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Using Genetic Testing to Improve Fed Cattle Marketing Decisions

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We estimate the value of using genetic information to make fed cattle marketing decisions. Efficiency gains result from sorting cattle into marketing groups, including more accurate optimal days-on-feed and reduced variability of returns to cattle feeding. The value of using genetic information to selectively market cattle ranged from $1–$13/head depending on how a producer currently markets cattle and the grid structure. Although these values of genetic information were generally higher than those reported in previous research, they were still not enough to offset the current cost of genetic testing (about $40/head).

Key words: fed cattle marketing, genetics, molecular breeding value, risk aversion, value of information

Introduction

The beef industry has promoted value-based marketing strategies since the early 1990s in an effort to improve the quality and consistency of beef products (Value-Based Marketing Task Force, 1990). Most notably, grid pricing, introduced in the mid–1990s, provides transparent price signals. Traditional cash pricing mechanisms, such as live weight and dressed weight pricing, are not based on the actual quality and yield grade of carcasses. As a result, above-average cattle are paid less than their cutout value and below-average cattle are paid more than their cutout value. Therefore, traditional pricing mechanisms inhibit information flow from beef consumers to cattle producers (Feuz, Fausti, and Wagner, 1993; Fausti, Feuz, and Wagner, 1998). Grid pricing, on the other hand, determines value based on the carcass merit of individual animals. Premiums and discounts that make up the grid reflect consumer preferences and transmit these signals upstream to cattle producers. Feedback on individual carcass performance and value provides an incentive for producers to make necessary changes to "their breeding, feeding, and sorting programs" (Johnson and Ward, 2005, p. 562).

The National Beef Quality Audit (NBQA) reported that the share of fed cattle marketed on a grid increased from 15% in 1995 to 34% in 2005 (National Cattlemen's Beef Association, 2006). However, grid pricing has yet to become the dominant fed cattle marketing strategy as many had projected (Schroeder et al., 2002), accounting for only 40%–45% of fed cattle marketings (Fausti et al., 2010). Ample literature has investigated producer incentives and disincentives to adopt grid pricing, and the fundamental marketing risk created by the system has been identified as the primary barrier to adoption (Fausti, Feuz, and Wagner, 1998; Anderson and Zeuli, 2001; Fausti and Qasmi,

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2002). Depending on the sample period, live weight, dressed weight, or grid pricing can have the highest returns, but variability is consistently highest for grid pricing (Feuz, Fausti, and Wagner, 1993; Schroeder and Graff, 2000; Anderson and Zeuli, 2001; Fausti and Qasmi, 2002; Lusk et al., 2003). This problem is further exacerbated by varying levels of risk aversion among cattle producers (Fausti and Feuz, 1995; Feuz, Fausti, and Wagner, 1995; Fausti, Wang, and Lange, 2013; Fausti et al., 2014).

The risk associated with buying and selling fed cattle has two main components: general price risk and informational (or carcass) risk (Fausti and Feuz, 1995). This paper focuses on the carcass risk associated with marketing fed cattle. That is, because marketing decisions are made prior to slaughter, carcass merit (yield grade, quality grade, and hot-carcass weight) is unknown. Therefore, better predictions of carcass quality may allow decision makers to improve their marketing decisions. Recent technological advancements in beef production, such as ultrasound technology and genetic testing, have made such information available. However, a producer would only be expected to use this technology if its benefits outweigh the costs. As a result, a branch of the agricultural economics literature evaluating the economic benefits of these technologies has emerged (Fausti et al., 2010).

For example, Lusk et al. (2003) and Walburger and Crews (2004) reported that using ultrasound technology to selectively market cattle, as opposed to simply marketing all cattle on a live weight, dressed weight, or grid basis, increased revenue by \$4–\$32/head. However, both of these studies held days-on-feed constant when making these comparisons. Koontz et al. (2008) contend that such an approach uses additional information to exploit pricing inefficiencies and is unlikely to change returns to producers in the long run. Therefore, they argue that improving meat quality and beef industry profitability requires changing the product form. They found that the value of using ultrasound measurements to sort cattle into groups that were marketed to optimize returns by choosing days-on-feed was between \$15 and \$25/head (Koontz et al., 2008).

Advances in cattle genomics have made genetic marker panels commercially available for a variety of traits. Independent validations have found that many of these markers are correlated with the traits they are designed to predict (DeVuyst et al., 2011; National Beef Cattle Evaluation Consortium, 2015). While previous literature has found considerable economic value (up to \$60/head) to using genetic information for selecting feeder cattle for placement in the feedlot (DeVuyst et al., 2007; Lusk, 2007; Lambert, 2008; Thompson et al., 2014), this information is not typically available prior to purchasing feeder cattle. Therefore, feedlots are limited to using this information to sort cattle into management groups that are most likely to achieve similar outcomes, known as marker-assisted management (Van Eenennaam and Drake, 2012). In previous research, marker-assisted management has been limited to sorting cattle by optimal days-on-feed. As a result, reported values of genetic information for marker-assisted management have consistently been less than \$3/head (DeVuyst et al., 2007; Lusk, 2007; Lambert, 2008; Thompson et al., 2014). Still, there remains potential for using the information derived from genetic testing to improve other management decisions within the feedlot that have yet to be evaluated, including how cattle are fed, how technologies such as implants and beta agonists are utilized, and how cattle are marketed.

Therefore, using the same dataset of genetic information and phenotypic outcomes for 10,209 commercially fed cattle as Thompson et al. (2014), we evaluate for the first time a marker-assisted management scenario in which genetic information is used to selectively target cattle to different marketing methods. The objective of this research is to estimate the expected value of genetic information for improving fed cattle marketing decisions, including decisions for both marketing method (live weight, dressed weight, or grid pricing) and timing to market (days-on-feed). Although several previous studies have attempted to estimate the value of genetic information, none have considered the potential of this information to improve fed cattle marketing decisions, other than days-on-feed. Therefore, the results of this analysis represent an important and unique contribution to the literature evaluating the economic value of genetic testing for beef cattle. In addition, previous research evaluating fed cattle marketing decisions examined either marketing method or optimal days-on-feed but did not evaluate these decisions simultaneously. This is important because accurately targeting cattle to the appropriate marketing method is only economically beneficial if cattle are appropriately managed once they are at market.

Data collected from commercially fed cattle are used to estimate regression equations characterizing phenotypic outcomes for average daily gain, dressing percentage, yield grade, and quality grade as a function of live-animal characteristics and genetic information. These equations and Monte Carlo integration are used to estimate expected net returns and expected utility for several marketing scenarios. Three baseline scenarios are created in which all cattle are marketed in a single group on a live weight, dressed weight, or grid basis without using any genetic information. These baseline scenarios are then compared with alternative marketing scenarios in which genetic information is known and used to sort cattle into groups to be targeted to specific marketing methods.

Conceptual Framework

Cattle feeders are assumed to maximize expected profit by choosing both how and when to market cattle. At placement in the feedlot, placement weight and purchase cost are the only variables known with certainty. Other profit determinants are a function of random growth and carcass characteristics, including average daily gain (*ADG*), dressing percentage (*DP*), yield grade (*YG*), and quality grade (*QG*). Although we assume that output prices are known by the decision maker at the time marketing decisions are made, it is unknown how animals will perform and, as a result, what weight and carcass quality they will achieve. Therefore, the feedlot operator's expected profit-maximization problem can be written as

$$\begin{aligned}(1)\qquad &\max_{\substack{j\in\{1,2,3\}\\ DOF_j\geq 0}} \int\int\int\int E\pi_{ij}(DOF_j, ADG_i, DP_i, YG_i, QG_i)\\ &\times f(ADG, DP, YG, QG)\,dADG\,dDP\,dYG\,dQG \;\forall\, i = 1,\ \ldots,\ n,\end{aligned}$$

where the feeder chooses the jth marketing method that maximizes expected profit for each ith animal and the optimal days-on-feed for each marketing group (DOF_j).

However, depending on their risk preferences, decision makers may not always prefer the alternative that generates the highest expected profit. Instead, preferences may also be influenced by the variability, covariance, and higher moments of the joint distribution of returns for each marketing alternative and the correlation of these returns among animals. Therefore, the single-animal objective function in equation (1) can be converted into an aggregate expected utility-maximizing portfolio of marketing strategies for a group of n animals:

$$\begin{aligned}(2)\qquad &\max_{\substack{p_{ij}\in\{0,1\}\\ DOF_j\geq 0\\ i=1,\ \ldots,\ n\\ j=1,2,3}} \int\int\int\int EU\left[\sum_{i=1}^{n}\sum_{j=1}^{3} p_{ij}\pi_{ij}(DOF_j, ADG_i, DP_i, YG_i, QG_i)\right]\\ &\times f(ADG, DP, YG, QG)\,dADG\,dDP\,dYG\,dQG \quad \text{s.t.} \sum_{j=1}^{3} p_{ij} = 1\;\forall\, i,\end{aligned}$$

where $U[\pi(\cdot)]$ is a constant absolute risk aversion (CARA) utility function and the feeder chooses whether or not the ith animal is targeted to the jth marketing method (p_{ij}) and the days-on-feed (DOF_j) for each jth marketing group. Under the assumption of risk neutrality ($U'' = 0$), equation (2) reduces to an expected profit-maximization problem similar to equation (1) given that the risk-neutral solutions for the aggregate and individual-animal objective functions are equivalent.

Fed cattle are primarily marketed by live weight pricing (*LIVE*), dressed weight pricing (*DRES*), and grid pricing (*GRID*). These three marketing methods differ primarily in whether the buyer or the seller bears the risk of carcass outcomes. When using live weight pricing, the packer and the feeder generally negotiate a carcass price based on the expected quality traits of a pen of cattle assessed through visual appraisal. This carcass price is then converted to a live-animal price by multiplying it by the expected dressing percentage. Net return for this scenario can be written as

$$\begin{aligned}\pi_{LIVE} &= P_{LIVE} \times FWT(PWT, ADG, DOF) \times (1 - PS) \times (1 - MR) \\ &\quad - PC(PWT, SEX) - FC(DOF) - YC(DOF) - IC(PC, DOF),\end{aligned} \tag{3}$$

where P_{LIVE} is the live weight price; FWT is final live weight, which is a function of placement weight (PWT), ADG, and DOF as $FWT = PWT + ADG \times DOF$; $PS \in [0,1]$ is pencil shrink; $MR \in [0,1]$ is mortality rate; PC is purchase cost of feeder cattle; FC is feed cost; YC is yardage cost; and IC is interest cost on the purchase of feeder cattle. Under this alternative the buyer takes on all of the carcass risk. Because these characteristics can be difficult to predict preharvest, live prices tend to undervalue high-quality cattle and overvalue low-quality cattle. The cost of genetic testing is not included in equation (3). Therefore, π_{LIVE} is defined as net return and not profit, and the improvement in the objective function from acquiring genetic information sets an upper limit on the cost of genetic testing.

Marketing cattle on a dressed basis is similar to live weight pricing except that the producer is paid based on the actual dressed weight, or hot-carcass weight, and the seller assumes the dressing percentage risk. In principle, the dressed price will be comparable to the live price adjusted for dressing percentage for the same pen of cattle. However, over time the average dressed price is expected to be greater than the average live price adjusted for dressing percentage given packers' incentive to offset errors in estimating dressing percentage (Feuz, Fausti, and Wagner, 1993). Net return for dressed weight pricing is

$$\begin{aligned}\pi_{DRES} &= P_{DRES} \times HCW(PWT, ADG, DOF, DP) \times (1 - MR) \\ &\quad - PC(PWT, SEX) - FC(DOF) - YC(DOF) - IC(PC, DOF) - TC,\end{aligned} \tag{4}$$

where P_{DRES} is dressed weight price; HCW is hot-carcass weight, which is a function of PWT, ADG, DOF, and DP; $HCW = [PWT + (ADG \times DOF)] \times DP$; and TC is transportation cost. Transportation cost was not included in equation (3) because the seller pays the transportation cost when cattle are sold on a dressed weight basis (or grid basis), whereas the buyer generally pays for trucking when cattle are sold based on live weight (Ward, Schroeder, and Feuz, 2001).

Lastly, when marketing cattle on a grid, the seller assumes the yield grade, quality grade, and dressing percentage risk for each individual animal. Net return is

$$\begin{aligned}\pi_{GRID} &= P_{GRID}(YG, QG, HCW) \times HCW(PWT, ADG, DOF, DP) \times (1 - MR) \\ &\quad - PC(PWT, SEX) - FC(DOF) - YC(DOF) - IC(PC, DOF) - TC,\end{aligned} \tag{5}$$

where P_{GRID} is the grid price, which is a function of YG, QG, and HCW outcomes. Although grids vary across the packing industry, they generally list a base price (P_{BASE}) for yield grade 3, Choice carcasses weighing between 600–900 pounds. Depending on how each carcass grades, this base price is then subject to an additive set of premiums and discounts for yield grade, quality grade, and weight outcomes, $P_{GRID} = P_{BASE} + premiums/discounts(YG, QG, HCW)$. In practice, packers use a variety of methods for determining the base price. Here we use Ward, Feuz, and Schroeder's (1999) formula to determine the base price, $P_{BASE} = P_{DRES} + [(Choice/Select\ spread) \times (plant\ average\ percent\ Select)]$, which assumes that the plant average percentage of Select is equal to the percentage of animals that graded Select or lower in our data set (45%).

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 (e.g.,

Table 1. Correlation Matrix of the Seven Molecular Breeding Values ($n = 9,465$)

	Molecular Breeding Value						
Molecular Breeding Value	**YG**	**MARB**	**ADG**	**HCW**	**REA**	**TDR**	**DOF**
YG	1.00						
MARB	−0.50	1.00					
ADG	−0.23	0.34	1.00				
HCW	0.06	0.09	0.35	1.00			
REA	0.73	−0.64	−0.39	0.08	1.00		
TDR	−0.33	0.28	0.04	−0.01	−0.19	1.00	
DOF	0.26	−0.15	−0.18	0.10	0.36	−0.17	1.00

Notes: Molecular breeding value abbreviations are yield grade (YG), marbling (MARB), average daily gain (ADG), hot-carcass weight (HCW), rib-eye area (REA), tenderness (TDR), and days-on-feed (DOF).

Ladd and Gibson, 1978). 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).

Data

Data for 10,209 commercially fed cattle from six different Midwestern feed yards were provided by Neogen, the parent company of commercial testing service Igenity.[1] Cattle represented year-round placements in 2007 and 2008. At placement, animals were weighed and a hair sample or tissue punch from ear tag application was collected for genetic testing. Genetic information was provided in the form of molecular breeding values (MBVs) for seven traits: yield grade, marbling, average daily gain (lbs./day), hot-carcass weight (lbs.), rib-eye area (in^2), tenderness (lbs. of Warner-Bratzler shear force [WBSF]), and days-on-feed (days) (Igenity, 2013).[2] The correlations among these seven MBVs are reported in table 1. Molecular breeding values are a continuous representation of an animal's genetic potential to express a given trait. Similar to expected progeny differences (EPDs), MBVs are reported in the units of the trait they represent. However, they are interpreted as the "relative differences expected in animals across breeds compared to their contemporaries" (Igenity, 2013, p. 2). For example, if two animals exposed to the same environmental and management conditions have marbling MBVs of -100 and 100, respectively, we would expect, on average, that these two animals' marbling scores would differ by 200 units ($100 - [-100] = 200$). Additional live-animal characteristics for days-on-feed, sex, and hide color were also provided, and carcass measurements for calculated yield grade, marbling score, and hot-carcass weight were collected at slaughter.

Deleting observations with missing data for live-animal characteristics and MBVs left 9,465 observations. The data consisted of seven "sets," each of which represented a different commercial feedlot, time period, or both. Nested within each set were contemporary groups, which were groups of animals that had an equal opportunity to perform: same sex, managed alike, and exposed to the same feed resources. A total of 242 contemporary groups had an average size of 39 animals per group.

Additional missing data were common for growth and carcass performance variables. Average daily gain, calculated yield grade, and marbling score had 1,795, 25, and 421 missing observations, respectively, and there were 3,692 missing observations for final live weight. Although final live weight was not used directly, it was essential to the estimation of dressing percentage (dressing percentage = hot-carcass weight/final live weight). Observations with missing data for these growth

[1] At least half of the cattle were fed in Iowa and Kansas.

[2] Each of these markers, except hot-carcass weight and days-on-feed, have been found to be significantly correlated with the traits they are designed to predict in independent validations (DeVuyst et al., 2011; National Beef Cattle Evaluation Consortium, 2015).

Table 2. Summary Statistics for Growth and Carcass Performance, Live-Animal Characteristics, and Molecular Breeding Values

Variable	*N*	Mean	Standard Deviation	Minimum	Maximum
Growth and carcass performance					
Average daily gain, lbs./day	7,670	3.390	0.803	0.370	7.383
Dressing percentage	5,773	0.627	0.028	0.490	0.827
Yield grade	9,440	2.704	0.853	0.056	5.905
Marbling score[a]	9,044	416.3	79.5	190.0	830.0
Live-animal characteristics					
Placement weight, cwt[a]	9,465	7.0	1.2	2.9	11.2
Days-on-feed, days[a]	9,465	176.0	35.4	81.0	308.0
Steer	9,465	0.826			
Black	9,465	0.623			
Molecular breeding values (MBV)					
Yield grade MBV	9,465	−0.054	0.073	−0.338	0.210
Marbling MBV	9,465	−21.661	28.017	−124.020	76.353
Average daily gain MBV, lbs./day	9,465	0.168	0.100	−0.229	0.482
Hot-carcass weight MBV, lbs.	9,465	27.231	8.969	−17.728	55.913
Rib-eye area MBV, in^2	9,465	−0.572	0.523	−2.172	1.588
Tenderness MBV, lbs. of WBSF[b]	9,465	−0.991	1.348	−5.900	2.920
Days-on-feed MBV, days	9,465	−2.628	2.811	−14.351	9.160

Notes: Molecular breeding values (MBVs) are reported in the units of the trait and reflect the differences expected in animals across breeds compared to their contemporaries (Igenity, 2013). 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 0.71 lbs. per day more than the animal with the lowest genetic potential for average daily gain $(0.482 - [-0.229] = 0.711)$.
[a]Summary statistics for marbling score, placement weight, and days-on-feed are only reported to one decimal place as a result of significant digits.
[b]Warner-Bratzler shear force.

Table 3. Joint Distribution of Observed Yield and Quality Grade Outcomes ($n = 9,029$)

	USDA Quality Grade				
USDA Yield Grade	Prime	Choice	Select	Standard	Total
1	< 1%	5%	8%	1%	14%
2	< 1%	20%	21%	1%	44%
3	< 1%	24%	12%	< 1%	37%
4	< 1%	4%	1%	< 1%	5%
5	0%	< 1%	< 1%	< 1%	<1%
Total	< 1%	54%	42%	3%	100%

and carcass performance variables were not deleted from the sample. Instead, regression equations characterizing these outcomes were estimated with their own maximum number of observations. Subsequent simulation analyses used the sample of 9,465 complete observations for live-animal characteristics and MBVs. Summary statistics for growth and carcass performance, live-animal characteristics, and MBVs are reported in table 2.

A joint distribution of observed yield and quality grade outcomes for the cattle in our sample is reported in table 3. The majority of cattle graded either yield grade 2 (44%) or 3 (37%) and quality grade Choice (54%) or Select (42%). The single most likely outcome is yield grade 3, Choice (24%). This distribution is similar to the distribution of yield grade and quality grade outcomes reported in the 2011 NBQA, which represented 7,941 animals from 28 federally inspected beef processing facilities throughout the United States (Moore et al., 2012, p. 5,146). Therefore, our sample is representative of the current distribution of carcass quality in the U.S. beef industry.

Table 4. Live Weight Prices, Dressed Weight Prices, and Grid Premiums and Discounts for 2014 ($/cwt)

Marketing Method		Average Prices	Maximum Grid[a]	Minimum Grid[b]
Live weight				
Steers		$154.31		
Heifers		$154.44		
Dressed weight				
Steers		$244.22		
Heifers		$244.21		
Grid	Base price[c]			
	Steers	$248.10	$250.78	$245.16
	Heifers	$248.09	$250.77	$245.15
	Quality grade adjustment			
	Prime	$19.26	$21.33	$18.35
	Choice	$0.00	$0.00	$0.00
	Select	($8.63)	($14.57)	($2.09)
	Standard	($20.84)	($23.92)	($17.72)
	Yield grade adjustment			
	1.0–2.0	$4.58	$4.58	$4.58
	2.0–2.5	$2.25	$2.25	$2.24
	2.5–3.0	$2.13	$2.13	$2.11
	3.0–4.0	$0.00	$0.00	$0.00
	4.0–5.0	($8.63)	($8.23)	($9.21)
	>5.0	($13.64)	($13.06)	($14.99)
	Carcass weight adjustment			
	400–500	($25.42)	($25.40)	($25.49)
	500–550	($22.19)	($22.80)	($19.62)
	550–600	($2.93)	($2.70)	($3.89)
	600–900	$0.00	$0.00	$0.00
	900–1,000	($0.24)	($0.19)	($0.24)
	1,000–1,050	($2.27)	($2.22)	($2.35)
	>1,050	($23.24)	($23.33)	($23.05)

Sources: Livestock Marketing Information Center (LMIC) spreadsheets based on USDA AMS reports LM_CT150 and LM_CT169 (U.S. Department of Agriculture, Agricultural Marketing Service, 2015b,a; Livestock Marketing Information Center, 2015).
[a]The "maximum grid" is the grid from the week with the highest Choice-Select spread for 2014 (September 22, 2014).
[b]The "minimum grid" is the grid from the week with the smallest Choice-Select spread for 2014 (February 2, 2014).
[c]The base price for the grid was calculated as the dressed weight price plus the Choice-Select spread times the percentage of cattle that graded Select or lower in our dataset (Ward, Feuz, and Schroeder, 1999). For example, the base price for the average price grid for steers was: $244.22 + 8.6345\% = 248.10$.

The relationship between live weight and dressed weight prices fluctuates throughout the year. Therefore, a simple average of weekly prices for the 2014 marketing year was used to avoid seasonal fluctuations in live weight and dressed weight prices. Weekly prices were obtained from Livestock Marketing Information Center (LMIC) spreadsheets, which are based on USDA Agricultural Marketing Service (AMS) reports (Livestock Marketing Information Center, 2015). Live weight and dressed weight prices for steers and heifers were obtained from the *5 Area Weekly Weighted Average Direct Slaughter Cattle Report* (U.S. Department of Agriculture, Agricultural Marketing Service, 2015b), and grid premiums and discounts were from the *5 Area Weekly Weighted Average Direct Slaughter Cattle Report – Premiums and Discounts* (U.S. Department of Agriculture, Agricultural Marketing Service, 2015a) (table 4). Two additional grids, representing the weeks with the maximum (September 22, 2014) and minimum (February 2, 2014) Choice-Select spread for 2014, were also evaluated to determine the sensitivity of our results to seasonal changes in the grid (table 4).

It is unknown how or when animals were weighed. Therefore, net returns to the baseline live weight and dressed weight marketing scenarios were "calibrated" using pencil shrink to impose market efficiency between these two marketing methods. That is, any inconsistencies in the relationship between actual (not simulated) final live weight and hot-carcass weight were standardized by increasing pencil shrink until the net returns for the live weight and dressed weight baseline marketing scenarios were equal. Pencil shrink was assumed to be 2%.

Feed costs were needed to calculate expected net returns. Given that observations of feed intake were unavailable, a dry matter intake (DMI) model was used following the National Research Council's (NRC) *Nutrient Requirements of Beef Cattle* (National Research Council, 2000).[3] The DMI model estimates "standardized" feed intake. Additional information needed to estimate expected net returns include a dry matter feed cost of \$230/ton (\$0.12/lb.), yardage cost of \$0.40/day, a 7% interest rate on the purchase of feeder cattle, a mortality rate of 1%, and transportation cost of \$16/head (Lardy, 2013; Ellis and Schulz, 2015).

Procedures

Predicting Growth and Carcass Performance Using Genetics

Mixed model regression equations characterizing phenotypic outcomes for average daily gain (*AGD*), dressing percentage (*DP*), yield grade (*YG*), and quality grade (*QG*) were estimated independently using restricted maximum likelihood (REML). Dependent variables were continuous in each of the four equations. In particular, *YG* and *QG* are often thought of in terms of discrete outcomes. However, calculated yield grade, as defined by the U.S. Department of Agriculture, Agricultural Marketing Service (1997), is a continuous function of backfat, kidney, pelvic, and heart fat, hot-carcass weight, and rib-eye area, and marbling score was used as a continuous representation of quality grade. Marbling scores of 200–299 are said to have traces of intramuscular fat and are graded Standard, 300–399 are Select, 400–699 are Choice, and scores over 700 are Prime (U.S. Department of Agriculture, Agricultural Marketing Service, 1997, 2006). The models were

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

where Y_{ijkl} is the dependent variable for the ith animal in the jth set and kth contemporary group for the lth equation, where $l = 1, 2, 3$, or 4 for ADG_{ijk}, DP_{ijk}, YG_{ijk}, and QG_{ijk}, respectively. The model included fixed effects for live-animal characteristics and genetic information, where PWT_{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; and MBV_{ijkm} are the seven MBVs characterizing yield grade, marbling, average daily gain, hot-carcass weight, rib-eye area, tenderness, and days-on-feed. Set random effects, $v_{jl} \sim N(0, \sigma_v^2)$; contemporary group random effects nested within sets (Greene, 2012), $u_{k(j)l} \sim (0, \sigma_u^2)$; and a random error term, $\varepsilon_{ijkl} \sim N(0, \sigma_\varepsilon^2)$, are also included in each equation. Yield grade MBV by days-on-feed and marbling MBV by days-on-feed interaction terms are also included as slope shifters in the *YG* and *QG* equations. In addition, a yield grade MBV by marbling MBV interaction is also included in the *YG* and *QG* equations to account for the positive phenotypic and genetic correlation between these two carcass traits (DeVuyst et al., 2011; Thompson et al., 2015).

Models were estimated using Proc Mixed in SAS (SAS Institute, Inc., 2013). A D'Agostino-Pearson K^2 omnibus test for skewness and kurtosis and a conditional variance test identified evidence of nonnormality and static heteroskedasticity. Sandwich estimators of the standard errors were

[3] For examples of the dry matter intake model see Lusk (2007) or Thompson et al. (2014).

estimated to obtain estimates of standard errors that were consistent in the presence of nonnormality and static heteroskedasticity (White, 1982). 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 Net Return Maximization for Alternative Marketing Scenarios

Baseline Marketing Scenarios

To determine the value of genetic information for improving fed cattle marketing decisions, three baseline marketing scenarios were created in which all cattle were marketed in a single group on a live weight, dressed weight, or grid basis. Expected net returns are a nonlinear function of the random terms. Therefore, because of Jensen's inequality, net returns calculated at the expected value of prediction equations will not equal expected net returns (Greene, 2012). For this reason, the integrals in equation (1) were evaluated using Monte Carlo integration. The Cholesky decomposition of the four-by-four variance-covariance matrix of the error terms in equation (6) was calculated and used to generate a multivariate normal distribution of 200 error terms for each of the four prediction equations for each animal in the sample ($n = 9,465$) using "intelligent," quasi-random Halton draws (Morokoff and Caflisch, 1995; Greene, 2012). Net returns were evaluated at each draw using observed MBVs for each animal in the sample, and the average across animals was expected net return. This process was repeated for days-on-feed from 100–200 days, and a grid search was used to determine the day at which expected net return was maximized for each of the three marketing scenarios.

Live-animal characteristics other than MBVs may also influence fed cattle marketing decisions. In particular, placement weight has a substantial impact on how long cattle are fed, how they are marketed, and, as a result, profitability. For this reason, placement weight was held constant at its mean value (700 lbs.) to separate this effect from the effect of genetic information.

Decision makers in the feedlot have access to information that can be used to sort cattle into different marketing groups without using genetic testing. However, access to the information necessary to imitate a "true" baseline marketing scenario is unavailable. Therefore, similar to previous research we assume naïve baseline scenarios in which all animals are marketed in a single group using the same marketing method (Schroeder and Graff, 2000; Lusk et al., 2003; Walburger and Crews, 2004). As a result, expected net returns for the baseline scenarios may be underestimated, and the values of information reported here are likely an upper bound on the value of genetic information for selectively marketing fed cattle.

Genetic Information Marketing Scenario

Baseline scenarios were compared with alternative marketing scenarios in which additional information was used to enhance fed cattle marketing decisions. The genetic information marketing scenario used the results of genetic testing to sort cattle into marketing groups based on their expected performance. To do this, a "decision rule" characterizing the relationship between expected net returns for each of the three marketing methods and MBVs for yield grade and marbling was developed using a random sample of 1,000 animals. Twenty discrete values for the yield grade and marbling MBVs were chosen to represent the range of MBVs observed in our sample, and a Monte Carlo integration procedure similar to the one described above was then used to estimate expected net returns for each unique combination of these values (400 times). Plotting the results on a three-dimensional surface allows us to visualize the decision rule by identifying which of the three marketing methods generated the highest expected net returns at various levels of genetic potential for yield grade and marbling.

Applying this decision rule to the data, the full sample of animals ($n = 9,465$) was sorted into three marketing groups (live weight, dressed weight, or grid pricing) based on their actual yield grade and marbling MBVs. Monte Carlo integration was used to estimate expected net returns for each group for 100–200 days-on-feed, and a grid search was used to determine the optimal days-on-feed. The overall expected net return was calculated as the weighted average expected net return across the three groups, where the proportion of cattle that fell into each group was used as the weight.

Perfect Information Marketing Scenario

While genetic information can be used to improve predictions of animal performance in the feedlot, it is not 100% accurate.[4] Therefore, we evaluated the potential of genetic testing by estimating a "perfect information" marketing scenario. This was identical to the genetic information marketing scenario described above, except that instead of sorting animals based on genetic information, each animal was sorted into the marketing group that maximized its own expected net return.

Expected Utility Maximization for Alternative Marketing Scenarios

The risk-return tradeoff associated with fed cattle marketing suggests that it is also important to consider how decision makers' risk preferences affect their marketing decisions. Given nonlinearities, the expected utility-maximizing solution for a single animal may differ from the solution if that animal was marketed as part of a group. Therefore, the objective function in equation (2) for a group of n animals is used to determine the optimal portfolio of marketing strategies for the full sample of animals ($n = 9,465$) for several levels of risk aversion.

Again, three baseline marketing scenarios were created in which all animals were marketed in a single group using live weight, dressed weight, or grid pricing. Distributions of net returns were used to calculate expected utility assuming a negative exponential utility function (Chavas, 2004), $U(\pi) = -e^{-r\pi}$, where $U(\pi)$ is the utility of the aggregate net returns for the full sample of $n = 9,465$ animals and r is the Arrow-Pratt absolute risk aversion coefficient. A range of risk aversion coefficients was evaluated; following Raskin and Cochran (1986) and Anderson and Dillon (1992), risk aversion coefficients of $r = 0.0000003$, $r = 0.0000006$, and $r = 0.0000010$ were determined to approximately represent slight, moderate, and severe risk aversion, respectively.

The expected utility-maximizing portfolio of marketing methods was then determined using a nonlinear mathematical programming model in GAMS (GAMS Development Corporation, 2013). The expected utility-maximization optimization poses significant computational challenges. The decision problem involves at least $3^{9,465\times101}$ possible combinations of marketing strategies and days-on-feed. As an integer programming problem, this is computationally infeasible to solve. Even after assuming away the days-on-feed joint decision,[5] there are still $3^{9,465}$ possible combinations of marketing methods. We explored reducing the number of head of cattle (i.e., genetic profiles) using Gaussian cubature (DeVuyst and Preckel, 2007) to a representative sample of 22 head that maintained the mean and variance/covariance structure of the data. The result was a discrete choice problem of 3^{22} or about 31.381 billion combinations of marketing methods. While it may be possible to solve the problem with several months of computational time, we chose a less computationally intensive approach. We approximated the discrete decision problem with a continuous, nonlinear optimization, or the equivalent of a relaxed nonlinear integer optimization. So the optimization problem simultaneously chose percentages of all animals to market with the three pricing methods.

[4] For further discussion of the accuracy of genetic marker panels, see Weber et al. (2012) and Akanno et al. (2014).

[5] Previous research has shown that fed cattle profit functions are often flat near the optimal days-on-feed (Pannell, 2006; Lusk, 2007). Therefore, days-on-feed for each marketing method is held constant at profit-maximizing baseline levels (live weight = 151 days, dressed weight = 179 days, and grid = 181 days).

The relaxed nonlinear integer problem took considerably less time to solve (twenty minutes to two hours), varying with starting point and risk aversion level.

The marketing scenario with the highest expected utility is the preferred marketing strategy for a given level of risk aversion. However, these values offer little insight into the value of information. For this reason, expected utilities were converted to certainty equivalents, which represent the amount of money a producer would have to receive to be indifferent between that payoff and a given gamble (Chavas, 2004). Given that the expected utility model is based on aggregate net returns, these certainty equivalents were then converted to $/head by dividing by the number of animals in the sample ($n = 9,465$). Differences in certainty equivalents for the expected utility-maximizing portfolio of marketing scenarios and the three baseline marketing scenarios for a given level of risk aversion can then be interpreted as the value of information inclusive of risk preferences.

Results and Discussion

Regression Equations

The mixed model regression estimates are reported in table 5. Each equation was estimated with its own maximum number of observations. Coefficients for live-animal characteristics—including placement weight, days-on-feed, sex, and hide color—generally exhibited the expected relationships.

Molecular breeding values influenced corresponding growth and carcass performance variables in expected directions. For example, the average daily gain MBV had a significant, positive effect in the average daily gain equation. The relative interpretation of MBVs implies a linear relationship with a coefficient of 1 between MBVs and the traits they characterize (Weber et al., 2012). Therefore, we tested the null hypothesis that the marginal effect of the average daily gain MBV was equal to 1, $H_0: \partial ADG/\partial MBV_{ADG} = 1$. Results indicated that the observed marginal effect, 0.757, was not statistically different from 1 ($t = -0.79$; $df = 7,437$; $P = 0.43$).

The hot-carcass weight MBV had a significant, positive effect on dressing percentage outcomes, as expected. However, because this MBV does not directly reflect genetic potential for dressing percentage, we were unable to test the hypothesis that this effect was equal to 1.

Due to interaction terms, the marginal effect of the yield grade MBV on yield grade outcomes was a function of days-on-feed and marbling MBV: $\partial YG/\partial MBV_{YG} = -0.382 - 0.002 \times DOF + 0.009 \times BMV_{MARB}$. Therefore, the test of the null hypothesis that this marginal effect was equal to -1, $H_0: \partial YG/\partial MBV_{YG} = -1$,[6] was conducted at the mean value of days-on-feed (176 days) and marbling MBV (-21.661). At these values, the marginal effect was approximately -0.929, and we failed to reject the null hypothesis that this value was -1 ($t = 0.46$; $df = 9,169$; $P = 0.65$).

Similarly, the marginal effect of the marbling MBV on quality grade outcomes was a function of days-on-feed and yield grade MBV: $\partial QG/\partial MBV_{MARB} = -0.148 + 0.005 \times DOF - 0.170 \times MBV_{YG}$. Therefore, the test of the null hypothesis that this marginal effect equaled 1, $H_0: \partial QG/\partial MBV_{MARB} = 1$, was conducted at the mean value of days-on-feed (176 days) and yield grade MBV (-0.054). At these values, the marginal effect was approximately 0.741, and we rejected the null hypothesis that this value was 1 ($t = -4.45$; $df = 8,779$; $P < 0.01$). This was consistent with the finding that MBVs underestimate the expected change in phenotypic outcomes relative to a change in MBVs (Weber et al., 2012). Despite advancements in the procedures for estimating MBVs, their accuracy still depends on the persistency of linkage disequilibrium between single nucleotide polymorphisms (SNP) and quantitative trait loci (QTL) and the relationship between training and target populations (Akanno et al., 2014). Therefore, it was not surprising that this effect shrunk toward 0 when the MBV procedure was applied to new data. Nevertheless, the marginal effect of the

[6] The marginal effect of the yield grade MBV on yield grade outcomes had an expected value of -1 because lower yield grade outcomes are more favorable.

Table 5. Mixed Model Regression Equations for Average Daily Gain, Dressing Percentage, Yield Grade, and Quality Grade

	Equation			
	ADG	*DP*	*YG*	*QG*
Variable	($n = 7,670$)	($n = 5,773$)	($n = 9,440$)	($n = 9,044$)
Intercept	1.961	0.340**	1.124	262.200**
Placement weight	0.205	0.010***	0.259***	17.990***
Days-on-feed	0.014*	0.002**	0.002	0.646
Days-on-feed squared	−4.00E−5***	−4.16E−6*	1.40E−5	0.001
Placement weight × days-on-feed	−0.002**	−5.00E−5*	−0.001*	−0.078***
Steer[a]	0.399***	0.004	−0.144***	−34.366***
Black[b]	0.023***	−9.70E−5	0.008	0.583
Yield grade MBV[c]	0.152	−0.007	−0.382	−154.670***
Yield grade MBV × days-on-feed	–	–	−0.002	0.819***
Marbling MBV	0.001	−6.96E−6	0.001	−0.148
Marbling MBV × days-on-feed	–	–	6.77E−6	0.005***
Yield grade MBV × marbling MBV	–	–	0.009***	−0.170
Average daily gain MBV	0.757**	−0.006**	0.028	−0.339
Hot-carcass weight MBV	0.001	1.21E−4***	0.003*	0.176*
Rib-eye area MBV	0.017	0.002	−0.345***	−11.406***
Tenderness MBV	0.002	1.92E−4	0.007	−1.027*
Days-on-feed MBV	−0.001	−2.00E−5	−9.00E−5	−0.266
Random effects[d]				
Set	0.236*	4.99E−4	0.136*	52.483
Contemporary group (Set)	0.101***	2.93E−4***	0.040***	388.960***
quasi-R^2 excluding MBVs[e]	0.463	0.562	0.404	0.130
quasi-R^2 including all variables[e]	0.470	0.565	0.470	0.193

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% levels. Dependent variables in the four equations are average daily gain (*ADG*), dressing percentage (*DP*), calculated yield grade (*YG*), and marbling score (*QG*).
[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.
[c] Molecular breeding value.
[d] Random effects for set and contemporary groups nested within sets are included in the estimation of each equation (i.e., mixed model regression equations) (Greene, 2012). Sets represent different commercial feedlots, time periods, or both, and contemporary groups are groups of animals that have had an equal opportunity to perform.
[e] Quasi-R^2 values are calculated as the squared correlations of the actual and predicted values including random effects.

marbling MBV was still statistically different from 0 ($t = 11.05$; $df = 8,779$; $P < 0.01$), indicating that higher genetic potential for marbling resulted in more favorable quality grade outcomes.

Expected Net Returns for Alternative Marketing Scenarios

Baseline Marketing Scenarios

For the set of animals used in this analysis and average 2014 prices, maximum expected net returns for the three baseline scenarios in which all animals were marketed in a single group on a live weight, dressed weight, or grid basis was −\$35.84, −\$34.25,[7] and −\$28.03/head, respectively (table 6). The finding that grid pricing generated the highest returns was consistent with Anderson and Zeuli (2001) and Walburger and Crews (2004). However, other studies have found that live weight and

[7] Calibration of live weight and dressed weight baseline marketing scenarios to market efficiency was conducted using actual final live weights and hot-carcass weights. Therefore, when applied to simulation analyses values of expected net returns for live weight and dressed weight marketing scenarios differed slightly due to differences in optimal days-on-feed.

Table 6. Expected Net Returns and Corresponding Optimal Days-on-Feed for Alternative Marketing Scenarios for 2014 Average Prices

Marketing Scenario	Proportion	Optimal Days-on-Feed	Expected Net Return	Standard Deviation
Baseline marketing scenarios			$/head	
Market all live weight		151	−$35.84	$27.07
Market all dressed weight		179	−$34.25	$27.09
Market all grid		181	−$28.03	$33.49
Genetic information marketing scenario				
Live weight	10%	146	−$57.74	$23.87
Dressed weight	17%	177	−$51.24	$21.86
Grid	73%	182	−$16.71	$28.28
Weighted average			−$26.68	$31.47
Perfect information marketing scenario				
Live weight	19%	143	−$26.76	$32.10
Dressed weight	19%	179	−$50.35	$21.15
Grid	62%	183	−$15.38	$28.21
Weighted average			−$24.19	$30.88

dressed weight pricing generate the highest returns (Feuz, Fausti, and Wagner, 1993; Fausti, Feuz, and Wagner, 1998; Schroeder and Graff, 2000; Lusk et al., 2003). As previously discussed, the marketing method that generated the highest returns depends on prices and quality characteristics of the cattle used in each study. Given the large, representative sample of cattle used in this study, the finding that grid pricing generated the highest returns suggests that the market has already started to adjust to higher-quality animals being targeted to grid pricing. This is consistent with Fausti et al. (2014), who found that the grid premium and discount structure is adjusting market signals to encourage producers to market on a grid and discourage live weight and dressed weight pricing.

Although grid pricing generated the highest expected net returns, it also had the highest standard deviation ($33.49). This result was consistent with the findings of previous research (Feuz, Fausti, and Wagner, 1993; Schroeder and Graff, 2000; Anderson and Zeuli, 2001; Fausti and Qasmi, 2002; Lusk et al., 2003) and has been identified as the primary barrier to adopting grid pricing (Fausti, Feuz, and Wagner, 1998; Anderson and Zeuli, 2001; Fausti and Qasmi, 2002).

Genetic Information Marketing Scenario

The decision rule indicated that net-return-maximizing decision makers would target animals with higher genetic potential for marbling to the grid and animals with lower genetic potential for marbling to either live weight or dressed weight pricing (figure 1). At lower levels of genetic potential for marbling, dressed weight pricing generated the highest expected net return for animals with lower yield grade MBVs and live weight pricing generated the highest expected net return for animals with higher yield grade MBVs.

Applying this decision rule to the data, 10% of cattle were targeted to live weight pricing, 17% to dressed weight pricing, and 73% to grid pricing (table 6). Investigation of the outcomes for individual marketing groups indicated that expected net return for live weight (−$57.74/head) and dressed weight (−$51.24/head) pricing decreased relative to their respective baseline scenarios, but expected net return for grid pricing increased to -$16.71/head. Therefore, the ability to identify animals that will perform poorly at slaughter and pull them off of the grid increased expected net return for grid pricing by more than $11/head. As a result, overall expected net return for the genetic information marketing scenario increased to −$26.68/head. Comparing this value with expected net return for the grid baseline marketing scenario, the expected value of genetic information

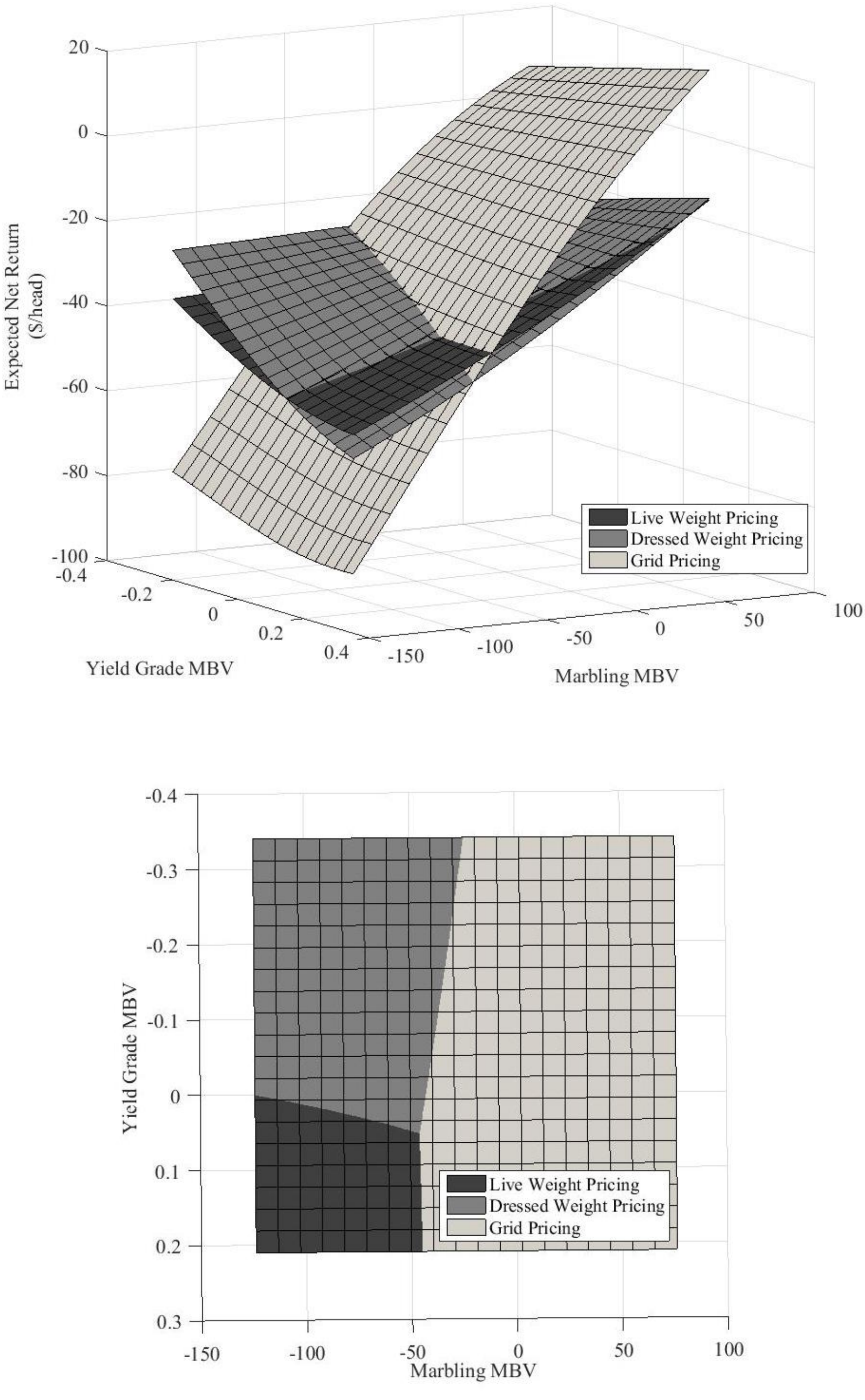

Figure 1. Three-Dimensional Surface and Corresponding Contour Plot of the Fed Cattle Marketing Decision Rule Using Molecular Breeding Values (MBV) Characterizing Yield Grade and Marbling for 2014 Average Prices

Table 7. Expected Value of Information for Alternative Marketing Scenarios Compared with Baseline Marketing Scenarios for Three Different Grids ($/head)

	Baseline Marketing Scenarios		
Alternative Marketing Scenarios	**Live Weight**	**Dressed Weight**	**Grid**
Average grid			
Genetic information	$9.16	$7.57	$1.35
Perfect information	$11.65	$10.06	$3.84
Maximum grid			
Genetic information	$13.00	$11.41	$2.47
Perfect information	$14.75	$13.16	$4.22
Minimum grid			
Genetic information	$5.28	$3.69	$0.59
Perfect information	$8.81	$7.22	$4.12

for a producer currently marketing cattle in a single group using grid pricing was $1.35/head ($-\$26.68 - [-\$28.03] = \$1.35$) (table 7). While this value is relatively low, it is important to remember that few producers currently market all of their cattle on the grid, as a result of higher variability. The value of genetic information for producers currently using live weight or dressed weight pricing was $9.16 and $7.57/head, respectively.

In addition to improvements in expected net returns, using genetic information to sort cattle into marketing groups also resulted in efficiency gains to cattle feeding. For example, relative to their respective baseline scenarios, optimal days-on-feed decreased for live weight (146 days) and dressed weight (177 days) pricing and increased for grid pricing (182 days) (table 6). This indicated that when sorted and targeted to their optimal marketing method, animals with lower genetic potential for marbling could be fed for fewer days and animals with higher genetic potential for marbling could be fed slightly longer to achieve more favorable quality grade outcomes.

Furthermore, the standard deviation of expected net return for all three marketing groups decreased relative to the standard deviations in their respective baseline scenarios. This is particularly important given that one of the primary motivations for sorting cattle into marketing groups was to reduce the variability among animals treated alike (Fausti, Wang, and Lange, 2013). More importantly, the standard deviation of overall expected net return for the genetic information marketing scenario ($31.47) was less than the grid baseline marketing scenario ($33.49). Therefore, in addition to improving the returns to cattle feeding, genetic sorting can also reduce the variability, or risk, associated with value-based marketing.

Sensitivity analysis was conducted using the grids associated with the maximum and minimum weekly Choice-Select spread for 2014. As expected, the decision rule for the maximum grid was similar to figure 1, with a lower marbling MBV threshold, indicating that a slightly larger portion of cattle were targeted to the grid (74%). The decision rule for the minimum grid was also similar to figure 1, with a slightly higher (lower) marbling MBV threshold at lower (higher) levels of genetic potential for yield grade. Contrary to expectations, when this decision rule was applied to the data, the portion of cattle targeted to the grid actually increased (77%). The lower Choice-Select spread made yield grade outcomes more economically important relative to quality grade outcomes, and, as a result, animals with higher yield grade MBVs were more likely to be targeted to the grid regardless of their genetic potential for marbling.

Other notable results for the maximum and minimum grid scenarios were qualitatively similar to the average pricing scenario described above. However, the values of genetic information for the maximum grid increased for each of the three baseline marketing scenarios and ranged from $2.47 to $13.00/head depending on how a producer currently markets cattle (table 7). Conversely, the values of genetic information for the minimum grid decreased and ranged from just $0.59 to $5.28/head.

Table 8. Optimal Marketing Portfolios and Certainty Equivalents for Alternative Marketing Scenarios for Three Levels of Risk Aversion and 2014 Average Prices

	Slight Risk Aversion ($r = 0.0000003$)		Moderate Risk Aversion ($r = 0.0000006$)		Severe Risk Aversion ($r = 0.0000010$)	
Marketing Scenario	**Proportion**	**Certainty Equivalent $/head**	**Proportion**	**Certainty Equivalent $/head**	**Proportion**	**Certainty Equivalent $/head**
Baseline marketing scenarios						
Market all live weight		−$58.01		−$75.00		−$104.42
Market all dressed weight		−$63.38		−$85.49		−$122.81
Market all grid		−$57.58		−$80.08		−$118.09
Expected utility-maximizing portfolio						
Live weight	31%		54%		81%	
Dressed weight	10%		3%		0%	
Grid	59%		43%		19%	
Overall		−$52.02		−$71.54		−$103.34

Notes: Days-on-feed for each marketing method is held constant at profit-maximizing baseline levels (live weight = 151 days, dressed weight = 179 days, and grid = 181 days).

Perfect Information Marketing Scenario

For the set of animals and prices used, perfect information dictated that 19% of cattle be targeted to live weight pricing, 19% to dressed weight pricing, and 62% to grid pricing (table 6). Expected net returns for the perfect information marketing scenario increased to −$24.19/head and the standard deviation decreased ($30.88), indicating that more accurate sorting could further increase returns and further decrease the variability associated with cattle feeding. As a result, values of perfect information were consistently higher than the values of genetic information and ranged from $4.12 to $14.75/head depending on how a producer currently markets cattle and which grid was used (table 7).

Expected Utility for Alterative Marketing Scenarios

Incorporating risk preferences into the model indicated that, as risk aversion increased, decision makers' preferences shifted away from grid pricing toward less risky live weight pricing (table 8). For example, certainty equivalents identified live weight pricing as the preferred baseline marketing method for moderate (−$75.00/head) and severe (−$104.42/head) levels of risk aversion, and the expected utility-maximizing portfolio targeted fewer animals to the grid and more animals to live weight pricing as risk aversion increased.

Despite differences in optimal marketing strategies, the range of values of information for selectively marketing cattle was largely unchanged when risk was considered, ranging from $1 to $19/head (table 9).[8] Instead, as risk aversion increased, values of information for producers currently using live weight pricing to market cattle decreased and values of information for producers using dressed weight and grid pricing increased. This result is consistent with Lambert (2008), who found that certainty equivalents fell as risk aversion increased, but the differences in certainty equivalents among cattle with different leptin genotypes did not change significantly. Therefore, our results

[8] Thaler's (1999) discussion of mental accounting indicates that decision makers may fail to appropriately quantify risk. That is, instead of maximizing the aggregate expected utility for a group of animals, decision makers may maximize expected utility on an animal-by-animal basis (i.e., "pockets of money"). Therefore, we also evaluated an expected utility objective function where animals were targeted to the marketing method that maximized expected utility for each individual animal. Although the values of information for this analysis were slightly lower, as would be expected, they were very similar to the results reported here for the aggregate expected utility-maximizing portfolio.

Table 9. Expected Value of Information for Alternative Marketing Scenarios Compared with Baseline Marketing Scenarios for Three Levels of Risk Aversion and 2014 Average Prices ($/head)

	Baseline Marketing Scenarios		
Risk Aversion	**Live Weight**	**Dressed Weight**	**Grid**
Slight risk aversion	$5.99	$11.36	$5.56
Moderate risk aversion	$3.46	$13.95	$8.54
Severe risk aversion	$1.08	$19.47	$14.75

indicate that risk aversion, while important for understanding how producers market cattle, did not have a substantial impact on the value of genetic information.

Conclusions

This study examined the value of genetic information for improving fed cattle marketing decisions. Results indicated that using genetic information characterizing yield grade and marbling to sort cattle into marketing groups (live weight, dressed weight, or gird pricing) and to determine optimal days-on-feed increased expected net returns by $1–$13/head depending on how a producer currently markets cattle and the grid structure. Despite differences in optimal marketing strategies, the range of the values of information was largely unchanged when risk was considered. In addition, the perfect information marketing scenario offered slight improvements over genetic information, but it shows that even improved genetic tests would not be economical unless the cost of testing plunged. Given the use of naïve baseline marketing scenarios, the values reported here are likely an upper bound on the value of genetic information for selectively marketing fed cattle.

Previous research examining the value of genetic information for marker-assisted management has been limited to sorting cattle by optimal days-on-feed (DeVuyst et al., 2007; Lusk, 2007; Thompson et al., 2014). In this study, we extend the definition of marker-assisted management to include a more holistic view of fed cattle marketing, including decisions for marketing method as well as timing to market. As a result, the values of genetic information for marker-assisted management reported in this study were generally higher than those reported in previous research. However, these values were still not enough to offset the cost of genetic testing.

Currently, Igenity offers a comprehensive profile of twelve genetic markers for $40/head (Igenity, 2015). In addition to markers characterizing carcass traits, such as yield grade and marbling, this profile also includes markers for maternal traits, docility, growth, feed efficiency, and tenderness. While this comprehensive profile is beneficial for producers using this information to make selection and breeding decisions (Thompson et al., 2014), most of this information is superfluous in the context of managing feedlot cattle. For this reason, commercial testing companies might consider marketing a reduced profile of markers relevant to a particular decision. For example, Igenity currently offers a reduced profile of six traits relevant to the selection of replacement heifers for a cost of $22/head (Igenity, 2015). A similar reduced profile of growth and carcass characteristics may provide the opportunity for cost-effective marker-assisted management of feedlot cattle. Additional sorting and management costs may be associated with implementing a selective marketing management scheme that are not considered here. It may also be possible to use random sampling to reduce the cost of genetic testing by measuring the genetic potential of a group of cattle without having to test each animal. To put the results of this study into context, consider that because cattle feeding is a competitive industry average profitability is close to 0. Therefore, the values of genetic information reported here represent meaningful economic value. However, it is important to caution that the results presented here are conditional on the set of animals and prices used in this analysis. In addition, the values of genetic information reported here will not persist in the long run. First adopters and owners of the genetic identification technologies may realize profitability gains (Lusk, 2007; Koontz et al., 2008), but selective marketing will eventually signal to buyers that animals marketed on a live weight or dressed weight basis are likely lower quality than animals targeted to the grid. As a result, the market will adjust by decreasing live weight and dressed weight prices relative to grid prices (Schroeder and Graff, 2000; Koontz et al., 2008; Fausti et al., 2014), and the value of information to the feedlot will dissipate. In fact, there is already some evidence of these general equilibrium effects in the fed cattle market (Fausti et al., 2014).

Nevertheless, value to consumers will remain. That is, although improved marketing decisions will increase returns to the feedlot in the short run, results also indicated that the potential for long-run efficiency gains will persist because of changes in the product form. Sorting cattle into marketing groups allowed producers to more accurately determine optimal days-on-feed. In addition, sorting cattle into marketing groups generally decreased the variability of expected net returns. Therefore, the use of genetic testing to selectively market cattle may encourage producers who might not otherwise do so to market cattle on a grid (Fausti et al., 2010; Fausti, Wang, and Lange, 2013). This will result in improved quality and consistency of beef products and improved transmission of market signals throughout the beef cattle supply chain and may help address consumer demand problems.

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