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Value of Genetic Information for Management and Selection of Feedlot Cattle

Nathanael M. Thompson, Eric A. DeVuyst, B. Wade Brorsen, and Jayson L. Lusk

We estimate the value of using information from genetic marker panels for seven economically relevant feedlot cattle traits. The values of using genetic information to sort cattle by optimal days-on-feed are less than \$1/head for each of the traits evaluated. However, the values associated with using genetic information to select cattle for placement are as much as \$38/head. The most economically relevant genetic traits are average daily gain and marbling. It would not be profitable at the current testing cost of \$38/head to sort cattle by optimal days-on-feed, but it could be profitable to use the genetic tests for breeding cattle selection.

Key words: beef cattle, genetics, molecular breeding value, value of information

Introduction

Genomic technology has the potential to generate value in each sector of the beef industry—seed stock, cow-calf, feedlot, and processing—by aiding in both management and selection decisions (Van Eenennaam and Drake, 2012). Commercial testing services can provide livestock producers with a range of genetic information, including parentage assignment, detection of genetic defects, and genetic markers, or single nucleotide polymorphisms (SNP) for qualitative traits, such as hide color, and quantitative traits, such as marbling score. Many quantitative traits, such as growth and carcass characteristics, are economically important but can be difficult to measure preharvest. Therefore, genetic markers associated with these traits may provide valuable information to decision makers prior to investing considerable time and expense. Although independent validations have found that many of these markers are correlated with the traits they are designed to predict (Van Eenennaam et al., 2007; DeVuyst et al., 2011; Hall et al., 2011; National Beef Cattle Evaluation Consortium, 2103), economists have considered few of these markers and their value to producers to date.

Early interest in genetic testing for beef cattle involved the leptin gene, which is associated with fat deposition (Fitzsimmons et al., 1998; Buchanan et al., 2002). Mitchell et al. (2009) found leptin genotype to be correlated with calf weaning weight and cow productive life. As a result, differences in annualized returns for dams with different genotypes range from \$15 to \$64 per head. Feedlot studies have had differing results with respect to the most profitable leptin genotypes (DeVuyst et al., 2007; Lusk, 2007; Lambert, 2008) but report differences in expected profit between

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Nathanael M. Thompson is graduate research assistant, Eric A. DeVuyst is professor, B. Wade Brorsen is Regents Professor and A.J. and Susan Jacques Chair, and Jayson L. Lusk is Regents Professor and Willard Sparks Endowed Chair in the Department of Agricultural Economics at Oklahoma State University.
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the best and worst performing genotypes of as much as $60 per head. These same studies found that the leptin genotype has little effect on optimal days-on-feed.

Today, leptin tests have been replaced with more accurate marker panels for a variety of economically relevant traits. These panels include several (potentially hundreds) of SNP to better predict phenotypic expressions (DeVuyst et al., 2011). Moreover, the availability of marker panels for several traits allows decision makers to better consider the chance that selecting for desirable attributes would have adverse effects on other economically relevant traits. Previous research has found economically meaningful relationships between genetic marker panel scores for average daily gain, tenderness, marbling, yield grade, and rib-eye area and growth and carcass characteristics such as average daily gain, feed efficiency, days-on-feed, hot-carcass weight, rib-eye area, yield grade, and quality grade (see DeVuyst et al., 2011, for an example). However, much remains to be learned about the economic value of utilizing such genetic information to improve feedlot profitability.

Prior research has provided useful, preliminary analysis of the biological and economic impacts of genetic marker panels. However, the limited data and simplified approach have failed to capture the full value of information obtained from genetic marker panels. To realize the full value of genetic information, it is important to determine whether cattle with different genetic makeups progress differently throughout the feeding process (Ladd and Gibson, 1978; Lusk, 2007). In other words, genetic markers do not directly influence profit, but they influence growth and carcass traits that, in turn, determine profitability. Accordingly, this study seeks to provide such an analysis using a large sample of cattle with considerable genetic diversity. Genetic information is conveyed as molecular breeding values (MBVs), which, like panel scores, represent an animal's propensity to express a given trait. Unlike discrete panel scores, MBVs are continuous, allowing for more precise depictions of the traits they characterize. In addition, genetic information is only useful if it conveys meaningful information beyond visual appraisal. Therefore, hide color is used to partially control for breed effects not considered in previous literature.

The increasing accuracy of genetic marker panels and the rapidly declining costs of genotyping present livestock producers with the opportunity to increase profitability by taking advantage of the information derived from genetic testing. However, the usefulness and value of this information will vary among the seed stock, cow-calf, feedlot, and processing sectors. The objective of this research is to estimate the expected value of genetic information for seven economically relevant traits at the feedlot stage, which results in two scenarios of value. First, genetic information could be used for marker-assisted management, sorting cattle that are already owned by a feedlot into management groups that are likely to perform similarly. Here we specifically focus on the value of using this information for choosing optimal days-on-feed. That is, what is the economic benefit of being able to feed cattle with differing genetics for different numbers of days-on-feed? Second, genetic information could be used for marker-assisted selection to differentially select cattle for placement in the feedlot.[1] In other words, how much more or less are animals with superior or inferior genetics worth compared to their contemporaries? Expected values of genetic information derived in this study have important implications, not just for decision makers in the feedlot sector, but for those throughout the beef cattle supply chain.

This study uses data from feedlot cattle to estimate the expected value of genetic information at the feedlot stage. Prediction equations for average daily gain, dressing percentage, yield grade, and quality grade are estimated using live-animal performance characteristics and MBVs for seven economically relevant traits. Prediction equations and a multivariate normal distribution of error terms are used as part of a stochastic simulation to estimate expected profits per head. The expected value of genetic information is calculated as the difference in expected profit, with and without genetic information, for both marker-assisted management and marker-assisted selection.

[1] In the animal science literature, marker-assisted selection specifically refers to using the results of genetic testing to assist in the selection of breeding stock (Van Eenennaam, van der Werf, and Goddard, 2011). However in this analysis, marker-assisted selection at the feedlot stage is defined as using genetic information to select feeder cattle for placement in the feedlot based on their genetic makeup.

Expected Profit Maximization and the Value of Information

Due to the capacity of large scale feeding operations, management of individual cattle with different feed rations or different expected sale dates is cost prohibitive. Therefore, feedlot cattle are managed in a group environment, such as pens or lots (Kolath, 2009). We assume that producers maximize expected per head profit for each group:

$$\begin{aligned}\max_{DOF_k \geq 0} E[\pi_k] \quad = \quad & \frac{1}{n_k}\sum_{i=1}^{n_k} P_{ik}(YG_{ik}, QG_{ik}, HCW_{ik}) \times HCW_{ik}(PW_{ik}, ADG_{ik}, DP_{ik}, DOF_k) \times \\ & (1 - MR) - PC_{ik}(PW_{ik}, SEX_{ik}) - FC_{ik}(W_{ik}, DOF_k) - \\ & YC_k(DOF_k) - IC_{ik}(PC_{ik}, DOF_k),\end{aligned} \tag{1}$$

where DOF_k is days-on-feed for the kth management group; n_k is the total number of animals in the kth group; and P_{ik} is dressed fed-cattle price, which is determined in part by yield grade, YG_{ik}, quality grade, QG_{ik}, and hot-carcass weight, HCW_{ik}, for the ith animal in the kth group. Hot-carcass weight is a function of placement weight, PW_{ik}, average daily gain, ADG_{ik}, and dressing percentage, DP_{ik}, $HCW_{ik} = (PW_{ik} + ADG_{ik} \times DOF_k) \times DP_{ik}$. MR is mortality rate, which is bounded by 0 and 1, PC_{ik} is the purchase cost of feeder cattle, FC_{ik} is feed cost, W_{ik} is weight, YG_{ik} is yardage costs, and IC_{ik} is interest cost on the purchase of feeder cattle. At placement, purchase cost and placement weight are the only variables known with certainty. Other profit determinants are a function of random growth and carcass characteristics ADG, DP, YG, and QG and the choice variable, DOF. Although the producer is assumed to have contracted a guaranteed future price grid, it is unknown how animals will develop and therefore what weight and carcass premiums or discounts they will receive. Information derived from genetic testing can be used to predict unknown growth and carcass characteristics. This information gives the feedlot the opportunity to differentially manage and select cattle based on genetic potential. Although acquiring this information incurs costs, it yields information that may increase profitability (Stigler, 1961).

Stigler (1961) first developed the economics of information, which has since been extended to many agricultural settings, including the value of genetic information in livestock production (Ladd and Gibson, 1978; Hennessy, Miranowski, and Babcock, 2004; DeVuyst et al., 2007; Lusk, 2007; Lambert, 2008). Typically, the value of information is calculated as "the difference between expected returns (or utility) using the information and expected returns without the information, with both expectations taken with respect to the more informed distribution" (Babcock, 1990, p. 63). Note that expected profit in equation (1) does not include genetic testing costs. As a result, the improvement in the objective function from acquiring genetic information sets an upper limit on the cost of genetic testing.

Data

Data for 10,209 cattle from six commercial feedlots were provided by Neogen, the parent company of Igenity. Animals were weighed at placement, and a hair sample or tissue punch from ear tag application was collected for genetic testing. Molecular breeding values characterizing average daily gain, hot-carcass weight, yield grade, rib-eye area, marbling, tenderness, and days-on-feed were provided. Although many breed associations are working toward developing breed-specific MBVs (MacNeil et al., 2010), much as they have done for expected progeny differences (EPDs), the MBVs used in this study were developed using a sample of commercial cattle.[2] Unlike EPDs, which represent the genetic potential of an animal as a parent, MBVs represent the genetic potential

[2] For more information on the development and validation of MBVs, see the National Beef Cattle Evaluation Consortium, Commercial Genetic Test Validation (National Beef Cattle Evaluation Consortium, 2103).

of an animal to express a given trait. Increases in MBVs increase the likelihood of expressing more favorable outcomes.[3] While MBVs (like EPDs) are reported in units of the trait, they "reflect the relative differences expected in animals across breeds compared to their contemporaries" (Igenity, 2013a, p. 2). That is, if two animals have marbling MBVs of -100 and 20, we would expect, on average, that these two animals' marbling scores would differ by 120 units. Additional live-animal characteristics for gender, hide color, average daily gain, and days-on-feed were also provided. At slaughter, data were collected for final live weight and carcass measurements for hot-carcass weight, back fat, rib-eye area, calculated yield grade, and marbling score.

Missing data were common for a few critical variables. Final live weight was unavailable for 4,436 observations. Although not used directly, final live weight is essential to the estimation of dressing percentage (dressing percentage = hot-carcass weight/final live weight). Additionally, 422 observations were missing for marbling score. After deleting these and other observations with missing data, 5,353 complete records were available for analysis. These data consist of six sets, each of which represents a different commercial feedlot or time period.[4] In addition, each set is divided into contemporary groups, which are defined as groups "of animals that have had an equal opportunity to perform: same sex, managed alike, and exposed to the same environmental conditions and feed resources" (Northcutt, 2005, p. 144). The 197 contemporary groups averaged 27 head per group with a range from 1 to 202 head. The sample is made up of 74% steers and 68% black-hided cattle (table 1). On average, cattle were fed for 165 days and finished with a yield grade of almost 3 and a marbling score of 412 (low Choice on the quality grade scale).[5]

Investigation of the empirical, joint yield- and quality-grade distribution suggests that cattle in the sample are of average quality (table 2). The majority of cattle grade either Select (44%) or low Choice (42%) on the quality-grade scale and yield grade two (46%) or three (40%) on the yield-grade scale, although the sample includes cattle in each yield-grade and quality-grade category.

To remove time-varying effects in our simulation, all animals are assumed to face the same market prices for March 2013. Purchase costs for feeder cattle are estimated using feeder cattle prices for steers and heifers based on placement weight (U.S. Department of Agriculture, Agricultural Marketing Service, 2013b). Finished cattle are assumed to be priced on a fixed grid with a base price of \$201.71/cwt. dressed, with appropriate premiums and discounts for yield grade, quality grade, and weight (table 3) (U.S. Department of Agriculture, Agricultural Marketing Service, 2013a).

Procedures

Average daily gain (ADG), dressing percentage (DP), yield grade (YG), and quality grade (QG) in equation (1) are assumed to be random variables. A mixed model regression equation for each of these growth and carcass characteristics is estimated such that the data generating process is specified as

$$\begin{aligned} Y_{ijkl} = {} & \beta_{0l} + PW_{ijk}\beta_{1l} + DOF_{ijk}\beta_{2l} + DOF_{ijk}^2\beta_{3l} + PW_{ijk}DOF_{ijk}\beta_{4l} + \\ & STR_{ijk}\beta_{5l} + BLK_{ijk}\beta_{6l} + \sum_{m=1}^{7} MBV_{ijkm}\beta_{7lm} + v_{jl} + u_{jkl} + \varepsilon_{ijkl}, \end{aligned} \tag{2}$$

where Y_{ijkl} is the dependent variable for the ith animal in the jth set and the kth contemporary group for the lth equation, where $l = 1, 2, 3, 4$ for ADG_{ijk}, DP_{ijk}, YG_{ijk}, and QG_{ijk}, respectively;

[3] Intuitively, more favorable outcomes are increases in a given trait (e.g., higher marbling score), except for yield grade, for which lower outcomes are more favorable.

[4] The majority of the cattle used in this study represent year-round placements in commercial feedlots in Iowa and Kansas in the year 2007 with a small number of placements (127 head) in January 2008.

[5] Marbling scores between 200–299 are said to have traces of intramuscular fat and are graded Standard, 300–399 or slight marbling are Select, 400–499 or small marbling are low Choice, 500–599 or modest marbling are average Choice, 600–699 or moderate marbling are high Choice, and scores over 700 are Prime (U.S. Department of Agriculture, Agricultural Marketing Service, 1997, 2006).

Table 1. Summary Statistics for Live-Animal, Carcass Performance, and Molecular Breeding Value Characteristics (*n*=5,353)

Variable	Mean	Standard Deviation	Minimum	Maximum
Live-Animal and Carcass Performance				
Placement weight (cwt)	6.83	1.22	2.94	11.16
Steer[a]	0.74			
Black[b]	0.68			
Average daily gain (lbs/day)	3.33	0.77	0.42	6.52
Days-on-feed	165.45	34.09	81.00	308.00
Final live weight (cwt)	12.09	1.42	7.06	17.27
Hot-carcass weight (cwt)	7.58	0.95	4.58	11.06
Dressing percentage	0.63	0.03	0.49	0.83
Rib-eye area (in^2)	12.90	1.66	8.30	20.90
Calculated yield grade	2.86	0.69	0.06	5.71
Marbling score	412.32	76.86	190.00	830.00
Molecular Breeding Values (MBV)				
Average daily gain MBV	0.18	0.10	−0.19	0.48
Hot-carcass weight MBV	27.63	9.24	−17.73	55.91
Yield grade MBV	−0.06	0.07	−0.34	0.21
Rib-eye area MBV	−0.63	0.51	−2.16	1.59
Marbling MBV	−22.53	28.24	−119.37	68.26
Tenderness MBV	−1.18	1.43	−5.90	2.92
Days-on-feed MBV	−2.58	2.99	−14.35	8.49

Notes: Molecular breeding values (MBVs) are reported in units of the trait, and reflect the differences expected in animals across breeds compared to their contemporaries (Igenity, 2013a). Therefore, mean MBVs offer little insight. Instead, the range of MBVs is more informative. For example, the range of average daily gain MBVs suggests that the animal with the highest genetic potential for average daily gain in the sample would be expected, on average, to gain approximately 0.67 lbs per day more than the animal with the lowest genetic potential for average daily gain $[0.48 - (-0.19)]$.

[a]Steer is a dummy variable equal to 1 if the animal was a steer and 0 otherwise.

[b]Black is a dummy variable equal to 1 if the animal was black hided and 0 otherwise.

Table 2. Empirical Distribution of Yield Grade and Quality Grade (*n*=5,353)

	Yield Grade					
Quality Grade	1	2	3	4	5	Total
Standard	0.0118	0.0155	0.0047	0.0006	0.0000	0.0325
Select	0.0620	0.2285	0.1364	0.0082	0.0002	0.4353
Low Choice	0.0211	0.1775	0.2057	0.0196	0.0009	0.4248
Average Choice	0.0024	0.0271	0.0404	0.0058	0.0002	0.0758
High Choice	0.0013	0.0080	0.0116	0.0041	0.0002	0.0252
Prime	0.0000	0.0024	0.0032	0.0007	0.0000	0.0064
Total	0.0986	0.4590	0.4018	0.0390	0.0015	1.0000

PW_{ijk} is placement weight; DOF_{ijk} is days-on-feed; STR_{ijk} is a dummy variable equal to 1 if the animal was a steer and 0 otherwise; BLK_{ijk} is a dummy variable equal to 1 if the animal had black hide and 0 otherwise; MBV_{ijkm} is the molecular breeding value of the mth economically relevant trait; $v_{jl} \sim N(0, \sigma^2_{v_l})$ is a set random effect; $u_{jkl} \sim N(0, \sigma^2_{u_l})$ is a contemporary group random effect nested within sets (Greene, 2012); and $\varepsilon_{ijkl} \sim N(0, \sigma^2_{\varepsilon_l})$ is an error term, where v_{jl}, u_{jkl}, and ε_{ijkl} are independent. A full set of MBV, days-on-feed interactions are also investigated as slope shifters in the YG and QG equations. Only the marbling MBV, days-on-feed interaction is statistically significant in both equations; all other MBV, days-on-feed interactions are therefore dropped from the models. Dependent variables YG and QG are both represented as continuous variables. Yield grade is a continuous variable as a function of backfat; kidney, pelvic, and heart fat; hot-carcass weight; and rib-eye area (U.S. Department of Agriculture, Agricultural Marketing Service, 1997), and the marbling score is used as a continuous representation of QG.

Table 3. Yield Grade, Quality Grade, and Carcass Weight Premiums and Discounts for Price Grid

Grid Component	Premium/ (Discount) $/cwt.
Base Price[a]	$201.71
Yield Grade (YG) Adjustment	
YG < 2	$4.58
2 ≤ YG < 3	$2.18
3 ≤ YG < 4	$0.00
4 ≤ YG < 5	($9.25)
YG ≥ 5	($15.02)
Quality Grade Adjustment	
Prime	$19.40
Choice	$0.00
Select	($2.69)
Standard	($17.87)
Hot-Carcass Weight (HCW) Adjustment	
HCW < 500	($25.48)
500 ≤ HCW < 550	($19.62)
550 ≤ HCW < 600	($3.89)
600 ≤ HCW < 900	$0.00
900 ≤ HCW < 950	($0.24)
950 ≤ HCW < 1000	($0.24)
HCW ≥ 1000	($21.99)

*Notes:*Discounts are designated by parentheses. *Source:* U.S. Department of Agriculture, Agricultural Marketing Service (2013a).
[a] The base price is the five-area weighted average for 65%–80% USDA Choice dressed weight for mixed lots of steers and heifers.

Models are estimated independently using Proc Mixed in SAS (SAS Institute, Inc., 2012). The D'Agostino-Pearson K^2 omnibus test for skewness and kurtosis rejects the null hypothesis of normality in each of the four prediction equations, and conditional variance tests identify static heteroskedasticity. Cluster robust standard errors are estimated to obtain estimates of standard errors that are consistent in the presence of nonnormality and heteroskedasticity (Liang and Zeger, 1986). Given the large sample size, asymptotic properties are relevant, and the small sample biases common with generalized method of moments estimators should be of little concern.

Expected Profit

Feed costs are also needed to calculate expected profits. Given that observations of feed intake were unavailable, a dry matter intake (DMI) model is used following the National Research Council's *Nutrient Requirements of Beef Cattle* (National Research Council, 2000).[6] The DMI model generates an estimate of "standardized" feed intake. That is, we ignore additional factors that may have influenced feed intake across different feedlots or time periods, such as weather. Much like holding prices constant, this approach places all animals on a level playing field in order to estimate an expected value of genetic information. Prior to calculating DMI, a projected live weight for each animal for each day on feed is estimated as

$$(3) \qquad W_{it} = PW_i + \left(\frac{LW_i - PW_i}{DOF_i}\right) \times t_i \quad \forall \quad t \in \{1, \ldots, DOF_i\},$$

where W_{it} is the weight of the ith animal at the tth day on feed, LW_i is final live weight, PW_i is placement weight, and DOF_i is days-on-feed. The NRC's DMI equation also allows for adjustment

[6] A constant cost-of-gain approach could also be used to estimate feed costs. However, such an approach is just a parallel shift of the revenue curve. The DMI model reflects that the cost of gain goes up as the cattle weight increases and thus provides concavity to the profit function.

Table 4. Dry Matter Intake Empty Body Fat Adjustment Factor for Beef Cattle

Empty Body Fat Percentage (EBF)	Body Fat Adjustment Factor (BFAF)
EBF < 23.8	1.00
23.8 ≤ EBF < 26.5	0.97
26.5 ≤ EBF < 29.0	0.90
29.0 ≤ EBF < 31.5	0.82
EBF ≥ 31.5	0.73

Source: National Research Council (2000).

factors for breed, percentage of empty body fat, growth hormones, air temperature, and muddy soils that may influence growth in the feedlot. Based on available information, a body fat adjustment factor (BFAF) is included in the analysis. The BFAF is determined by empty body fat percentage (EBF) (Perry and Fox, 1997):

$$(4) \qquad EBF_{it} = \left(\frac{0.35\left(0.39\frac{W_{it}}{2.20}\right) + 21.60YG_i - 80.80}{0.39\left(\frac{W_{it}}{2.20}\right)} \right) \times 100.$$

Essentially, the BFAF corrects for over prediction of DMI as animals become larger (table 4) (National Research Council, 2000).

Using this information, we then estimate DMI (lbs/day) for the ith animal for the tth day on feed as

$$(5) \qquad DMI_{it} = \left(0.96\left(\frac{W_{it}}{2.20}\right)\right)^{0.75} \times \frac{(0.24NE_m - 0.05NE_m^2 - 0.11)}{NE_m} \times BFAF_{it} \times 2.20,$$

where NE_m is the net energy required for maintenance, which is set to a constant of two megacalories per kilogram (National Research Council, 2000). Finally, cumulative dry matter intake ($CDMI$) of the ith animal is

$$(6) \qquad CDMI_i = \sum_{t=1}^{DOF_i} DMI_{it}.$$

Additional information needed to estimate expected profit includes dry matter cost of \$230/ton (\$0.12/lb.), yardage costs of \$0.40/day, a 7% interest rate on the purchase of feeder cattle, and a mortality rate of 1% (Lardy, 2013).[7] This information can be used in conjunction with equations (2)–(6) to estimate profit per head.

However, expected profit in equation (1) is nonlinear. Therefore, because of Jensen's inequality, profit calculated at the expected value of prediction equations will not equal expected profit (Greene, 2012). For this reason, stochastic simulation is used to estimate expected profit per head. The Cholesky decomposition of the four-by-four variance-covariance matrix of the error terms from equation (2) is calculated and used to generate a multivariate normal distribution of 1,000 error terms for each of the four prediction equations for each animal in the sample. Profit per head is evaluated at each draw using actual live-animal characteristics and MBVs. The average across draws is expected profit per head. This process is repeated for days-on-feed from 150 to 200.

Marker-Assisted Management

The advantage of genetic testing is the ability to differentially manage or select cattle based on unobservable growth and carcass characteristics. As a result of producer interest in which MBVs

[7] Costs for sick treatments, which are generally assessed on an animal-by-animal basis (for example, \$1 per head for each pull plus material costs), are not included. Information on animals being pulled for sick treatment was not available.

are most economically relevant, the primary objective here is to determine the value associated with each individual genetic marker panel. To do so, cattle are divided into quartiles for each of the seven MBVs, and the expected profit per head is calculated for each quartile.[8] A grid search is then employed to determine the days-on-feed that maximizes expected profit per head for each group. This approach makes it possible to identify which MBVs capture the most economic value. Marker-assisted management is the process of using genetic information to sort cattle already in the feedlot into management groups that are most likely to achieve similar endpoints (Van Eenennaam and Drake, 2012). Although it can include several objectives, such as implant strategies and value-added marketing, marker-assisted management for this analysis is limited to optimal marketing dates, or days-on-feed. The value of genetic information associated with marker-assisted management (VOI_{MAM}) for a given trait is calculated by comparing expected profit when a feedlot can differentially choose optimal marketing dates for each quartile of a given trait relative to the case where all cattle are fed for the same number of days-on-feed:

$$(7) \qquad E[VOI_{MAM}] = \sum_{i=1}^{4} \frac{E[\pi_{Qi}]}{4} - E[\pi_{ALL}],$$

where π_{Qi} is maximum profit for the ith quartile and π_{ALL} is maximum profit when all cattle in the sample are fed for the same number of days-on-feed.

Marker-Assisted Selection

At the feedlot stage, marker-assisted selection involves differentially selecting cattle for placement based on genetic information. Feedlots are still expected to feed both high- and low-quality cattle. However, access to genetic information allows feedlot operators the opportunity to place premiums on cattle with superior genetic potential and discounts on cattle with poor genetics. The maximum value of genetic information associated with marker-assisted selection (VOI_{MAS}) for a given trait is calculated by comparing expected profits for the best performing quartile relative to the case where genetic information is unavailable and all cattle are fed for the same number of days-on-feed:[9]

$$(8) \qquad E[VOI_{MAS}] = \max\{E[\pi_{Q1}],\, E[\pi_{Q2}],\, E[\pi_{Q3}],\, E[\pi_{Q4}]\} - E[\pi_{ALL}].$$

Although currently genetic information is not typically available to feedlots prior to purchasing feeder cattle (Kolath, 2009), knowledge of the value associated with marker-assisted selection at the feedlot stage is important. These values provide estimates of the premiums or discounts that feedlots could place on cattle with varying levels of genetic potential, or a bid-price differential. In addition, knowledge of the traits that generate the most value to the feedlot sector may also guide selection decisions in the breeding sectors. The values reported here reflect short-run partial equilibrium effects. If the majority of feedlots begin selecting for MBVs—or if breeders begin to selecting for certain MBVs—then the returns to a genetic trait will change as a result of changes in supply and demand for the trait.

Equations (7) and (8) treat the "base" scenario as the maximum expected profit when all cattle are fed for the same number of days-on-feed (π_{ALL}), rather than using actual observed returns.[10] This

[8] The choice of four groups used in this analysis is subjective. However, Cargill Cattle Feeders utilize a four group management system to "allow for efficient management within a group production environment by preventing groups with too few animals, while still allowing us to come close to maximizing the genetic potential of each animal" (Kolath, 2009, p.105).

[9] The expected value of marker-assisted selection in some previous studies has been calculated as the difference in expected profit per head for the best and worst performing quartiles (or genotypes). However, this assumes that the original state of nature involves the feedlot owning all cattle from the worst performing quartile, which is likely not the case.

[10] Observed returns based on pen-level cost data were unavailable. However, access to this information would not have changed our approach to estimating the expected value of genetic information. This additional data may have been used to calibrate the intake equations, but even this may have been inappropriate given the potential for differences in feed rations across time and space.

approach allows us to confidently make comparisons across all animals in the sample. Alternatively, these same comparisons may not be appropriate when using actual observed returns, given that the cattle were fed under different conditions. For example, the dataset consists of animals from several commercial feedlots over multiple time periods. Therefore, differences in marketing decision rules among feedlots as well as differences in input and output prices over time influence the observed days-on-feed decisions and returns to cattle feeding. In addition to these obvious differences, unobservable constraints (such as capacity constraints and weather conditions) are also likely to influence the observed outcomes. However, feedlots do not have a constant days-on-feed expectation with or without genetic information. Therefore, the values reported here are likely upper bounds on the value of genetic information.

Multiple-Trait Marker-Assisted Management and Selection

Genetic information characterizing economically relevant traits may also be supra- or subadditive. That is, managing for multiple traits simultaneously may increase the value associated with marker-assisted management or marker-assisted selection. If cattle are divided into quartiles for each MBV, simultaneously managing for two traits yields sixteen potential management groups. Again, a grid search is employed to determine days-on-feed that maximizes the expected profit per head for each group. The expected value of marker-assisted management and marker-assisted selection is estimated similarly to equations (7) and (8), except that each group no longer makes up an equal proportion of the sample.

Further, there is also interest in the value of utilizing the entire profile of genetic information simultaneously. That is, instead of utilizing genetic information for one or two traits, what is the value of managing cattle based on their overall performance? This inquiry requires a slightly different approach than the procedures described above. First, we must find the days-on-feed that maximizes the expected profit per head for each animal in the sample. However, when looking at each animal individually, live-animal characteristics other than MBVs will influence optimal days-on-feed. For example, animals with lower placement weights will obviously command higher optimal days-on-feed. For this reason, placement weight, gender, and hide color are held constant at their mean values in order to separate these effects from those of genetic information. Following a stochastic simulation procedure similar to that described above, we can then determine the expected profit-maximizing number of days-on-feed for each animal in the sample. As has been previously discussed, individual management is cost prohibitive in a feedlot setting. Therefore, animals are sorted into quartiles based on their individual performance (optimal days-on-feed), and a single expected profit-maximizing number of days-on-feed is determined for each quartile. Dividing cattle into quartiles also provides us with an estimated value of the entire genetic profile that is comparable to the other values of genetic information reported here.

Results

Regression estimates for growth and carcass characteristics *ADG*, *DP*, *YG*, and *QG* are reported in table 5. Missing observations for dependent variables in the sample are deleted so that all four equations have the same number of observations ($n = 5,353$).[11] Coefficients for live-animal characteristics generally exhibit expected relationships. Heavier placement weights increase predicted values for *ADG*, *DP*, *YG*, and *QG*. Growth and carcass characteristics *ADG*, *DP*, and *QG* display a concave relationship with days-on-feed, increasing at a decreasing rate, but only in the *DP* equation are linear and squared terms both statistically significant. Consistent with expectations, the effect of days-on-feed on each of the performance characteristics is diminished as placement weight

[11] Each of the four equations is also estimated with its own maximum number of observations to investigate fragility. Differences are minimal, and results are presented as is for conciseness.

Table 5. Mixed Model Regression Results for Average Daily Gain, Dressing Percentage, Yield Grade, and Quality Grade Prediction Equations (*n*=5,353)

	Equation			
Variable	***ADG***	***DP***	***YG***	***QG***
Constant	2.2582*	0.3830**	1.0798	218.1700**
Placement weight	0.1805	0.0094**	0.2079***	22.8606***
Days-on-feed	0.0097	0.0019*	0.0039	1.2387**
Days-on-feed^2	−2.00E-05	−3.55E-06*	2.69E-06	−0.0006
Placement weight × days-on-feed	−0.0014*	−4.00E-05	−0.0006	−0.1145***
Steer	0.3923***	0.0001	−0.1452***	−34.2965***
Black	0.0225*	−0.0003	0.0217	4.0083**
Average daily gain MBV	0.3877***	−0.0055*	0.0081	−11.6896
Hot carcass weight MBV	0.0026**	0.0001***	0.0024	0.3596***
Yield grade MBV	0.2221**	−0.0089	−0.7557***	−10.1476**
Rib-eye area MBV	−0.0341	0.0023	−0.3241***	−9.3658***
Marbling MBV	0.0004	−7.89E-06	−0.0022	0.1504
Marbling MBV × days-on-feed	–	–	2.40E-05**	0.0033***
Tenderness MBV	0.0126**	0.0002	0.0018	−0.8510
Days-on-feed MBV	1.00E-05	−3.00E-05	−0.0040*	−0.4305
Random effects[a]				
Set	0.2185*	0.0005*	0.1219	60.8511
Contemporary group	0.1104***	0.0002***	0.0370***	491.6800***

Notes: Joint tests for marbling MBV and marbling MBV, days-on-feed interactions are statistically significant at the 1% level in both the YG (df $= 2,5128$; $F = 41.44$) and *QG* (df $= 2,5128$, $F = 306.91$) equations. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. Dependent variables in the four equations are average daily gain (*ADG*), dressing percentage (*DP*), calculated yield grade (YG), and marbling score (*QG*).
[a]Random effects for set and contemporary groups nested within sets are included in the estimation of each equation (i.e., mixed model regression Greene, 2012). Sets represent a different commercial feedlot and/or time period, and contemporary groups are groups of animals that have had an equal opportunity to perform.

increases, which is suggested by the negative coefficient of the placement weight, days-on-feed interaction terms. Steers have higher *ADG* and lower YG and *QG* compared to heifers. Additionally, black-hided cattle have higher *ADG* and *QG*.

Molecular breeding values influence corresponding fed cattle traits in the expected direction. Average daily gain MBV positively influences actual *ADG*, hot-carcass weight MBV positively influences actual *DP*, yield grade and rib-eye area MBVs negatively influence YG, and marbling MBV positively influences actual *QG*. Each of these effects except for the marbling MBV is statistically significant at the 1% level. However, a joint test of the marbling MBV and marbling MBV, days-on-feed interaction terms in the *QG* equation is statistically significant at the 1% level (df $= 2,5128$; $F = 306.91$). Additional effects of MBVs on growth and carcass characteristics offer many interesting relationships. Most notably is the significant, inverse relationship between yield and quality grade. Higher yield grade and rib-eye area MBVs decrease *QG*, and higher marbling MBV increases YG.[12] These cross-trait MBV effects suggest the need to consider multiple MBVs when making management or selection decisions.

Prediction equations are used as part of a stochastic simulation to estimate expected profit according to equation (1) for days-on-feed from 150 to 200. Results indicate that if a feedlot was restricted to pick the same marketing date for all cattle, maximum expected profit of $146.14 per head would be realized at 185 days-on-feed. This result is higher than mean actual days-on-feed observed in the sample of 165 days,[13] but is well within the range of observed values, which has a maximum of 308 days. A variety of circumstances contribute to the discrepancy between predicted and observed days-on-feed. One potential explanation is the unobservable constraints faced by

[12] Marbling MBV has a negative coefficient in the YG equation. However, the marbling MBV, days-on-feed interaction is positive. Therefore, the sum of the two effects is positive and jointly significant at the 1% level (df $= 2,5128$; $F = 41.44$) over the range of days-on-feed analyzed (150–200).

[13] At the mean actual days-on-feed observed in the sample of 165 days expected profit would be $135.44 per head. Therefore, an additional twenty days-on-feed increased expected profit by about $10.70 per head.

Table 6. Maximum Expected Profit ($/head) and Optimal Days-on-Feed for Quartiles of Economically Relevant Molecular Breeding Values

	Quartile			
Molecular Breeding Value	**Q1**	**Q2**	**Q3**	**Q4**
Average daily gain				
Expected profit	$125.19	$140.23	$151.61	$168.35
Days-on-feed where expected profit is maximized	181	184	185	187
Hot-carcass weight				
Expected profit	$129.21	$141.46	$149.73	$164.56
Days-on-feed where expected profit is maximized	185	184	187	186
Yield grade				
Expected profit	$158.42	$147.69	$143.53	$135.06
Days-on-feed where expected profit is maximized	187	184	185	185
Rib-eye area				
Expected profit	$161.83	$154.00	$145.37	$125.34
Days-on-feed where expected profit is maximized	192	188	185	181
Marbling				
Expected profit	$121.05	$140.93	$156.57	$167.41
Days-on-feed where expected profit is maximized	181	185	185	188
Tenderness				
Expected profit	$143.05	$142.21	$146.47	$152.98
Days-on-feed where expected profit is maximized	187	185	185	184
Days-on-feed				
Expected profit	$149.46	$146.65	$146.62	$141.93
Days-on-feed where expected profit is maximized	187	185	185	183

Notes: If all cattle are fed for the same number of days-on-feed, maximum expected profit of $146.14 per head would be realized at 185 days-on-feed.

feedlot operators (Boys et al., 2007), such as differences in input and output prices actually faced when the cattle were on feed and the prices we use in this simulation.[14] In addition, feedlot operators may be risk averse. Therefore, cattle may be harvested prior to reaching maximum profits in order to avoid the potentially large discounts associated with higher yield grades if cattle are overfed.

Optimal days-on-feed and expected profits per head are determined at the quartiles of MBVs for each economically relevant trait (table 6). Results indicate differences in expected profit among quartiles ranging from $8 per head for days-on-feed MBV to $46 per head for marbling MBV. Higher MBVs increase expected profit for all traits except yield grade, rib-eye area, and days-on-feed. The inverse relationship between expected profit and MBVs characterizing yield grade and rib-eye area is likely the result of the inverse relationship between yield grade and quality grade. More favorable yield grade and rib-eye area outcomes result in less favorable quality grade. Therefore, for the budgeted price grid, yield-grade premiums are insufficient to offset lower quality-grade premiums (or higher quality-grade discounts). Despite differences in expected profit, optimal endpoints for the quartiles of each trait are similar to the uniform endpoint for all cattle in the sample of 185 days-on-feed.

Marker-assisted management increases expected profit for each of the economically relevant traits evaluated. The ability to choose optimal marketing dates for each quartile of the rib-eye area MBV increases expected profit to $146.63 per head, resulting in the highest value of genetic information for marker-assisted management, $0.49 ($146.63 − $146.14) per head (table 7). Rib-eye area partially determines yield grade, which is directly reflected in the price grid. However, the value of marker-assisted management associated with the yield grade MBV is only $0.03 per head. Therefore, the rib-eye area MBV appears to capture markers that are more economically sensitive

[14] The corn-to-dressed fed cattle price ratio in 2007 ($4.20/146.37 = 0.029$) is similar to the price ratio used in this analysis ($6.44/201.71 = 0.032$). However, the current price grid rewards higher quality grades, incentivizing feedlot operators to feed cattle longer. The use of a price grid from the period when cattle were actually fed may lead to more similar results between predicted and actual days-on-feed. However, because we are ultimately interested in the current value of genetic information to producers, the use of a current price grid is appropriate.

Table 7. Expected Value of Marker-Assisted Management and Marker-Assisted Selection at the Feedlot Stage for Molecular Breeding Values Characterizing Economically Relevant Traits

	Value of Information ($/head)	
Molecular Breeding Value	Marker-Assisted Management	Marker-Assisted Selection
Average daily gain	$0.20	$22.21
Hot-carcass weight	$0.10	$18.42
Yield grade	$0.03	$12.28
Rib-eye area	$0.49	$15.69
Marbling	$0.35	$21.27
Tenderness	$0.04	$6.84
Days-on-feed	$0.02	$3.31

Notes: The value of marker-assisted management is calculated by comparing expected profit when a feedlot can differentially choose optimal marketing dates for each quartile of a given trait relative to the case where all cattle are fed for the same number of days-on-feed. The value of marker-assisted selection at the feedlot stage is calculated by comparing expected profits for the best performing quartile relative the case where all cattle are fed for the same number of days-on-feed.

to days-on-feed than the yield grade MBV. The expected value of marker-assisted management for other key profit determinants of marbling, average daily gain, and hot-carcass weight are $0.35, $0.20, and $0.10 per head. In general, low values associated with marker-assisted management are partially influenced by limited differences among optimal days-on-feed for the quartiles of each trait and the uniform endpoint for all cattle in the sample. This result is consistent with the findings of previous research (DeVuyst et al., 2007; Lusk, 2007; Lambert, 2008) and supports the finding that agricultural profit functions are often flat near the optimum (Pannell, 2006).

Results also indicate that expected profits could be increased considerably if a feedlot could differentially select cattle based on genetic information for each trait. Marker-assisted selection for the MBV characterizing average daily gain increases expected profits to $168.35 per head, resulting in the highest value of genetic information for selection, $22.21 ($168.35 − $146.14) per head (table 7). The ability to select for animals with higher average daily gain will result in heavier finished weights or fewer days-on-feed, both of which increase profitability. Similarly, MBVs characterizing marbling and hot-carcass weight generate value for selection of $21.27 and $18.42 per head. These results are similar to the findings reported by Lusk (2007), who found values for marker-assisted selection at the feedlot stage for leptin genotype of approximately $23 and $28 per head for steers and heifers.[15]

The above results estimate the value of marker-assisted management and marker-assisted selection when focusing on a single economically relevant trait. However, the ability to manage or select for multiple traits may further increase expected profits and the value of genetic information. For example, a feedlot operator could simultaneously manage or select for MBVs characterizing average daily gain and marbling (table 8). When each management group is fed for its own optimal number of days-on-feed, expected profits across all sixteen groups increase to $146.62 per head.[16] Therefore, the value of multiple-trait marker-assisted management for average daily gain and marbling MBVs is $0.47 ($146.62 − $146.14) per head. The group comprising the fourth quartiles for both traits generates the highest expected profit of $176.57 per head, resulting in a value of multiple-trait selection for average daily gain and marbling MBVs of $30.43 ($176.57 − $146.14) per head.

Similar analyses are conducted for each pairwise combination of the seven MBVs to determine the value of genetic information when simultaneously managing or selecting for multiple economically relevant traits (table 9). Results indicate that the highest value of multiple-trait marker-assisted management is realized when simultaneously managing yield grade and rib-eye area MBVs, $0.79 ($146.93 − $146.14) per head. Similar to single-trait management, the economic impacts of

[15] Other studies either did not report values of marker-assisted selection or reported values that were not comparable given differences in the estimation of the value of marker-assisted selection at the feedlot stage.

[16] The sum across groups of each group's expected profit multiplied by its effective proportion of the sample.

Table 8. Maximum Expected Profit ($/head), Optimal Days-on-Feed, and Effective Proportion of Management Groups for Simultaneous Management of Average Daily Gain and Marbling Molecular Breeding Values

		Quartile for Average Daily Gain MBV			
		Q1	**Q2**	**Q3**	**Q4**
Quartile for Marbling MBV	**Q1**	$111.13 (181) [0.11]	$120.79 (180) [0.07]	$132.02 (181) [0.05]	$146.40 (184) [0.02]
	Q2	$127.58 (183) [0.07]	$139.82 (187) [0.07]	$144.21 (185) [0.06]	$159.82 (185) [0.05]
	Q3	$141.66 (180) [0.04]	$148.72 (189) [0.07]	$159.73 (188) [0.07]	$169.56 (190) [0.07]
	Q4	$149.80 (188) [0.03]	$161.49 (188) [0.04]	$164.69 (188) [0.07]	$176.57 (192) [0.11]

Notes: Numbers in parentheses are days-on-feed for each group where expected profit ($/head) is maximized. Numbers in brackets are the proportion of cattle in the sample for each group.

the rib-eye area MBV appear to be more sensitive to days-on-feed than other economically relevant traits. The highest value of multiple-trait marker-assisted selection is realized when selecting for MBVs characterizing hot-carcass weight and marbling, $37.56 ($183.70 − $146.14) per head. Although selecting cattle based on multiple economically relevant traits increases the expected value of genetic information, this information is generally subadditive.[17] This result is intuitive given the positive correlation among many of the marker panels. The values reported in table 9 may underestimate the value of genetic information that would be available if the entire profile of genetic information were used.

We estimate the value of the entire profile of genetic information by "indexing" animals based on performance (optimal days-on-feed). Because this approach is slightly different from the previous analyses, it requires that we estimate a new "base" scenario. That is, the stochastic simulation is reassessed, holding placement weight, gender, and hide color constant at their mean values. Results indicate that if a feedlot were restricted to pick a uniform marketing date for all cattle, maximum expected profits of $142.68 per head would be realized at 189 days-on-feed. Cattle are then indexed based on their individual genetic performance. That is, the expected profit maximizing days-on-feed is determined for each individual animal in the sample. However, because individual management is cost prohibitive, cattle are divided into quartiles based on each animal's optimal days-on-feed. The ability to sort cattle into quartiles based on the performance of their entire genetic profile increases expected profit to $144.97 per head, resulting in a value of marker-assisted management of $2.29 per head ($144.97 − $142.68).[18]

Conclusions

This study estimates the expected value of genetic information at the feedlot stage. Using data from 5,353 feedlot cattle, prediction equations for growth and carcass traits average daily gain, dressing percentage, yield grade, and quality grade are estimated using live-animal characteristics

[17] The value of simultaneously selecting for two traits is less than the sum of the values when selecting for each trait individually.

[18] Dividing cattle into quartiles based on each animal's individual profit-maximizing number of days-on-feed allows us to generate a value of the entire profile of genetic information that is comparable to the other values of genetic information reported here. However, the expected profit when each animal is fed for its own optimal number of days-on-feed is $153.56 per head. This figure results in a much higher value of marker-assisted management of $10.88 per head ($153.56 − $142.68).

Table 9. Expected Value of Marker-Assisted Management and Marker-Assisted Selection at the Feedlot Stage for Pairwise Combinations of Molecular Breeding Values Characterizing Economically Relevant Traits

Pairwise Combinations of Molecular Breeding Values	Value of Information ($/head)	
	Marker-Assisted Management	Marker-Assisted Selection
Average daily gain-Hot-carcass weight	$0.37	$33.58
Average daily gain-Yield grade	$0.39	$31.92
Average daily gain-Rib-eye area	$0.66	$26.44
Average daily gain-Marbling	$0.47	$30.43
Average daily gain-Tenderness	$0.42	$30.07
Average daily gain-Days-on-feed	$0.38	$23.87
Hot-carcass weight-Yield grade	$0.22	$31.83
Hot-carcass weight-Rib-eye area	$0.70	$32.61
Hot-carcass weight-Marbling	$0.50	$37.56
Hot-carcass weight-Tenderness	$0.30	$28.80
Hot-carcass weight-Days-on-feed	$0.23	$23.76
Yield grade-Rib-eye area	$0.79	$24.38
Yield grade-Marbling	$0.49	$27.15
Yield grade-Tenderness	$0.26	$16.86
Yield grade-Days-on-feed	$0.15	$16.75
Rib-eye area-Marbling	$0.67	$23.08
Rib-eye area-Tenderness	$0.70	$20.25
Rib-eye area-Days-on-feed	$0.62	$22.08
Marbling-Tenderness	$0.59	$23.94
Marbling-Days-on-feed	$0.47	$24.00
Tenderness-Days-on-feed	$0.23	$10.52

Notes: The value of marker-assisted management is calculated by comparing expected profit when a feedlot can differentially choose optimal marketing dates for each quartile of a given trait relative to the case where all cattle are fed for the same number of days-on-feed. The value of marker-assisted selection at the feedlot stage is calculated by comparing expected profits for the best performing quartile relative the case where all cattle are fed for the same number of days-on-feed.

and molecular breeding values for seven economically relevant traits. Prediction equations and a multivariate normal distribution of error terms are used as part of a stochastic simulation to estimate expected profit per head for each day-on-feed. A grid search is employed to determine the optimal number of days-on-feed and maximum expected profits both with and without genetic information.

The expected value of genetic information for marker-assisted management is low when sorting cattle into management groups for one or two economically relevant traits (less than $1 per head) and when cattle are sorted based on their entire profile of genetic information (less than $3 per head). However, the value associated with selecting and feeding cattle based on genetic potential is rather high (as much as $22 per head for single-trait selection and $38 per head for multiple-trait selection). Should feedlots have the opportunity to obtain genetic information prior to purchasing feeder cattle, the values of marker-assisted selection reported here may be of value in determining bid-price differentials. Even with improved accuracy of genetic marker panels for economically relevant traits, the qualitative implications of these results are similar to those reported in previous literature evaluating the value of genetic testing for leptin genotype (DeVuyst et al., 2007; Lusk, 2007; Lambert, 2008). This study identifies average daily gain and marbling as the most economically relevant feedlot cattle traits. The estimated values of marker-assisted management and marker-assisted selection reported in this study may be overestimates of their true values if the same information could be obtained by visual appraisal. Although a hide-color dummy variable is used to partially control for breed effects, additional characteristics, such as frame size and muscling, may be observable independent of breed. Therefore, estimated values of genetic information are likely an upper bound for traits that may have the potential to be partially determined without genetic testing.

To put the results of this study into context, consider that the net returns to finishing steers and heifers in Kansas have averaged −\$31.45 and −\$19.32 per head over the past ten years (Tonsor and Dhuyvetter, 2013). The values of marker-assisted selection reported here represent meaningful economic value to the cattle feeding industry. Comparing the value of information with the cost of genetic testing services is also instructive. Currently, Igenity offers a profile of marker panels that includes each of the traits evaluated in this study (except hot-carcass weight and days-on-feed) for \$38.00 per head (Igenity, 2013b).[19] Despite the low value of using genetic information to sort and optimally choose days-on-feed, the potential for using such strategies remains. As genomic testing technology continues to advance, the potential for declining costs of genetic testing and the development of markers for other important feedlot profit drivers, such as disease resistance and feed efficiency, may lead to cost-effective marker-assisted management in the feedlot sector (Van Eenennaam and Drake, 2012). In addition, random sampling could be used to measure the genetic potential of a group of cattle without having to test each animal. Still, the functional value of genetic information at the feedlot stage continues to be the ability to improve the genetic distribution of cattle entering the feedlot. These improvements will need to take place in the industry's breeding sectors. In particular, selection for desirable traits in the seed-stock sector will accelerate the rate of genetic gain (Weaber and Lusk, 2010; Van Eenennaam, van der Werf, and Goddard, 2011). However, selecting breeding stock for traits that are valuable in the feedlot sector may or may not be advantageous in other sectors. Although beyond the scope of this research, the impacts of these traits on other sectors must be considered.

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[19] This profile also includes additional traits not included in this study, such as maternal calving ease, docility, and stayability.

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