly:

$$Wts_j = \frac{wt_j}{\sum_{j=1}^N wt_j} * N$$

Where Wts_j is the weight for farm j computed for this study, wt_j is the weight variable (scalar) for the j^{th} farm assigned in the ARMS data, and N is the total number of observations.

3.2 Models

The model used in this study includes two stages: 1) an adoption decision model assessing the factors influencing the adoption of two breeding technologies, AI and ET and/ or sexed semen and 2) an adoption impact model assessing the impact of these breeding technologies on farm productivity and profitability.

3.2.1 Adoption Decision Model

3.2.1.1 Economic and Econometric Model Set-up

As a part of genetic selection and breeding programs, dairy farmers adopt AI, ET and/or sexed semen technologies among the major breeding technologies on their farms. Assessment of the extent of adoption and the characteristics of adopters is the subject of this research. Through

this model, we seek to determine the factors influencing the adoption of AI, ET and sexed semen technologies and how each of these factors affects the likelihood of adoption.

The 2005 ARMS dairy version includes the following two questions regarding adoption of breeding technologies on dairy farms:

- During 2005, did the farm (operation) use artificial insemination (AI) as part of the genetic selection and breeding program? Answer: YES or NO
- During 2005, did this operation use embryo transplants or sexed semen (ETSS) as part of the genetic selection and breeding program? Answer: YES or NO

We assume that farm households make rational decisions. Farm households maximize a utility function that ranks the household's preferences among available technological choices. The farmer's adoption decision is to either adopt or not adopt. These adoption decisions are influenced by a number of demographic, socioeconomic and other factors.

Let U_o and U_N be the representations of the expected benefits from old (traditional) breeding technologies and new breeding technologies, respectively. The dairy farmer decides to adopt a new breeding technology if $U_N^* = U_N - U_o > 0$. The net benefits due to adoption of the new breeding technology, U_N^* which is latent to farmers, is assumed to be a function of different farm attributes, management considerations and the farm's sources of information (Nicholson et al., 1999).

Utility $U_N^* = f(F, M, I)$ where F are farm and farmer attributes; M represents management considerations associated with the technology and farm; and I includes the farm's sources of information about the technology. If X is the vector containing all of the variables in F , M and I , and α is the coefficient vector of X , then $U_N^* = X\alpha + e$, where e is a random error

term distributed normally with mean zero and variance one. So, the observable choice D (decision) to adopt new breeding technologies will be as follows:

$$D_N = 1 \text{ if } U_N^* > 0; D_N = 0, \text{ otherwise}$$

In our case, if AI^* and $ETSS^*$ are unknown variables denoting the net benefits of adopting these technologies, respectively, then AI^* and $ETSS^*$ depend on several variables (whose vectors are X_1 and X_2 , respectively, with β_a and β_b respective coefficients) such that

$$ETSS^* = X_1\beta_a + \varepsilon_1$$

$$AI^* = X_2\beta_b + \varepsilon_2$$

Then, $ETSS = 1$ if $ETSS^* > 0$ and $AI = 1$ if $AI^* > 0$.

Error terms ε_1 and ε_2 are associated with the two equations, respectively. Artificial insemination has value 1 for adoption and 0 for non-adoption, and ETSS likewise.

Given AI and ETSS are adopted as breeding technologies, the adoption decisions of AI and ETSS are assumed to be related. This implies that the random error terms in the equations are correlated. If so, we need to account for the joint probability rather than by using separate probit models for each. So, a bivariate probit model would be more appropriate than single probit equations. In the bivariate probit, the covariance of $[\varepsilon_1, \varepsilon_2]$ equals a constant ρ , rather than zero as is assumed in the case of individual probit models. In practical terms, this implies that the decision to adopt one technology is related to the decision to adopt another.

According to Greene (2008), the bivariate probit is a natural extension of the probit model, allowing two equations whose general specification follows:

$$y_1^* = X_1'\beta_1 + \varepsilon_1, \quad y_1 = 1 \text{ if } y_1^* > 0, 0 \text{ otherwise}$$

$$y_2^* = X_2'\beta_2 + \varepsilon_2, \quad y_2 = 1 \text{ if } y_2^* > 0, 0 \text{ otherwise}$$

$$E[\varepsilon_1|X_1, X_2] = E[\varepsilon_2|X_1, X_2] = 0,$$

$$Var[\varepsilon_1|X_1, X_2] = Var[\varepsilon_2|X_1, X_2] = 1$$

$$Cov[\varepsilon_1, \varepsilon_2|X_1, X_2] = \rho$$

(Greene, 2008).

The bivariate normal cumulative distribution function (CDF) is:

$$Pr(X_1 < x_1, X_2 < x_2) = \int_{-\infty}^{x_2} \int_{-\infty}^{x_1} \phi_2(z_1, z_2, \rho) dz_1 dz_2. \text{ This is denoted as } \Phi_2(x_1, x_2, \rho).$$

The density is:

$$\phi_2(x_1, x_2, \rho) = \frac{e^{\left(\frac{1}{2}\right)(x_1^2 + x_2^2 - 2\rho x_1 x_2)/(1-\rho^2)}}{2\pi(1-\rho^2)^{1/2}}$$

(Greene, 2008), where $\phi_2(\cdot)$ and $\Phi_2(\cdot)$ are the bivariate normal density and bivariate cumulative distribution functions, respectively.

Artificial insemination technology was introduced during the 1950s and is considered as a successful and farmer-friendly technology. Many previous studies about AI suggested that it has been extensively used in dairy farms (Johnson and Ruttan 1997, Hillers et al. 1982, Barber 1983). A recent study by Khanal et al. (2010) based on ARMS data found that AI was adopted by 81.4% of the U.S. dairy farms in 2005, while ETSS technologies were adopted by 10% of the farms. Artificial insemination seems to be a well-adopted technology on dairy farms while ETSS are emerging, still diffusing technologies. Previous studies about ETSS (e.g., Arendonk and Bijma 2003; Weigel, 2004; De Vries et al. 2008) suggest wider adoption of ET and sexed semen in near future. There is the involvement of semen that has been collected by artificial means in the use of both ET and sexed semen. For instance, the use of ET and/or sexed semen require that sperm will have been artificially collected, whether or not both or all three technologies are adopted on the same farm. Thus for practical purposes, adopters of ET and/or sexed semen are a subset of AI adopters since there would be very few cases where ETSS were used by farmers without AI. Thus the assumption in this study is that AI adopting farms select to either use or not

use ETSS. Having the situation that ETSS appears on the farms where AI is adopted, there is no difference in observability in adoption pattern of the set $(ETSS=0 \cap AI=0)$ and the set $(ETSS=1 \cap AI=0)$. This suggests the case of bivariate probit with selection.

In the bivariate setting, there may be the condition where data on y_1 would be observed only when y_2 equals one. This type of estimator was proposed by Van De Ven and Van Praag (1981) and is used in several studies (Boyes et al. 1989; Greene 1992; Kaplan and Venezky 1994; Greene 1998; Mohanty 2002). In the setting of bivariate probit with selection, the model is

$$z_{i1} = \beta' X_{i1} + \varepsilon_{i1}, y_{i1} = \text{sgn}(z_{i1})$$

$$z_{i2} = \beta' X_{i2} + \varepsilon_{i2}, y_{i2} = \text{sgn}(z_{i2})$$

$$\varepsilon_{i1}, \varepsilon_{i2} \sim BVN(0,0,1,1,\rho),$$

$$(y_{i1}, X_{i1}) \text{ is observed only when } y_{i2} = 1$$

Where y_{i1} is the observation of y_1 for the i^{th} individual and y_{i2} is the observation y_2 for individual i . So, observations y_{i1} and y_{i2} depend on the sign of the z_{i1} and z_{i2} , respectively. In the bivariate with selection setting, y_1 is not observed unless $y_2 = 1$. So, there would be three observed outcomes on this selection model. These three types of observations in the sample with their unconditional means are:

$$y_{i2} = 0: \text{Prob}(y_{i2} = 0 | X_{i1}, X_{i2}) = 1 - \Phi(X_{i2}'\beta_2)$$

$$y_{i1} = 0, y_{i2} = 1: \text{Prob}(y_{i1} = 0, y_{i2} = 1 | X_{i1}, X_{i2}) = \Phi_2(-X_{i1}'\beta_1, X_{i2}'\beta_2, -\rho)$$

$$y_{i1} = 1, y_{i2} = 1: \text{Prob}(y_{i1} = 1, y_{i2} = 1 | X_{i1}, X_{i2}) = \Phi_2(X_{i1}'\beta_1, X_{i2}'\beta_2, \rho).$$

The log likelihood for the bivariate probit with selection is

$$\begin{aligned} \text{Log}L = & \sum_{y_2=1, y_1=1} \log \Phi_2[\beta_1, X_{i2}'\beta_2, \rho] + \sum_{y_2=1, y_1=0} \log \Phi_2(-X_{i1}'\beta_1, X_{i2}'\beta_2, -\rho) - \\ & \sum_{y_2=0} \log \Phi(X_{i2}'\beta_2). \end{aligned} \text{ (Greene 2008; LIMDEP Version 9).}$$

Meng and Schmidt's (1985) partial observability model has a formulation similar to the bivariate probit model with sample selection, proposed by Van De Ven and Van Praag (1981).

Meng and Schmidt's (1985) model has the following set up:

If $y_1=1$, both y_1 and y_2 are observed.

If $y_1=0$, then only y_2 is observed.

(Greene, 2008; LIMDEP Version 9.0).

Van De Ven and Van Praag (1981) proposed and applied a correction method analogous to Heckman's (1979) method of correcting sample selection. They derived the likelihood of the proposed model of bivariate probit with sample selection correction. They applied this model in the study of the propensity for accepting deductibles in health insurance on the basis of stated preferences. Estimation results resembled maximum likelihood estimates.

Boyce et al. (1989) analyzed the bank credit scoring problem using a censored probit framework with a choice based sample. In the study, y_1 was whether the loan was granted while y_2 was whether the loan was defaulted. Since default on the loan can be made only if the loan is granted, the case was, y_2 is observed only when $y_1=1$. Similar to the model of Van de Ven and Van Praag (1981) and the likelihood function suggested by Meng and Schmidt (1985), they computed estimates of the probability of loan grant and loan default using bivariate probit with selection.

Greene (1992) also conducted a similar study on credit scoring. Greene (1992) used the same model as Van De Ven and Van Praag (1981) and that used by Boyce et al. (1989): bivariate probit with selection. They found similar conclusions. Obubuafo et al. (2008) studied awareness and adoption of the Environmental Quality Incentive Program (EQIP) by cow-calf producers. They used a bivariate probit designing two equations, first an awareness equation and second an

application (adoption) equation. Since farmers apply for EQIP if they are aware of the program, they used Meng and Schmidt's (1985) framework in their study.

Mohanty (2002) studied factors determining the employment of teenager workers. The paper showed the combined role of the teenager's employment participation decision and the employer's hiring decision of teenagers. Misleading evidence of hiring discrimination among black teenagers, which was prevalent when computing separate probabilities, disappeared when estimated in an appropriate bivariate framework. This paper followed the censored bivariate probit approach developed by Meng and Schmidt (1985), allowing interaction between the employer's hiring decision and the worker's participation decision. More precisely, the paper explains that the worker is employed if he/she actively looks for a job ($SEEK = 1$) and is also selected by the employer ($SEL = 1$). If both $SEEK_i$ and SEL_i are observed for each i , the employment probability can be estimated from the bivariate probability. The $SEEK$ variable is observed for all individuals in employment probability but the SEL variable is not because when $SEEK=0$, the intersection of $SEEK$ and SEL have same observation (i.e. $SEEK=0 \cap SEL = 1$ is observed the same as $SEEK=0 \cap SEL=0$). So, the paper used Meng and Schmidt's (1985) partial observability model. The Meng and Schmidt (1985) model is very similar to the bivariate probit model with sample selection developed by Van de Ven and Van Praag (1981) in the formulation of the probability and likelihood (Greene, 2002; Mohanty, 2002).

Kaplan and Venezky (1994) used a bivariate probit model with sample selection framework to study literacy and voting behavior. People who are voting must be registered voters. The voting response of respondent y_v is observed only when they are registered for vote y_r . The error terms in separate probit equations (u_v and u_r) may have non-zero covariance. So, they found bivariate probit with sample selection best suitable to address this issue.

3.2.1.2 Statistical Test for Zero Correlation

The relationship between AI and ETSS suggested that the bivariate probit with sample selection was the most appropriate for the present study. This should be confirmed by a formal statistical test. A statistical test for zero correlation is used to check whether there is statistical significance associated with using separate probit models for the two technologies or bivariate probit with selection. The test is $H_0: \rho = 0$ against $H_a: \rho \neq 0$. The likelihood ratio test can be used to test this null hypothesis of no correlation between the two technologies.

To use the likelihood ratio test, we should note that when $\rho = 0$, then the bivariate probit becomes two independent univariate probits. So, the LR statistic can be computed from the difference between the bivariate probit log likelihood and the sum of the two log likelihoods of the independent univariate probits as follows:

$LR\text{-statistic} = 2 [\ln L_{bivariate} - (\ln L1 + \ln L2)]$ where $\ln L1$ and $\ln L2$ result from the univariate probit models. This converges to a chi-squared variable with one degree of freedom (Greene, 2008). Thus, if the statistic is greater than 3.84, then the null hypothesis is rejected at the 95% confidence level.

3.2.1.3 Marginal Effects

The marginal effect for continuous variables in the probit model is:

$$\frac{\partial E[Y|x]}{\partial x} = \left\{ \frac{dF(X'\beta)}{d(X'\beta)} \right\} \beta = f(X'\beta)\beta$$

In the case of a dummy variable for a binary independent variable d , the marginal effect would

be: Marginal effect = $\Pr[Y = 1|\bar{x}_*, d = 1] - \Pr[Y = 1|\bar{x}_*, d = 0]$

where \bar{x}_* denotes the means of all the other variables in the model (Greene, 2008).

The bivariate probit model is the extension of the probit. There are several marginal effects associated with the bivariate probit model. The first step could be the derivatives of

$Prob[y_1 = 1, y_2 = 1|x_1, x_2]$ as follows:

$$\frac{\partial \Phi_2(x'_1\beta_1, x'_2\beta_2, \rho)}{\partial x_1} = \phi(x'_1\beta_1) \Phi\left(\frac{x'_2\beta_2 - \rho x'_1\beta_1}{\sqrt{1-\rho^2}}\right) \beta_1$$

(Greene, 2008).

We can evaluate several conditional means and their partial effects as we have two dependent variables, y_1 and y_2 . If x is defined as $X = (X_1 \cup X_2)$ and, $X'_1\beta_1 = X'_1\gamma_1$, Greene (2008) has shown different conditional probabilities and their marginal effects as:

$$Pr[y_1 = 1, y_2 = 1|X] = \Phi_2[X'\gamma_1, X'\gamma_2, \rho]; \quad \frac{\partial \Phi_2}{\partial X} = g_1\gamma_1 + g_2\gamma_2$$

$$E[y_1|y_2 = 1, X] = Pr[y_1 = 1|y_2 = 1, X] = \frac{Pr[y_1=1, y_2=1|X]}{Pr[y_2=1|X]} = \frac{\Phi_2(X'\gamma_1, X'\gamma_2, \rho)}{\Phi(X'\gamma_2)}$$

We can obtain the marginal effects for $y_2|y_1$ by respecifying the model with y_1 and y_2 reversed.

For $E[y_2|y_1=1, X]$, the marginal effect of this function is:

$$\frac{\partial E[y_1|y_2, X]}{\partial X} = \left(\frac{1}{\Phi(X'\gamma_2)}\right) \left[g_1\gamma_1 + \left(g_2 - \Phi_2 \frac{\Phi(X'\gamma_2)}{\Phi(X'\gamma_2)} \right) \gamma_2 \right]$$

$$\text{Where } g_{ij} = \phi(W_{ij}) \Phi \left[\frac{W_{ij} - \rho_i^* W_{ij}}{\sqrt{1 - \rho_i^{*2}}} \right]$$

$$W_{ij} = q_{ij}z_{ij}; \quad Z_{ij} = X'_{ij}\beta_j, \quad q_{i1} = 2y_{i1} - 1 \text{ and } q_{i2} = 2y_{i2} - 1$$

$$\text{so that } q_{ij} = 1 \text{ if } y_{ij} = 1 \text{ and } -1 \text{ if } y_{ij} = 0, \quad \rho_i^* = q_{i1} q_{i2} \rho \quad \text{and } j = 1, 2.$$

(Greene, 2008; LIMDEP version 9).

3.2.1.4 Heteroskedasticity

The assumption of homoskedasticity assumes that for each value of x , the values of y are distributed about their mean value following a probability distribution, i.e. $var(y|x) = \sigma^2$. Violation of this equal variance assumption is called heteroskedasticity. Alternatively, variable y_i and random error term e_i are said to be heteroskedastic. Presence of heteroskedasticity in data

does not affect the assumption of unbiasedness and consistency but creates inefficiency in linear regression estimates. Greene (2008) mentioned the trend of using a robust “sandwich” estimator for asymptotic covariance matrix estimation to account for the standard error in probit models. Since ARMS includes a complex survey design and cross sectional data, it has more possibility of heteroskedastic error terms. Mishra and El-Osta (2008) used the Huber-White sandwich robust variance estimator in their study using ARMS data in logistic distributions. We used the “Robust” option in LIMDEP which adjusts for such heteroskedastic standard errors (LIMDEP, Version 9).

3.2.1.5 Independent Variables Used in the Adoption Equation

Farm Size: Farm size is an important factor in the adoption decision of technology. Previous studies on adoption of technologies in dairy have included herd size as the indicator of farm size. Herd size as an indication of farm size allows for analysis of the scale response of the technology. It requires extra management and effort to manage bulls and to mate them with cows, especially in larger farms. In using bulls for breeding, there will also be the chance of physical injuries. So, as herd size expands, natural breeding using a bull may be less feasible, implying the adoption of AI, ET and/or sexed semen. So, the number of milk cows on the farm, NMILKCOW, is included as an explanatory variable in the adoption decision model. In the McBride et al. (2004) and Foltz and Chang (2002) rbST adoption studies, number of milk cows was included to consider influence of adoption by size. Though larger farms may be more likely to adopt, this size impact may increase at a decreasing rate (McBride et al., 2004). El-Osta and Morehart (2000) found that the likelihood of adopting capital-intensive technologies increases with size and reaches a peak at a size of 358 milking cows, while the likelihood of adopting a management intensive technology decreases as farm size increases, reaching its lowest at 129 milking cows, beyond which it rises with farm size. However, this finding may not have exact

implications in terms of our peak milking cow figures as their study was based on 1993 ARMS data with the farms surveyed having an average herd size of 57 cows (El-Osta and Morehart, 2000).

Though genetically superior milking cows may be considered capital- intensive (El-Osta and Morehart, 2000), breeding technologies such as AI, ET, and sexed semen can generally be considered as management intensive rather than capital intensive. All require appropriate time management, specialized knowledge, and skill such as accurate detection of estrus for successful use.

Farmer Characteristics: Younger people are generally considered to be more receptive to new ideas and, thus, are expected to be the greater adopters of advanced technologies, as shown in most adoption studies. To examine whether this is the case for these breeding technologies, age of the principal operator, AGE, is included in the model. Previous studies illustrate that breeding technologies are information and knowledge-intensive (Johnson and Ruttan, 1997). Planning horizon of the farmer also affects adoption decision of a technology. The consideration of continuation of farming in the next several years may influence the decision. Dairy producers with longer planning horizons may be more interested in investing in the development of human capital or other capital that supports AI and/or ETSS adoption. Previous adoption studies have also included planning horizon (McBride et al., 2004). In this study, TENYEARS, a dummy variable having value 1 if the farmer (operator) is planning to continue the operation for the next ten years, is included. Farmer education has been consistently used in adoption studies. Younger and more educated farmers were the more likely the adopters in case of rbST (McBride et al., 2004). More educated farmers are expected to more likely adopt new technologies. So, the principal operator's education is also included in the model as a separate variable. EDUC is a dummy variable having the value 1 if the principal operator is a college graduate or beyond.

Farm specialization is another variable of interest. Likelihood of being a top producer increased with specialization of the farm (El-Osta and Morehart, 2000). The ratio of dairy enterprise revenues to total farm revenues indicates degree of specialization in dairy. So, the specialization is the ratio of the value of dairy production to the total value of production in farm. Another farmer characteristic is farmer's work in an off-farm job. This variable has resulted in mixed findings in terms of technology adoption decisions. The lower the off-farm income, the more was 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 et al., 2005). Fernandez-Cornejo (2007) found that farm efficiency decreases when off-farm activities increase. In this study, dummy variable OFFARM is included, taking a value of 0 if both the operator and the spouse do not work off the farm for wages or salary, else 1.

Location Factors: Technology adoption differs across regions. Location factors account for geographic and regional differences in climate, production systems and cultural perceptions about the technology (McBride et al., 2004). Technology adoption studies (McBride et al., 2004; El-Osta and Morehart, 2000; Fernandez-Cornejo and McBride, 2002) have included location variables in adoption decision equations. El-Osta and Morehart (2000) included dairy production locations as "WEST" (farms located in the western US) and "NORTH" (farms located in the northern US). Khanal et al. (2010), however, assumed the regional differences in dairy technologies and management practices may be associated with differences in farm size. In this study, two dummy variables for West and South are included to capture the regional differences. Dummy variable WESTUS includes the Pacific (CA, OR, and WA), West (AZ, ID, and NM) and Southern Plains (TX) states. The SOUTHUS dummy variable includes the Appalachia (KY, TN, and VA) and Southeastern (FL and GA) states. The U.S. states covered under WESTUS and

SOUTHUS in our study is shown in Figure 3.2. Figure 3.2 also shows the base survey states not included under WESTUS and SOUTHUS.

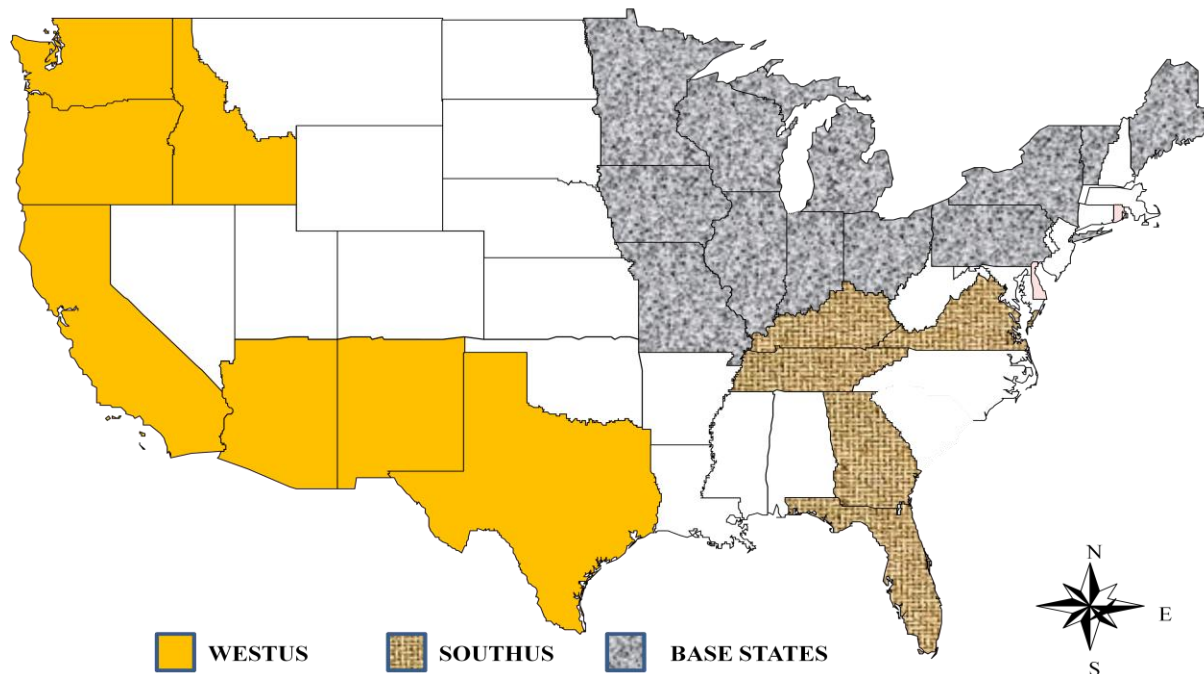


Figure 3.2: Survey States Included Under WESTUS and SOUTHUS

Adoption of Other Technologies and Management Practices: According to Johnson and Ruttan (1997), “..an understanding of principles of breeding and genetics, as well as performance data collection, management and analysis, are often necessary in order to use the new breeding technology effectively.” This implies that the adoption of some other technology or milk production system or management practices may be complementary with breeding technologies. So, adoption of some particular technologies, management practices or production systems can influence the adoption decision of breeding technologies. Studies related to the adoption of dairy technologies (McBride et al., 2004; Foltz and Chang, 2002) have found differences in the probability of adoption when accounting for other technologies in the adoption equation. Khanal et al. (2010) have found complementary relationships between dairy technologies, management practices and/or production systems. Their study found that having a parlor milking system on

the farm was the most common factor that increased the likelihood of adoption of most of the other technologies, management practices and production systems on dairy farms. We include dummy variable, PARLOR, having value =1 if it is adopted on the farm.

3.2.2 Farm Impact Model

3.2.2.1 Model Set-up

A farm impact model assesses the impact of the adoption of breeding technologies (AI and ET and/or sexed semen) on farm productivity and farm profitability. Milk production per cow is used as an indicator of farm productivity while net returns variables are used as indicators of farm profitability.

If Y_i is the productivity or profitability of the farm, expressed in terms of dollars or amount milk produced, then it is a function of vectors of explanatory variables (X_i) and two dummy variables for adoption of breeding technologies (AI and ETSS), ETSS being a dummy variable having value =1 if ET and/or sexed semen is adopted.

$$Y_i = X_i' \alpha + \beta_1 AI_i + \beta_2 ETSS_i + e_i$$

where α is the vector of parameters for independent variables other than AI and ETSS, AI and ETSS are two dummy variables having value 1 for adoption and 0 for non-adoption, with β_1 and β_2 as respective parameters. Estimate e_i is the random error term.

From the previous discussions on the adoption decision model, we know that farmers will adopt each technology if the benefit associated with adoption is higher than the cost associated with adopting. Let AI^* and $ETSS^*$ be unknown variables denoting this benefit factor. AI^* and $ETSS^*$ depend on several variables (say, whose vectors are β_a and β_b) 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 $AI^* > 0$.

Other technologies adopted on the farm also have the influence on productivity and profitability. So, if T' is a vector of other technologies, management practices, and production systems on the farm, we can rewrite our model as:

$$Y_i = X_i'\alpha + \beta_1 AI_i + \beta_2 ETSS_i + T_i'\omega + e_i, \text{ where } \omega \text{ is the coefficient vector.}$$

3.2.2.2 Accounting for Endogeneity and Self-Selection Bias Issues

The above mentioned equation can be estimated using the Ordinary Least Squares (OLS) regression technique. However, the estimators computed using a simple OLS technique may be biased and inconsistent if there is a problem of the presence of the correlation between the explanatory variables and error terms. If there is potential for such a problem, it should be tested and corrected for to reduce bias and obtain a more consistent approximation of the estimator.

Explanatory variables which have such correlation with the error term are said to be endogenous and the least squares estimator fails to estimate accurately in this case (Hill et al., 2008). We suspect that AI and ETSS are endogenous. This problem can be addressed by administration of appropriate instrumental variables.

Hill et al. (2008) have explained that the endogeneity problem may arise due to one or more of the following reasons: 1) measurement problems (the explanatory variable is measured with error), 2) the case where an omitted variable is correlated with explanatory variables, then resulting in the error term being correlated with explanatory variables, 3) simultaneous equation bias, and 4) when a lagged dependent variable is in the model (due to serial correlation).

Any of the reasons mentioned above may cause endogeneity. In our study, there is a need to test for potential endogeneity of ETSS and AI in impact (profit, revenue, and cost) equations. If endogeneity is detected, ETSS and AI should be replaced with appropriate instrumental variables (Greene, 2008). Several previous studies (Foltz and Chang, 2002; Fernandez-Cornejo et al., 2002; Fernandez-Cornejo and McBride, 2002) have used predicted probabilities from the

adoption decision model (probit equation) as instrumental variables in a profit equation. Foltz and Chang (2002) showed that the probability of adoption can serve as an instrument for adoption of that technology (in their study, the case was rbST adoption). El-Osta et al. (2007) used predicted probabilities as instruments in a multinomial regression model.

Note that AI and ETSS decisions are related to each other as described in the adoption decision model. So, to account for the endogeneity, if detected, predicted probabilities from a bivariate probit model can be used as instruments in the productivity/ profitability equations to account for joint probability of adoption. So, after replacing AI and ETSS variables with their predicted probabilities, our equation would be:

$$Y_i = X_i' \alpha + \beta_1 \widehat{AI}_i + \beta_2 \widehat{ETSS}_i + T_i' \omega + e_i, \text{ where } \widehat{AI}_i \text{ and } \widehat{ETSS}_i \text{ are the predicted probabilities.}$$

Self selection could be an issue here. We have not assigned farmers as adopters and non-adopters; they have chosen themselves to be adopters / non-adopters. Thus, the two categories of farmers as adopters and non-adopters may be systematically different, leading to differences in farm performance, but that difference may not be solely due to the adoption of technology of interest (Greene, 2002; Fernandez-Cornejo and McBride 2002). If we ignore self-selection bias in estimating the impact, then this equation would lead to inconsistent estimates. Since larger farms are more likely to adopt many advanced technologies, management practices or production systems, the impact of a particular one on farm profitability and productivity may be biased unless accounted for using the impact of others using selection bias correction (Khanal et al., 2010).

Selection-bias can be corrected for using self-selection variables in the impact estimation equation. Heckman's (1979) procedure is applicable. This involves computing self-selection variables from the adoption decision model and then placing them in the impact model. From the bivariate probit with selection equation in the adoption decision model, selection terms, or the inverse Mill ratios (λ), are calculated and used as variables in the productivity/ profitability

equations. We obtain two selection variables ($\widehat{\lambda}^a$ and $\widehat{\lambda}^b$) from the bivariate probit model for AI and ET, respectively.

The selection variable or inverse Mills ratio is the ratio of the normal density function and cumulative normal distribution. In the bivariate probit, the selection variables are given as:

$$\widehat{\lambda}_i^a = \phi(W^a) \frac{\Phi[(W^a - \rho AI_i)/(1 - \rho^2)^{\frac{1}{2}}]}{\Phi_2}$$

$$\widehat{\lambda}_i^b = \phi(W^b) \frac{\Phi[(W^b - \rho ETSS_i)/(1 - \rho^2)^{\frac{1}{2}}]}{\Phi_2}$$

$$W^a = -X_i^a \widehat{\alpha}_1 \text{ and } W^b = -X_i^b \widehat{\alpha}_2$$

(Abdulai et al., 2008).

Where Φ_2 denotes the bivariate normal cumulative distribution with probability density function as ϕ_2 .

So, the final farm impact model is as follows:

$$Y_i = X_i' \alpha + \beta_1 \widehat{AI}_i + \beta_2 \widehat{ETSS}_i + T_i' \omega + \theta^a \widehat{\lambda}_i^a + \theta^b \widehat{\lambda}_i^b + e_i$$

Fernandez-Cornejo and McBride (2002) also included both a predicted probability and an inverse Mills ratio as regressors in farm impact models to account for endogeneity and self-selectivity issues. They computed probabilities and inverse Mills ratios from separate probit equations of the adoption decision model. Abdulai et al. (2008) included the inverse Mills ratio from a bivariate probit model in their study regarding joint estimation of information acquisition and adoption of new technologies. Our model is consistent with these previous studies in using the tools, but is different in the sense that it uses both predicted probabilities and inverse Mills ratios from a bivariate probit with selection equation.

A study by Wahba (2007) regarding returns to overseas work experience is also worth mentioning here. This study estimated the wage differential between waged employees who are

return migrants and those who are non-migrants. Two potential selection biases due to the migration decision and wage employment participation (labor market participation) were taken into account. The study regarded Egypt, where purpose of migration was employment and temporary overseas work experience was affecting wages. Wahba mentioned that there may be two potential selection biases: one is migration selection bias because migrated returnees may not be representatives of a random sample, but are self-selected. The second bias in selection could be on wage work as returnees have alternatives of not entering the wage market, e.g., being self-employed). To handle this situation, Wahba used a two-step Heckman (1979) approach but with extended correction terms. In the first step, two selection equations are jointly estimated using maximum likelihood bivariate probit with selection. In the second stage, the wage equations were estimated through simple OLS including the correction terms (computed from bivariate probit results) as additional regressors.

3.2.2.3 Test for Endogeneity and Overidentifying Restrictions

To check whether predicted probabilities of AI and ETSS from adoption decisions are appropriate versus the actual values for AI and ETSS, we tested for the significance of predicted values for AI and ETSS, PredAI and PredETSS, respectively in a multiple regression with all Xs, AI, ET and PredAI and PredETSS as regressors. Since in our case, joint significance of AI and ETSS was found, we included both the predicted values of AI and ETSS (i.e. PredAI and PredETSS) in model estimation when either was significant. If not, we chose AI and ETSS instead of their predicted values. This procedure is based on suggestions by Wooldridge (2006) for testing endogeneity and overidentifying restrictions, whose general procedure is as follows:

- Estimate the reduced form equation for the suspected endogenous variable and obtain the residual of the equation as \hat{v} .

- Add \hat{v} as an independent variable in the structural equation which also includes the suspected endogenous variable as an independent variable.
- Regress the equation and check for the significance of \hat{v} . If \hat{v} , in the structural equation, is statistically different from zero, we conclude that the suspected variable is indeed endogenous.

If endogeneity was detected following this procedure, we included predicted values in structural equations. After choosing predicted or actual ones from the above mentioned procedure, we also included λ_1 and λ_2 (self-selection variables) as exogenous regressors and checked for their significance. We dropped those in the structural equation if neither were significantly different from zero while both λ_1 and λ_2 were included if either was significant.

3.2.2.4 Heteroskedasticity Correction in the Model

We say that heteroskedasticity is present when a sequence of random variables has different variances. This violates the assumption of equal variances in least squares estimation. If there is heteroskedasticity, OLS estimators remain unbiased and consistent, but are inefficient. So, OLS will be no longer result in the BLUE (Best Linear Unbiased Estimator).

There are several procedures to correct for heteroskedasticity. We can stabilize the variances by transformation of the dependent variables. If there is a prior expectation about the form of heteroskedasticity, we can use a Generalized (or weighted) least squares estimator instead of OLS. If there is suspicion of the presence of heteroskedasticity, but we are unaware of the type of heteroskedasticity, then HCCM (Heteroskedasticity Consistent Covariance Matrix) estimators are used to obtain more efficient standard errors of the OLS estimates (Long and Ervin, 2000). Long and Ervin (2000) studied different methods of HCCM, suggesting that if the number of observations is less than 250, HC3 (HCCM estimator based on hat matrix) would

perform better. They suggested that if the sample size is more than 500, any HCCM-based test (White, HC1, HC2, and HC3) performs well.

As a robust covariance matrix, the White estimator is one of the common estimators, which is:

$$Est.Var[b] = (X'X)^{-1} \sum_{i=1}^n e_i^2 x_i x_i' (X'X)^{-1} \text{ (LIMDEP, version 9)}$$

To account for the heteroskedasticity in the impact equations, we used the “Heteroscedasticity” option that corrects heteroskedasticity through the corrected White estimator (LIMDEP, version 9).

3.2.2.5 Variables in Farm Impact Models

- **Dependent Variables**

Dependent variables in the impact models are variables accounting for farm productivity, profitability, cost, and revenues. Dairy enterprise net returns over total costs are included as the indication of farm profitability while milk per cow is the indication of farm productivity. The gross return (revenue) and the total and allocated cost variables are also used as dependent variables.

Dairy enterprise net returns are the difference between gross returns and total costs. 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. Each of the following variables is used in a separate equation as a dependent variable to assess impact.

Dairy enterprise level net returns include net returns over total cost (NETTOT) and Net returns over operating costs (NETOPER). NETTOTCWT is net returns over total costs per hundredweight of milk produced. Net returns over total costs per milk cow is represented as the variable NETTOTCOW. The measures used for operating costs per hundredweight of milk produced and per cow are NETOPCWT and NETOPCOW, respectively.

Different revenue and cost measures are included in the farm impact models. Revenue measures include gross returns per hundredweight of milk produced (GROSSCWT) and gross returns per cow (GROSSCOW). Different total, operating and allocated cost measures are also included as dependent variables. Total costs per hundredweight and per cow (TOTALCWT and TOTALCOW); operating costs per cwt and per cow (OPERCWT and OPERCOW) and allocable costs per cwt and per cow (ALLOCWT and ALLOCOW) are included as cost measures.

- **Explanatory Variables**

Demographic and Socio-Economic Factors: Previous adoption studies show that farm productivity and profitability are influenced by demographic and socio-economic factors. So, farm size, farm specialization, farmer characteristics (age, education, and work in an off-farm job) are included in the adoption impact models. Location variables are also included to account for differences in productivity and profitability due to region. A brief description of these variables is already given in the adoption decision model.

Farm size is consistently used in impact studies. Farm size (number of milk cows) was positively related with milk per cow and profit per cow in previous studies (Foltz and Chang, 2002). McBride et al. (2004) found that the size of operation has a positive impact on operating margin per unpaid labor hour while impact was not significant in milk yield. As there are expected economies of size involved in dairy, profitability is expected to increase with number

of milk cows. A squared term of number of milk cows is also of interest. This study includes both number of milk cows and the squared of number of milk cows as independent variables.

Farmer's education is expected to have positive influences on productivity and profitability. More educated farmers and more specialized operations have been shown to have higher milk yield per cow (Foltz and Chang, 2002; McBride et al., 2004). El-Osta and Morehart (2000) also found that the more specialized operations are more likely to be in the top producer (performer) group. Similar to the adoption decision model, variables WESTUS and SOUTHUS were included to capture regional differences in production.

Adoption of Other Technologies: Farm profitability and productivity may be influenced by several other technologies, management practices and production systems. Previous findings showed that the adoption of other technologies has a significant impact on milk per cow and profit per cow (Foltz and Chang, 2002; McBride et al., 2004). Milk production system or milking facilities adoption can uniquely influence profitability and productivity. This model includes three variables for production system- Parlor, Graze, and milking 3 times daily.

Parlor: Milking facilities affect the productivity of the farm. The cost of stanchion technology is generally lower than that of parlor technology for small farms (Tauer, 1998; Katsumata and Tauer, 2008). Tauer (1998) found that parlor technology was more cost efficient in barns with greater than 160 cows, suggesting significantly associated economies of size. PARLOR had a positive, however non-significant, impact on yield per cow and operating margin per unpaid hours while the impact on profit per cow and operating margin per hundredweight were negative (Foltz and Chang, 2002; McBride et al., 2004). Thus, a dummy variable indicating whether a parlor is adopted is included in adoption impact model.

Milking 3 Times Daily: Milking three times daily is associated with higher milk production. Studies have shown a 6 to 19% increase in production associated with a third

milking (Amos et al., 1985; DePeters et al., 1985; Gisi et al., 1986; Goff, 1977; Logan et al., 1978; Lush and Shrode, 1950; Pearson et al., 1979; Pelissier et al., 1978; Poole, 1982; and Kruij et al., 2000). Erdman and Varner (1994) found that the increase in yield due to increase in milking frequency is by a certain fixed amount (certain kilogram) rather than a percentage increase. An additional advantage to milking three times daily is that it partially solves the problem of milk quality deteriorating in the late stages of lactation to the point where it cannot be used for cheese (Sorensen et al., 2001). Therefore, a dummy variable to account for 3 times milking daily is included.

Grazing (Pasture-based Dairying): Grazing can range from slight to extensive on dairy farms. Dairy operations may be pasture-based, where grazing on pasture contributes the majority of forage needs during grazing season. As discussed by Gillespie et al. (2009), pasture-based operations are defined in various ways such as management-intensive grazing, those that use pasture as the primary forage source in the grazing season (Taylor and Foltz, 2006); farms where animals obtain 40% of their forage needs during the summer months from pasture (Hanson et al., 1998); and the operations where at least 25% of the annual forage requirement is obtained from pasture and animals are grazed for at least four months (Dartt et al., 1999). The definitions have general agreement on overall concept of “pasture-based.” Gillespie et al. (2009) categorized operations as conventional, semi-pasture based and pasture-based. In their multinomial logit framework, they considered “pasture-based” operations as those that obtain 50-100% of the total forage ration for milk cows from pasture during the grazing season. Pasture-based or grazing operations may have the different associated farm productivity and profitability from non grazing operations. Increased interest in pasture-based dairying has emerged due to increased demand for “natural” milk products and the fact that some pasture-based operations may qualify as organic with additional management changes. There are different findings about the profitability of

pasture-based dairy systems (Gillespie et al., 2009; Hanson et al., 1998; Dartt et al., 1999; Foltz and Lang, 2005). Gillespie et al. (2009) found that the semi-pasture based operations were less profitable than conventional systems on an enterprise basis while pasture-based operations were not significantly different in profitability from other systems. This study includes GRAZE as a dummy variable, having a value of 1 if more than 50% of the total forage for milk cows during grazing season is obtained from pasture, otherwise 0.

“SUMTECH” Variable: Variable SUMTECH is a summation of the adoption of eight different technologies or management practices on a dairy farm. As an indicator of the number of relevant technologies adopted on the farm, variable SUMTECH provides a measure of the intensity of adoption. The farms with higher values of SUMTECH can be interpreted as the greater technology adopters. SUMTECH includes: 1) holding pen with udder washer, 2) milking units with automatic take offs, 3) computerized milking system, 4) computerized feeding system, 5) using rbST on the farm, 6) DHIA membership, 7) using a nutritionist to purchase or formulate feed, and 8) accessing the internet for dairy information. For detailed descriptions of each technology and management practice, we refer to Khanal et al. (2010).

CHAPTER 4

RESULTS AND DISCUSSION

The results of adoption decision models and farm impact models developed in Chapter 3 are presented in this chapter. First, the breeding technology adopter characteristics are presented. Demographic, socio-economic, and financial characteristics of the adopters and non-adopters are compared. Then, results of the adoption decision and farm impact models are presented and discussed. The adoption decision model includes the results of separate probits and a bivariate probit with selection. The farm impact models show the least squares regression results, accounting for endogeneity and self-selection bias wherever necessary. Each data unit (farm) used in these analyses is weighted on the basis of the weights assigned in ARMS and are corrected for potential heteroskedasticity. The econometric software LIMDEP, version 9, was used for analysis.

4.1 Characteristics of Adopters and Non-Adopters

Adopter and non-adopter differences across various demographic, socioeconomic, and farm financial characteristics are presented in Table 4.1. Mean differences of the adopters and non-adopters are statistically tested using paired t-tests. These results are based on 1,814 observations of ARMS 2005 data employing pair-wise two-tailed delete-a-group Jackknife t-statistics at the 90% confidence level or more. There were 15 replicates and 28 degrees of freedom using the jackknife. For greater detail on this estimation procedure using ARMS, the reader is referred to Dubman (2000). The null hypothesis in two-tailed paired t-tests was $B1=B2=0$, where $B1$ and $B2$ are respective variable means of adopters and non-adopters.

Our results presented in Table 4.1 shows the characteristics of adopters and non-adopters.

Table 4.1 Weighted Mean Differences between Breeding Technologies, Adopters and Non-Adopters, 2005.

Item	Non-Adoption, 2005	Adoption, 2005
.....Artificial Insemination (AI).....		
Number of farms	9,710 ^b	42,527 ^a
Size		
Acres	384.0	413.2
Number of milk cows	116.1 ^b	162.6 ^a
Demographics		
Farmer age	52.1	51.0
Farmer college degree	0.116 ^b	0.171 ^a
Farmer's off farm work hours per year	140.664	124.859
Other		
Debt-asset ratio	0.144	0.146
Milk per cow, cwt/year	133.024 ^b	177.142 ^a
.....Embryo Transfer and/or Sexed Semen (ETSS).....		
Number of farms	46,804 ^a	5,433 ^b
Size		
Acres	396.7 ^b	503.2 ^a
Number of milk cows	147.5 ^b	209.6 ^a
Demographics		
Farmer age	51.6 ^a	47.6 ^b
Farmer college degree	0.132 ^b	0.408 ^a
Farmer's off farm work hours per year	121.701	180.308
Other		
Debt-asset ratio	0.143	0.172
Milk per cow, cwt/year	164.18 ^b	209.95 ^a

^{a-d}: Means within a row with different superscripts differ at $P < 0.10$.

Source: USDA, ARMS Data, Dairy Survey, 2005

Number of milk cows for AI adopters were significantly higher than for non-adopters with an average 163 milk cows for adopters. Adopters of AI were more highly educated: 17.1% of adopters held 4-year college degrees while just 11.6% of the non-adopters had college degrees. Milk yield per cow of AI adopters was significantly higher than that of non-adopters (average 177.14 cwt/year for adopters versus 133.02 cwt/year for non-adopters). Overall, AI adopters had more milk cows, were having higher education (college degree and beyond) and produced higher milk yield per cow.

Mean results suggest that the adopters of ETSS had more acres of land and a significantly higher number of milk cows. The portion of adopters having 4-year college degrees was greater than that of non-adopters. Adopters of ETSS also received higher milk yields (average 209.95 cwt/year) per cow than non-adopters (average 164.18 cwt/year). Overall, ETSS adopters had more acres of land, had more cows, and were relatively younger and more educated than non-adopters.

4.2 Adoption Decision Model

4.2.1 Descriptive Statistics

Table 4.2 shows the weighted general descriptive statistics of dependent and independent variables used in the adoption decision models. In total, 1,748 observations were used in the data set representing the dairy farms (producers) of 24 different states in the U.S. This is cross-sectional data for 2005.

Artificial insemination is used by most dairy farmers. Johnson and Ruttan (1997) have described AI as one of the farmer-friendly technologies that experienced rapid initial diffusion in dairy. Consistent with this, our data shows a high rate of AI adoption: around 77.9% of the dairy farms inseminated their cows via AI in 2005. Our data also shows that ET and sexed semen are still diffusing technologies in dairy, as they were adopted by 11% of the dairy farms.

Average age of the dairy farmers in this survey was 51 years, with a standard deviation of 11 years. Twenty-one percent of the farmers were college graduates or beyond. TENYEARS is a dummy variable indicating whether the farmer plans to continue farming for next 10 years or more. This is an indication of the planning horizon of the farm. Descriptive statistics suggests that 60.5% of the farms planned to continue farming for the next ten years or more. Data shows that 47.5 % of the principal operators or their spouses worked off the farm for wages or salary. Regarding the size of the operation, dairy farms in 2005 had 322 milk cows on their farms, on

Table 4.2 Weighted Descriptive Statistics: Dependent and Independent Variables in Adoption Decision Model

Variable	Definition	Mean	Std.Dev.
Dependent variables			
AI	Dummy variable; whether artificial insemination is adopted in the dairy farm in 2005; 1 if adopted, 0 if not	0.779	0.414
ETSS	Dummy variable; whether embryo transplant and /or sexed semen is adopted in the farm in 2005; 1 if adopted, 0 if not	0.113	0.317
Independent Variables			
AGE	Continuous variable; Principal operator's age	51.467	11.193
TENYEARS	Dummy Variable; Continuation of farm operation; 1 if operator plans to continue the operation for next 10 years or more	0.605	0.488
EDUC	Dummy variable; Principal operator's education level; 1 if principal operator is college graduate or beyond	0.209	0.4069
OFFARM	Dummy variable; Operator's off-farm job; 1 if Principal operator or spouse work off-farm for wages or salary	0.475	0.4995
SPECLIZE	Farm specialization, share of dairy in total farm value of production (Dairy/VPRODTOT)	0.849	0.17
NMILKCOW	Continuous variable; Number of milk cows in the farm/1000	0.322	0.608
WESTUS	Regional dummy; if farm is located in western US (Pacific- CA, OR, WA or West- AZ,ID, NM or Southern Plain- TX), WESTUS=1, else 0	0.212	0.409
SOUTHUS	Regional dummy; if farm is located in Southern US (Appalachia- KY,TN, VA or Southeast-FL, GA), SOUTHUS=1, else 0	0.172	0.378
PARLOR	Dummy variable; if parlor is adopted in the farm, Parlor=1, else 0	0.685	0.465

Source: USDA, ARMS Data, Dairy Survey, 2005

average. However, as indicated by the higher standard deviation, the number of milk cows across farms varied widely. Having a parlor as the milking facility on dairy farms was common: 68.4% adopted parlors in 2005. The portion of the farms located in the western U.S. (CA, OR, WA, AZ, ID, NM, and TX) was higher than the southern part (KY, TN, VA, FL, and GA) in 2005.

4.2.2 Separate (Univariate) Probit Results

Table 4.3 shows the parameter estimates for univariate (separate) probit equations for AI and ETSS. In computation of the separate probit models, we disregard the potential relationship between adoption decisions of these technologies. Each probit equation has 1,748 observations and 10 parameters. In both equations, principal operator's education level, off farm work, and farm specialization were significant at the 10% level. In addition, operator age and the longer planning horizon (TENYEARS) were significant in the ETSS equation while regional variables were significant in the AI adoption equation. Results suggest that the adopters of ETSS were younger, had longer planning horizons, and were more likely to hold college degrees. Principal operators or their spouses having an off farm job were the less likely adopters of ETSS. More specialized dairy farms had greater probabilities of ETSS adoption. Adopters of AI were more likely to hold college degrees. More specialized farms had higher probabilities of AI adoption. Principal operators or their spouses working off-farm for wages or salary were the less likely adopters of AI than non off-farm workers. Coefficients of regional variables suggest that the farms located in the western and southern regions were the less likely adopters of AI than those in the base region.

4.2.3 Test for Zero Correlation

As discussed in the methodology, there is potential correlation between the adoption decisions of AI and ETSS on dairy farms. In such a case, the estimation of the bivariate probit will be more appropriate than separate probits. A statistical test for zero correlation of the error terms is used to check whether there is statistical significance associated with using separate probit models for the two technologies or bivariate probit with selection. We used a likelihood ratio test to test the null hypothesis of no correlation between the adoptions of the two technologies. The likelihood ratio test statistic is obtained using the formula $LR\text{-}statistic = 2 [\ln L_{bivariate} - (\ln L_1 + \ln L_2)]$. Log

Table 4.3 Estimated Separate Probit Equations.

Variables	ETSS		AI	
	Estimates	Standard errors	Estimates	Standard errors
Constant	-1.5699***	0.3784	0.2151	0.2618
AGE	-0.0111**	0.0044	-0.0035	0.0035
TENYEARS	0.4488***	0.1010	0.0019	0.0842
EDUC	0.8183***	0.1001	0.3930***	0.1094
OFFARM	-0.2131**	0.0873	-0.2552***	0.0741
NMILKCOW	0.0153	0.1106	0.4535	0.3351
SPECLIZE	0.5724*	0.3012	1.3881***	0.1987
WESTUS	-0.0634	0.1470	-0.6900***	0.1269
SOUTHUS	-0.0513	0.1893	-0.8634***	0.1372
PARLOR	0.1130	0.1006	-0.3377	0.8844
Log Likelihood function		-524.631		-743.617
Pseudo R ²		0.12		0.10
No. of observations 1748				

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

Source: USDA ARMS data, Dairy Survey, 2005

likelihood functions of the two separate probits ($\ln L1$ and $\ln L2$) are obtained from the separate probit equations. These are reported in Table 4.3 as: -524.63 and -743.617 for the ETSS and AI equations, respectively. $\ln L_{bivariate}$ is -1235.97. So, the LR-statistic is 64.554, greater than the critical value of the chi-square distribution of $\chi^2 = 3.84$ at the 95% confidence level, indicating the rejection of the null hypothesis of no correlation. This suggests the use of bivariate probit with selection rather than separate probit equations.

4.2.4 Bivariate Probit with Selection Results

Full information maximum likelihood estimates were computed for the bivariate probit with selection model. Estimates were based on 1,748 observations with 21 parameters. Since AI adopters select for the use of ETSS in dairy farms, we formulated the selection model based on

AI. LIMDEP command “selection” set the model to be fitted for the Van de Ven and Van Praag (1981) bivariate probit model with selection (Greene, 2009- LIMDEP version 9). To obtain efficient estimators accounting for heteroskedasticity in the data, robust standard errors were computed. “Robust” computes a weighted covariance matrix as a sandwich between standard errors.

Table 4.4 shows the coefficients of estimates and standard errors from the bivariate probit with selection model. Farmers having college degrees or beyond were the more likely adopters of AI and ETSS. The education coefficient was significant in ETSS. Number of milk cows was not significant in the separate probit equations, but was highly significant in the bivariate probit estimation. Highly significant and positive coefficients of NMILKCOW and SPECLIZE in the AI equation suggest that the larger operations with more cows and greater specialization had greater probabilities of AI adoption. Principal operator or spouse’s off farm job had negative effects on both AI and ETSS adoption. An off-farm job may be associated with a number of factors, but one of them is less time availability for the farm. Thus, the effect of holding an off-farm job on AI and ETSS adoption in our analysis is as expected since these technologies are more management intensive. Age was negatively associated with ETSS adoption. Another interesting variable not significant in AI, but in ETSS, is TENYEARS. This suggests that the probability of ETSS adoption was higher in farms that had longer planning horizons. Most of our results have expected signs and are consistent with previous adoption studies.

In the two-equation system, there are several available marginal effects, and we need to choose which is of greater interest. Literature, however, is still unclear about partial effects of “what on what?” According to Greene (2009, LIMDEP version 9), there are mainly two models - the base case y_1, y_2 , a pair of correlated probit models, and $y_1|y_2=1$, the bivariate probit with sample selection, whose conditional means are identical, as follows:

$E[y_1|y_2 = 1] = \Phi_2[w_1, w_2, \rho]/\Phi(w_2)$, where Φ_2 is the bivariate normal cumulative distribution function (CDF) and Φ is the univariate normal CDF.

LIMDEP analyzes the conditional mean of

$$E[y_1|y_2 = 1, x_1, x_2] = Prob[y_1 = 1|y_2 = 1, x_1, x_2, \rho]/Prob[y_2 = 1|x_1]$$

Table 4.4 Estimated Bivariate Probit Model with Sample Selection

ETSS			AI	
Variables	Estimates	Standard errors	Estimates	Standard errors
Constant	-1.4538**	0.6492	0.1951	0.2675
AGE	-0.0104**	0.0041	-0.004	0.0036
TENYEARS	0.4556***	0.1179	0.0161	0.0818
EDUC	0.8008***	0.1017	0.4088***	0.1151
OFFARM	-0.2105*	0.1075	-0.2633***	0.0801
NMILKCOW	0.0221	0.1672	0.4383***	0.0962
SPECLIZE	0.4246	0.6331	1.3947***	0.1906
WESTUS	-0.0709	0.2761	-0.6930***	0.1162
SOUTHUS	-0.0256	0.4435	-0.8652***	0.1373
PARLOR	0.0934	0.0983	0.0387	0.0824
Rho (1, 2)	0.44	(Selection model based on AI)		
Log Likelihood function -1235.97				
No. of observations 1748				

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

Source: USDA ARMS data, Dairy Survey, 2005

Marginal effects in the bivariate probit setting may have come from different contributors (i.e. those from vector of the first set of variables or from the vector set of the second). Table 4.5 shows the total marginal effects of the respective variables (partial effects for $E[y_1|y_2 = 1]$ with respect to the vector of characteristics). The mean estimate of $E[y_1|y_2 = 1]$, which is the proportion of $Prob [ETSS=1, AI=1] / Prob[AI=1]$, is 0.105. Total effects are the sum of 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, LIMDEP, Version 9). Total effects of age, education, farmer's long term planning horizon, and off farm job were significant and had expected signs. A one year increase in the age of the farmer decreased the probability of adoption of ETSS, given AI has been adopted, by 0.0018. TENYEARS, EDUC, OFFARM, SPECLIZE, PARLOR, WESTUS, and SOUTHUS are dummy variables. Dairy operations that planned to continue their operation for next ten years or more had probabilities of adoption of ETSS, given AI had been adopted, that were 8.5 points higher than those of non-adopters. The total effect of education (college degree or beyond) had the strongest effect. This suggests that the more educated farmers may be better able to manage information intensive breeding technologies. Having a college degree or beyond increased the probability of adoption of the breeding technologies by 0.187. The principal operator and/or his/her spouse's holding an

Table 4.5 Marginal Effects of the Adoption of ETSS and AI

Variables	Total effect		Mean of X
	Coefficient	Std. error	
AGE	-0.0018***	0.0007	50.920
TENYEARS	0.0852***	0.0182	0.497
EDUC	0.1870***	0.0294	0.171
OFFARM	-0.0333*	0.0173	0.508
NMILKCOW	-0.0060	0.0254	0.147
SPECLIZE	0.0469	0.0696	0.847
WESTUS	0.0075	0.0275	0.112
SOUTHUS	0.0255	0.0396	0.046
PARLOR	0.0185	0.0182	0.420
Partial derivatives of $E[y_1 y_2 = 1]$ with respect to vector of characteristics, estimated at mean X			
Estimates of $E[y_1 y_2 = 1] = 0.1053$			

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

Source: USDA ARMS data, Dairy Survey, 2005

off-farm job reduced the probabilities of adoption of breeding technologies of ETSS, given AI had been adopted, by 0.033.

4.3 Farm Impact Models

4.3.1 Descriptive Statistics

Table 4.6 shows the general descriptive statistics of the dependent variables used in the farm impact models. Profitability and productivity measures and revenue and cost measures were used as dependent variables. Net returns over total cost (NETTOT), Net returns over operating costs (NETOPER), and those in per hundredweight and per cow bases (NETTOTCWT, NETTOTCOW, NETOPCWT, NETOPCOW) include revenue and expenses associated with the dairy enterprise. Dairy farmers received total revenue of \$17.95 per cwt milk produced with total cost of 27.87 per cwt milk produced, for a negative net return of \$9.92 per cwt of milk produced. If we examine on a per cow basis, farmers generated revenues of \$2,925.48 with total costs of \$4,164.01 involved, for a negative \$1238.61 in net returns over total costs per cow. These negative results over total costs, however, are not surprising because the costs involved here are economic costs, including fixed costs. Average net returns over operating costs per cwt of milk produced were \$5.02 and per cow were \$880.36. Average allocated costs per cwt of milk produced were \$12.93, while on a per cow basis, \$2,045.12. Large standard deviations indicate that there were wide variations in returns and costs across farms.

Table 4.7 shows the descriptive statistics of independent variables used in the impact models. Average age of the principal operator was 51 years. Twenty one percent of the dairy farmers (principal operators) of the farm were college graduates or beyond. Approximately 48% of the farm's principal operator and/or his/her spouse worked off the farm for a job or salary. Number of milk cows on the farm varied widely, with the average number of milk cows of 322.

Table 4.6 Weighted Descriptive Statistics of Dependent Variables Used in Impact Model

Variables	Definition	Mean	Std. Dev.
Profitability, productivity and income measures			
NETTOT	Net returns over total cost, dollars	-43,128.53	477,959.03
NETOPER	Net returns over operating cost, dollars	169,926.8	634,723.25
NRTOTCWT	Net returns over total cost per hundredweight of milk produced, dollars	-9.92	12.87
NRTOTCOW	Net returns over total cost per cow, dollars	-1,238.61	1,362.92
NROPCWT	Net returns over operating cost per hundredweight of milk produced, dollars	5.02	5.10
NROPCOW	Net returns over total cost per cow, dollars	880.36	820.78
MLKPERCOW	Milk yield per cow	165.96	52.42
Revenue measures of the farm			
GROSSCWT	Gross returns per hundredweight of milk produced (Revenues per cwt)	17.95	3.65
GROSSCOW	Gross returns per cow (Revenues per cow)	2,925.48	924.46
Cost measures of the farm			
TOTALCWT	Total costs per hundredweight of milk produced	27.87	13.72
TOTALCOW	Total costs per cow	4,164.01	1262.70
OPERCWT	Operating cost per hundredweight of milk produced	12.93	4.83
OPERCOW	Operating cost per cow	2,045.12	762.48
ALLOCWT	Allocated costs per hundredweight of milk produced	14.94	10.66
ALLOCOW	Allocated costs per cow	2,118.97	960.14

Source: USDA, ARMS Data, Dairy Survey, 2005

Table 4.7 Weighted Descriptive Statistics of Independent Variables Used in Impact Models

Variables	Definition	Mean	Std. Dev.
AGE	Continuous variable; Principal operator's age in years	51.467	11.194
EDUC	Dummy variable; Principal operator's education level; 1 if principal operator is college graduate or beyond	0.209	0.407
OFFARM	Dummy variable; Operator's off-farm job; 1 if Principal operator or spouse work off-farm for wages or salary	0.475	0.499
NMILKCOW	Continuous variable; Number of milk cows in the farm/1000	0.322	0.609
NCOWS^2	Square of NMILKCOWS variable	0.474	2.781
SPECLIZE	Farm specialization, contribution of the dairy production value in total farm value of production (Dairy/VPRODTOT)	0.849	0.17
WESTUS	Regional dummy; if farm is located in western US (Pacific- CA, OR, WA or West-AZ, ID, NM or Southern Plain- TX), WESTUS=1, else 0	0.212	0.409
SOUTHUS	Regional dummy; if farm is located in Southern US (Appalachia- KY, TN, VA or Southeast- FL, GA), SOUTHUS=1, else 0	0.173	0.378
PARLOR	Dummy variable; if parlor is adopted in the farm, Parlor=1, else 0	0.685	0.465
GRAZE	Dummy variable; 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	Dummy variable; 1 if cows are milked 3 times a day, 0 if two times or less	0.149	0.357
SUMTECH	Sum of the eight dummy variables for 8 different technologies or management practices of dairy; value ranges from 0 to 8	2.91	1.88
AI	Dummy variable; whether artificial insemination is adopted in the dairy farm in 2005; 1 if adopted, 0 if not	0.789	0.415
ETSS	Dummy variable; whether embryo transplant and /or sexed semen is adopted in the farm in 2005; 1 if adopted, 0 if not	0.113	0.317

Source: USDA, ARMS Data, Dairy Survey, 2005

The specialization variable indicates that an average of 84.9% of the total value of farm production was contributed by the dairy enterprise in most of the farms.

Technology adoption variables were quite interesting. About two thirds (68.5%) of the dairy farms used parlors in their operations. Approximately 14.9% of the farms milked 3 times daily. AI was adopted by 78.9% of the farms while ETSS was adopted by 11.3% of the farms. Twenty-two percent of the farms were pasture-based (obtained more than 50% of the total forage requirement from pasture during the grazing season). This varied widely with a standard deviation of 0.416. The SUMTECH variable indicates that dairy farms, on average, adopted approximately 3 of 8 technologies and management practices: holding pens with udder washers, milkers with automatic take-offs, computerized feeding system, computerized milking system, assessing internet for information, membership with DHIA, recombinant bovine somatotropin (rbST) and use nutritionist to formulate or purchase feed.

We included two location variables, SOUTHUS and WESTUS to capture the location differences. Of the total dairy farms, 21.2% of dairy farms were located in WESTUS - Pacific (CA, OR, WA, AZ, ID, NM, TX), while the SOUTHUS (KY, TN, VA , FL, GA) had 17.3% of the dairy farms under study.

4.3.2 Farm Impact and Cost Measures

Tables 4.8 through 4.11 show the OLS results of profitability, productivity and cost measures of the farm.

4.3.2.1 Net Returns over Costs

Table 4.8 shows the parameter estimates of equations for enterprise net returns over total costs and enterprise net returns over operating costs. Age is significantly negative in the NETTOT equation. A one year increase in the age of the principal operator was associated with a decrease in net returns over total costs of \$2,794.81. Highly significant result of NMILKCOW

indicates that the net returns over total and operating costs increase with herd size. The western U.S. had both net returns over total costs and net returns over operating costs that were lower than those of the base region (North Central and Northeast). Significant negative coefficients of SUMTECH in both net returns equations indicate that the costs involved in adoption of subsequent technology (among eight) may be higher than the returns, reducing net returns. Neither AI nor ETSS was significantly different from zero at the 10% level.

4.3.2.2 Milk Yield per Cow

In Table 4.8, the right-most two columns show the parameter estimates and respective standard errors of the milk yield per cow equation. An adjusted R^2 value of 0.39 suggests that around 39% of the variation in milk yield per cow is explained by the model. Age of the farmer, education, off-farm job, and farm specialization are significant at the 1% significance level. Coefficients of grazing, milking 3 times, and sum of the technologies were also highly significant (at the 1% level). A negative coefficient of education, indicating an annual decrease in cwt of milk produced per cow by 9.38, was unexpected. Greater opportunities associated with the college degree may be one of the explanations. The negative coefficients of off farm job and age suggest that principal operator or spouse's off farm job and older age were associated with lower milk yield. The SPECLIZE coefficient suggests that more specialized dairy farms had higher milk yield per cow, as expected. Pasture-based dairy operations were getting lower milk yield per cow than those using conventional dairies. Our results suggest that milking three times was associated with a higher milk yield of approximately 21 cwt milk produced per cow than 2 times milking. Coefficients of number of milk cows and squared number of milk cows were not significantly different from zero at the 10% significance level. The positive and highly significant coefficient of SUMTECH suggests that those farms adopting greater numbers of

Table 4.8 Farm Impact: OLS Estimators of Net Returns over Total and Operating Costs, and Milk Yield per Cow

Dep. Variables	NETTOT		NETOPER		MLKPERCOW	
Indep. Variables	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Constant	59791.20	101990.10	48759.60	87901.30	160.45***	10.26
AGE	-2794.81**	101990.10	-1529.20	1000.22	-0.84***	0.09
EDUC	38879.80	1247.09	39268.80	30134.03	-9.38***	3.14
OFFARM	31811.90	42198.80	15782.80	18263.21	-8.15***	1.98
NMILKCOW	0.103D+07*	23151.50	0.159D+07***	347546.90	2.21	6.70
NCOWS^2	-58672.70	529970.50	9956.69	107843.50	-0.89	1.11
SPECLIZE	-62668.10	185139.60	-33334.60	73611.19	34.99***	7.80
WESTUS	-106456.00*	86015.67	-128221***	44819.42	-5.31	3.37
SOUTHUS	-42322.10	62241.99	-37962.70	25704.09	-4.75	4.63
PARLOR	-22223.50	31527.73	23479.60	21605.49	-1.48	2.48
GRAZE	15928.00	26676.31	9685.65	7446.18	-7.49***	2.74
M3TIMES	16074.00	104922.00	103462	88393.98	20.88***	4.21
SUMTECH	-27712.20**	13813.91	-13338.00**	93336.34	12.11***	0.81
AI	26718.80	19282.51	25410.60	21152.75		
ETSS	-45212.40	34891.38	-31952.80	32439.23		
PREDAI					1.25	2.09
PREDETSS					14.98***	5.01
LAMDAA					7.92***	2.43
LAMDAB					7.91***	2.10
Model fit	Adj. R ²	0.27	Adj. R ²	0.72	Adj. R ²	0.39
Model test	F [14, 1733]	46	F [14, 1733]	329.3	F [16, 1731]	71.3

***= Significant at 1%, **= Significant at 5%, * = Significant at 10%; D+aa or D-aa: multiply by 10 to +aa or -aa

Source: USDA, ARMS Data, Dairy Survey, 2005

technologies and management practices received higher milk yield per cow in 2005. A significant and positive coefficient of PREDETSS at the 1% level suggests that higher probabilities of ETSS technology adoption have a positive impact on milk yield per cow. This is after accounting for endogeneity and potential self selection issues. Significant *lamda* coefficients showed that there was self-selection bias associated with the milk yield equation, which required correction to reduce bias.

4.3.2.3 Net Returns over Cost per Unit of Input and Output

Table 4.9 shows the parameter estimates for net returns over total expenditures per cwt and cow bases and net returns over operating expenditures per cwt and per cow bases. These measures are consistently used in several farm impact studies as indicators of farm profitability. Short (2000) and Short (2004) included these measures as performance characteristics of dairy farms. Foltz and Chang (2002) used net returns over total costs per cow. McBride et al. (2002) considered net returns over operating costs per cwt. Gillespie et al. (2009) included net returns over total costs per cwt and per cow.

Results suggest that the older farmers have lower net returns over total costs for both per cwt and per cow measures as well as for net returns over operating expenses per cow. A one year increase in age of the principal operator is associated with lower net returns of 11 cents over total costs per cwt milk produced, lower net returns over operating costs of \$7.92 per cow, and \$13 lower net returns over total costs per cow. Furthermore, education had positive and significant coefficient in all equations except that of returns over total costs per cow. This suggests that farmers with college degrees or beyond had greater net returns over both total and operating costs. A college degree was associated with \$2.94 more net returns over total costs per cwt and \$4.11 more net returns over operating costs per cwt. Farmers with college degrees received \$186.67 more returns over operating costs than those not having a degree. A principal operator

Table 4.9 Farm Impact: OLS Estimators of Net Returns over Total and Operating Costs per CWT and COW

Dep. Variables	NRTOTCWT		NRTOTCOW		NROPCWT		NROPCOW	
Inde.Variables	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Constant	-38.66***	6.72	-3657.71***	712.88	-12.09**	4.93	571.95**	272.28
AGE	-0.11***	0.024	-13.04***	2.80	0.01	0.01	-7.92***	1.80
EDUC	2.94**	1.29	223.44	145.64	4.11***	0.97	186.67***	71.39
OFFARM	-0.02	0.55	16.18	58.29	-0.17	0.25	-72.85*	39.13
NMILKCOW	7.009***	1.55	1446.30***	208.73	0.60	0.86	310.77***	120.36
NCOWS^2	-1.16***	0.38	-212.28***	51.78	-0.11	0.20	-40.60*	21.10
SPECLIZE	19.44***	3.42	1730.77***	383.88	7.83***	2.57	513.86**	211.41
WESTUS	-1.05	0.90	-168.27*	100.12	-1.93***	0.37	-295.66***	60.99
SOUTHUS	-4.76***	1.58	-526.52***	183.95	-3.92***	1.14	-222.06**	103.37
PARLOR	4.27***	0.67	562.33***	74.70	1.67***	0.36	163.34***	46.53
GRAZE	-3.76***	0.84	-310.91***	81.22	-0.26	0.32	-19.23	51.44
M3TIMES	-2.20***	0.76	-62.66	119.19	-0.43	0.42	76.14	89.21
SUMTECH	1.99***	0.18	139.26***	21.45	0.08	0.09	54.82***	14.89
AI	12.58***	3.20	1010.62***	316.84	8.54***	2.14	149.97***	49.46
ETSS	5.82**	2.82	463.92	290.82	6.86***	2.10	-94.95	186.14
LAMDAA	-5.24***	1.65	-513.93***	177.62	-5.15***	1.35	-159.02***	63.58
LAMDAB	-4.52**	1.82	-457.24***	188.32	-5.27***	1.43	-127.45***	53.37
Model fit	Adj. R ²	0.27	Adj. R ²	0.25	Adj. R ²	0.08	Adj. R ²	0.09
Model test	F [16, 1731]	42.2	F [16, 1731]	38.0	F [16,1731]	10.1	F [16,1731]	11.2

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

Source: USDA, ARMS Data, Dairy Survey, 2005.

and/or his/her spouse having off farm job received \$72.85 lower net returns over operating costs per cow than those not having an off-farm job.

Highly significant positive coefficients of number of milk cows indicate that farm size is positively associated with net returns over total and operating costs on both per cwt and per cow bases. Coefficients of $NCOWS^2$ are also significant and negative, suggesting that the maximum net returns over total costs per cwt were obtained when herd size is around 3,021. Similarly, increases in numbers of milk cows increase net returns over total costs per cow until the herd size reaches around 3,400. The peak point to have maximized net returns over operating costs per cow, on the other hand, was found to be around 3,827. The maximum level of milk cow number is as suggested by the squared term. Inclusion of the quadratic term places a restriction of a minimum or maximum level and may not be the actual representation. However, the quadratic term allows for greater flexibility. Farm specialization is another important factor. Our Results suggested that the more specialized dairy operations had higher net returns per cow and per cwt in 2005. If there are significant economies of size associated, then specialization in that particular enterprise would increase mean financial performance (Purdy et al., 1997). Purdy et al. (1997) further suggested that the trend of specialization in dairy is likely to continue. Moving from 100% diversification (0% of income from milk) to 100% specialization resulted in a \$19.44 increase in net returns over total costs per cwt and a \$7.83 increase in net returns over operating costs per cwt milk produced. On a per cow basis, the increases were \$1,730.77 and \$513.86, respectively. Overall positive impact of specialization on net returns is demonstrated by the results. Purdy et al. (1997) also found increased financial performance associated with specialization in dairy. McBride et al. (2004), however, found an unexpected negative coefficient for specialization in dairy. Overall, signs and coefficients of demographic and farm characteristics variables in profitability measures in our study are as expected.

Farms having parlors were getting higher net returns over total and operating costs on both per cwt of milk produced and per cow bases. Significant positive impacts included: higher net returns of \$562.33 and \$163.34 over total and operating costs, respectively, were shown to be associated with parlor adoption on per cow bases. On a per cwt milk produced basis, parlor adopters received additional net returns of \$4.27 over total costs and \$1.67 over operating costs, respectively, than non-adopters. Results suggest that the pasture-based dairy operations received lower net returns over total costs than conventional dairy farms on both per cwt and per cow bases. Net returns over total costs per cow for pasture-based dairy operations were \$310.91 less than that of non-pasture based. Similarly, pasture based operations experienced lower net returns of \$3.76 over total costs per hundredweight of milk sold. Milking 3 times daily was also negative and significant in the NRTOTCWT equation, suggesting a decrease of \$2.20 in net returns over total costs on per cwt milk produced basis. Milking 3 times daily was not significant in other measures. Coefficients of AI were highly significant and positive in all profitability equations in Table 4.9, indicating a positive impact of the adoption of AI on net returns per cwt milk produced and per cow. Remarkable increases in net returns over total costs by around \$12.58 and \$1,010.62 on per cwt and per cow basis, respectively, were associated with AI adoption. Results of NROPCWT and NROPCOW equations suggest that AI adopters had \$8.54 greater net returns over operating costs per cwt milk produced than non-adopters, while on a per cow basis, the measure was \$149.97.

Adoption of ETSS was significant and positive in net returns over total and operating costs per cwt milk produced bases while those on per cow bases were not significant. Results show that higher net returns of around \$5.82 over total costs and around \$6.86 over operating costs, both on per cwt milk produced bases, were associated with ETSS adoption over non-adoption. Every net return measure on Table 4.9 showed that the adoption of modern dairy

technologies (among eight under SUMTECH) was associated with higher profitability. Significant increases in net returns over total costs by \$1.99 and \$139.26 were associated with adoption of each subsequent technology among eight on per cwt of milk produced and per cow bases, respectively. Similarly, positive net returns of around \$54.82 over operating costs per cow were associated with each subsequent technology adoption.

Highly significant coefficients of *lamdas* in all profitability equations in Table 4.9 are particularly noticeable. This suggests that there would have been selection bias present if we had not accounted and corrected for it. If we had not included selection bias variables (LAMDA and LAMDAB) in those regressions, then the estimators of other variables would have biased coefficients.

4.3.2.4 Gross Returns on the Farm

Gross returns are the total return measures of the dairy enterprise. In 2005, farmers received \$19.23 of gross returns per hundredweight of milk produced and around \$3,052.80 per cow, on average (Table 4.6). Least squares estimates of variables on gross returns per hundred weight of milk produced and gross returns per cow equations are shown in Table 4.10. GROSSCWT and GROSSCOW are gross return measures per cwt of milk produced and per cow bases. Having a college degree or beyond had a significantly positive effect on gross returns per cwt milk produced. Principal operator's age had a negative effect on gross returns per cow. Off-farm job negatively affected both gross returns (per cwt milk produced and per cow bases) measures. As farms became more specialized in dairy, they realized lower gross returns per cwt milk sold than diversified farms in 2005.

Results suggested that having a parlor in the dairy operation was negatively associated with gross returns. Pasture-based dairies had lower gross returns per cow than conventional. As indicated by the SUMTECH coefficient, greater technology adopters (adopting a greater number

Table 4.10 Farm Impact: OLS Estimators of Overall Farm Revenue (Gross Returns) and Total Costs per CWT and Cow

Dep. Variables	GROSSCWT		GROSSCOW		TOTALCWT		TOTALCOW	
Indep. Variables	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Constant	24.07***	1.29	3381.25***	291.39	43.15***	2.55	5647.95***	432.05
AGE	-0.008	0.007	-15.95***	1.72	0.15***	0.02	-1.23	2.83
EDUC	0.76***	0.23	-12.74	64.12	1.56**	0.68	-39.94	93.86
OFFARM	-0.49***	0.15	-210.10***	36.56	-0.17	0.55	-225.19***	56.42
NMILKCOW	0.39	0.41	74.13	118.22	-8.41***	1.75	-1421.56***	186.42
NCOWS^2	-0.06	0.05	-22.61	18.12	1.27***	0.146	193.26***	38.14
SPECLIZE	-5.89***	1.28	139.79	231.86	-16.31***	2.26	-1050.56***	339.67
WESTUS	-1.15***	0.23	-267.26***	64.14	0.21	0.65	-130.68	99.19
SOUTHUS	0.81	0.21	89.01	146.0	2.35*	0.80	415.32*	218.26
PARLOR	-0.59***	0.24	-106.54**	52.91	-3.87***	0.78	-614.97***	80.68
GRAZE	0.19	0.21	-90.30*	50.63	4.06***	0.88	218.46***	76.96
M3TIMES	-0.03	0.24	326.30***	82.26	1.89***	0.54	364.87***	104.63
SUMTECH	-0.03	0.06	202.62***	14.17	-2.03***	0.20	61.22***	21.02
AI					-4.34***	0.88		
ETSS					0.36	0.70		
PREDAI	-0.52***	0.14	-21.98	50.56			-236.9***	81.75
PREDETSS	-0.96*	0.56	-35.02	116.15			412.79***	124.38
LAMDAA			152.35**	68.17			395.94***	102.79
LAMDAB			146.53**	58.86			311.73***	84.35
Model fit	Adj. R ²	0.14	Adj. R ²	0.32	Adj. R ²	0.29	Adj. R ²	0.15
Model test	F [14, 1733]	21.5	F [14, 1733]	53.0	F [14,1733]	53.5	F [16,1733]	20.9

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

Source: USDA, ARMS Data, Dairy Survey, 2005

of modern dairy technologies) received higher gross returns per cow. Those milking 3 times per day received higher gross returns per cow than those milking 2 times. The coefficient of PREDAI suggested that the gross returns per cwt of milk produced of the farms adopting AI were less than those not adopting by \$0.52. A similar interpretation can be made for the -0.96 coefficient of PREDETSS. As indicated by significant *lamda* coefficients, there was a self-selection bias issue associated with the gross returns per cow equation and the estimators would have been biased had we not included the *lamdas* as regressors. Differences on per cow bases, particularly with the technologies, can generally be attributed to influence of the technologies on efficiency.

4.3.2.5 Cost Measures on the Farm

After the analysis of net returns over costs and gross returns, we move to the analysis of enterprise costs in dairy farms. Knowing the revenues and different cost equations of the farm helps understanding the profitability of the farms more clearly. Cost results include regression results of total, operating and allocated cost measures. Total cost is the sum of allocated cost and operating cost. The coefficients of different variables on those different cost equation more explicitly show which variables or technologies have strong effects on total cost and also whether the effect is more towards allocated costs or operating costs. The total cost equation is shown in Table 4.10 while operating and allocated cost equations estimators are in Table 4.11.

Results suggest that an increase in age of the operator by one year increased total costs per cwt of milk produced by 15 cents. The positive coefficient of education is not expected and may be counterintuitive in total costs per cwt milk produced. However, the coefficient of education on a per cow basis is negative and non-significant. Results show that an off-farm job reduces total costs per cow by \$225.19. Highly significant coefficients of milk cows and the squared term in both per cwt and per cow bases suggest that an increase in milk cow numbers on

the farm reduces the total costs of the farm up to a point. Coefficients suggested that the optimum level of cost minimization was at 3,310 milk cows on a per cwt milk produced basis, while on a per cow basis, it was at around 3,670. The milk cow number we discussed to minimize cost is as suggested by the squared term. Inclusion of the quadratic term places a restriction of a minimum or maximum level and may not be the actual representation. However, the quadratic term allows for greater flexibility. More specialized dairy operations were able to reduce total costs. Region-wise, southern farms had higher total costs per cwt produced and per cow than the northern states. Farms having a parlor in the operation, those adopting AI, and adopting the modern dairy technologies (among eight in SUMTECH) were able to reduce total costs per cwt of milk produced. Adopters of AI had \$4.34 less total costs per cwt of milk produced than non adopters. Results showed that the higher total costs per cow were associated with the adopters of pasture-based operations and adopters of milking 3 times daily. The negative coefficient of PREDAI in the total costs per cow equation also showed lower total costs associated with AI adoption. Adoption of ETSS, on the other hand, was shown to have higher total costs per cow than non-adoption, as suggested by PREDETSS. The positive coefficient of ETSS was, however, non-significant in total costs per cwt of milk produced.

Parameter estimates of operating costs and allocated or fixed costs on per cwt of milk and per cow bases are shown in Table 4.11. Number of milk cows is significant (at 5% or more) in all cost measures, indicating that herd expansion is associated with reducing the operating costs per cwt of milk and per cow bases and also the allocated costs per cwt of milk and per cow bases. Farm specialization was also shown to have a positive impact on reducing both operating costs and allocated costs. Parlor adopters had lower operating costs and allocated costs than non-adopters on both per cwt of milk and per cow bases. Results suggested a positive association of education (college degree or beyond) with both allocated cost measures. Operating costs per

Table 4.11 Farm Cost Measures: OLS Estimators of Total Operating and Allocated Costs per CWT and Cow

Dep. Variables	OPERCWT		OPERCOW		ALLOCWT		ALLOCOW	
Indep. Variables	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Constant	25.54***	2.96	2809.3***	250.18	23.56***	1.73	2608***	158.38
AGE	0.002	0.01	-8.03***	1.63	0.13 ***	0.02	8.04***	1.78
EDUC	-1.33	0.57	-199.41***	62.11	1.38***	0.51	223.62***	61.87
OFFARM	-0.23	0.23	-137.26***	33.30	-0.02	0.41	-80.31**	40.23
NMILKCOW	-0.89****	0.53	-236.64**	106.70	-6.67***	1.15	-1236.9***	144.28
NCOWS^2	0.10*	0.09	17.98	16.59	1.08***	0.28	180.53***	37.32
SPECLIZE	-8.51***	1.67	-374.06*	193.76	-11.23***	1.72	-554.21***	151.42
WESTUS	0.50	0.32	28.39	55.12	-0.39	0.69	-129.04*	69.79
SOUTHUS	2.78***	0.75	311.07***	102.35	0.78	1.04	66.39	123.34
PARLOR	-1.71***	0.30	-269.88***	44.69	-2.50***	0.47	-330.02***	49.76
GRAZE	0.45	0.31	-71.06*	40.72	3.57***	0.67	294.95***	57.67
M3TIMES	0.31	0.34	250.15***	73.57	1.54***	0.49	115.44**	57.02
SUMTECH	-0.13	0.08	147.80***	13.06	-1.94***	0.13	-85.67***	13.86
AI	-4.71***	1.23						
ETSS	-1.69	1.16						
PREDAI			-171.96***	44.84	-1.29***	0.33	5.81	24.94
PREDETSS			59.92	105.32	1.37*	0.83	323.24***	129.85
LAMDAA	2.12***	0.73	311.38***	57.51				
LAMDAB	1.92**	0.77	273.98***	46.09				
Model fit	Adj. R ²	0.09	Adj. R ²	0.21	Adj. R ²	0.37	Adj. R ²	0.28
Model test	F [16, 1731]	11.8	F [16, 1731]	30.5	F [14,1733]	73.7	F [14,1733]	49.76

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

Source: USDA, ARMS Data, Dairy Survey, 2005

cow, on the other hand, were significantly lower for the farmers with college degrees than without them. An off-farm job was associated with a reduction of both allocated and operating costs per cow. Our results suggest that the older the operator, the lower the operating costs per unit, but the higher the allocated costs.

Coefficients of GRAZE suggest that the pasture-based operations had lower operating costs per cow but higher allocated costs than non pasture-based operations. Milking 3 times daily was associated with higher operating and allocated costs per cow and higher allocated costs per cwt of milk produced. SUMTECH coefficients suggest that adoption of modern dairy technologies reduced allocated costs per cwt milk produced and allocated costs per cow. However, higher operating costs per cow of \$147.80 for each subsequent technology adoption (among eight) was suggested by the result.

Results suggest that significant reductions in operating and allocated costs per cwt of milk produced and operating costs per cow were associated with AI adoption. Coefficients of PREDETSS in allocated costs per cwt of milk produced and allocated costs per cow equations suggested that ETSS adoption resulted in significantly higher allocated costs than non-adoption. Significant coefficients on LAMDAA and LAMDAB in operating costs per cwt and operating costs per cow equations suggest that there would have been selection bias had we not included the self selection variables in the equations.

4.3.3 Multicollinearity Diagnostic Test

Highly correlated independent variables may cause statistical problems. This situation is called multicollinearity. Wide swings in the parameter estimates, high standard errors of coefficients, and wrong signs of coefficients may result from multicollinearity. Multicollinearity can be analyzed in terms of the effect of the intercorrelation of the regressors on the variances of the least squares coefficient estimators. Variance inflation factors (VIF), an effect of

intercorrelation of the regressors on the variance of least squares coefficient estimates, can be used to diagnose multicollinearity. Following is the general formula of VIF: $VIF_k = 1/(1 - R_k^2)$, where R_k^2 is the R^2 obtained when the k^{th} regressor is regressed on the remaining variables. There is no consensus on what values of the variance inflation factor suggest multicollinearity. Some authors suggest values greater than 10 suggest problems (Chatterjee and Price, 1991), while others suggest 30 or 40 as the benchmark value (Greene, 2009: LIMDEP version 9). Table 4.12 shows the VIF of each variable. Results suggest that none of the variables seems problematic.

Table 4.12: Results of Multicollinearity Diagnostic Test

Variables	Variance Inflation Factor
Constant	0
TENYEARS	1.13
AGE	1.08
EDUC	1.08
OFFARM	1.04
NMILKCOW	6.72
NCOWS^2	5.01
SPECLIZE	1.08
WESTUS	1.40
SOUTHUS	1.26
PARLOR	1.43
GRAZE	1.21
M3TIMES	1.48
SUMTECH	2.05
AI	1.23
ETSS	1.12

CHAPTER 5

SUMMARY AND CONCLUSIONS

5.1 Summary

Milk production is one of the important components of U.S. agriculture. Milk has a farm value of production second after beef among livestock industries. The trend in the dairy industry shows that milk production per cow is significantly increasing while the number of milk cows is decreasing. Overall milk production per year is increasing despite the declining milk cow numbers. This increase in productivity is attributed to advancements and adoption of modern dairy technologies. Breeding technologies are one of the important components of this structural change in dairy as they directly affect genetics and reproductive performance of the farm. The adoption decision of modern breeding technologies such as AI, ET, and sexed semen on the dairy farm is affected by several socioeconomic, demographic, and other factors. Past literature provides ample technical description of technologies and their methods of operation. However, the factors associated with the adoption decisions of these breeding technologies and their actual impacts on farm profitability have not been understood. This study analyzed the factors affecting the adoption of AI, and ET and/or sexed semen, and their impacts on farm profitability. First, the characteristics of adopters and non-adopters of these breeding technologies were assessed. Then, adoption decision models and farm impact models were estimated.

The dairy version of the ARMS, 2005, was used for this study. Altogether, there were 1,814 usable observations in the data. Previous studies have explained AI as a widely adopted, farmer-friendly technology and ET and sexed semen technologies as relatively newer, still diffusing technologies. Embryo transplant and sexed semen technologies are suggested to have potentially wider adoption in the near future. Consistent with previous findings, our results also

suggest wider adoption of AI (around 79% of farms). Embryo transplant and/or sexed semen technologies were adopted by around 11% of dairy farms in 2005. We attempted to account for the probable correlation of the adoption decisions of these breeding technologies, different from most of the adoption studies where separate probit equations were generally used. Results from two separate probits for these two adoption equations are also shown. The assumption of potential correlation between adoption decisions was confirmed by a formal statistical test. A correlation coefficient term (correlation between the error terms of two individual probit equations) significantly different from zero suggested the use of a bivariate probit model rather than individual probits.

This study also explored some technical and practical patterns of how these breeding technologies are operated on the farm. There is the involvement of semen that has been collected by artificial means in the use of both ET and sexed semen. The use of ETSS requires that sperm will have been collected, artificially, whether or not both or all three technologies are adopted on the same farm. Since there would be very few cases where ETSS were used by farmers without AI, adopters of the former could actually be considered as a subset of the latter, implying selection. This suggested the selection based on AI (i.e., AI adopters select either to use or not use ETSS). Thus, a bivariate probit with selection model was used to study the adoption.

Relatively younger and more educated farmers had higher probabilities of adoption of both breeding technologies. The significant negative total marginal effect of age suggested that younger farmers are the more likely adopters of breeding technologies. Embryo transplant and sexed semen technologies being relatively newer, a stronger marginal effect of age in the ETSS equation than that in AI further supports that younger people are more receptive to new ideas regarding the adoption of technology. The result also supports previous findings about education and the information-demanding nature of breeding technologies, as breeding technologies were

considered “knowledge and information intensive” (Johnson and Ruttan, 1997). Our results suggested that as farms become more specialized in dairy, the probability of breeding technology adoption increases. More specialized farms are more focused on higher milk production and may be interested in adopting the technologies that have short-term as well as long-term effects on milk production. Furthermore, farms with longer planning horizons of continuing operation for 10 years or more had higher probabilities of breeding technology adoption. The longer planning horizon was also significant in the separate probit equation of ETSS, but not that of AI. This further provides insight about the adoption decision in relation to the nature of the technologies.

The ET involves increased reproductive performance of the female and sexed semen allows the farmer to increase the supply of replacement heifers. Thus, these technologies are not adopted simply to increase the current season’s milk yield, but for long-term economic benefits. As ETSS involves more technical expertise and demands more specialized equipment, farmers planning to be in the business over an extended period may be more interested in purchasing the necessary equipment and developing the human resources needed for successful adoption. The finding of a negative effect of an off-farm job on probability of adoption is as expected, as breeding technologies are management-intensive. Our results support that the hypothesis that probability of adoption increases with an increase in the number of milk cows. This suggests that larger farms are the more likely adopters of breeding technologies.

Farm productivity and profitability were analyzed by estimating the impacts of demographics and socio-economic factors, adoption of other technologies, and regional differences on net returns, milk yield per cow, farm revenues, and farm costs equations using least squares regressions. The actual assessment of the farm impact due to technology adoption is always an issue in impact studies. To assess the impact of a particular technology, we need to

isolate the effects through appropriate correction procedures. In this study, endogeneity and self-selection bias issues were tested in each equation and corrected when necessary.

Principal operator's age negatively affected most of the profitability measures and annual milk yield per cow. Farmers having a college degree or beyond received higher net returns over total and operating costs on both per cwt and cow bases. This suggests that younger and more educated operators can better manage the farm for higher net returns. Principal operator and/or spouse's work off the farm negatively affected net returns over operating costs per cow, around \$73 less than those not working off-farm. Off-farm work also affected milk yield per cow. Having an off-farm job results in less time available for on-farm work, and thus might have resulted in lower efficiency of the farm.

Profitability and productivity also depended on the number of milk cows in the operation. Our results suggest that, with an increase in farm size, net returns over costs per cwt of milk produced and per cow increase. These results suggest the dairy industry has significant associated economies of size. Our results also clearly show that an increase in farm size is significantly associated with decreases in both operating and allocated costs, and thus an increase in net returns. As farms became more specialized in dairy, they were able to reduce both operating and allocated costs on both per cow and per cwt of milk produced bases. This less proportional increase in costs associated with size and specialization results in significant positive net returns over costs and higher milk yield per cow.

Results suggest that the adoption of modern dairy technologies is associated with higher net returns over total and operating costs, in general. Though profit depends on the nature of a specific technology, adoption of modern dairy technologies is associated with higher net returns over costs in general. A higher return over total costs per cow of \$139.26 was associated with each subsequent adoption of modern technology (among eight considered in this study). On the

bases of both per cow and per cwt of milk produced, the farmer having a parlor incurred lower operating and allocated costs, resulting in higher net returns over both total and operating costs. Some previous studies also suggested lower costs per unit with parlor adoption for larger farms, though a parlor is considered as capital intensive (Tauer, 1998; Katsumata and Tauer, 2008). Results suggested that milking 3 times per day involved both higher allocated and operating costs. Our result showed slightly higher total costs than revenues per cwt of milk produced, though this was not significant on a per cow basis. Farms milking 3 times daily had higher milk yields, a higher yield of 20.88 cwt of milk per cow annually than those milking 2 times or less.

Grazers (pasture based operations) had higher allocated costs and lower operating costs than non-pasture based operations. Milk yield per cow was lower for pasture-based operations. Total costs were higher than total revenues for grazers, resulting in negative net returns over total costs on both per cow and per cwt milk bases. Pasture-based operations require larger land area for grazing than non-pasture based operations. So, the higher allocated cost results from the cost of land. Our findings regarding costs and net returns are as expected and consistent with previous findings regarding pasture-based operations.

We accounted for endogeneity and self-selection issues that might have incurred in the impact study of breeding technologies. Thus, the coefficients about breeding technologies in this study are expected to be closer approximations than those not accounting for the issue. Results suggested AI to be a significantly profitable breeding technology on both per cwt milk produced and per cow bases. Higher milk yield per cow was associated with AI adoption. AI adopters were more efficient in reducing total costs than non-adopters. Results also showed the major portion of the total costs involved in AI come from operating costs rather than allocated costs. Embryo transplant and/or sexed semen adoption was also suggested to result in higher milk yield and positive net returns over total and operating costs per cwt milk produced. The impacts on net

returns over total and operating costs per cow were non-significant. Results of cost equations suggested that a higher allocated cost per cow is involved in ETSS adoption. Total costs involved on a per cow basis were also suggested to be higher with ETSS adoption than non-adoption. Despite the significantly higher costs, a positive net return over total and operating costs per cwt milk produced was experienced by ETSS adopters since it was associated with higher milk yield per cow.

Our results suggest positive, significant, and higher net returns over total and operating costs associated with both AI and ETSS adoption, at least on a per cwt milk produced basis. Higher allocated costs were suggested to be involved in ETSS adoption while the major portion of total costs in AI comes from operating expenses. The coefficient of ETSS should be interpreted accordingly because we have assumed ETSS adoption as a subset of AI adoption based on the observations and practicality. This suggests that the ETSS adopters are also the AI adopters and AI adopters select for ETSS adoption. So, the impact we see on ETSS in our study also encompasses AI. In the rare cases where ETSS is adopted without AI, the impact of ETSS on farm profitability and productivity may be different from our result.

5.2 Conclusions and Recommendations

This study showed that adoption of breeding technologies in the U.S. was influenced by farm characteristics, operator characteristics, adoption of other technologies, and regional differences. The study also showed the impact of demographics and socio-economic factors, adoption of other technologies, and regional differences on net returns, milk yield per cow, farm revenues, and farm costs. The following conclusions and recommendations can be drawn from our results:

- Breeding technologies, affecting reproductive performance of the herd and productivity and profitability, play an important role in the profitability of dairy farms.

- Artificial insemination and ET and/or sexed semen adopters, in general, have more milk cows, are relatively younger and more educated, and produce higher milk yield per cow than non-adopters. The farms having longer planning horizons are the more likely adopters of ETSS.
- More accurate impact assessment of a particular technology on profitability requires isolation of that from others. Depending upon the case, accounting for endogeneity and self-selection issues in impact studies can correct bias and provide more approximate estimates.
- Our results suggest positive, significant, and higher net returns over total and operating costs associated with both AI and ETSS adoption, at least on a per cwt milk produced basis. Higher allocated costs were found to be involved in ETSS adoption while the major portion of total costs in AI comes from operating expenses.
- Our findings regarding size and specialization suggest that the larger and more specialized farms are the recipients of higher net returns. Based on our results, dairy farms can increase size to capture the higher net returns. The adoption of ETSS may help increase the number of milk cows by increasing the supply of replacement heifers, but significant allocated cost involved in the adoption should also be considered.
- Since some part of the costs involved in ETSS may be for conducting artificial insemination, larger farms that had already adopted AI may consider ETSS adoption. Adoption decisions on a farm, however, would be based on the added advantages of ETSS adoption versus the additional costs of adopting these.
- In addition to costs, technical knowledge and information requirements for breeding technologies could be a hindrance in the diffusion of breeding technologies, particularly ETSS. Extension agents and/or specialists are suggested to consider more educated,

younger farmers with larger farms as quick adopters of breeding technologies. Further, farms that plan to continue operation for a number of years are suggested to be potential ETSS adopters.

5.3 Limitations

Based on the literature, we said that ETSS allows for an increased supply of replacement heifers and improved reproductive performance in the herd. We also suggested that farmers judge the advantages accordingly. One of the limitations and beyond the scope of this study is determining the actual number of replacement heifers produced or how much reproductive performance is improved annually on a particular farm due to the adoption of ETSS. Another limitation we faced using ARMS data was the inseparability between ET and sexed semen adopters. Since the ARMS question was designed such that they were not separated, we have treated ET and/or sexed semen as one technology, “ETSS.” Though the 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 the near future. The actual impact of the sexed semen technology, once when it becomes more diffused would be a further interest of study. Since farmer’s perceptions about the profitability of the technology may also affect the adoption decision, inclusion of perception questions in the ARMS dairy survey could lead to more insights.

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VITA

Aditya was born in a very beautiful Himalayan country, Nepal. After completion of his higher secondary level education in science from New Horizon Higher Secondary School, he joined Institute of Agriculture and Animal Sciences, Tribhuvan University, Nepal, in 2002. He completed his bachelor of sciences in agriculture in 2006. Then, he worked as a project officer in a non-governmental organization called LI-BIRD, Nepal, for two years.

Aditya started his master's program in the Department of Agricultural Economics and Agribusiness at Louisiana State University in the Fall of 2008. Upon completion of his master's degree, Aditya will pursue a doctorate.