ABSTRACT

Adopting technologies such as artificial insemination, and the associated improvements in beef herd genetics better position livestock producers to meet anticipated demand increases for high-quality beef. If we examine the factors that influence technology adoption, then we will be better able to envision the producer operations of the future. This research examines Missouri cow-calf producer survey data to determine the impact that producer, operation, and management characteristics; production risk; and location have on the adoption of reproductive technologies regionally. Binary choice models are estimated to assess adoption of artificial insemination and estrus synchronization (AIES).

Factors Influencing Beef Reproductive Technology Adoption

By Lisa M. Elliott, Joe L. Parcell, David J. Patterson, Michael F. Smith, and Scott E. Poock




Lisa M. Elliott is an Assistant Professor in the Department of Economics at South Dakota State University. Joe L. Parcell is an Associate Professor, both in the Department of Agricultural & Applied Economics at the University of Missouri. David J. Patterson and Michael F. Smith are both Professors in the Department of Animal Sciences at the University of Missouri. Scott E. Poock is a Professor in the Department of Veterinary Medicine at the University of Missouri.

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Introduction

Today's consumers are demanding higher quality beef. This is demonstrated by the 17.2 percent growth in sales between 2009 and 2010 of Certified Angus Beef, a registered brand that sets a standard to ensure that consumers receive high-quality beef that is superior in taste, tenderness, and consistency (Kay, 2011). The growth in consumer demand for high-quality beef may result in producers adapting their operations to produce higher quality animals. The economic environment will influence the rate at which producers adapt their operations. When producers' margins narrow and profits decrease, producers may be even more likely to adopt new technologies in their operation in order to raise cattle that can obtain a premium.

Technology adoption can allow producers to meet the expected increase in demand for high-quality beef. For instance, adopting artificial insemination (AI) technology will allow producers to more quickly improve their animals' genetics. Using high-accuracy proven sire genetics through AI can improve the percentage of calves that grade prime. Twenty-nine percent of the University of Missouri Thompson Farm calves (2008-2011) graded prime using proven genetics, while nationally only three percent of calves grade prime (Dailey, 2012). If we are able to examine the factors that influence technology adoption, then we will be better able to envision producer operations of the future. This research examines, "What factors influence beef producers to adopt artificial insemination and estrus synchronization (AIES) technologies?"

Adoption of reproductive technologies can improve the reproductive efficiency in a livestock operation. The reproduction process plays a vital role in a livestock operation; however, only 35 percent of U.S. cattle producers use some type of reproductive technology (USDA, 2009). The AI and estrus synchronization (ES) technologies can aid in reproductive management in herds. These technologies can increase production efficiency and enhance genetic characteristics that can create higher quality beef. However, the adoption of AI and ES technologies is less than 10 percent in the U.S. Therefore, it is critical to identify the factors that influence technology adoption in the beef industry. The objective of this study is to explain the impact of producer, operation, and management characteristics; production risk; and location on beef reproductive technology adoption using cow-calf producer survey data. The study uses regional survey data where Missouri ranks third in the country in terms of number of beef cows (NASS, 2012). The study results can be a reflection of the factors that influence beef reproductive technology adoption regionally.

Due to the lack of literature on livestock technology adoption, many questions exist about the determinants of technology adoption in the livestock industry. Technology adoption has been widely investigated in the area of crop production. Factors affecting crop technology adoption have included hedging against production risk and human capital (Koundouri, Nauges, and Tzouvelekas, 2006). Jensen (1982) and Just and Zilberman (1983) have pointed to risk as being a key factor in technology adoption. This paper contributes by identifying factors that influence technology adoption in the livestock industry. Specifically, this study will examine the effects of producer, operation, and management characteristics; production risk; and location on producers' technology adoption decisions.

Various technologies are available to producers to enhance their operations' reproductive efficiency. Reproductive efficiency can be measured by conception rate, live calving rate, weaning rate, and the number of days between successive calvings (Parish, 2010). Reproductive technologies include ES, AI, palpation for pregnancy, ultrasound, pelvic measurement, body condition scoring, semen evaluation, and embryo transfer (USDA, 2009).

The most used technologies include semen evaluation (20 percent of U.S. cow-calf producers have adopted the technology), palpation for pregnancy (18 percent), and body condition scoring (14 percent). AIES have been adopted by only eight percent of producers (USDA, 2009). The adoption of these technologies is positively correlated with herd size (USDA, 2009). Approximately 79 percent of producers with herds of 200 or more cows use at least one type of reproductive technology. Only 25 percent of operators with one cow to 49 cows have adopted a reproductive technology (USDA, 2009).

The quality of a producer's calf crop depends on genetics of the dam and sire and proper management. AI allows producers to use sire genetics that may be superior to the genetics of bulls maintained in a herd. In addition, using AI allows a producer to raise his or her own replacement heifers. AI gives the producer the ability to improve calf crop quality by influencing both sire and dam genetics. Not only does AI improve calf quality, but it also can decrease calving difficulties and, thus, improve reproductive efficiency. Calf crop improvement can be seen through higher weaning weights, better post-weaning performance, higher carcass quality and more productive replacement heifers (Blezinger, 2010).

For producers to successfully administer AI with ES, producers must learn insemination and semen handling techniques. Reproductive management, which includes heat detection, herd health, nutrition, and sire selection, is essential. To use these technologies, operations need the proper facilities and equipment.

ES manipulates the females' estrous cycles so that cows and heifers are brought into heat and can be bred at the same time. It improves the efficiency of AI and allows producers to spend less time monitoring females for heat. This technology also allows the calves to be uniform at calving and at weaning. Producers can realize efficiencies from AIES technologies. Thus, they can capture value. For example, feedlot buyers can improve their performance when they have animals of similar genetics and age, so they may pay a premium for uniform-looking calves.

When deciding whether to adopt AIES, producers weigh the costs that they'll incur and the benefits that they could realize. Costs include the difference between administering AI and purchasing bulls. Costs associated with AI include building facilities, employing an AI technician, hiring additional labor, buying semen, feeding nutritional supplements, and dispensing hormones needed to administer ES. The benefits of using this technology include producing higher quality calves and being able to raise replacement heifers instead of buying these animals outside of the operation. These higher quality uniform animals will demand a premium because of their superior characteristics. If additional revenue earned from selling the higher quality calves outweighs the costs associated with using the AI and ES technologies, then producers will benefit from adopting the technologies.

U.S. cattle producers have described that lack of time and labor was the major factor constraining them from using AIES. Cost, difficulty, and lack of facilities are other factors constraining them from adopting reproductive technologies (USDA, 2009). In the Missouri cow-calf producer survey (University of Missouri, 2008), labor was also the most cited reason for not adopting these reproductive technologies. Lack of facilities, lack of training, and cost were other constraining factors. These reasons are related to operation type and management characteristics. Other factors such as producer characteristics, production risk, and location can also influence technology adoption. The costs and benefits of adopting these technologies can be embedded in producer characteristics, operation type, operation management, production risk, and location.

This study's findings suggest that AI technology adoption is influenced by producer characteristics, operation type, operation management, and production risk. Operation type and production risk are the largest influencers of AI technology adoption. The adoption of ES, the complementary technology to AI, is influenced by producer characteristics, operation type, operational management, and production risk. Operation type and production risk are the largest influencers of ES adoption. Location did not affect adoption of AI or ES.

Literature Review

Few studies have looked at technology adoption in the livestock sector. The majority of technology adoption literature is focused on crop production. Several studies have investigated technology adoption in the dairy industry (e.g., Saha, Love, and Schwart, 1994; El-Osta & Morehart, 2000; Foltz & Chang, 2002; Abdulai & Huffman, 2005; Gillespie et al., 2009).

Of the few studies about beef industry technology adoption, Wozniak (1987) studied early adoption of a cattle feed additive among Iowa farmers. Wozniak (1993) researched the adoption of growth hormone implant technology and feed additive technology in Iowa. Ward et al. (2008) studied the adoption of reproductive management practices by Oklahoma cattle producers. They specifically analyzed adoption given a defined breeding season, and they measured whether cow/heifer pregnancy exams were performed and whether bulls were checked for soundness.

Researchers haven't yet considered the specific reproduction management economics of AI or ES adoption in the beef industry. The adoption of these practices have been explored in other livestock sectors. Adoption of AI in Indian dairy cattle has been studied by Singh, Sinha, and Verma (1979). Using a chi-square test, the research team found a positive significant association between improved producer aspirations and early adoption and between extension contact with producers and early adoption. This suggests the need for research into the relationship between factors and AI technology adoption. Other studies have considered factors influencing AI adoption in different livestock sectors, including the U.S. hog industry (i.e., Gillespie, Davis, and Rahelizatovo, 2004) and buffaloes in India (i.e., Saini, Sohal, and Singh, 1979).

AIES have different costs and benefits associated with using them. Adopting AI requires a heavy investment in managerial skills (Gillespie, Davis, and Rahelizatovo, 2004). As producers better understand how to use the technologies, they will see their costs decline. AI does provide a cost-effective way to increase one's quality of genetics within the operation without having to invest in expensive breeding males (Gillespie, Davis, and Rahelizatovo, 2004). Breeding technologies such as AI have allowed for more timely production of more consistent animals (Gillespie, Davis, and Rahelizatovo, 2004). AI can make it easier to produce replacement females due to the ability to acquire genetics outside of the herd (Gillespie, Davis, and Rahelizatovo, 2004). Gillespie, Davis, and Rahelizatovo (2004) explained that AI does require some investment in equipment and quality labor. Xu and Burton (1998) noted that the use of ES and fixed-time AI could improve herd performance, but they also noted that adoption of such technology will be determined by economic forces.

Producer Characteristics

Producer characteristics have been used as a factor to explain technology adoption. These characteristics have often been referred to as human capital, or an individual's skills and knowledge. Welch (1978) suggested that human capital contributes to agricultural production through work and allocative ability. Schultz (1981) has suggested that human capital reflects the effectiveness and productivity of persons as economic agents. Producer characteristics have been found to affect farmers' decisions to adopt technology. In the technology adoption literature, producer characteristics variables have included age, experience, and whether an individual is an information seeker (e.g., Wozniak, 1987). In addition, education has been a producer characteristic that has been found to affect technology adoption (e.g., Wozniak, 1987; Abdulai & Huffman, 2005; Wozniak, 1993).

Operation Characteristics

Operation characteristics can be measured by looking at financial information, management, and operation structure. Just and Zilberman (1983) found correlation between the adoption of technology and economies of size. This indicates that larger firms are more likely to adopt technology than smaller firms. Saini, Sohal, and Singh (1979) used correlation coefficients to find that farm size and herd size were not related to buffalo AI adoption in India. Singh, Sinha, and Verma (1979) did not find a significant association with socioeconomic status, herd size, number of dairy cows and size of land holdings to AI technology adoption in India. Economies of size have been found in beef cow-calf operations (Langemeier, McGann, and Parker, 1996; Miller et al., 2001; Ramsey et al., 2005). Gillespie, Davis, and Rahelizatovo (2004) suggested that a producer's goal structure – profit maximization or lifestyle maintenance – can influence technology adoption.

Production Risk and Location

Agriculture technology adoption has been examined under uncertainty (e.g., Saha, Love, and Schwart, 1994; Purvis et al., 1995; Koundouri, Nauges, and Tzouvelekas, 2006; Baerenklau & Knapp, 2007). In looking at dairy technology adoption, Saha, Love, and Schwart (1994) developed a conceptual model for measuring technology adoption while accounting for imperfect information. Koundouri, Nauges, and Tzouvelekas (2006) expanded upon the Saha, Love, and Schwart (1994) model by introducing production risk under uncertainty and incomplete information. Koundouri, Nauges, and Tzouvelekas (2006) examined the role that production risk played as a result of water shortages in Greek irrigation adoption.

Gillespie, Davis, and Rahelizatovo (2004) explored the influence of production risk on technology adoption. They hypothesized that hog producers who raise breeding stock are likely to adopt AI to improve the genetic quality of their stock; however, they did not find a significant relationship. This study will use production risk to explain the adoption of reproductive technology. Specifically, AI technology adoption as a reproductive management tool can be viewed through the same lens as risk reduction affecting crop technology adoption because cattle producers face reproduction risk.

The risk-reducing benefits of AI include, but are not limited to, decreased calving problems and fewer calf losses (Patterson, Wood, and Randle, 2000). Cattle producers who use AI accelerate genetic improvement of their herds by keeping the heifers of artificially inseminated cows (Patterson, Wood, and Randle, 2000). Production risk of producers can be measured through reproductive risk exposure of their operations.

Empirical studies have addressed risk by including location dummy variables where some have been found significant (e.g., Colmenares, 1976; Cutie, 1976). One's level of risk can be related to the specific uncertainty related to his or her region. The location of the producer's operation can influence technology adoption through the spatial relationship between one's operation and the environment and resources one has in the area.

This study differs from previous research in the following ways. First, this study looks at AIES adoption in cattle producers. This paper will use the theoretical framework from Koundouri, Nauges, and Tzouvelekas (2006) that introduces production risk into a model looking at technology adoption under uncertainty and incomplete information. This research will show if Missouri livestock producers adopt technology in order to hedge against production risk like crop farmers do.

Procedures and Empirical Model

A University of Missouri 2008 survey of cow-calf producers provided information about producer and operation characteristics such as producer age and experience; operation size and composition, such as commercial, purebred, and/or registered; and cattle breeds raised on the producers' operations. Nearly 1,200 surveys were distributed, 200 were returned with addresses unknown, and 193 surveys were returned completed. The survey included questions about demographics, the farm operation, herd structure, on- and off-farm income, location, use of AIES, herd replacement method, calf management practices, and marketing practices.

The survey shows that 18 percent of producers use AI. Almost the same amount use AIES. Across the U.S., 7.6 percent of producers use AI; the percentage of individuals who use ES is almost identical (USDA, 2009). Producers who did adopt AI applied it to an average of 41 percent of their herds, according to the MU survey results.

The structural equation cannot be estimated, so a reduced form is estimated. The uncertainty cost premium represents the value of gaining more information. In the empirical model, information's influence on technology adoption will be measured by using proxy variables that represent producer characteristics. The producer characteristic variable of carcass data use is assumed to be positively correlated with the farmer's level of information. The variable of carcass data is measured by whether producers would be willing to use carcass performance data to help them make future herd management decisions.

Following from Equations 3 and 4, two models are estimated. The first model's dependent variable is a binary variable that describes whether an individual adopts AI. The second model, much like the first, looks at ES adoption with the dependent variable being binary and with the same explanatory variables as the first model.

The binary choice model is estimated using a probit model, i.e., assume that v_{1i} is $N(0,\sigma^2)$ and that $\Phi(.)$ is the cumulative of the normal distribution. The specification of this model is specified for the current study as:

(1) Adoption of Artificial Insemination = *f*(producer characteristics, operation type, management characteristics, production risk, location),

and

(2) Adoption of Estrus Synchronization = *f*(producer characteristics, operation type, management characteristics, production risk, location).

This study will use producer, management, and operation characteristics; production risk; and location to determine the value of new information to a producer.

Variables are used to measure producer characteristics, operation type, management characteristics, production risk, and location. Producer characteristics variables are age, whether an individual would like to use carcass data for production decisions and total agricultural assets. The carcass data variable suggests the extent to which a producer uses information. The operation characteristic variable of herd size is measured by number of cows in an operation. The operation type variable describes whether an individual raises registered cattle. This variable indicates whether a person belongs to a registered cattle organization and suggests whether an operator targets a higher value market. A producer's perceived importance of herd uniformity is one management characteristic variable. Calving season length is another proxy for management. Calving season length suggests an operator's reproductive management practices and the amount of labor and genetics used in maintaining a herd. Management proxy variables help to determine whether an operator uses a labor-intensive management approach. Production risk is captured by assessing the percentage of replacement heifers that a producer raises. Because risk is inherent in the process of raising animals, including replacement heifers, a producer who raises replacement heifers faces more reproduction risk than a producer who buys developed replacement heifers from another producer. Location is represented by the north and south regions of Missouri. Missouri has a diverse landscape, and it is expected that each region will have unique resources, including soil quality, landscape, vegetation, and climate.

Table 1 explains each variable and its expected sign and Table 2 explains each variable's descriptive statistics used in the models. Table 2 shows that on average producers that adopt AI are younger, more willing to use carcass data, raising more on-farm replacement heifers, more likely to be a registered operation, and are more located in southern Missouri as compared to those who do not use AI. In addition, AI adopters have larger operations, have higher assets, see uniformity as an important management factor, and have a lower herd calving length as compared to non-AI adopters on average. However, the models will show which factors are significant in explaining technology adoption.

It is expected that the explanatory variables will have the same sign in both models. Age will be negatively related to adoption, according to literature findings. As producers age, it is expected that they will be less likely to adopt new technologies that require a financial and time investment because they have a shorter time horizon to capture the benefits. It takes additional financial investment and time to learn about AIES. The carcass data variable is expected to be positively related to adoption. Producers who are willing to use carcass data in decision making are expected to be more likely to adopt technology. A producer who is willing to use carcass data in his or her decisions may be willing to acquire additional information about AIES and use that information to decide whether to adopt the technology. The assets variable is measured by a producer's overall total agricultural assets. The assets variable is expected to be positively correlated with technology adoption. Because using technologies requires an upfront investment, producers with more assets would be better positioned to finance the technology investment.

The herd size variable is measured by the number of cows in an operation. Herd size is expected to be positively correlated with adoption. Larger operations would be more likely to adopt technologies because they could capture economies of size. The registered herd variable will have a positive relationship with adoption. Producers who have a registered herd will likely strive to raise higher valued cattle that can be sold for higher prices. Operations that market higher valued cattle are likely better positioned to offset the costs of AI.

The management proxy variables of uniformity importance and calving season length represent a producer's management of his or her herd. The management characteristic proxy of uniformity importance is expected to be positively related to technology adoption. If uniformity is important to the producer, then the producer will likely raise uniform herds. Uniform herds are a reflection of a labor-intensive management strategy because raising a uniform herd involves more management in culling cows and using quality genetics. A producer who uses a more labor-intensive management style is more likely to adopt AIES because these technologies do require more management. If an operator has additional management capacity available, then he or she would be more likely to adopt the technologies. The calving season length is a proxy for management type and is expected to be negatively related to adoption. A short calving season signals an operation that uses more management because producers must monitor their herds for breeding and use quality genetics to achieve the short calving season. As the calving span widens, the probability of technology adoption decreases because the calving span is influenced by genetics and management. Again, using technologies involves more management, so an operation with the management capacity may be more likely to undertake AIES technologies.

The proxy variable for production risk, heifers raised on-farm, is expected to be positively related to adoption. Producers who raise more replacement heifers at home face more reproduction risk than producers who buy replacement heifers. Producers who accept more production risk by raising their replacement heifers on the farm would want to reduce their reproductive risk by using AIES. By adopting reproductive technologies, a producer can use higher quality genetics and increase the likelihood of developing quality replacement animals.

The size of the survey participants' operations are shown in Table 3. This table shows that these survey data are somewhat skewed toward producers with larger operations. Sixty-four percent of the survey participants have operations with more than one hundred cows. By comparison, 10 percent of U.S. producers would fit in that category.

Results

The regression model results look at AIES adoption, which is estimated by probit regressions. The regressions use the same explanatory variables, and this allows one to see the effect that these variables have on adoption of a reproductive technology, AI, and its complementary technology of ES.

Marginal effects are calculated in the two probit regressions that look at adoption of AIES. These are calculated so that the magnitude of the effect on the dependent variable can be shown. The marginal effects are calculated by averaging the individual effects. This method has been preferred instead of figuring the marginal effects at the variable means because it is unlikely that any observation would have the mean value for all variables (Hoetker, 2007). The marginal effects are calculated by designating the binary response variables of carcass data usage, assets, registered herds, uniformity importance, calving season length, heifers raised on-farm, and location. The age and herd size variables are continuous variables. This is noted because marginal effects are partial changes in a quantity of interest. The marginal effects of the dummy variables are the probability changes from zero to one. The variables designated as continuous will have marginal effects that are changes in probabilities when the variable increases by unity.

All of the explanatory variables representing producer, management, and operation characteristics; production risk; and location have the expected signs in the AI adoption model. All of the variables are significant, except the variables of use carcass data, assets, herd size, and location. See Table 4.

Operation type has the largest marginal impact; the probability for the producer to adopt AI rises by 40.1 percent when the variable changes from zero to one. When production risk changes from zero to one, the probability for the producer to adopt AI rises by 18.3 percent. Both management proxy variables have a significant marginal effect on adoption with the uniformity importance variable increasing AI adoption by 13.6 percent and the calving season length variable decreasing AI adoption by 6.7 percent when the variables change from zero to one. Producer characteristics have the lowest impact on adoption, according to their marginal impact. The only producer characteristic marginal effect that is significant is age. As age increases by one year, probability of AI adoption decreases by 0.4 percent.

Operation type and production risk have the largest impact. Location has no effect on AI adoption. Management characteristics have a modest impact on AI adoption, and producer characteristics have a minimal impact on AI adoption.

Table 5 presents results of the ES adoption model. Variables that weren't found to be significant are location, herd size and uniformity importance. All variables have the expected signs.

The marginal effects point to results similar to those found in the AI adoption model. Operation type and production risk have the largest impact on ES adoption. Again, operation type has the largest marginal impact; the probability for a producer to adopt ES rises by 33.1 percent when the producer changes from not having a registered herd to having a registered herd. Production risk, which is represented by heifers raised on-farm, has a marginal effect of increasing the probability that a producer will adopt ES by 15.9 percent when the variable increases from zero to one. Calving season length, which represents management, has a marginal effect. As the calving span widens, the probability of ES adoption decreases by 7.7 percent. The uniformity importance variable that represents management did not have a significant marginal effect. The age and carcass data usage variables have significant marginal effects. These variables represent producer characteristics. As age increases by one year, the probability of adopting ES decreases by 0.7 percent. When an individual is willing to use carcass data in his or her decision making, the probability of ES adoption increases by 10 percent. As assets increase, ES adoption likelihood increases by 10.7 percent. Location – north Missouri or south Missouri – did not have a significant marginal effect on technology adoption.

Producer characteristics, operation type, management characteristics, and producer risk influence adoption of AIES. However, location was not found to influence adoption decisions. The findings show that operation type and production risk have the greatest impact on technology adoption. Management characteristics have a modest impact. Operation type and production risk have a greater marginal effect on AI adoption than on ES adoption. Management characteristics have more influence on AI adoption compared with ES adoption because both proxy variables are significant in the AI adoption model. Producer characteristics have the least impact on adoption. The findings show that agricultural assets do play a role in ES adoption, the complementary technology to AI. This finding is interesting because many studies show that producer characteristics have a significant influence on technology adoption, but few studies go further to find the marginal effect. The operation type variable shows that this has the greatest impact on adoption. The production risk finding leads us to expect that operations with greater production risk would be more likely to adopt technologies that can reduce their risk.

Implications

Producers have indicated through surveys that the top barriers for technology adoption include cost and lack of labor, time, and facilities. These barriers suggest that management characteristics and operation type influence technology adoption. This study points to other factors that affect technology adoption regionally. It suggests that operation type and production risk have the greatest influence on the beef industry adopting technology. The findings show that livestock producers hedge against risk like crop producers do. Management characteristics have a modest impact on producers adopting reproductive technologies, and producer characteristics have a small impact on adoption. Operation size was not found to be a significant variable in AIES adoption, which contrasts with the technology adoption literature.

Livestock producers considering using AIES technologies need to understand their own operation structure, management style, and their target market to evaluate whether these technologies would be a benefit to their operation. These technologies have the ability to increase the producer's calf crop quality and increase the operation's reproductive efficiency. This research has shown the producer, operation, and management characteristics influence the adoption of AIES technologies. A younger producer may be more likely to adopt these technologies since their time horizon is longer to reap the benefits of improved efficiencies in the operation as compared to an older producer. In addition, a cattle operation that raises breeding stock may gain value in using AIES technologies, since they are in the business of selling top genetic breeding animals. A livestock manager that uses a more intensive management style could be a good fit to use these technologies, since they already have a management structure conducive to utilizing the technologies. Also, producers who raise replacement heifers may want to evaluate whether adopting these technologies may help them hedge some of their operation's reproductive production risk. In addition, livestock managers using AIES technologies should evaluate whether they are choosing the best sires to meet their operation's goals and target markets.

Future research should look into factors that might influence intensity of reproductive technology adoption in the beef industry. Also, the role of production risk should be explored further. A national survey could be developed in order to obtain better production risk and management variables in order to examine regional differences.

Previous research has mainly studied technology adoption in crop production and has focused on studying the influence of demographics, socioeconomic factors, operation structure, producer characteristics, and production risk on adoption. This study goes beyond previous research in that it examines the effects of producer, management and operation characteristics; production risk; and location on beef technology adoption. The results of this study will provide extension and policy advocates with a better understanding of the factors that influence technology adoption in the beef industry, so they can better target individuals for technology education and training. In addition, policy-makers who advocate technology adoption will be better able to develop policies and provide proper technology adoption incentives for producers who raise high-quality animals and who have higher production risk.

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Appendix

Conceptual Model

This theoretical framework extends upon the Koundouri, Nauges, and Tzouvelekas (2006) study that uses production uncertainty with incomplete information to analyze efficient technology adoption. Producers are assumed to be risk averse utilizing a vector of inputs x with x_w to produce an output with a technology represented by a well-behaved production function f(.). Output prices are denoted by p, and input prices are defined by r. Producers face production risk related to reproduction. In other words, a producer risks whether all females will calve and whether calves survive to be sold on the market. This risk is affected by nature. Risk is introduced by using *e*, a random variable whose distribution is considered to be exogenous to a producer's action. Only production risk is considered, and prices are assumed to be nonrandom with the producer being a price-taker.

Reproduction is assumed to be essential in the production process. Efficiency in production, which is dependent on the reproductive technology, is represented by including a function h(α) within the production function. Producers are heterogeneous in that reproductive efficiency is reliant upon the producer's characteristics and the operation's management, which is represented by the vector α within h(.). A producer who is risk-neutral has a ratio of input prices to output prices that is equal to the reproductive input's expected marginal product. The production function is $q=f[h(\alpha)\ x_w,x]$. Producers are challenged to maximize the expected utility of profit, allowing for risk aversion, as shown in Equation 3 as,

(3)
$$\max_{\mathbf{x},\mathrm{x_w}} E[U(\boldsymbol{w})] = \max_{\boldsymbol{x},x_w} \int \{U[pf(\varepsilon, h(\alpha), x_w, \mathbf{x}) - \mathrm{r_w x_w} - \mathbf{r}'\mathbf{x}]\} dG(\varepsilon).$$

It is assumed that future profit streams following adoption are not known with certainty. Uncertainty could be due to not knowing the expected technology performance or not understanding how to properly use the technology. Adopting technology incurs sunk costs. For these reasons, further information may provide additional value, and as such, producers may delay adoption in order to get more information. Therefore, a premium could enter the adoption condition. The expected utility of profit for adoption is represented by $E[U(w_i^1)]$, and the expected utility of profit for not adopting is represented by $E[U(w_i^0)]$. The variable VI, assumed ≥0, represents the value of additional information, which depends on fixed costs and the level of uncertainty related to the technology and producer. The structural equation cannot be estimated, so a reduced form will be estimated. The farmer will choose to adopt the technology if and only if the following holds. Y_i^* is an unobservable random index for each producer where each identifies his or her propensity to adopt a technology shown as,

(4) $Y_i^* \equiv E[U(w_i^1)]-E[U(w_i^0)]-VI>0$

The indirect utility of farmer *i* if he or she is a non-adopter is,

(5) $Y_{0i} = z'_{01}\ \alpha_0 + m'_{0i}\ \alpha_0{}^m + \gamma_{0i}$.

However, if the farmer i is an adopter, the equation is,

(6) $Y_{1i} = z'_{1i}\ \alpha_1 + m'_{1i}\alpha_{-1}{}^m + \gamma_{1i}$.

Vector z includes the producer and management characteristics, operation type and location; m is the vector of production risk, which brings uncertainty into the model. The vector α is the set of parameters to be estimated, and γ is the error term. Based on the empirical studies mentioned in the literature review, the z vector of explanatory variables of producer, operation and management characteristics and location will be taken from the survey results. As the technology is more efficient for reproduction, it is expected that risk-averse producers with greater profit uncertainty are more likely to adopt technology to hedge against production risk.

Table 1. Explanations and Expected Signs of Explanatory Variables

Variable	*(Expected sign)*	Explanation
Age	(-)	Age of producer, years
Use Carcass Data	(+)	Producer wants to use carcass data [1=Yes, 0=No]
Assets	(+)	Total of Agricultural Assets in Dollars [1= $250,001 and greater, 0=less than $250,001]
Herd Size	(+)	Number of cows on operation
Registered Herd	(+)	Herd Registered [1=Yes, 0=No]
Uniformity Importance	(+)	Cow herd uniformity important in developing herd- [1=Yes, 0=No]
Calving Season Length	(-)	Length of calving season [1=3 months and greater, 0=1 month through 2 months]
Heifers Raised %	(+)	% raised on-farm [1=51-100%, 0=0-50%]
Location	*(na)*	Location of Missouri producer [1=South, 0=North]

Table 2. Overall Survey Descriptive Statistics

	Overall		AI Adopters			Non-AI Adopters		
Variables	Mean	S.D.	Mean	S.D.	#	Mean	S.D.	#
Age	58.15	13.98	53.83	12.11	48	59.12	14.21	213
Use Carcass Data	0.67	0.47	0.89	0.32	46	0.62	0.49	201
Assets	0.78	0.41	0.87	0.34	46	0.76	0.43	202
Number of Cows	169.69	166.27	184.08	168.09	48	166.39	166.39	209
Heifers Raised %	0.50	0.50	0.86	0.35	49	0.42	0.49	211
Uniformity Importance	0.86	0.35	0.96	0.2	48	0.84	0.37	200
Calving Season Length	0.80	0.40	0.72	0.45	47	0.82	0.39	204
Registered Herd	0.17	0.38	0.57	0.5	47	0.08	0.27	196
Location	0.56	0.50	0.59	0.50	49	0.56	0.50	212

 # refers to number of observations

Table 3. Comparison of Survey Producers' Operation Size Distribution

Operations	1-49	50-99	100-499	500+
% U.S. (2007)	79%	11%	9%	1%
% Missouri (2007)	75%	16%	9%	0.2%
% Missouri Survey Data	13%	19%	58%	6%

**(NASS, 2007)*

Table 4. Probit Regression of AI Adoption

Parameters	Coef.	Standard Error	*p*-value	Marginal Effect	Marginal Effect *p*-value
(Intercept)	-1.060	1.081	0.33		
Producer Characteristics					
Age	-0.027	0.011	0.02**	-0.004	0.015**
Use Carcass Data (1=yes)	0.532	0.395	0.18	0.082	0.143
Agricultural Assets (1=$250,001 and greater)	0.239	0.378	0.53	0.038	0.514
Operation Characteristics					
Herd Size	0.001	0.001	0.34	0.000	0.337
Operation Type					
Registered Herd (1=yes)	1.676	0.312	0.00***	0.401	0.000***
Management Characteristics					
Uniformity Important (1=yes)	1.039	0.556	0.06*	0.136	0.011**
Calving Season (1= > 3 months)	-0.414	0.193	0.03**	-0.067	0.027**
Production Risk					
Heifers Raised (1= > 50%)	1.083	0.316	0.00***	0.183	0.000***
Location					
Location (1 = south)	0.088	0.278	0.75	0.014	0.751

N=193	
Log likelihood=	-57.11
Likelihood ratio chi-square test=	80.04
Prob > chi-square=	0.000
McFadden's Pseudo R-square=	0.412

****-Significant at <1% level, **-Significant at <5% level, *-Significant at <10% level*

-Dependent Variable- AI Adoption (1=yes)

Table 5. Probit Regression of ES Adoption

Parameters	Coef.	Standard Error	*p*-value	Marginal Effect	Marginal Effect p-value
(Intercept)	0.122	1.107	0.91		
Producer Characteristics					
Age	-0.042	0.013	0.00***	-0.007	0.000***
Use Carcass Data (1=yes)	0.645	0.416	0.12	0.100	0.079*
Agricultural Assets (1=$250,001 and greater)	0.706	0.417	0.09*	0.107	0.054*
Operation Characteristics					
Number of Cows	0.001	0.001	0.24	0.000	0.229
Operation Type					
Registered Herd (1=yes)	1.448	0.311	0.000***	0.331	0.000***
Management Characteristics					
Uniformity Important (1=yes)	0.308	0.467	0.51	0.048	0.480
Calving Season (1= > 3 months)	-0.465	0.201	0.02**	-0.077	0.016**
Production Risk					
Heifers Raised (1= > 50%)	0.947	0.327	0.00***	0.159	0.002***
Location					
Location (1 = south)	0.161	0.284	0.571	0.027	0.569
N=181					
Log likelihood=		-54.20			
Likelihood ratio chi-square test=		69.36			
Prob > chi-square=		0.000			
McFadden's Pseudo R-square=		0.390			

****-Significant at <1% level, **-Significant at <5% level, *-Significant at <10% level*

-Dependent Variable- Estrus Synchronization Adoption (1=yes)