Selected Paper Submission

2001 AAEA Meetings
Chicago, IL
August 5-8, 2001

Title: Value of Ultrasound-based Predictions of Carcass Quality Grade

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Subject Area: Production Economics

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Introduction

Since the early 1980s, the beef industry has faced a significant decline in consumer demand (Koontz et al). Fausti, Feuz and Wagner attribute this decline in beef demand to two things: changes in consumer lifestyles (i.e., eating healthier diets that include less beef) and changes in relative prices (i.e., other meat products became cheaper relative to beef products). Today consumer demands for beef have changed, emphasizing quality as the top priority. The challenge faced by the beef industry is that higher quality must be balanced against the need to reduce waste associated with external fat. In order to meet quality demands, some cattle have to be fed longer, which has a negative effect: excess external fat amounts (backfat) rapidly increase.

Current market signals emphasize a desire for high quality beef while holding external fat to an acceptable level. Problems exist, however preventing the clear transmission of demand signals from consumers through the beef supply chain to cattle producers. Inaccurate pricing information as well as producer uncertainty about cattle quality is at the root of the demand problems faced by the beef industry today. The industry would clearly benefit from research that focuses on improving management practices at the cow/calf and feedlot levels of the beef production chain.

Perhaps the most critical production point in the beef supply chain is at the feedlot level just prior to slaughter. Traditionally feeder cattle arrive at the feedlot, get placed into groups to be fed out, and are slaughtered as a group on the same day. In a live or dressed weight pricing system, cattle are sold in pen-sized lots on an average price basis (i.e., every animal in the pen receives the same price). Thus, the same value is placed on all cattle in the same group regardless of individual quality (Brethour, 2000b).

Average pricing cannot provide adequate, accurate information to producers because this system does not allow for price discovery that is based upon the quality of the product. Costs at the feedlot level may be reduced through average pricing, but the accuracy of pricing signals suffers tremendously as a result (Feuz). Producers do not see differentiation in prices for fed cattle while there may be distinct differences in cattle quality. Average pricing does not provide a system of incentives for changes in the production of beef. Since profit is the ultimate goal in the business world and price is the most important signal back to producers, price incentives must be clear in order for production, management and marketing decisions to reflect what consumers want. Price incentives are especially critical between the producer and processor levels of the supply chain (Schroeder et al.).

The three traditional cash pricing systems are live, dressed weight, and dressed weight and grade (Fausti, Feuz and Wagner). Dressed weight and grade pricing (or grid pricing) is actually value-based (i.e., cattle are valued individually using discounts and premiums for specific carcass characteristics). Despite this fact, this method is unpopular among beef producers. Two factors contributing to grid pricing's lack of popularity are: (1) producers don't have complete trust in the subjective carcass grading done by USDA graders; and (2) there is a time lag between when the animal is sold and when the check is received for the sale (Fausti, Feuz and Wagner). Determining which pricing system to use is a critical decision as it dictates which production characteristics will be rewarded. Selling animals based on live weight only rewards producers for average daily gain. In contrast, the dressed weight and grade pricing system rewards quality (Fausti, Feuz and Wagner).

Value-based marketing (VBM, also referred to as grid pricing) represents an alternative to the traditional average price system of marketing finished cattle. The beef industry uses these terms to describe this marketing strategy and its ability to pass signals from consumers backward through each link in the marketing chain to the cow-calf producers (Thonney). These economic signals are clearly and accurately communicated in a VBM system (Cross and Whittaker). It is considered by some to be the ideal strategy for the beef industry to regain market share (Fausti, Feuz and Wagner). In a VBM system, cattle are priced on an individual basis. This means that the correct market signals voiced by consumers are more likely to reach beef producers (Feuz). Each animal receives a price that is based on the quality of the carcass produced when the animal is slaughtered. Animals that meet or exceed standards receive price premiums, and those who fail to meet standards receive price discounts (Fausti, Feuz and Wagner). The benefits of VBM to the beef industry are that prices derived from VBM convey more accurate and complete consumer demand and price information back through the supply chain than an average pricing system (Fausti, Feuz and Wagner).

From the perspective of some individual fed cattle producers, however, VBM may or may not be an attractive option. As a general principle, cattle of above average quality receive a higher price through VBM than they would through average pricing. On the other hand, cattle of below average quality receive a higher price through average pricing (Cross and Savell). Producers typically have a choice of how to price their finished cattle. The dilemma for producers is that this decision must be made at the feedlot before the quality of the cattle is known. Cattle cannot currently be sorted or priced based on the eventual USDA quality grade that is designated to each carcass. Uncertainty related to carcass quality prior to slaughter is a significant obstacle to the adoption of VBM by fed cattle producers (Cross and Savell).

Thane and Whittaker suggest that the beef industry’s future viability would be based on improving production efficiency through the use of strategies involving new technologies such as instrument grading. Since this task would be impossible with traditional grading methods, instrument grading appears to be a necessary condition for the successful adoption and continuation of a VBM system. Instrument grading replaces subjective human grading with objective grading equipment. Some examples of technology which could potentially be used in instrument grading include digital A mode ultrasound and video image analysis (Forrest).[1]

As a result of this situation, suggestions began to be made that instrument grading technology may be the most effective means of improving the marketing of feedlot cattle through a VBM system. Recently, ultrasound technology has been researched for this very purpose. Ultrasound was considered for its potential as a predictor of carcass value and quality prior to slaughter (Whittaker et al.). Using ultrasound to predict the final carcass characteristics of feedlot cattle can increase efficiency and facilitate the transition from average pricing to a VBM (Koontz et al.). The simplest description of ultrasound is the measurement of echoes bouncing off soft tissues (Houghton and Turlington). Sound waves from the ultrasound equipment are passed through a transducer into the animal and reflected off the different tissues in the body. The image created by the reflection of the sound waves is then projected onto a screen for analysis (Houghton and Turlington).[2] According to Brethour (2000b) ultrasound technology can provide the operator with fast results and be affordable at the same time.

Many studies have been done on the usefulness of ultrasound data taken on live animal subjects in predicting carcass merits. The majority of this research has been performed by animal scientists who have focused more on technical considerations and implications for production practices rather than economic applications. McCauley, Thane and Whittaker used ultrasound in their study to predict and classify percentages of marbling using a neural network

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[1] See Forrest for more examples of instrument grading equipment.

[2] See Houghton and Turlington for more description of the ultrasound process.

based boolean logic technique known as Adaptive Logic Networks. These ultrasound measurements were taken with a different kind of ultrasound equipment than Brethour used on the data set used in this research.[3] Perkins, Green and Hamlin conducted a study using ultrasound technology and two relatively inexperienced ultrasound technicians to predict carcass backfat and marbling. They found that ultrasound measurements taken on cattle before slaughter were reasonably accurate in predicting backfat and marbling.

In 1991 Brethour found correlation between ultrasound estimates of marbling and carcass marbling (Brethour 2000a). Herring et al. (1998) also found correlation between these two variables in a study on the accuracy of four real-time ultrasound software systems. They found correlation with two of the four ultrasound systems analyzed in their study. Another study by Thane and Whittaker tested for correlation between ultrasound marbling estimates taken on live cattle and actual marbling scores as well as ultrasound marbling estimates taken on the same cattle after slaughter and the actual marbling scores. They found that the ultrasound estimates taken from live cattle correlated better with actual marbling scores than did the estimates taken from the slaughtered cattle. This discovery is extremely important because it proves that ultrasound estimates can be used in predicting actual carcass traits.

Brethour (2000b) utilized a model for marbling that was nearly 80% accurate in determining if a carcass would grade Choice or not. His research is the most similar in comparison to the research that is conducted in this paper. In this research Brethour used and compared three kinds of models testing the accuracy of backfat and marbling ultrasound estimates. Brethour does not however, attempt to determine what if any economic benefits ultrasounding live cattle might hold. Brethour only tested the accuracy of ultrasound estimates

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[3] See Brethour (2000b) for a complete description of the ultrasound equipment used to obtain the data set used in this research.

taken at different times during the feeding period. Few have focused on the economic aspect of ultrasound research.

Walker identified the factors determining the economic benefit of ultrasounding cattle as feedlot management preference, demographics of the cattle, and accuracy of the marketing method used. Koontz et al. evaluated these benefits by measuring the economic returns to feeding operations that sorted animals into pens for the duration of the feeding process. The sorting process was based on ultrasound readings and the pens were determined based on similar return potential of cattle weights, yield grades and quality grades. The ultimate goal of their work was to determine the value of being able to pinpoint the optimal marketing timing of fed cattle. Their study found that sorting cattle at the feedlot returned \$11-\$25 per head. These figures are based on a technique known as backcasting where the ultrasound technology is assumed to be 100% accurate in its predictions. As a result, this assumption places a higher estimate of returns on the sorting procedure then one would realistically expect. Lusk et al. reported average revenue increases of \$5.33 per head. Skalland was cited in Lusk et al. reporting average revenue increases of \$10 per head to \$17 per head respectively.

Objectives

This paper will take a different look at the use of ultrasound to achieve the general objective of assessing the potential of ultrasound data on live animals to reduce uncertainty related to quality grade prior to slaughter. This research is unique as its methodology provides an empirically sound framework for evaluating ultrasound predictions under a variety of market conditions. In contrast to Brethour (2000b), this research will be more specific by concentrating on the carcass trait, marbling. This analysis will use a more straightforward, simplistic version of the modeling used in Brethour. Where Brethour's research ends at predicting carcass traits, this research will continue to explore the economics of ultrasound research. The task of placing a value on ultrasound technology will be taken one step further than the work of Koontz et al. by also addressing optimal marketing methods. Koontz et al. measured the economic returns of sorting cattle and this research will measure the value of information derived from the predicting ability of ultrasound data.

Specific objectives of this paper are twofold: (1) to predict carcass quality grade from ultrasound measurements; and (2) to estimate the value of the information provided by carcass quality grade predictions based on ultrasound estimates. To achieve the first objective, ultrasound data will be used in a logit model to estimate the probability of an individual animal grading USDA Choice or higher. The second objective—determining the value of ultrasound-based predictions—will be accomplished using a Bayesian analysis framework.

Data and Methods

Ultrasound data collected and provided by Brethour (Personal Data Set) was used to estimate the probability of an individual animal grading USDA Choice or higher (> = Choice). The initial data set consisted of 292 Angus and Angus X Hereford steers with an average age of 12 months and an average placement weight of 390 kg. Soon after arrival at the feedlot, an initial ultrasound estimate for marbling was taken. About 90 days later a second estimate was taken. Brethour, who is certified by the Animal Ultrasound Practitioners Association, made all of the ultrasound estimates. Marbling measurements were taken until a consistant estimate could be found. The cattle were on feed for an average of 148 days and were group-fed in pens of 25.

This data was also used in a previous study by Brethour (2000b) focused on using ultrasound data to predict carcass characteristics.[4] All of the cattle were processed at the IBP

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[4] Further detail of the data used in this paper can be found in Brethour (2000b).

plant in Emporia, Kansas. Processing the steers for Brethour's study was completed when an experienced USDA grader estimated marbling scores to the nearest 0.1 unit.

The actual USDA quality grades assigned to the cattle in this data set are influenced by what are known as regards. That is, the IBP plant at which the cattle were slaughtered felt as though some of the cattle were not correctly graded. In these cases, the carcasses were railed or set aside until they could be regarded or re-graded by another USDA grader. However, since IBP is paid based on these quality grades regardless of how they may be determined, it is still appropriate to use this data in this analysis (Brethour, Personal e-mail).

Due to incomplete data, observations on 80 of the steers were removed prior to modeling the data. The final data set consists of observations on 212 animals. Table 1 shows a summary of the data. Marbling scores range from 1 to 10 with 10 being the highest amount of marbling (Brethour, Personal e-mail). The average carcass marbling score for this data set is 5.64, which is representative of a low Choice carcass.

The set of 212 cattle were priced using both live and grid pricing systems. A base price ($107/cwt) for the grid pricing system was taken from the average price for 500 to 700 pound weekly boxed beef cutout values from January of 1996 to January of 2001. The live price ($65.75/cwt) used in this research was the average weekly Western Kansas live price for 1100 to 1300 pound steers from January of 1996 to January of 2001 (Livestock Marketing and Information Center). Average carcass premium and discount values added to the base price were taken from *National Carcass Premiums and Discounts for Slaughter Steers and Heifers* covering the period from October 1996 to December 1998 (USDA-AMS). Premiums and discounts for USDA quality grades, USDA yield grades and carcass weights were used.

Table 2 shows the pricing data used to determine the value of each animal in both live and grid pricing systems. For simplicity, the base price, live price and average premium and discount values were all rounded to the nearest \$0.25. The live price value of an animal is determined by multiplying the live price by the slaughter weight of the animal. The grid price value of an animal is determined by adding or subtracting premium and discount values based on the quality grade, yield grade and carcass weight of the animal from the base price. This new modified base price is then multiplied by the slaughter weight of each animal. Average grid and live revenue per head are determined for the steers that graded Choice or better and the steers that graded less than Choice.

The probability models were estimated with a binary quality grade variable (< Choice; >= Choice) as a function of the ultrasound marbling estimates. Quality grade is obviously not binary. There are, in fact, four relevant quality grades for finished cattle (Prime, Choice, Select, Standard). However, on most VBM price grids, cattle grading Choice or higher will not be discounted (and may receive some premium) while cattle grading less than Choice will be discounted (Fausti, Feuz and Wagner et al.). Thus, in evaluating which pricing method (average or grid) will maximize returns for a given animal, the critical distinction is whether the animal's carcass will grade Choice or not. For this reason, a binary choice model was appropriate for this investigation.

The estimation of two probability models using two different levels of ultrasound information will permit comparison of the value of ultrasound readings taken at different times in the feeding process. These models are represented as follows:

(1) $QG = \mathrm{f}(MB1)$, and

(2) $QG = \mathrm{f}(MB2)$,

where *QG* is a binary variable indicating whether a carcass is Choice or Not Choice; *MB1* is the ultrasound estimate of marbling taken upon arrival at the feedlot and *MB2* is the ultrasound marbling estimate taken 90 days into the feeding period. The probabilities derived from these models will be used in the Bayesian analysis to determine the value of the ultrasound data.

The logistic distribution forms the basis for the logit models. The logistic cumulative distribution function is given by the following (based on Greene, p. 638):

$$\text{(3)} \qquad \text{Prob(Y=1)} = \frac{e^{\beta' x}}{1+e^{\beta' x}},$$

where β is a matrix of coefficients and $\boldsymbol{x}$ is a matrix of independent variables (*MB1* and *MB2*). In each of the models above, the independent variable (*QG*) has a value of 1 if the observed quality grade is USDA Choice or higher and a value of 0 if the observed quality grade is lower than USDA Choice (i.e., Select or Standard).

In a logit model, maximum likelihood estimation (MLE) is used to estimate values for β. The probit model (i.e., a binary choice model based on the normal distribution) is also commonly used in estimation with a binary dependent variable. The logit model was chosen for this application because of its mathematical convenience. In most situations, logit and probit models yield consistent probability estimates (Greene).

Determining the value of ultrasound-based prediction was accomplished using Bayesian analysis.[5] The states of nature (θ) used in the ultrasound analysis are quality grade > = Choice (θ_1) and quality grade < Choice (θ_2). These states of nature represent the two subsets of cattle that represent the basic units of analysis throughout the paper. The logit models calculate the probability that a given animal will fall into one of the groups, and the results of valuing the

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[5] See Eidman, Dean and Carter for a description of the Bayesian analysis process.

cattle using grid and live pricing systems in chapter three are reported for the same groups. This information can be incorporated into the decision evaluation through the application of Bayes' formula (Anderson, Dillon and Hardaker):

$$(4) \qquad \text{Prob}\left(\theta \mid \text{Z}\right) = \frac{\text{Prob}\left(\theta\right)\text{Prob}\left(\text{Z} \mid \theta\right)}{\text{Prob}\left(\text{Z}\right)},$$

where θ again represents a given state of nature and Z represents a prediction related to that state of nature.

Pricing cattle on either grid or live basis represents a choice between two marketing strategies for fed cattle. These marketing strategies become the actions (grid (a_1) and live (a_2)) that could be taken by a cattle producer given the states of nature in which he produces. The final element needed to begin the Bayesian analysis of the ultrasound data is to identify the prior probabilities P(θ). Again, these probabilities are subjective expectations regarding the states of nature. In the ultrasound analysis, the prior probability $P(\theta_1)$ is 0.65 for quality grade > = Choice and the prior probability $P(\theta_2)$ for quality grade < Choice is 0.35. These probabilities were chosen based on an assumption that the majority of the cattle in the data set would grade > = Choice. The conditional, joint, and posterior probabilities are calculated and used to calculate the marginal value of the ultrasound data. This value represents the per head benefit that incorporating the ultrasound data into the decision process can bring to a cattle producer.

Results

Live and grid pricing results are summarized in Table 3. The first numbers reported are the average grid prices for the cattle. The revenues summarized in this table were calculated using the pricing data presented in Table 2. Average revenues using both pricing systems are reported for all cattle and then broken into Choice and Not Choice cattle groups. The disincentive to adopt grid pricing is evident in this table of data. The difference in average revenue between Choice and Not Choice cattle for the grid pricing system is $74.30. In contrast, the average difference in revenue between Choice and Not Choice cattle for the live pricing system is only $2.34. This illustrates the fact that live pricing does not discourage the production of lower quality cattle. This is the current state of the market for fed cattle. A producer who does not know what his cattle will grade has an incentive to price cattle on a live basis to avoid the risk of losing revenue on lower quality cattle. On a grid a producer runs the risk of receiving significant discounts if his cattle are of a lower quality than expected. On average Choice cattle receive $27.07 more in total revenue when priced on a grid than when priced in a live pricing system. The higher quality of the cattle is rewarded through grid pricing with more premiums and fewer discounts. Not Choice cattle receive on average $44.62 less in total revenue when priced on a grid than when priced in a live pricing system.

The results of the two logit models (equations 1-2) used in this research are reported in Table 4. The coefficient estimates as well as the standard errors for the coefficients are also reported in Table 4. The signs on the estimated coefficients in the models are consistent with economic theory and beef industry structure. In particular, *MB1* has a positive relationship with *QG* in Model 1 and the *MB2* variable has a positive relationship with *QG* in Model 2. The positive marbling coefficients for *MB1* and *MB2* indicate that as these coefficients increase, the probability that an animal will grade Choice is increased. This relationship is expected since marbling is the primary determinant in the quality grade assigned to a beef carcass (Fausti, Feuz and Wagner). In the first model using *MB1* as the primary independent variable, both the intercept and *MB1* are significant at the 0.01 level. The second logit model using *MB2* in place of *MB1* had a similar outcome. In this model, both the intercept and *MB2* are also significant at the 0.01 level.

The estimated coefficients in each of the logit models were incorporated into the logistic function (equation 3) to begin the process of deriving the posterior probabilities for the Bayesian analysis. A subjective decision threshold was then used as a benchmark to interpret the probability estimates from the logit models. In this analysis, a decision threshold of 0.80 was used. That is, the probability estimate obtained from the logistic distribution function had to be at least 0.80 in order to assume that the model was predicting an observation to be Choice.

The 212 data observations for quality grade were used in combination with the logistic function results in a contingency table to specifically evaluate the accuracy of each predicted observation from the logistic functions. The results of the evaluation of the logit models are shown in Table 5. This contingency table consists of the number of true positive, true negative, false positive and false negative observations. In this example positive refers to Choice cattle and negative refers to Not Choice cattle. For example, an animal will be true positive if its probability estimate is greater than the decision threshold and its USDA quality grade is Choice or higher. That is, the animal was predicted to be a Choice animal by the logit model and was a Choice animal according to the USDA quality grade. An animal will be false positive if its corresponding probability estimate is greater than the decision threshold but its actual USDA quality grade is less than Choice.

True positive, true negative, false positive and false negative fractions are also presented in Table 5. The true positive fraction, for example, is calculated by taking the total number of observations that are true positive and dividing it by the total number of actual Choice cattle in the data set. In the Bayesian analysis, these fractions are used to derive posterior probabilities and are analogous to the price forecasts in the example from chapter two.

There were 177 Choice and 35 below Choice cattle in the data set. Model 2 provided the most accurate prediction of Choice cattle by correctly identifying 145 true positive observations or about 82% of the actual number of Choice cattle. The model falsely identified (false negative fraction) the remaining 18% of Choice cattle as less than Choice. Model 1 correctly identified 138 true positive observations or about 78% of the actual number of Choice cattle respectively. Model 1 and Model 2 correctly identified 23 and 26 true negative observations or about 66% and 74% of the actual number of Not Choice cattle respectively.

Looking at the fractions in combinations, Model 2 has the highest total percentage of correctly predicted quality grades (82% Choice and 74% Not Choice). Model 2 also has the lowest total percentage of incorrectly predicted quality grades (26% Choice and 18% Not Choice). The least effective model in accurately predicting quality grade is Model 1. Model 1 correctly predicted 78% Choice and 66% Not Choice while incorrectly predicting 34% Choice and 22% Not Choice.

The Bayesian analysis results will show if the previous results favoring Model 2 are repeated when the value of the ultrasound information from each model is determined. The two states of nature in this analysis were quality grade < Choice and quality grade >= Choice. The subjective prior probabilities associated with each state of nature were 0.35 for < Choice observations and 0.65 for >= Choice observations (i.e., subjective expectation that 65% of cattle in the pen will be >= Choice and 35% will be < Choice). The actions evaluated are pricing cattle on a grid and live basis.

The results of the Bayesian analysis done on Model 1 and Model 2 are shown in Tables 6 and 7, respectively. Many of the components of these tables are identical in both models. The prior probabilities discussed above are a constant in this Bayesian analysis. The values associated with the actions in each state of nature come from Table 3.1. These values are the average revenues per head using both actions (grid or live pricing) in both states of nature (>=Choice carcass or <Choice carcass). The results of the expected values of the actions using the prior probabilities (the no data problem) are the same in all three models since the same revenues and prior probabilities are represented in all of the models. Without any data, the optimal decision given the prior probabilities is to take the action associated with the average revenue per head of \$847.07 (price the cattle on a grid). In this case grid pricing averages just under \$2.00 more per head in revenue than does pricing cattle using the live pricing system.

The posterior probabilities derived for both models are summarized in Table 8. These numbers represent the probabilities of each state of nature given a certain prediction ($P(\theta|Z)$). The value of the data calculated for both models is also shown in Table 8. Model 2 has the highest value of \$8.42 per head, followed by Model 1 with \$6.38 per head. The value of a perfect predictor, that is an analysis with a model that is 100% accurate in predicting quality grade, is the same in both models with a value of \$15.62 per head.

The second ultrasound estimate is truly the strongest quality grade predicting variable in this analysis. Again, this second estimate was taken about 90 days after the first ultrasound estimate and about 58 days before the cattle were slaughtered. Therefore, these results show that of the two points in the feeding period the optimal time to conduct an ultrasound estimate is closer to the slaughter date. These results also show that of both combinations of ultrasound estimates Model 2 was the optimal model to use to predict carcass quality grade. For the purpose of this analysis, the second ultrasound estimate data would be the only information beneficial (in terms of value) to determining quality grade before slaughter.

Conclusion

The general objective of this paper was to assess the potential of ultrasound data on live animals to reduce uncertainty related to quality grade prior to slaughter. This study has immediate implications at feedlots to help producers make better marketing decisions about their cattle. Producers can be notified by the feedlot before slaughter as to the quality of their cattle based on ultrasound estimates taken to predict carcass quality. This would reduce producer risk surrounding how and where cattle should be marketed. Producers would also have quicker feedback as to which breeding stock produced the quality of cattle they desire.

In the future, feedlots may be able to use ultrasound technology to sort fed cattle into more uniform groups. While this would commingle cattle from different producers into the same group, the cattle would be more uniform in terms of the composition of carcass traits when they are ready to be slaughtered. Currently, cattle are grouped as lots in which they arrived at the feedlot from the cattle producer. In this case, when the feedlot determines that the pen of cattle is say about 60% Choice, the entire pen will be slaughtered whether or not all of the cattle are ready. Sorting and commingling cattle from different owners can help ensure that each animal is slaughtered at an appropriate endpoint. Obviously, this kind of production system requires that individual animals be identified by owner throughout the feeding process for the purpose of allocating costs. Even if individual animals are identified, allocation of feed costs can be problematic when cattle from different owners are commingled.

Producers contracting with packers to lock in a live price for their cattle are trying to mitigate the risk of price volatility as well as uncertainty surrounding the quality of their cattle prior to slaughter. If the producer feeds his or her cattle at a feedlot using ultrasound technology then the producer has better information about his or her cattle and more options when it comes time to market the cattle. Ultrasound gives producers more complete information necessary to make decisions regarding the marketing of their cattle. Instead of depending on a visual appraisal of the cattle from the feedlot or a contract from the packer, a producer with ultrasound information has an alternative to contracting on a live basis with the packer. While contracting is an existing form of vertical coordination within the beef industry, ultrasound would provide producers with an additional method of vertical coordination where an increase in the quantity and quality of information between the producer, feeder and packer helps transmit clearer market signals originating from the consumer.

The government also has an interest in facilitating the coordination of various agricultural industries as a means of improving source verification. While ultrasound technology per se is not related to source verification, the use of ultrasound technology at the feedlot level may encourage additional management practices such as sorting cattle into more uniform groups and keeping track of them using electronic identification. These management practices and technologies do facilitate source verification within the beef industry. The government would have a great interest in these management practices as they relate to issues of food safety. Identifying a food safety problem and then being able to efficiently and accurately locate the source of the problem has significant value to the government. Thus, in the future it can be speculated that the possibility does exist for the government to become more involved in the increased adoption of a VBM system by taking such actions as subsidizing some of the costs of ultrasound incurred by cattle producers.

The primary limitation of this study is that a limited number of situations were evaluated. Only one set of prior probabilities, grid premium and discount values, base and live prices, decision threshold level, and data were used in this study. Multiple studies similar to the one presented in this paper should be conducted to determine if the results found in this paper could be generalized. Sensitivity analysis needs to be conducted on the prior probabilities, grid premium and discount values, base and live price levels and decision threshold values.

An area for research may be to investigate a real-life example of ultrasound application through a case study on a cow/calf producer operation or a feedlot operation. A look into how ultrasound technology is used in either of these types of operation could yield interesting and useful results. An examination of how ultrasound technology has changed either of the above operations and what kinds of impacts the use of this technology has had on the success of either operation could be helpful as other producers consider the adoption of this technology.

The application of ultrasound research is a vast topic requiring a substantial amount of future research. This paper is a start in the right direction and is a contributing factor to finding a solution to the price information and uncertainty problems faced by the beef industry today.

Table 1: Data Summary

	Marbling Score 1[a]	***Marbling Score 2***[a]	**Carcass Marbling Score**[a]	**Slaughter Weight**[a]	***Quality Grade***[b]
Average	4.11	4.76	5.64	1285.97	2
Standard Deviation	0.39	0.57	0.90	98.32	1
Minimum	3.20	3.27	3.80	928.00	1
Maximum	5.08	6.13	8.80	1513.00	9

[a] Source: Brethour (Personal Data Set).

[b] Source: IBP, Emporia, Kansas as reported in Brethour (Personal Data Set).

Table 2: Summary of Pricing Data

Carcass Characteristic	**Average Premium/Discount ($)**
Base Price[a]	107.00
Live Price[a]	65.75
Quality Grade[b]	
Prime	5.75
Choice	0.00
Select	-7.00
Standard	-17.00
Dark Cutter	-30.75
Yield Grade[b]	
1-2	1.75
2-2.5	0.75
2.5-3	0.75
3-3.5	-0.25
3.5-4	-0.25
4-5	-14.25
5+	-20.00
Carcass Weight[b]	
400-500	-21.00
500-550	-16.75
550-600	0.00
600-900	0.00
900-950	0.00
950-1000	-15.75
1000+	-20.00

[a] Source: Livestock Marketing and Information Center.

[b] Source: USDA-AMS. *National Carcass Premiums and Discounts for Slaughter Steers and Heifers,* October 1996-December 1998.

Table 3: Live and Grid Pricing Results

	Averages ($ per Head)		
	All Cattle	**Choice Cattle**	**Not Choice Cattle**
Grid Price	105.16	106.89	96.41
Grid Revenue	860.76	872.98	798.95
Live Revenue	845.53	845.91	843.57
Number of Observations	212	177	35

Table 4: Parameter Coefficients of Quality Grade Probability Model for Fed Cattle

	Model 1	**Model 2**
Intercept	-11.5142	-11.2244
	(2.4981)	(2.1906)
Marbling 1	3.3142	N/A
	(0.6468)	(N/A)
Marbling 2	N/A	2.8423
	(N/A)	(0.5002)

Note: Standard error values shown in parenthesis.

Table 5: Logit Models Contingency Table

	Data Observations			
	True Positive	**True Negative**	**False Positive**	**False Negative**
MB 1	138	23	12	39
MB 2	145	26	9	32

	Fractions			
	True Positive	**True Negative**	**False Positive**	**False Negative**
MB 1	0.7797	0.6571	0.3429	0.2203
MB 2	0.8192	0.7429	0.2571	0.1808

Table 6: Bayesian Analysis of Model 1

States of Nature (θ)	**Actions (Pricing)**		**Prior Probabilities**
	grid (a_1)	**live (a_2)**	**P(θ)**
Quality Grade > = Choice (θ_1)	872.98	845.91	0.65
Quality Grade < Choice (θ_2)	798.95	843.57	0.35

States of Nature (θ)	**Posterior Probabilities P(θ) P(Z|θ) / P(Z)**	
	Z1	**Z2**
Quality Grade > = Choice (θ_1)	0.8085	0.3837
Quality Grade < Choice (θ_2)	0.1915	0.6163

Actions (Pricing)	**Expected value using prior probabilities P(θ)**
grid (a_1)	847.07
live (a_2)	845.09

Actions (Pricing)	**Expected value using posterior probabilities P(θ) P(Z|θ) / P(Z)**	
	P (θ|Z_1)	P (θ|Z_2)
grid (a_1)	858.8	827.36
live (a_2)	845.46	844.47

Table 7: Bayesian Analysis of Model 2

States of Nature (θ)	**Actions (Pricing)** **grid (a_1)**	 **live (a_2)**	**Prior Probabilities P(θ)**
Quality Grade > = Choice (θ_1)	872.98	845.91	0.65
Quality Grade < Choice (θ_2)	798.95	843.57	0.35

States of Nature (θ)	**Posterior Probabilities P(θ) P(Z|θ) / P(Z)** **Z1**	 **Z2**
Quality Grade > = Choice (θ_1)	0.8554	0.3113
Quality Grade < Choice (θ_2)	0.1446	0.6887

Actions (Pricing)	**Expected value using prior probabilities P(θ)**
grid (a_1)	847.07
live (a_2)	845.09

Actions (Pricing)	**Expected value using posterior probabilities P(θ) P(Z|θ) / P(Z)** P (θ|Z_1)	 P (θ|Z_2)
grid (a_1)	862.27	821.99
live (a_2)	845.57	844.30

Table 8: Summary of Posterior Probabilities and Calculated Values of the Data

	Posterior Probabilities		**Value of**
	P (θ|Z_1)	**P (θ|Z_2)**	**the Data**
Model 1			$6.38
Quality Grade > = Choice	0.808545	0.383742	
Quality Grade < Choice	0.191455	0.616258	
Model 2			$8.42
Quality Grade > = Choice	0.855418	0.311284	
Quality Grade < Choice	0.144582	0.688716	

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