Beef Bull Attribute Valuations with Implicit Market Segmentation

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Introduction

Unlike much of the pork and poultry industries, the beef cattle industry is not vertically integrated (Vestal et al., 2013). Genetic variation is one of the contributing factors to the relative absence of vertical integration in the beef cattle industry (Brester, 2002). No single breed or crossbreed is superior for all attributes that are ideal for any situation (Brester, 2002). Cattle producers with varying production systems and end-use marketing arrangements desire bulls with specific performance and genetic traits. Given the existence of quality differentiations in bull attributes and heterogeneous demand for bulls with specific characteristics, a fundamental condition for the existence of market segmentation is met (Costanigro and McCluskey, 2011). Most previous research estimates average marginal valuations of bull attributes assuming a homogeneous production structure using a linear hedonic model. To date, there have been few attempts to identify and estimate attribute valuations across segmentations of beef bulls. Bekkerman, Brester, and McDonald (2013) is the one exception using a quantile regression to estimate marginal valuations of beef bull attributes across the price distribution. More work understanding and identifying the segmentations of bulls can improve accuracy in marginal valuation estimates of bull characteristics and help cattle producers make better production and marketing decisions.

The beef bull auction is a typical example of a heterogeneous agricultural market where differentiated products abound. Unlike the relative high concentration of feedlot and processing sectors, the beef seed stock industry consists of many small breeders developing region-specific genetics for targeted market niches. A set of heterogeneous bull buyers identify the most-valued traits in a bull that will maximize their production profitability based on their own production conditions. Bull sellers usually provide bull buyers with sale catalogs containing physical and genetic information of the bull. A sale catalog commonly contains information of simple performance measures (SPMs) and expected progeny differences (EPDs). SPMs are mostly physical characteristics that are measurable through simple methods such as sex, breed, hide color, bull weights, and average daily gain etc. EPDs are statistical predictions of the phenotypic performance of a bull's progeny. Examples of EPDs include various weights (e.g., birth and weaning weight), maternal carving ease, marbling, and ribeye area.

Applications of the hedonic regressions abound, from housing economics to the field of agricultural products. Hedonic analysis of vegetable quality differentiation originated in the 1930s (i.e., Waugh, 1928) and slowly expanded to other agricultural products. Agricultural economists have long been utilizing the hedonic modeling to estimate the implicit prices of attributes for a variety of food products (Costanigro and McCluskey, 2011), including apples (Carew, 2000), beef (Hahn, Kenneth, and Mathews, 2007; Ward, Lusk, and Dutton, 2008), and wine (Costanigro, McCluskey, and Mittelhammer, 2007; Pomarici et al., 2017).

The initial efforts to discuss the existence of market segmentation in hedonic modeling were by Straszheim (1974). A considerable number of studies on housing markets have made important contributions to the development of hedonic modeling (Costanigro and McCluskey, 2011). Some studies on housing markets indicate that accuracy of out-of-sample prediction improves when models are estimated for individual 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). In the field of beef bull markets, bulls are treated as undifferentiated products in most studies (e.g., Jones, et al., 2008; Franken and Purcell, 2012). Only one study has examined quality differentials of beef bulls across price distributions (Bekkerman, Brester, and McDonald, 2013). The lack of hedonic studies on beef bull segmentation is somewhat surprising, given the heterogeneous preferences among producers and growing importance of heritable attributes in the bull market.

A bull buyer purchases the bull with specialized heritable characteristics that they expect these desirable traits would be passed on to the progeny (Walburger, 2002). The value of a bull is determined by the implicit valuations of genetic attributes that the bull carries on. Bull market segmentation generates groups of bulls that share the maximal degree of internal homogeneity and the maximal degree of external heterogeneity. Bull buyers would focus on a certain segment to select the traits that fit their regional environment and end-product uses. For example, cattle producers who buy bulls for production of replacement females place relatively high valuations on maternal and reproductive performance characteristics. Producers who sell their calves at weaning would pay more attention to calving ease, growth rate, and weaning weight. Cattle producers who retain ownership of their calves until slaughter would place increased importance on carcass quality characteristics, such as yield and quality grade (Greiner, 2009).

A variety of segmentation methods have been used in empirical studies. Generally, these methods can be categorized as a-priori approach and post-hoc approach (Michel and Kamakura, 2001). The former is commonly seen in some real estate literature where the number of segments is determined in advance on certain geographic variables. The latter is called post-hoc because the number of segments is derived from the results of statistical analysis. Although the family of cluster techniques is extremely large, most studies adopting post-hoc segmentation use cluster analysis. Cluster analysis has been used as a heuristic technique (Michel and Kamakura, 2001). Data clustering approach in the form of cluster analysis often exhibits a higher prediction error rate than a-priori approach based on geographical variables (e.g., Bourassa, Hoesli, and Peng, 2003). Costanigro, Mittelhammer, and McCluskey (2009) suggest a use-based approach such as local polynomial regression clustering (LPRC) shows greater effectiveness (i.e., lowest median percentage error rate) over clustering analysis and pooled modeling in price predictions.

Prior research has indicated the existence of non-uniform marginal values of bull attributes across price segments (Bekkerman, Brester, and McDonald, 2013). However, some researchers have professed that although price is widely used as a quality cue, the effects of price on quality perception are significantly different across individuals and products being evaluated (Lichtenstein and Burton, 1989). Therefore, segmentation by end-use might have a stronger link to valuations of certain characteristics than the price paid. Although numerous hedonic studies have empirically identified segmentations for various products, no attempts have been made to investigate end-use clustering of beef bulls on bull attribute valuations.

The objectives of this study are first to identify the distinct market segments of bulls based on implicit prices of end-use attributes, and second to estimate and compare marginal valuations of bull attributes for each segmentation. LPRC is used to segment bulls with similar values of bull attributes. Market segmentation is important because it allows for a non-uniform assessment of implicit valuations of bull attributes across targeted submarkets. Cattle producers can easily identify targeted bulls with desired traits and position their strategies for specific market niches. Hedonic regression estimates across the spectrum of bulls provide cattle producers an improved understanding of how buyers' valuation of bull attributes vary for each bull segment. Knowledge of whether the non-uniform marginal valuations exist, how they change, and which attributes are related can help cattle producers make strategic decisions and improve profitability.

Conceptual Framework

The key assumptions for the existence of the hedonic price analysis of beef bulls are similar to the assumptions of perfect competition (e.g., Dhyvetter et al., 1996; Mallory et al., 2016). It is assumed that a bull buyer chooses the bull that contains a utility-maximizing bundle of attributes given prices and a budget constraint. Bull sellers are assumed to choose a profit-maximizing combination of input that contributes to the generation of quantity of bull characteristics given factor prices and the technology available. The first-order conditions of each maximization problem define two families of indifference surfaces relating to the levels of bull attributes and their corresponding valuations: bull buyer's bid and bull seller's offer functions (Costanigro and McCluskey, 2011). The bid function indicates the amount a bull buyer is willing to pay for a series of levels of bull traits holding utility and income fixed. Symmetrically, the seller's offer function represents the price a bull seller is willing to accept for selling a bull with a bundle of attributes holding profit fixed. The hedonic price function is found by tracing the points of tangency between bid and offer surfaces, $p = p(x)$, where x is a vector of bull attributes.

When either the structure of demand or the structure of supply changes across bull segments, estimating separate price functions is needed (Costanigro and McCluskey, 2011). This happens when vectors of bull attribute levels diverge greatly that two bulls are no longer within the same category, and the costs of the bundled attributes in these two bulls will differ. Cattle producers place different values on bulls based on end-product use. Hedonic price functions are the locus of tangency points between offer and bid functions. Considering the bull market is segmented by attributes valuations, then the hedonic price of the general form becomes $p = p^s(x_s)$, $s = 1, \dots, m$, where m denotes the number of segments. The marginal willingness to pay for the jth attribute in the segment s becomes $\frac{\Delta p^s}{\Delta x_j}$. Bulls within the same segment share similar implicit prices of attributes.

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 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 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.

Data collected during the test include bull weights at various ages, scrotal circumference, frame score, ultrasound scan data, average daily gain (ADG), 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 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 breed. 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.

Methods and Procedures

Local polynomial regression (LPR) is a nonparametric procedure to estimate the regression curve at any given point, x_i, by locally fitting the relationship between dependent variables ($\boldsymbol{y}$) and independent variables ($\boldsymbol{x}$) in a moving fashion (Cleveland, Devlin, and Grosse, 1988). That is, for each point x_i, the regression curve can be estimated via a Taylor approximation adjusting the approximation performance of data around the point x_i through kernel weighting. Generally, data points close to the point x_i has better approximation than those far off. The choice of bandwidth decides the complexity of the model and brings a tradeoff between variance and bias, i.e., a larger value of bandwidth reduces variance and can result in a larger bias. Similarly, the choice of order of polynomial is also of great importance for LPR. Fitting polynomials of higher order reduces the bias but increases variance at the same time. It is evidenced that odd order fits are preferred over even order fits because the former outperform the latter at the interior points and the latter suffers from low efficiency (Fan, 1993; Fan and Gijbels, 1995). A higher order of polynomial reduces bias by taking a higher-order Taylor expansion about the point x_i, it also results in a higher variability due to the increased number of parameters to be estimated. In this study, we estimate a local linear regression by choosing the order of polynomials equals one, i.e., $p = 1$. The local linear regression relaxes the restriction of parametric functional form, such as linear regression function, and estimates the functional relationship between independent variables and dependent variables nonparametrically, i.e., allows the data to determine the functional form (Costanigro, Mittelhammer, and Mccluskey, 2009). The nonparametric estimates provide the foundation for aggregating data into clusters based on the similarity in values. Once the data clusters are specified, linear regression are estimated parametrically for each cluster. The methodology and its rational in each of these three steps are described in more details in the following graphs.

- *Step one: Local Polynomial Regression*

In the first step, for the relationship $\boldsymbol{y} = m(\boldsymbol{x}) + u$, an LPR is estimated, where $\boldsymbol{y}$ is the $1 \times n$ vector of dependent variables, and $\boldsymbol{x}$ is the $k \times n$ vector of independent variables. To mitigate scale effects and minimize issues with numerical optimization, all continuous independent variables and independent variables are scaled by their respective means. Discrete variables are not scaled because they are bounded between 0 and 1. For each observation i, $\boldsymbol{x_i} = (x_{1i}, x_{2i}, \dots, x_{\mathrm{k}i})$. The unknown regression function $m(\boldsymbol{x})$ for $\boldsymbol{x}$ around $\boldsymbol{x_i}$ can be approximated locally by a polynomial of order p via Taylor expansion,

$$m(\boldsymbol{x}) \approx m(\boldsymbol{x_i}) + m'(\boldsymbol{x_i})(\boldsymbol{x} - \boldsymbol{x_i}) + \frac{m''(x_i)}{2!}(\boldsymbol{x} - \boldsymbol{x_i})^2 + \cdots + \frac{m^{(p)}(x_i)}{p!}(\boldsymbol{x} - \boldsymbol{x_i})^p \tag{1}$$

where $\boldsymbol{x} - \boldsymbol{x_i}$ is a $1 \times k$ vector. For local linear regression (LLR), $p = 1$, higher-order terms are ignored and $m(\boldsymbol{x_i})$ and $m'(\boldsymbol{x_i})$ are treated as parameters, Equation (1) reduces to

$$\widehat{m(\boldsymbol{x})} = \widehat{\beta_0(\boldsymbol{x_\iota})} + (\boldsymbol{x} - \boldsymbol{x_i})\widehat{\beta_1(\boldsymbol{x_\iota})} \tag{2}$$

where $\widehat{\beta_0(\boldsymbol{x_\iota})}$ and $\widehat{\beta_1(\boldsymbol{x_\iota})}$denote $m(\boldsymbol{x_i})$ and $m'(\boldsymbol{x_i})$, respectively.

The minimization problem for the full set of n observations becomes a weighted least squares problem and can be written as

$$\min_{\widehat{\beta_0(x_\iota)}, \widehat{\beta_1(x_\iota)}} \sum_{i=1}^{n} \left[y_i - \widehat{\beta_0(\boldsymbol{x_\iota})} - (\boldsymbol{x} - \boldsymbol{x_i})\widehat{\beta_1(\boldsymbol{x_\iota})}\right]^2 K_h(\boldsymbol{x_i}, \boldsymbol{x}) \tag{3}$$

where K_h is a kernel weighting function assigning weights to each datum point, and h is a bandwidth controlling the size of the local neighborhood. We adopt the most commonly used data-driven bandwidth selection algorithm, i.e., least squares cross validation (Hall, 1983; Stone, 1984). Given the multi-dimensional spaces in a multivariate setting, this study uses a vector of bandwidths instead of a singular bandwidth. Compared to bandwidth, the choice of kernel function has relatively limited effects on model results. Although the Epanechnikov kernel is optimal in terms of Average Mean Integrated Square Error (AMISE), it has discontinuous first derivatives that may be undesirable, so the Gaussian kernel is chosen instead in this study (Wand and Jones, 1995; Henderson and Parmeter, 2015). One of the difficulties in LPR estimation in this study is that independent variables are mixed containing both discrete and continuous regressors. Specifically, sale season and sale year are treated as unordered and ordered discrete variables, respectively. The inclusion of discrete variables does not affect the rate of convergence of $\widehat{m(\boldsymbol{x})}$ in Equation (2). Estimation of derivatives of the discrete variables is treated in a local-constant fashion (Henderson and Parmeter, 2015). Over all, the main objective of this this step is to obtain an n by k matrix of $\widehat{\boldsymbol{\beta}(\boldsymbol{x_\iota})}$values.

- *Step Two: Ward Clustering*

Following Costanigro, Mittelhammer, and McCluskey (2009), we use the Ward algorithm to group estimates on the basis of similarity of the $\widehat{\boldsymbol{\beta}(\boldsymbol{x_\iota})}$ values. The Ward's algorithm starts with n clusters by treating each observation in $\widehat{\boldsymbol{\beta}(\boldsymbol{x_\iota})}$ as a cluster. The objective is to generate the targeted number of m groups that the sum of squared deviations (SSD) is minimized. At each step, the pair of clusters whose fusion leads to the minimum increase in the variance within clusters, i.e., SSD, are combined (Wishart, 1969). The objective function is specified as

$$\min_{g=1,\dots,m} \sum_{i=1}^{n} \sum_{g=1}^{m} \left(\widehat{\boldsymbol{\beta}(\boldsymbol{x_\iota})} - \widehat{\widehat{\boldsymbol{\beta}_{\boldsymbol{g}}}}\right)^2 \qquad (4)$$

Where $\widehat{\widehat{\boldsymbol{\beta}_{\boldsymbol{g}}}}$ is the gth group centroid, $g = 1, \dots, m$.

- *Step Three: Hedonic Models*

Once the data are clustered, the cluster-specific hedonic regressions are performed. We estimate regression models for each class of data using both standardized and unstandardized data. The standardized coefficients provide an evaluation of the relative importance of each bull attribute in explaining bull prices. The value of each bull is estimated with a standard log-linear hedonic model. The linear specification in this step is consistent with the order of polynomials in Equation (4).

$$lnp_i = \beta_0 + \sum_{j=1}^{J} \beta_j X_{ij} + \sum_{k=1}^{K} \delta_k Z_{ik} + \sum_{t=1}^{T} \gamma_t I_t + \varepsilon_{it} \tag{5}$$

where lnp_i is the logged form of price for bull i. X_{ij} contains $j = 1, \dots, J$ simple performance measures, ultrasound information, and EPD values available to buyers in the sale catalog. Simple performance measures include dam age, age at sale, actual birth weight, weaning weight, average daily gain, frame score, and adjusted scrotal circumference.[1] Ultrasound measures are provided for adjusted ribeye area, adjusted rib fat, and adjusted intermuscular fat. Finally, EPDs characterizing birth weight, weaning weight, maternal milk, ribeye area, rib fat, and intermuscular fat are also included in X_{ij}. Z_{ik} contains marketing variables to control for sale order and season of the sale (1 = spring, 0 = fall), and I_t are time fixed effects. ε_i is the independently and identically distributed error term, and β_0, β_j, δ_k, and γ_t are parameters to be estimated.

Preliminary Results

- **Table 2** displays the summary statistics of variables for the whole sample and for each of the two clusters identified. Some interesting differences emerge in the means of the two groups providing insight into the purchasing behaviors of buyers in group #1 and group #2. However, these differences do not provide insight into differences in bull buyer preferences for these traits – implicit valuation of the traits.
- To better understand differences in buyer marginal valuations of bull traits hedonic regression models are estimated for both of the groups identified by the local polynomial regression clustering. The hedonic models were first estimated using the non-standardized data (results

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

not shown). A Chow test indicates that the hedonic regression coefficients are significantly different for the two groups. However, it is difficult to identify differences in the relative importance of each trait in explaining bull prices due to differences in scale for independent variables.

- For this reason, we estimated the hedonic regressions again after standardizing the data. Results are reported in **Table 3**. Again, results of the Chow test indicate that the hedonic regression coefficients are significantly different between the two groups. This also allows for a better comparison of the relative importance of each trait for each group.
- **Figure 1** displays the standardized hedonic model coefficients for each of the bull attributes graphically. Viewing the results this way brings several important results to light.
    - There are a set of traits that are important to all bull buyers regardless of implicit class. This includes commonly valued bull traits such as birth weight (which is directly associated with calving ease) and average daily gain (which is a common proxy for growth potential).
    - Beyond these universally important traits there does appear to be some segmentation among buyer valuation of some of the remaining traits.
    - Group #1 appears to place relatively higher values on maternal (maternal milk) and reproductive (scrotal circumference) traits. These are traits that would be important to a wide range of bull buyers. Hence, this is the larger of the two groups in terms of size.
    - Group #2 appears to place relatively higher values on carcass quality characteristics (marbling and ribeye area). This segment is the smaller of the two groups and also has a higher average sale price. Once can presume that these are more commercial

operations with opportunities to capture premiums for higher quality carcasses (e.g., retained ownership into the feedlot).

Implications

- Conventional pooled regression modeling does not reveal the heterogeneous valuations on bull attributes and may be subject to aggregation bias.
- Results suggest that bull buyers value beef bull attributes differently, and there is some evidence that this segmentation may be associated with end use of calves (sell at weaning, produce replacement heifers, or retain ownership).
    - There are some traits that are universally important to all bull buyers
    - The two segments identified seem to imply bull buyers either value reproductive and maternal traits or carcass quality traits.
- Estimating hedonic modeling in implicitly identified market segments improved the estimation of bull attribute marginal valuations.

Table 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
Dam age (years)	5.51	2.70	2.00	16.00
Age at sale (days)	423.71	33.86	348.00	539.00
Birth weight (lbs.)	79.67	9.17	49.00	117.00
Weaning weight (lbs.)	693.12	77.61	463.00	1,007.00
Average daily gain (lbs./day)	4.06	0.40	3.02	5.63
Frame score[2]	5.74	0.66	3.60	8.30
Adjusted scrotal circumference (cm)[3]	36.91	2.38	32.00	48.00
Adjusted ribeye area (square inches at 12th rib)[3]	13.04	1.33	9.40	19.40
Adjusted rib fat (inches at 12th rib)[3]	0.31	0.09	0.09	0.78
Adjusted percent intramuscular fat (%)[3]	3.73	1.15	1.25	8.82
Birth Weight EPD (lbs.)[4]	1.97	1.52	-4.20	6.90
Weaning Weight EPD (lbs.)[4]	48.28	9.56	19.00	83.00
Maternal Milk EPD (lbs.)[4]	24.27	5.22	7.00	41.00
Ribeye area EPD (square inches)[4]	0.33	0.27	-0.39	1.63
Rib fat EPD (inches)[4]	0.01	0.02	-0.16	0.23
Marbling EPD[4,5]	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] 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, rib fat, 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).

Table 2. Summary Statistics for the Pooled Sample and Two Implicit Clusters Identified

Variable	Pooled Data	Group #1[1]	Group #2[1]	Difference[2]
Sale price ($/head)	2075.46	1855.62	2464.19	
	(1.80)	(1.79)	(1.76)	***
Sale Order	47.01	51.45	40.19	
	(33.60)	(34.36)	(31.24)	***
Dam age (years)	5.51	5.60	5.36	**
	(2.70)	(2.68)	(2.74)	
Age at sale (days)	423.71	423.48	424.07	
	(33.86)	(34.33)	(33.14)	
Birth weight (lbs.)	79.67	80.87	77.82	
	(9.17)	(8.86)	(9.33)	***
Weaning weight (lbs.)	693.12	694.04	691.72	
	(77.61)	(79.71)	(74.31)	
Average daily gain (lbs./day)	4.06	4.04	4.10	***
	(0.40)	(0.39)	(0.41)	
Frame score	5.74	5.81	5.64	***
	(0.66)	(0.66)	(0.64)	
Adjusted scrotal	36.91	37.08	36.65	***
circumference (cm)	(2.38)	(2.35)	(2.41)	
Adjusted ribeye area (square	13.04	13.00	13.09	
inches at 12^{th} rib)	(1.33)	(1.36)	(1.28)	
Adjusted rib fat (inches at 12^{th}	0.31	0.31	0.33	***
rib)	(0.09)	(0.09)	(0.09)	
Adjusted percent	3.73	3.54	4.01	***
intramuscular fat (%)[3]	(1.15)	(1.05)	(1.24)	
Birth Weight EPD (lbs.)	1.97	2.25	1.53	***
	(1.52)	(1.44)	(1.53)	
Weaning Weight EPD (lbs.)	48.28	46.89	50.42	***
	(9.56)	(9.79)	(8.79)	
Maternal Milk EPD (lbs.)	24.27	23.34	25.71	***
	(5.22)	(5.25)	(4.83)	
Ribeye area EPD (square	0.33	0.29	0.39	***
inches)	(0.27)	(0.26)	(0.27)	
Rib fat EPD (inches)	0.01	0.00	0.01	***
	(0.02)	(0.02)	(0.02)	
Marbling EPD	0.31	0.25	0.41	
	(0.28)	(0.25)	(0.28)	***
Sale Season	0.76	0.79	0.70	***
	(0.43)	(0.40)	(0.46)	
Number of Observations	1705	1032	673	

[1] Group #1 and Group #2 were identified implicitly using the local polynomial regression gradients and the Ward clustering algorithm.

[2] Statistically different difference between Group #1 and Group #2. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 3. Hedonic Regression Model Results Using Standardized Data

Variable	Pooled Model	Group #1	Group #2
Sale Order	-0.068 ***	-0.062 ***	-0.068 ***
Dam age (years)	-0.006 **	-0.003	-0.009 **
Age at sale (days)	0.03 ***	0.03 ***	0.029 ***
Birth weight (lbs.)	-0.019 ***	-0.018 ***	-0.017 ***
Weaning weight (lbs.)	0.012 ***	0.021 ***	-0.001
Average daily gain (lbs./day)	0.023 ***	0.027 ***	0.017 ***
Frame score	0.015 ***	0.006 *	0.027 ***
Adjusted scrotal circumference (cm)	-0.008 ***	-0.016 ***	0.004
Adjusted ribeye area (square inches at 12th rib)[3]	0.016 ***	0.011 **	0.024 ***
Adjusted rib fat (inches at 12th rib)	0.005	0.005	-0.003
Adjusted percent intramuscular fat (%)[3]	0.014 ***	0.009 *	0.025 ***
Birth Weight EPD (lbs.)	-0.051 ***	-0.045 ***	-0.058 ***
Weaning Weight EPD (lbs.)	0.014 ***	0.011 **	0.021 ***
Maternal Milk EPD (lbs.)	0.009 ***	0.014 ***	0.001
Ribeye area EPD (square inches)	0.002	0.008	0.000
Rib fat EPD (inches)	-0.002	-0.005	0.002
Marbling EPD	-0.004	0.006	-0.017 **
Sale Season	0.119 ***	0.112 ***	0.125 ***
Year Fixed	Yes	Yes	Yes
Constant	2.992 ***	2.983 ***	3.029 ***
Adjust R Square	0.85	0.85	0.84
RMSE	0.100	0.099	0.097
MSE[1]	0.079	0.079	0.078
Number of Observations	1705	1032	673

Notes: Chow test statistic shows that the coefficients are statistically different at the 1% level.
[1] Obtained from leave one out cross validation test.

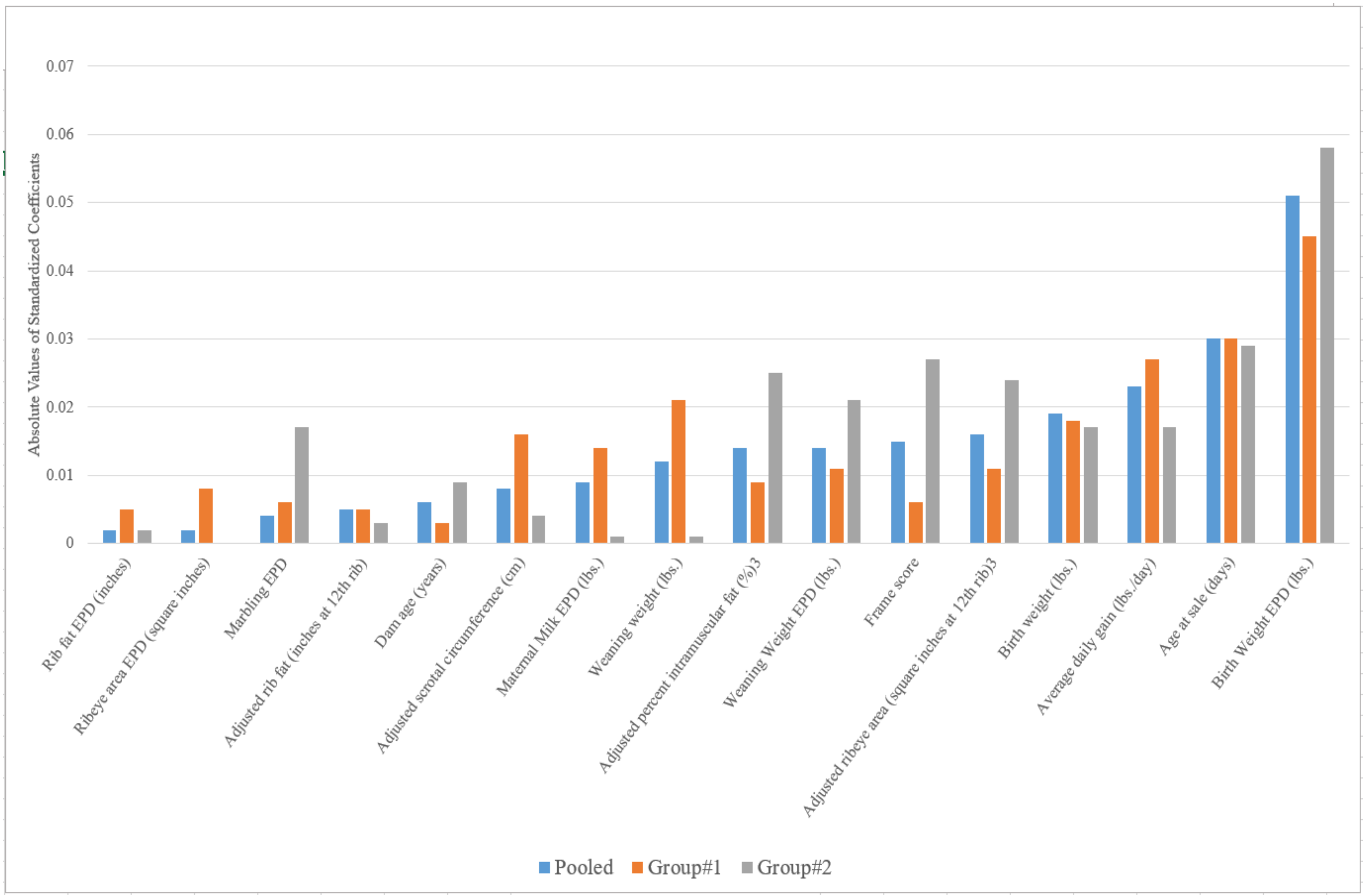

Figure 1. Marginal valuation of bull attributes by trait.

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