ESSAYS ON SEASONAL VARIATION IN FED CATTLE PROFITABILITY AND THE VALUE OF BEEF BULL ATTRIBUTES

by

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This dissertation is dedicated to my parents, my sister, and their loved ones.

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LIST OF ABBREVIATIONS

ADG- Average daily gain

CCI - Comprehensive climate index

CDF – Cumulative distribution function

C-S – Choice-select

DoF - Days on feed

DP - Dressing percentage

EPD - Expected progeny difference

FG - Feed to gain

FMM- Finite mixture model

FSD - First degree stochastic dominance

HCW- Hot carcass weight

PW - Placement weight

QG - Quality grade

SSD - Second degree stochastic dominance

SPM - Simple performance measure

YC - Yardage cost

YG - Yield grade

VC - Veterinary cost

ABSTRACT

The first essay investigates if bull buyers' marginal valuations of Angus bull attributes have changed over time using 17 years of bull auction data from Indiana. Results indicate statistically significant time effects on some traits (e.g., ribeye area, percent intermuscular fat, ribeye area expected progeny difference [EPD], and maternal milk EPD). Not all of these effects align with prior expectations. Nonetheless, results have important implications for the beef industry in terms of signaling quality ques and incorporating proven information in the form of EPDs.

The second essay identifies heterogeneity in bull buyer valuations of bull attributes across latent class using a FMM. Results indicate evidence that bull buyers have heterogeneous preferences for bull attributes. A three-class FMM is identified as providing the best view of bull buyer heterogeneity. Although results do not perfectly align with the bull buyer segments hypothesized, the end-use of claves produced does influence the latent class identified. These results have implications for beef industry as a whole for the improvement of beef products.

The third essay examines seasonal variation of fed cattle profitability by considering seasonality of choice-select price spread and seasonal weather impact on cattle feedlot performance and carcass characteristics. Seasonality of choice-select price spread is empirically identified and is incorporated into the estimation and simulation of cattle feeding profitability. Results indicate that cattle profitability and variability are subject to the influence of both seasonal weather conditions and seasonality in choice-select price spread. Results could help producers make efficient management decisions through enhanced predictive capacity by using expected seasonal weather information and predicted seasonal price trend.

CHAPTER 1. TEMPORAL CHANGES IN ANGUS BULL ATTRIBUTES VALUATIONS IN THE MIDWEST

1.1 Introduction

Unlike pork and poultry, the beef industry supply chain is characterized by several disaggregated sectors: seed-stock, cow-calf, stocker/backgrounder, feedlot, and processor. The lack of coordination among these sectors makes it difficult to signal consumer preferences upstream to cattle producers. Despite attempts by the beef industry to better align the quality and consistency of beef products with consumer preferences, there remains a lack of evidence that the industry's breeding sectors (seedstock and cow-calf) are properly incentivized to invest in genetic improvements necessary to meet these demands (Thompson, 2018). One way to evaluate the effectiveness of translation of consumer demand into producer investment in genetic improvement is to investigate directly producers' valuations of bull attributes. Bull selection is one of the most important decisions faced by cow-calf producers. Herd bulls represent half of the genetic makeup of marketable calves and are the quickest way to influence genetic progress in the beef herd. Better understanding how producers in the industry's breeding sectors value herd bull characteristics provides an important perspective into the beef industry's progress towards addressing the broader problem of aligning beef products with consumer preferences.

Bull auctions are a common mechanism for the purchase/sale of bulls, making available unique data on both sale price and detailed production information. For this reason, hedonic analyses of bull auction data have been performed by a number of researchers (e.g., Chvosta et al., 2001; Jones et al., 2008; Bekkerman et al., 2013). However, due to data limitations, existing studies tend to focus on the average valuation of carcass quality traits at a particular point in time.

There are a variety of reasons why bull buyers' marginal valuations of some bull attributes may have changed over time but two likely reasons for shifts in these values could be due to the introduction of grid pricing and increased acceptance of expected progeny differences (EPDs) technology. First, grid pricing was introduced in the mid-1990s with the purpose of aligning the quality and consistency of beef products with consumer preferences. Growth in the market share of grid pricing has been steadily increasing as the grid premium and discount structure has slowly adjusted carcass quality market signals to incentivize marketing on a grid (Fausti et al., 2010; Fausti et al., 2014). If this value-based marketing approach has been successful at signaling consumer preferences up the beef cattle supply chain, the marginal valuation of carcass quality characteristics (e.g., marbling and rib-eye area) among the industry's breeding sectors should have likely changed over time to better align end products with consumer preferences. This would be reflected by increasing (decreasing) marginal valuations of carcass traits over time for traits positively (negatively) correlated with higher beef quality.

Second, the perception of information contained in EPDs may be subject to changing valuations among producers. EPDs indicate performance potential of a bull's progeny. EPDs were initially introduced for production traits and have been further developed for carcass performance traits (Walburger, 2002; Franken and Purcell, 2012). According to diffusion theory, time is one of the four main elements in the diffusion of innovation (Rogers, 2003). Therefore, it is hypothesized that as producers become more familiar with this technology and learn how to apply it, they may increase the value placed on EPDs for certain traits. Although EPDs have been around for over three decades, EPD information is believed to be currently underutilized by cow-calf producers (Decker, 2018). Although the concept of learning and familiarization associated with EPDs has been previously discussed (Franken and Purcell, 2012), time effects of learning on valuation of

EPDs are not well studied. It is also possible that the valuations of EPDs have decreased over time if producers overvalued the information contained in EPDs initially.

Researchers have sought to examine the impact of carcass-quality traits and EPDs on the price of bulls. Walburger (2002) examined and compared the roles of reproduction traits (e.g., scrotal circumferences and birth weight), average daily gain, and ribeye area in determining the price of bulls using bull sales in east-central Alberta, Canada from 1989 to 1993 and from 1989 to 2000. Their study identified a fallen trend in importance of reproduction traits relative to average daily gain and ribeye area, and interpreted this as a sign of shift in attribute selection in response to increasing market demand for high quality beef. Jones et al. (2008) also found that one of the carcass EPDs (i.e., ribeye area) has a significantly greater marginal effect on price than either birth weight EPD or yearling weight EPD. Vanek et al. (2008) estimated ranch-specific hedonic regressions using standardized bull auction data from four registered U.S. Red and Black Angus producers during 2005-2006. Parameter estimates were ranked and compared within each regression to decide the relative influence of bull attributes on the price of bulls. They found carcass quality traits ranked as either the first or second most important across the four regressions.

Few efforts have been made to systematically investigate the temporal change of bull attribute valuations over a continuous time frame. Boyer et al. (2019) estimated and compared yearly hedonic regressions from 2006 to 2016 to examine if Southeast U.S. cow-calf producers' valuation of bull attributes have changed over time using bull sale data from Tennessee. Year-to-year regression results offer a non-parametric approach to examining changes in the valuation of various traits. However, inconsistent influences of some bull attributes on the price of bulls over time make it difficult to identify systematic trends in the marginal valuation of bull attributes that a more parametric approach would afford. In addition, their study failed to incorporate carcass quality traits due to data limitations. Franken and Purcell (2012) estimated the average value of a relatively complete set of bull attributes from a pooled model using bull sale data in Missouri from 2000 to 2010. The authors mention an attempt to model time-varying parameters, but ultimately rely on a "more conventional" pooled model given "no systematic trends were identified" (Franken and Purcell, 2012). Applications of hedonic price models to other contexts have more explicitly taken up the issue of changing preferences for attributes over time, mainly in the real estate literature (e.g., Chen and Harding, 2016; Hanson et al., 2018). A more systematic evaluation of potential time effects on bull attribute valuations is needed to address important industry questions, such as quality signaling and learning and familiarization associated with EPDs. Even a null result serves to inform these issues and has implications for the beef industry.

The objective of this study is to investigate if producers' marginal valuations of Angus bull attributes in the Midwest have changed over time. Previous literature has largely overlooked potential temporal effects on the marginal valuations of bull attributes, and those that have considered these effects have fallen short of addressing important industry questions. Data used in this study contain a more complete set of bull attributes observed over an extended time series compared to previous research allowing investigation of potential systematic trends in producers' marginal valuations of bull attributes parametrically. Hedonic price models are estimated using 17 years of bull auction data (2002-2018) from bull auctions in the state of Indiana to investigate the hypothesized changes in producers' valuations of Angus bull attributes over time. It is important to acknowledge that our results are limited in scope by both the time period available and the geography of the data used in this study. Readers should be careful not to generalize our results given that producers in other regions may have responded differently to incentives and information changes for a variety of reasons.

Study results indicate that some Angus bull attributes exhibit statistically significant changes in valuation over time for Midwest bull buyers. Specifically, bull buyer valuations of carcass traits adjusted ribeye area, ribeye area EPD, adjusted percent intermuscular fat, and marbling EPD and reproductive and maternal traits adjusted scrotal circumference and maternal milk EPD show statistically significant changes over the time period studied. However, not all of these effects move in the hypothesized directions. For example, the effects of time on the carcass traits show mixed directional impacts on bull values (some increasing in value and others decreasing). Nonetheless, important industry implications can be drawn from these results.

1.2 Conceptual Framework

The price of a bull is determined by the value of the characteristics and attributes it possess. Rosen (1974) set forth the theoretical foundation for the hedonic pricing model adopted in this study. Each individual bull, $Q_i\ (i = 1, \ldots, n)$, possesses a bundle of characteristics or attributes $X_{ij}\ (j = 1, \ldots, J)$. Collectively, the J attributes in X_{ij}, where $X_{ij} = \{X_{i1}, \ldots, X_{iJ}\}$ make up Q_i. The price of bull i, P_i, can be specified as a function of its characteristics, $P_i = f\left(X_{ij}\right)$. Coefficient estimates from the hedonic regression, β_j, then indicate the marginal valuation of attribute j.

Temporal variation of β_j in the hedonic model has rarely been investigated. Most existing studies applying the hedonic model to bull prices implicitly enforce the assumption of constant valuation of bull attributes over the time period evaluated. Constant valuation may be reasonable in the short run when market structure is stable, especially in cases where cross-sectional data are used. That is, at any point in time, the supply of bull attributes is fixed because many bulls are available for sale at various competing auctions (Blank et al., 2016). Therefore, prices of a particular set of bull attributes are ultimately determined by the demand for them, and the demand is largely driven by prevailing economic factors (Vestal et al., 2013).

In the case of cross-sectional time-series bull auction data, the above assumption of constant attribute valuations is violated given that changes in market factors may directly influence the valuation of certain traits, and β_j becomes the average marginal effect across the entire time period evaluated hiding potentially important time effects. For example, changes in incentives and information are likely to influence the value that producers place on certain bull attributes. Therefore, time plays an important role and needs to be internalized into the valuation of bull attributes. Expressing the marginal valuation of attribute j as a function of time t, $\beta_j(t)$, represents the marginal valuation of attribute j at time t. In other words, bull attribute valuations are specified as a function of time to test the hypothesis of temporal variation in bull buyer valuations of bull attributes and investigate the time path of these changes.

1.3 Data

Data used in this study were provided jointly by Indiana Beef Evaluation Program (IBEP) and bull owners who subscribed their bulls for testing. The IBEP for bull testing and sale has been conducted for more than 40 years at Feldun-Purdue Ag Center in Bedford, Indiana (IBEP, 2019). This performance test program provides cattle producers with an opportunity to evaluate their bulls for growth performance and carcass characteristics as well as structural and breeding soundness. IBEP Bull Sales consist only of bulls that are in the upper 67% for growth performance within each respective breed or on the entire test and have also passed evaluations for good disposition as well as structural and breeding soundness. This selection criterion is in place to help improve the quality of beef cattle herd across the state of Indiana and its neighboring states. IBEP bull tests are conducted bi-annually in the summer and winter, where the summer test is for bulls born between

May 1 and October 31 of the previous year and the winter test is for bulls born between January 1 and April 30 of that year. The bulls are allowed a 21-day pretest period before test and the test lasts 125 days. Therefore, summer-tested bulls are sold in October and winter-tested bulls are sold in April.

Table 1.1 Summary Statistics of Bull Attributes (n = 1,705)

Variable	Mean	Standard Deviation	Minimum	Maximum
Sale price ($/head)[1]	2,665.81	1,253.59	1,100.00	11,000.00
Age at sale (days)	423.71	33.86	348.00	539.00
Average daily gain (lbs./day)	4.06	0.40	3.02	5.63
Birth weight (lbs.)	79.67	9.17	49.00	117.00
Adjusted scrotal circumference (cm)[2]	36.91	2.38	32.00	48.00
Adjusted ribeye area (square inches at 12th rib)[2]	13.04	1.33	9.40	19.40
Adjusted percent intramuscular fat (%)[2]	3.73	1.15	1.25	8.82
Birth weight EPD (lbs.)[3]	1.97	1.52	-4.20	6.90
Maternal milk EPD (lbs.)	24.27	5.22	7.00	41.00
Ribeye area EPD (square inches)	0.33	0.27	-0.39	1.63
Marbling EPD[4]	0.33	0.95	-0.24	1.33

[1] Sale prices were adjusted into 2018 dollars using PPI by commodity for farm products: steers and heifers (U.S. Bureau of Labor Statistics, 2019).

[2] Adjusted measures of scrotal circumference, ribeye area, rib fat, and percent intermuscular fat are all adjusted to a common age of 365 days.

[3] Expected progeny differences (EPDs) measure a bull's genetic ability to transmit a particular trait to his progeny compared to that of other bulls.

[4] Marbling EPD is measured on a numerical scale of marbling scale. A numerical score of 1 is associated with Utility and 10 is Prime Plus on the USDA quality grade scale (American Angus Association, 2019)

Data collected during the test include body weight at various ages, scrotal circumference, ultrasound scan data, and average daily gain. Bull owners are required to submit pretest information such as bull birth date, birth weight, weaning weight, and breed registration number. Expected progeny differences are obtained on each bull from their respective breed association. These data are recorded, compiled, and reported to the bull owners and are disseminated to potential buyers at auction through sale catalogs. Sale data for this study span from 2002 to 2018. Bull prices are converted to 2018 dollars (U.S. Bureau of Labor Statistics, 2019). Because the majority (74%) of the bulls sold during this time period were Angus, this study only considers Angus bulls. Excluding bulls that were not sold or bulls with incomplete information, 1,705 observations were available for this study. Summary statistics are reported in Table 1.1.

1.4 Methods and Procedures

1.4.1 Pooled Hedonic Model

Prior to estimating a model with time-varying parameters, the first step is to estimate the conventional pooled hedonic model as a baseline where the value of each bull is estimated with a standard log-linear hedonic model:

(1)
$$lnp_{it} = \beta_0 + \sum_{j=1}^{J} \beta_j X_{itj} + \sum_{k=1}^{K} \delta_k Z_{itk} + \varepsilon_{it}$$

where lnp_{it} is the logged form of price for bull i in time t. X_{itj} contains $j = 1, \dots, J$ simple performance measures, ultrasound information, and EPD values available to buyers in the sale catalog. Simple performance measures include age at sale, average daily gain, actual birth weight, and adjusted scrotal circumference.[1] Ultrasound measures are provided for adjusted ribeye area and adjusted percent intermuscular fat. Finally, EPDs characterizing birth weight, maternal milk, ribeye area, and marbling are also included in X_{itj}. Z_{itk} contains variables to control for sale order, season of the sale (1 = spring, 0 = fall), and a time trend. ε_{it} is the independently and identically distributed error term, and β_0, β_j, and δ_k are parameters to be estimated.

The general pooled hedonic model is also useful for identifying the model specification used throughout the rest of the paper. That is, additional bull attributes beyond what is provided in the regressions here are available to buyers in the sale catalog. However, many of these traits are correlated and thus present potential multicollinearity problems. Similar to Boyer et al. (2019), we investigate multicollinearity using Pearson correlation coefficients and variance inflation factors (VIFs) for all available possible independent variables. Based on the results of this analysis, a subset of relevant bull attributes was chosen to be included as independent variables in the hedonic regression models to ensure multicollinearity is not an issue in our estimation.

1.4.2 Bi-Yearly Hedonic Models

Using the general specification identified in the pooled hedonic regression in (1) with the exception of the time trend variable, we also estimate individual hedonic regression models for two-year sub-periods. These bi-yearly models (eight regressions in total) were selected over annual regressions to provide a smaller number of overall models for review and to increase the number of

[1] Adjusted measures are adjusted to a common age of 365 days.

observations in any one regression model. The results from these models are used to investigate temporal changes in the bull attribute valuations over time non-parametrically.

1.4.3 Hedonic Model with Continuous Time Trend Interaction

Previous examples of empirical investigations of temporal changes in attribute valuations in a hedonic model framework are limited, with most being found in the hedonic real estate literature (e.g., McMillen, 2008; Rambaldi and Rao, 2011; Fesselmeyer et al., 2012; Chen and Harding, 2016; Hanson et al., 2018). The existing literature generally suggests two methods to estimate the change in attribute valuation over time: (i) breaking the data into discrete time periods and (ii) incorporating a time trend interaction for characteristics of interest. The nature of the hedonic model favors the latter given that splitting the data forces a subjective choice of when to break the data and occludes independent testing of an overall trend vs. separate trends for individual attributes. Hence, the focus of our analysis is on a hedonic model with continuous time trend interactions.[2]

The focus is then on functional form of these time trend interaction variables. Discussions of functional form in hedonic price models are well established (e.g., Halvorsen and Pollakowski, 1981; Cassel and Mendelsohn, 1985; Cropper et al., 1988), and generally rely on the Box-Cox transformation test (Box and Cox, 1964). Based on the assumption that attribute valuations change gradually over time as producers adjust and adapt to incentives and

[2] Models evaluating changes in attribute valuations across discrete time periods, such as a "Chow-like" test for the equality of parameters between discrete time periods and an Oaxaca-Blinder decomposition, were performed to test robustness of our results. Results from these models were generally consistent with the results of the time trend interaction models and are available from the authors upon request.

information, the elements of β_j in equation (1) can be represented as a continuous function of time (t):

(2) $$\beta_j(t) = b_{0j} + b_{1j} t^{(\lambda)}$$

where $t^{(\lambda)}$ is the Box-Cox (1964) transformation:

(3) $$t^{(\lambda)} = \begin{cases} \dfrac{t^{\lambda} - 1}{\lambda}, if\ \lambda \neq 0 \\ \ln(t), if\ \lambda = 0. \end{cases}$$

The Box-Cox transformation embodies several common functional forms that may represent the relationship of bull attribute valuations with time, including logarithmic $(\lambda = 0)$, square root $(\lambda = 0.5)$, and linear $(\lambda = 1)$. The parameter λ can also be estimated by maximum likelihood estimation to determine the transformation that best fits the data. In addition, a quadratic form of the change in attribute valuation over time is also considered where:

(4) $$\beta_j(t) = b_{0j} + b_{1j} t + b_{2j} t^2.$$

This allows the flexibility for the change in attribute valuation over time to change direction over the sample period.

Inserting equation (2) into equation (1) yields:

$$lnp_{it} = \beta_0 + \sum_{j=1}^{J} (b_{0j} + b_{1j} t^{(\lambda)}) X_{itj} + \sum_{k=1}^{K} \delta_k Z_{itk} + \varepsilon_{it}. \tag{5}$$

Equation (5) can be estimated by including a continuous time trend interaction with X_{ij}, where t represents the year of the sale, $t = 1, \ldots 17$. In practice, only a subset of the variables in X_{ij} that are hypothesized to change with time are interacted with the time trend variable.

While the functional form of the time trend interaction is important for understanding the time path of changes in producer preferences, it is important to point out that the primary objective here is a descriptive analysis of the general trends in attribute valuations over time and not a predictive analysis of future bull buyer preferences. Hence, while it is important to consider the robustness of the functional form assumption, the ultimate functional form is not critical for gaining insights into general trends in attribute valuations.

Further, we only apply the Box-Cox transformation test to the time trend interaction variables. A similar investigation of functional form could also be applied to the baseline characteristics and even price. However, given that focus of this manuscript is dealing with changes in attribute valuations over time, we focus our efforts on the treatment of functional form for the time trend interactions specifically, and leave the treatment of functional form for the other variables for future research.

1.5 Results

1.5.1 Pooled and Bi-yearly Hedonic Regressions

Parameter estimates from the pooled and bi-yearly hedonic price models are reported in Table 1.2. All of the independent variables in the pooled model are statistically significant and are generally consistent with previous literature (Dhuyvetter et al., 1996; Jones et al., 2008; Kessler et al., 2017; Boyer et al., 2019; Franken and Purcell, 2012; Vanek et al., 2008; Walburger, 2002). Nonetheless, the marginal effects in the pooled model represent average marginal effects across the entire 17-year time period and may be masking important changes in evolving bull buyer preferences over time.

Bi-yearly hedonic price models allow for a first glimpse at these potential changes in bull attribute valuations in a non-parametric framework. Traits such as age, actual birth weight, average daily gain, and birth weight EPD have a consistent and statistically significant impact on bull prices as expected. However, traits such as adjusted ribeye area and maternal milk EPD are only consistently statistically significant in the latter part of the time period evaluated. Adjusted scrotal circumference is generally negative and statistically significant in the first half of the time period. A number of other traits offer inconsistent effects on bull prices. Therefore, a more robust investigation of potentially changing bull buyer preferences is warranted.

1.5.2 Hedonic Model with Continuous Time Trend Interaction

A hedonic model with continuous time trend interactions is fitted to parametrically trace changing preferences in bull buyer valuations of bull attributes. Five functional forms of the time trend interaction were considered as part of a Box-Cox transformation test and are presented in Table 1.3. The logarithmic, square root, and linear models performed similarly in terms of model fit statistics. Estimating the Box-Cox transformation that best fit the data resulted in a $\lambda = 0.85$, which resulted

Table 1.2 Baseline Pooled Hedonic Price Model for All Years (2002-2018) and Bi-Yearly Hedonic Price Models

		Years							
Variable	Pooled (2002-2018)	02-03	04-05	06-07	08-09	10-11	12-13	14-15	16-18[1]
Intercept	4.487***	4.495***	6.726***	5.629***	6.343***	6.576***	6.181***	6.125***	6.216***
Age	0.003***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
Average daily gain	0.133***	0.223***	0.240***	0.138***	0.159***	0.150**	0.107**	0.234***	0.044
Birth weight	-0.005***	-0.003	-0.005***	-0.008***	-0.010***	-0.005**	-0.002	-0.007***	-0.004**
Adjusted scrotal circumference	0.011***	-0.002	-0.020**	0.017**	-0.010	0.011	0.003	0.001	0.006
Adjusted ribeye area	0.057***	0.090***	0.016	0.025	0.037**	-0.046**	0.038**	0.038**	0.045***
Adjusted percent intermuscular fat	0.031***	-0.005	0.040	0.030	0.075***	0.013	0.033*	0.043**	0.010
Birth weight EPD[2]	-0.065***	-0.049***	-0.067***	-0.055***	-0.066***	-0.077***	-0.069***	-0.052***	-0.075***
Maternal milk EPD	0.010***	0.003	0.004	0.003	0.007	0.010	0.012***	0.009**	0.011***
Ribeye area EPD	0.073*	-0.397***	0.159	0.274***	0.094	0.502***	0.061	-0.061	-0.057
Marbling EPD	0.103**	0.446**	-0.180	-0.050	-0.290**	0.012	-0.039	-0.020	-0.040
Sale order	-0.004***	-0.003***	-0.004***	-0.004***	-0.005***	-0.007***	-0.006***	-0.006***	-0.005***
Sale season	0.225***	0.034	0.101*	0.427***	0.455***	0.431***	0.153***	0.409***	0.396***
Sale Year	0.055***								
n	1,705	227	215	247	206	189	188	198	235

Notes: Dependent variable in all regressions is log of bull sale prices adjusted to 2018 dollars. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

[1] Observations from 2016, 2017, and the Spring sale in 2018 are included in the 2016-2018 bi-yearly model.

[2] Expected progeny differences (EPDs) measure a bull's genetic ability to transmit a particular trait to his progeny compared to that of other bulls.

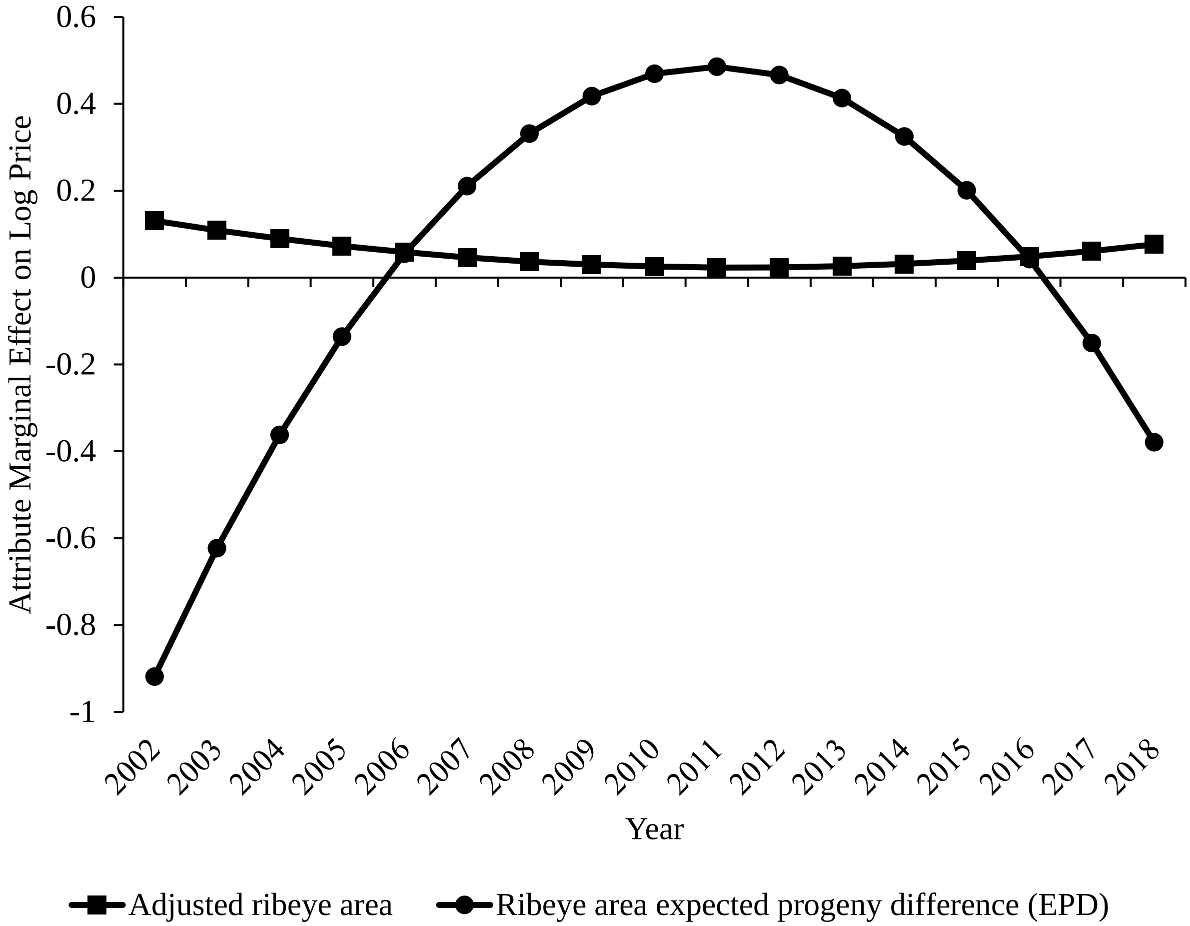

Figure 1.1 Bull Attribute Marginal Effects Across Time for Adjusted Ribeye Area and Ribeye Area Expected Progeny Difference (EPD)

in parameter estimates very similar to the linear model where $\lambda = 1$. However, model fit statistics clearly indicated that the quadratic functional form provided the best overall fit (Table 1.3). For this reason, the discussion of results below will focus on the results from the quadratic time trend interaction model unless noted otherwise.

Before looking more closely at the traits that exhibit statistically significant time trends, it is important to first take note of the traits that were not interacted with the time trend but still have significant impacts on bull prices. Traits such as age, average daily gain, birth weight, and birth weight EPD consistently and significantly influenced bull prices in the expected directions, but did not exhibit significant changes over time (Table 1.3). This result is not surprising given the fundamental importance of these particular traits as they relate to the common objectives of producing low birthweight calves with high growth potential.

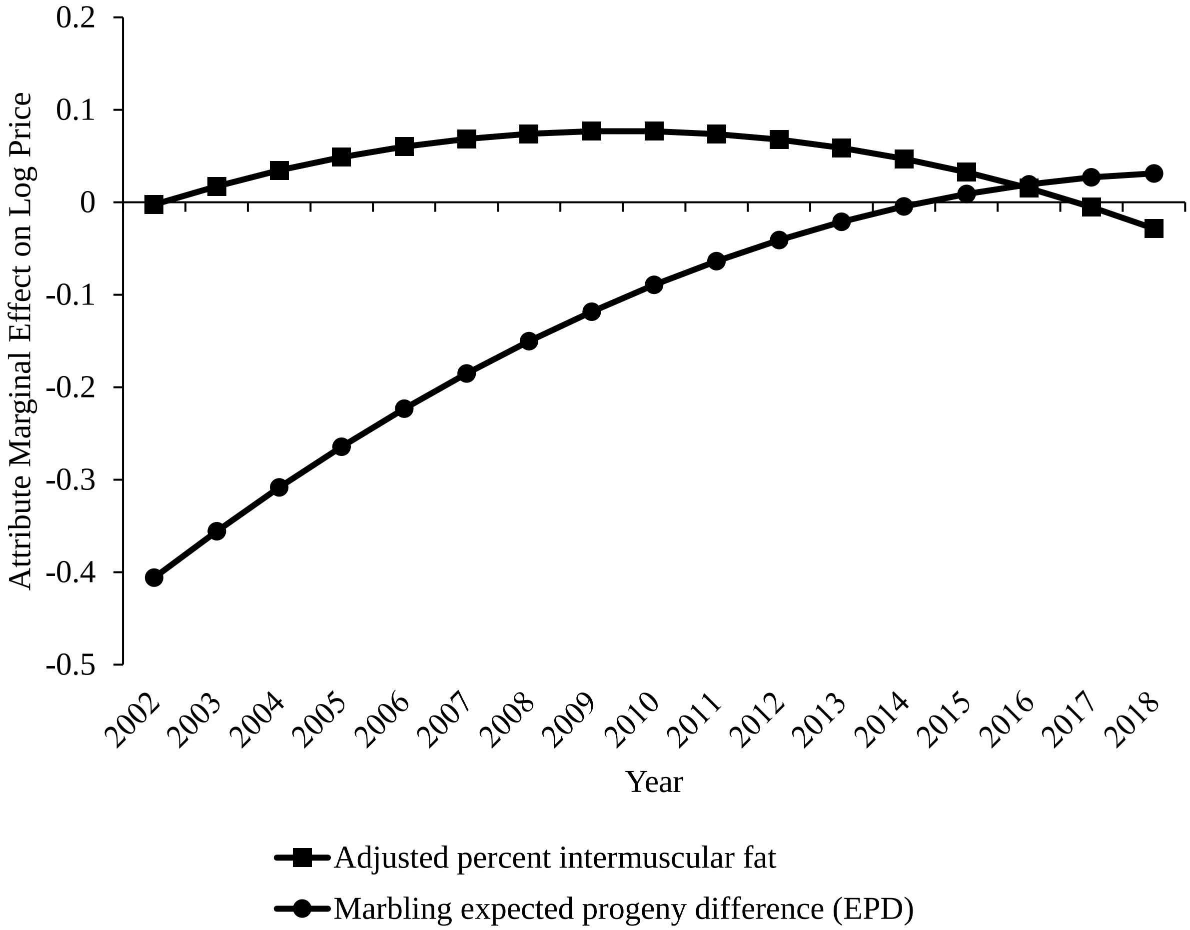

Figure 1.2 Bull Attribute Marginal Effects Across Time for Adjusted Percent Intermuscular Fat and Marbling Area Expected Progeny Difference (EPD)

Traits that did exhibit significant changes over time can be divided into two groups: carcass characteristics and reproductive and maternal traits. Each of the carcass characteristics exhibited evidence of statistically significant changes in bull buyer valuations over the time period evaluated. Tracing out the quadratic form of these marginal effects over time can be useful for visualizing these changes. The adjusted ribeye area marginal effect was positive throughout the time period and convex with respect to time (Figure 1.1). That is, it is decreasing during the early sub-period and then increasing steadily in recent years. This sort of effect can be corroborated by comparing this result with the bi-yearly regression results (Table 1.2). It is also important to contrast this result with the marginal effect for ribeye area EPD, which was concave over the time period evaluated (Figure 1.1).

The adjusted percent intermuscular fat marginal effect also exhibited a concave relationship with time, increasing steadily in the early part of the study period before waning in recent years (Figure 1.2). The marbling EPD marginal effect did not exhibit a statistically significant interaction with time in the quadratic model. However, evidence from the models with functional forms that did not impose sign reversal (i.e., logarithmic, square root, and linear) did show evidence that the marbling EPD marginal effect did significantly change over time (Table 1.3). Hence, although the quadratic form had the best fit overall, it does not appear to be the best fit for all of the traits evaluated. In particular, the marginal effect of the marbling EPD on bull price appears to be to have been increasing at a decreasing rate over the time period studied, without actually turning down in recent years.

Table 1.3 Hedonic Price Models with Natural Log, Square Root, Linear, Box-Cox, and Quadratic Functional Forms of the Time Trend Interaction (n = 1,705)

Variable	Natural Log Time Trend Interaction	Square Root Time Trend Interaction	Linear Time Trend Interaction	Box-Cox Time Trend Interaction	Quadratic Time Trend Interaction
Intercept	4.8447***	5.1905***	5.7657***	5.7856***	5.7349***
Age	0.0024***	0.0024***	0.0024***	0.0024***	0.0023***
Average daily gain	0.1384***	0.1373***	0.1332***	0.1343***	0.1151***
Birth weight	-0.0045***	-0.0045***	-0.0047***	-0.0046***	-0.0042***
Adjusted scrotal circumference	-0.0169**	-0.0286***	-0.0244***	-0.0218***	-0.0314***
Adjusted ribeye area	0.1068***	0.0913***	0.0555***	0.0577***	0.1551***
Adjusted percent intermuscular fat	0.1441***	0.1637***	0.1284***	0.1138***	-0.0254
Birth weight EPD	-0.0675***	-0.0674***	-0.0654***	-0.0662***	-0.0705***
Maternal milk EPD	-0.0102*	-0.0142**	-0.0033	-0.0045	-0.0079
Ribeye area EPD	-0.1221	0.0618	0.2937***	0.2118*	-1.2494***
Marbling EPD	-0.4377*	-0.4945**	-0.1598	-0.2144	-0.4592*
Adjusted scrotal circumference × time trend	0.0133***	0.0131***	0.0036***	0.0048***	0.0051**
Adjusted ribeye area × time trend	-0.0261***	-0.0133*	-0.0004	-0.0010	-0.0254***
Adjusted percent intermuscular fat × time trend	-0.0490***	-0.0408***	-0.0092***	-0.0109***	0.0243**
Maternal milk EPD × time trend	0.0091***	0.0076***	0.0012***	0.0019**	0.0027*
Ribeye area EPD × time trend	0.1058	0.0181	-0.0180**	-0.0131	0.3482***
Marbling EPD × time trend	0.2242**	0.1721***	0.0200*	0.0347	0.0549
Adjusted scrotal circumference × time trend squared					-0.0001
Adjusted ribeye area × time trend squared					0.0012***
Adjusted percent intermuscular fat × time trend squared					-0.0014***
Maternal milk EPD × time trend squared					-0.0001
Ribeye area EPD × time trend squared					-0.0175***
Marbling EPD × time trend squared					-0.0015
Sale order	-0.0041***	-0.0042***	-0.0044***	-0.0044***	-0.0046***
Sale season	0.2377***	0.2445***	0.2552***	0.2540***	0.2760***
Sale Year	0.0205**	-0.0116	-0.0652**	-0.0681***	-0.0179
λ				0.8508***	
-2 LL	798.3	789.7	786.1	782.3	598.2
AIC	840.3	831.7	828.1	826.3	652.2
AICC	840.9	832.2	828.7	826.9	653.1
BIC	954.6	945.9	942.4	946.0	799.1

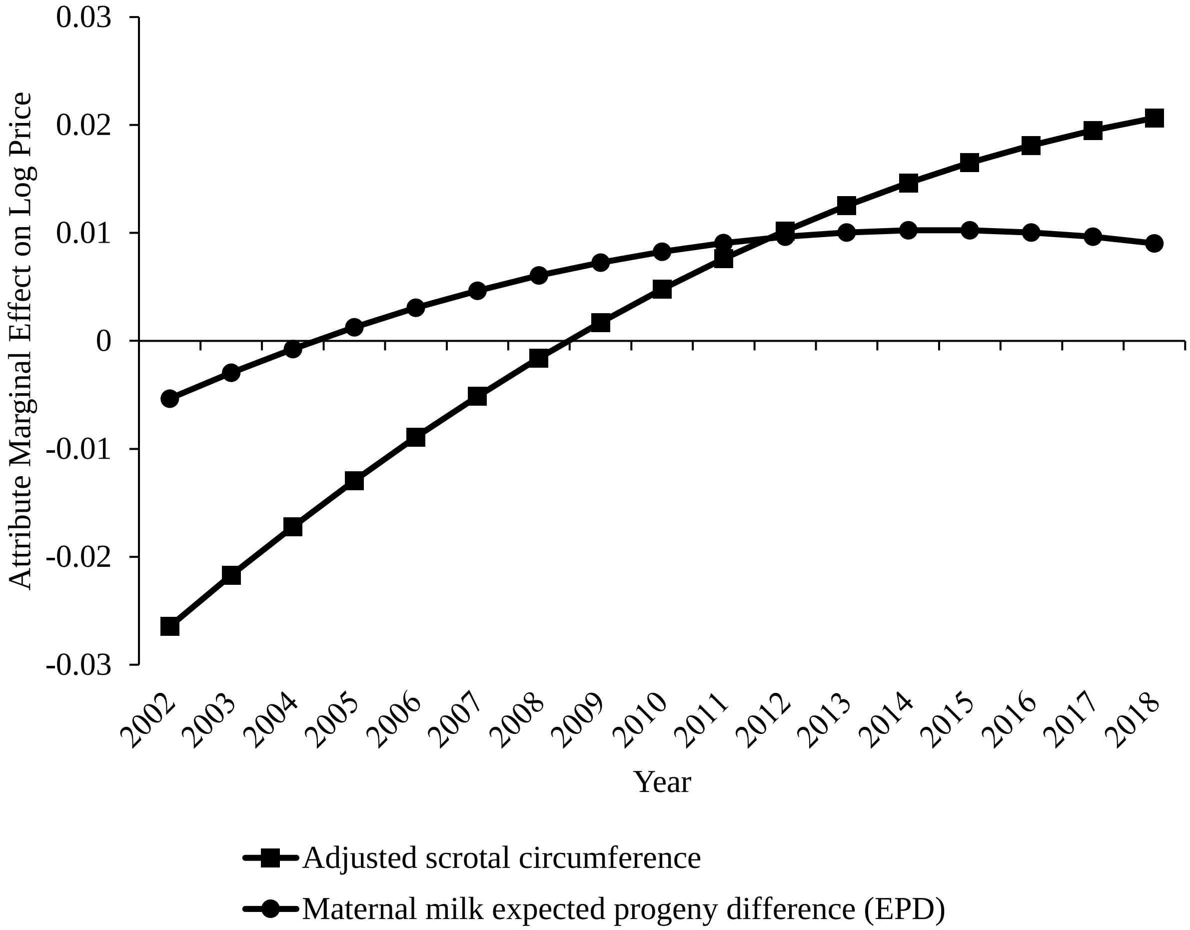

Figure 1.3 Bull Attribute Marginal Effects Across Time for Adjusted Scrotal Circumference and Maternal Milk Expected Progeny Difference (EPD)

The second group of variables that exhibited statistically significant changes in producer attribute valuations over the time period are reproductive and maternal characteristics. Adjusted scrotal circumference is a direct measure of reproductive performance and is often positively associated with bull prices (Walburger, 2002). However, our results indicate that in the early part of the time period bull buyers in our sample significantly reduced the price they were willing to pay for bulls with larger scrotal circumference. While it is not clear why this was the case, our results indicate that producers' marginal valuation of this trait has increased steadily over the time period (Figure 1.3), and at present adjusted scrotal circumference does not appear to significantly affect bull prices.

Finally, maternal milk EPD is a measure of a bull's female offspring's ability to produce milk for her offspring as measured by the difference in average weaning weight of a bull's female progeny. While there are a number of factors a producer might consider when thinking about producing replacement females, maternal milk EPD serves one component of mothering ability. Our results indicate maternal milk was largely unimportant for explaining bull prices during the early part of the time period, but it has increased steadily and currently has a positive and significant effect on bull prices (Figure 1.3).

1.6 Discussion

Results from the models above clearly indicate that bull buyer preferences for some traits have evolved over the past nearly two decades as hypothesized. However, the directions and functional forms of these changes did not necessarily align with a priori expectations.

1.6.1 Changing Valuation of Carcass Traits

The combined results of the carcass quality trait interactions with time offer a mixed view of bull buyers' response to incentives produced by grid pricing to invest in carcass quality traits. It appears as though bull buyers are placing positive value on ribeye area which is a key factor in determining yield grade, a key component of the grid pricing premium and discount structure. However, the two measures of ribeye area, ultrasound and EPD, have both increased and decreased at various points during the time period evaluated. As for intermuscular fat/marbling, the other major component of grid pricing premiums and discounts, our results indicate that bull buyers' marginal valuations of ultrasound measures of adjusted percent intermuscular fat have waned in recent years to a point of indifference following steady growth early in the sample period. Marginal valuations of the marbling EPD have generally increased over the time period evaluated. However, it is important to point out that this increase has been from a deleterious effect on bull prices in the early part of the sample period to not significantly different from zero in recent years. Therefore, our results fail to offer conclusive evidence as to whether or not incentives provided by grid pricing are clearly signaling bull buyers in our sample to invest in improvements in carcass quality characteristics.

When considering this result, a few important points should be taken into consideration. It is important to point out that the time period used here does not include the introduction of grid pricing which happened in the mid-1990s. Hence, our time period starts nearly 7 years after the initial introduction of grid pricing. Therefore, it is possible that some adjustments to bull buyer valuations of these carcass traits took place prior to what is measured here. However, our results identify statistically significant time effects over the time period evaluated suggesting continued adjustment to the incentives provided by grid pricing. Further, research has shown that growth in the market share of grid pricing has been slow and steady as the grid premium and discount structure has slowly adjusted carcass quality market signals to incentivize marketing on a grid (Fausti et al., 2010; Fausti et al., 2014). Recent trends have seen the proportion of fed cattle marketed on negotiated grids decline slightly and those marketed via formula pricing appears to have stabilized in recent years (Schroeder et al., 2019).

The other point to consider here is the underlying incentive for cow-calf producers to invest in quality traits given the structure of the beef industry. The typical cow-calf producer has little incentive to invest in bulls that produce calves with higher carcass quality given the majority of feeder cattle in the U.S. are sold via auctions in which sellers are paid by weight and information is sparse. Some previous studies, such as Vanek et al. (2008), have indicated that statistically significant carcass trait effects on bull prices are sufficient evidence to support cow-calf producer responsiveness to grid pricing signals. We are less enthusiastic about this point in light of the results from our analysis indicating potentially complex time effects of these traits on bull prices.

It is also important to point out that the data evaluated by Vanek et al. (2008) are from bull auctions at four large commercial seed-stock ranches. The buyers at those such sales are likely to be larger, commercial cow-calf producers who are more likely to be involved in actively seeking value-added marketing arrangements such as private treaty sales or retained ownership. However, according to the 2017 U.S. Census of Agriculture, nearly half of all U.S. beef cattle are raised on farms with less than 100 head (USDA NASS, 2019). It is these smaller operations that likely represent the majority of buyers in our sample from IBEP sales, which may explain why our results are mixed with respect to producer valuations of carcass traits. Hence, we agree with Vanek et al.'s (2008) assertion that the evidence of significant carcass trait effects on bull prices may be the result of a segment of the beef industry's breeding sector concentrating on improving carcass quality. While we are unable speak to this issue directly in this research, it is important for the industry to consider how current price signals are being transmitted to various industry segments and if this is meeting industry objectives for improved quality and consistency of beef products.

1.6.2 Changing Valuation of Expected Progeny Differences

Our results do not support the hypothesis of consistently increasing emphasis on EPD measures as a result of learning and familiarization associated with the technology. Instead, results are mixed, with EPD measures for some traits significantly influencing bull prices but not changing over the time period (birth weight EPD), others increasing (maternal milk EPD and marbling EPD), and still others increasing and then decreasing (ribeye area EPD).

The EPDs for some traits were introduced more than 10 years prior to the start of our time period. So again, some learning and familiarization could have a happened prior to the start of our analysis and our results represent a period that has already reached stabilization of bull buyer valuation of these traits. For example, the birth weight EPD consistently and significantly influenced bull prices. This is not surprising given that the birth weight was one of the first traits for which EPDs were introduced and birth weight has been and will continue to be a fundamental trait used in bull selection.

For the EPDs that did exhibit statistically significant changes over the time period evaluated, the maternal milk EPD followed the hypothesized time path of slow, steady improvement. However, it is difficult to distinguish how much of this increase in value came from learning and familiarization with EPD information and how much was from an increase in interest in this trait, maybe due to producers in the study region increasing their propensity to produce their own replacement heifers increasing the value of maternal milk to them as cow-calf producers. It is also important to point out that Decker (2018) identified maternal milk as a trait that producers should be careful about selecting for optimal performance given that these cattle often fail to perform at their genetic potential and often have increased maintenance requirements.

The two carcass EPDs (ribeye EPD and marbling EPD) offer little conclusive evidence of producer confidence in EPD technology for carcass traits. It is hard not to notice the inverse relationship between the ribeye area EPD and the adjusted ribeye area measured by ultrasound (Figure 1.1). Keeping in mind that these are two measures of the same underlying trait, it is hard not to speculate about this relationship. Anecdotally, it seems as though bull buyers may have been substituting between adjusted ribeye area measured by ultrasound and the ribeye area EPD, with a recent trend towards placing more value on adjusted ribeye area measured by ultrasound and deterioration of bull buyers' attitudes toward EPD measures of ribeye area.

In light of these results, it is important to point out that bull buyer perceptions of EPDs are tied to particular traits. That is, just because the EPD for one trait wanes in terms of its influence on what bull buyers are willing to pay for bulls, EPDs characterizing other traits, as indicated in our results, may play an important role in bull selection. Therefore, in response to Decker's (2018) point that EPD technology is underutilized by producers, our results suggest that more research is needed to understand which traits producers are using EPDs for, which traits they are not, and why? While our research is able to shed light on this issue, additional research is needed to answer these questions to improve the technology and the way that it is communicated to producers. Decker (2018) believes that this is critical to a more profitable and sustainable beef industry.

1.7 Conclusion

The objective of this paper was to investigate if Midwest bull buyers' marginal valuations of Angus bull attributes have changed over time using 17 years of bull auction data from the state of Indiana. Results indicate that bull buyers exhibit statistically significant changes in their valuation of several bull attributes over the time period, including carcass traits ribeye area, ribeye area EPD, and marbling EPD as well as reproductive and maternal traits for scrotal circumference and maternal milk EPD. However, the directions and functional forms of these changes did not necessarily align with a priori expectations. Trends in carcass quality trait impacts on bull values were mixed across the time period with some increasing and others decreasing. Hence, we conclude that while there is some evidence of quality signals from grid pricing being received by bull buyers, these signals are not uniformly implemented and may be waning if these producers are not being rewarded for these investments. This is an issue that the beef industry should take very seriously in terms of providing an incentive structure that efficiently signals quality cues throughout a disaggregated supply chain. We also find a mixed effect of time on bull buyer marginal valuation of EPDs. In practice, it turned out to be very difficult to differentiate between learning and familiarization associated with EPDs and the actual demand for particular traits. Nonetheless, EPDs are a proven technology, and overcoming communication and implementation barriers could improve the profitability and sustainability of beef production.

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CHAPTER 2. IMPLICIT MARKET SEGMENTATION AND ATTRIBUTE VALUATION OF BEEF BULLS

2.1 Introduction

Beef cattle production in the United States (U.S.) is characterized by diverse production and management systems. Much of this diversity occurs in the industry's disaggregated breeding sectors (i.e., seed-stock and cow-calf), which are made up of many small, independent producers. According to the 2017 U.S. Census of Agriculture the average U.S. cow-calf herd size is 41 cows (USDA NASS, 2020). Cow-calf producers look for bulls with specific traits and genetic potential that align with the needs of their specific cow herd when purchasing herd sires. Cow herd needs depend on average age of the herd, production and management system, and end-use marketing arrangements for calves (Allaire, 1985).

Given the existence of quality differentiations in bull attributes and heterogeneous demand for bulls with specific characteristics, a fundamental condition for the existence of submarkets within the market for bulls is met (Costanigro and McCluskey, 2011). Existing studies (e.g., Jones al., 2008; Dhuyvetter et al, 1996) tend to focus on average valuations of bull attributes assuming a homogeneous production structure using linear hedonic models. To date, there have been few attempts to identify and estimate attribute valuations across bull buyer segments. Bekkerman, Brester, and McDonald (2013) is the one exception, using a quantile regression to estimate marginal valuations of bull attributes conditional on price. While price is a convenient cue of quality, it may not be the best identifier for segmenting bull buyer submarkets. Therefore, more work is needed to identify and understand bull buyer submarkets to improve the accuracy of marginal valuations of bull attributes. This has important implications for seed-stock producers (i.e., those selling bulls), cow-calf producers (i.e., those buying bulls), and the industry as a whole as they seek to improve the quality and consistency of beef products.

The bull auction system is an example of a heterogeneous agricultural market where differentiated products abound (Brimlow and Doyle, 2014; Bekkerman, Brester, and McDonald, 2013). Unlike relatively high concentration in the feedlot and processing sectors, the breeding sectors of the U.S. beef industry consist of many small seed-stock and cow-calf operations producing genetics appropriate for targeted markets. A set of heterogeneous bull buyers identify the most-valued traits in a bull that will maximize their profitability based on their unique production conditions and marketing arrangements. When purchasing, bull buyers make bidding decisions primarily based on the observed and predicted performance measures contained in a sale catalog. A sale catalog commonly contains information of simple performance measures (SPMs) and expected progeny differences (EPDs) for bulls being sold. SPMs are mostly physical characteristics that are measurable through simple methods such as sex, breed, hide color, weights (e.g., birth weight, weaning weight, etc.), and average daily gain. EPDs are statistical predictions of the phenotypic performance of a bull's progeny. Examples of EPDs include various weights (e.g., birth weight, weaning weight, etc.), maternal calving ease, marbling, and ribeye area. These differentiated performance measures can provide bull buyers with comparable valuation of the same trait from animal to animal of the same breed that they can factor into their bidding decisions (Dhuyvetter et al., 1996).

Hedonic analyses of agricultural products were initiated by Waugh (1928) and has since been extensively utilized to estimate the marginal valuation of attributes for a variety of agricultural products due to its empirical efficiency in quantifying valuation of each attribute in a differentiated product. The effects of market segmentation on prices has long been discussed in the real estate literature (e.g., Straszheim, 1974). Houses are commonly segmented into groups based on observable criteria, such as neighborhood socioeconomic factors or geographic location, and separate hedonic functions are estimated for each group. Some studies indicate that accuracy of out-of-sample prediction improves when models are estimated for individual housing market segments rather than prediction based on a single aggregated market model (Goodman and Thibodeau, 1998; Bourassa, Hoesli, and Peng, 2003; Chen, Cho, and Roberts, 2009).

Several studies have been carried out to identify submarkets of hedonic models for different agricultural products, especially for wine. For instance, a local polynomial regression clustering (LPRC) approach was used to segment wines with similar values of wine attributes (Costanigro, Mittelhammer, and McCluskey, 2009). Caudill and Mixon (2016) estimate the finite mixture model (FMM) of wine prices both including and excluding concomitant variables and show that both estimation results display better aggregate out-of-sample performance than the LPRC model results. Caracciolo and Furno (2020) propose a method that combines the advantages of FMM with the strengths of quantile regression to identify wine submarkets. The finite mixture quantile regression unveils additional heterogeneity of estimators at different quantiles within each class.

Bulls are often treated as undifferentiated products in previous studies (e.g., Jones, et al., 2008; Franken and Purcell, 2012). Only one study has examined quality differentials of bulls across quantiles of the price distribution (Bekkerman, Brester, and McDonald, 2013). While Bekkerman, Brester, and McDonald (2013) find non-constant marginal valuations of bull attributes across the price distribution, we hypothesize that segmentation on price may not be the most efficient method of identifying bull buyer submarkets. Although price is frequently used as a quality cue for consumer products, such as wine, its applicability to bull markets is less clear. We hypothesize that buyer preferences for bull traits are more closely linked to the end-use of the calves produced than the price paid. For example, cattle producers who sell their calves at weaning likely place higher values on calving ease, growth rate, and weaning weight characteristics when purchasing a herd sire. Alternatively, cattle producers who buy bulls for production of replacement females likely place relatively high valuations on maternal and reproductive performance characteristics. Finally, cattle producers who retain ownership of their calves until harvest may place increased importance on carcass characteristics, such as yield and quality grade, if they plan to market fed cattle using grid pricing (Greiner, 2009).

The objective of this study is to identify heterogeneity in bull buyer valuations of bull attributes across latent classes using a FMM. The FMM has become a standard approach to identify the existence of heterogeneity in consumers' valuations towards product attributes. Its potential application in hedonic modeling has shown improvement in precision of hedonic estimates in real estate research (e.g., Ugarte, Goicoa, and Militino, 2004; Belasco, Farmer, and Lipscomb, 2012). In this study, the FMM is used to identify bull buyer segments with differing preferences for bull attributes.

2.2 Conceptual Framework

According to standard hedonic price analysis (Rosen, 1974), the price of a bull is determined by the valuation of the attributes it contains. In particular, the price of any bull i, which is drawn from n observations, is a function of bull attributes x_i, $P_i = P(x_i;\beta)$, and β indicates a vector of implicit prices of bull attributes. Conventionally, implicit prices of bull attributes are the same for any bull indicating homogeneous preferences among bull buyers. Under this assumption, an aggregated analysis is performed to show that bull prices follow a single distribution of buyer preferences. However, if bull prices are a mixture of G distributions, the price function above becomes $P_i = P_g(x_i; \beta_g)$, $g = 1, \dots G$ and $G < n$. Bull buyers from class g share the same valuation of bull attributes, which is characterized by the common vector, β_g.

A single hedonic analysis ignoring heterogeneity can yield misleading estimates of attribute valuations. This is because bull buyers are heterogeneous and they are likely to assign differential importance weights to various bull traits, and valuation of bull attributes is not likely to be constant for all bull buyers. That is to say, bull buyers select the traits that fit their production systems and end-use marketing arrangements.

2.3 Data

Data used in this study were provided jointly by Indiana Beef Evaluation Program (IBEP), bull performance test program in Tennessee, and bull owners who subscribed their bulls for testing. The IBEP for bull testing and sale was conducted at the Feldun-Purdue Ag Center in Bedford, Indiana (IBEP, 2019). The Tennessee bull performance test was carried out at the Middle Tennessee AgResearch and Education Center in Spring Hill, Tennessee (University of Tennessee, Department of Animal Science, 2017). These performance test programs provide cattle producers with a chance to determine the performance, EPDs, and quality characteristics of their bulls before being sold and help improve the quality of beef cattle herd across the state of Indiana and Tennessee and their neighboring states.

Bull performance tests are conducted bi-annually both in Indiana and Tennessee. In Indiana, the summer test is for bulls born between May 1 and October 31 of the previous year, and the winter test is for bulls born between January 1 and April 30 of that year. In Tennessee, the August test is for bulls born between September 1 and December 15 of the previous year, and the November test is for bulls born between December 16 and March 15 of the year preceding test.

Data collected during the test include age at sale, bull weights at various ages, scrotal circumference, frame score, ultrasound scan data, average daily gain, and EPDs for production performance and carcass characteristics of their offspring. Bull owners need to report pretest information such as bull birth date and birth weight. These data are recorded, complied, and reported to bull owners and are disseminated to potential buyers at auction through sale catalogs.

Sale data for this study span from 2006 to 2018. Bull prices are converted to 2018 dollars (U.S. Bureau of Labor Statistics, 2019). Because the majority of the bulls sold during this time period were Angus, this study only considers Angus bulls. Excluding bulls that were not sold or bulls with incomplete information, 1,903 observations, of which 1,263 are from Indiana and 640 are from Tennessee, are available for this study. Summary statistics are reported in Table 2.1.

Table 2.1Summary Statistics of Bull Attributes for the Pooled Sample (n = 1,903)

Variable	Mean (Std. Dev.)	Minimum	Maximum
Sale price ($/head)[1]	2,843.09 (1,587.51)	657.08	13,420.00
Age at sale (days)	424.16 (31.46)	346.00	539.00
Birth weight (lbs.)	77.34 (8.45)	51.00	117.00
Average daily gain (lbs./day)	4.25 (0.52)	3.07	6.73
Frame score[2]	5.76 (0.62)	3.60	7.80
Adjusted scrotal circumference (cm)[3]	36.89 (2.36)	30.60	47.00
Adjusted ribeye area (square inches at 12th rib)[3]	13.00 (1.29)	9.50	19.90
Adjusted percent intramuscular fat (%)[3]	3.93 (1.12)	1.25	8.82
Birth Weight EPD (lbs.)[4]	1.76 (1.45)	-4.20	6.00
Weaning Weight EPD (lbs.)[4]	51.89 (8.65)	0.34	86.00
Maternal Milk EPD (lbs.)[4]	25.42 (5.10)	0.26	41.00
Ribeye area EPD (square inches)[4]	0.36 (0.27)	-0.80	1.63
Marbling EPD[4,5]	0.37 (0.26)	-0.30	1.33

[1] Sale prices were adjusted into 2018 dollars using PPI by commodity for farm products: steers and heifers (U.S. Bureau of Labor Statistics, 2019).

[2] Frame score is calculated as a function of hip height and bull age based on Beef Improvement Federation (BIF) guidelines (BIF, 2016). Frame score is a 1-9 scale, where 1 is extremely small and 9 is extremely large.

[3] Adjusted measures of scrotal circumference, ribeye area, and percent intermuscular fat are all adjusted to a common age of 365 days.

[4] Expected progeny differences (EPDs) measure a bull's genetic ability to transmit a particular trait to his progeny compared to that of other bulls.

[5] Marbling EPD is measured on a numerical scale of marbling scale. A numerical score of 1 is associated with Utility and 10 is Prime Plus on the USDA quality grade scale (American Angus Association, 2019).

2.4 Methods and Procedures

The conventional pooled model, which assumes homogenous values of bull characteristics, is our baseline model where the value of each bull is estimated with a standard log-linear hedonic model:

(1)
$$y_i = \beta_0 + \sum_{j=1}^{J} \beta_j X_{ij} + \sum_{k=1}^{K} \delta_k Z_{ik} + \varepsilon_i$$

where y_i is the logged form of price for bull i. X_{ij} contains $j = 1, \dots, J$ SPMs, ultrasound information, and EPD values available to buyers in the sale catalog. SPMs include age at sale, actual birth weight, average daily gain, frame score, and adjusted scrotal circumference.[3] Ultrasound measures are provided for adjusted ribeye area and adjusted percent intermuscular fat. Finally, EPDs characterizing birth weight, weaning weight, and maternal milk are also included in X_{ij}. Z_{ik} contains variables to control for state where bulls were sold (1 = Indiana, 0 = Tennessee) and sale year fixed effects. ε_i is the independently and identically distributed error term, and β_0, β_j, and δ_k are parameters to be estimated. For notational convenience, we have lower case x to denote the collected vectors of X and Z in the following context.

2.4.1 Finite Mixture Model (FMM)

An FMM is employed to identify latent submarkets of bulls and explore the heterogeneity in bull buyers' valuation towards various bull attributes. Suppose that a population of bull buyers can be characterized into G latent classes based on different implicit prices of bull attributes. In this

[3] Adjusted measures are adjusted to a common age of 365 days.

context, the price of any bull P_i can be thought as drawn from a population consisting of an additive mixture of G latent classes, in different proportions, π_g. A G-component FMM of bull prices can be written as:

(2)
$$f(y_i \mid x_i, \beta_g, \pi_g) = \sum_{g=1}^{G} \pi_g f_g(y_i | x_i, \beta_g)$$

where $f_g(\cdot)$ is the density function for class g, y_i is the log of price, β_g is class-specific parameters, and π_g denotes the percentage chance of belonging to a given class g with $\sum \pi_g = 1$, and $0 \leq \pi_g \leq 1$. In this study, a common normal distribution is assumed for each class:

(3)
$$f_g(y_i | x_i, \beta_g) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{y_i - x_i\beta_g}{2\sigma^2}\right).$$

Empirically, $f(\cdot)$ describes a mixture of linear regression models. The likelihood function for the observed data P_i is:

(4)
$$L(\beta, \pi | x) = \prod_{i=1}^{n} \left[\sum_{g=1}^{G} \pi_g f_g(y_i | x_i, \beta_g)\right].$$

The log likelihood function is:

(5)
$$logL(\beta, \pi | x) = \sum_{i=1}^{n} log\left\{\sum_{g=1}^{G} \pi_g f_g(y_i | x_i, \beta_g)\right\}.$$

The maximum likelihood estimates of $\widehat{\beta_g}$ and $\widehat{\pi_g}$ can be obtained by solving the log likelihood equation using numerical methods, such as the Quasi-Newton method. The estimated posterior probability can be calculated using Bayes rule: $\hat{\pi}_{g,i} = \frac{\hat{\pi}_g f_g(y_i|x_i,\hat{\beta}_g)}{\sum_{g=1}^{G} \hat{\pi}_g f_g(y_i|x_i,\hat{\beta}_g)}$. This indicates the membership probability of observation i belonging to class g. In some studies, π_g may be further specified as a logistic function of observable covariates, such as demographic and attitudinal information (Wedel, 2002). FMM allows us to exploit the underlying heterogeneity without additional requirement of such information. Previous studies have shown that FMM, either with or without these concomitant variables are statistically identified (Caudill and Mixon, 2016). The FMM is estimated using PROC FMM in SAS (SAS Institute Inc., 2013).

Models with two to 10 components, or latent classes, are considered, and common information measures such as Akaike Information Criterion (AIC), Schwartz-Bayesian Information Criterion (BIC), and consistent AIC (CAIC) are investigated to identify the optimal number of latent classes, G. We also use the relative entropy index to evaluate the classification performance of the FMM based on the posterior probabilities of the FMMs (Wedel and Kamakura, 2000). The index is computed as:

(6)
$$E_G = 1 - \frac{\sum_g \sum_i -\pi_{g,i} \ln(\pi_{g,i})}{n\, ln(G)}.$$

E_G is bounded between 0 and 1. A higher value of E_G indicates greater precision of latent class separation. E_G cannot be used as a direct diagnostic criterion to select the optimal number of classes, but it may be used to identify problematic over extraction of latent classes and assess how well the latent classes are separated (Masyn, 2013).

2.4.2 Robustness Check –Deterministic Classes and Standardized Data

Coefficients estimated using the FMM represent the marginal effect of a one unit change in each bull attribute on the log of bull price. Given our interest in better understanding how bull buyers in different latent classes value bull attributes differently, examining the relative importance of bull traits within latent classes may sharpen the delineation of bull buyer classes. Comparing sizes of coefficients directly within each latent class might be misleading given all attributes have different units and variances.

Pindyck and Rubinfeld (1998) suggest standardizing data based on class specific means and standard deviations to get coefficients that represent the relative importance of independent variables in a multiple regression context. Given the nature of the FMM, the probability-weighted estimation of attribute valuations across latent classes does not allow for data standardization. Therefore, we assign observations to deterministic classes based on predicted class membership probabilities from the FMM. That is, each observation is assigned to the latent class for which it has the highest probability of class membership[4]. Data are then standardized for each class by subtracting the mean value of each variable from its observed value and dividing the result by the variable's standard deviation. Standard hedonic models are then estimated for each deterministic class.

Estimation of deterministic hedonic models for the three latent classes differs from the FMM in that the posterior probabilities of class membership are used in the estimation of the parameter estimates for the FMM. However, in the deterministic version of the three-component model, the posterior probabilities are only used to assign bulls into deterministic classes and are not directly involved in the estimation of model coefficients. Estimated coefficients in the

[4] We use 45% as the threshold to assign each observation to corresponded class, and only less than 20 observations undecided. Model results is robust after deleting these undecided observations.

standardized hedonic models represent the relative importance of each trait in explaining log of bull prices. For example, a standardized coefficient of 0.7 indicates that a one standard deviation changes in the independent variable results in a 0.7 standard deviation change in the log of bull price (Pindyck and Rubinfeld, 1998).

2.5 Results and Discussion

Results from the pooled hedonic regression are reported in Table 2.2. Parameter estimates are generally consistent with the results from previous literature (e.g., Dhuyvetter et al., 1996; Jones et al., 2008; Vanek, Watts, and Brester, 2008; Franken and Purcell, 2012; Boyer et al., 2019). However, if different bull buyers' value various traits unequally, aggregating the data into a pooled model may hide important information about how different segments of bull buyers value bull traits.

2.5.1 Finite Mixture Model (FMM)

In determining the optimal number of latent classes for the FMM, both AIC and CAIC favor the three-class FMM; BIC favors the pooled model. These findings are not surprising given the literature has shown that AIC and CAIC tend to favor models with a higher number of classes and BIC tends to favor models with fewer classes (Wedel and Kamakura, 2000).

The relative entropy values for the two- and three-class FMMs are 0.31 and 0.67, respectively, suggesting a higher level of distinctiveness for observations across the three-class model. Therefore, we determine based on the information criteria and relative entropy index there is sufficient evidence of heterogeneity in buyer preference for bull traits to justify the FMM, and model results of three-class FMM appear to be the most useful for examining heterogeneity in bull buyer preferences for bull attributes. Examining differences in the magnitudes and significance of parameter estimates across the three latent classes offers some interesting insights.

Class #3 is the largest latent class – 73% of the buyers in our sample belong this class on average (Table 2.2). Buyers in this class tend to place higher value on birth weight and frame score than buyers in the other two classes. Birth weight is a direct measure of calving ease, with lower birth weights being more favorable given they are associated higher calving ease (fewer instances of dystocia). Frame score is a measure of mature size, likely making it a proxy for salable weight of calves. Calving ease (birth weight) and salable weight (frame score) are traits that are important for all bull buyers when purchasing herd sires, and appear to be particularly important for buyers in class #3. Bull buyers in class #3 also place relatively high value on growth traits, such as average daily gain and weaning weight EPD, birth weight EPD, and adjusted scrotal circumference, although these traits do not necessarily distinguish class #3 from classes #1 and #2.

Table 2.2 Model Results of Pooled Model and Three-Class Finite Mixture Model (FMM) (n = 1,903)

Variable	Pooled Hedonic Model	Three-Class FMM Class #1	Three-Class FMM Class #2	Three-Class FMM Class #3
Intercept	1.651 ***	1.063 ***	2.086 ***	1.780 ***
Age	0.001 ***	0.001 ***	0.0003 ***	0.001 ***
Birth weight	-0.002 ***	0.001 ***	-0.001 *	-0.003 ***
Average daily gain	0.067 ***	0.090 ***	0.056 ***	0.070 ***
Frame score	0.053 ***	-0.009 ***	0.032 ***	0.062 ***
Adjusted scrotal circumference	0.006 ***	0.009 ***	0.002	0.006 ***
Adjusted rib eye area	0.026 ***	0.055 ***	0.019 ***	0.025 ***
Adjusted percent intramuscular fat	0.016 ***	0.021 ***	0.007	0.014 ***
Birth weight EPD	-0.042 ***	-0.083 ***	-0.025 ***	-0.040 ***
Weaning weight EPD	0.004 ***	0.009 ***	0.002 ***	0.004 ***
Maternal milk EPD	0.004 ***	0.002 **	0.006 ***	0.004 ***
Rib eye area EPD	0.02	-0.008	-0.006	0.025
Marbling EPD	-0.011	0.093 ***	-0.031	-0.015
Origin	-0.034 ***	-0.205 ***	-0.003	-0.04 ***
Sale year fixed effects	Yes	Yes	Yes	Yes
%	100%	7%	20%	73%
Log Likelihood	1,511.889		1,683.800	
AIC	-2,971.779		-3,201.600	
BIC	-2,827.448		-2,740.900	
CAIC	-2,801.450		-3,012.388	
Predicted price ($/head)	$2,463	$2,336	$2,170	$2,539

Notes: Dependent variable in both the pooled model and three-component FMM is log of bull sale prices adjusted to 2018 dollars. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 2. 1 Results of Pooled Model and Deterministic Class Hedonic Models Using Standardized Data

		Deterministic Classes Assigned from the Finite Mixture Model (FMM)[1]		
Variable	Pooled Hedonic Model	Class #1	Class #2	Class #3
Intercept	3.269 ***	3.081 ***	3.061 ***	3.334 ***
Age	0.022 ***	0.042 ***	0.012 ***	0.024 ***
Birth weight	-0.017 ***	0.006 ***	-0.007 **	-0.024 ***
Average daily gain	0.035 ***	0.049 ***	0.026 ***	0.035 ***
Frame score	0.033 ***	-0.006 ***	0.023 ***	0.04 ***
Adjusted scrotal circumference	0.014 ***	0.021 ***	0.003	0.014 ***
Adjusted rib eye area	0.034 ***	0.076 ***	0.023 ***	0.03 ***
Adjusted percent intramuscular fat	0.018 ***	0.022 ***	0.006 *	0.015 ***
Birth weight EPD	-0.061 ***	-0.11 ***	-0.04 ***	-0.058 ***
Weaning weight EPD	0.037 ***	0.075 ***	0.019 ***	0.033 ***
Maternal milk EPD	0.022 ***	0.008 ***	0.027 ***	0.017 ***
Rib eye area EPD	0.005	-0.002 **	-0.003	0.008 **
Marbling EPD	-0.003	0.024 ***	-0.009 **	-0.004
Origin	-0.034 ***	0.208 ***	0.002	0.041 ***
Sale year fixed effects	Yes	Yes	Yes	Yes
n	1,903	130	247	1,526

Notes: Dependent variable in all regressions is log of bull sale prices adjusted to 2018 dollars. Independent variables are standardized for each regression (pooled model and for each class) by subtracting the mean value of each variable from its observed value and dividing the result by the variable's standard deviation. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

[1] Observations are assigned to deterministic classes based on predicted class membership probabilities from the three-class finite mixture model. That is, each observation is assigned to the latent class for which it has the highest probability of class membership.

Based on these findings, it seems likely that class #3 represents typical U.S. cow-calf operations. It is the largest latent class in our sample probabilistically (73%), making it likely that class #3 represents smaller farms that are common in the U.S. cow-calf sector. According to the 2017 U.S. Census of Agriculture, the average U.S. cow-calf herd size is 41 cows, and 77% of U.S. cow-calf operations have less than 50 cows (USDA NASS, 2020). Bull buyers in class #3 also appear to emphasize the traits that we would expect these farms to value in terms of a herd sire – calving ease and salable weight. Producing a predictable and low-maintenance calf crop would be particularly important for smaller, often part-time, operations. In addition, the focus on saleable weight aligns with the incentives signaled through the expected marketing channels for these producers. That is, these farms are expected to be more likely to sell calves at weaning at a local auction where sellers are paid solely on appearance and weight, and additional information about genetic potential or carcass quality is sparse.

Class #2 represents next largest latent class in our model – 20% of buyers in our sample are in this class on average (Table 2.2). Identifying a distinguishing feature of class #2 is difficult. Class #2 places the highest marginal value on maternal milk EPD, although the magnitude of this effect relative to the other two classes makes it difficult to characterize this as a defining feature of the producers in class #2. Probably more notable is the lack of emphasis on traits such as birth weight and birth weight EPD, adjusted scrotal circumference, adjusted percent intermuscular fat, and weaning weight EPD relative to bull buyers in classes #1 and #3. In addition, the mean predicted sale price, $2,170 (Table 2.2), for bulls in class #2 is the lowest of the three classes in our model. In conjunction with the individual parameter estimates, this seems to suggest that bull buyers in class #2 are “value buyers.” That is, they do not look for any particular traits when purchasing a herd sire. Instead, they likely focus on getting a certified quality bull with the lowest price.

Finally, class #1 represents the smallest latent class in our model – just 7% of buyers in our sample are expected to be in this class on average (Table 2.2). The distinguishing feature of class #1 is the emphasis on carcass traits adjusted ribeye area, adjusted percent intermuscular fat, and marbling EPD relative to the other two classes. Ribeye area is an estimate of muscular development of the beef carcass and one of the primary determinants of yield grade. Yield grade measures of the quantity of retail cuts from the carcass and one of the two main components of the grid pricing system for beef carcasses. Intermuscular fat and marbling EPD both measure beef quality, with more fat corresponding to higher quality grades. Quality grade is the other main component of the grid pricing system for beef carcasses. Based on this finding, bull buyers in class #1 are expected to be more likely to seek out value-added marketing arrangements for their calves, such as private treaty sales or retained ownership. This again aligns with our a priori hypothesis that the end-use of calves may contribute to bull buyer segments. Producers who sell their calves at weaning at a local auction have little to no incentive to invest in carcass traits given they are paid based solely on weight and information tends to be sparse. Whereas producers who seek out value-added marketing arrangements for their calves are more likely to be incentivized to invest in carcass traits through mechanisms such as grid pricing.

Previous research has indicated the presence of statistically significant carcass traits in pooled bull price hedonic models are sufficient evidence that grid pricing has successfully signaled quality cues up the beef cattle supply chain to the industry's breeding sectors (Jones et al., 2008; Vanek, Watts, and Brester, 2008). However, these signals are likely more nuanced than indicated by previous literature. In particular, the results of this analysis confirm Vanek, Watts, and Brester's

(2008) assertion that evidence of significant carcass trait effects on bull prices in a pooled model may be the result of a segment of the beef industry's breeding sector concentrating on improving carcass traits. Notably, less than 10% of bull buyers in our sample emphasize carcass traits when purchasing herd sires.

In addition to carcass traits, buyers in class #2 also place added emphasis on birth weight EPD and weaning weight EPD relative to the other two classes. Buyers in class #2 also place emphasis on average daily gain and adjusted scrotal circumference although these traits do not distinguish them from buyers in classes #1 and #3.

2.5.2 Robustness Check – Deterministic Classes and Standardized Data

Regression results for the hedonic models based on the three deterministic latent bull buyer classes identified by the FMM are reported in Table 2.3.[5] The same general trends seem to emerge. However, as expected, the standardized coefficients sharpen the delineation of the latent classes. Figure 2.1 plots the standardized coefficients for the three deterministic classes and the pooled model providing a more easily digestible view of the results.

Bull buyers in class #3 still place more emphasis on lower birth weight and higher frame score than bull buyers in the other two classes (Table 2.3). The standardized coefficients also indicate that bull buyers in class #3 also place relatively more value on ribeye area EPD. At first glance, this result seems contradictory to the results from the FMM, which indicate producers in class #1 placed emphasis on carcass characteristics. However, considering the size of this effect in concert with the adjusted ribeye area (a different measure of the same trait) effect and the marbling

[5] Deterministic OLS regression models for the three latent classes were also estimated using unstandardized data (results available from the authors upon request). The signs, significance, and magnitude of the coefficient estimates are generally consistent with FMM model results.

traits, there is evidence that producers in class #3 are consistently emphasizing carcass traits in their bull buying decisions (Figure 2.1). Instead, the results from the standardized hedonic models support our hypothesis that bull buyers in class #3 are likely typically smaller cow-calf operations which focus on calving ease and salable weight.

Bull buyers in class #2 continue to be characterized by their lack of emphasis on several bull attributes relative to their peers. They also have the lowest overall observed bull price, $1,951 (Table 2.4). Again, this suggests that bull buyers in class #2 are value buyers, who pay more attention to the price than to any particular bull attributes. Difference of average prices among these three classes are significant. Differences are also found to be significant between class#1 and class#3 for adjusted percent intramuscular and ribeye area EPD. In addition, birth weight, average daily gain, frame score, adjusted scrotal circumference, and weaning weight EPD are found to be significantly different between class#1 and class#3. However, no differences are found to be simultaneously significant among these three classes except prices of beef bull. It seems to suggest the unobserved heterogeneity may be due to buyers' varied preferences to beef bulls.

Bull buyers in class #1 are still characterized by value placed on carcass traits adjusted ribeye area, adjusted percent intermuscular fat, and marbling EPD. In particular, adjusted ribeye area is the second largest influencer of bull prices (in absolute value) for bull buyers in class #1 (Figure 2.1). Further, bull buyers in class #1 also emphasize birth weight EPD and weaning weight EPD relative to bull buyers in the other two classes. Again, this supports the assertion that bull buyers in class #1 are like more commercially oriented, specifically in the sense that they are likely seeking out value added marketing arrangements, such as private treaty sales and retained ownership, in order to take advantage of investments in carcass traits.

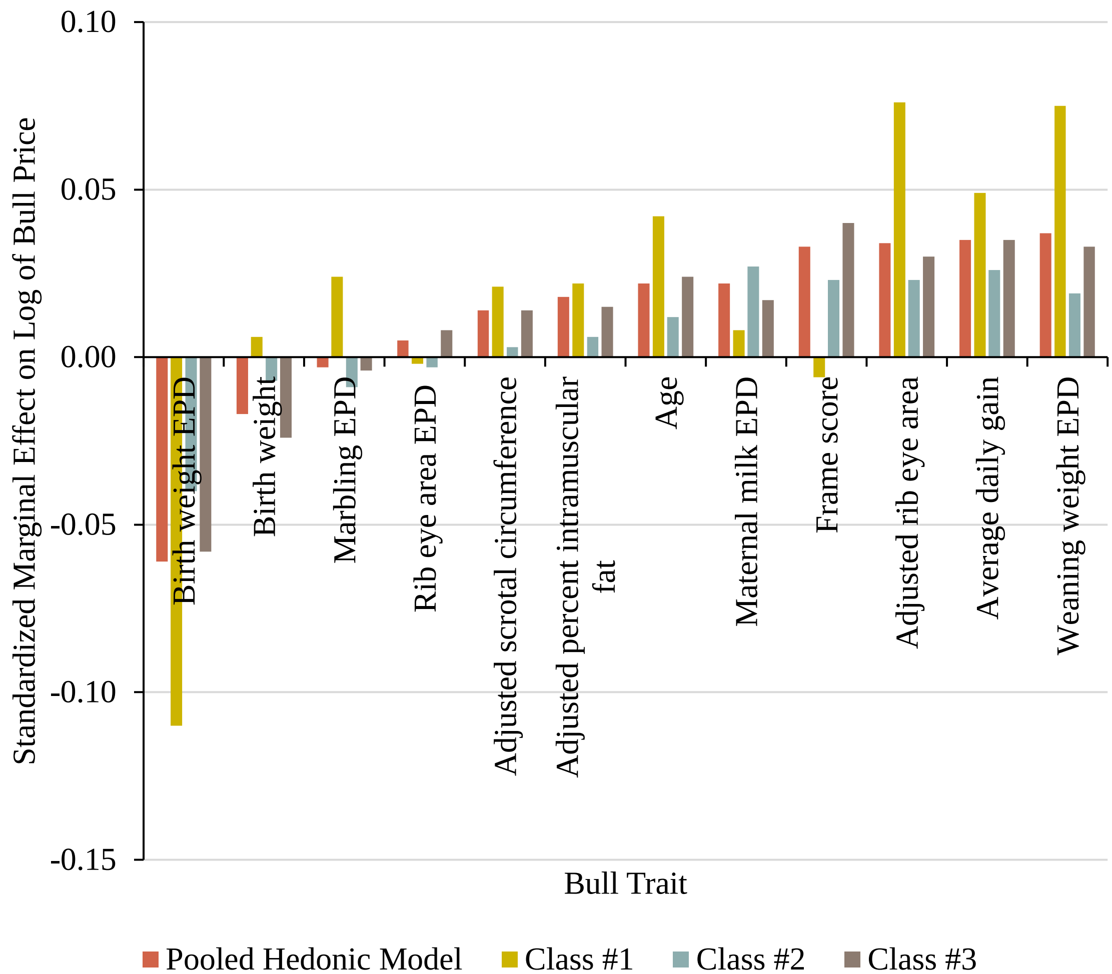

Figure 2.1 Standardized marginal effects on log of bull price for the pooled OLS hedonic regression model and the deterministic OLS hedonic models for the three latent classes from the finite mixture model (FMM)

2.6 Conclusions

Bulls are characterized by quality differentiations and bull buyers are assumed to have heterogeneous preference for bull attributes. In this study, FMM approach is applied to identify bull submarkets implicitly and examine bull buyers' heterogeneous preferences for bull attributes. Results indicate evidence that bull buyers have heterogeneous preferences for bull attributes. A three-class FMM is identified as providing the best view of bull buyer heterogeneity. Although our results do not perfectly align with the bull buyer segments hypothesized a priori (sell at weaning, produce replacement heifers, and retain ownership), the end-use of calves produced does seem to influence the latent classes identified.

These results have implications for the beef industry as decision makers seeking to improve the quality and consistency of beef products. Previous research has indicated that statistically significant carcass traits in pooled hedonic models are sufficient evidence to support the responsiveness of the industry's breeding sector to grid pricing signals. However, we show here that different bull buyers' value different bull attributes differently. Therefore, pooled model results mask important information about the effectiveness of quality cues. Our results clearly indicate a small proportion (< 10%) of the bull buyers in our sample emphasize carcass traits in their bull purchasing decisions. This is not surprising given that very few cow-calf producers actually retain ownership of calves through finishing. Instead, the majority of feeder cattle in the U.S. are sold via local auctions where sellers are paid solely on weight and physical appearance and information is sparse providing little to no incentive to invest in bulls that produce calves with improved carcass traits.

It is important to note that these results are derived from a relatively small sample of bull buyers over a relatively small geographic area (Indiana and Tennessee) and rely on university sponsored bull test programs. Therefore, it is difficult to speculate on how these results would generalize to the broader population of bull buyers. It seems likely that these results are at least somewhat generalizable, although we would expect the specific proportions of buyer types to vary widely depending on geographic location and type of bull sale. Nonetheless, it continues to be important for the beef industry to consider how current price signals are being transmitted to various industry segments and if this is meeting industry objectives for improved quality and consistency. Our results indicate that it may be necessary to provide additional incentive structures to the beef cattle supply chain to further advance the quality of U.S. beef.

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CHAPTER 3. SEASONAL VARIATION IN FED CATTLE PROFITABILITY INCLUDING BOTH PRODUCTION AND PRICE RISK

3.1 Introduction

The cattle feeding industry is characterized by volatile returns, fluctuating between large profits and heavy losses within short periods of time (Tonsor, 2017). Cattle feeders have to decide when and how to market cattle to maximize expected returns and manage risk. Previous literature has identified two primary sources of risk associated with buying and selling fed cattle: production risk and general price risk (Fausti and Feuz, 1995).[6] Like most agricultural activities, beef cattle production and marketing are vulnerable to seasonal climate risk (Mark, Jones, and Mintert, 1997). That is, both sources of risk may be conditional on the season the animal is fed/marketed. For example, production characteristics such as feedlot performance (e.g., average daily gain and feed-to-gain ratio) and carcass merit (e.g., yield grade and quality grade) may be impacted by the season in which animals are fed. Similarly, output prices follow seasonal patterns that are driven by supply and demand for beef products (Mark, Jones, and Mintert, 1997; Peel and Meyer, 2002). To date, the interaction of seasonal production and price risks on fed cattle returns is unknown. To our knowledge, this is the first study that incorporates seasonal production and price risks in the analysis of fed cattle profit distributions.

A sizable body of literature has been developed identifying factors affecting cattle feeding profitability. Feeder cattle price and animal performance (Forristall, May, and Lawrence, 2002; Lewis et al., 2016; Tang et al., 2017) have been found to impact fed cattle profit variation. Among

[6] Fausti and Feuz (1995) characterize production risk as "informational" risk – or the uncertainty associated with the quantity and quality of salable beef products from individual cattle. Here we use the term production risk to indicate that this is the risk associated with producing physical output. That is, until the animal is harvested the quantity and quality of beef produced is unknown.

the carcass characteristics, carcass weight is the dominant contributor to revenue variation followed by marbling score, fat thickness and ribeye area (Feuz, 1998). The choice-select price spread is another determinant of fed cattle grid price (Fausti, Feuz, and Wagner, 1998; Fausti and Qasmi, 2002) since more than 80% of the beef belong to these two categories (Pruitt, Rapper, and Peel, 2013).

Seasonality is an important factor often overlooked in previous research. Seasonal weather conditions contribute to cattle feeding profitability first through cattle performance and carcass quality. Biological performance has been shown to follow seasonal patterns and influence cost of gain seasonally, which in turn contributes to profit variability (Mark, Jones, and Minert, 1997; Lawrence, Wang, and Loy, 1999; Piao and Baik, 2015). Weather is multifaceted and natural seasonality in cattle feedlot profitability is determined by many weather variables, such as temperature, relative humidity, wind speed, and solar radiation (Mader, Johnson, and Gaughan, 2010). Using a recently developed Comprehensive Climate Index (CCI) and comparable temperature stress threshold (Mader, Johnson, and Gaughan, 2010), Belasco, Cheng, and Schroeder (2015) analyzed the relationship between temperature related stress and cattle feedlot performance, i.e., average daily gain and feed conversion rate. However, Belasco, Cheng, and Schroeder (2015) do not consider seasonal weather effects on carcass merit, quality grade and yield grade, which are considered in the current study.

Similarly, seasonal price patterns have been previously documented, specifically, the seasonality in the Choice-Select (C-S) price spread (Robert Hogan, Anderson, and Schroeder, 2009; McCully, 2010; Frank and Parcell, 2017). The choice-select price spread reflects demand and supply of two distinguished markets for these two quality grades. When demand for choice beef is high and supply of choice beef is low, the choice-select price spread is wide. Seasonal beef demand and supply causes narrow/wide C-S price spread at different times of the year. Specifically, the spread is the narrowest in February as demand for choice beef is low and supply is high; the spread becomes wide during May and June and during October and November when demand for high quality beef is strong while fewer cattle grading choice are supplied (Figure 3.1).

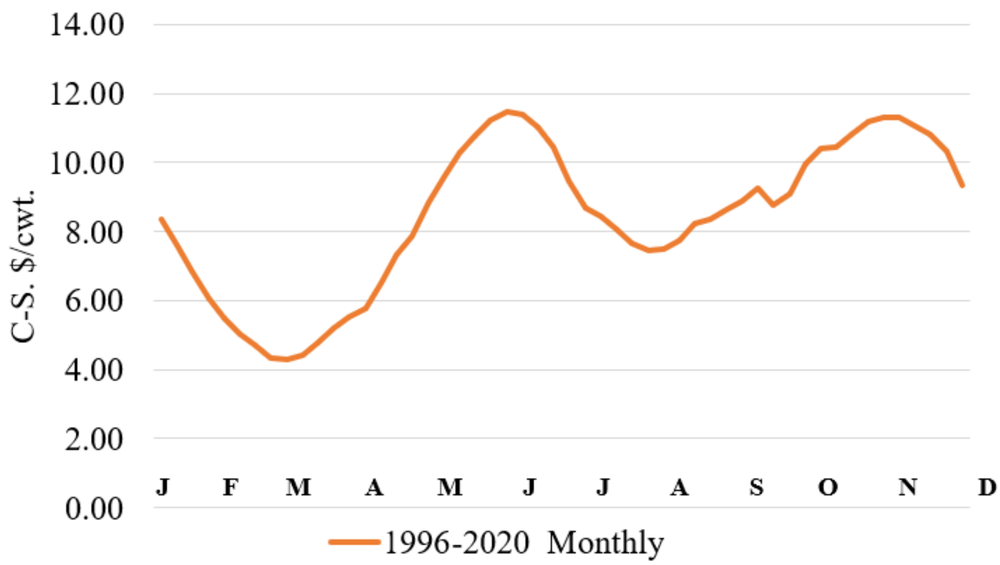

Figure 3.1 Seasonal Trend of Weekly C-S Spread during 1996-2020
Data source: Livestock Marketing Information Center (LMIC)

Belasco et. al., (2009) evaluates production risk associated with cattle performance and examines profit distributions by using high and low variability in fed cattle prices. Past research has also modeled production risk using a multivariate dynamic regression accounting for the multi-dimensional relationship between these biological outcomes (e.g., Belasco, Ghosh, and Goodwin, 2009). Belasco et al. (2010) incorporates price risk into cattle feeding profitability in the form of quality risk and examines trade-offs between quality and performance outcomes. In their study, A times series model is estimated using weekly grid pricing data to obtain predicted premiums/discounts and standard errors for profit simulation. A relatively recent study by Belasco, Cheng, and Schroeder (2015) examines impact of extreme weather stress on cattle feedlot performance and profitability. Although seasonality in cattle performance is examined, but seasonal effects of fed cattle prices, specifically choice-select price spread, on cattle feeding profitability is not controlled for in their analyses. While these studies are helpful to understand the roles of both risks in determining cattle profit variability, they tend to focus on one or the other.

A good understanding of the role of weather effects on cattle performance across placement seasons can help producers project cost of feeding cattle through harvest and help adjust production operation on time. C-S price spread, as the major component of the grid pricing system, determines the grid price differentials over time. Accounting for price risks and utilizing seasonal price information may help producers increase cattle feeding profits and manage risks. The purpose of this study is to examine the seasonal variation in fed cattle profitability considering both production and price (specifically C-S price spread) risk. While it is reasonable to expect that some decision makers may have internalized seasonal differences in expected returns to cattle feeding through experience, empirical evidence to support this is limited. Further, this sort of implicit recognition of seasonal variation in fed cattle profitability is likely to focus on the first moment, overlooking second moment impacts. Here we explicitly examine the first and second moment impacts by evaluating distributions of returns to cattle feeding conditional on seasonal weather impacts.

3.2 Economic Framework

Cattle producers are assumed to maximize expected profits. Generally, there are three sources of uncertainty that contribute to cattle feeding profitability (Williams, 1975): feedlot performance, cattle price, and feed cost. Specifically, cattle sold through grid pricing are mainly affected by carcass grades such as quality grade (*QG*) and yield grade (*YG*). Feedlot performance mainly includes average daily gain (ADG), feed-gain ratio (FG), and health status. We use veterinary cost (VC), the cost of individual health treatment received when the individual animal is either ill or injured at the feedlot, to indicate the health status of an animal. These elements are regarded as cattle production inputs and are subject to seasonal weather effects depending on placement seasons (Hahn, 1985). Following Key and Sneeringer (2011), the beef cattle production can be expressed as:

$$y_{ij} = f(x_{ij}, w_{ij}; \beta_j), \tag{1}$$

where y_{ij} is output (e.g., ADG, FG, VC, QG, YG) of animal i placed in the feedlot in the jth season, which is a function of x_{ij}, a comprehensive set of seasonal weather variables w_{ij}, and parameters. Fed cattle are assumed to be sold under grid pricing. The expected profit maximizing function is given by:

$$\max_{DoF_{ij}>0} E\left[\pi_{ij}\right] = P_{ij}^{G} f\left(x_{ij}, w_{ij}; \beta_j\right) - \sum_l c_{lij}\, x_{lij}, \tag{2}$$

where P_{ij}^{G} is the grid price of beef cattle output, and c_{lij} is the price of input l.

Consider two identified placement seasons j and q with two different seasonal weather conditions, respectively: low weather stress (w^L) and high weather stress (w^H). Assuming input price is held constant at $\bar{c}$, the expected profit is higher for placement season j than placement season q : $E\left[\pi_{ij}\middle|w = w^L\right] > E[\pi_{iq}|w = w^H]$, if $P_{ij}^{G} \geq P_{iq}^{G}$. However, outcomes of profit comparison could be indeterministic if $P_{ij}^{G} < P_{iq}^{G}$. In both cases, hold either output prices (P^G) or weather conditions (w) constant could lead to the pure effect of a change in profitability attributing to one or the other. However, accounting for seasonal variation in both weather condition and grid prices is imperative to reveal the combination effects of both on profitability.

The grid price is determined by the yield grade (*YG*), quality grade (*QG),* and hot carcass weight (*HCW*) of each individual animal. Feed cost (*FC*) is determined by feed price (*FP*, \$/lb.), feedlot performance and number of days on feed (*DoF*). These unknown determinants of profit, along with several other variables that are known at the time of feedlot placement, such as placement weight (*PW*), placement season (*PS*), and purchase cost of feeder cattle (*PC*), consist of the main component of expected profits of cattle feeding:

$$\max_{DoF_{ij}>0} E\left[\pi_{ij}\right] = P_{ij}^{G}(YG, QG, HCW) \times HCW_{ij}(PW, ADG, DoF, DP) - PC_{ij}(PW, SEX) - FC_{ij}(FP, ADG, FG, DoF) - VC_{ij} - YC_{ij}\,(DoF) - IC_{ij},$$

$$\forall\ i = 1, \ldots, n\ \ and\ j \in \{1,2,3,4\} \qquad (3)$$

where the cattle producer chooses the optimal days on feed for animal i placed in the *j*th placement season to maximize expected profit (π_{ij}); grid price P_{ij}^{G} (\$/cwt.) is determined by carcass characteristics, i.e., YG, QG, HCW; the base price (P^{B}) is the market value of a carcass determined as QG Choice, YG 3, and HCW weighing between 650 and 950 pounds; the gird price of each slaughtered animal (P_{ij}^{G}) is an additive function of base price (P^{B}), premiums (P_{ij}^{M}), and discounts (P_{ij}^{D}) determined by its own carcass characteristics: $P_{ij}^{G} = P^{B} + P_{ij}^{M} - P_{ij}^{D}$; hot carcass weight ($HCW_{ij}$) is a function of PW, ADG, DoF, DP: $HCW_{ij} = \left(PW_{ij} + ADG_{ij} \times DoF_{ij}\right) \times DP_{ij}$, where DP_{ij} is dressing percentage; purchase cost (PC_{ij}) equals the feedlot placement weight of the feeder cattle multiplied by the market value of the feeder cattle at the time delivery to the feedlot, which is largely determined by PW and animal sex (SEX); feed cost (FC_{ij}) is defined as $FC_{ij} = FP_{ij} \times ADG_{ij} \times FG_{ij} \times DoF_{ij}$; yardage cost ($YC_{ij}$) is feedlot's fixed charge per head multiplied the number of days the animal was on feed in the feedlot; we follow Belasco et. al (2009a) to define interest cost (IC_{ij}) as $IC_{ij} = \left\{PC_{ij} + \frac{1}{2[FC_{ij}+VC_{ij}+YC_{ij}]} \times DoF_{ij} \times \frac{IR_{ij}}{365}\right\}$, where IR_{ij} is the fixed annual interest rate.

3.3 Data

3.3.1 Weather Data

In this study, seasonal dummy variables were explored to explain differences in cattle production traits. However, potential endogeneity concerns lead us to replace season dummies with weather variables to better identify how seasonal weather differences influence cattle performance. Very few previous studies have attempted to model beef cattle performance as a function of weather outcomes directly (e.g., Belasco et al., 2015), and even fewer have included measures of precipitation. Precipitation can cause mud issues. Mud has been identified as one of the biggest issues in feedlot, especially open feedlot, and causes cattle to have higher efforts to walk through affecting performance (Grandin, 2016).

Hourly historical precipitation data (in inches) were collected from weather stations closest to each feedlot from the National Oceanic and Atmospheric Administration (NOAA). The hourly precipitation data for the feedlots in this study are only available until the end of 2013, and daily precipitation data over the feeding period during years 2014 and 2015 were used to accompany each observation that was kept in feedlot beyond 2013. Hourly/daily precipitation data were aggregated across the days on feed for each observation and were then merged into cattle production data.

Weather variables used for calculating CCI, such as ambient temperature (Ta), wind speed (WS), relative humidity (Rh), and solar radiation (Ra) for 2004-2015 were retrieved from the National Solar Radiation Database (NSRDB). Formulas for CCI computations can be found in Mader, Johnson, and Gaughan (2010). A later correction to the wind speed in CCI is available from Wang et al (2018). Similarly, hours each animal exposed to extreme cold/hot exceeding the severe threshold (Table 3.1) were aggregated and merged into cattle production data.

Table 3.1 Selected comprehensive climate index thermal stress thresholds

Environment	Hot Condition	Cold Condition
No Stress	<25	>0
Mild	25 to 30	0 to -10
Moderate	>30 to 35	<-10 to -20
Severe	>35	<-20

Note: modified from Mader, Johnson, and Gaughan (2010).

Figure 3.2. illustrates different percentiles and mean of cumulative hours of stress for each month. Winter months and summer months present more extreme days in Southwestern Iowa. For example, for cattle placed in the middle of winter (summer), one can expect as high as around 240 hours of cumulative severe CCI stress during January (July) alone. Table 3.1. lists the CCI index thermal stress thresholds as defined in Mader, Johnson and Gaughan (2010). Figure 3.3 illustrates different percentiles of aggregated precipitation for each month. Summer months clearly have the highest level of precipitation across seasons. Winter months in this region tend to be drier relative to other seasons.

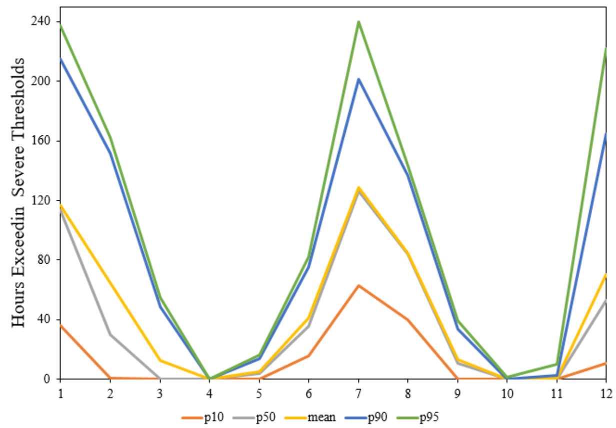

Figure 3.2 Monthly Boxplot for the Number of Severe Hours
According to CCI, by Month,1998-2017

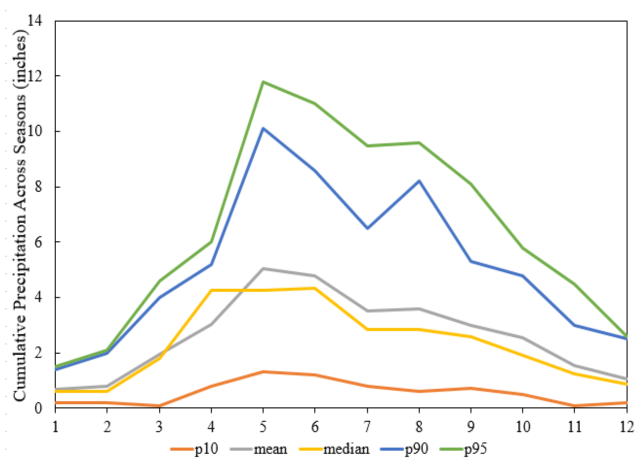

Figure 3.3 Monthly Boxplot for the Cumulative Precipitation,
by Month, 1980-2013

Table 3.2 Summary Statistics of Cattle Performance Carcass Characteristics by Placement Season for 2005-2015

Placement Season[a]	Spring		Summer		Fall		Winter	
	Steer	Heifer	Steer	Heifer	Steer	Heifer	Steer	Heifer
Cattle Performance								
Placement Weight	800	759	764	693	701	674	702	635
# of Health Treatments	0.23	0.48	0.28	0.22	0.26	0.18	0.37	0.4
Veterinary Costs	14.82	17.50	22.98	19.72	24.63	17.52	26.95	27.69
Days on Feed	132	130	144	148	156	156	149	149
Dry Matter Intake (lb.)	3,001	2,687	3,321	3,066	3,444	3,089	3,478	3,282
Feed-to- Gain Ratio	6.29	6.57	6.4	6.97	6.66	7.19	6.63	6.76
Average Daily Gain	3.67	3.18	3.68	3.05	3.38	2.8	3.49	3.22
Dressing %	61.40	61.50%	61.40%	61.80%	61.50%	61.90%	61.50%	61.80%
Harvest Weight	1,281	1,173	1,287	1,136	1,224	1,115	1,231	1,125
Feedlot Gain	481	414	523	443	523	441	529	489
Carcass Quality								
Yield Grade	2.83	2.90	2.95	3.02	2.89	3.11	2.84	3.02
Marbling Score	433.30	479.14	407.93	421.48	421.93	456.91	427.14	466.73
Hot-Carcass Weight (lb.)	786.58	721.12	790.45	701.77	752.36	690.21	756.89	694.73
# Finished Head	185	81	668	209	574	175	838	223
# Head Died in Feedlot	0	2	7	0	13	3	18	5

[a] *Placement season: Spring = March-May, Summer = June-August, Fall = September-November, Winter = December-February.*

Note: *Summary statistics in the table exclude death loss and result in 2,303 steers and 698 heifers. Ten heifers and 38 steers died during the feedlot phase.*

3.3.2 Feedlot Production Data

Data for 2,256 steers and 688 heifers originate from the Tri-County Steer Carcass Futurity Cooperative (TCSCFC) in Lewis, Iowa. Data were collected from November 2004 through February 2015. Ten heifers and 38 steers died and result in incomplete variables from these observations. These 48 dead cattle data were excluded from the study and result in a complete summary statistic for 2,265 steers and 688 heifers. Individual cattle data used in this study include feedlot performance data, hot carcass data, and related prices and costs. The feedlot data include cattle sex, placement weight, placement date, days on feed, feed-to-gain ratio, average daily gain. Hot carcass data were collected after the cattle were slaughtered, measured, and recorded. Hot carcass data include hot carcass weight, USDA yield grade, marbling score, and dressing percentage. Other data used in this study include feeder cattle prices and feed costs. Feeder steer/heifer prices were determined by TCSCFC staff based on animal's weight, frame size, and muscling. Some factors are held constant at the median of the observed values for simulating distributions of profits. PW, feeder cattle price, and DoF are fixed at the median of 710 (lbs.), 97($/cwt.), and 145 (days), respectively. Dressing percentage (DP) is assumed to be deterministic using the average value of the sample observation (Mean=61.53%, S.T. dev. = 0.02).[7] Feed price (FP) is assumed to be deterministic ($0.12/lb.). While there is known to be seasonality in many feed inputs (e.g., corn price), it is assumed that many commercial feedlots are aware of this

[7] Previous research has estimated a dressing percentage equation as a function of animal characteristics. However, given the lack of variability in observed values, these models often tend to have very low explanatory power. The median value is 61.59%.

seasonality and hedge this price risk[8]. The fixed yardage cost (*YC*) per day is \$0.40. Annual interest rate (*IR*) is assumed to be 7%. All prices and costs have been adjusted to 2017 dollars using producer price index (PPI) from the Federal Reserve Bank of St. Louis. Table 3.2 displays the summary statistics of data for cattle performance in the feedlot and carcass characteristics.

Table 3.3 Joint Distribution of Observed Yield and Quality Grade Outcomes (n=2953)

USDA Yield Grade	USDA Quality Grade				
	Prime	Choice	Select	Standard	Total
1	0% (n=0)	<1% (n=37)	3.83% (n=113)	<1% (n=24)	5.89% (n=174)
2	<1% (n=7)	27.97% (n=826)	19.40% (n=573)	1.02% (n=30)	48.63% (n=1436)
3	<1% (n=29)	31.43% (n=928)	9.01% (n=266)	<1% (n=10)	41.75% (n=1233)
4	<1% (n=4)	2.74% (n=81)	<1% (n=22)	0% (n=0)	3.62% (n=107)
5	0% (n=0)	<1% (n=3)	0% (n=0)	0% (n=0)	<1% (n=3)
Total	1.35% (n=40)	63.49% (n=1875)	32.98% (n=974)	2.17% (n=64)	100% (n=2953)

[8] This raises the question, "If feedlots can hedge input price risk (i.e., corn price), why wouldn't we expect them to hedge their output price risk (i.e., fed cattle price)?" In general, we would expect a commercial feedlot to hedge at least a portion of their output price risk. However, for grid pricing, which is of primary interest in this study, there is no mechanism to hedge variation in the premium/discount structure. That is, while a live cattle futures contract is available, this only hedges the general price risk associated with the base price in the grid. It does not protect producers from seasonal variation in the premium/discount structure, mainly the choice-select spread.

A joint distribution of observed yield and quality grade outcomes for the cattle in our sample are listed in Table 3.3. The majority of cattle are either in yield grade 2 (48.63%) or yield grade 3 (41.75%) and quality grade Choice (63.94%) or select (32.98%). The highest occurrence is yield grade 3, quality grade choice (31.43%). This distribution is similar to the current carcass quality in the U.S. beef industry (Moore et al., 2012, p. 5,146; Thompson et al., 2016).

3.4 Methods and Procedures

3.4.1 Statistical Analysis

Observations are split into two groups based on warm/cool placement seasons following Belasco et al. (2015). Cattle placed in the spring and summer are categorized as a warm seasonal group, and cattle placed in the fall and winter are categorized as a cool seasonal group. Splitting observations into two relatively homogeneous groups aims to obtain more precise seasonal weather effects on cattle feedlot performance and characteristics.

The general forms of feedlot performance and hot-carcass quality characteristics for two groups of cattle are specified as:

$$y_{ijk} = \beta_{0jk} + \beta_{1kj}PS_{ijk} + \beta_{2jk}Steer_{ijk} + \beta_{3jk}DoF_{ijk} + \beta_{4jk}\log(\mathrm{pw})_{ijk} + \beta_{5jk}Treat_{ijk} + \beta_{6jk}DoF_{ijk}^2 + \beta_{7jk}DoF_{ijk} \times \log(pw)_{ijk} + \beta_{8jk}Hour_{ijk} + \beta_{9jk}Precip_{ijk} + \beta_{10jk}Hour_{ijk} \times Precip_{ijk} + \beta_{11jk}Hour_{ijk} \times Precip_{ijk} \times Season_{ijk} + \varepsilon_{ijk} \quad (4)$$

where y_{ijk} is the dependent variable for the ith animal placed in the jth placement season for the kth equation, where k=1, 2, 3, 4, 5 for average daily gain (ADG_{ijk}), feed-to-gain ratio

(FG_{ijk}), veterinary costs (VC_{ijk}), quality grade (QG_{ijk}), and yield grade (YG_{ijk}), respectively. PS_{ijk} is a dummy variable equal to 1 if the animal is placed in the winter/summer and 0 otherwise; Steer is a dummy variable equal to 1 if the animal is steer and 0 otherwise; $\log(PW)_{ijk}$ is the log of placement weight;$Treat_{ijk}$ is the number of independent health treatments received by an individual animal during the feeding period; DoF_{ijk} is days on feed, which is the number of days the animal was fed in the feedlot; $Hour$ is the cumulative hours the animal is exposed to the "severe" weather condition during the feeding period; $Precip_{ijk}$ is the accumulated hourly precipitation over the feeding period in the feedlot $\varepsilon_{ijk} \sim N(0,\sigma^2)$ is an error term. The square of days on feed and its interaction with log of placement weight are incorporated into the model to examine its nonlinear effects on animal feedlot performance and carcass characteristics conditional on initial placement weights. It is possible that hours of stress and precipitation has joint effects across seasons, and a two-way interaction and a three-way interaction of weather variables and placement season is incorporated into the model.

Dependent variables are all continuous in each of the five equations. Yield grade is a continuous function of external fat thickness, hot carcass weight, the amount of kidney, pelvic, and heart fat, and the area of the ribeye muscle (USDA-AMS, 2017). Although quality grade depends on the degree of maturity and marbling score, marbling score is typically used to as a proxy for quality grade. Marbling scores of 200-299 are graded Standard, 300-399 are Select, 400-699 are Choice, and score over 700 are prime (Dan, Goodson, and Savell, 2013; USDA-AMS, 2006).

Not each of the individual animal received individual health treatment in the feedlot. The value of veterinary costs is censored at zero for approximately 78.73% of the observations in the data. The veterinary costs exclude chute and drug costs for cattle prior to enter the feedlot. Ignoring the heteroscedasticity in the Tobit model would lead to inconsistency and asymptotic bias of the parameter estimates (Hurd, 1974). Therefore, the multiplicative heteroscedasticity model for veterinary costs is estimated as a Tobit model. Maximum Likelihood Estimation is used to estimate veterinary cost model by specifying the log-likelihood function as:

$$\ln L = \sum_{y_i>0} -\frac{1}{2}\left[\log(2\pi) + \ln\sigma^2 + \boldsymbol{z}_i'\boldsymbol{\alpha} + \frac{\left(y_i - \boldsymbol{x}_i'\boldsymbol{\beta}\right)^2}{\sigma^2\exp\left(\boldsymbol{z}_i'\boldsymbol{\alpha}\right)}\right] + \sum_{y_i=0}\ln\left[1 - \Phi\left(\frac{\boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma^2\exp\left(\boldsymbol{z}_i'\boldsymbol{\alpha}\right)}\right)\right] \qquad (5)$$

where Φ is the normal CDF. The two parts correspond to the regression for the non-limit observation with positive veterinary costs and the relevant probabilities for the limit observations with zero veterinary costs (Green, 2012). The Harvey's Multiplicative Heteroscedasticity Model is estimated in Stata 15 (StataCorp, 2017).

Likelihood ratio tests are performed to test the null hypothesis of variance homoscedasticity against the appropriateness of multiplicative heteroscedasticity assumption. Tests statistics for all four models reject the null, indicating that specified variance across observations is impacted by the specified variables (Table 3.4).

Table 3.4 Likelihood Ratio Test Results

Model	ADG		FG		VC		MS		YG	
	Cool	Warm	Cool	Warm	Cool	Warm	Cool	Warm	Cool	Warm
Unrestricted	-1209.41	-834.73	-1417.13	-980.63	-2636.38	-1527.60	709.34	486.14	-1369.02	-931.65
Restricted	-1247.45	-877.94	-1527.90	-1024.79	-6078.58	-4236.97	661.27	473.46	-1412.89	-948.40
LR Statistic (df=12)	76.08	86.42	221.54	88.32	6884.40	5418.74	96.14	25.36	87.74	33.50
P-Value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

In the presence of heteroscedasticity, each model is estimated using Harvey's Multiplicative Heteroscedasticity model and $\varepsilon_{ijk} \sim N\left(0, \sigma_{ijk}^2\right)$. The variance is unique for each animal and is estimated as

$$\sigma_{ijk}^2 = \sigma_{jk}^2 \exp\left(z'_{ijk}\alpha_{jk}\right) \tag{6}$$

where z_{ijk} contains independent variables that affect the variance, and α_{jk} are parameters of the variance component. The variables in z_{ijk} are the same as x_{ijk}, but without the intercept, which is captured by the σ_{jk}^2 term. Allowing the variance influenced by the specified independent variables reveals insights into how risks are affected by cattle performance and hot-carcass characteristics – specifically seasonal variation in production risk (Belasco et al., 2009).

3.4.2 Choice-Select Price Spread Structural Model

To account for the effects of seasonal variation of C-S price spread on fed cattle profitability, we estimate a Basic Structural Model (Harvey, 1990) to extract the unobserved seasonal component from the overall level of C-S price from each observation using average quarterly times series data of C-S price spread. The Basic Structural Model assumes that an economic time-series consists of several independent component: a trend, a seasonal, and an irregular component. In our study, the basic structural model for quarterly C-S price spread can be written as: $CS_t = T_t + S_t + \delta_t$ where CS_t is the quarterly C-S price spread series, T_t is the trend component capturing smooth pattern that C-S price spread exhibits, S_t is the systematic pattern of time-varying phase in four different seasons, and δ_t is an irregular component that represents the residual variation. The seasonal component is modeled as the stochastic dummy form, and the irregular component is modeled as a stationary autoregressive moving average (ARMA) by model structural selection criteria, i.e., AIC and BIC.

The extracted seasonal component (where $S_t = CS_t - T_t - \delta_t$) represents the repetitive and predicable deviation of quarterly choice-select price differentials from the annual mean of choice-select price ($8.34/cwt.). The mean values and standard deviations of the extracted seasonal component for each season are fed into a random normal distribution an adjustment of the annual mean of C-S price. A negative/positive value of the extracted component is below/above the annual mean and indicates a narrow/wide C-S price spread in that season[9]. BSM is estimated using PROC UCM in SAS (SAS Institute Inc., 2013).

3.4.3 Monte Carlo Simulation

To simulate profits across seasons, parameter estimates from Equation 4 and Equation 6 are used to calculate predicted means, Pearson correlation matrix, and predicted variance-covariance matrices to generate multivariate normal distributions (MVN) of these five dependent variables for each observation. Draws are taken from the MVN distribution to obtain simulated cattle performance, hot carcass characteristics, and C-S price spread, and ex ante profits are calculated for each draw. Feed costs and fed cattle prices derived from these values, are essentially conditional on factors faced by cattle feeders at the time of cattle placement are analyzed and incorporated into the profit function.

[9] The mean values of the extracted seasonal component for spring, summer, fall, and winter are: -0.85$/cwt., 1.07$/cwt., 1.16$/cwt., and -0.94$/cwt, respectively. The standard deviations of the extracted component for spring, summer, fall, and winter are: 1.25, 1.10, 1.14, 1.13, respectively. The discounts for select beef retrieved from the adjusted rand normal distribution do not exceed the discounts for standard beef for each season.

Specifically, the simulation of fed cattle profitability can be broken down into three steps. Step 1) The variance-covariance matrix of the five biological outcomes modeled in equation (4) is determined for each individual animal using the fixed Pearson correlation coefficients and the variance equations for each of the five models. That is, the entire covariance structure is allowed to vary with observations while holding the correlation coefficients constant. The correlation coefficient is computed as the ratio of the covariance to the product of the corresponded standard deviations. The diagonal terms of the variance-covariance matrices are determined as the product of the correlation coefficient and the heteroskedastic error variances, which are predicted by the variance equations in (4), and the off-diagonal elements, or the covariance terms, are the product of the correlation coefficient and the square roots of the heteroskedastic error variances for each outcome and each individual animal.

Step 2) Using the animal specific variance-covariance matrices described in Step 1, cattle performance and carcass characteristics are simulated 1,000 times for each observation from a multivariate normal (MVN) distribution across seasons:

$$\begin{bmatrix} \widetilde{ADG_{ik}} \\ \vdots \\ \widetilde{YG_{ik}} \end{bmatrix} \sim MVN\left(\begin{bmatrix} \widehat{ADG_{ik}} \\ \vdots \\ \widehat{YG_{ik}} \end{bmatrix}, \begin{bmatrix} \rho_{ADG,ADG}\widehat{\sigma^2_{ADG}} & \cdots & \rho_{ADG,YG}\widehat{\sigma_{ADG}}\widehat{\sigma_{YG}} \\ \vdots & \ddots & \vdots \\ \rho_{YG,ADG}\widehat{\sigma_{YG}}\widehat{\sigma_{ADG}} & \dots & \rho_{YG,YG}\widehat{\sigma^2_{YG}} \end{bmatrix} \right), \tag{7}$$

where the "$\left[\widetilde{ADG_{ik}}, \dots \widetilde{YG_{ik}}\right]$" indicates a randomly drawn vector of biological values from the MVN distribution; the mean of the distribution of the vector are the estimated biological outcomes $\left[\widehat{ADG_{ik}}, \dots, \widehat{YG_{ik}}\right]$; $\widehat{\sigma^2_{ADG}}$ are estimated variance from equation (6); ρ is the correlation coefficient in the five-by-five covariance matrix of parameters; $\left[\rho_{ADG,ADG}\widehat{\sigma^2_{ADG}}, \dots, \rho_{YG,YG}\widehat{\sigma^2_{YG}}\right]$ are diagonal terms of the variance-covariance matrices; and $\left[\rho_{ADG,YG}\widehat{\sigma_{ADG}}\widehat{\sigma_{YG}}, \ldots, \rho_{YG,ADG}\widehat{\sigma_{YG}}\widehat{\sigma_{ADG}}\right]$ are the off-diagonal terms of the variance-covariance matrices.

Step 3) Simulated biological outcomes obtained from MVN simulation are fed into equation (3) to determine ex-ante profit for each draw. The C-S price spread is assumed independent from the five biological variables. Hence, this is a partial equilibrium model where output prices are exogenous[10]. However, it is important to note that with grid pricing the output price is a function of yield grade and quality grade outcomes for individual animals.

3.4.4 Stochastic Dominance Analysis

Stochastic dominance analysis is performed to rank the preferred placement season regarding cattle feedlot profitability[11]. First-degree stochastic dominance (FSD) and second-degree stochastic dominance (SSD) are used to discriminate the ranking of cattle performance across seasons. FSD assumes that decision makers prefer more to less (Chavas, 2004). Alternative A dominates B by FSD if $F_A(x) \leq F_B(x)\ \forall\ x$, where F indicates the CDF of the corresponding alternative. Graphically, the CDF of A must always lie below and to the right of CDF of B to satisfy this condition. However, FSD is not able to identify the dominant alternative when two CDFs cross. In such case, second-degree stochastic dominance (SSD) has stronger discriminating power. SSD assumes decision makers are risk averse (Chavas, 2004). Alternative A is preferred to alternative B if $\int_{-\infty}^{x^*} F_A(x)dx \leq \int_{-\infty}^{x^*} F_B(x)dx\ \forall\ x^*$, which indicates the cumulative area under the CDF of A is smaller than the cumulative area under the CDF of B.

[10] Output price is exogenous is because grid structure is picked exogenously outside of the model.
[11] We use McFadden Test (McFadden, 1989) to perform stochastic analysis pair-wisely to determine the ranking order of placement seasons under different scenarios.

3.5 Economic Results

Table 3.5 and Table 3.6 display the maximum likelihood estimation results for average daily gain (ADG), feed-to-gain ratio (FG), veterinary cost (VC), marbling score (MB), and yield grade (YG) for cattle placed in the cool season and warm season, respectively. Results allow us to evaluate the effect of precipitation, hours of stress, and their interaction with placement season on the mean and variance of each biological variable. Direct interpretation of coefficients is not sufficient to draw conclusions about the impact of weather factors on cattle feedlot performance and carcass characteristics given the existence of two-way and three-way interaction terms in the model. Moreover, magnitudes and directions of these effects are largely determined by the actual accumulative levels of CCI and precipitations during feeding period for each animal. For cattle placed in the cool season, coefficients are significantly associated with three-way interaction for cattle feedlot performance, indicating cattle biological performance are affected by the interaction of many weather factors including temperature, solar radiation, humidity, and wind speed (Mader, 2003). Seasonal weather factors significantly contribute to the variance of cattle biological variables except for veterinary cost and yield grade for cattle placed in warm season.

Table 3.5 Estimation Results for Cattle Placed in the Cool Season

	ADG		**Feed-to-Gain Ratio**		**Veterinary Cost**		**Marbling Score**		**Yield Grade**	
Variable	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
Steers	0.4181***	0.5716***	-0.2373***	-0.2564*	10.4666***	-0.1345	-0.0752***	-0.6528***	-0.2173***	0.1117
	(0.0374)	(0.1382)	(0.0519)	(0.1358)	(2.2531)	(0.2200)	(0.0171)	(0.1305)	(0.0493)	(0.1362)
Winter (W)	-0.0687*	0.3634***	0.2591***	0.9160***	-3.5461***	0.2866*	0.0246**	-0.0049	0.0406	0.0479
	(0.0358)	(0.1067)	(0.0394)	(0.1051)	(1.2651)	(0.1517)	(0.0115)	(0.1027)	(0.0380)	(0.1013)
Days on Feed	-0.0649**	0.0941	0.1334***	0.3205***	0.7594	0.4571***	0.0340***	0.1667*	0.0860***	0.2628***
(DoF)	(0.0322)	(0.0990)	(0.0335)	(0.1002)	(1.0244)	(0.1382)	(0.0101)	(0.0906)	(0.0324)	(0.0905)
Log of Placement	-1.8344***	3.1239	5.5103***	7.9288***	20.6808	9.8056***	0.6343***	2.8307	1.6201**	6.5246***
Weight (log(pw))	(0.6904)	(2.0482)	(0.7315)	(2.1056)	(21.8868)	(2.8645)	(0.2123)	(1.9058)	(0.6848)	(1.9287)
Treat	-0.0549***	0.1272***	0.0616***	0.1977***	43.7528***	1.2323***	-0.0047	0.2353***	-0.0690***	0.0376
	(0.0180)	(0.0459)	(0.0198)	(0.0491)	(0.7654)	(0.0704)	(0.0068)	(0.0541)	(0.0173)	(0.0495)
DoF Squared	0.0000	0.0000	0.0000	-0.0002**	-0.0003	-0.0002**	0.0000***	-0.0001**	-0.0001***	-0.0001**
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0007)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)
DoF×log(pw)	0.0101**	-0.0151	-0.0197***	-0.0417***	-0.1034	-0.0603***	-0.0041***	-0.0187	-0.0087**	-0.0328***
	(0.0044)	(0.0132)	(0.0046)	(0.0133)	(0.1403)	(0.0185)	(0.0014)	(0.0121)	(0.0044)	(0.0122)
Hours (H)	-0.0943***	0.0217	0.2016***	0.0496	-1.4746**	0.2634***	0.0017	-0.1661***	-0.0290**	-0.0879**
	(0.0150)	(0.0433)	(0.0155)	(0.0407)	(0.6047)	(0.0646)	(0.0044)	(0.0450)	(0.0145)	(0.0437)
Precipitation (P)	-0.0200***	0.0092	0.0351***	0.0344***	-0.1838	0.0130	-0.0012	-0.0213	-0.0085*	0.0070
	(0.0047)	(0.0137)	(0.0043)	(0.0125)	(0.1469)	(0.0183)	(0.0015)	(0.0148)	(0.0046)	(0.0134)
H×P	0.0013	0.0005	-0.0011	-0.0014	-0.0178	0.0036	0.0001	0.0016	0.0027*	-0.0012
	(0.0015)	(0.0042)	(0.0016)	(0.0038)	(0.0718)	(0.0073)	(0.0004)	(0.0043)	(0.0014)	(0.0042)
H × P ×W	0.0038***	-0.0079***	-0.0110***	-0.0181***	0.1512***	-0.0183***	0.0001	0.0042**	-0.0007	-0.0034*
	(0.0006)	(0.0020)	(0.0009)	(0.0019)	(0.0445)	(0.0042)	(0.0002)	(0.0019)	(0.0007)	(0.0019)
Intercept	15.7402***	-22.2709	-30.4143***	-57.2673***	-162.2299	-65.6928***	1.3787	-24.5164*	-9.6997**	-47.7982***
	(4.7826)	(14.3001)	(5.0069)	(14.7127)	(150.6609)	(19.9822)	(1.4719)	(13.2644)	(4.7317)	(13.3809)
Log Likelihood	-1209.41		-1417.127		-2636.384		709.3403		-1369.02	

Notes: n=2953. Standard deviations are in the parentheses. Single, double, and triple asterisks (*, **, ***) indicates significance at the 10%, 5%, and 1% level, respectively.

Table 3.6 Estimation Results for Cattle Placed in the Warm Season

	ADG		**Feed-to-Gain Ratio**		**Veterinary Cost**		**Marbling Score**		**Yield Grade**	
Variable	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
Steers	0.5164***	0.3119***	-0.6074***	-0.2750***	1.3580	-0.3212*	-0.0748***	-0.2504**	-0.1663***	0.0338
	(0.0311)	(0.1000)	(0.0408)	(0.1050)	(1.8514)	(0.1824)	(0.0122)	(0.1014)	(0.0364)	(0.0994)
Summer (S)	0.0739	-0.5307*	-0.4122***	-0.8774***	9.6189**	0.3441	-0.1084***	-0.6143**	0.0264	0.2767
	(0.0874)	(0.2980)	(0.0951)	(0.3010)	(4.7690)	(0.4966)	(0.0287)	(0.2543)	(0.0873)	(0.2512)
Days on Feed	-0.1028***	0.0972	0.1316***	0.0731	-1.1179	-0.4489**	0.0133	0.1442	0.0341	-0.0128
(DoF)	(0.0319)	(0.1109)	(0.0408)	(0.1078)	(1.8165)	(0.1917)	(0.0121)	(0.1066)	(0.0387)	(0.1057)
Log of Placement	-2.5812***	1.7599	4.8298***	0.9282	-30.9104	-8.7994***	0.3841*	3.1850	1.1774*	-0.1922
Weight (log(pw))	(0.6031)	(2.0304)	(0.7493)	(2.0402)	(31.2266)	(3.2716)	(0.2258)	(1.9674)	(0.6983)	(1.9486)
Treat	-0.1805***	0.2457***	0.0800***	0.2444***	46.1565***	1.3901***	-0.0212***	-0.0468	-0.1024***	0.0305
	(0.0263)	(0.0662)	(0.0294)	(0.0630)	(1.2538)	(0.0952)	(0.0067)	(0.0598)	(0.0244)	(0.0636)
DoF Squared	0.0000	-0.0002**	0.0000	-0.0002**	-0.0019	0.0001	0.0000	-0.0001	0.0000	-0.0001
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0016)	(0.0002)	(0.0000)	(0.0001)	(0.0000)	(0.0001)
DoF×log(pw)	0.0154***	-0.0047	-0.0161***	0.0017	0.2419	0.0625***	-0.0016	-0.0191	-0.0031	0.0087
	(0.0040)	(0.0140)	(0.0052)	(0.0137)	(0.2228)	(0.0234)	(0.0015)	(0.0135)	(0.0048)	(0.0134)
Hours (H)	-0.0807	-0.1444	0.0401	-0.5928***	0.0861	0.1687	-0.0259	0.1293	-0.0195	-0.0283
	(0.0494)	(0.1374)	(0.0548)	(0.1604)	(2.3738)	(0.2535)	(0.0161)	(0.1319)	(0.0508)	(0.1272)
Precipitation (P)	-0.0259***	-0.0053	0.0127	-0.0432*	-0.2206	0.0425	-0.0076***	0.0029	-0.0106	-0.0015
	(0.0068)	(0.0198)	(0.0087)	(0.0232)	(0.3519)	(0.0355)	(0.0022)	(0.0188)	(0.0068)	(0.0186)
H×P	0.0014	-0.0256***	-0.0108***	-0.0114	0.2353	-0.0108	0.0016*	-0.0197**	-0.0009	-0.0025
	(0.0028)	(0.0093)	(0.0031)	(0.0091)	(0.1642)	(0.0167)	(0.0009)	(0.0083)	(0.0031)	(0.0078)
H × P × S	-0.0010	0.0243***	0.0212***	0.0322***	-0.1835	-0.0050	0.0002	0.0198***	0.0018	0.0008
	(0.0021)	(0.0085)	(0.0023)	(0.0077)	(0.1244)	(0.0126)	(0.0007)	(0.0067)	(0.0024)	(0.0066)
Intercept	21.4831***	-17.3636	-27.8494***	-12.3023	150.8297	63.5344***	3.4550**	-25.4633*	-5.8501	-3.9098
	(4.3567)	(14.6456)	(5.4095)	(14.6715)	(228.3259)	(23.9434)	(1.6152)	(14.1951)	(5.0543)	(14.0348)
Log Likelihood	-834.733		-980.6333		-1527.5967		486.137		-931.6516	

Notes: n=2953. Standard deviations are in the parentheses. Single, double, and triple asterisks (*, **, ***) indicates significance at the 10%, 5%, and 1% level, respectively

Precipitation significantly affects average daily gain indicating that cattle growth may be affected by feedlot mud problems during wet periods. Veterinary cost incurred by cattle placed in cool season tend to be more prevalently related to weather conditions than those placed in the warm season. Yield grade of beef cattle placed in cool season is significantly associated with CCI and precipitation. Similarly, marbling score of beef cattle placed in the warm season are impacted by the interaction effects of CCI and precipitation. This finding is evidenced by some studies in the field of animal science that beef quality, i.e. yield grade and quality grade is associated with climate conditions (e.g., Piao and Baik, 2015; Mader, 2003).

Overall, the significance is more prevalent in the cool-season model, which could be due to the fact that cattle placed in the warm season are heavier on average relative to cattle placed in the cool season as heavier cattle tend to be more mature and are likely to have more natural immunities (Belasco, et al., 2009a). Our results show weather factors not only impact the mean of the distribution but also variance of these variables, which could provide us with a more holistic explanation of risk management implications.

3.6 Simulation Analysis Results

3.6.1 Biological Variables

Table 3.7 displays the summary statistics of simulated predicted average daily gain, feed-to-gain ratio, veterinary cost, marbling score, and yield grade across seasons under four scenarios. Simulation of performance and carcass variables are randomly drawn from an MVN distribution using the linear combination of the parameter estimates from equation (4) as the mean and a dynamic structure constructed from the variance component from both equations as the variance-covariance matrix.

Table 3.7 Summary Statistics of Predicted Average Daily Gain, Feed-to-Gain Ratio, Yield Grade, Marbling Score, and Veterinary Costs Across Seasons Under Different Weather Conditions.

	Scenario 1[a]		Scenario 2[b]		Scenario 3[c]		Scenario 4[d]	
	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
ADG								
Spring	3.39	0.66	2.90	0.61	3.27	0.59	2.80	0.56
Summer	3.66	0.58	3.25	0.55	3.55	0.54	3.16	0.51
Fall	3.47	0.49	3.38	0.50	3.27	0.50	3.24	0.51
Winter	3.36	0.58	3.21	0.59	3.24	0.58	3.18	0.60
FG								
Spring	6.96	0.96	7.52	1.27	7.21	1.02	7.95	1.80
Summer	6.32	0.68	6.74	0.85	6.48	0.67	7.03	1.11
Fall	6.42	0.57	6.56	0.62	6.84	0.59	6.84	0.70
Winter	6.72	0.82	6.95	0.92	6.99	0.83	7.03	0.98
Veterinary								
Spring	27.92	22.26	27.97	23.78	26.12	23.11	26.72	23.54
Summer	22.29	26.28	22.90	27.04	21.50	27.01	22.14	26.99
Fall	22.68	25.59	22.83	25.65	24.39	26.50	24.18	27.09
Winter	24.50	24.71	24.94	24.74	25.75	25.90	25.53	26.93
YG								
Spring	2.90	0.49	2.71	0.47	2.88	0.47	2.70	0.45
Summer	2.99	0.57	2.84	0.55	2.97	0.55	2.83	0.53
Fall	2.89	0.55	2.87	0.55	2.84	0.48	2.88	0.47
Winter	2.92	0.58	2.88	0.59	2.91	0.51	2.93	0.50
Marbling								
Spring	462.57	102.21	435.90	97.10	470.68	113.92	471.38	117.23
Summer	420.29	68.39	396.60	64.07	417.90	73.12	411.65	71.91
Fall	428.47	77.15	425.36	72.88	429.91	63.64	429.19	63.02
Winter	436.21	78.01	431.40	71.51	438.69	68.34	436.88	66.69

[a]Scenario 1: when CCI and precipitation are the median.
[b]Scenario 2: when precipitation is at the 90th percentile, and CCI is at the median.
[c]Scenario 3: CCI is at the 90th percentile, and precipitation is at the median.
[d]Scenario 4: both CCI and precipitation are at the 90th percentile.

We create four different scenarios by setting CCI and precipitation at different levels. Cattle have the best growth rate per day and feed conversion efficiency under scenario 1 (the baseline scenario). In this scenario, summer-placed cattle display the highest average daily gain and the lowest feed-to-gain ratio across season. Spring-placed cattle have the lowest average daily gain and highest feed-to-gain ratio. When cumulative precipitation increases from the median (18.55 inches) to the 90th percentile (38.60 inches) (scenario 2), both average daily gain and feed conversion efficiency decline for all seasons. Average daily gain and feed-to-gain ration show substantial decrease (21% and 7%, respectively) for cattle placed in summer when precipitation is increased. Veterinary cost increases across seasons suggesting year-round losses could happen due to wet and muddy condition. Both yield grade and marbling score decrease across seasons indicating a trade-off between quality grade and yield grade under the scenario of excessive seasonal precipitation.

When CCI is increased from the median to the 90th percentile (in scenario 3), both average daily gain and feed efficiency reduce relative to scenario 1 as expected. But average daily gain and feed-to-gain ratio have different reduction patterns under each scenario across seasons. Specifically, cattle placed in all seasons display greater reduction in average daily gain under scenario 2 relative to scenario 3. This suggests that muddy feedlots generate greater negative effects on cattle growth rate. Warm-placed cattle display greater reduction in feed efficiency in scenario 2 relative to scenario 3, while cool-placed cattle display greater reduction in feed efficiency in scenario 3 relative to scenario 2. This finding indicates that warm-paced cattle are more sensitive to excessive precipitation and cool-placed cattle are more vulnerable to temperature stress. One of the reasons may be that cattle paced in warm season have relatively heavy placement weight compared to their counterparts that are placed in cool season. It may be because that heavier cattle are less vulnerable to wet conditions than lighter-weight cattle (Mark, 2002). In this scenario, cattle placed in the fall experienced the largest reduction in productivity across all seasons. Veterinary cost increases for cattle placed in the cool season. Yield grade decreases across season and marbling score increases in most seasons except for summer. Both yield grade and quality grade improve under the scenario of seasonal temperature stress expect that marbling score slightly decreases for summer-placed cattle.

When both precipitation and CCI are at the 90th percentile (scenario 4), average daily gain and feed-to-gain ratio show a consistently decrease across seasons. Excessive precipitation and humidity are strong modifiers of temperature stress effects (Hahn, 1985), and these combined effects exert more adverse effects on cattle productivity relative to scenario 3. Cattle placed in warm season show greater reduction in average daily gain and feed efficiency relative to cattle placed in cool season. Summer in Iowa is typically a hot and rainy season. The cumulative precipitation during the feeding period is greater than 20 inches and may cause muddy problems for open feedlots[12]. Similarly, feedlots become muddy in spring when snow melts and the ground thaws (Grandin, 2016). Therefore, cattle placed in spring and summer show consistently lower productivity across four scenarios than cattle placed in fall and winter under each scenario. Similar to scenario 3, veterinary cost increases for cattle placed in the cool season. Yield grade decreases in most seasons expect in winter, and marbling score increases in most seasons except in summer. Again, a trade-off between yield grade and quality grade is observed under this scenario.

Overall, cattle feedlot growth rate and feed efficiency decrease under weather-stress conditions. Cattle placed in spring have the highest marbling score across seasons under each scenario. Cattle placed in summer have the lowest marbling score. Yield grade decreases in most

[12] Muddy problem is hard to control and manage when annual rain fall is more than 20 inches (Grandin, 2016).

seasons under each scenario. Quality grade decreases under scenario 2 and increases in most seasons under scenarios 3 and 4. A trade-off between yield grade and quality grade is observed in scenario 3 and scenario 4. A trade-off is also observed between yield grade and cattle performance under each weather-stress scenario. An improvement in yield grade is typically accompanied with a reduction in cattle growth rate and feed efficiency under weather-stress scenarios. Similarly, improvement in quality grade is coupled with decrease in growth rate and feed efficiency under scenario 3 and scenario 4. This finding aligns with previous study that there exists a trade-off between and within carcass quality component and performance component (Belasco, Schroeder, and Goodwin, 2010).

Veterinary cost increases across seasons under scenario 2 suggesting adverse effects of precipitation on health status for spring-placed cattle. Cattle placed in the spring have the largest veterinary costs across four seasons, followed by winter, fall, and summer in all scenarios except that summer-placed cattle have slightly higher veterinary cost than fall-placed cattle in scenario 2. Cattle placed in cool season have consistently higher veterinary cost relative to scenario 1.

Table 3.8 Summary Statistics and Stochastic Dominance Rankings of Predicted Profits of Cattle Placed in Four Seasons and Sold Under Grid Pricing

Season	Ranking[a]	Mean	Std.	CV[b]	L05[c]	Median	U95[d]	U99[e]
Scenario 1								
Spring	4	-18.31	88.13	-4.81	-160.06	-17.97	120.79	173.53
Summer	1	64.57	83.96	1.30	-69.93	63.82	201.87	253.51
Fall	2	49.04	75.92	1.55	-67.50	45.39	170.14	229.80
Winter	3	9.67	86.70	8.97	-124.43	4.49	151.86	213.94
Scenario 2								
Spring	4	-63.16	99.25	-1.57	-204.64	-69.41	108.83	169.99
Summer	2	25.46	86.31	3.39	-105.62	23.27	178.67	229.01
Fall	1	34.51	72.81	2.11	-80.88	34.07	149.80	200.25
Winter	3	-13.00	81.30	-6.25	-144.54	-13.28	116.62	165.89
Scenario 3								
Spring	4	-36.29	92.86	-2.56	-185.09	42.09	118.81	177.05
Summer	1	52.07	81.78	1.57	-75.80	49.84	189.87	244.65
Fall	2	7.52	67.25	8.94	-97.32	6.93	115.14	154.96
Winter	3	-17.84	75.57	-4.24	-138.02	-17.53	104.93	148.07
Scenario 4								
Spring	4	-98.88	121.08	-1.22	-293.90	-120.48	110.21	165.09
Summer	2	0.01	97.32	9732.00	-134.57	-10.52	192.16	245.35
Fall	1	5.69	70.77	12.44	-106.56	9.94	118.31	154.10
Winter	3	-22.72	81.61	-3.59	-152.81	-13.56	105.95	142.19

[a] Ranking by FSD or SSD.
[b] CV is the coefficient of variation (standard deviation/mean).
[c] L05 represents the 5th percentile; [d]U95 represents the 95th percentile; [e]U99 represents the 99th percentile.

3.6.2 Distributions of Profits Across Seasons

Figure 3.4 displays cumulative distribution functions (CDFs) of predicted profits of cattle placed in four seasons under four scenarios. Summary statistics and stochastic dominance ranking are displayed in Table 3.8. Under scenario 1 (baseline scenario), summer has the highest expected profit of $64.57/head, and spring is the least profitable with an expected loss of $18.31/head. The stochastic dominance analysis indicates that summer dominates all other placement seasons in the first degree, with the highest expected profit and the greatest probability of being profitable (78.94%), followed by fall ($49.04/head, 75.92%) and winter ($9.67/head, 52.27%). Cattle producers are characterized as risk-neutral in this scenario, ceteris paribus, would prefer to place cattle in the summer as summer brings higher profits at every probability level relative to other seasons (Lambert and Lowenberg-DeBoer, 2003).

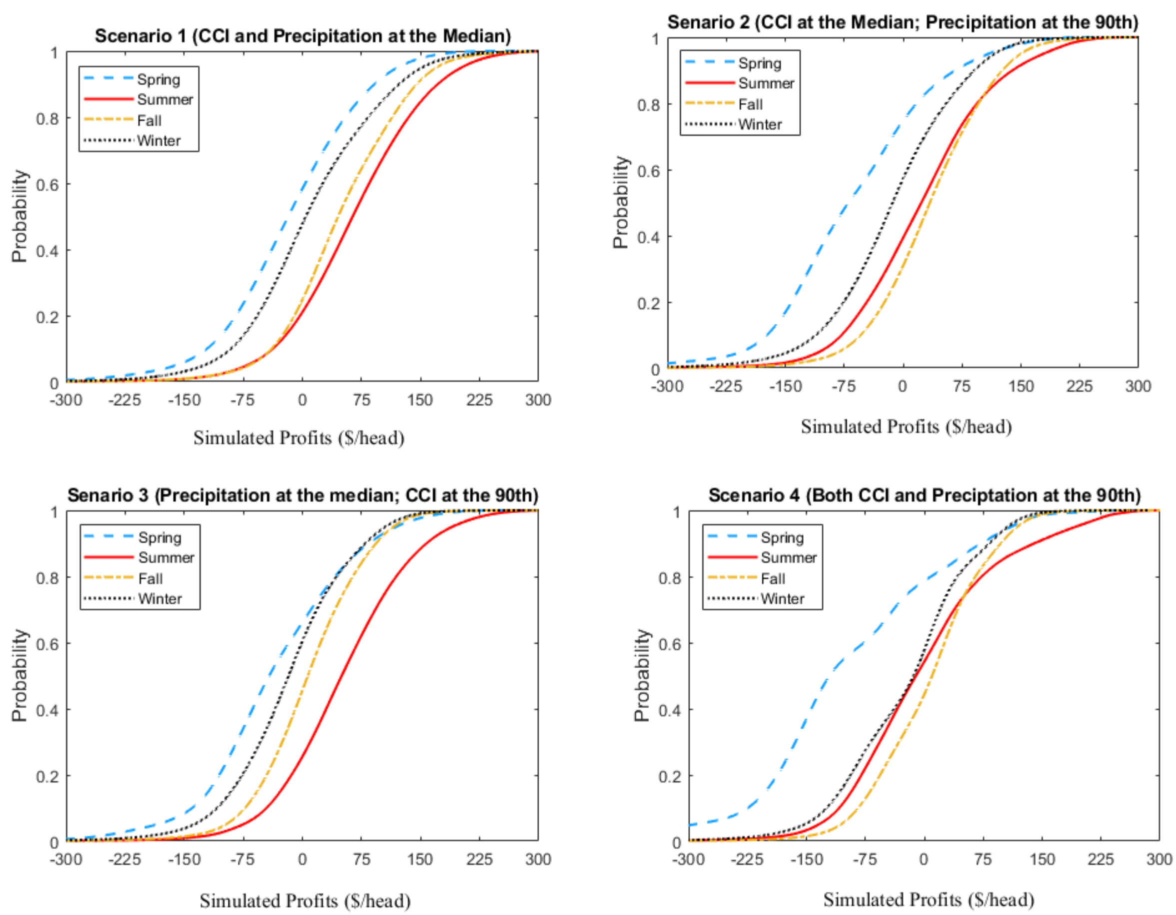

Figure 3.4 Cumulative Distributions for the Simulated Profits of Cattle Placed in Four Seasons under Four Scenarios.

When cumulative precipitation is increased from their median to the 90th percentile in scenario 2, profits and the probability of being profitable decrease. Stochastic dominance analysis indicates fall placement dominates summer placement in the second degree, with the highest expected profits ($34.51), and the greatest probability of being profitable (69.12%), followed by summer ($52.07/head, 60.66%), winter (-$13.00, 42.81%), and spring (-$63.16, 25.23%). One of the main reasons that fall dominates summer in this scenario is because fall-placed cattle have higher average daily gain and lower feed-to-gain ratio than summer-placed cattle. It is likely that fall is relatively cooler and drier than summer, and combined effects of cool-temperature and excessive precipitation in the fall is not as great as combined effects of extreme heat and excessive precipitation in summer when the cattle enter the feedlot. Assuming producers are risk-averse by SSD, they tend to place cattle in the fall, ceteris paribus, given that the chances of having upside variability is higher if he placed cattle in the fall and are more likely to get high profits.

For scenario 3, CCI is increased from the median (259.90 hours) to the 90th percentile (426.50 hours), while precipitation is held at the median. Similar to scenario 1, summer has the highest expected profit of $52.07/head with the great likelihood of being profitable (74.44%). The stochastic dominance analysis indicates summer is the dominant season by the second degree, followed by fall ($7.52, 54.42%), winter (-$17.84, 39.53%), and spring (-$36.29, 33.86%). A comparison of scenario 2 and scenario 3 reveal that the degree to which reduction of growth rate due to temperature stress and excessive precipitation are different and varies by placement season. Similarly, cattle producers are risk-averse to downside variability and tend to place cattle in the summer to avoid losses of profitability.

In scenario 4 (combination of scenario 2 and 3), fall dominates all other seasons by second degree, with the highest expected profits of $5.69/head. The probability of being profitable is 55.65% for cattle placed in the fall. Summer is the second most profitable season ($0.01/head, 45.75%), followed by winter (-$22.72/head, 42.31%) and spring (-$98.88, 21.36%). In this scenario, cattle placed in warm season tend to be more vulnerable to weather stress relative to cattle placed in cool season. Cattle placed in the fall and winter show relatively efficient growth rate and feed efficiency than cattle placed in spring and summer, which reduce number of days to feed to reach a targeted harvest weight and translate into relatively lower feed costs and higher profits.

Figure 3.5 shows the probability of the simulated profits being below \$0/head (shown in white), between \$0 and \$26.83/head (light grey), and above \$26.83/head (dark grey) for cattle placed in four seasons under four scenarios. \$26.83 is the overall mean of profit in scenario 1. Probability of profit loss is consistently higher in spring under each scenario compared to other seasons. Cattle placed in spring have more than 50% chance of financial loss on average under each scenario with the highest probability (79%) in scenario 4. Similarly, the highest probability of profit loss happens in scenario 4 when cattle are placed in summer. It suggests that the combination of temperature stress and excessive precipitation generates greater adverse impacts than any of the two factors alone on profitability of summer-placed cattle.

For cattle placed in the cool season, Scenario 3 shows more than 10% of decrease in profitability when hours of exposure to cold stress significantly increased. Numbers of such probabilities are less than 10% in warm seasons under scenario 2, indicating seasonal temperature stress is a more pervasive threat than precipitation for cattle placed in fall and winter. Precipitation generates greater loss of profitability for cattle placed in spring and summer suggesting the high occurrence of muddy problems in spring when snow melts and ground thaws (Grandin, 2016) and in wet and hot summer.

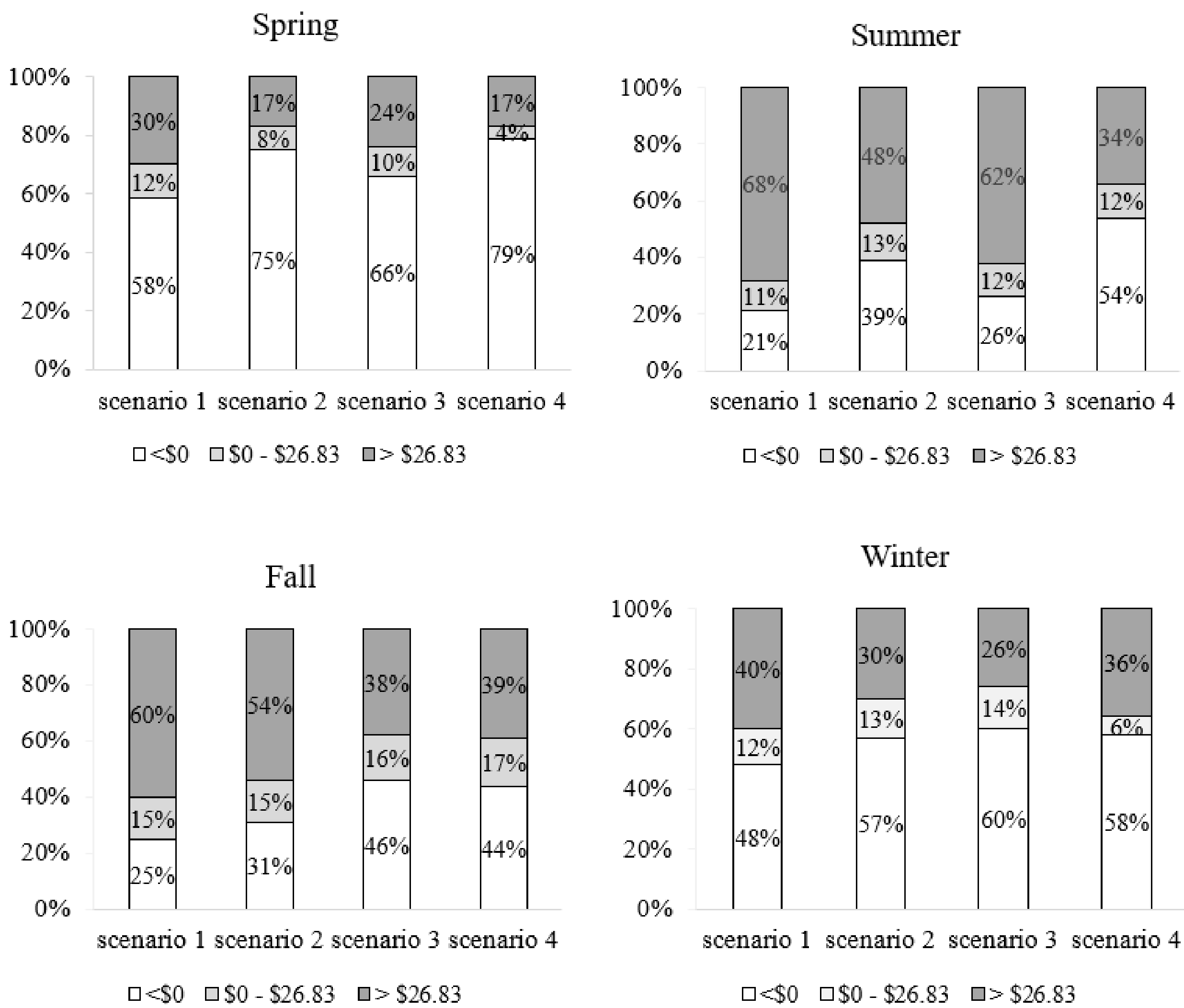

Figure 3.5 Probability of Fed Cattle Profitability Across Seasons under Four Scenarios (notes: probability that the Profitability is less than $0 (white), between $0 and $26.83 per head (light grey), and greater than $26.83 per head (dark grey) across seasons. 26.83 is the overall mean of simulated profits in the base scenario)

These scenario results indicate that cattle feeding profitability are greatly affected by seasonal weather factors. Adverse weather conditions reduce cattle growth rate and feed efficiency. Lower average daily gain and poor feed efficiency lead to low feed intake per day, slow weight growth, and end up with light-weight carcass. Light-weight carcass could bring a lower revenue and subsequently a lower profit. Precipitation causes muddy feedlot and is negatively associated with cattle profitability.

Seasonal variation in grid price is one of the main determinants in fed cattle profitability. It contributes to the seasonal profit variability from two aspects. First, carcass quality grade and yield grade are subject to the effects of seasonal weather conditions. Our model results and simulation outcome indicate that weather have significant effects on beef quality, which indicates the embedded weather-related risk associated with cattle production. Second, choice-select price spread, as the main component of grid price, displays seasonal patterns and determines premiums/discounts of majority of the graded beef. The uncertainty about seasonal choice-select price spread at the time of placement reflects the price risk associated with fed cattle marketing.

Profit variability are affected by seasonal weather conditions as both cost and revenue are associated with performance and carcass quality, respectively. The trade-offs between and within performance variables and carcass qualities identified under different weather conditions further suggest that profits variability could be elevated due to varied forces codetermining the direction and sizes of profitability variability in cattle feeding. For example, losses of profits due to inefficient cattle performance in the feedlot caused by weather stress could be exacerbated/comprised by low/high quality cattle output to which discounts/premiums are applied (Table 3.9).

Table 3.9 Grid Premiums and Discounts for Four Seasons ($/cwt)

Grid Price [a]	Spring	Summer	Fall	Winter
Base price	195.41	195.41	195.41	195.41
Quality grade adjustment				
Prime	8.66	8.92	9.11	8.72
	(4.09)	(4.15)	(4.44)	(4.27)
Choice	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Select[b]	-7.45	-8.81	-9.34	-7.74
	(1.18)	(0.81)	(1.00)	(0.80)
Standard	-18.46	-19.35	-19.70	-18.55
	(7.34)	(7.38)	(7.51)	(7.14)
Yield grade adjustment				
1.0-2.5	1.88	1.89	1.85	1.85
	(0.58)	(0.57)	(0.61)	(0.61)
2.5-3.0	0.80	0.79	0.80	0.82
	(0.18)	(0.19)	(0.20)	(0.48)
3.0-4.0	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
4.0-5.0	-8.35	-8.27	-8.55	-8.43
	(1.13)	(0.96)	(1.56)	(1.15)
>5.0	-11.99	-12.01	-12.19	-12.04
	(1.25)	(0.97)	(1.64)	(1.10)
Carcass weight adjustment[c]				
400-500	-29.41	-29.47	-28.73	-29.53
	(1.86)	(1.90)	(4.66)	(1.84)
500-550	-21.26	-21.35	-20.76	-21.16
	(1.97)	(2.04)	(3.66)	(1.82)
550-600	-8.87	-8.99	-8.70	-8.80
	(1.68)	(1.73)	(2.06)	(1.48)
600-900	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
900-1000	-1.55	-1.63	-1.68	-1.74
	(0.51)	(0.61)	(0.58)	(0.56)
1,000-1,050	-7.37	-7.41	-7.22	-7.25
	(0.49)	(0.41)	(1.13)	(0.40)
>1.050	-22.33	-22.18	-22.30	-23.00
	(2.89)	(3.04)	(4.08)	(2.52)

Sources: Livestock Marketing Information Center (LMIC) spreadsheets based on USDA AMS reports LM_CT155.

[a] Cattle placed in the middle one season are sold after five months and thus premiums and discounts from the season following feeding season are applied, e.g., grid prices of fall are applied to cattle placed in the spring.

[b] Calculated from the overall mean adjusted by a random normal distribution using the mean of and standard deviation of extracted seasonal component from the basic structural model.

3.7 Summary and Conclusion

Beef cattle production and marketing follow seasonal trends. Few studies have examined beef cattle profitability incorporating both production and price risk. This study examines cattle performance (i.e., average daily gain, feed-to-gain ratio, and veterinary cost) and carcass characteristics (i.e., yield grade and quality grade) accounting for weather factors and simulate profit distributions of fed cattle under different weather conditions. There is a lack of empirical studies on valuating impact of precipitation on cattle feeding profitability. Our model incorporates hours of cattle exposure to seasonal weather stress and aggregated precipitation over feed period, and model results indicate adverse effects of temperature stress and excessive precipitation on cattle performance and cattle feeding profitability. Previous study has observed and acknowledged the existence of seasonal pattern of fed cattle price, especially choice-select price spread. To fully account for seasonal variation of fed cattle price in profit variability, we estimate a basic structural model to extract seasonal component of choice-select price spread to be used for a rand normal distribution and be incorporated into estimation of profit distribution across seasons under varied scenarios of weather conditions.

We identified trade-offs between and within carcass quality and cattle performance. These trade-offs vary with weather conditions. For example, a trade-off between yield grade and quality grade is observed under the scenario of excessive precipitation suggesting a reduction of quality grade is accompanied by an improvement in yield grade. We also find trade-offs between yield grade improvement and growth rate/feed efficiency reduction in most seasons.

Overall, weather conditions have negative effects on cattle profitability. This impact varies with placemen season. Typically, cattle placed in warm season are more vulnerable to excessive precipitation, and cattle placed in cool season are more sensitive to temperature stress. We also find that combined effects of temperature stress and excessive precipitation have greater impact on cattle placed in warm season regarding profitability. For the first time, our study fully account for seasonal variation of both price risk and production risk into cattle profitability modeling. We are able to examine economic impact quantifiably using scenario simulation using combinations of temperature stress and precipitation at different levels. A better understanding of seasonal weather effects and seasonal price risk on fed cattle profitability will help producer reduce risk and make efficient management decisions through enhanced predictive capacity by using expected seasonal weather and predicted seasonal price trend.

Finally, our paper contributes to the literature of fed cattle profitability associated with production and marketing by providing a framework that allows us to evaluate seasonal profit variability accounting for both price risk and production risk. Elucidated weather effects, especially precipitation, would be conducive to the development of cattle industry and enhance management of feedlot operations.

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