THREE ESSAYS ON VALUE-ADDED BEEF STRATEGIES

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The undersigned, appointed by the dean of the Graduate School, have examined the dissertation entitled:

THREE ESSAYS ON VALUE-ADDED BEEF STRATEGIES

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a candidate for the degree of doctor of philosophy, and hereby certify that, in their opinion, it is worthy of acceptance.

Professor Joe Parcell

Professor Harvey James, Jr.

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Professor Dave Patterson

To Matt Elliott, My Love, My Friend and Future Husband-

Thank you for your love, support, and encouragement along this path in completing my doctoral degree. I look forward to us making our own path in life together.

and

To my Mom and Dad, Robert and Norma Rees-

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THREE ESSAYS ON VALUE-ADDED BEEF STRATEGIES

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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. The first essay 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. The results show that producer, operation and management characteristics and production risk influence adoption of artificial insemination and estrus synchronization. The operation type and production risk variables have the most influence on technology adoption.

The second essay explores the product life cycle of a value-added marketing strategy that was created for a new value-added quality heifer program. The new product that was examined is a component of the Show-Me-Select Heifer Replacement program. Known as the Tier II program, the new value-added heifer program essentially created a new product (higher quality bred heifers) by requiring minimum sire expected progeny difference (EPD) accuracies for calving ease and by setting expected calf and carcass performance measurements. The hedonic study shows that the Tier II heifers receive a

premium compared with traditional Show-Me-Select heifers. Because the Tier II program is in its infancy stage, premium values are still being determined.

The third essay explores risk and tradeoffs, and it determines what buyers are willing to pay to feel indifferent about purchasing calves from alternative sire groups. The essay considers four sire groups in its analysis: a high-accuracy sire group, a low-accuracy sire group, a natural service sire group and a composite sire group that is an average of the other sire groups. The high-accuracy and low-accuracy sire groups represent calves that were born to females that had been artificially inseminated using estrus synchronization.

The cost data used for the stochastic dominance analysis were obtained through the University of Missouri cost-return projected budgets. Three years of calf returns data were collected from the University of Missouri Animal Sciences Unit. The averages and distribution from the actual data are combined with the average and distribution of input-output prices to simulate the returns of feeding out the different sire groups' calves in order to approximate the economic cost-return budgets over time. To compare these management strategies, net return distributions were used with the partial budgets.

The study found that buyers who are the most risk-taking will prefer to buy calves that were born to females bred by natural service bulls. Buyers who are slightly risk-takers to moderately risk-averse will prefer to buy high-quality calves that were born to artificially inseminated females bred with high-accuracy sires because they have a higher probability of earning more revenue. Less risk-averse individuals may be wealthier, more educated and innovative. Buyers who are strongly risk-averse will prefer to buy a mixed sire group.

Chapter I

BACKGROUND

The U.S. beef industry contributed $73 billion in retail value to the U.S. economy in 2009 (ERS, 2010). Forty-three percent of the beef industry's value is created by cattle and calf production (ERS, 2010). Value chain inefficiencies challenge the U.S. beef industry. The industry has been unable to integrate all stages of the beef value chain (Parcell et al., 2008). Market value chain inefficiencies exist because of biological lag, information problems and the inability to meet consumer demands (Parcell et al., 2008). These problems explain the historically small investments made to market beef based on quality at value chain stages prior to the processing stage (Parcell & Franken, 2009a). One step in creating a true value market system is to know the value for quality bred heifers (Parcell, Franken, Cox, Patterson & Randle, 2010). Data for this study come from Missouri, which has the third highest beef cow inventory in the U.S (NASS, 2011). Because Missouri is a significant cattle-producing state, it provides good representation of U.S. cow-calf producers.

This research, "Three Essays on Value-Added Beef Strategies," is structured into three topics. The first study, "Factors Influencing Beef Reproductive Technology Adoption," 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 beef reproductive technologies. This research uses University of Missouri survey data collected from 193 cow-calf producers in 2008. Binary choice models are estimated to assess adoption of artificial insemination and estrus synchronization (AIES). The study's results will provide extension and policy advocates with a better understanding of the factors that influence technology adoption in the beef industry. The research on this topic is covered in Chapter II.

The second essay, "Value of Minimum Sire Accuracy Traits in Bred Heifer Price," explores the product life cycle of a value-added quality heifer program. The research objective is to utilize primary-level cattle data to examine the magnitude of value-added characteristic premiums of minimum sire EPD accuracies (Tier II) and to determine the value of traditional characteristics of a quality heifer program, Show-Me-Select. The research provides a better understanding of the product life cycle of a new value-added heifer program. Producers who receive more accurate information will be able to make more informed decisions. This topic is covered in Chapter III.

The third essay, "Returns and Risk Preferences of Coordinated Beef Sire Genetics," is a stochastic dominance analysis of buyers' willingness to buy calves born through the reproductive technology adoption by cow-calf producers. Specifically, the study uses stochastic dominance and stochastic efficiency with respect to a function to assess the alternative risk management decision making that buyers use in deciding whether to buy calves born by using new technology or a bundle of technologies. The main objective is to identify the buyers, according to risk level, who would buy calves born through using a timed and synchronized technology with minimum genetic requirements. To compare these management strategies, the study uses net return distributions and partial budgets. Specifically, simulated net revenue probability density functions of the management choices are compared at different risk aversion intervals using stochastic dominance with respect to a function (King & Robison, 1981). The study results could provide insight to policy-makers and extension personnel. The results can inform policy-makers' decisions because they'll better understand the degree to which individuals' risk preferences affect producers' management decisions. Individuals in extension can distribute the information to producers and buyers who can use the information to make better management decisions. This topic is discussed in Chapter IV.

These topics are interlinked because technology adoption in the beef industry will create value in the supply chain. This analysis explores factors that influence buyers to purchase calves that have been born to heifers bred using technology. In addition, it shows what a buyer should be willing to pay to be indifferent between purchasing alternative sire groups. This study will specifically evaluate the potential value characteristics that technologies can create for a market. Chapter V will conclude this study.

This research finds that not only do producer characteristics and the producer's operation type affect technology adoption, but production risk and a producer's management characteristics also influence reproductive technology adoption in the beef industry. The study shows that a producer's type of operation – whether that producer raises registered cattle – and the production risk that the producer's operation faces have the greatest influence on technology adoption in the beef industry. The second study finds that the higher quality heifers, known as Tier II heifers, have received a premium for their value-added characteristic of using minimum sire accuracies. These heifers can produce high-quality calves that can be used as replacement heifers, or they can produce carcasses that grade high on the rail. The final study found that cattle buyers who are high risk-takers will prefer to buy natural service sire calves. Buyers who are moderate risk-takers to moderately risk-averse prefer to buy calves born from females that were bred artificially using estrus synchronization (ES) using high-accuracy sires. This group may reflect individuals who are more educated, wealthier and innovative. Cattle buyers who are strongly risk-averse will prefer a mixed calf sire group because they desire diversification in their investments.

These results show that certain beef producers are more inclined to adopt reproductive technologies. These producers have the opportunity to use the technology to create a value-added product, such as quality bred heifers (Tier II), that can earn them premiums. The Tier II heifer program's product life cycle must be monitored to ensure that Show-Me-Select Heifers is ready to create a new value-added product when the Tier II heifer product is starting to trend toward the end of its life cycle. Products must continue to evolve over time in order for producers to have the opportunity to continue to receive premiums for value-added products. The study shows that certain cattle buyers prefer to buy high-quality calves that were born using AIES. A producer's market for high-quality calves will be buyers who are moderate risk-takers to moderately risk averse. It is important that the market has buyers who prefer to buy these animals so that there is a market for a producer's value-added product.

Chapter II

FACTORS INFLUENCING BEEF REPRODUCTIVE TECHNOLOGY ADOPTION

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 will result in producers adapting their operations to produce higher quality animals. 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. This will result in operation structure changes. 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 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.

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, & 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, pregnancy 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). Artificial insemination and estrus synchronization (AIES) have been adopted by only 8 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, 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 producer characteristics. Other factors such as management and production risk can also influence technology adoption. The costs and benefits of adopting these technologies can be embedded in producer and operation characteristics, 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., Foltz & Chang, 2002; El-Osta & Morehart, 2000; Saha, Love, & Schwart, 1994; Abdulai & Huffman, 2005).

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, Vestal, Doye and Lalman (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 AI or ES adoption in the beef industry. 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 causality 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, & Rahelizatovo, 2004) and buffaloes in India (i.e., Saini, Sohal, & Singh, 1979).

AIES have different costs and benefits associated with using them. Adopting AI requires a heavy investment in managerial skills (Gillespie et al., 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 et al., 2004). Breeding technologies such as AI have allowed for more timely production of more consistent animals (Gillespie et al., 2004). AI can make it easier to produce replacement females due to the ability to acquire genetics outside of the herd (Gillespie et al., 2004). Gillespie et al. (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 et al. (1979) used correlation coefficients to find that farm size and herd size were not related to buffalo AI adoption in India. Singh et al. (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, McGrann, & Parker, 1996; Miller et al., 2001; Ramsey et al., 2005). Gillespie et al. (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 et al., 1994; Purvis, Boeggess, Moss, & Holt, 1995; Baerenklau & Knapp, 2007;

Koundouri et al., 2006). In looking at dairy technology adoption, Saha et al. (1994) developed a conceptual model for measuring technology adoption while accounting for imperfect information. Koundouri et al. (2006) expanded upon the Saha et al. (1994) model by introducing production risk under uncertainty and incomplete information. Koundouri et al. (2006) examined the role that production risk played as a result of water shortages in Greek irrigation adoption.

Gillespie et al. (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, & Randle, 2000). Cattle producers who use AI accelerate genetic improvement of their herds by keeping the heifers of artificially inseminated cows (Patterson et al., 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 et al. (2006) that introduces production risk into a model looking at technology adoption under uncertainty and incomplete information. This research will see if livestock producers adopt technology in order to hedge against production risk like crop farmers do.

Conceptual Model

This theoretical framework extends upon the Koundouri et al. (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 $\mathbf{x}$ with $\mathbf{x}_{\mathbf{w}}$ to produce an output with a technology represented by a well-behaved production function $f(\cdot)$. Output prices are denoted by $\mathbf{p}$, and input prices are defined by $\mathbf{r}$. Producers face production risk related to reproduction. In other words, a producer risks whether all females will calve and whether calves survive to market sell time. This risk is affected by nature. Risk is introduced by using $\boldsymbol{e}$, 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 $h(\boldsymbol{\alpha})$ 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 $\boldsymbol{\alpha}$ 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(α) $x_{w,}$x]. Producers are challenged to maximize the expected utility of profit, allowing for risk aversion, as shown in Equation 2.1 as,

(2.1)

$$\max_{\mathbf{x}, \mathrm{x_w}} E[U(\boldsymbol{w})]$$

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

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,

(2.2)

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

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

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

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

(2.4) $$Y_{1i} = z'_{1i}\, \alpha_1 + m'_{1i}\alpha_1^m + \gamma_{1i}.$$

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 $\boldsymbol{\alpha}$ is the set of parameters to be estimated, and $\boldsymbol{\gamma}$ 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.

Procedures and Empirical Model

A University of Missouri 2008 survey of 193 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 approximately 200 surveys were returned completed. The survey included questions about demographics, farmographics, 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 artificial insemination and estrus synchronization (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.

Following from Equations 2.3 and 2.4, 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 $\Phi(\cdot)$ is the cumulative of the normal distribution. The specification of this model is specified for the current study as:

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

and

(2.6) 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. The hypotheses tested are:

- *H1- Producer characteristics significantly influence technology adoption. Age has a negative influence, and willingness to use carcass data and agricultural assets have positive influences.*

- *H2- A registered herd operation and herd size have positive significant relationships with technology adoption.*

- *H3- Management characteristics have a positive significant relationship with technology adoption because of the importance of herd uniformity, and a wider calving span has a negative influence.*

- *H4- Production risk has a positive significant relationship with technology adoption.*

- *H5- Location has a significant relationship with technology adoption.*

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 2.1 explains each variable and its expected sign, and Table 2.2 explains each variable's descriptive statistics used in the models.

Table 2.1- 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]

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.

Table 2.2- 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

The size of the survey participants' operations is shown in Table 2.3. This tables 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 100 cows. By comparison, 10 percent of U.S. producers would fit in that category.

Table 2.3- 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)*

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 and a complementary technology.

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 2.4.

Table 2.4- 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)

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 2.5 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.

Table 2.5- 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)

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 producer characteristics and operation type influence technology adoption. This study points to other factors that affect technology adoption. 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.

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 survey could be developed in order to obtain better production risk and management proxy variables. A summary of the hypotheses tested and this study's findings are

- *H1- Producer characteristics significantly influence technology adoption. Age has a negative influence, and willingness to use carcass data and agricultural assets have positive influences.*—This hypothesis was supported for all variables in the ES adoption model. However, in the AI adoption model, the only variable that was significant was age.

- *H2- A registered herd operation and herd size have positive significant relationships with technology adoption.*—The registered herd variable was the only variable to be significant in both adoption models.

- *H3- Management characteristics have a positive significant relationship with technology adoption because of the importance of herd uniformity, and a wider calving span has a negative influence.*—This hypothesis was supported for the calving season length variable in both adoption models. However, the uniformity importance variable was only supported in the AI adoption model.

- *H4- Production risk has a positive significant relationship with technology adoption.*—This hypothesis was supported in both adoption models.

- *H5- Location has a significant relationship with technology adoption.*—This hypothesis was not supported in either adoption model.

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.

Chapter III

VALUE OF MINIMUM SIRE ACCURACY TRAITS IN BRED HEIFER PRICE

Introduction

By definition, physical attributes of animals are bundled together, which makes it difficult for buyers or sellers to determine the value of a specific attribute. These attribute levels are either determined through genetics or management. Over time, management practices may lead to new or new levels of genetic characteristics being added to heifers, which, in essence, would create a new product. Products have a natural profit life cycle. Profits will increase as sales increase, and as time passes, the competitive environment will drive profits to zero. This suggests the need for products to evolve over time into new products, e.g., product line extensions, so that positive profits continue to occur in the competitive economic setting. It is vital to understand the length of the product life cycle so that the ingenuity process timeline can be known and so that new products enter the market at the optimal time to preserve positive profits. A product's life cycle can be explored by examining the value of a new characteristic as a product changes over time. This research aims to answer, "Are producers willing to pay a premium for value-added heifers?"

Product life cycles or brand line extensions have been rarely explored in the livestock sector. Product life cycles are investigated heavily in the area of marketing. This study will explore the product life cycle of a new value-added marketing strategy for a quality heifer program (heifers with additional value characteristics). The premiums will be shown for this stacked value-added product. The premiums will allow for the exploration of this new product's life cycle.

The new product that will be examined is related to the Show-Me-Select Heifer Replacement program. Standards must be met with respect to management, production and genetics in order for heifers to qualify to be sold in Show-Me-Select-sanctioned sales. One requirement of the program is that the producer must have owned the animal 60 days prior to breeding. Health examinations and vaccinations at weaning, prior breeding and pregnancy exams are required for the program. SMS requires the animal to be dehorned, scurs removed and treated for parasites 30 days prior to sale. The sire's breed and pedigree birth weight EPD information is required for the heifer. In addition, the heifer must weigh at least 800 pounds, have a body score of "5" and be free of blemishes to be entered in the program. The program started in 1997. More than 23,000 heifers have been sold in Show-Me-Select sales during the program's life.

The program evolved in 2008 when a higher quality standard for heifers, known as the Tier II, was created. If heifers' sires meet expected progeny difference (EPD) accuracies, the heifer can be sold as a Tier II heifer. However, if the heifer doesn't qualify for the Tier II classification, it can still be sold as a Show-Me-Select heifer if it meets the other basic requirements. The Tier II program has essentially created a new product (higher quality bred heifers) by using minimum EPD accuracies for calving ease and expected calf and carcass performance measurements. Managing for maximum EPD accuracies is used to increase the probability of creating a higher quality offspring. EPD accuracies are indicators of reliability in EPD estimates. The higher the accuracy, the higher the probability that the offspring will meet an estimated EPD level. The value of the new Tier II added value product attribute and the traditional characteristics of Show-Me-Select heifers will be explored. The resulting information will help to determine buyers' willingness to pay and the speed at which buyers react to the availability of a new animal attribute. Producers who understand the value of specific heifer characteristics can make better culling and replacement decisions; this affects the operation's profitability. Hedonic analysis can estimate the marginal implicit value of heifer characteristics. If producers know the relationships that consumers form between purchases and product characteristics, then they will be better able to maximize profit because they can aim to put appropriate amounts of characteristics in their products (Ladd & Suvannunt, 1976; Parcell et al., 2010). Cattle producers could use that information to better manage the type of offspring that they produce, so they can realize the highest profits.

Literature Review

Gedikoglu and Parcell (2009) studied the product and profit life cycle of a quality heifer program (Show-Me Select Heifers). They found that marketing is vital to value-added programs generating premiums and profits in the long-run. They found that the simulated price premiums were close to the actual premiums (Gedikoglu & Parcell, 2009).

A dairy bull hedonic study identified values of EPD characteristics and bull popularity and the probability of whether the semen would be in short supply (e.g., Richards & Jeffrey, 1995). They suggest that hedonic pricing is better than using a lifetime profit index to identify the value of characteristics. They argue that the representative average farm cost and returns data used to create a lifetime profit index likely does not represent all producers. They also point out that lifetime indexes use average costs and that producers should be more concerned with marginal costs associated with genetic improvements. Richards and Jeffrey (1995) suggest that the hedonic model implicitly includes the lifetime contribution of the sire's offspring.

Previous research on the price-characteristic relationship includes research on cow-calf pairs (e.g. Parcell, Schroeder & Hiner, 1995) and purebred bulls (e.g. Dhuyvetter, Schroeder, Simms, Bolze & Geske, 1996). This research follows prior research by Parcell et al. (1995) and Parcell, Dhuyvetter, Patterson and Randle (2006). Both studies examined characteristics (heifer characteristics, calf and carcass expected characteristics and market factors) that impact heifer/cow price variation.

It has been found that females bred by artificial insemination receive a premium (Parcell et al., 1995, Parcell et al, 2006, Parcell et al., 2008). Females that will calve within a short span receive a premium (Parcell et al., 2006; Parcell et al, 2010). Synchronized AI heifers received a premium of $25 to $80 per head (Parcell et al., 2010; Parcell et al., 2008). Parcell et al. (2006) found that buyers are willing to pay a higher premium for pens bred to the same sire. A heifer that is bred to an Angus sire has been found to sell at a price premium (Parcell et al., 1995, Parcell et al., 2006).

A heifer's weight has been found to influence price (Parcell et al., 1995, Parcell et al., 2006). Weight is normally expressed in a quadratic or squared weight term. However, Parcell et al. (2006) found a linear relationship between weight and price, which is due to heifers needing to qualify for the program. Parcell et al. (2006) specified birth weight as natural logarithm functional form, so that lower expected birth weights could be discounted relative to higher expected birth weights. However, that study did not find discounts for higher birth weights because heifers in the dataset had to meet minimum birth weight EPD requirements. Calf carcass characteristics, such as carcass weight, marbling and ribeye area, have been found to be significant in explaining price (Parcell et al., 2006). Marbling and milk are specified in a logarithmic form, so lower scores are discounted in that study.

Pen size has been commonly used as a predictor of animal value (Bailey, Peterson & Brorsen, 1991; Faminow & Gum, 1986; Parcell et al., 1995, Schroeder, Mintert, Brazle & Grunewald, 1988; Turner, McKissick & Dykes, 1993; Ward, 1992). Typically, buyers prefer larger lots and lots with heifers bred to the same sire, and they pay the highest prices during the mid-point of the sale (Parcell et al., 2006)

Conceptual Model

Hedonic price modeling can be used to estimate the marginal implicit value of product characteristics from variation in price among heterogeneous products. Lancaster (1971) and Rosen (1974) are often credited with deriving the theoretical underpinnings of the modern hedonic pricing models, but evidence of the hedonic model's conceptual format being applied can be traced to Court (1939) and Waugh (1916).

The hedonic frameworks suggest that a heterogeneous product can be represented as an aggregation of homogenous characteristics (Chwelos, Berndt & Cockburn, 2004). Through hedonic modeling, a heterogeneous good can be viewed through its characteristic make-up. Griliches (1971) and Pakes (2001) have identified that the hedonic regression is a reduced form of optimizing behavior. Hedonic prices are implicit prices of product characteristics, and they are revealed as the prices of differentiated products (Rosen, 1974).

A consumer's utility depends on the degree to which specific characteristics appear in the products they purchase (Ladd & Suvannunt, 1976). A consumer selects a variety of products that gives a mixture of product characteristics and that maximizes their utility (Ladd & Suvannunt, 1976). Ladd and Suvannunt (1976) show that consumer demand for products depends on a product's characteristics, a product's price and a consumer's income. They explain that a product's price equals the aggregated values of the product's characteristics. The marginal value of each product characteristic equals the marginal implicit price of a characteristic multiplied by the marginal yield of the characteristic. If a premium is shown for certain characteristics and the premium at least covers the cost of incorporating the characteristic into the product, then the producer will adapt his or her product and marketing strategies to meet the market demand (Waugh, 1928).

The hedonic theoretical model for agricultural commodities is grounded with the research of Ladd and Martin (1976). Following from the work of Ladd and Martin and Ladd and Suvannunt (1976), the hedonic model framework will be extended to quality-differentiated bred heifers. A bred heifer will be considered an input that produces calves.

Ladd and Martin (1976) explain that the input prices equals the summation of characteristic values. The characteristic value is found by multiplying the yield of the characteristic by the value for one unit of the characteristic. Demand for a product is affected by the product's characteristics. Ladd and Martin's (1976) model is a neoclassical firm model that defines the production function as the amount of input characteristics needed for the production process. This model allows one to look at products that are heterogeneous. Heterogeneity in products can be achieved by creating a product that has different amounts of several characteristics or creating one product that contains a characteristic that other products lack. It can also arise if all products contain unique characteristics. Thus, a product can be thought of as a collection of characteristics.

The Ladd and Martin (1976) theoretical model will be used. First, the variables of the framework will be defined.

v_{ih}= quantity of the ith input in the hth product

r_i = price paid for the ith input

p_h= price received for product h

q_h= quantity of the hth output produced

x_{jih}= amount of characteristic j provided by one unit of input i and included in product h

x_{jh}= total quantity of characteristic j into product h

This framework assumes that x_{jih} are parameters that the producer cannot control. Where Equation 3.1 represents the production function for product h,

(3.1) $\quad q_h = F_h(x_{1\cdot h}, x_{2\cdot h}, \ldots, x_{m\cdot h}).$

Equation 3.1 states that the output of h is influenced by the quantities of input characteristics. The total quantity of a characteristic can be influenced by characteristics of inputs that create that characteristic. Where this is defined in Equation 3.2 as, (3.2) $x_{j \cdot h} = X_{jh}\big(v_{1h}, v_{2h}, \dots, v_{nh}, x_{j1h}, x_{j2h}, \dots., x_{jnh}\big)$.

Where the production function is expressed in Equation 3.3 as,

(3.3) $q_h = G_h(v_{1h}, v_{2h}, \dots, v_{nh}, x_{11h}, x_{12h}, \dots., x_{mnh})$.

The firm's profit-maximizing function is defined in Equation 3.4 as,

(3.4) $\pi = \sum_{h=1}^{H} p_h\, F_h(x_{1 \cdot h}, x_{2 \cdot h}, \dots, x_{m \cdot h}) - \sum_{h=1}^{H} \sum_{i=1}^{n} r_i v_{ih}$.

From the profit function, first-order conditions can be expressed in Equation 3.5 as,

(3.5) $dF_h/\, dv_{ih} \; = \sum_j (dF_h \,/\, dx_{j \cdot h})(dx_{j \cdot h}/\, dv_{ih})$ that

$$d\pi/dv_{ih} \; = p_h \sum_{j=1}^{m} (dF_h \,/dx_{j \cdot h})\; (dx_{j \cdot h}/dv_{ih}) - \; r_i = 0$$

Where Equation 3.6 is found by rearranging Equation 3.5 to solve for r_i as,

(3.6) $r_i = \; p_h \sum_j (dF_h/\, d\, x_{j \cdot h})(dx_{j \cdot h}/dv_{ih})$.

$\partial x_{j.h}/\partial v_{ih}$ is the marginal yield of characteristic j of the hth product from the ith input; $\partial F_h/\partial x_{j.h}$ is the marginal physical product from one characteristic unit j used to create the hth product; and $p_h \partial F_h/\partial x_{j.h}$ is the value of the marginal product of the jth characteristic used to produce output h. It can be interpreted as the marginal implicit (or imputed) price paid for the jth product characteristic used in product h. This lets $p_h dF_h/\, dx_{j \cdot h} \; = \; T_{jh}$ (Ladd & Martin, 1976). Where Equation 3.7 is defined as,

(3.7) $r_i = \; \sum_j T_{jh}(dx_{j \cdot h}/\, dv_{ih})$.

$T_{jh} dx_{jh}/dv_{ih}$ is the value of the marginal yield of the j[th] characteristic by using the i[th] input for the production of h (Ladd & Martin, 1976). It is assumed that $dx_{j \cdot h}/dv_{ih} = x_{jih} = constant$ and $T_{jh} = constant$. This allows for the creation of Equation 3.8. This means that the yield of each characteristic by an input is not affected by how the input is used (Ladd & Martin, 1976). In application to this study, this assumption means that an additional pound of feed will have the same yield across heifers. With T_{jh} being constant, this means that the marginal implicit price is constant with a change in a characteristic across all heifers. Where Equation 3.8 is defined as,

(3.8) $r_i = \sum_j T_{jh} x_{jih}$

However, Ladd and Martin (1976) provide a quadratic adaption to the model if T_{jh} is not assumed to be constant. This is seen in equation 3.9. The functional forms of the variables will be created by conceptual knowledge of the industry. Equation 3.9 is defined as,

(3.9) $r_i = \sum_j x_{jih} B_j + \sum_j x_{jih}^2 B_{jj} = \sum_j x_{jih}(B_j + x_{jih} B_{jj})$.

For example, the variable for the number of heifers in a pen is expressed in a quadratic form. The marginal implicit price for the number of heifers in a pen can be represented as, $(\beta_1 + \beta_2 * x_{number\ of\ head})$. The betas are the estimated parameters.

This hedonic framework is applied to estimate the marginal implicit values of quality bred heifers' characteristics. This shows how Tier II heifers' values have developed during the program's creation.

Data

Sale data used for this study comes from Show-Me-Select (SMS) Replacement Heifers Inc. between 2008 and 2010. To ensure that the program enrolls quality bred animals, a producer must prove that heifers have met minimum quality and health criteria throughout their lives before those animals can be entered in a sale. A heifer that meets the criteria will be given a "Show-Me-Select" ear tag.

For the Tier II classification, the heifer's sire must meet the minimum accuracy benchmark in the traits of calving ease (direct; .65), calving ease (maternal; .3), weaning weight (.75), carcass weight (.20) and marbling (.20). Calving ease accuracies are important to the probability of a heifer having a female that could be used as a replacement heifer and having that calf with little or no assistance from the producer. The other accuracies point to the potential for the heifer to give birth to a superior calf that has the ability to gain more weight at weaning and produce a superior carcass.

The data were collected from seven sale locations throughout Missouri from 2008 to 2010. The subset of those data used for this study's analysis included information for 2,162 heifers. Both spring- and fall-bred heifers are included in the data. The spring sales were held in May, and the fall sales were held in November and December. Summary statistics for selected variables used and the expected signs for variables are reported in Table 3.1.

Table 3.1- Data Summary Statistics and Expected Signs of Variables used in the Hedonic Heifer Price Regression

Item	Avg	SD	Exp. Impact
Avg price of heifer in pen ($/head)	1268.38	216.46	NA
Avg Weight of heifer in pen	1098.67	114.63	+
Percentage of pens AI sired	46.49	49.88	+
Calving Period *(% of pens calving in specified period)*			
January and February	39.20	48.83	+
March, April and May	30.62	46.10	Default
August and September	17.24	37.78	+
October and November	12.94	33.57	+
Calving span between first and last expected birth for pen (d)	6.65	24.91	-
Calf production EPDs *(only for angus pens with 1 sire)*			
Birth Weight	0.32	1.53	-
Weaning Weight	48.71	9.08	+
Yearling Weight	90.47	14.41	+
Maternal Milk	25.08	7.09	+
Carcass EPDs *(only for angus pens with 1 sire)*			
Carcass Weight	8.96	6.58	+
Marbling	1.35	4.53	+
Ribeye Area	0.24	0.19	+
Sale Location *(% of pens sold at location)*			
Northeast	13.47	34.15	?
North central	8.70	28.18	?
West central	13.12	33.77	Default
Southeast	20.15	40.12	?
Southwest	40.84	49.16	?
South central	3.68	8.51	?
No. of head per pen	2.60	18.83	+
Percentage of pens sold in Fall	70.67	45.54	?
Percentage of pens with ALL Tier II heifers			
Tier II in 2008 *(n=51)*	1.49	12.13	+
Tier II in 2009 *(n=42)*	1.70	12.92	+
Tier II in 2010 *(n=51)*	2.61	15.93	+
Percentage of pen with more than one sire used	33.93	47.35	-
Percentage of heifers in pens with Angus sire used	56.44	49.59	+

Empirical Model

A hedonic model was used to acquire the heifer’s value, expected calf and carcass value and market characteristics. The hedonic framework refers to assigning an economic value to each characteristic of a bundled product. Each bred heifer was purchased due to its collective characteristics (e.g. breed, calving span). The hedonic model was used to estimate the marginal contribution of each characteristic to the bred heifer's total price.

The explanatory variables used in the hedonic price model will represent the areas of physical characteristics, genetic characteristics, expected performance characteristics of calves and market factors following from Parcell et al. (2006). Thus, the average price of a heifer in a pen is a function of a set of physical characteristics, genetic characteristics, expected performance characteristics of calves and market factors.

Two models will be estimated where the average price of the bred heifer in pen *i* for sale *k* is a function of:

(3.10) $$\text{Price}_{ik} = f(\text{Physical and Genetic Characteristics}_{ik}, \text{Calves Expected Performance Characteristics}_{ik}, \text{Market Factors}_{ik})$$

The only difference between the models is that model 1 has a Tier II dummy variable for each year, and model 2 has just one Tier II dummy variable.

Heifer characteristics analyzed include weight, Angus breed, heifers bred using AI, expected calving month, expected calving span and pens with more than one sire used. Calf expected progeny difference (EPD) values (birth weight, weaning weight, yearling weight and maternal milk), carcass EPDs (carcass weight, marbling and ribeye area) and market factors (year, location, season, lot order and pen size) will be used to examine the impact on heifer prices. In addition, the impact of pens with all Tier II heifers (the sires of heifers' calves met minimum accuracies) will be studied.

Prices used in the model represent the average heifer price per head for a pen of heifers. Thus, some characteristics are aggregate pen averages. Previous research has specified weight as a non-linear relationship; however, in this study, the heifers have a minimum weight requirement in order to enter the sale. Heifer weight is expressed linearly to capture the greater price for a higher quantity of beef and the ability to calve easier. A binary variable was created to represent whether the pen of animals were Angus or Angus-cross. The variable was set to one when all heifers in the pen where Angus. A premium was expected for Angus pens. A binary variable was created for pens where all heifers were artificially inseminated; in this case, the variable was set to one. It was expected that AI pens would receive a premium.

Four binary time variables (January/February, March/April/May, August/September and October/November) were created to represent the expected calving month for a pen of heifers. The January/February expected calving time was expected to be positive because it is the closest calving date relative to a sale date. Compared with heifers expected to calve later in the year, heifers expected to calve in January/February require less pre-calving investment from the producer and will have a calf marketable sooner than the heifers that calve later in the year. Heifers that calve in August/September and October/November should also carry a premium because calves born in these time periods will be weaned between February and May, a non-peak period for calves coming onto the market. Thus, these calves will receive a premium due to the seasonality of the area's cattle production. A binary variable was created to represent a pen's calving span. It was set to one when the difference between the first heifer and last heifer expected to give birth is greater than 30 days. A discount is expected due to additional management needed for same different aged calves and for non-uniform calves having less value. A binary variable was created to indicate whether all heifers in a pen were bred by the same sire, and it was set to one when the pen had more than one sire used to represent a discount.

One data specification change was made with respect to EPD values. The EPDs of birth weight, maternal milk and marbling needed to be expressed in a natural logarithmic format. These values ranged from negative to positive values. All EPD values had a constant (25) added to them to avoid the issue and preserve the variance. However, the constant was subtracted when stimulating impacts of the variables. These values were then interacted with a dummy variable that was created by interacting whether a pen held Angus heifers (1=yes) and whether the pen only had one sire used to breed the heifers (1=yes). The dummy variable designated that the pen held Angus heifers and had only one sire used. This procedure was done because EPD levels vary across breeds and only pens with one sire could be used because sires have different EPDs. The EPDs used in this analysis are only from pens with Angus animals and pens where one sire was used to breed the heifers. Expected birth weights were expressed in natural logarithmic form so that greater weights would be discounted relative to lower weights. Expected birth weight was not found to be significant, which was not unexpected due to the SMS program requiring that a minimum birth weight EPD must be met. Both expected weaning and yearling weight was expected to result in premiums for heavier weights. Expected maternal milk is expressed in logarithmic form so that lower milk EPDs are discounted. It was expected that higher milk levels would result in a premium due to the potential for female progeny to have higher milk production that would contribute to the growth of calves.

Besides calf EPDs, carcasses EPDs are also used in the analysis. Expected carcass weight and ribeye area were expressed linearly. Marbling was expressed in a natural logarithmic form. Marbling was expressed in this form so that lower scores would be discounted due to the loss in grid value. Expected carcass weight was expected to show a premium for higher weights, which represents that amount of meat a calf would produce. In addition, it was expected that premiums would be shown for carcasses with a higher ribeye area, a highly valuable cut of meat.

Market factors were also used in the analysis. Binary variables were created for six regions of Missouri: northeast, north central, southeast, southwest, south central and west central. West central served as the default. Some differences may exist regionally due to differences in localized markets. A binary variable was created for the season of the sale; the variable was set to one when the sale was held in fall. Lot order was expressed in a quadratic form with the expectation that pens that sell later are discounted relatively as buyers start to leave the sale. Pen size was specified in a quadratic form with the expectation that larger pens relative to smaller pens would receive a premium.

Three binary variables were created in model 1 to indicate pens with all Tier II females for 2008, 2009 and 2010. However, in model 2, there is one Tier II dummy variable that provides the average Tier II premium for 2008 to 2010. The Tier II females have additional requirements for the sire that include minimum accuracies being met. Show-Me-Select started the Tier II classification in 2008. This classification has created a new value-added product. Product life theory predicts that profits will increase as sales increase (Gedikoglu & Parcell, 2009). This theory suggests that that products will go through four stages: introduction, growth, maturity and decline (Gedikoglu & Parcell, 2009). It suggests that profits start out as negative and grow positive in the introduction stage (Gedikoglu & Parcell, 2009). It is expected that negative premiums may grow into positive premiums for the Tier II pens. According to the product life theory, as a product approaches the end of its lifecycle, profits will become negative due to the competitive environment (Gedikoglu & Parcell, 2009). This suggests that products must continue to adjust with new characteristics in order to preserve profit margins. However, as the Show-Me-Select Tier II program continues, premiums will likely continue to increase for these heifers with the Tier II "product" moving from the introduction stage into the growth and maturity stages.

Results

Regression results from the estimation of equation 3.10 are reported in Table 3.2 and Table 3.3. The ordinary least squares hedonic model explained 46 percent of the variation in heifer prices across pens in model 1. In model 2, 45 percent of the variation was explained. Positive parameters indicate a premium relative to the base heifer price, and negative parameters indicated a discount to the base price. The majority of the coefficients for physical characteristics and market factors were significant in both models. Model 2 and model 1 produced similar results. The one notable difference between the models was found in the marbling variable. The marbling variable was found to be significant in model 2, but it wasn't significant in model 1.

Table 3.2- Model 1 (Tier II by Year)- Quality Bred Heifer Characteristic Demand Model Price estimates (dependent variable average price per pen and coefficients refer to dollars per head)

Item		Coefficient	SE	P Value
Avg Weight of heifer in pen***		0.82	0.03	<0.01
Pens AI sired***		42.29	10.00	<0.01
Calving Period (default= March, April and May)				
January and February***		47.12	10.36	<0.01
August and September***		177.09	20.06	<0.01
October and November***		159.18	20.70	<0.01
Calving Span = 1 if greater than 30 d		-3.52	14.74	0.81
Calf production EPDs (only for angus pens with 1 sire)				
Birth Weight (logarithmic)		165.29	191.43	0.39
Weaning Weight		2.03	3.88	0.60
Yearling Weight***		-10.14	2.39	<0.01
Maternal Milk (logarithmic)		-134.81	95.97	0.16
Carcass EPDs (only for angus pens with 1 sire)				
Carcass Weight***		13.41	2.43	<0.01
Marbling (logarithmic)		477.34	665.66	0.47
Carcass Ribeye Area		-41.46	81.09	0.61
Sale Location (default = West central)				
Northeast		1.80	13.74	0.90
North central***		-122.70	22.23	<0.01
Southeast***		-93.67	14.70	<0.01
Southwest***		-105.60	12.42	<0.01
South central***		-144.28	18.75	<0.01
Lot order***		6.94	0.75	<0.01
Lot order squared***		-0.07	0.01	<0.01
Head per pen***		39.74	3.00	<0.01
Head per pen squared***		-2.40	0.34	<0.01
Season = 1 if Fall***		-42.94	19.85	0.03
Pens with all Tier II heifers				
Tier II in 2008	*(n=51)****	-78.42	26.31	<0.01
Tier II in 2009	*(n=42)*	32.72	28.39	0.25
Tier II in 2010	*(n=51)****	111.47	23.98	<0.01
Pen with more than one sire used = 1***		-58.77	10.65	<0.01
Pens with all Angus Sires = 1		9.20	10.93	0.40

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

Table 3.3- Model 2 (Tier II Average) Quality Bred Heifer Characteristic Demand Model Price estimates (dependent variable average price per pen and coefficients refer to dollars per head)

Item	Coefficient	SE	P Value
Avg Weight of heifer in pen***	0.82	0.03	<0.01
Pens AI sired***	41.66	10.06	<0.01
Calving Period (default= March, April and May)			
January and February***	49.42	10.41	<0.01
August and September***	171.77	20.16	<0.01
October and November***	159.87	20.82	<0.01
Calving Span = 1 if greater than 30 d	-5.29	14.83	0.72
Calf production EPDs (only for angus pens with 1 sire)			
Birth Weight (logarithmic)	-47.62	188.45	0.80
Weaning Weight	6.02	3.82	0.12
Yearling Weight***	-12.40	2.35	<0.01
Maternal Milk (logarithmic)	-130.79	96.19	0.17
Carcass EPDs (only for angus pens with 1 sire)			
Carcass Weight***	15.78	2.39	<0.01
Marbling (logarithmic)*	1140.74	651.99	0.08
Carcass Ribeye Area	-104.79	80.19	0.19
Sale Location (default = West central)			
Northeast	-0.36	13.82	0.98
North central***	-127.40	22.36	<0.01
Southeast***	-96.91	14.78	<0.01
Southwest***	-107.42	12.49	<0.01
South central***	-147.37	18.85	<0.01
Lot order***	7.29	0.75	<0.01
Lot order squared***	-0.07	0.01	<0.01
Head per pen***	39.13	3.02	<0.01
Head per pen squared***	-2.33	0.34	<0.01
Season = 1 if Fall**	-46.87	19.95	0.02
Pens with all Tier II heifers			
Tier II *(n=144)**	30.43	16.01	0.06
Pen with more than one sire used = 1***	-60.85	10.71	<0.01
Pens with all Angus Sires = 1	12.64	10.97	0.25

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

The results of model 1 will be described because model 2 was so similar. Model 2's differences included the Tier II and marbling variables, and their results will be discussed, too. Heifer characteristics that were significant at the less than 1% level were heifer weight, AI heifer pens, expected calving span and pens with multiple sires used.

These findings are consistent with previous studies. A 1-pound increase in heifer weight led to a $0.82 per head increase in bred heifer price. This value represents the cull value of the heifer in the future. Artificially inseminated heifer pens will garner a $42.29 per head increase in heifer price. This indicates that buyers believe that AI provides premiums for the future value of the heifer's calf. Heifers that were scheduled to calve in January/February receive $47.12 per head premium compared with heifers expected to calve in the March/April/May period. This is likely because the calving dates are earlier in the spring with respect to the default, and this gives producers more time to put weight on calves before they sell at weaning in the fall. This gives calves more time to utilize forage before the dry summer months and is valuable to producers because they do not have to invest more resources in a heifer prior to calving. For the August/September calving period, heifers received a $177.09 premium per animal. Heifers expected to calve in October/November receive a $159.18 a head premium. Premiums received for these animals most likely reflect the idea that the calves will be weaned in the spring, when feeder cattle prices have historically hit their highs. Thus, the feeder cattle market's seasonality creates premiums for animals sold in the off-season (spring).

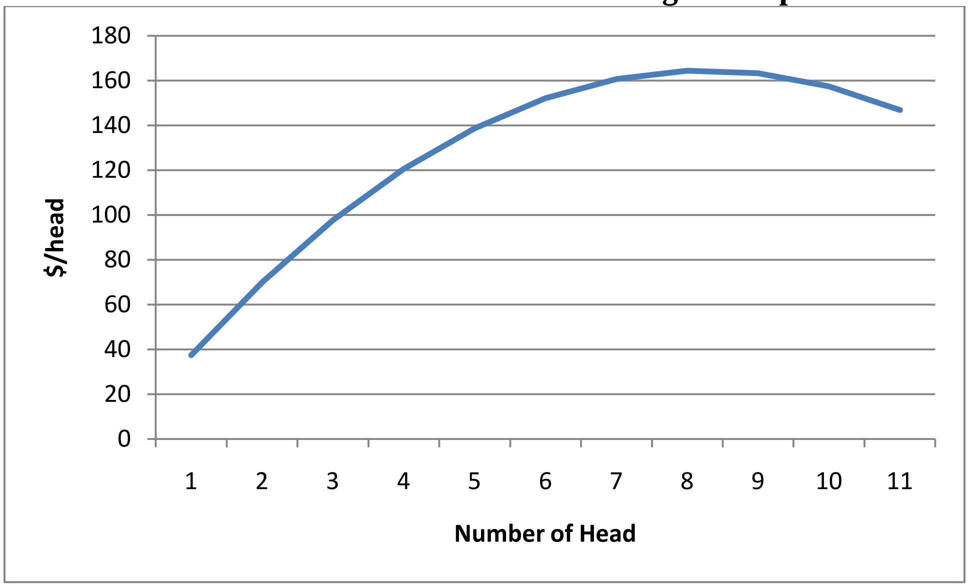
Heifer pens that had more than one sire used in breeding had a $58.77 discount per head. When one sire is used to breed heifers, the heifers tend to have more uniform calves. It was interesting to find that the Angus breed was not significant in determining bred heifer price. This contrasts with other findings that have found that Angus cattle receive a premium.

The calf and carcass EPDs that were significant in model 1 at the less than 1 percent level were yearling and carcass weight. The calf and carcass EPDs of birth weight, weaning weight, maternal milk, marbling and ribeye area were not significant. Previous research found that these variables were significant in explaining price. A 1-pound increase in yearling weight was found to have $10.14 discount per head. The relationship was expected to be in the opposite direction. A 1-pound increase in carcass weight was found to yield a premium of $13.41 per head. Heavier carcasses have more sellable pounds of meat.

In model 2, an increase in the natural logarithmic of marbling was found to increase a heifer's price. The relationship is linear. For each 0.1 increase in marbling score, an animal earns a $4.50 premium. This indicates that sellers are being compensated for using higher quality genetics that can produce a higher quality meat. This makes sense since a primary indicator of USDA carcass quality is marbling. Ribeye area was not found to be a significant indicator of bred heifer price in either model. This is surprising because the ribeye area is one of the highly priced cuts of beef. It appears that buyers are willing to pay for most heifer characteristics and some calf and carcass expected characteristics. In addition, regional price differences were found for north central, southeast, southwest and south central regions compared with the west central region. These regional results are similar to previous findings.

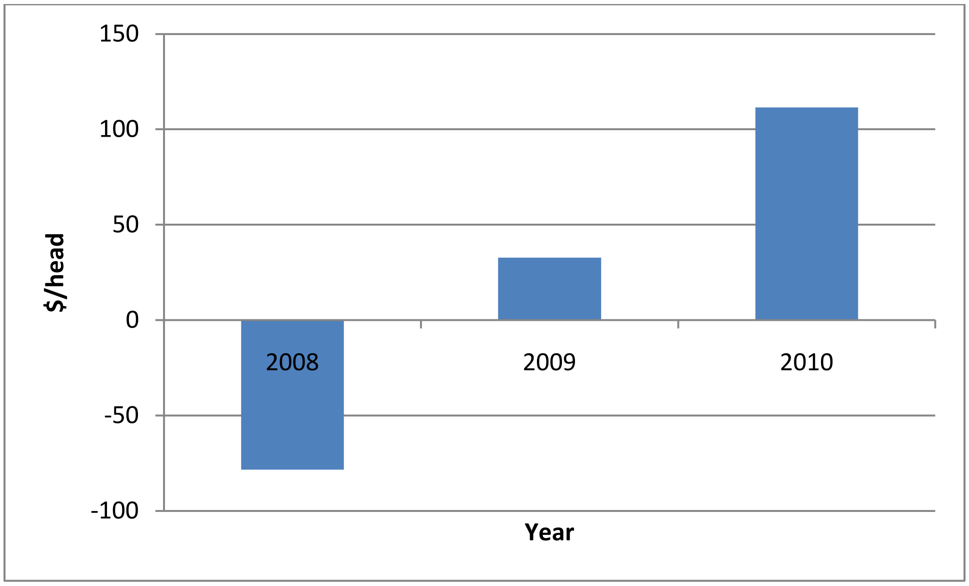
Lot order was shown to have a quadratic relationship to price because the squared term was significant. Heifers sold in the fall received a discount of $42.94 per head. The number of animals in the pen was shown to have a quadratic relationship with bred heifer prices; Parcell et al. (2006) found the same result. Chart 3.1 illustrates the quadratic relationship between number of heifers and price. The value of impact for the range of one to 11 heifers in a pen was simulated in the graph using the regression coefficient. For example, a pen of four heifers will obtain $444.90 a pen premium compared with a pen with one heifer.

Chart 3.1- Effect of Number of Heifers on Average Price per Bred Heifer in the Pen



The Tier II variable was found to be significant for 2008 and 2010 in model 1. The Tier II program began in 2008, so buyers may not have understood the value of a Tier II animal. In 2008, animals that were in an all Tier II pen received $78.42 per head discount. In 2010, the Tier II premium was $111.47 per head. Chart 3.2 shows the Tier II premiums or discounts for the 2008 to 2010. From 2008 to 2010, premiums for Tier II heifers increased. In model 2, a Tier II $30.43 premium was found for the period over 2008 through 2010. Producers will choose to raise more Tier II heifers if the premiums are large enough to offset the cost of using high-accuracy sires.

Chart 3.2- Premiums/Discounts for Tier II Heifer 2008-2010



The Tier II program could benefit from potential marketing efforts to increase awareness of the characteristics and value of Tier II heifers. Because the program is still in the introductory stage of the product life cycle, it could benefit from marketing dollars being spent and moving the product into the growth stage. Marketing dollars spent in the introductory stage can have large impacts in the long run by decreasing the time that a product spends in the introductory stage and increasing the time that a product spends in the growth stage. The growth stage is characterized by increased sales and increasing profits. The marketing investment could increase producer participation in the Tier II program, build buyers' understanding of Tier II heifers' value and increase buyers' willingness to pay for these high-quality animals. The increase in premiums from 2009 to 2010 could be related to producers better understanding the value of Tier II heifers and realizing the value that they can earn from using high-accuracy sires to breed their heifers.

Because the Tier II program is in its infancy stage, premium values are likely still being determined. In accordance with the product life cycle theory, sales of Tier II animals should continue to increase and premiums should continue to grow for these animals. The Show-Me-Select program should be brainstorming ideas for a new product of even higher quality. Doing such will allow producers to earn premiums for their high-quality animals. Otherwise, the competitive environment will eventually drive profits to zero. Downward trending Tier II premiums and sales will indicate that Tier II has entered the maturity stage of its product life cycle. The growth stage – the time at which profits reach their maximum – is an ideal time to introduce a new value-added product so that producers can preserve quality premiums.

Implications

This study uses transaction-level data to estimate marginal implicit values for bred heifer characteristics including the value of minimum sire accuracies. This study finds that heifers that are bred to sires with quality genetics receive premiums. In addition, the higher quality heifers, known as Tier II heifers, have received a premium for their value-added characteristics. The Tier II program requires minimum sire accuracies so that heifers raise higher quality calves that can be used as replacement heifers or that can produce carcasses that grade high on the rail. However, it needs to be noted that some heifers sold may not be tagged as Tier II heifers, but they still meet the Tier II characteristics.

The implicit marginal prices determined for Tier II heifers shows the buyers' willingness to pay for the animal with respect to the expected value that the heifer creates over her lifespan and the genetics that the heifer passes to her calves, which may be raised as breeding bulls or replacement heifers.

In order for producers to develop Tier II heifers, they incur costs to produce these higher quality heifers. In addition to meeting the standard requirements for the Show-Me-Select Program, they also must use high-accuracy sires to breed the heifers that they are developing for the Tier II program. Producers will incur additional costs as they spend more time managing the heifers and spend more money on quality genetics that meet the program's requirements.

Producers who already participate in the Show-Me-Select program and use artificial insemination to breed heifers would incur additional costs if they were to upgrade to producing Tier II heifers. This is because Tier II heifers must be bred with a sire that has high accuracies for calving ease, weaning weight, carcass weights and marbling. The only additional cost for these producers would be buying a higher cost, higher quality sire semen that meets the required sire accuracies for the Tier II program. A producer who already participates in the Show-Me-Select program and who uses a bull for natural service (where the EPDs don't meet the required accuracies) for their herd would incur higher costs to transition to producing Tier II heifers. This producer would have to start using artificial insemination and purchasing sire semen that meets the minimum required EPD accuracies. Using artificial insemination would require that the producer invest additional time, labor and equipment, too.

Parcell and Franken (2009b) determined net present value estimates for Show-Me-Select heifers. They investigated the impact that these heifers had on improved calving quality and consistency. These heifers were created to be high-quality “reproductive machines.” Compared with an average animal, these heifers are expected to lose fewer calves and produce more productive calves. The heifer’s offspring are expected to be more consistent throughout the heifer’s life. These heifers’ improved dam productivity and calf consistency added an additional $187 per head to the value of a bred heifer in 2008. The present value of an average heifer was estimated to be $918. The Show-Me-Select heifer value was $1,105. The higher value of these animals is due to these heifers producing an even higher valued first offspring due to minimum sire accuracies used to breed the heifer. It is expected that this first offspring will grade better on the rail or could become a better replacement heifer than the offspring of a Show-Me-Select heifer that is not bred to a sire with minimum accuracies.

The hedonic approach gives a better measure of buyers’ willingness to pay for certain heifer characteristics. One reason for this is that net present value estimates normally only incorporate the value of an animal’s offspring and assume that its offspring is sold and not kept to improve the overall genetic make-up of the herd. Due to this, present value estimates of quality heifers are most likely underestimated.

More research needs to focus on identifying the value-added characteristics that receive premiums. Such research would help individuals better understand and improve the value marketing chain. In addition, more research should investigate the extent to which premiums for new value characteristics change throughout a product’s life. This will allow market participants to better understand the life cycle of a new value characteristic and more readily adapt their product line to capture premiums.

Chapter IV

RETURNS AND RISK PREFERENCES OF COORDINATED BEEF SIRE GENETICS

Introduction

Agricultural producers must make management decisions – for instance, technology adoption decisions or significant management change decisions – under uncertainty. Producers compare expected profits realized by adopting a technology with the costs of adopting and using the technology. Making this comparison allows a producer to decide if a new technology should be used in his or her operation.

Cattle producers must make many management decisions, and they make these decisions as they're uncertain about markets, weather and production. Artificial insemination (AI) technology adoption gives beef producers the opportunity to use high-quality genetics in breeding cattle. This gives producers the ability to produce high-quality female breeding animals and potentially raise calves that later could be finished and grade high on the rail. This technology can allow producers to better meet the ever-growing demand for high-quality beef. Producers know that they would incur costs, experience risks, need to acquire technical knowledge and need to hire labor if they adopt the AI technology; however, they also know that taking a risk by adopting technology presents an opportunity to gain profits. This is linked to the value that buyers associate with purchasing quality calves born through artificial insemination and estrus synchronization (AIES) technologies. This study examines, "According to buyers' risk preferences, what would buyers be willing to pay to feel indifferent about purchasing calves from alternative sire groups?"

Alternative sire groups that will be used in this study are a high-accuracy sire group, low-accuracy sire group, natural service sire group and a composite sire group that is an average of all sire groups. The high-accuracy and low-accuracy sire groups represent calves that were born to females that had been artificially inseminated using estrus synchronization. Estrus synchronization (ES) is a method that allows for females to be bred at approximately the same time. In other words, the calves are born in a narrow calving window. ES is a management technology that allows producers to have more uniform calves, which are desirable to buyers. The natural service group represents calves that were born to females that were bred by a bull traditionally and without regard to which bull or without regard to expected progeny difference (EPD) levels.

This study uses actual calf data, pre-condition data, feed-out data and carcass performance data for each calf's sire group. The averages and distribution from the actual data are combined with the average and distribution of input-output prices from a five-year period to simulate the returns of feeding out the different sire groups' calves in order to approximate the economic cost-return budgets over time. A set of 1,000 scenarios, by the calf's sire group, is estimated from the data and used for risk efficiency assessment. Compiling the primary data from such a data set would require significant personnel and financial resources beyond the scope of the research project.

In order to compare the management strategies, net revenue probability density functions of the management choices will be compared at different risk aversion intervals using stochastic dominance with respect to a function (King and Robison, 1981) and stochastic efficiency with respect to a function (Hardaker & Lien, 2003). Stochastic dominance with respect to a function (SDRF) will allow rankings of the sire groups to be linked to a specific risk interval, risk-taking, slightly to moderately risk-averse and strongly risk-averse. Premiums and or discounts will be given for individuals to be indifferent to the different sire groups according to the risk preference. In addition, the stochastic efficiency with respect to a function method will be used to identify how the dominance ranking of sire groups may differ across a given risk interval, such as risk-taking or slightly to moderately risk-averse or strongly risk-averse. Graphs that represent how the dominance may change across the risk interval will be shared.

This research should give insight into the willingness one would pay to be indifferent to the different sire groups according to their level of risk acceptance. The confidence premiums or discounts can indicate a sire group buyer's (e.g., feedlot) value range for being indifferent between receiving the premium/discount as a lump sum and receiving the future revenue of a less dominant sire group. Feedlots make decisions about the cattle that they buy to fatten, and they make these decisions without knowing feeder cattle pricing and performance and carcass grid pricing and feed costs. This study will show a buyer's sire group preference according to his or her desire to accept risk.

Literature Review

Stochastic dominance analysis has been widely used in the agriculture sector to compare producers' risk management choices. Specifically, stochastic dominance with respect to a function has been used most frequently for stochastic dominance analysis. This analysis is used in pair-wise comparisons that are mutually exclusive and has been more widely used in crop production (e.g. Klemme, 1985; Ritchie, Abawi, Dutta, Harris & Bange, 2004). The technique has been used to study various livestock management decisions that include contract alternatives (e.g. Johnson & Foster, 1994; Parcell & Langemeier, 1997) and technology adoption (e.g. Farquharson, 1991).

Stochastic dominance with respect to a function does not require a normal distribution or assume specific risk preferences as first- and second-degree stochastic dominance (Johnson & Foster, 1994). Stochastic dominance with respect to a function allows individual risk preferences to differ according to the absolute risk aversion coefficients in the specific interval (Farquharson, 1991). In addition, stochastic dominance with respect to a function is more discriminating of the efficient set than compared with first- and second-degree stochastic dominance. First-degree stochastic dominance assumes positive marginal utility for individuals. Second-degree stochastic dominance assumes that marginal utility is positive and decreasing. This invokes risk aversion in assuming that the utility function is concave.

Another approach is called stochastic efficiency with respect to a function (SERF). It ranks alternatives according to certainty equivalents as risk premiums for specific preference ranges simultaneously (Hardaker, Richardson, Lien, & Schumann, 2004). The SERF method differs from SDRF in that SERF simultaneously compares each alternative with the other. The SDRF method performs pairwise comparisons (Hardaker & Lien, 2003). Compared with SDRF, SERF has an additional assumption in that all risk aversion measures are of the same functional form as the lower and upper bound functions (Meyer, Richardson & Schauman, 2009). This approach allows for smaller efficient sets and gives cardinal rankings of payoffs (Hardaker et al., 2004).

SERF's output can be shown graphically, which shows how the efficient set may change over the span of the risk aversion upper and lower bounds.

Many studies have used the stochastic dominance with respect to a function method. The Farquharson (1991) study uses stochastic dominance with respect to a function to look specifically at the potential of adoption of a new twinning technology in Australian beef cattle. A Nebraska beef cattle study compares differences in calving dates using stochastic dominance with respect to a function (Carriker, Clark, Adams & Sandberg, 2001).

In order to implement stochastic dominance with respect to a function, the researcher must define the risk preferences represented by the absolute risk-aversion coefficients. An individual's risk preference is reflected in the concavity of his or her utility function. Greater concavity represents more risk aversion. In the literature, this has been done by arbitrarily picking absolute risk-aversion intervals or by empirically acquiring the intervals from producer surveys. Other studies use intervals that have been supported in empirical studies.

Some of the studies have measured preferences for livestock producers (e.g. Wilson & Eidman, 1983; Tauer, 1986). Surveys can capture risk preferences through self-ranking questions, interval approach questions or hypothetical choice questions (Fausti & Gillespie, 2000). A comparative risk analysis shows that Louisiana cow-calf producers are less risk-averse than South Dakota producers (Fausti & Gillespie, 2000).

A New York study of dairy farmers used risk intervals based on the work of King and Robison (1981) and based on results of a risk preferences study of farm students

(Tauer, 1986). They found that the New York producers were slightly more risk-preferring than the Minnesota swine producers in the Wilson and Eidman (1983) study.

Wilson and Eidman (1983) state that the literature has suggested that producers' absolute risk-aversion coefficients range from -0.0002 to 0.0012. Seventy-eight percent of the Minnesota swine producers were shown to be risk-neutral to risk-averse being in the range of -0.0002 to -0.0001 (Wilson, Eidman, 1983). The King and Robson (1981) study produced coefficients in this range for Michigan farmers. King and Robison (1981) state that research has shown that the absolute risk-aversion interval should be between -0.0001 and 0.0010 because individual choices are most greatly affected within this scale. Wilson and Eidman's risk intervals (1983) have been used by other studies (e.g. Parcell & Langemeier, 1997). The literature has shown that risk aversion under uncertainty influences a producer's input use and technology adoption (Isik & Khanna, 2002).

Binswanger (1980) found that certain characteristics could be related to an individual's preferences for risk. He found that wealthier, better educated and more innovative individuals are more likely to be less risk-averse.

Conceptual Model

Buyers' decisions are made under uncertainty and are affected by the individual's risk preferences and expectations (King & Robison, 1981). Expected utility theory allows for utility maximization that incorporates expectations and preferences (King & Robison, 1981). For an expected utility example- $\mathbf{w}$ = initial wealth, $\mathbf{x}$ = random and $\boldsymbol{\pi}$ = monetary value of risk. This is represented in Equation 4.1 as,

(4.1) $Eu(w+x) = u(w+Ex - \pi)$.

The theoretical underpinnings for Equation 4.1 is sourced to the quantitative definition of risk, which is the idea that individuals are willing to pay someone else to assume the risk for them. The expected utility of the initial wealth, **w** plus the random variable **x** is equal to the utility of the initial wealth plus the investment's mean profitability (Ex) minus **π**, the monetary value of the risk. The variable **π** is not objective since the monetary value of risk varies from one preference to another. In order to measure risk, a restriction must be put on the utility function or distribution of returns or both (Levy, 1992). The arrow-pratt risk premium can solve **π**.

Stochastic Dominance with Respect to a Function (SDRF)

Stochastic dominance with respect to a function (SDRF) developed by Meyer (1977) allows for ranking uncertain alternatives. The absolute risk-aversion function (Arrow, 1971; Pratt, 1964), r(x), is demonstrated by equation 4.2 as,

(4.2) $r(x)= -u''(x)/u'(x)$

The values of absolute risk aversion measure the degree of concavity or convexity in the utility functions, and they indicate whether an individual is a risk-taker, a risk-averter or is risk-neutral. A negative risk aversion coefficient indicates a risk-taker, a positive coefficient indicates a risk-averter, and coefficient of zero represents a risk-neutral person.

Meyer's work (1977) created the idea of restricting the risk-aversion coefficient for stochastic dominance. An interval representation of an individual's risk preferences was created by putting a lower and upper bound on the interval. The restriction puts the coefficients in a given interval $r_1(x) < r(x) < r_2(x)$. This is solved by finding the utility function u(x) that satisfies Equation 4.3 as, (4.3) $r_1(x) \leq -\frac{u''(x)}{u'(x)} \leq r_2(x) \quad \forall x \in [0,1],$

while minimizing the following

(4.4) $\int_0^1 [G(x) - F(x)]u'(x)dx.$

Equation 4.4 is equal to the difference between the expected utilities of F(x) and G(x). If given an interval of risk preferences for a group of individuals and the minimum of this difference is positive, then F(x) is unanimously preferred to G(x). This implies that the expected utility of F(x) is always greater than G(x). If the minimum is zero, then it is possible that the individuals in that risk interval are indifferent between the two alternatives, so their choices are unable to be ranked. However, if the minimum is negative, then F(x) can't be unanimously preferred to G(x). Then Equation 4.5 should be used. It is expressed as,

(4.5) $\int_0^1 [F(x) - G(x)]u'(x)dx.$

Equation 4.5 should be minimized in order to determine whether G(x) is unanimously preferred to F(x). However, complete ordering is not ensured by this method because it is possible that the minimum Equation 4.4 and Equation 4.5 could be negative, which implies that neither distribution is unanimously preferred by the group of individuals.

Stochastic Efficiency with Respect to a Function (SERF)

The SERF method (Hardaker & Lien, 2003) can be expressed where, U(w) is the utility function of an individual with the performance criteria as wealth, **w**. It is assumed that the alternatives that are being compared have uncertain outcomes with **w** being stochastic. Probability density functions (PDFs) that represent the outcomes for n risky alternatives are noted by, $f_1(w)$, $f_2(w)$,…, $f_n(w)$. The subjective expected utility hypothesis states that the utility of the risky alternative is the individual's expected utility for that option, being the weighted probability average of the utilities of the associated alternatives. This is defined as follows in Equation 4.6,

(4.6) $$U(w) = EU(w) = \int U(w)f(w)dw = \int U(w)dF(w).$$

Because the individual's risk aversion is not known, we use a risk-aversion function r(w) where the individual's risk lies between the upper and lower bounds denoted by $r_1(w)$ and $r_2(w)$. For each alternative given a chosen utility function, the function for utility with respect to risk aversion and the stochastic outcome **w** is outlined in equation 4.7 as,

(4.7)
$$U\big(w, r(w)\big) = \int U\big(w, r(w)\big)dF(w) = \sum_{i=1}^{m} U\big(w_i,\ r(w)\big)P(w_i), \qquad r_1(w) \leq r(w) \leq r_2(w).$$

$P(w_i)$ is the probability for states **i** that there are **m** states for each alternative option. The cumulative distribution functions (CDFs) for the associated alternatives are converted to points on the distribution for a set of finite values of **w**. Then, each is converted to its utility for the associated risk aversion coefficients, and then, each utility is multiplied by its associated probability. This calculates a weighted average of the alternatives' utilities and allows for evaluating the function for a discrete point of r(w) to describe the relationship between U and r(w) for an option. The ordering of alternatives is done by converting the utilities into certainty equivalents (CE). This is accomplished by taking the inverse of the utility function shown as follows in Equation 4.8,

(4.8) $$CE\big(w, r(w)\big) = U^{-1}(w, r(w)).$$

This allows for the CEs to be calculated for each alternative for a set of bounded **r** values. As discussed in Hardaker and Lien (2008), the SERF analysis can be applied to any utility function; however, a negative exponential function will be used to represent the unknown utility function. A negative exponential function is used to assume constant absolute risk aversion. Hardaker and Lien (2008) argue that this is a reasonable approximation because the range of risk alternatives that are being compared is small relative to the individual's wealth.

Data and Relative Risk Transformation

Partial budgeting will be used to isolate changes in income and expenses directly associated with the chosen management strategy. This will allow us to see the changes in revenue due to management strategy. The partial budgets will be used to create distributions using a simulated specification of distribution, such as a normal used in King and Robinson (1981). These distributions will be used to perform a stochastic dominance with respect to a function analysis.

The management strategies that will be evaluated in this study will are the traditional non-reproductive technology of natural service of cattle, AI with low-accuracy, AI with high-accuracy and a composite base group, which is simulated based on the weighted average performance for all calves. This approximates the average co-mingled pen typically observed beyond on the farm or in a feedyard.

The high-accuracy sire group refers to calves that were born to females that were bred through AI using semen that met minimum EPD accuracies. Using high-accuracy sires gives females a higher probability of producing a higher quality calf. The low-accuracy sire group consists of calves born to females that were bred through AI using sires with low-accuracy EPDs, meaning that the females had a lower probability of producing calves that were similar to the sire's EPDs. The natural service sire group is composed of calves that were born to females that were bred traditionally by bulls. Producers who use a natural service sire are not incorporating AI breeding methods into their herd. The final group is a composite group that averages all of the previously discussed sire groups.

Accuracies associated with EPD values represent a measure's level of confidence. Higher accuracies reflect a higher probability that the EPD level will be observed. The high-accuracy group had sires that meet the Show-Me-Select Replacement Heifer program's requirements: 0.065 score for direct calving ease, 0.30 score for maternal calving ease, 0.75 score for weaning weight, 0.20 score for carcass weight and 0.20 score for marbling.

Using AI gives producers access to superior sires with highly desirable genetic traits. All sire groups sourced from AI-bred cows used a timed and synchronized program. Using an ES program provides many benefits. For instance, calves tend to be more uniform at weaning. However, using AIES has additional costs associated with it that aren't incurred when using a bull for natural service. Costs for additional labor, equipment and training; increased management; and implementation are incurred when using AIES technologies.

Carcass performance for calves in all groups was recorded. The high-accuracy group performed well on a quality-grade basis. This group graded 100 percent Choice or better and 66 percent to 67 percent Certified Angus Beef (CAB) or better. The composite group only yielded 36 percent or better CAB. The high-accuracy group produced more high-value carcasses than the average group.

The data used for the stochastic dominance with respect to a function analysis represents producer cost data obtained through University of Missouri cost-return projected budgets and three years of calf returns data from pilot data collected by the University of Missouri Animal Sciences Unit. Table 4.1 shares descriptive statistics of the data used to create the revenue simulations. The sire groups are abbreviated with (NS) representing natural service, (LA) representing low-accuracy, (HA) representing high-accuracy and mixed representing the average group. For the beef-cow producer, dam cost and performance adjustments were made for animal cohort represented by the bundled technology package. Table 4.2 shows the premiums, discounts and cost of feeder calves.

Table 4.1- Descriptive Statistics for Sire Groups used for Revenue Simulations

	NS	LA	HA	Mixed
Marketing Characteristics				
Age (months, average for sire group)	13.88	14.32	13.59	14.03
Dressing percentage (avg. group)	59.06%	61.05%	60.13%	59.83%
% Prime	2.00%	8.00%	23.00%	14.00%
S.D. % Prime	0.13	0.27	0.42	0.34
% Choice	65.00%	57.00%	67.00%	63.00%
S.D. % Choice	0.48	0.50	0.47	0.48
% Select	27.00%	15.00%	0.00%	10.00%
S.D. % Select	0.45	0.36	0.00	0.30
% CAB (of sire group)	21.00%	29.00%	53.00%	40.00%
S.D. % CAB	0.41	0.45	0.50	0.49
Average yield grade	2.6	3	2.9	2.88
Feedlot Production Characteristics				

In weight (lbs., average for sire group)	597.22	685.44	668.41	650.85
Days on feed (average for sire group)	178.49	63.05	154.47	165.48
Average daily gain (lbs., average for sire group)	2.80	2.75	2.89	2.78
Feed conversion (average for sire group)	6.55	7.14	6.91	6.93
Treatment cost ($/head, average for sire group)	11.88	3.20	1.22	5.17
No. Sick (% of sire group)	39.78%	12.87%	4.17%	17.68%
Pre-Conditioning Characteristics				
Days Pre-Conditioning	53.32	55.39	55.75	54.97
Average daily gain (lbs., average for sire group)^^	2.01	2.03	2.86	2.34
Cost per lb. of gain (average for sire group)^^	0.55	0.54	0.45	0.50
Feed conversion (average for sire group)^^	6.32	6.19	5.18	5.79
Calf Production Characteristics				
Weaning weight (lbs, average for sire group)	490.01	572.89	509.24	522.27
Weaning age (months)	6.13	7.02	6.55	6.66

^^ Out-weight is computed on a shrink weight basis, or the in weight into the feedyard

Table 4.2- Premiums and Discounts used for Simulations

	Average	Standard Deviation
Grade		
PRIME	$7.20	$1.94
SELECT	-$8.58	$7.13
AVG. CHOICE HIGHER (CAB)	$1.98	$1.06
Yield Grade		
1.0-2.0,<.1"	$2.57	$0.91
2.0-3.0,<.3"	$1.20	$0.32
3.0-4.0,<.7"	-$0.12	$0.15
4.0-5.0,<1.2"	-$13.75	$0.28
5.0/UP,>1.2"	-$19.24	$0.04
Light & Heavy Weight Carcasses		
WEIGHT		
400-500LBS.	-$22.96	$4.53
500-550LBS.	-$16.07	$1.08
550-600LBS.	-$2.53	$2.83
600-900LBS.	$0.00	$0.00
550-900LBS.	$0.00	$0.00
900-950LBS.	-$0.82	$1.01
950-1000LBS.	-$9.27	$7.55
Over 1000LBS.	-$19.23	$0.77
HIDE BRAND LOCATION	$0.02	$0.19
Base Live Cattle Price		
$/cwt dressed	$136.59	$16.06
Corn Index	$1.10	$0.18

Partial budgeting was used to derive profits per head for an average pen in each alternative sire group. The partial budgeting was done by using production and carcass performance data collected for each sire group. The base price and quality and yield grade premiums and discounts were allowed to vary over a five-year period. Feed cost is associated with the average cost to feed out an animal; however, corn cost was not allowed to vary. The calf cost was computed by using a three-year weighted average price. Revenue is calculated by using average revenues derived from five years of base price and grid value information.

The simulated data were created by allowing the model to make 1,000 randomly drawn replications from the summary statistics, listed in Tables 4.1 and 4.2, to calculate revenue from weaning to slaughter. The variables used in the model included quality grade (stochastic), yield grade (fixed), feeder calf price (stochastic with it being tied to a price slide), live cattle price (stochastic), feed price index (stochastic), days on feed (fixed), average daily gain (fixed) and feed efficiency (fixed).

The sire group data for age, dressing percentage, in weight, days on feed, average daily gain, feed conversion, treatment costs, number sick, days on pre-conditioning, average daily gain, cost per pound of gain, feed conversion, weaning weight and weaning age were from 2006 calf returns data. Percentage of animals ranking in the various quality grades was based on 2006 to 2010 calf returns data. The premiums and discounts for quality grade, yield grade, light and heavy weight carcasses were all based on average values of 2006 to 2010 data. The premium and discount price data was obtained through the USDA Livestock Marketing Information Center. The average live cattle base price was based on data from 2006 to 2010.

The quality grades were based on a normal distribution. The light and heavy weight carcasses variable was not stochastic. The Dhuyvetter and Schroeder (2000) price slide equation was used for feeder cattle prices and is based on live cattle prices (fixed), corn price (stochastic) and in weight (stochastic). The feed cost index is an index for 2006 to 2010. The corn price index was based on historical prices, and the base is an average of December 2005 to May 2006 data. The corn price data was obtained through the CME Group. A truncated normal distribution was used for live cattle prices. In addition, a truncated normal distribution (truncated to approximately the minimum and maximum) was used for the percentage of quality grades and yield grades for the different sire groups.

Days on feed was calculated by subtracting in-weight from out-weight, or live weight, and dividing by average daily gain. It should be noted that out-weight, or live weight, was not stochastic; however, in-weight was stochastic, and average daily gain was stochastic. The yardage cost was calculated by multiplying days on feed by $0.39/day.

Table 4.3 shows the simulation revenue data statistics for mean and standard deviation for the revenues associated with each sire group.

Table 4.3- Simulation Revenue Data Statistics

	Natural service	Low-accuracy	High-accuracy	Mixed
Average	$-82.77	$-78.98	$-32.22	$-69.28
S.D.	133.23	68.05	78.11	77.91

Gross revenue per head was largest for the high-accuracy sire group. The high-accuracy animals were lighter than the low-accuracy group; however, their carcass performance more than offset the weight difference when looking at revenue per head. The high-accuracy group returns per head were highest at a negative $32.22.

Relative Risk Transformation

This study performs SDRF and SERF on the alternatives of natural sire, AI chosen for low-accuracy and AI chosen for high-accuracy. The natural sire group represents calves that were born to heifers that were bred through natural service. The low-accuracy group represents calves that were born to heifers that were artificially inseminated with sires that are unproven through EPDs. The high-accuracy group represents calves that were born to heifers that were artificially inseminated with sires that have proven EPDs.

In order to perform stochastic dominance with respect to function analysis, absolute coefficient of variation intervals must be chosen. This study will use Wilson and Eidman's (1983) intervals, shown in Table 4.4. Risk neutrality is designated in interval 4. As the interval values become more negative, the individual is more of a risk-taker. As one moves toward the other end of the interval, the values are more positive, meaning that the individuals are more strongly risk-averse. Three intervals are created that look at risk-takers, slightly to moderately risk-averse individuals and strongly risk-averse individuals. The risk-taking interval will be created by combining interval two and three. The slightly to moderately risk-averse interval is created by combining intervals five and six. The strongly risk-averse interval is created by using interval seven.

Table 4.4- Interval Values (Wilson & Eidman, 1983)

Interval No.	Interval Value ($r(\pi)$)
1	$(-\infty, -0.002)$
2	(-0.0005, -0.0001)
3	(-0.0002, 0)
4	(0.0001, 0.0001)
5	(0, 0.0002)
6	(0.0001, 0.0003)
7	(0.0002, 0.001)
8	$(0.0003, \infty)$

However, these intervals must be transformed as Raskin & Cochran (1986) suggest because the intervals are based on units. They describe their transformation as follows in Equation 4.9,

(4.9) $c=x/w, \qquad r(w)=cr(x).$

w is equal to profits per head, and **x** is equal to the level of income used in Wilson and Eidman (1983). These include $29,917 in income for the risk-preferring category. The risk-neutral category is designated with the average income of $29,068, and the average income for the risk-averse category is $39,044. These incomes are used for the transformation discussed previously. The transformed risk-aversion coefficients are represented by r(w), and r(x) are the risk-aversion coefficients used in Wilson and Eidman (1983). In this study, **w** is designated as average revenue per head for a mixed lot. In this case, **w** is $900.45.

Table 4.5- Transformed Interval Values

Interval No.	Risk Category	Interval Value ($r(\pi)$)
1	Risk-taking	(-0.0166, 0)
2	Slightly/Moderately Risk-averse	(0, 0.0130)
3	Strongly Risk-averse	(0.0087, 0.0434)

Results

The input data for this analysis are the revenue data that were created from the 1,000 replications in the simulation model with using some fixed variables and other stochastic variables. Stochastic dominance analysis is performed on the data. The method of stochastic dominance with respect to a function (SDRF) and stochastic efficiency with respect to a function (SERF) are performed.

SDRF

SDRF was used with the created risk-aversion values to identify the alternative with the highest expected utility for a specific risk-preference range. The groups' rankings are abbreviated in the table with High-Accuracy (H), Low-Accuracy (L), Mixed-Average Group (M) and Natural Service (N). Table 4.6 shows the results.

Table 4.6- Ranking of Sire Groups between Risk-Aversion Coefficients and Confidence Premiums for the Second-Most Preferred Alternative

Risk Type	Risk Interval	Ranking (Most Preferred to Least Preferred) *(with respect to lower risk coefficient)*	Confidence Premium *2^{nd} Alt. Lower/Upper*
Risk-Taking	-0.02 to 0	N, H, M, L	71.12/-50.54
Slight/Mod. Risk-averse	0 to 0.01	H, M, L, N	37.06/31.12
Strongly Risk Averse	0.01 to 0.04	M, H, L, N	65.69/31.92

SDRF shows that the most preferred sire group changes with respect to the given risk type. The rankings are shown in relationship to the lower bound because when moving towards the upper bound of the risk interval, rankings may change. Looking at the dominance with respect to the lower end gives a starting point for comparison. SERF will show the extent to which the rankings change over the risk interval's spread. The risk-taking preference shows that the natural service sire group is most preferred and is followed by high-accuracy, mixed and low-accuracy. When the risk preferences move to being slightly to moderately risk-averse, high-accuracy is the highest ranked, and it's followed by mixed, low-accuracy and natural service. As the risk-taking preference moves to strongly risk-averse, mixed is most preferred and is followed by high-accuracy, low-accuracy and natural service. Mixed is ranked third for risk-taking individuals and moves to the second-most preferred alternative for slightly to moderately risk-averse individuals, and for strongly risk-averse individuals, it is the dominant strategy.

Confidence premium needed for individuals to be indifferent between using the natural service sire group and changing to the high-accuracy sire group ranged from

\$71.12 to negative \$50.54 between the upper and lower bounds of the probability distributions. For slightly to moderately risk-averse individuals, the amount needed for individual to change from using high-accuracy to mixed ranged from \$37.06 to \$31.12. For an individual who is strongly risk-averse, the confidence premium would be between \$65.69 and negative \$31.92 for an individual to move from mixed to a high-accuracy group.

SERF

The results from SERF show how the ranking changes over associated risk interval. Chart 4.1 shows a risk-taking risk interval. It shows that natural service is dominant in the most risk-taking part of the interval; however, as one's risk preference level moves to being less risk-taking in the interval, high-accuracy becomes the most dominant. The graph also shows how the other alternatives converge on the least risk-taking part of the risk-taking interval. With the risk interval being risk-taking, it is shown that high-accuracy is the second most dominant in the more risk-taking part of the interval. Natural service ranks second when moving toward the less risk-taking part of the interval. As one moves toward the least risk-taking portion of the interval, mixed becomes the second-most dominant, and natural service becomes the second-most dominant in the least risk-taking part of the interval. The third-most dominant alternative is mixed at the level of being more risk-taking. Moving along the risk interval to being less risk-taking, the natural service sire group becomes third in dominance. However, as one moves to the least risk-taking part of the interval, mixed becomes the third-most dominant. Low-accuracy is the fourth preferred across the entire risk interval of risk-taking.

Chart 4.1- Stochastic Efficiency with Respect to a Function under a Neg. Exponential Utility Function- Risk-taking

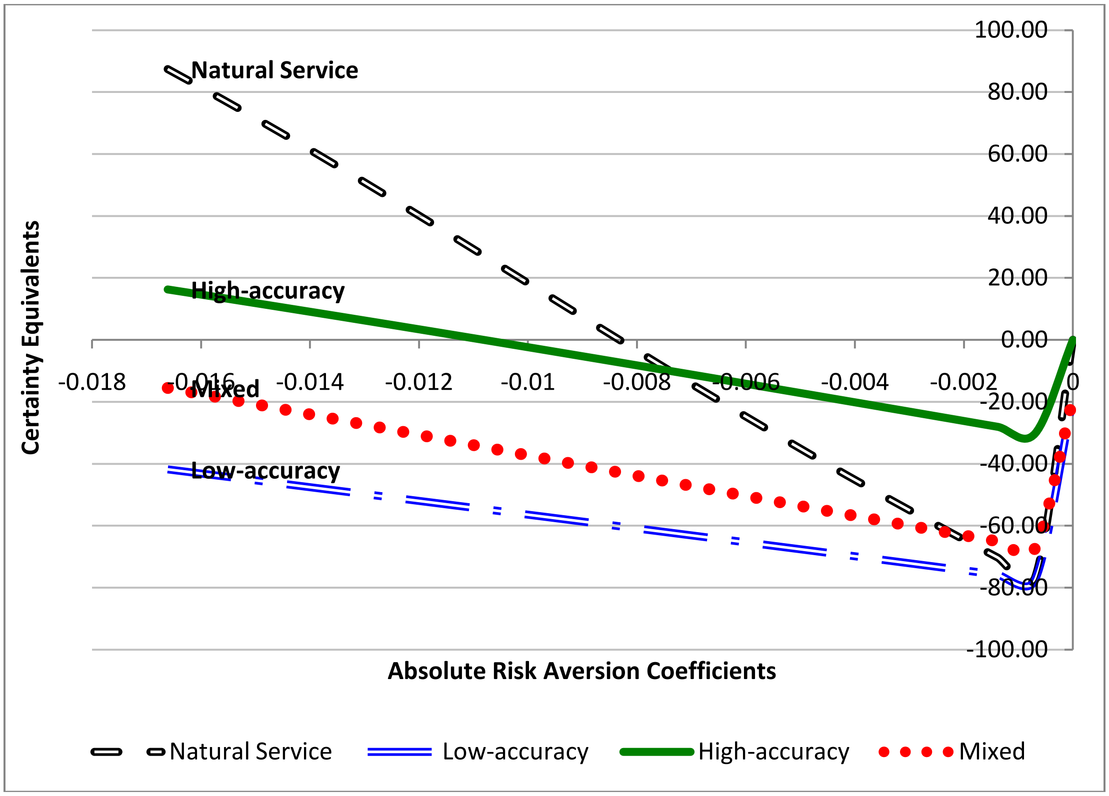


Chart 4.2 shows the SERF results for the slightly to moderately risk-averse. This shows that high-accuracy is the most dominant over the entire interval. Mixed is the second-most dominant alternative. The third-most dominant alternative is low-accuracy. The fourth-most dominant alternative is natural service at the slightly risk-averse interval level.

Graph 4.2- Stochastic Efficiency with Respect to a Function under a Neg. Exponential Utility Function- Slightly/Moderately Risk-averse

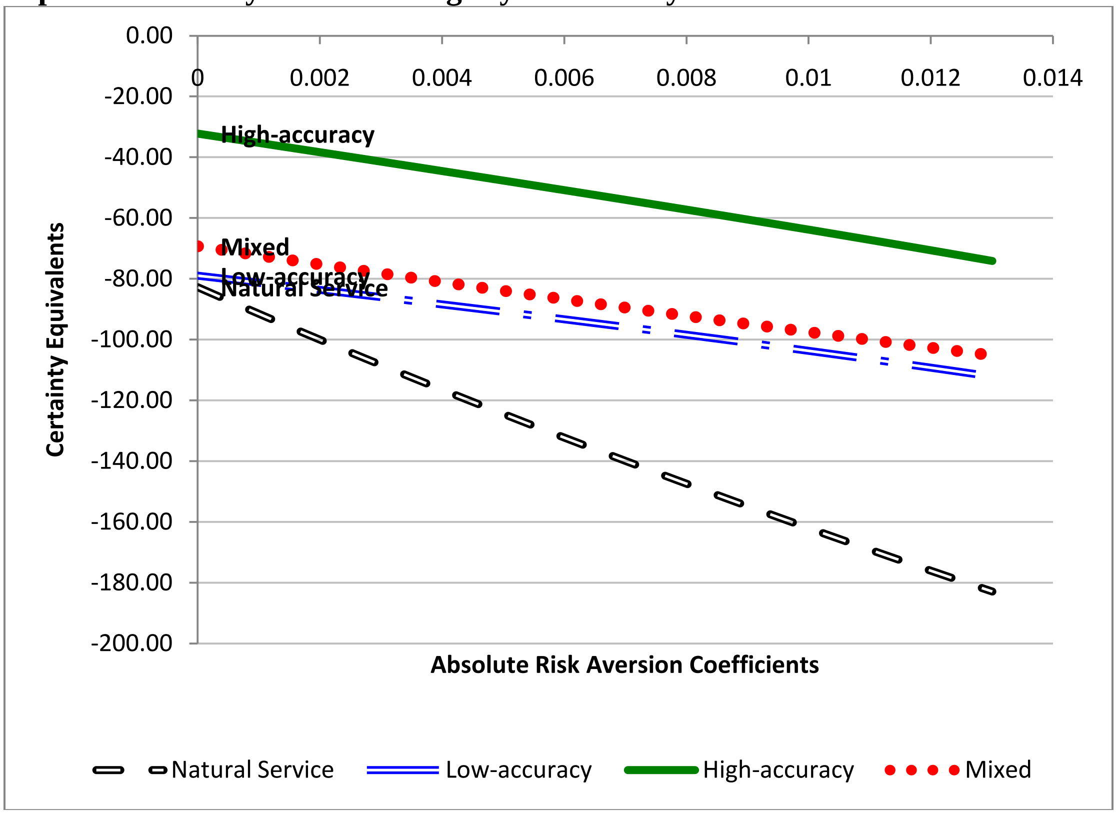
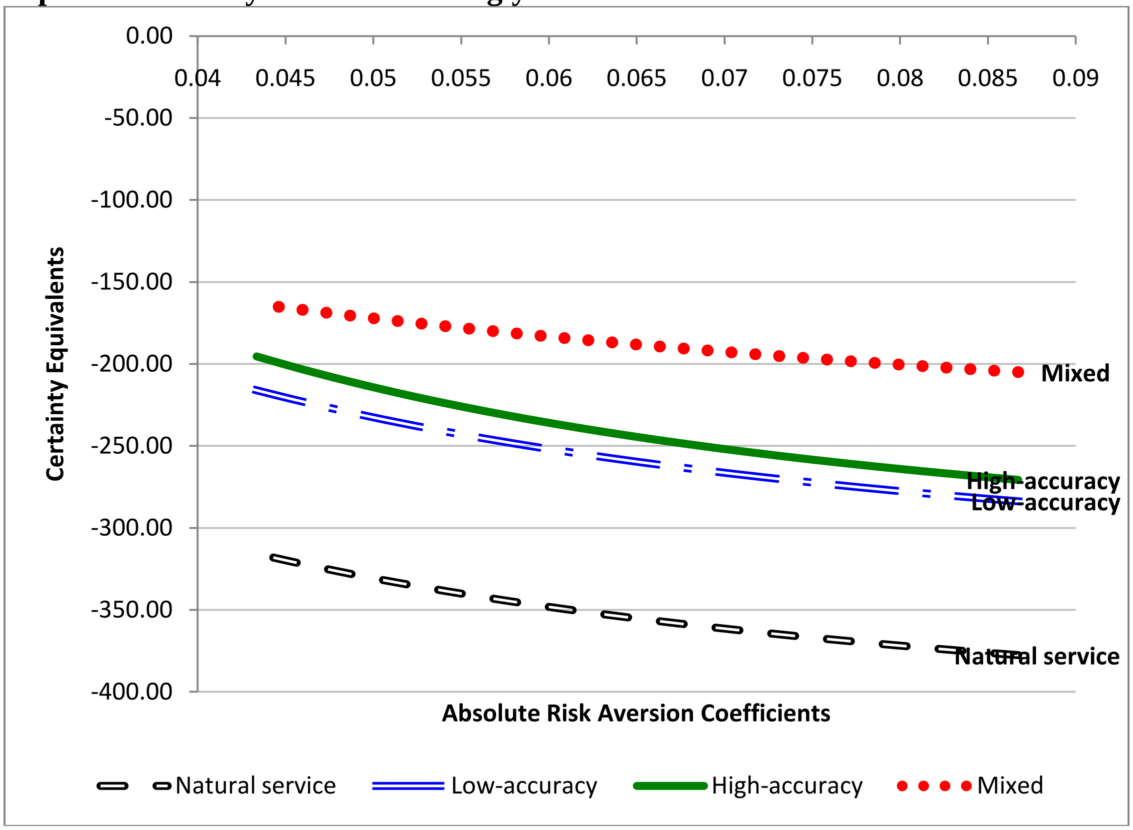


Chart 4.3 shows the SERF results for the strongly risk-aversion interval. The mixed sire group was the most dominant in the strongly risk-averse interval. The second-most dominant sire group is high-accuracy. The confidence premium between mixed and high-accuracy expands when moving to the most risk-averse part of the interval. The third-most desired alternative is the low-accuracy sire group. The confidence premium between high-accuracy and low-accuracy is narrow throughout the interval. The fourth-most dominant alternative is the natural service sire group.

Graph 4.3- Stochastic Efficiency with Respect to a Function under a Neg. Exponential Utility Function- Strongly Risk-averse



Implications

This study provides valuable insight into the sire-group preferences for feeder cattle buyers with respect to their risk preference. The natural service sire group is the most preferred alternative for individuals who are on the most risk-taking part of the risk-taking interval. High-accuracy is the dominant alternative on the less risk-taking part of the risk-taking interval. High-accuracy is the most dominant alternative for the slightly to moderately risk-averse individuals. The most dominant alternative for strongly risk-averse individuals was the mixed sire group.

Buyers who are the most risk-taking will prefer calves that were born to females bred by natural service bulls. A buyer who is strongly risk-taking will prefer the natural service group because it has the highest probability of the highest returns. Risk-taking buyers are able to receive the highest revenue (difference between the cost of buying and feeding out the feeder calves and the revenue from selling their carcasses) for this alternative. Buyers who are slightly risk-takers to moderately risk-averse will prefer to buy high-quality calves that were born to females bred through AI using high-accuracy sires because of their probability of earning the most revenue. Buyers who are strongly risk-averse will prefer to buy a mixed sire group.

The risk-taking individuals are those who are more accepting of variability in returns. The slightly to moderately risk-averse individuals are those who are less willing to accept variability in returns. This group may reflect individuals who are more educated, wealthier and innovative. However, as the individual is more strongly risk-averse, it is expected that he or she will prefer the mixed sire group. This supports the idea that individuals who are more strongly risk-averse will want more diversified revenue streams. This finding is a reflection of this. Buyers who are strongly risk-averse strongly oppose year-to-year swings in revenue or are financially insecure.

Based on returns, it is expected that buyers who are slightly risk-taking to moderately risk-averse will choose to purchases calves born by females bred by high-accuracy sires using AIES technologies. Doing this affords buyers with a higher percentage of calves that grade high and receive quality premiums. It also decreases animal treatment costs because the animals have superior genetics and decreases management costs because the calves are more uniform and require less sorting. Thus, the AIES technology is appealing to not only slightly risk-taking individuals but also to moderately risk-averse individuals.

Buyers who are very strongly risk-averse will buy a diversified set of calves, so they can spread their risk across different calf types. However, if quality carcass premiums, feeder cattle price or feed costs change in the future, then this will adjust the dominance of alternatives in accordance to risk levels. If a buyer's education level, wealth, or innovativeness change, then that buyer's risk preference and calf-purchasing preferences may also change.

This study's results could provide insight to policy-makers and extension professionals. This can inform policy-makers' decisions because they would understand factors that affect individuals' risk preferences and the effect that those preferences have on management decisions. Individuals in extension can distribute the information to help buyers and producers to make better management decisions.

Chapter V

CONCLUSION

This study explores factors that influence beef producers' adoption of reproductive technologies. It also examined the value of high-quality heifers and the potential product life cycle of a quality heifer program. Additionally, the study researched cattle buyers' preferences for different types of calf groups with respect to an individual's appetite for risk. It is important to understand the factors that are likely related to beef producers adopting technology because it gives a glimpse of future producers in the industry. It is also important to explore whether value-added beef products receive premiums. This information is valuable to producers because it can help them decide whether to invest in producing value-added heifers. In addition, it is important to identify characteristics of buyers who prefer to buy value-added calves. Such information will help producers know whether a market exists for their products.

Chapter 2 uses Missouri cow-calf producer survey data to examine the impact that producer, operation and management characteristics; production risk; and location have on the adoption of beef reproductive technologies. The results show that producer, operation and management characteristics and production risk influence adoption of AIES. The operation type and production risk variables have the most influence.

Chapter 3 shows the marginal implicit values of value-added heifers, and their traditional characteristics. The marginal implicit value of heifers that used sires with high-accuracy EPDs showed that there was a premium for Tier II heifers. The higher value-added product appears to be in the infancy stage of its product life cycle. The Tier II heifer program started in 2008. In that year, Tier II heifers received a discount of $78 compared with regular Show-Me-Select Heifers. In 2009, the Tier II heifers received a premium of $33. In 2010, the premium increased to $111. An investment in marketing could increase producer participation in the Tier II heifer program, and it would likely improve buyers' understanding of the program and increase their willingness to pay for high-quality Tier II animals.

Chapter 4 shows that buyers who are high risk-takers will buy calves born to females bred through natural service by bulls. Buyers who are slightly risk-taking to moderately risk-averse will prefer calves born to females bred through AIES with high-accuracy sires. This group may reflect individuals with better education, more wealth and more innovativeness. On the other hand, buyers who are strongly risk-averse will buy mixed lots of calves. Buyers who are strongly risk-averse are expected to buy mixed lots because they want to diversify their investments. It is shown that the AIES technology used to breed female cattle and to produce high-quality offspring is desirable to feeder cattle buyers who are slightly risk-taking to moderately risk-averse. If a buyer becomes more educated, wealthier or innovative, that person's risk preferences may change and cause them to be less risk-averse. As a result, they may change to buying calves that were born from an AIES-bred heifer.

Understanding the factors that influence beef technology adoption can lead to better understanding the future structure of livestock operations, which will face changes in demand and increased competitiveness. A new stacked value characteristic in heifers – quality heifers bred to a sire with high accuracies – shows that value-added livestock can receive premiums. Buyers who are slightly risk-taking to moderately risk-averse prefer to buy calves created through AIES technologies. By understanding potential buyers of products created through technology, producers can better understand buyers who would be interested in buying their products.

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VITA

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