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Implicit Market Segmentation and Valuation of Angus Bull Attributes

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Previous hedonic assessments have largely relied on the assumption that bull buyers have homogeneous demands for bull attributes. However, quality differentiations and heterogeneous demands support the existence of submarkets. This analysis investigates market segments using a finite mixture model and 13 years of bull auction data. Results indicate that valuations of bull attributes vary across implicit buyer segments. Differences in demand may be influenced by a variety of factors, including—but not limited to—farm goals, labor availability, and end-use marketing arrangements for calves. Results have important implications for signaling quality cues throughout the industry's breeding sectors.

Key words: beef carcass quality, end-use marketing, finite mixture model

Introduction

Beef cattle production in the United States 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 US Census of Agriculture, the average US cow–calf herd size is 41 cows (US Department of Agriculture, 2017). When searching for a herd sire, cow–calf producers look for bulls with specific traits that align with the needs of their cow herd. These needs depend on a number of factors, including farm goals, average age of the herd, production and management system, and end-use marketing arrangements for calves (Allaire, 1981). For example, larger, commercially oriented operations may be more likely to invest in genetic improvements in carcass-related attributes of their herds (Gentner and Tanaka, 2002). Smaller operations, on the other hand, might place more emphasis on cost considerations due to financial vulnerability associated with changing input and output prices (McBride and Mathews, 2011). Still other operators, such as retirees and part-time operators, may select bulls based on convenience (e.g., lower birth-weight bulls, meaning fewer calving problems) due to labor constraints (McBride and Mathews, 2011). For these reasons, it is not difficult to see why different producers would value various bull attributes differently.

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Hedonic analyses of agricultural products were initiated by Waugh (1928) and have since been extensively utilized to estimate the marginal valuation of product attributes. Existing studies using hedonic models to examine bull auction data tend to focus on average valuations of bull attributes assuming homogeneous producer demands (Dhuyvetter et al., 1996; Jones et al., 2008; Vanek, Watts, and Brester, 2008; Franken and Purcell, 2012, e.g.,). However, the existence of quality differentiations in bull attributes and heterogeneous demand for bulls with specific characteristics meet a fundamental condition for the existence of submarkets (Costanigro and McCluskey, 2011).

The effects of market segmentation on prices in hedonic models have long been discussed in the real estate literature (Straszheim, 1974, e.g.,), and studies indicate that the accuracy of out-of-sample prediction improves when models are estimated for housing market segments rather than for a single aggregated market model (Goodman and Thibodeau, 1998; Bourassa, Hoesli, and Peng, 2003; Ugarte, Goicoa, and Militino, 2004; Chen et al., 2009; Belasco, Farmer, and Lipscomb, 2012). More recently, several studies have attempted to extend this segmented hedonic model approach to agricultural products, specifically wine. Costanigro, Mittelhammer, and McCluskey (2009) use a local polynomial regression clustering (LPRC) approach to segment wines with similar values of wine attributes. Caudill and Mixon (2016) use a finite mixture model (FMM) to estimate attribute values for wine segments, including and excluding concomitant variables to predict class membership. Their results indicate that FMM produced better out-of-sample performance than the LPRC model results. Caraccioli 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 among estimators at different quantiles within each class.

Despite knowledge of differences in derived demands for bull attributes among bull buyers and models equipped to handle these differences, to date there have been few attempts to identify and estimate attribute valuations across bull buyer segments. The one exception is Bekkerman, Brester, and McDonald (2013), who find nonconstant marginal valuations of bull attributes across the price distribution using a quantile regression. While price is a convenient cue of quality, we hypothesize that segmentation on price may not be the most efficient method of identifying bull buyer submarkets. We hypothesize that bull buyers' derived demands for bull traits are more closely linked to farm-specific characteristics 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. Additionally, cattle producers with labor constraints who are unable to routinely monitor for calving problems might prefer bulls with lower birth weights. Finally, cattle producers retaining 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).

More work is needed to identify and understand bull buyer submarkets to improve the accuracy of marginal valuations of bull attributes. The objective of this study is to identify heterogeneity in bull buyer valuations of bull attributes across latent classes using an FMM. 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 cattle and products.

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 $\boldsymbol{x}_i$, $P_i = P(\boldsymbol{x}_i; \boldsymbol{\beta})$, where $\boldsymbol{\beta}$ indicates a vector of implicit prices of bull attributes. Conventionally, implicit prices of bull attributes are the same for any bull, indicating homogeneous demands among bull buyers. Under this assumption, we perform an aggregated analysis to show that bull prices follow a single distribution of derived demands. However, a single hedonic analysis may yield misleading estimates of attribute valuations if bull buyers are heterogeneous and assign different importance weights to various bull traits.

Heterogeneity among bull buyers is evidenced by the complexity and variety of bull buyers' (i.e., cow–calf producers') objective functions. For example, some bull buyers may choose bulls to minimize cost at a certain level of output (McBride and Mathews, 2011). While cost minimization is a necessary condition for profit maximization, it is not sufficient. Therefore, other bull buyers may choose bulls to expressly maximize expected profits (Gentner and Tanaka, 2002). Alternatively, other bull buyers may maximize expected utility when choosing herd sires (Gentner and Tanaka, 2002). In addition to each of these single objectives, it is likely that many farms face multiobjective optimization problems when choosing bulls for their farms.

In addition to various farm objectives, a variety of constraints also likely influence bull purchase decisions. For example, many part-time operators likely face labor constraints leading to convenience demands for traits that reduce labor needs. Similarly, capital or cash flow constraints may prohibit some farms from purchasing higher priced, higher returning bulls. In addition to these common constraints, a variety of other factors also influence the farm's optimization problem, including average age of the herd, genetic potential of the herd, environment, production and management system, and end-use marketing arrangements for calves (Allaire, 1981).

Therefore, based on the variety of objectives and constraints that influence bull purchase decisions, it is unlikely that bull buyers have homogeneous derived demands for bull attributes. Moreover, this heterogeneity does not allow for a uniform theoretical framework for the bull-purchasing decision. Instead, if bull buyers' derived demands are heterogeneous, bull prices are a mixture of G distributions and the price function above becomes $P_i = P_g(\boldsymbol{x}_i;\boldsymbol{\beta}_g)$, $g = 1,\ldots,G$ and $G <$. In this case, bull buyers from class g share the same valuation of bull attributes, which is characterized by the common vector $\boldsymbol{\beta}_g$.

Data

Data used in this study were provided jointly by two bull performance testing programs—the Indiana Beef Evaluation Program (IBEP) and the Bull Development and Evaluation Program at the University of Tennessee—and bull owners who subscribed their bulls for testing. The IBEP bull test is conducted at the bull development facility on the Feldun-Purdue Agriculture Center in Bedford, Indiana (Indiana Beef Evaluation Program, 2019). IBEP Performance Tested Bull Sales are held at the Springville Feeder Auction Market in Springville, Indiana. The Bull Development and Evaluation Program was carried out at the Middle Tennessee AgResearch and Education Center in Spring Hill, Tennessee (University of Tennessee Department of Animal Science, 2019). These performance testing programs provide cattle producers with an opportunity to evaluate the growth performance, carcass characteristics, docility, and structural and breeding soundness of their bulls before offering them for sale.

Bull performance tests are conducted biannually in both 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 the test.

Data collected during the test include age at sale, body weight at various ages, scrotal circumference, frame score, carcass characteristics derived from ultrasonography, average daily gain, hoof angle, and claw shape. Prior to sale, expected progeny differences (EPDs) are adapted from respective breed association databases. Bull owners are required to report pretest information such as bull birthdate, birth weight, weaning weight, and pedigree information. These data are recorded, compiled, and reported to bull owners and disseminated to potential buyers at auction

Table 1. Summary Statistics of Bull Attributes for the Pooled Sample (*N* = 1,903)

Variable	Mean	Minimum	Maximum
Sale price ($/head)[a]	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 (lb)	77.34 (8.45)	51.00	117.00
Average daily gain (lb/day)	4.25 (0.52)	3.07	6.73
Frame score[b]	5.76 (0.62)	3.60	7.80
Adjusted scrotal circumference (cm)[c]	36.89 (2.36)	30.60	47.00
Adjusted ribeye area (sq. inches at 12th rib)[c]	13.00 (1.29)	9.50	19.90
Adjusted percentage intramuscular fat (%)[c]	3.93 (1.12)	1.25	8.82
Birth weight EPD (lb)[d]	1.76 (1.45)	-4.20	6.00
Weaning weight EPD (lb)[d]	51.89 (8.65)	0.34	86.00
Maternal milk EPD (lb)[d]	25.42 (5.10)	0.26	41.00
Ribeye area EPD (sq. inches)[d]	0.36 (0.27)	-0.80	1.63
Marbling EPD[d,e]	0.37 (0.26)	-0.30	1.33

Notes: Values in parentheses are standard deviations.
[a] Sale prices were adjusted into 2018 dollars using PPI by commodity for farm products: steers and heifers (US Bureau of Labor Statistics, 2019).
[b] Frame score is calculated as a function of hip height and bull age based on Beef Improvement Federation (BIF, 2021). Frame score is on a scale from 1 to 9, where 1 is extremely small and 9 is extremely large.
[c] Adjusted measures of scrotal circumference, ribeye area, and percentage intermuscular fat are adjusted to a common age of 365 days.
[d] Expected progeny differences (EPDs) measure a bull's genetic ability to transmit a particular trait to his progeny compared to that of other bulls.
[e] Marbling EPD is measured on a numerical scale of marbling score. A numerical score of 1 is associated with Utility and 10 is Prime Plus on the USDA quality grade scale (American Angus Association, 2019).

through sale catalogs. Sale data for this study span from 2006 to 2018. Bull prices are converted to 2018 dollars using the monthly Producer Price Index for farm products, slaughter steers and heifers (US Bureau of Labor Statistics, 2019). Because the majority of the bulls sold during this period were Angus, this study only considers Angus bulls. Excluding bulls that were not sold or bulls with incomplete information gives us 1,903 observations, of which 1,263 are from Indiana and 640 are from Tennessee, available for this study. Table 1 reports summary statistics.

Methods and Procedures

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

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

where y_i is the logged form of price for bull i and X_{ij} contains $j = 1,\ldots,J$ simple performance measures (SPM), ultrasound information, and EPD values available to buyers in the sale catalog.[1] SPMs include age at sale, actual birth weight, average daily gain, frame score, and adjusted scrotal circumference.[2] Ultrasound measures are provided for adjusted ribeye area and adjusted percentage 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 the state in which bulls were sold (1 = Indiana, 0 = Tennessee) and sale year fixed effects; ε_i is the *i.i.d.* error term; and β_0, β_j, and δ_k are parameters to be estimated.

Finite Mixture Model (FMM)

We employ a FMM to identify latent submarkets of bulls and explore the heterogeneity in bull buyers' valuation of 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 context, the price of any bull, P_i, can be thought of 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

$$f\left(y_i \mid \boldsymbol{x}_i, \boldsymbol{\beta}_g, \pi_g\right) = \sum_{g=1}^{G} \pi_g f_g\left(y_i | \boldsymbol{x}_i, \boldsymbol{\beta}_g\right), \tag{2}$$

where X and Z from equation (1) are concatenated into a single vector, $\boldsymbol{x}_i$, for notational convenience; $f_g(\cdot)$ is the probability density function for the gth latent class; y_i is the log of price; $\boldsymbol{\beta}_g$ is a vector of class-specific parameters; and π_g denotes the percentage chance of belonging to a given class g, with $\sum \pi_g = 1$, and $0 \le \pi_g \le 1$. Here, each class is assumed to follow a normal distribution:

$$f_g\left(y_i | \boldsymbol{x}_i, \boldsymbol{\beta}_g\right) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{y_i - \boldsymbol{x}_i \boldsymbol{\beta}_g}{2\sigma^2}\right). \tag{3}$$

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

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

The log-likelihood function is

$$\log L(\boldsymbol{\beta}, \pi | \boldsymbol{x}) = \sum_{i=1}^{n} \log\left\{\sum_{g=1}^{G} \pi_g f_g\left(y_i | \boldsymbol{x}_i, \boldsymbol{\beta}_g\right)\right\}. \tag{5}$$

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[1] SPMs are mostly physical characteristics that are measurable through simple methods such as sex, breed, hide color, weights (e.g., birth weight, weaning weight), 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), maternal calving ease, marbling, and ribeye area.

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

The maximum likelihood estimates of $\widehat{\boldsymbol{\beta}_g}$ and $\widehat{\pi_g}$ can be obtained by solving the loglikelihood equation using numerical methods, such as the quasi-Newton method. The estimated posterior probability can be calculated using Bayes' Rule: $\hat{\pi}_{g,i} = \frac{\widehat{\pi}_g f_g\left(y_i | \boldsymbol{x}_i, \widehat{\boldsymbol{\beta}}_g\right)}{\sum_{g=1}^{G} \widehat{\pi}_g f_g\left(y_i | \boldsymbol{x}_i, \widehat{\boldsymbol{\beta}}_g\right)}$. 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). The FMM allows for the exploitation of underlying heterogeneity without the additional requirement of such information. Previous studies have shown that the FMM, either with or without these concomitant variables, is statistically identified (Caudill and Mixon, 2016). The FMM is estimated using PROC FMM in SAS (SAS Institute, Inc., 2016).

Models with two to ten components, or latent classes, are considered, and common information measures—such as the 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

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

where 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).

Robustness Check—FMM Estimation Using Standardized Data

Coefficients estimated using the FMM represent the marginal effect of a 1-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 the magnitude and direction of coefficients directly within each latent class might be misleading given that the 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 within-class data standardization.[3] Therefore, the pooled data are standardized by subtracting the overall mean value of a variable from its observed value and dividing the result by the variable's standard deviation. The FMM is re-estimated using the standardized data. Estimated coefficients in the 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 1-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).

[3] Deterministic ordinary least squares regression models for the three latent classes were also estimated using standardized data (see Appendix Table A1). Each observation is assigned to the deterministic class for which it has the highest probability of class membership. The signs, significance, and magnitude of the coefficient estimates are consistent with FMM model results. To test the effects of those observations with similar class membership probabilities, we use 40% as the threshold to assign each observation to a corresponding class. Only 11 observations did not have a class with at least a 40% probability of class membership. Model results are robust after deleting these observations.

Table 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	Class 2	Class 3
Intercept	1.651***	1.780***	2.086***	1.063***
Age	0.001***	0.001***	0.0003***	0.001***
Birth weight	−0.002***	−0.003***	−0.001*	0.001***
Average daily gain	0.067***	0.070***	0.056***	0.090***
Frame score	0.053***	0.062***	0.032***	−0.009***
Adjusted scrotal circumference	0.006***	0.006***	0.002	0.009***
Adjusted rib eye area	0.026***	0.025***	0.019***	0.055***
Adjusted percentage intramuscular fat	0.016***	0.014***	0.007	0.021***
Birth weight EPD	−0.042***	−0.040***	−0.025***	−0.083***
Weaning weight EPD	0.004***	0.004***	0.002***	0.009***
Maternal milk EPD	0.004***	0.004***	0.006***	0.002**
Rib eye area EPD	0.020	0.025	−0.006	−0.008
Marbling EPD	−0.011	−0.015	−0.031	0.093***
Origin	−0.034***	−0.040***	−0.003	−0.205***
Sale year fixed effects	Yes	Yes	Yes	Yes
Percentage of sample (%)	100	73	20	7
Log-likelihood	1,511.89		1,683.80	
Akaike information criterion	−2,971.78		−3,201.60	
Bayesian information criterion	−2,827.45		−2,740.90	
Consistent Akaike information criterion	−2,801.45		−3,012.39	
Predicted price ($/head)	2,463	2,539	2,170	2,336

Notes: The dependent variable in both the pooled model and the three-component FMM is the log of bull sale prices adjusted to 2018 dollars. Single, double, and triple asterisks (*, **, ***) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Results and Discussion

Table 2 reports results from the pooled hedonic regression. Parameter estimates are generally consistent with the results from previous literature (Dhuyvetter et al., 1996; Jones et al., 2008; Vanek, Watts, and Brester, 2008; Franken and Purcell, 2012; Boyer et al., 2019, e.g.,). However, if bull buyers value various traits differently, aggregating the data into a pooled model may hide important information about how different segments of bull buyers value bull traits.

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 that 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. Based on the information criteria and relative entropy index, we therefore determine that there is sufficient evidence for heterogeneity in buyer derived demands for bull traits to justify the FMM, and the model results of the three-class FMM appear to be the most useful for examining this heterogeneity.

Before examining differences in the magnitudes and significance of parameter estimates for bull attributes across the three latent classes, it is important to examine whether other control variables (e.g., state and year of sale) influence class membership. A Chow test indicates that in a pooled

Table 3. Summary Statistics of Bull Attributes for the Deterministic Classes Assigned from the Three-Class Finite Mixture Model (FMM)

	Deterministic Classes Assigned from the Finite Mixture Model (FMM)		
	Class 1 (N = 1,526)	Class 2 (N = 247)	Class 3 (N = 130)
Variable	**Mean**	**Mean**	**Mean**
Sale price ($/head)[a]	2,986.37	1,951.34	2,855.51
Age at sale (days)	424.10	424.52	424.22
Birth weight (lb)	77.06	78.26	78.94
Average daily gain (lb/day)	4.26	4.19	4.16
Frame score[b]	5.78	5.67	5.70
Adjusted scrotal circumference (cm)[c]	36.93	36.61	37.07
Adjusted ribeye area (sq. inches at 12th rib)[c]	13.01	12.94	13.06
Adjusted percentage intramuscular fat (%)[c]	3.95	3.77	3.97
Birth weight EPD (lb)[d]	1.74	1.86	1.72
Weaning weight EPD (lb)[d]	52.27	50.20	50.60
Maternal milk EPD (lb)[d]	25.53	24.85	25.31
Ribeye area EPD (sq. inches)[d]	0.37	0.32	0.40
Marbling EPD[d,e]	0.38	0.34	0.36
State[g]	**Percentage (%)**	**Percentage (%)**	**Percentage (%)**
Indiana (N = 1,263)	77	15	8
Tennessee (N = 640)	87	9	4
Year[h]			
2006 (N = 147)	79	14	7
2007 (N = 157)	76	17	7
2008 (N = 153)	78	14	8
2009 (N = 143)	77	17	6
2010 (N = 131)	77	15	8
2011 (N = 149)	83	11	6
2012 (N = 147)	82	11	6
2013 (N = 175)	84	9	7
2014 (N = 167)	86	7	7
2015 (N = 85)	75	14	11
2016 (N = 155)	81	14	6
2017 (N = 156)	79	15	5
2018 (N = 128)	81	13	6

Notes: 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.

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

[b] Frame score is calculated as a function of hip height and bull age based on Beef Improvement Federation (BIF, 2021). Frame score is on a scale from 1 to 9, where 1 is extremely small and 9 is extremely large.

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

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

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

[f] A χ^2 test for differences in proportions rejects the null hypothesis that these proportions in each class are the same for Indiana and Tennessee ($\chi^2 = 28.55$; p-value < 0.01).

[g] A χ^2 test for differences in proportions fails to reject the null hypothesis that these proportions in each class are the same each year ($\chi^2 = 18.12$; p-value $= 0.80$).

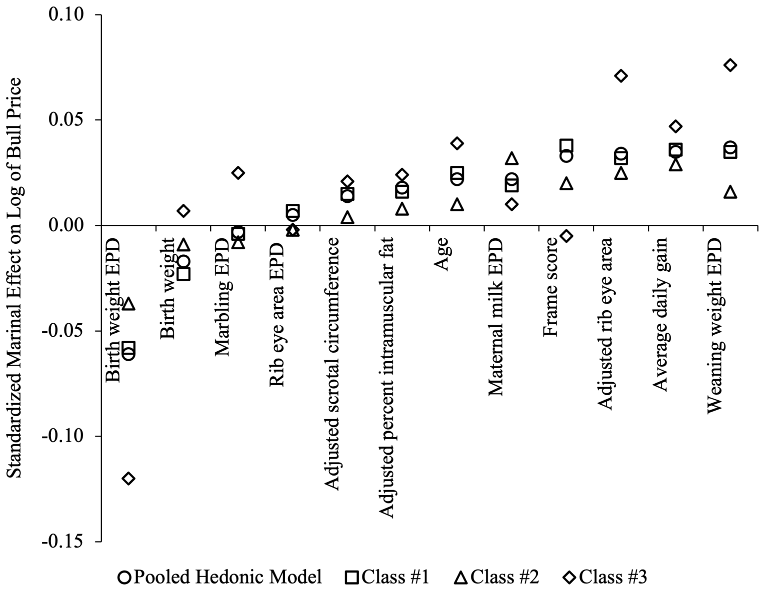

Figure 1. Models' Standardized Marginal Effects on the Log of Bull Price

Notes: Models are the pooled ordinary least squares (OLS) hedonic regression model and the deterministic OLS hedonic models for the three latent classes from the finite mixture model (FMM).

hedonic model (no implicit segments) demands for bull attributes are significantly different for producers in the Indiana and Tennessee subsamples ($F = 17.63$, p-value < 0.01). Therefore, it is important to make sure that these differences are not influencing the implicit classes identified in the FMM. To do so, each observation is deterministically assigned to the latent class for which it has the highest probability of class membership in the FMM. Then the proportion of observations from each state in each class is determined (Table 3). A χ^2 test for differences in proportions rejects the null hypothesis that these proportions are the same for sales in Indiana and Tennessee ($\chi^2 = 28.55$, p-value < 0.01). However, the proportions of observations in each class are relatively similar, with no obvious clustering of one state's observations in any particular class. While this difference is statistically significant, it is not enough to cause concern that regional heterogeneity is driving the classes in the FMM.

Previous studies have also identified temporal heterogeneity in producer demand for bull attributes (Boyer et al., 2019; Tang et al., 2020). Therefore, given that the data analyzed here span a 13-year period, it is important to make sure that temporal heterogeneity in producer demands for bull attributes is not influencing the implicit classes identified in the FMM. Again, examining the proportion of observations from each year in each class (Table 3), a χ^2 test for differences in proportions fails to reject the null hypothesis that these proportions are the same each year ($\chi^2 = 18.12$, p-value $= 0.80$). Therefore, despite the fact that producer valuations for traits vary over time, the latent classes identified in our analysis are not influenced by this temporal heterogeneity.

Class 1

Class 1 is the largest latent class—73% of the buyers in our sample belong to this class on average (Table 2). Buyers in this class tend to place higher value on birth weight—a reasonable indicator of dystocia risk—and frame score than buyers in the other two classes. Lower birth weight tends to be more favored because it is associated with greater calving ease (fewer instances of dystocia) and less labor. 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

Table 4. Model Results of Pooled Model and Three-Class Finite Mixture Model Using Standardized Data (FMM) (N = 1,903)

Variable	Pooled Hedonic Model	Three-Class FMM Class 1	Class 2	Class 3
Intercept	3.338***	3.401***	3.090***	3.505***
Age	0.022***	0.025***	0.010***	0.039***
Birth weight (lb)	−0.017***	−0.023***	−0.009*	0.007***
Average daily gain (lb/day)	0.035***	0.036***	0.029***	0.047***
Frame score[a]	0.033***	0.038***	0.020***	−0.005***
Adjusted scrotal circumference (cm)[b]	0.014***	0.015***	0.004	0.021***
Adjusted rib eye area (sq. inches at 12th rib)[b]	0.034***	0.032***	0.025***	0.071***
Adjusted percentage intramuscular fat (%)[b]	0.018***	0.016***	0.008	0.024***
Birth weight EPD (lb)[c]	−0.061***	−0.058***	−0.037***	−0.120***
Weaning weight EPD (lb)[c]	0.037***	0.035***	0.016***	0.076***
Maternal milk EPD (lb)[c]	0.022***	0.019***	0.032***	0.010**
Rib eye area EPD (sq. inches)[c]	0.005	0.007	−0.002	−0.002
Marbling EPD[c,d]	−0.003	−0.004	−0.008	0.025***
Origin	−0.034***	−0.040***	−0.003	−0.205***
Sale year fixed effects	Yes	Yes	Yes	Yes
Percentage of sample (%)	100	73	20	7
Log-likelihood	1,399.55		1,683.80	
Akaike information criterion	−2,797.10		−3,201.60	
Bayesian information criterion	−2,791.50		−2,740.90	
Consistent Akaike information criterion	−2,687.84		−3,012.39	
Predicted price ($/head)	2,463	2,539	2,170	2,336

Notes: The dependent variable in both the pooled model and the three-component FMM is the log of bull sale prices adjusted to 2018 dollars. Single, double, and triple asterisks (*, **, ***) denote statistical significance at the 10%, 5%, and 1% levels, respectively.
[a] Frame score is calculated as a function of hip height and bull age based on Beef Improvement Federation (BIF, 2021). Frame score is on a scale from 1 to 9, where 1 is extremely small and 9 is extremely large.
[b] Adjusted measures of scrotal circumference, ribeye area, and percentage intermuscular fat are adjusted to a common age of 365 days.
[c] Expected progeny differences (EPDs) measure a bull's genetic ability to transmit a particular trait to his progeny compared to that of other bulls.
[d] Marbling EPD is measured on a numerical scale of marbling score. A numerical score of 1 is associated with Utility and 10 is Prime Plus on the USDA quality grade scale (American Angus Association, 2019).

all bull buyers when purchasing herd sires and appear to be particularly important for buyers in class 1. Bull buyers in class 1 also place relatively high value on growth traits (e.g., average daily gain and weaning weight EPD, birth weight EPD, and adjusted scrotal circumference), although these traits do not necessarily distinguish class 1 from classes 2 and 3.

Table 4 reports regression results for the FMM estimation using standardized data. The same general trends emerge. However, as expected, the standardized coefficients sharpen the delineation of the latent classes. Figure 1 plots the standardized coefficients for the three latent classes and the pooled model, providing a more easily digestible view of the results. Bull buyers in class 1 still place more emphasis on lower birth weight and higher frame score than bull buyers in the other two classes. The standardized coefficients also indicate that bull buyers in class 1 place relatively more value on ribeye area EPD than producers in classes 2 and 3. This result seems contradictory to the results from the FMM using unstandardized data, which indicate that producers in class 3 place more 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 traits, there is little evidence that producers in class 1 are consistently emphasizing carcass traits in their bull-buying decisions (Figure 1).

Based on these findings, it seems likely that class 1 represents typical US cow–calf operations. It is the largest latent class in our sample probabilistically (73%), making it likely that class 1 represents the smaller farms that are common in the US cow–calf sector. According to the 2017 US Census of Agriculture, the average US cow–calf herd size is 41 cows, and 77% of US cow–calf operations have fewer than 50 cows (US Department of Agriculture, 2017). Bull buyers in class 1 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. This class of producers prefers low labor requirements, a result of lower birth weight and lower risk of dystocia. In addition, the focus on salable 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

Class 2 represents next largest latent class in our model—20% of buyers in our sample are in this class on average (Table 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 class 2 producers. Probably more notable is the lack of emphasis on traits such as birth weight and birth weight EPD, adjusted scrotal circumference, adjusted percentage intermuscular fat, and weaning weight EPD relative to bull buyers in classes 1 and 3.

Bull buyers in class 2 continue to be characterized by their lack of emphasis on several bull attributes relative to their peers when using the FMM with standardized data (Figure 1). It is interesting to note that the mean predicted sale price for bulls in class 2 is the lowest of the three classes in our model, \$2,170/head (Table 2). In conjunction with the individual parameter estimates, this seems to suggest that bull buyers in class 2 are "value buyers" who select bulls with a cost-minimization mentality. That is, they do not look for any particular traits when purchasing a herd sire. Instead, they likely focus on purchasing a thoroughly evaluated, performance-tested bull. Again, these are likely smaller, part-time operations that are most financially vulnerable to the variability in initial bull purchase cost, which represents 20%–40% of annual bull costs (McBride and Mathews, 2011; Greiner and Miller, 2021).

Class 3

Finally, class 3 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). The distinguishing feature of class 3 is the emphasis on the carcass traits adjusted ribeye area, adjusted percentage intermuscular fat (IMF), 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 the quantity of retail cuts from the carcass and is one of the two main components of the grid pricing system for beef carcasses. IMF and marbling EPD both measure beef quality, with greater IMF corresponding to higher quality grades. Quality grade is the other main component of the grid pricing system for beef carcasses.

In the model with standardized data, class 3 buyers are still characterized by the value they place on the same carcass traits (Figure 1). In particular, adjusted ribeye area is the second-largest influencer of bull prices (in absolute value) for bull buyers in class 3. Further, bull buyers in class 3 also emphasize birth weight EPD and weaning weight EPD relative to bull buyers in the other two classes.

Based on these findings, bull buyers in class 3 are more likely to be commercially oriented operations that seek out value-added marketing arrangements for their calves (e.g., private treaty sales or retained ownership) to capitalize on investment in carcass quality. 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 that they are paid based solely on weight and information tends to be sparse. However, producers who seek out value-added marketing arrangements for their calves are more likely to have an incentive to invest in carcass traits through mechanisms such as grid pricing.

Previous research has indicated that the presence of statistically significant carcass traits in pooled bull price hedonic models provides 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.

Conclusions and Implications

In this study, an FMM approach is applied to identify implicit bull buyer submarkets and examine bull buyers' heterogeneous derived demands for bull attributes. Results indicate evidence of heterogeneous demands for bull attributes among bull buyers. A three-class FMM is identified as providing the best view of bull buyer heterogeneity. Differences in attribute valuations across latent classes of bull buyers appear to be associated with various aspects of producers' production and management systems, including, but not limited to, farm goals, labor availability, and end-use marketing arrangements for calves.

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 they rely on university-sponsored bull-testing programs. Therefore, it is difficult to speculate 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. Evidence of heterogeneous demands for bull attributes has 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 cattle and products.

First, anytime there is discussion of market segmentation of a product, there will be obvious implications for the supplier of that product (in this case, seed-stock producers). While it is likely that most seed-stock producers are aware of differences in bull buyer demands for different bull attributes, tangible identification of potential bull buyer segments, the relative size of those segments, and the traits that each segment prioritizes are valuable information for seed-stock producers. This information allows seed-stock producers to identify which segment or segments they are targeting and tailor their breeding programs and marketing efforts toward their target customers.

Second, it is important to consider the implications of our results for bull buyers or cow–calf producers. While our results do not necessarily provide information that will help bull buyers make better bull-purchasing decisions or improve profitability, the information provided in this analysis may serve as a sort of benchmark for cow–calf producers to examine their bull-buying practices. For example, what bull buyer segment are they most likely to fall in and does that align with their farm goals? What bull traits do they prioritize when purchasing bulls and how do their demands for bull traits compare with their peers? Evaluating the answers to these questions relative to the results from our analysis would benefit any operation. It is unlikely that this sort of benchmarking exercise would change bull-purchasing behaviors for most bull buyers, although it may for some. In either case, information that can aid cow–calf producers in examining and improving their bull-purchasing behaviors is valuable to their operations.

Finally, our results have implications for the beef industry as a whole as it seeks to improve the quality and consistency of beef products. Previous research has indicated that statistically significant carcass traits in pooled hedonic models using bull auction data provide 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 may mask important information about the effectiveness of quality cues. Our results 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 United States 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. Therefore, it continues to be important for the beef industry to consider how current price signals are being transmitted to various industry segments and whether 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 US beef.

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Appendix A

Table A1. Results of Pooled Model and Deterministic Class Hedonic Models Using Standardized Data

Variable	Pooled Hedonic Model (N = 1,903)	Deterministic Classes Assigned from the Finite Mixture Model (FMM) Class 1 (N = 1,526)	Class 2 (N = 247)	Class 3 (N = 130)
Intercept	3.338***	3.409***	3.082***	3.509***
Age	0.022***	0.025***	0.011***	0.039***
Birth weight (lb)	−0.017***	−0.024***	−0.007**	0.007***
Average daily gain (lb/day)	0.035***	0.035***	0.027***	0.047***
Frame score[a]	0.033***	0.040***	0.022***	−0.005***
Adjusted scrotal circumference (cm)[b]	0.014***	0.014***	0.003	0.021***
Adjusted rib eye area (sq. inches at 12th rib)[b]	0.034***	0.030***	0.023***	0.072***
Adjusted percentage intramuscular fat (%)[b]	0.018***	0.015***	0.007*	0.024***
Birth weight EPD (lb)[c]	−0.061***	−0.058***	−0.038***	−0.120***
Weaning weight EPD (lb)[c]	0.037***	0.034***	0.018***	0.076***
Maternal milk EPD (lb)[c]	0.022***	0.017***	0.028***	0.010***
Rib eye area EPD (sq. inches)[c]	0.005	0.008**	−0.003	−0.002**
Marbling EPD[c,d]	−0.003	−0.004	−0.008**	0.025***
Origin	−0.034***	−0.041***	−0.002	−0.208***
Sale year fixed effects	Yes	Yes	Yes	Yes

Notes: The dependent variable in all regressions is the 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. Single, double, and triple asterisks (*, **, ***) denote statistical significance at the 10%, 5%, and 1% levels, respectively. 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. To test the effects of those observations that are indifferent between classes. We use 40% as the threshold to assign each observation to corresponded class, and only 11 observations were undecided. Model results is robust after deleting these undecided observations.

[a] Frame score is calculated as a function of hip height and bull age based on Beef Improvement Federation (BIF, 2021). Frame score is on a scale from 1 to 9, where 1 is extremely small and 9 is extremely large.

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

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

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