Journal of Agricultural and Resource Economics 32(2):306–329

Economic Value of Selecting and Marketing Cattle by Leptin Genotype

Jayson L. Lusk

Recent research has identified genetic diversity in the ability of animals to manufacture and recognize leptin, a protein that regulates appetite and weight. This paper determines the economic value of using information on leptin genotype to select and manage beef cattle. Results reveal that the economic value of using genotypic information to sort cattle by optimal endpoint is only about $2/head for steers and $1/head for heifers; however, the value of using genotypic information to optimally select and feed only certain genotypes is $23/head for steers and $28/head for heifers. The difference in per head profit between the best and worst performing genotype is over $28 on the date the cattle were actually marketed and increases to $60 if each genotype is optimally marketed.

Key words: cattle marketing, days on feed, genetics, growth models, leptin, value of information

Introduction

Debate over the causes and consequences of the rise in human obesity has spawned a plethora of research. One line of research has focused on genetic causes for obesity and has identified the critical role of leptin in regulating body weight (Friedman and Halaas, 1998). Leptin is a protein-hormone that regulates appetite and metabolism. Fat cells stored by the body produce and release leptin into the bloodstream. Receptors in the brain recognize leptin levels as a signal to suppress or promote appetite; when more fat cells exist, more leptin is produced, and appetite is suppressed. Research has shown genetic diversity in the ability of humans and other mammals to produce and recognize leptin, and has led to the identification of the "obese gene," also known as the leptin gene.

A fortunate externality of the work on human obesity has been the recognition that leptin plays an important role in appetite and weight gain of food-producing animals. Whereas weight gain often entails negative consequences for humans, it is the primary goal of commercial livestock operations. Concentrations of leptin in the bloodstream of livestock have been shown to be significantly related to key variables affecting profitability. For example, Geary et al. (2003) found that serum concentrations of leptin, obtained 24 hours before slaughter, were significantly correlated with marbling, yield grade, and dressing percentages in beef cattle. Such findings have prompted research

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Jayson L. Lusk is professor and Willard Sparks Endowed Chair, Department of Agricultural Economics, Oklahoma State University. The author would like to thank Wade Brorsen, David Lambert, Donald Nkrumah, Jim Tate, Ted Schroeder, Clem Ward, and two anonymous reviewers for helpful suggestions and comments; all remaining errors are my own.

Review coordinated by George C. Davis.

to easily identify cattle with differing leptin levels. Genetic typing, which can be carried out by sending a hair follicle or tissue sample to a lab, offers one promising means of obtaining such information.[1]

Buchanan et al. (2002), Fitzsimmons et al. (1998), and others have identified genetic variation in the leptin gene, which controls leptin production. Such findings are important because certain types of leptin are less well recognized by receptors in the brain, meaning that some types of animals, even if they possess ample stores of energy and thus high concentrations of leptin, fail to suppress appetite and modify metabolism; instead, they continue to deposit fat. Differences in leptin genotype have been found to affect cattle performance. As examples, Fitzsimmons et al. (1998) found that genotypic differences in the locus of the leptin gene were significantly related with carcass fat measurements in beef bulls, and Schenkel et al. (2005) found that variation in leptin genotype was associated with variation in lean yield and tenderness in beef cattle. Other studies have shown that leptin genotype is not significantly related to breed, suggesting knowledge of leptin genotype conveys meaningful information above and beyond breed or lineage (Nkrumah et al., 2005; Schenkel et al., 2005).

Despite these biological findings, there has been little work devoted to quantifying the economic value of knowing leptin genotype.[2] The advent of genetic typing is timely as there is increased emphasis on value-based marketing whereby cattle producers must consider quality characteristics prior to making marketing decisions. Schroeder and Graff (2000) and McDonald and Schroeder (2003) illustrate the economic value of accurate knowledge of cattle quality. For example, Schroeder and Graff reported that average revenues could be improved by \$15.14/head to \$34.74/head if producers knew the quality and yield grades of their cattle prior to slaughter and optimally directed each animal to the proper marketing method (e.g., live weight, dressed weight, or grid basis).

Although there is an increasing need for producers to know the quality of their cattle before slaughter, there is currently little objective information on which to make these judgments. Genetic testing provides a way for producers to potentially obtain information about carcass characteristics prior to slaughter, and it presents a method that is potentially less invasive, less time consuming, and more economical than other methods of estimating pre-harvest carcass quality such as live-animal ultrasound or blood serum tests.[3] Despite the potential benefits, it is currently unknown whether information about leptin genotypic can improve cattle marketing decisions. Accordingly, this research seeks to provide such information.

The agricultural economics literature on valuing genetic traits in crops and livestock has a long history (e.g., Ladd and Gibson, 1978). The typical approach to valuing information is to calculate "… 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). Recent theoretical analyses have investigated how genetic information influences incentives to invest and

[1] Genetics companies currently offer user-friendly products to collect tissue samples during ear-tagging. Geneticists are presently working on "real-time" methods to carry out genetic testing on the farm or feedlot.

[2] A study by Lambert, DeVuyst, and Moss (2006), conducted at the same time as this research, is one exception.

[3] A few studies have investigated the value of using ultrasound technology to better predict carcass characteristics pre-harvest (e.g., see Lusk et al., 2003; or Brethour, 2000), and a number of large commercial feedlots regularly utilize the technology. One important difference in ultrasound and genetic technologies is that whereas ultrasound measures of backfat and marbling change throughout time, genetics do not. Consequently, if an animal's genotype is identified at any point during the marketing channel, the information potentially remains useful throughout its life.

engage in product differentiation activities and the effects of genetic information on product uniformity (Hennessy, Miranowski, and Babcock, 2004).

More germane to this analysis, a few papers have focused on the value of genetic information in the beef industry. For example, Chvosta, Rucker, and Watts (2001) examined the value of performance information on beef bulls by investigating variation in bull sales prices. They found traditional measures of performance were more valuable than information on expected progeny difference. Probably the most similar study to the present analysis is that by Lambert, DeVuyst, and Moss (2006). Using a data set consisting of 180 head of cattle, they found that the expected value of genotypic information was not significantly different than zero in terms of using the information to choose a marketing date; however, significant differences in profitability were found across the three leptin genotypes they investigated.

The expected value of information related to leptin genotype results from two sources. First, a feedlot could use the information to select and feed only certain genotypes—i.e., selection. Second, a feedlot could use the information to better manage the distribution of genotypes it already possesses by optimally choosing days on feed—i.e., management. The objective of this paper is to provide an estimate of the value of information from both sources.[4]

The value of information resulting from selection is determined by investigating differences in revenue and profitability across seven leptin genotypes. To fully explore the issue, both static and optimization analyses are conducted. In the static analysis, the profitability of a set of cattle is evaluated "as is" on the dates the cattle were actually slaughtered given certain price and cost assumptions. In the optimization analysis, the optimal number of days on feed is determined and profitability across genotypes is compared at each genotype's predicted optimum. To estimate the value of information related to management, the expected profit obtained when a feedlot can differentially choose an optimal marketing date for each genotype is compared to the case when the feedlot cannot differentially feed genotypes and is restricted to pick a uniform endpoint for all genotypes.

Data and Methods

Data

Data consist of carcass-level information on 1,668 head of cattle all fed in the same commercial feedlot between August and November 2004. Upon placement at the feedlot, animals were weighed, ultrasound readings were taken to estimate backfat thickness, and a sample of hair was taken from each animal to identify genotype. Animals were re-weighed and backfat ultrasound measures were taken up to three additional times prior to slaughter. At slaughter, data were collected on live weight, marbling score, quality grade, yield grade, and hot carcass weight. Table 1 reports summary statistics.

To analyze genetic variation in the leptin gene, geneticists investigate single nucleotide polymorphisms or SNPs, which are DNA sequence variations that occur when a

[4] Here output prices are treated as exogenous; however, as Babcock (1990) showed, the value of information need not be positive if the use of information changes output prices. The effect of genetic information on output prices is an issue left for future work.

Table 1. Summary Statistics: Means by Genotype (N = 1,668 head)

	Genotype							
Variable	Type1	Type2	Type3	Type4	Type5	Type6	Type7	p-Value[a]
Input Variables:								
Placement Weight (lbs.)	722.13	688.92	653.93	696.34	685.58	684.38	708.03	< 0.01
Ultrasound Backfat Measure at Placement (inches)	0.102	0.092	0.080	0.095	0.089	0.096	0.107	< 0.01
Frame Score at Placement	6.79	6.99	6.80	6.70	6.75	6.62	6.28	0.02
Days on Feed	138.49	141.55	138.66	142.39	137.10	139.85	134.79	0.02
Percent Steer	67.20%	58.40%	57.80%	66.10%	67.60%	70.80%	79.30%	0.01
Percent Managed via BF Method[b]	31.30%	24.20%	16.40%	27.00%	24.80%	29.90%	37.90%	0.04
Output Variables:								
Percent Choice	44.00%	45.00%	39.80%	45.90%	39.20%	46.40%	58.60%	0.20
Marbling Score[c]	39.76	39.67	38.67	40.37	38.94	40.82	44.31	< 0.01
Calculated Yield Grade	2.67	2.69	2.70	2.66	2.81	2.89	3.08	< 0.01
Plant Backfat (inches)	0.465	0.462	0.467	0.464	0.477	0.503	0.546	< 0.01
Dressing Percentage	63.86%	63.59%	63.18%	63.85%	63.30%	63.41%	62.81%	< 0.01
Live Weight at Slaughter (lbs.)	1,245.08	1,213.50	1,168.55	1,229.90	1,206.58	1,213.35	1,238.45	< 0.01
Number of Observations	134	269	128	392	408	308	29	
Percent of Observations	8.03%	16.13%	7.67%	23.50%	24.46%	18.47%	1.74%	

[a] The p-value associated with an ANOVA test that the means are equivalent across genetic types.

[b] *BF Method* is a dummy variable identifying whether the feedlot operator used ultrasound measures to attempt to feed animals to a constant backfat at slaughter.

[c] *Marbling Score* corresponds to quality grade as follows: 10–29 = Standard, 30–39 = Select, 40–49 = low Choice, 50–59 = Choice, 60–69 = upper Choice, and 70–99 = Prime.

single nucleotide (A, T, C, or G) in the genome sequence is altered across chromatid pairs. For example, an SNP might change the DNA sequence A**A**GGCT to A**T**GGCT. Based on findings reported by Schenkel et al. (2005), two particular SNPs were expected to influence leptin production and they serve as the focus of this analysis: UASMS2 and EXON2FB.[5] Both SNPs contain two alleles (C or T) and can either be homozygous (e.g., CC or TT) or heterozygous (CT). This means there are three possible outcomes for each SNP (CC, CT, or TT), making nine possible genotypes available for this analysis. Three genetic combinations occurred with very low frequencies in the population, and cattle with these combinations were simply pooled in an "other" group. For ease of exposition, the remainder of the paper focuses on seven genotypic categories simply referred to as type1 through type7, where:

- type1 = (EXON2FB-CC; UASMS2-CC),
- type2 = (EXON2FB-CC; UASMS2-CT),
- type3 = (EXON2FB-CC; UASMS2-TT),
- type4 = (EXON2FB-CT; UASMS2-CC),
- type5 = (EXON2FB-CT; UASMS2-CT),
- type6 = (EXON2FB-TT; UASMS2-CC), and
- type7 = (all other EXON2FB, UASMS2 combinations).

As shown in table 1, most of the cattle were of the type4 or type5 genotype. Together, these two types comprised almost 48% of the cattle in the sample. Only 29 animals (or 1.7% of the sample) were of "other," type7 genotypes. For virtually every variable reported in table 1, the hypothesis that means are equivalent across all seven genotypes is rejected at the $p = 0.05$ level or lower based on an ANOVA test; however, it should be noted these are unconditional comparisons of means, not holding constant other factors. Although only comprising 1.7% of the sample, type7 cattle tended to be the fattest. They had higher marbling scores, higher yield grades, and lower dressing percentages than all other genotypes. Type6 cattle had the second highest average marbling score and yield grade. Type3 cattle had the lowest mean marbling score and type4 cattle had the lowest mean yield grade. Type1 cattle had the highest average live weight at slaughter; however, this may simply be due to the fact that this genotype also had the highest average placement weight. Indeed, the fact that each genotype differs both in "input" characteristics such as placement weight and "output" characteristics such as yield grade makes it difficult to determine the extent to which variation in output characteristics are a result of differences in genotype simply by looking at means, recognizing, of course, that genotype is also likely to influence input characteristics.

Interest lies in calculating revenue and profit for each animal in the data set. To remove any time-varying effects that may have occurred in the market, it is assumed that all animals faced the same market prices. Weekly dressed weight prices for USDA Choice cattle, reported as the over 80% Choice five-market weighted average by the USDA/Agricultural Marketing Service (AMS), were averaged for the year 2004 and were used as the base price in the grid. Weekly grid premiums and discounts were obtained from the USDA/AMS National Carlot Meat Report or "Blue Sheet" for the year 2004,

[5] The EXON2FB SNP has also been referred to as R25C in previous animal science literature.

Table 2. Pricing Grid Used in Revenue Calculations

Grid Component	$/cwt
Base Price [a]	134.00
Quality Grade Adjustment: [b]	
Prime	8.29
Choice	0.00
Select	-8.72
Standard	-18.25
Yield Grade Adjustment: [b]	
1.0 to 2.0	2.93
2.0 to 2.5	1.67
2.5 to 3.0	1.24
3.0 to 3.5	-0.08
3.5 to 4.0	-0.08
4.0 to 5.0	-13.70
> 5.0	-18.04
Carcass Weight Adjustment: [b]	
< 500 lbs.	-21.69
500 to 550 lbs.	-14.98
950 to 1,000 lbs.	-7.44
> 1,000 lbs.	-18.04

[a] Grid base price is based on the 2004 weekly average of the 80% USDA Choice dressed weight price for the five-market weighted average as reported by the USDA/AMS.
[b] Adjustments are based on averages of grid premiums and discounts reported by the USDA/AMS for year 2004.

and the average of these values was used to formulate the grid shown in table 2. Table 3 reports the cost data used in the analysis. The average feeder prices reported by the USDA/AMS for 2003 were averaged for use in the analysis.

Static Marketing Analysis

As an initial step, a static analysis is conducted where revenues and profits are calculated for the time at which each animal was actually marketed. Such an approach avoids the difficulty in predicting output characteristics had the animal been slaughtered sooner or later than its actual slaughter date. To carry out the analysis, per head revenue for all 1,668 head is determined by multiplying each animal's dressed weight by the grid base price and adding/subtracting the appropriate premiums/discounts shown in table 2. Because accurate data on dry matter intake was unavailable for each animal, costs were simply calculated using cost of gain figures reported by Mark, Jones, and Mintert (2002a,b). In particular, per head costs were determined as: *(placement weight in lbs.)*(feeder cattle price in $ / lb.) + (live weight at slaughter in lbs. − placement weight in lbs.)*(cost of gain in $ / lb.)*. Per head profit is the difference in per head revenue and cost. Comparing mean profits across genotypes provides a rough estimate of the value of selection.

A simple comparison of means, however, obscures the fact that cattle feeders are able to observe other characteristics when purchasing and feeding cattle, such as frame score and placement weight. Specifically, a simple comparison of means across genotypes does not control for differences in other potentially observable characteristics. To investigate whether differences in profit across genotype persist after controlling for other measurable characteristics, a conditional analysis is carried out, where per head profit and revenue is regressed on input variables listed in table 1 including genotypic dummy variables.

Table 3. Assumptions Used in Cost Calculations

Description	Steer Price/Cost	Heifer Price/Cost
Feeder Cattle Prices by Placement Weight ($/cwt):[a]		
0 to 349	117.33	107.31
350 to 399	117.33	103.92
400 to 449	113.36	101.71
450 to 499	107.55	96.60
500 to 549	101.87	93.66
550 to 599	96.75	92.08
600 to 649	93.85	88.29
650 to 699	93.56	87.22
700 to 749	90.67	85.73
750 to 799	88.93	84.18
800 to 849	87.44	81.09
850 to 899	83.74	79.89
900 to 949	81.11	76.64
950 to ·	78.56	76.64

Description	Steer Price/Cost	Heifer Price/Cost
Cost of Gain by Placement Weight ($/cwt):[b] [only in static analysis]		
0 to 599	49.92	53.10
600 to 699	49.90	52.39
700 to 799	49.61	54.79
800 to ·	51.74	58.13
Cost of Feed (dry matter basis $/ton): [only in optimization analysis]		
0 to ·	117.65	117.65
Additional Per Day Costs ($/head/day): [only in optimization analysis]		
0 to ·	0.05	0.05
Fixed Cost ($/head): [only in optimization analysis]		
0 to ·	8.00	8.00
Interest Rate (%): [only in optimization analysis]		
0 to ·	8.00%	8.00%

[a] Average western Kansas feeder prices as reported by the USDA/AMS for year 2003.
[b] Based on Mark, Jones, and Mintert (2002a, b).

The idea here is to investigate whether profits vary by factors potentially observable before animals are placed on feed and decisions about selection and sorting are made. Comparing both conditional and unconditional means across genotypes is informative and important. Although one might be tempted to conclude that only conditional differences are relevant, it is important to recognize that genotype might influence many of the input variables, and as a result might yield a single measure that serves as a proxy for a variety of input variables. Further, although ultrasound backfat is observable, it can be a costly and time-intensive statistic to obtain; thus, even if differences in ultrasound backfat at placement explain some of the differences in profitability across genotype, genotypic information might be useful in lieu of ultrasound backfat measures.

Optimization Analysis

Although the static analysis described above represents a simple and straightforward method to determine the value of genotypic information for selection, it likely fails to capture the full value of knowing leptin genotype. It might be profitable to feed certain genotypes longer or shorter than others. For example, a genotype that deposits fat quickly needs to be marketed earlier before receiving yield discounts than a genotype requiring a longer feeding time to achieve the Choice quality grade. To address this issue, additional analysis is carried out where the optimal number of days on feed is determined for each genotype.

Such an analysis requires that a number of models be estimated to predict output variables such as yield grade, quality grade, and weight for *every* potential day on feed. Although there are a number of equations needed to implement such an analysis, five equations require econometric modeling using the available data: live weight, backfat, marbling, ribeye area, and dressing percentage. In selecting the functional forms to model these five variables, particular attention was paid to three issues. First, the literature from animal science and biology was consulted. Second, the data set contains repeated measures for live weight and backfat for each animal, but only contains measures of marbling, ribeye area, and dressing percentage at slaughter. For variables with repeated measures, "true" growth models can be estimated; but for the latter variables, we are restricted to an investigation of how these measures vary across animals that happened to be slaughtered at different endpoints. Finally, in selecting functional form, it was important for model predictions to be commensurate with intuition and a priori expectations.

One of the key variables affecting profitability is live weight, for which the data set contains repeated measures on each animal throughout time. In the animal science literature, body weight growth is frequently modeled using one of a variety of so-called sigmoid growth models. These functions are characterized by a parameter (or parameters) that relates current body weight to an estimate of initial weight and asymptotic mature weight [see Staniar et al. (2004) for a discussion and comparison of several sigmoid functions]. This research makes use of the so-called Brody growth curve, a type of sigmoid growth model commonly used in the analysis of beef cattle weight growth (e.g., see Kaps, Herring, and Lamberson, 1999). The general model is written as:

$$W_t = A - (A - W_0)e^{kt} + \varepsilon_t , \tag{1}$$

where W_t is live weight at time t, A is a parameter representing asymptotic mature weight (e.g., maximum attainable weight), W_0 is a parameter representing placement weight at $t = 0$, and k is a parameter representing the ratio of maximum growth rate to mature size referred to as a maturing rate index; ε_t is a mean-zero, normally distributed error term. Typically the parameters A, W_0, and k are estimated as constants; however, for this analysis, each is parameterized as a linear function of exogenous input variables and dummy variables for each genotype. For example, let $\mathbf{X}_i$ be a matrix where the columns represent animal i's genotype (i.e., six dummy variables), gender, frame score at placement, ultrasound backfat at placement, and a dummy variable indicating whether the feedlot attempted to feed the animal to a constant backfat. In our empirical analysis, we let $A = \mathbf{X}_i\boldsymbol{\beta}$, where $\boldsymbol{\beta}$ is a conformable vector of coefficients relating input variables and genotype to asymptotic mature weight. A similar approach is taken to parameterize W_0 and k.

In addition to containing repeated measures on weight, the data set also contains repeated backfat measures. Backfat is a primary driver of yield grade, which is, in turn, a primary driver of price in the grid pricing system. When modeling body weight growth, it is important to utilize a functional form that imposes the widely accepted a priori assumption that body weight must increase at a decreasing rate—a feat accomplished by using the Brody growth curve. However, previous studies, such as Brethour (2000), show that backfat growth is exponential over time, meaning backfat increases at an increasing rate.

In keeping with Brethour (2000), the following model is used to determine how backfat changes with days on feed:

$$(2) \qquad bfat_t = bfat_0 e^{\gamma t} + \varepsilon_t,$$

where, $bfat_t$ is projected backfat as measured by ultrasound at t days on feed, $bfat_0$ is backfat thickness at placement, γ is a parameter to be estimated representing the rate of increase in backfat, and ε_t is a mean-zero, normally distributed error term. Rather than estimating a single parameter, γ, for the entire data set, γ is instead parameterized as a linear function of input variables and dummy variables for each genotype.

Attention is now turned to determining how marbling changes throughout time. Although quality grade is a discrete outcome (e.g., Prime, Choice, Select, or Standard), grade is primarily based on the level of intramuscular marbling. The data set contains information on each carcass's final marbling score, where 10–29 = Standard, 30–39 = Select, 40–49 = low Choice, 50–59 = Choice, 60–69 = upper Choice, and 70–99 = Prime. Unfortunately, the data set only contains marbling scores at slaughter. As such, one option is to simply estimate a simple linear model to investigate how final marbling score varied with final number of days on feed. Such an approach, however, would not represent a "true" growth model.

Fortunately, the animal science literature reports models showing how marbling progresses over the feeding period. Again, our particular data set does not contain measures of marbling at placement (mbs_0). However, we can obtain an estimate of mbs_0 using the growth model estimated by Brethour (2000) to "backcast" each animal's marbling score at placement. In particular, Brethour estimated the following model (using his notation): $Y = I + kt^m$, where I, k, and m are parameters, Y is marbling, and t is days on feed. Using two data sets, Brethour (2000) estimates I at 3.10 and 3.39, k at 0.00214 and 0.00000000123642, and m at 1.55 and 3.42. After a bit of algebra, it can be shown that initial marbling at placement (mbs_0) is equal to:

$$mbs_0 = \big(((mbsF - I)/k)\hat{}(1/m) - T\big)\hat{}m * k + I,$$

where $mbsF$ is the final marbling score at slaughter and T is the total number of days on feed. Using Brethour's estimates, mbs_0 is calculated for each animal in the present data set [the above equation is evaluated using both estimates in Brethour (2000) and an average is taken of the two]. Once these were obtained, the following exponential growth model was fit to the data:

$$(3) \qquad mbs_t = mbs_0 e^{\lambda t} + \varepsilon_t,$$

where mbs_t is marbling score at time t, mbs_0 is the projected marbling score at placement, λ is a parameter to be estimated representing the rate of increase in marbling, and t is days on feed. As before, we parameterize λ as a linear function of input variables and dummy variables for genotype.

Other variables needed to carry out the analysis are estimates of how (a) dressing percentage, (b) ribeye area, and (c) percentage of kidney, pelvic, and heart fat (KPH) vary throughout time. An estimate of dressing percentage is needed because the base price in the grid is multiplied by the carcass weight (not live weight) and because yield grade is determined, in part, by carcass weight. Thus, a dressing percentage must be estimated such that the estimated live weight in equation (1) can be converted to a carcass weight at each day on feed. Estimates of ribeye area and KPH are needed to calculate yield grade. Specifically, the USDA formula for calculating yield grade is: $2.5 + 2.5(bfat_t) + 0.02(KPH_t) + 0.0038(W_t)(dressing\ percent_t) - 0.32(ribeye\ area_t)$.

Unfortunately, there are no repeated measures for dressing percentage, ribeye area, and KPH in the data set, and the animal science literature does not report growth models for these variables. While there are not repeated measures of these variables throughout time for each animal, there is reasonably large variation in total number of days on feed across animals (from a low of 98 days to a high of 226 days). Thus, the final carcass measures of dressing percentage and ribeye area are used to estimate simple regression models where the dependent variables are specified as a function of total days on feed and input variables including genotype. This approach provides a rough approximation for how dressing percentage and ribeye area vary across time. KPH was extremely uniform in the data set, and as such, it is fixed at the constant value of 2.25% in the analysis.

In addition to these revenue considerations, several equations are needed to calculate cost throughout the feeding period. Rather than relying on a simple cost of gain calculation as in the static analysis, feed intake for each animal is estimated for each day on feed. To accomplish this task, the widely used dry mater intake model reported in the National Research Council's *Nutrient Requirements of Beef Cattle* (2000) is used. The model has been utilized in academic work such as Tedeschi, Fox, and Russell (2000) and is used in the Cornell Net Carbohydrate and Protein System. The model is as follows:

$$(4)\qquad Dry\ Matter\ Intake\ in\ lbs_t = \left[\left(0.96(W_t/2.2)\right)^{0.75}(0.2435NE_{ma} - 0.0466NE_{ma}^2 - 0.1128)/NE_{ma}\right] * (Empty\ Body\ Fat\ Adjustment\ Factor) * 2.2,$$

where NE_{ma} is the net energy value of diet for maintenance, which is set at a constant value of 2.0 Mcal/kg, and where the empty body fat (EBF) adjustment factor takes the following values: 1.0 for $EBF < 23.8$, 0.97 for $23.8 \le EBF < 26.5$, 0.90 for $26.5 \le EBF < 29.0$, 0.82 for $29.0 \le EBF < 31.5$, and 0.73 for $EBF \ge 31$. Because EBF is not provided in the data set, it is estimated via the equation provided in Perry and Fox (1997):

$$(5)\qquad EBF_t = \frac{0.351\left(0.389(W_t/2.2) + 21.6(yieldgrade_t) - 80.8\right)}{0.389(W_t/2.2)}100.$$

Cumulative dry matter intake in lbs. on day t is:

$$(6)\qquad Cumulative\ Dry\ Matter\ Intake_t = \sum_{i=1}^{t} Dry\ Matter\ Intake_i.$$

Given the models described above, profit can be predicted for any particular day on feed. Specifically, profit per head on day t is given by:

$$(7)\qquad \pi_t = P(mbs_t, yieldgrade_t) * W_t * DP_t - (W_0 * FCP) * \left(1 + (r * t)/365\right) - Cumulative\ Dry\ Matter\ Intake_t * CDMI - PDC * t - FC,$$

where P is the dressed weight grid price ($/lb.) which is a function of yield and quality grade, DP_t is the dressing percentage, FCP is the price of feeder cattle ($/lb.), r is the annual interest rate, *CDMI* is the cost of dry matter intake ($/lb.), *PDC* represents additional per day costs, *FC* denotes fixed costs, and all other variables are as previously defined. To carry out an "unconditional" optimization, the input variables $frame$, $bfat_0$, W_0, and mbs_0 are set at their respective genotypic- and gender-specific means. Once these input values are set, profit/head is calculated for $t = 1$ to 250 for each genotype using the estimated prediction equations discussed above and equation (7).

Because of Jensen's inequality, profit calculated at the expected value of the prediction equations will not equal expected profit, which is the statistic ultimately of interest. To calculate expected profit, a stochastic simulation is carried out for each day on feed t. In particular, the error variance-covariance matrix was calculated for the five prediction equations (live weight, backfat, marbling, dressing percentage, and ribeye area). The Cholesky decomposition of the variance-covariance matrix was used to generate a distribution of 1,000 error terms for each of the five equations. Per head profit was calculated at each draw and the average across draws was taken to calculate expected profit. The process was repeated for $t = 1$ to 250, for each genotype, and for each gender.

For a more robust analysis, two optimization objectives were considered. First, the value of t which generated the highest expected profit *per head* for each genotype was identified. Although maximizing profit per head is perhaps the most intuitive approach (and in addition this approach generates profit estimates in units that are easily comparable to other studies), it may not accurately represent firm behavior. In particular, feedlots may have capacity constraints and may be unable to easily expand. Thus, the second approach taken identifies the value of t generating the highest expected profit per head *per day* for each genotype. This latter approach is likely to better account for the opportunity cost of the feedlot's capital.

In addition to the "unconditional" analysis, a similar "conditional" optimization analysis is also conducted where $frame$, $bfat_0$, W_0, and mbs_0 are allowed to vary by gender, but where they are set a common value for all genotypes. This conditional analysis is important because it is theoretically possible that a feedlot could find two animals with identical frame scores, backfat at placement, placement weight, etc., but differ by genotype. The question is whether there is still value in knowing genotype even if two animals are so similar. Thus, the conditional analysis shows the effect of genotype, holding constant the available input variables except days on feed.

As a final part of the optimization analysis, the value of genetic information in optimally choosing days on feed is calculated by comparing expected profit when a feedlot can differentially choose an optimal marketing date for each genotype relative to the case when the feedlot cannot differentially feed genotypes and is restricted to pick a uniform endpoint for all genotypes. This calculation requires an estimate of the expected profit for cattle of all genotypes for each day on feed. This figure is calculated by assuming the distribution of genotypes is the same as that in the present sample (see the last row of table 1) and taking a weighted average of expected profit across genotype at each day, i.e.,

$$\pi_{t,all} = \pi_{t,type1} * 0.0803 + \pi_{t,type2} * 0.1613 + \ldots + \pi_{t,type6} * 0.1847 + \pi_{t,type7} * 0.0174.$$

Results

Table 4 reports results from the static marketing analysis. Two ordinary least squares (OLS) model specifications are reported. In the first, the unconditional effect of genotype on revenue and profit is reported without controlling for input characteristics. These unconditional effects are informative because knowledge of genotype provides information about input characteristics as well as output characteristics, as evidenced by the ANOVA test findings shown in table 1. To the extent that none of the input variables were observable, the unconditional means would be the relevant comparison. Further, genotype is perhaps the only truly exogenous input variable (except gender and days on feed) and as such, the unconditional means reveal the reduced-form effects of genotype on revenue and profit. As shown by the table 4 results, when comparing unconditional means, type1 cattle generate the highest revenue whereas type4 cattle generate the highest profit. Type3 cattle exhibit the lowest revenue and profit and are therefore set as the baseline of comparison in the regressions.

In the second model specification presented in table 4, regressions are estimated where per head revenue and profit are modeled as a function of several input variables and dummy variables identifying genotype.[6] Although the unconditional results in table 4 suggest that genotypic information can have significant economic value in determining which type of animals a feedlot would wish to purchase, differences in placement weight, ultrasound backfat at placement, frame score, and days on feed may explain some of the differences in revenue and profitability. The conditional results in table 4 suggest this is indeed the case. For example, animals with higher placement weights exhibit higher profits, and cattle with lower backfat measures at placement have higher revenues. Some genotypes such as type1 have higher average placement weights and backfat measures (as reported in table 1), but the regression results in table 4 suggest it is these differences which contribute to the fact that type1 cattle tend to have the highest unconditional mean revenue—i.e., the dummy variable associated with type1 is not statistically significant in the unconditional econometric models.

It might be questioned why the conditional results in table 4 show steers to be significantly less profitable than heifers, when both genders would be expected to be equally profitable in equilibrium. The reason is that the regression shows the effect of steer versus heifer holding constant input factors. In reality, however, these factors are not held constant and the steer-heifer price differential will reflect not only differences in gender but also expected differences in other input characteristics that are likely correlated with gender. Indeed, the unconditional difference in mean profitability between steers and heifers in the static analysis is only \$108.68 – \$109.11 = –\$0.43, a difference that is not statistically significant (p-value = 0.89).

Although differences in input variables explain some of the differences in revenue/profit, significant differences remain for some genotypes. For example, type4 and type2 cattle exhibit significantly higher revenue and profit than type3 cattle, about \$11–\$14/head more profit, even after differences in input variables are held constant. In fact, differences in placement weight, backfat, frame score, days on feed, percent steer, and percent managed by the backfat method only explain $[(22.85 - 11.24)/22.85] * 100 = 50.82\%$ of the difference in profit between type2 and type3 cattle, where 22.85 is the

[6] The joint hypothesis that all genotype, gender interactions are zero in the unconditional models cannot be rejected at any standard significance level according to an F-test. Thus, a single regression is presented for both genders.

Table 4. Effect of Genotype on Revenue and Profit: Ordinary Least Squares Regression Coefficients (N = 1,668 head in each regression)

	Revenue		Profit	
Variable	Unconditional Effect of Genotype	Conditional Effect of Genotype	Unconditional Effect of Genotype	Conditional Effect of Genotype
Intercept	952.257***	−127.899	91.837***	−353.294***
	(10.303)	(97.534)	(5.394)	(75.414)
Placement Weight		1.867***		0.942***
		(0.196)		(0.151)
Placement Weight^2		−0.001***		−0.0004***
		(0.0001)		(0.0001)
Ultrasound Backfat at Placement		−602.017***		−126.679
		(168.867)		(130.568)
Ultrasound Backfat at Placement^2		317.109		−156.271
		(598.393)		(462.678)
Frame Score at Placement		−11.058		−0.597
		(15.153)		(11.717)
Frame Score at Placement^2		0.527		−0.589
		(1.082)		(0.836)
Days on Feed		1.399		0.171
		(0.820)		(0.634)
Days on Feed^2		0.003		0.003
		(0.003)		(0.002)
Steer (1 = steer; 0 = heifer)		4.742		−31.431***
		(6.523)		(5.043)
BF Method[a]		3.023		1.915
		(6.032)		(4.664)
Type1[b]	70.094***	9.947	23.943***	8.164
	(14.403)	(8.866)	(7.541)	(6.855)
Type2[b]	51.362***	15.746**	22.848***	11.237**
	(12.491)	(7.637)	(6.540)	(5.905)
Type4[b]	65.800***	17.285**	28.514***	14.247**
	(11.832)	(7.263)	(6.195)	(5.615)
Type5[b]	31.804***	4.862	8.304	3.385
	(11.783)	(7.170)	(6.169)	(5.544)
Type6[b]	39.907***	10.006	11.178	5.346
	(12.239)	(7.492)	(6.408)	(5.793)
Type7[b]	53.331**	7.855	6.527	−0.301
	(23.742)	(14.449)	(12.431)	(11.172)
R^2	0.03	0.65	0.02	0.23

Notes: Double and triple asterisks (*) denote statistical significance at the 5% and 1% levels, respectively. Numbers in parentheses are standard errors.

[a] *BF Method* takes the value of 1 if feedlot attempted to feed animal to a constant backfat; 0 otherwise.

[b] Effects of all other genotypes are estimated relative to *type*3 baseline.

unconditional mean difference and 11.24 is the conditional mean difference as shown in table 4. The difference in profit between the best and worst performing genotypes is over $28/head in the unconditional comparisons and over $14/head in the conditional comparisons. These findings suggest there may be significant value to using genotypic information to select and feed only certain types of cattle. These values are economically large; the revenue differences, which are as high as $70/head in the unconditional analysis, are almost twice the amount reported in previous studies that estimated the increase in revenue obtainable from choosing the best marketing method for each animal (e.g., Schroeder and Graff, 2000). A profit difference of $14/head is also substantial in comparison with historical returns to finishing cattle. For example, Lawrence (2007) reported that from 1996 to 2005, returns to finishing steers averaged $31.14/head.

While it is useful to investigate profits on the days the animals were actually slaughtered, it is important to determine whether animals of different genotypes progress differently throughout the feeding process and whether it may be optimal to market some genotypes differently than others. Table 5 reports estimates associated with the prediction models relating key carcass characteristics to days on feed. Results suggest the live weight model fits the data very well with an R^2 of 0.88. The number of observations in the live weight model is greater than the number of cattle because repeated weight measures were taken on animals throughout the feeding period. Results indicate that type1 and type2 cattle have significantly higher asymptotic mature weight than type3 cattle. Gender, frame score, and backfat measures at placement have significant impacts both on asymptotic weight and on the growth rate parameter k. The backfat model also fits the data well with an R^2 of 0.69. All coefficients except that associated with type7 are statistically different than zero at the 0.05 level of significance. The dressing percentage and ribeye area models do not fit the data as well as the other models, with R^2 values of 0.09 and 0.20, respectively.

The models shown in table 5 were used, along with a stochastic simulation, to determine the expected profit (both per head and per day) for each $t = 1$ to 250 days on feed. Table 6 reports summary results of the unconditional optimization segregated by gender and optimization objective, where the input variables of placement weight, backfat at placement, marbling score at placement, and frame score are set at genotypic- and gender-specific means. Overall, results suggest large differences in the optimal endpoint depending on the optimization objective. When profit/head is the goal, the optimal number of days on feed for most genotypes is around 160 days; however, the optimal number of days on feed falls to around 80 days for most genotypes when profit/head/day is maximized.

It is instructive to compare the results reported in table 6 with the number of days the cattle were actually fed. As shown in table 1, most genotypes were actually fed around 140 days. The results suggest profit/head could have been increased by feeding the animals slightly longer, whereas profit/head/day could have been increased had the animals been fed fewer days. An important caveat to this statement is that differences in the "optimal" endpoint and the endpoint to which the cattle were actually fed could simply reflect differences in the prices faced by the feedlot managers and the prices shown in tables 2 and 3. Either way, it is also not surprising to find that the estimated optimal profit reported in table 6 exceeds the average profit reported in table 4 (over twice as much in many cases), as the former approach reflects an overt attempt to

Table 5. Prediction Models for Optimization Analysis

Independent Variable	Live Weight Model[a]			Backfat Model[b]	Marbling Model[c]	Dressing Percent Model[d]	Ribeye Area Model[d]
	Function: A	Function: W_0	Function: k	Function: γ	Function: λ		
Constant	−763.025*** (66.134)	606.163*** (8.796)	−24.460*** (1.220)	12.249*** (0.502)	1.931*** (0.065)	58.458*** (1.798)	10.721*** (1.377)
Type1	39.477** (17.232)	57.930*** (11.609)	0.378 (0.249)	−1.450*** (0.268)	−0.010 (0.034)	0.454 (0.250)	0.374** (0.192)
Type2	67.549*** (15.375)	34.759*** (10.070)	1.095*** (0.228)	−1.530*** (0.229)	−0.003 (0.029)	0.263 (0.215)	0.159 (0.164)
Type4	28.160** (14.309)	35.932*** (9.554)	0.456** (0.226)	−1.600*** (0.215)	0.026 (0.027)	0.492*** (0.204)	0.366** (0.156)
Type5	25.718 (13.936)	22.791** (9.521)	0.279 (0.214)	−0.580*** (0.215)	0.000 (0.028)	0.092 (0.202)	−0.133 (0.154)
Type6	14.185 (14.259)	18.194 (9.894)	0.105 (0.217)	−1.270*** (0.227)	0.046 (0.028)	0.141 (0.211)	−0.110 (0.161)
Type7	−16.981 (28.691)	42.900** (19.190)	−0.400 (0.443)	−0.760 (0.409)	0.139*** (0.052)	−0.530 (0.407)	−0.292 (0.312)
Steer	754.983*** (27.292)	73.706*** (4.844)	4.478*** (0.308)	2.282*** (0.179)	−0.040*** (0.026)	−0.643 (0.180)	0.033 (0.138)
BF Method	3.912 (11.179)	—	0.863*** (0.118)	−2.300*** (0.114)	0.029 (0.021)	0.122 (0.165)	−0.353*** (0.127)
Placement Weight	—	—	—	−0.009*** (0.006)	0.0002** (0.00001)	0.003*** (0.001)	0.007* (0.001)
Frame Score at Placement	218.395*** (8.746)	—	1.682*** (0.087)	0.731*** (0.059)	0.011** (0.000)	−0.134 (0.057)	−0.108*** (0.044)
Backfat at Placement	3,149.631*** (155.900)	—	14.229*** (1.430)	—	1.037*** (0.240)	6.530*** (1.870)	−7.212 (1.433)
Days on Feed	—	—	—	—	—	0.034 (0.022)	−0.028 (0.017)
Days on Feed^2	—	—	—	—	—	−0.0001 (0.0001)	0.0001*** (0.0000)
R^2		0.88		0.69	0.97	0.09	0.20
Observations		5,456		3,372	1,668	1,668	1,668

Notes: Double and triple asterisks denote statistical significance at the 5% and 1% levels, respectively. Numbers in parentheses are standard errors.

[a] The model, $W_t = A - (A - W_0)e^{(k/1,000)t}$, was estimated by nonlinear least squares.

[b] The model, $bfat_t = bfat_0 e^{(\gamma/1,000)t}$, was estimated by nonlinear least squares.

[c] The model, $mbs_t = mbs_0 e^{(\lambda/1,000)t}$, was estimated by nonlinear least squares.

[d] The models are linear-in-parameters and were estimated by ordinary least squares.

manipulate days on feed to achieve higher profit levels. Although the profit levels reported in table 6 are large (about \$280 when maximizing profit/head), the figures are not outside the range of values actually observed around this time period. For example, Lawrence (2007) reported estimated returns to finishing steers as high as \$386/head in late 2003.

Results in table 6 reveal that as animals of different genotypes are moved toward their optimal marketing date, type2 steers (heifers) tend to generate the highest level of per head profitability at \$303/head (\$260/head) with type3 steers (heifers) lagging far behind at \$237/head (\$203/head). This relative ranking is generally consistent with the

Table 6. Summary Results from Profit Optimization: Unconditional Analysis

	Genotype						
Outcomes	Type1	Type2	Type3	Type4	Type5	Type6	Type7
Steers (optimize profit per head):							
Days on feed where expected profit per head is maximized	158	164	177	169	164	154	143
Expected profit per head at optimal day ($/head)	278.650	303.136	237.345	287.740	269.533	298.732	268.941
	(60.191)	(60.397)	(66.083)	(58.676)	(65.859)	(61.454)	(59.790)
	[1.903]	[1.910]	[2.088]	[1.856]	[2.083]	[1.943]	[1.891]
Steers (optimize profit per day):							
Days on feed where expected profit per day is maximized	81	79	88	77	80	135	110
Expected profit per day at optimal day ($/head/day)	1.953	2.149	1.600	1.918	1.924	2.080	2.209
	(0.637)	(0.647)	(0.573)	(0.665)	(0.637)	(0.448)	(0.542)
	[0.020]	[0.020]	[0.018]	[0.021]	[0.020]	[0.015]	[0.017]
Heifers (optimize profit per head):							
Days on feed where expected profit per head is maximized	160	170	156	157	158	163	129
Expected profit per head at optimal day ($/head)	237.173	260.037	202.606	241.864	221.163	227.804	220.226
	(56.529)	(57.028)	(57.592)	(54.989)	(57.798)	(56.120)	(57.120)
	[1.788]	[1.803]	[1.821]	[1.739]	[1.828]	[1.775]	[1.806]
Heifers (optimize profit per day):							
Days on feed where expected profit per day is maximized	78	76	93	125	87	87	77
Expected profit per day at optimal day ($/head/day)	1.623	1.786	1.381	1.750	1.491	1.530	2.254
	(0.713)	(0.730)	(0.654)	(0.477)	(0.652)	(0.651)	(0.796)
	[0.023]	[0.023]	[0.021]	[0.015]	[0.021]	[0.021]	[0.025]

Notes: Results are unconditional in that placement weight, backfat at placement, marbling score at placement, and frame score vary across genotype; they are set at the respective gender- and genotypic-specific means. Numbers in parentheses are standard deviations; numbers in brackets are standard errors.

static analysis, and as can be seen by the size of the standard errors, the differences across the best and worst performing genotypes are statistically significant. A similar result is observed for the profit/head/day optimization: type3 cattle exhibit the lowest level of per day profit whereas type2 cattle rank second highest. One small difference across the static and optimization analyses is that type4, while being the most profitable genotype in the static analysis, now ranks behind type 2 cattle in the optimization analysis both in terms of profit/head and profit/head/day. When comparing across optimization objectives, it is clear that type7 cattle, while being relatively unattractive on a per head basis, perform well on a profit per day basis. To further illustrate some of the issues at hand, figure 1 presents expected profit/head for type3, type4, and type7 steers as days on feed move from 50 to 250 days. Figure 2 reports the same results on a profit/head/day basis.

Table 7 reports results of a conditional optimization analysis where placement weight, backfat at placement, marbling score at placement, and frame score are held at constant levels for all genotypes (at the overall means for each gender). As might be expected, there is less heterogeneity in profits across genotypes when differences in input variables are held constant. However, type2 cattle still perform well, ranking highest regardless of optimization objective or gender. Cattle type3 and type7 still perform worse than the other genotypes in the conditional analysis on a per head basis, and type7 cattle fall from the highest ranking genotype in terms of profit/day to the lowest ranking genotype when input characteristics are held constant.

The primary results of this paper are presented in table 8, which shows the value of information related to selection and management. If a feedlot were restricted to pick the same marketing date for all seven genotypes, results indicate that the optimal number of days on feed (per head basis) would be 164 days for steers and 163 days for heifers, and expected profit would be \$280.31/head for steers and \$232.33/head for heifers. However, if a feedlot could optimally pick an endpoint for each genotype, expected profits would increase to \$282.88/head for steers and \$233.37/head for heifers. Thus, the value of genetic information to choose an optimal marketing date (i.e., the value of information for sorting) is about \$2.57/head (\$282.88 – \$280.31) for steers and \$1.04/head (\$233.37 – \$232.33) for heifers, results that are not statistically different than zero as evidenced by the size of the standard errors. Similar results are obtained when the optimization objective is profit/head/day. The results regarding the value of information for sorting is constant with the finding that agricultural profit functions are often rather flat near the optimum (see Pannell, 2006).

Table 8, also shows, however, that the expected profit can be significantly increased if a feedlot selected and fed only the best genotype (type2 if maximizing profit/head and type7 if maximizing profit/head/day) rather than being restricted to feed all genotypes in proportion to their representation in the sample. When maximizing profit/head, the value of genetic information for selection is \$22.82/head for steers and \$27.70/head for heifers. Again, these figures are quite large in comparison with the returns to finishing steer calves (\$31.14/head) over the past decade (Lawrence, 2007). When maximizing profit/head/day, the value of genetic information for selection is \$0.25/head/day for steers and \$0.67/head/day for heifers.

As a final step, it is important to ask how sensitive the results are to changes in assumptions about input and output prices which fluctuate across time. Table 9 reports results of a sensitivity analysis conducted to determine the effect of changes in prices

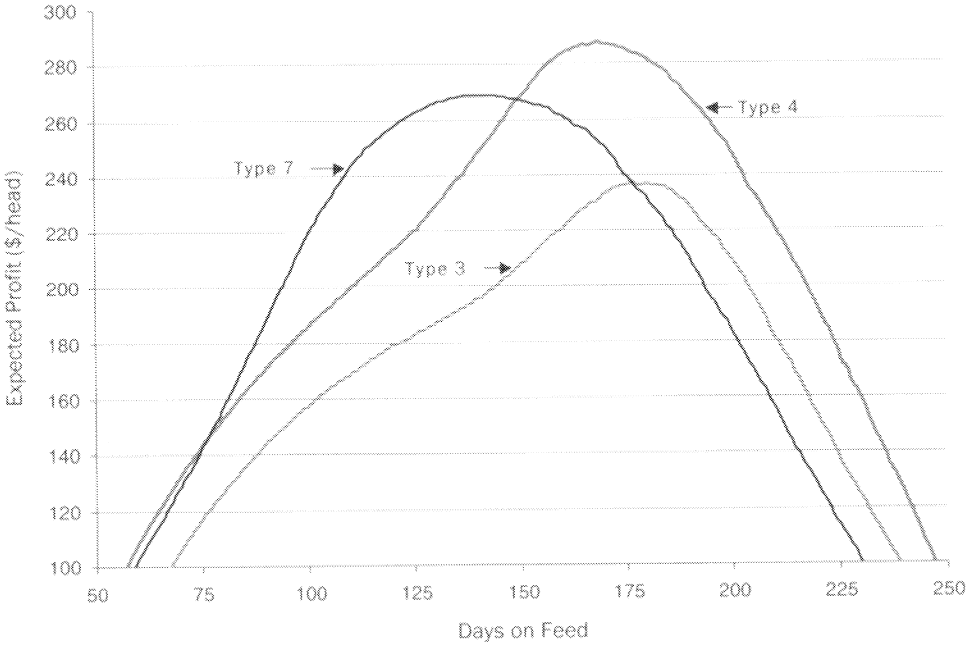

Figure 1. Expected profit per head for type3, type4, and type7 steers

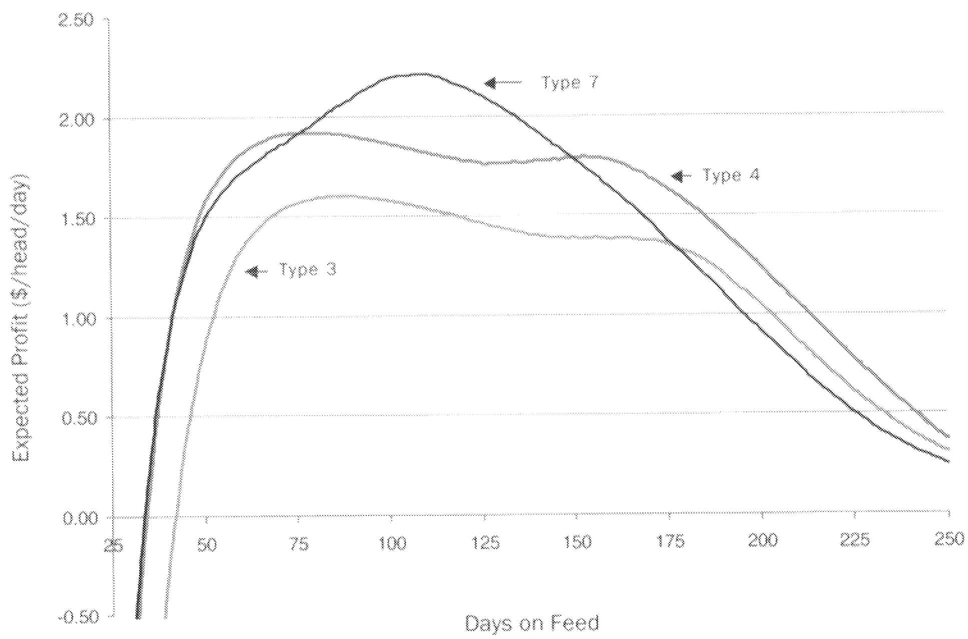

Figure 2. Expected profit per head per day for type3, type4, and type7 steers

Table 7. Summary Results from Profit Optimization: Conditional Analysis

	Genotype						
Outcomes	Type1	Type2	Type3	Type4	Type5	Type6	Type7
Steers (optimize profit per head):							
Days on feed where expected profit per head is maximized	166	163	161	166	161	163	158
Expected profit per head at optimal day ($/head)	297.401	302.393	260.851	296.136	273.245	285.962	269.900
	(58.406)	(60.036)	(66.592)	(58.258)	(65.383)	(61.778)	(63.082)
	[1.847]	[1.898]	[2.106]	[1.842]	[2.068]	[1.954]	[1.995]
Steers (optimize profit per day):							
Days on feed where expected profit per day is maximized	78	78	78	79	80	78	79
Expected profit per day at optimal day ($/head/day)	2.034	2.120	1.891	1.961	1.927	1.949	1.843
	(0.656)	(0.655)	(0.650)	(0.647)	(0.637)	(0.652)	(0.640)
	[0.021]	[0.021]	[0.021]	[0.020]	[0.020]	[0.021]	[0.020]
Heifers (optimize profit per head):							
Days on feed where expected profit per head is maximized	164	167	155	161	154	159	152
Expected profit per head at optimal day ($/head)	241.265	254.166	207.809	234.608	221.893	224.277	202.486
	(56.201)	(56.681)	(57.802)	(55.235)	(58.018)	(55.653)	(54.869)
	[1.777]	[1.792]	[1.828]	[1.747]	[1.835]	[1.760]	[1.735]
Heifers (optimize profit per day):							
Days on feed where expected profit per day is maximized	83	81	137	136	137	135	130
Expected profit per day at optimal day ($/head/day)	1.615	1.726	1.426	1.577	1.510	1.534	1.438
	(0.666)	(0.675)	(0.441)	(0.442)	(0.441)	(0.446)	(0.459)
	[0.021]	[0.021]	[0.014]	[0.014]	[0.014]	[0.014]	[0.015]

Notes: Results hold constant input factors for all genotypes. Regardless of genotype, placement weight, backfat at placement, marbling score at placement, and frame score are set at 714, 0.093, 29.24, and 6.05 for steers and 641, 0.093, 30.04, and 8.09 for heifers. Numbers in parentheses are standard deviations; numbers in brackets are standard errors.

Table 8. Value of Leptin Information in Selection and Sorting Beef Cattle

Marketing Strategy	Expected Profit from Unconditional Analysis (Steers)	Expected Profit from Unconditional Analysis (Heifers)
Results When Optimization Objective Is Expected Profit per Head ($/head):		
Optimally market cattle when all genotypes are restricted to be sold on the same day (164 days for steers, 163 days for heifers)	280.313 (1.733)	232.334 (1.732)
Market each genotype optimally	282.878 (1.958)	233.370 (1.789)
Market only the best genotype optimally (type2 for both steers and heifers)	303.136 (1.910)	260.037 (1.803)
Value of genotypic information for selection	22.823 (2.579)	27.703 (2.500)
Value of genotypic information for sorting	2.565 (2.615)	1.036 (2.490)
Results When Optimization Objective Is Expected Profit per Day ($/head/day):		
Optimally market cattle when all genotypes are restricted to be sold on the same day (81 days for steers, 87 days for heifers)	1.958 (0.080)	1.588 (0.020)
Market each genotype optimally	1.970 (0.019)	1.622 (0.020)
Market only the best genotype optimally (type7 for both steers and heifers)	2.209 (0.017)	2.254 (0.025)
Value of genotypic information for selection	0.251 (0.082)	0.666 (0.032)
Value of genotypic information for sorting	0.012 (0.082)	0.034 (0.028)

Note: Numbers in parentheses are standard errors.

on the profitability of each genotype and the value of information. In particular, the unconditional optimization analysis for steers reported in table 7 was re-conducted increasing (*a*) the cost of feed, (*b*) the grid base price, (*c*) the USDA Select discount in the grid, (*d*) the yield grade 4 discount in the grid, or (*e*) the feeder cattle price by 1% and calculating arc elasticities using the results reported in table 7 as the baseline. Results in table 9 associated with change in profitability are as expected: profitability of each genotype decreases with increases in the cost of feed, increases in the base grid price, decreases in the Select discount, decreases in the yield grade 4 discount, and decreases in feeder cattle prices. Profitability is especially sensitive to changes in the grid base price and feeder cattle price. A 1% increase in the grid base price increases expected maximum profits by about 4% when maximizing profit/head and from 4.3% to 6.9% when maximizing profit/head per day. A 1% increase in feeder cattle price decreases expected maximum per head profit by about 2.5% and expected maximum per head-per day profit from 2.3% to 4.6% depending on the genotype.

Focusing first on the results when the optimization objective is profit/head, it is clear that the value of information is relatively unaffected by changes in the cost of feed, the yield grade discount, or changes in feeder cattle price. A 1% increase in the grid base

Table 9. Effect of Changes in Cost and Price Assumptions on Profitability and Value of Information: Sensitivity Analysis for Steers in the Unconditional Optimization Analysis

	Effect of a 1% Increase in ...				
Variable	Cost of Feed	Grid Base Price	Select Discount	Yield Grade 4 Discount	Feeder Cattle Price
Arc Elasticities When Optimization Objective Is Expected Profit per Head (%):					
Maximum E[Profit] for type1	-0.67	4.43	-0.03	-0.08	-2.52
Maximum E[Profit] for type2	-0.61	4.01	-0.03	-0.07	-2.20
Maximum E[Profit] for type3	-0.85	4.88	-0.04	-0.11	-2.80
Maximum E[Profit] for type4	-0.65	4.13	-0.03	-0.05	-2.34
Maximum E[Profit] for type5	-0.70	4.42	-0.04	-0.11	-2.47
Maximum E[Profit] for type6	-0.59	3.96	-0.01	-0.07	-2.23
Maximum E[Profit] for type7	-0.57	4.14	0.00	-0.04	-2.50
Value of information for selection	-0.02	0.95	0.01	0.05	0.10
Value of information for sorting	-0.12	-0.57	0.73	-0.01	0.04
Arc Elasticities When Optimization Objective Is Expected Profit per Day (%):					
Maximum E[Profit] for type1	-0.57	6.36	-0.41	0.00	-4.28
Maximum E[Profit] for type2	-0.51	5.71	-0.37	0.00	-3.82
Maximum E[Profit] for type3	-0.68	6.85	-0.44	0.00	-4.62
Maximum E[Profit] for type4	-0.57	6.31	-0.40	0.00	-4.19
Maximum E[Profit] for type5	-0.57	6.31	-0.39	0.00	-4.01
Maximum E[Profit] for type6	-0.53	4.62	-0.07	-0.03	-2.34
Maximum E[Profit] for type7	-0.50	4.30	-0.03	-0.01	-2.73
Value of information for selection	-0.06	-10.09	2.83	-0.08	7.25
Value of information for sorting	-0.49	-36.81	10.89	-1.07	42.01

price, however, increases the value of information for selection by 0.95% and decreases the value of information for sorting by 0.57%. Increasing the select discount by 1% increases the value of information for sorting by 0.73%. With the exception of the effect of the grid base price on the value of information, the signs of the elasticities are similar when the optimization objective is profit/head/day. The magnitude of elasticities, however, is much larger when the optimization objective is profit/head/day. For example, a 1% increase in feeder cattle price increases the value of information for sorting by 42%. This large percentage change is a result of the fact that value of sorting in terms of $/head/day is small in magnitude. In the baseline case (see table 8), the value of genotypic information for sorting steers is $0.0116. Increasing the price of feeder cattle by 1% increases the value to $0.0165. This change (a $0.0049 increase), while small in absolute terms, is large in percentage terms: $(0.0049/0.0116) * 100 = 42\%$.

Conclusions

The objective of this paper was to determine the economic value of using information on leptin genotype to select and manage cattle. Using a data set of 1,668 commercially fed beef cattle, both static and optimization analyses were conducted for seven distinct genotypic categories. In the static analysis, profits were compared across genotypes given the carcass characteristics that animals actually possessed at slaughter. In the optimization analysis, a number of models were employed to predict the optimal number of days on feed for each genotype and expected profit was compared at each genotype's optimum number of days on feed.

Results of the static analysis reveal statistically and economically significant differences across genotypes. Type2 and type4 cattle generated the highest profit levels, generating over \$23/head more profit than type3, the worst performing genotype. Even after controlling for observable factors, such as frame score and placement weight, the difference in profit from the worst and best performing genotype was in excess of \$14/head. In the optimization analysis, type2 cattle remained the highest profit-generating genotype when the optimization objective was profit/head, but type7 was the most profitable on a profit/head/day basis in the unconditional analysis. In the optimization analysis, type2 steers generated over \$66/head and \$0.55/head/day more profit than the worst performing genotype.

Overall, results reveal that the value of using leptin information to optimally choose days on feed is relatively small (about \$2.57/head for steers and \$1.04/head for heifers), but the value of using leptin information to optimally select cattle is relatively high (over \$22/head for both steers and heifers). The results presented here, in terms of their qualitative implications, are similar to those reported by Lambert, DeVuyst, and Moss (2006), who found that the value of genotypic information for sorting was not statistically different than zero, but that there were statistically significant differences in profitability across the three genotypes they studied.

It is prudent to compare the value of information with the cost of genotypic information. At present, there are no commercial companies selling genetic tests for only the two markers studied in this analysis; however, IGENITY (a business unit of Merial Ltd., a large animal health company) currently charges \$37.50/head for a profile of markers which includes the two leptin markers examined here. The leptin markers make up about 25% of the profile. Thus, assuming relatively small fixed costs, an approximate cost estimate for leptin information alone is $\$37.50 * 0.25 = \$9.38$/head.

The results of this analysis indicate that while it is important to properly choose the number of days to feed cattle, it is perhaps more important to start off with the right kind of cattle. The value of genetic information, as determined by this study, is that it will allow cattle producers to purchase and feed animals of certain genotypes, while avoiding cattle of other genotypes. Although the present study indicated a small and insignificant value to using genotype to manage cattle by choosing differential endpoints, the potential for using such strategies remains. In particular, future work is aimed at further refining the prediction equations, especially the feed intake and marbling equations. Clearly, it would be expected that variations in the leptin gene would be strongly associated with feed intake. Unfortunately, suitable data were unavailable to model dry matter intake as a function of days on feed and genotype. Another important component of refining the prediction models rests with identifying additional variations in the leptin gene, and indeed, animal scientists are reporting new variations at a rapid pace.

A final area of inquiry worthy of future research relates to the assumption of input and output price exogeneity that was employed in the present analysis. In long-run equilibrium, feedlots would be expected to bid up the price of more productive genotypes and to bid down the price of less productive genotypes until the point at which all genotypes are equally profitable. Resulting price differences across genotypes would reflect differences in marginal productivity. The ultimate recipients of the welfare gains resulting from improvements in the ability to identify leptin genotype will be the owners of fixed assets: owners of the most productive genetic stock, owners of leptin identification technology, and consumers who benefit from lower prices and/or higher quality resulting from a supply chain better coordinated by improved information.

[*Received October 2006; final revision received March 2007.*]

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