Beef Reproductive Technology Adoption- Impact of Production Risk and Capitals

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The United States beef industry has a competitive advantage in the world supply of beef because of the industry's ability to meet the consumers' demand for high quality beef (Patterson, Wood, & Randle, 2000). Recently, the United States has trailed Brazil in the adoption of artificial insemination in the beef industry (Patterson et al., 2000). Artificial insemination along with estrus synchronization are technologies that can aid in reproductive management in herds. These technologies can increase production efficiency, as well as enhance genetic characteristics that can create higher quality beef. However, the adoption of these technologies is < 10%. Therefore, it is critical to identify the factors that influence adoption of technology in the beef industry.

Technology adoption has been widely investigated in agriculture mainly in the area of crop production. Factors for the adoption of crop technology 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 the adoption of technology (as cited in Koundouri et al., 2006). These factors can be used to determine if they influence adoption of technology in the livestock industry. Also we will look at how capitals such as, natural, human, social (trust) and produced capital (Bebbington, 1999) affect producers' technology adoption. The objective of this study is to explain the impact of natural, human, production and social capital, as well as production risk, on adoption of beef reproductive technology using the cow-calf producer survey data.

The findings of this research suggest that AI technology adoption is influenced by human capital, measured by age and information usage, as well as natural capital, represented by nine Missouri regions. Age is shown to have an inverse relationship to AI technology adoption, while

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information usage has a positive influence on adoption. The AI adoption intensity model points to human capital and production risk playing a role. Human capital measured by willingness to use carcass data information in production is shown to have a positive influence on intensity of AI adoption. Production risk measured by the percentage of replacement heifers raised within the operation is found to have a positive influence on intensity of AI adoption. The results of the interaction between production risk, measured by percentage of replacement heifers raised on the operation, and human information capital, point to producers being less likely to adopt AI technology intensively to hedge against production risk when a producer is willing to use carcass data in their operation.

The results that look at the complementary technology usage of estrus synchronization, that can be used to increase the efficiency of AI administration, point to human, social and natural capitals having an influence. Human capital measured by age and information usage of culling cows due to calf performance have a negative and positive influence, respectively, on estrus synchronization adoption. Social capital (trust), measured by being a member of a registered cattle organization, has a positive influence on estrus synchronization adoption. Natural capital, measured by the inclusion of regional variables, e.g., nine Missouri regions, influences estrus synchronization adoption.

Literature Review

Most research in technology adoption in agriculture has been focused on crop production. However, there are a few studies that have looked at technology adoption in the livestock sector. There are several studies that have investigated technology adoption in the dairy industry (e.g., Foltz & Chang, 2002; El-Osta & Morehart, 2000; Saha, Love, & Schwart, 1994; Abdulai & Huffman, 2005); whereas, fewer studies have looked at technology adoption in beef production. Wozniak (1987) looked into early adoption of a cattle feed additive among Iowa farmers. Also, Wozniak (1993) looked at the adoption of growth hormone implant technology, along with feed additive technology in Iowa. One aspect of Ward, Vestal, Doye, and Lalman (2008) is the adoption of reproductive management practices of Oklahoma cattle producers. They specifically analyzed adoption given a defined breeding season, whether cow/heifer pregnancy exams were performed and whether bulls were checked for soundness.

Currently, no research has been found on artificial insemination or estrus synchronization adoption in the beef industry. Adoption of artificial insemination of dairy cattle in India has been studied by Singh, Sinha, and Verma (1979). Singh et al. (1979) found a positive significant association with improved aspiration and extension contact with early adoption using a chi-square test. This suggests the need for research into causality between factors and artificial insemination technology adoption. Other studies have looked at the factors influencing adoption of artificial insemination in different livestock sectors, including the hog industry in the United States (i.e., Gillespie, Davis, & Rahelizatovo, 2004) and buffaloes in India (i.e., Saini, Sohal, & Singh, 1979).

The adoption of artificial insemination requires a heavy investment in managerial skills (Gillespie et al., 2004). Artificial insemination 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 artificial insemination have allowed for more timely production of more consistent animals (Gillespie et al., 2004). Artificial insemination 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 artificial insemination does require some investment in equipment, and that while quality labor is critical since this method does require training. Xu and Burton (1998) noted that the use of estrus synchronization and fixed-time AI could improve herd performance, but they noted that adoption of such technology will be determined by economic forces.

Uncertainty

Agriculture technology adoption has been examined under uncertainty (e.g., Saha, Love, & Schwart, 1994; Purvis, Boggess, 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) have looked at the role production risk due to water shortage plays in irrigation adoption in Greece.

Gillespie et al. (2004) have looked at production risk. They have hypothesized that hog producers who raise breeding stock are more likely to adopt artificial insemination to improve the genetic quality of their stock; however, they did not find a significant relationship (Gillespie et al, 2004). This study will use production risk to explain the adoption of reproductive technology adoption. Specifically, the adoption of artificial insemination technology as a reproductive management tool can be viewed through the same lens of risk reduction as crop technology adoption because cattle producers face reproduction risk. The risk reducing benefits of artificial insemination include, but are not limited to, decreased calving problems along with fewer calf losses (Patterson et al., 2000). In addition, cattle producers who use artificial insemination improve the genetics of their herd by keeping the heifers of artificial inseminated cows (Patterson et al., 2000). Production risk of producers can be measured through their reproductive risk exposure of their operations in addition to the degree of dependability on the operation for their livelihood.

Empirical studies have addressed risk by including location dummy variables where some have been found significant (e.g., Colmenares, 1976; Cutie, 1976 as cited in Feder et al., 1985). One's level of risk can be related to the specific uncertainty related to their region. The location of the producers can indicate natural capital. Natural capital includes the environment and resources one has available.

Human Capital

Human capital has been used as a factor to explain technology adoption. Human capital is the skill and knowledge that an individual possesses. In citing Welch (1978), Feder et al. (1985) recalled that human capital contributes to agricultural production through work ability and allocative ability. Schultz (1981) has suggested that human capital reflects the effectiveness and productivity of persons as economic agents (as cited in Singh, 2000). Human capital has been found to affect farmers' decision to adopt technology. In the technology adoption literature, proxy variables for human capital have included age, information gathering and experience (e.g., Wozniak, 1987). In addition, education has been used to measure human capital (e.g., Wozniak, 1987; Abdulai & Huffman, 2005; Wozniak, 1993).

Social Capital

Feder et al. (1985) has emphasized the importance of the role of the social environment in technology adoption. However, this idea has been sparsely even attempted to be looked at in the literature. Putnam (1993) has measured social capital by the number of organization membership, indicating an individual's level of trust and leading to mutual trust within an organization.

Saini et al. (1979) has been one of the few studies that have investigated the relationship between social participation and technology adoption. They have found that social participation, which was measured by the level of participation in social institutions, has a positive relationship to adoption of artificial insemination in buffaloes in India (Saini et al., 1979). They have used the method of calculating the correlation coefficient (Saini et al., 1979). It has been found that tribal affiliations have a positive relationship to technology adoption (Isham, 2000).

Production Capital

Production capital can be measured by looking at the financial information and herd structure of the producer. According to Just and Zilberman (1983), they have found a correlation between the adoption of technology and economies of size which indicated that larger firms were more likely to adopt sooner as compared to smaller firms (as cited in Vestal, Ward, Doye, & Lalman, 2006). Saini, Sohal, and Singh (1979) have found that farm size and herd size was not related to buffalo artificial insemination adoption in India by performing correlation coefficients. Singh et al. (1979) have not found a significant association with socioeconomic status, herd size, number of dairy cows and size of land holdings to artificial insemination technology adoption in India. Economies of size have been found for beef cow-calf operations (Langemeier, McGrann, & Parker; Miller et al.; Ramsey et al., Short as cited in Ward et al., 2008). Gillespie et al. (2004) have pointed to the importance of the goal structure of the producer whether it is profit maximization or lifestyle goals.

This study differs from previous research in the following ways. First this study looks at artificial insemination and estrus synchronization adoption in cattle producers, which is an important factor in enhancing productivity. This paper will incorporate trust into 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 contribute to the literature by examining the role social capital plays into a technology adoption model under uncertainty and incomplete information. One will be able to see if livestock producers adopt technology in order to hedge against production risk like crop farmers. The influence of social capital, trust, in agriculture technology adoption has not been investigated in the context of a developed country. In addition, this study will add to the sparse literature that investigates intensity of technology adoption.

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. This study extends their work by also examining intensity of adoption through using the hurdle model framework. In addition, this study will introduce social capital into the reduced form model in order to determine the influence of trust on technology adoption and whether one's level of trust affects the producer's response to risk.

Producers are assumed to be risk averse utilizing a vector of inputs to produce an output with a technology represented by a well-behaved production function $f(\cdot)$. Output prices are denoted by $\mathbf{p}$, while input prices are defined by $\mathbf{r}$. The producer is faced with production risk related to reproduction which is related to whether all females will calve and their calves survive to market sell time. This risk is affected by nature. This risk is introduced by using e, a random variable whose distribution is considered to be exogenous to a producer's action. Only production risk is considered, as output and input prices are assumed nonrandom (i.e., producers are assumed to be price takers in both markets).

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 $h(\alpha)$ within the production function. Producers are heterogeneous in that reproductive efficiency is reliant upon the producer's characteristics and management of the operation which is represented by the vector α within $h(\cdot)$. A producer that is risk-neutral has a ratio of input prices to output prices equal to the reproductive input's expected marginal product.

Now, the producer's decision on whether to adopt a reproductive technology will be incorporated into the previous general model. 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 the production risk.

It is assumed that future profit streams following adoption are not known with certainty which could be due to not knowing the expected technology performance or not knowing how to properly run the technology. The adoption of technology does include sunk costs. For these reasons, further information may provide additional value; producers may delay adoption in order to get more information. Therefore, a premium could enter the adoption condition. A producer's value for new information is dependent upon the fixed cost and uncertainty of the technology along with the producer's characteristics.

This study will be using human, produced, social and natural capital along with production risk which will influence the value of new information to the producer. The literature suggests some hypotheses that will be tested-

- *H1- Human capital will significantly influence technology adoption with age having a negative influence and information gathering and usage having a positive influence.*
- *H2-Social capital will have a positive significant relationship on technology adoption*
- *H3- Produced capital will have a positive significant relationship on technology adoption through herd size.*
- *H4- Natural capital will have a significant relationship on technology adoption.*
- *H5- Production risk will have a positive significant relationship on technology adoption.*

Procedures and Empirical Model

A University of Missouri 2008 survey on 193 cow-calf producers provided information on producer and operation characteristics such as producer age and experience, size and composition (commercial, purebred, and/or registered) of operations, and cattle breeds. Nearly 1200 surveys were distributed, 200 were returned with address unknown, and approximately 200 surveys were returned completed. The survey covers the areas of demographics, farmographics, herd structure, on- and off- farm income, location, use of AI and estrus synchronization, herd replacement method, and calf management and marketing practices.

The survey showed that 18% of producers used artificial insemination, while almost the same amount used artificial insemination and estrus synchronization. Across the United States, 7.6% of producers use artificial insemination while the percentage of individuals who use estrus synchronization is almost identical (USDA, 2009).

The structural equation can not be estimated, so a reduced form is estimated. The uncertainty cost premium represents the value of gaining more information. In the empirical model, proxy variables for the producer's human capital represent the role of information in the producer's adoption decision. Human capital is captured by age, whether a producer culls cows due to calf performance and whether the producer wants to use performance data in their decision making. In addition, this model adds to Koundouri et al. (2006) by using social capital as well. The human and social capital variables are assumed to be positively correlated with the farmer's level of information.

The equation to be estimated is:

$$Y_{1i} = \mathbf{z}'_{\mathbf{1i}}\boldsymbol{\alpha}_{\mathbf{1}} + \mathbf{m}'_{\mathbf{1i}}\boldsymbol{\alpha}^{\mathbf{m}}_{\mathbf{1}} + [\mathbf{m} \times \mathbf{k}]'_{1i}\boldsymbol{\alpha}^{\mathbf{k}}_{\mathbf{1}} + v_{1i}, \quad (1)$$

Vector **z** includes all capital variables, **m** is the vector of production risk which brings uncertainty into the model and **[m** x **k]** is the vector that contains the interaction of production risk and the capitals of human and social. The vector $\boldsymbol{\alpha}$ is the set of parameters to be estimated and $\boldsymbol{v}$ is the error term.

Based on the empirical studies that are mentioned in the literature review, the **z** vector of explanatory variables for the capitals of human, social, production and natural will be taken from the survey results.

Three models are estimated. The first model's dependent variable is a binary variable on whether an individual adopts artificial insemination. The second model looks at the influence on the intensity of adoption by using the percentage of the herd that is artificially inseminated as the dependent variable. The third model, much like the first, looks at estrus synchronization adoption with the dependent variable being binary 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} in N $(0,\sigma^2)$ and that $\Phi(\cdot)$ is the cumulative of the normal distribution. The specification of this model can be seen in the equation below. In addition, a truncated regression model is estimated to look at the intensity of adoption that will be conditional on whether Y_i in (*) is equal to 1 with the dependent variable as the percentage of the herd in which an operator uses artificial insemination, while the explanatory variables used are the same as in the first model. The truncated regression is truncated at one, such that the empirical model specification is:

(2) Adoption of AI = *f*(human capital, social capital, produced capital, natural capital, production risk, production risk*human capital, production risk*social capital).

(3) Intensity of AI Adoption= *f*(human capital, social capital, produced capital, natural capital, production risk, production risk*human capital, production risk*social capital).

(4) Adoption of Estrus Synchronization = *f*(human capital, social capital, produced capital, natural capital, production risk, production risk*human capital, production risk*social capital).

Results

Proxy variables are used to measure the capitals of human, production, social and natural, along with production risk. Proxy variables for human capital are age, whether an individual would like to use carcass data for production, and whether an individual culls cows due to calf performance. The last two variables of human capital point to the aspect of information use in human capital. The proxy variable for social capital is whether an individual raises registered cattle. This variable indicates that a person belongs to a registered cattle organization. This variable represents an association where trust can be fostered. Production capital is represented by herd size. Production risk is captured by the percentage of replacement heifers that a producer raises. Natural capital is represented by nine regions of Missouri as cited in Horner et al. (2009). Production risk is measured by the percentage of replacement heifers a producer raises on their operation.

In addition, the interaction term for human capital and production risk is created by using age multiplied by the percentage of replacement heifers one raises. The other human capital and production risk term is created by whether an individual would like to use carcass data in production multiplied by the replacement heifers raised. The social capital and production risk interaction term is created by whether an individual raises registered animals multiplied by replacement heifers raised. The following tables provide an explanation and descriptive statistic of the variables used in the model.

Table 1- Explanation of Explanatory Variables

Variable	Explanation
Age	Number of years old
Use Carcass Data	Producer wants to use carcass data [1=Yes, 0=No]
Registered Herd	Herd Registered [1=Yes, 0=No]
Number of Cows	Number of Cows in Operation
% Heifers Raised On-Farm	% raised on-farm [1=0-25%, 2=26-50%, 3=51-75%, 4=76-100%]
Cull Calf Performance	Performance pre-weaning-factor leads to culling cows- [1=Yes, 0=No]

Table 2- Descriptive Statistic

	Overall				Adopters		Non-Adopters	
Variables	Mean	Std. Dev	#	%	Mean	Std.Dev	Mean	Std. Dev
Age	57.95	14.36			53.83	12.11	58.88	14.68
Use Carcass Data	0.67	0.47			0.89	0.32	0.62	0.49
Registered Herd	0.15	0.36			0.53	0.51	0.07	0.25
Number of Cows	169.69	166.27			184.08	168.09	166.39	166.08
% Heifers Raised	2.53	1.38			3.57	0.98	2.29	1.35
Cull Calf Performance	0.82	0.39			0.96	0.20	0.78	0.41
Valid N (listwise)	143.0				30.00		123.00	
Dependent								
AI Adoption								
Yes			49	0.18				
No			217	0.82				
TOTAL			266					
Estrus Adoption								
Yes			43	0.18				
No			196	0.82				
TOTAL			239					
AI Adoption Intensity%	41.49	33.25	49					

The first two regression model results look at the AI adoption and intensity of AI adoption. The AI adoption model is estimated by a probit regression. However, the intensity of AI adoption is estimated through a truncated regression. The final regression looks at adoption of estrus synchronization, which is estimated by a probit regression. All regressions use the same explanatory variables, which allow one to see the different impacts these variable have on adoption of complementary technologies and intensity of technology adoption.

Table 3- Probit Regression of AI Adoption

Parameters	Coefficient	Standard error	*p*-value
(Intercept)	-4.523	15.227	0.767
Age	-0.068*	0.038	0.075
Use Carcass Data	4.135	15.063	0.784
Cull Calf Performance	1.197**	0.500	0.017
Number of Cows	0.001	0.001	0.392
Herd Registered	1.442	1.054	0.171
% Heifers Raised On-Farm	0.752	3.817	0.844
Regions	0.058*	0.034	0.083
Age*Prod.Risk	0.011	0.011	0.312
Data*Prod.Risk	-0.844	3.770	0.823
Registered*Prod.Risk	-0.000	0.289	0.999

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

The human capital proxy of age and cull calf performance are significant in AI adoption. Age has an inverse relationship, while cull calf performance information has a positive relationship with AI adoption. In addition, the natural capital proxy variable of regions is significant in AI adoption. The following table shows the results of the intensity of AI adoption model.

Table 4- Truncated Regression of AI Adoption Intensity

Parameters	Coefficient	Standard error	*p*-value
(Intercept)	-2488.877	99.473	0.000
Age	4.685	4.916	0.341
Use Carcass Data	2400.125***	100.528	0.000
Cull Calf Performance	-107.216	92.176	0.245
Number of Cows	0.030	0.057	0.597
Herd Registered	-48.410	157.297	0.758
% Heifers Raised On-Farm	624.782***	41.842	0.000
Regions	-0.730	2.639	0.782
Age*Prod.Risk	-1.215	1.294	0.348
Data*Prod.Risk	-577.066***	32.320	0.000
Registered*Prod.Risk	23.099	41.210	0.575

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

When a producer is willing to use carcass data, the less likely he is to adopt the AI technology intensively to hedge against production risk. The human capital of a producer willing to use carcass data in their production is more likely to adopt the AI technology more intensively. The production risk of raising a high percentage of replacement heifers is likely to cause the individual to adopt AI technology more intensively. Human capital plays a role in AI adoption as well in intensity of AI adoption. Production risk plays a role in the intensity of AI adoption. The following table has the results of the adoption of estrus synchronization model.

Table 5- Probit Regression of Adoption of Estrus Synchronization

Parameters	Coefficient	Standard error	*p*-value
(Intercept)	-2.908	18.218	0.873
Age	-0.088*	0.045	0.052
Use Carcass Data	3.178	18.104	0.861
Cull Calf Performance	1.253**	0.542	0.021
Number of Cows	0.001	0.001	0.221
Herd Registered	2.023*	1.127	0.073
% Heifers Raised On-Farm	0.336	4.567	0.941
Regions	0.057*	0.034	0.098
Age*Prod.Risk	0.012	0.012	0.332
Data*Prod.Risk	-0.441	4.533	0.923
Registered*Prod.Risk	-0.183	0.308	0.552

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

Human capital variables of age and cull calf performance information influence adoption of estrus synchronization. They have the expected signs with age having an inverse relationship and cull calf performance information having a positive relationship with estrus synchronization adoption. In addition, social capital (trust) plays a role in estrus synchronization with herd registered having an expected positive effect on estrus synchronization adoption. Also, human capital measured by regions influences adoption of estrus synchronization.

Human capital plays a role in AI adoption, estrus synchronization adoption and intensity of AI adoption. Natural capital influences adoption of reproductive technology adoption. Production risk plays a role in intensity of AI adoption. However, with estrus synchronization social capital influences adoption.

- *H1- Human capital will significantly influence technology adoption with age having a negative influence and information gathering having a positive influence.*-- This hypothesis held in both types of adoption and intensity of adoption
- *H2-Social capital will have a positive significant relationship on technology adoption*.—This hypothesis held with estrus synchronization adoption.
- *H3- Produced capital will have a positive significant relationship on technology adoption through herd size.* —This hypothesis did not hold.
- *H4- Natural capital will have a significant relationship on technology adoption.*—This hypothesis held with both estrus synchronization and AI adoption.
- *H5- Production risk will have a positive significant relationship on technology adoption.*—This hypothesis held in intensity of adoption.

Conclusions and Implications

This research points to human capital playing a role in the adoption and intensity of adoption of reproductive technology in the beef industry. It appears that production risk influences not the initial adoption stage, but rather the intensity of AI technology adoption. Social capital plays a role when an individual uses a complementary, more advanced technology, to increase efficiency of another basic technology. This was demonstrated in estrus synchronization technology adoption. Also, natural capital was found to influence adoption of reproductive technology. Further research should examine the role of social capital in complementary technology usage. Also, the effects of natural capital on technology adoption should be further explored.

Previous research has mainly looked at technology adoption in crop production and has focused on looking at the influence of demographics, socioeconomic and operation structure on adoption.

Koundouri et al. (2006) examined the effects of human capital and production risk on irrigation adoption. This study goes beyond previous research in that it will examine the effects of capitals, including social capital, and production risk on beef technology adoption. The results of this study will allow extension and policy advocates a better understanding of the factors that influence technology adoption in the beef industry. This will allow them to better target individuals for technology education and training. In addition, policy-makers who advocate technology adoption will be better able to develop policies with proper incentives for individuals to adopt technology.

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