ECONOMIC VALUE OF LEPTIN GENOTYPE

INFORMATION IN BEEF CATTLE

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TABLE OF CONTENTS

LIST OF TABLES

Table Page

LIST OF FIGURES

Figure Page

CHAPTER I

INTRODUCTION

Background

Leptin is a protein hormone that is produced and released by stored fat cells in blood serum and communicates through receptors in the brain to regulate appetite and metabolism in the body (Friedman and Halass 1998). Upon receiving signals of the amount of energy stored as fat in the body, appetite is encouraged or curbed. During starvation leptin levels fall and a metabolic response takes place in the body to promote appetite. According to Houseknecht et al. (1998), there is variation in the leptin gene and in its receptors, and thus, not all humans and animals produce and recognize leptin in the same way.

Body composition and weight gain are the primary goals of commercial livestock production. In 1998, Houseknecht et al. suggested that as a metabolism modifier, leptin and its expression should be studied to improve the productive performance of animals. Further findings from animal testing indeed showed that the level of leptin an animal possesses highly correlates to many profitable variables. Geary et al. (2003) found marbling, yield grade and dressing percentages in beef cattle significantly positively correlated with pre-slaughter blood serum levels of leptin. With the practicality of using leptin to predict the level of fat deposition, new technology has been developed to identify cattle with different leptin levels. Producers and feedlot operators are now able to readily distinguish cattle with varying leptin genotypes through the testing of a DNA sample.

Problem Statement

Various research, including that by Buchanan et al. (2002), Fitzsimmons et al. (1998), Lagonigro et al. (2003), and Nkrumah et al. (2005) has shown that variation exists in the leptin gene and the leptin promoter region of animals. These findings suggest that animals do not produce the same type of leptin. Some animals may continue to deposit fat when they have an adequate supply of energy due to certain types of leptin being less recognizable to the brain's receptors. These variations have been positively linked to cattle performance, fat measurements, lean yields, beef tenderness, (Fitzsimmons et al. 1998; Kononoff et al. 2005; Schenkel et al. 2005) and feed intake (Lagonigro et al. 2003; Nkrumah et al. 2005).

Although many biological studies concerning leptin and its associated physical correlations have been completed, little regard has been given to the economic gains that could be obtained due to this information. In recent years the marketing of fed cattle has increasingly moved from a pen basis where animals are all valued at an average price to a more complex system of grid or value-based pricing. The move toward value-based pricing, according to Ward, Schroeder, and Fuez (2001), allows for more accurate communication of value between beef markets and producers by rewarding producers who supply higher quality cattle and properly discounting beef of lower quality.

However, the complexities of a value based marketing system require producers to know more about their cattle prior to slaughter. By applying premiums and discounts based on variations in carcass weight, yield grade, and quality grade to a specified base price, the grid price is determined. Base prices, premiums and discounts all can vary over time and across packers. Greer and Trapp (2000) state that the trade-off of quality and yield and the costs of gain per pound, the relationships between feeding costs, weight, and premiums and discounts for quality and yield grades make the decision making process complex. They further imply that the genetics of the animal and the economic conditions both influence when the economic endpoint occurs for feeding. Therefore, there is an increasing need for producers to have carcass level information prior to slaughter to determine to the optimal time on feed in order to most profitably market their cattle. Schroeder and Graff (2000) and McDonald and Schroeder (2003) demonstrate the value of carcass knowledge prior to slaughter. For example, Schroeder and Graff (2000) showed that if accurate knowledge of cattle quality and yield grades were used to market each animal optimally, on a dressed-weight, live-weight, or grid basis, average revenues of $15.14/head to $34.74/head could be realized. Koontz et al. (2000) also examined the economic returns that could be earned by feedlot operations that used ultrasound to sort animals prior to marketing to find increased returns of between $11 and $25 per head.

Genetic testing is one potential solution to producers' need for pre-harvest information. Carcass level data can be obtained in a quicker, potentially less invasive, and more economical manner than other methods used to acquire similar information such as live-animal ultrasound or blood serum testing. Still, producers and feeders need to know if economic gains could be acquired by using leptin information in breeding selection, feeding practices, and marketing methods before deciding whether to adopt this technology.

Objectives

The objective of this research is to provide feeders and producers with information about the economic value of using leptin genotyping as a tool in production and marketing decisions. This information can be valued in two specific ways: the value of leptin information for selecting cattle and the value of leptin information to sort and market cattle according to their most optimal end point. Specifically, this paper seeks to determine if differences in profitability exist across leptin genotypes in beef cattle given certain price and cost assumptions. Furthermore, the research will determine whether these differences result from variations in observable traits. For example, differences in observable characteristics at placement, such as weight or frame score, may explain many of the differences in revenue and profitability of cattle. Beyond this, the research will determine the value of leptin genotype information when implemented in selection, feeding, and marketing decisions.

Organization of the Study

Relevant literature is reviewed in Chapter II. The conceptual framework is presented in Chapter III. Empirical procedures and data sources are in Chapter IV. Chapter V presents the findings of the study. Chapter VI contains a summary, conclusion and recommendations, and suggestions for future research.

CHAPTER II

REVIEW OF LITERATURE

Much of the previous research about the leptin, or obesity, gene has been done from a biological perspective. Several studies have been undertaken to determine leptin's role in the body and its association with observable characteristics. Furthermore, research has been conducted concerning the current beef industry and how information, genetic or other types, could be helpful in attaining higher revenues and making better management decisions.

Leptin: A Biological Perspective

Leptin has many functions in the body of humans and other species. According to Houseknecht et al. (1998) leptin is a protein that is secreted from adipose tissue. It has various roles in the body, but is vital in regulating energy and metabolism (Nkrumah et al. 2005), and according to Freidman and Halaas (1998), it plays a critical role in regulating body weight. Mutations exist in the leptin and leptin receptor genes that have been linked to obesity (Houseknecht et al. 1998). These variations cause differences in the way leptin is secreted and recognized in the body causing some forms to be less recognizable to the brains receptors

In a study done by Geary et al. (2003), links were established between leptin levels and carcass composition in beef cattle. Blood samples were taken twenty-four hours prior to slaughter, and serum concentrations of leptin were then analyzed in regard to carcass measurements in the harvested cattle. The findings indicate positive correlations of leptin with marbling score, fat depth, kidney pelvic and heart fat, and quality grade in the sample. Also, leptin was significantly linked to dressing percentage and calculated yield grade in the cattle. Therefore, leptin seems to have a significant association with carcass composition.

Berg et al. (2003) and Fabian et al. (2003) found positive correlations with leptin and back fat measurements and feed intake in swine and showed leptin concentrations to be consistent with breed-specific carcass traits for growth, leanness, and pork quality. Other research concerning bovine leptin (Buchanan et al. 2002; Fitzsimmons et al. 1998; Kononoff et al. 2005; Nkrumah et al. 2005; and Schenkel et al. 2005) reported that different single nucleotide polymorphisms (SNPs), small genetic variations that occur within the DNA sequence, exist in the bovine leptin gene. Buchanan et al. (2002) and Kononoff et al. (2005) report significant associations between a SNP of leptin and beef carcass fat levels. Fat characteristics of beef bulls studied by Fitzsimmons et al. (1998) were found to be associated with a microsatellite, or a short segment of DNA that has a repeated sequence, near the obesity gene. Nkrumah et al. (2005) studied associations between SNPs in UASMS, the leptin promoter region, with a variety of growth, feed, and carcass traits. Their research found that UASMS2 was significantly associated with blood serum levels of leptin, feed intake, and fat measurements. By evaluating SNPs in both the leptin and leptin promoter genes, Schenkel et al. (2005) identified significant associations with leptin and lean yield, fatness, and beef tenderness. These results indicate that leptin information could be useful in identifying carcass characteristics and feeding behavior in live animals.

Applications to Animal Agriculture

Beef consumers today place emphasis on high quality, uniform products. In order to achieve this, cattle must be fed in a more optimal way and valued on an individual basis as opposed to all animals being fed and marketed in the same way. Uniformity and consistency are especially difficult in the beef industry due to the long biological lag in production, the inability to control the environment of cattle coming to feedlots from producers in different regions with different management practices, and the broad diversity of genetics which vary across breeds and across individual animals.

According to various research including that by Schroeder et al. (1997) and Schroeder and Graff (2000), fed cattle marketed on an average or pen basis inhibit communication of consumer preferences to producers. This, and the ability to more accurately determine beef quality attributes, is critical if improvements are to be made in the beef industry. In the past, typical feedlot operations separated cattle into pens on the day they arrived to be fed out and marketed at the same time. In live or dressed weight marketing strategies, these cattle are then marketed based on a pen average where all animals receive the same price independent of their individual quality. In recent years more animals are being marketed on a value or grid based system. The intent of grid pricing is to assign higher prices to higher quality cattle and to pay lower prices to cattle of lesser quality (Ward, Fuez, and Schroeder, 1999; Ward, Schroeder and Fuez, 2001).

Ward, Fuez, and Schroeder (1999) state that carcass level information is valuable to feedlot operators and producers. Not only can more accurate information about cattle quality be used to influence marketing practices, but it can also be implemented into procurement and production methods. In other words, using grid pricing, feedlot operators have more incentive to alter their practices or augment the types of cattle they purchase in order to obtain cattle that more readily fit a grid.

Using knowledge of leptin genotypes in cattle feeding and marketing could also have positive implications for beef uniformity and quality consistency. It is proposed by Williams (2002) that the ability to estimate carcass traits in live animals will allow for sorting and selection based on carcass merit. Kononoff et al. (2005) and Hennessy, Miranowski, and Babcock (2004) state that in order to deliver uniform products, more must be known about the genetic makeup of the individual animals and a system for sorting cattle into similar feeding and marketing groups must be developed. According to Perry and Fox (1997), tools are needed to predict feed consumption and carcass composition in individual animals. If methods were established to affordably do so, improved uniformity could be reached, feeding methods and marketing techniques could be individually assigned or assigned to similar groups, and feedlot values could be maximized as cattle are marketed appropriately (Kononoff et al. 2005; Schroeder and Graff 2000).

Economic Value of Information

Hennessy, Miranowski, and Babcock (2004) develop two methods of valuing information in production decisions. First, they evaluate sorting and improved returns due to differentiation, and then they value the use of information in individual specific production decisions. Ward, Schroeder, and Fuez (2001) propose that producers could best recognize the long term value of information by using the information in their management decisions. Management such as sorting of cattle may help reduce the variability in individual carcasses. Further, they suggest that implementing ultrasound or some other method of determining carcass traits prior to slaughter could improve the management of quality and yield grades and help to signal when to market cattle. Research by Greer and Trapp (2000) concluded that the length of time animals are on feed is another management method that can increase profits for producers and feedlot operators.

In an attempt to determine the value of information in the marketing of beef, Schroeder and Graff (2000) valued each carcass in their study by the method (live weight, dressed weight, grid basis) that resulted in the highest revenue. Their results show that gains in revenue could be realized if producers had better knowledge of the quality and yield grades of their cattle prior to marketing and then incorporated that knowledge into marketing decisions as opposed to simply marketing all cattle using the live weight, dressed weight, or grid based method. Specifically, when using the method resulting in the highest price, prices were \$15.14 more per head than when all cattle were marketed on a dressed weight basis, \$18.67 more per head than when selling all cattle on a grid, and \$34.74 more per head than when live weight pricing was used. These results indicate that substantial returns could be obtained by producers if they had more accurate per-harvest carcass data for their cattle and marketed them in the most optimal method.

Koontz et al. (2000) examined the economic returns that could be earned by feedlot operations that used ultrasound to sort animals prior to marketing. Cattle were divided into more uniform pens and then marketed in a method that maximizes returns on the basis of weight, yield grade, and quality grade. The returns were between $11 and $25 per head when each animal was marketed at its optimum marketing date depending on the number of pens in which the animals were sorted. Thus, there appear to be sizeable economic gains to sorting prior to marketing. However, it should be noted that the study may have overestimated the value of the ultrasound by assuming that the technology was 100% accurate in its ability to "backcast" the carcass characteristics, and the study did not consider economic gains from choosing the best marketing method for the animals.

Lusk et al. (2003) estimated the value of using ultrasound technology to improve cattle marketing decisions by marketing animals in the most optimal method. They stated that the use of ultrasound technology has value in two primary ways, the ability to sort cattle into more homogenous groups and market them using the most optimal method and sorting similar groups in order to feed the animals the most optimal length of time. Focusing only on the use of ultrasound to determine optimal marketing method, they found revenues could be increased between $5 and $33 per head when ultrasound was used to choose the best marketing method over simply marketing all cattle on a dressed weight or grid basis, respectively, without ultrasound information.

Work was also done to determine the potential of ultrasound information to reduce the uncertainty of marbling prior to harvest (Ferguson and Anderson 2001). A Bayesian framework was implemented to value the ultrasound data. It was found that by using information in decision making to sort and market cattle using the optimal method, grid or live weight basis, added returns from \$6.38 to \$8.42 could be attained depending on the posterior probabilities of the cattle grading choice or above.

Aside from deriving value from information by sorting and optimally marketing cattle, genetic management and selection may also be guided by the use of genetic information to increase profitability. Robertson and Parcell (2006) sought to determine whether managing genetics has an impact on the quality of beef carcasses by determining the value of retaining seedstock based on the high quality of carcasses with the same genetics. Results indicated that knowledge of genetic information for more than one generation increased the likelihood of the carcasses grading prime, but may not affect the likelihoods of Choice or Select grading carcasses. However, the study only considered the retention of heifers from superior quality dams and did not consider genetic selection based on EPDs.

Economic Value of Leptin Genotype Information

While recent research broadly covers the economic value of using technology, primarily ultrasound, and genetics in production and marketing decisions, little has been done to determine the economic value of genotypic information related to leptin when implemented by producers and feedlot operators. Lambert, DeVuyst, and Moss (2006) recently valued the effects of genetic information regarding leptin. Using performance data and leptin genotype information on 180 feedlot steers their work measured the value of information related to leptin. A distribution of returns was derived based on days on feed and a group of animal characteristics.

They concluded that leptin genotype was not statistically significant in determining the optimal number of days to feed an animal. However, results indicated that variations existed in the distribution of net returns across genotypes. Their study is limited, however, by a small sample size, the use of only one SNP that has been linked to leptin diversity, and by the fact that while the study appears to determine variations in mean profits, it is unclear how costs were calculated and if the costs varied across genotype. Further, only genotypic characteristics were used to explain profits, and it was not considered whether profit variations were simply explained by observable phenotypic traits.

Furthermore, Bullinger et al. (2006) expanded the work done by Lambert, DeVuyst, and Moss (2006) using 590 crossbred steers to estimate growth models, with and without genotypic information, for rib-eye area, backfat, weight, and marbling score and then forecasted these traits over a range of days on feed. Then, the estimated traits were used to calculate expected profits and to find the optimal number of days on feed for each animal. Their results were similar to those of Lambert, DeVuyst, and Moss (2006) in that they found little value in using leptin genotype information in determining optimal days on feed, but significant differences in carcass value, and thus profitability. Again, the research was limited by the use of only one SNP of leptin genotype and a small sample of cattle at one feedlot. Lastly, the research only implemented the use of grids rewarding marbling, and, therefore, cannot be considered adequate for comparison to other grid types.

Originality of the Research

The present study extends past research in a variety of ways. Carcass level information on a large sample of 1,668 feedlot cattle, along with leptin genotype information on two SNPs, is used. Sensitivity to assumptions about grid pricing is investigated by using multiple grids in predicting the expected profits of the data set. Furthermore, not only are the existence of variations in revenues across genotypes examined, but consideration is also given to other input variables to determine if profitability variations can be simply explained by the differences in observable traits. Efforts are made to determine the value of using genotypic information to improve production and marketing decisions.

CHAPTER III

CONCEPTUAL FRAMEWORK

The Profit Maximizing Firm

The primary goal of the firm is to maximize revenue while minimizing costs, or in other words to maximize profits. In order to increase profits, a producer must develop carcass traits by feeding animals a certain number of days on feed, but feeding additional days also has accompanying costs that must be considered in order to determine the most economically optimal endpoint. Another challenge facing feeders is the biological nature of beef production, which makes it difficult for cattlemen and feedlot operators to determine an animal's exact internal characteristics before slaughter and, therefore, difficult to determine the most profitable number of days to feed the animal. In the past, cattlemen have relied on observable traits and sometimes on ultrasound measures to best determine the optimal endpoint in which to feed their cattle.

Profits can be impacted in multiple ways during the feeding period. First, over time, changes occur in the animal's ribeye area, hot carcass weight, backfat, and kidney, heart, and pelvic fat. All of these traits are directly linked to the animal's yield grade. Alternatively, quality grade is affected due to increases in intramuscular fat over time. Lastly, each additional day on feed accompanies the costs associated with maintaining and holding the animal. Both quality and yield grade tend to increase over time;

however, while increases in quality grade typically increase profits, simultaneous increases in yield grade have a negative effect on carcass value. Given the trade-off between quality and yield grade that determine the animal's profit on a grid and the economic conditions such as feed costs and cattle prices, producers face complex decisions about the most economically optimal points at which to market their cattle.

These relationships can be further illustrated by the maximizing the profit function:

$$(1) \qquad \underset{t}{Max}\ \pi_i = [\mathrm{W_i}(t) \cdot P_i(YG_i(t), QG_i(t))] - Cost_i(t)],$$

where revenue is simply the weight of the animal *W*, which is a function of time, multiplied by price, *P*, which is a function of quality grade, *QG*, and yield grade, *YG*, which are both functions of time, and where cost, *Cost*, also varies over time. By optimizing profits with respect to time, it can be shown that weight, changes positively with time, but increases at a decreasing rate:

$$(2) \qquad \frac{\partial W}{\partial t} > 0, \ \ \frac{\partial^2 W}{\partial t^2} < 0.$$

Furthermore, quality grade and yield grade both increase over time, but these changes have opposite effects on price over time as shown by:

$$(3) \frac{\partial P}{\partial t} = \frac{\partial P}{\partial \mathrm{YG}} \cdot \frac{\partial \mathrm{YG}}{\partial \mathrm{t}} + \frac{\partial \mathrm{P}}{\partial \mathrm{QG}} \cdot \frac{\partial \mathrm{QG}}{\partial \mathrm{t}} \quad \text{where, } \frac{\partial P}{\partial \mathrm{YG}} < 0, \frac{\partial \mathrm{YG}}{\partial \mathrm{t}} > 0, \frac{\partial \mathrm{P}}{\partial \mathrm{QG}} > 0, \text{and} \ \frac{\partial \mathrm{QG}}{\partial \mathrm{t}} > 0.$$

Therefore, an economically optimal point exists where the balance of costs and price premiums are maximized.

The Value of Information

The economic theory of information states that while obtaining information is costly, it can be useful in improving decisions. Previous knowledge is updated with the new knowledge and the decision is then reexamined based on the new information set. According to Babcock (1990), the value of the information to an individual producer or feeder is shown by the difference between the expected returns using the information and the expected returns without the information:

(4) $$\text{Value of Information} = E(\pi \mid \text{Information}) - E(\pi \mid \text{No Information}).$$

The aggregate value of information is then the sum of all of the individuals' values. Therefore, genetic information that could predict unobservable traits pre-slaughter and help in making production and marketing decisions could assist producers and feeders in improving the profitability of their decisions.

With no information on genotype, producers and feeders simply purchase random distributions of cattle to feed. If information was available concerning more profitable genotypes of cattle, producers could then purchase specific types of cattle to feed and increase the likelihood of achieving higher profits. Similarly, the use of genotypic information in sorting and feeding more homogenous groups of cattle would increase the likelihood of correct timing of marketing cattle versus trying to feed and market all types of cattle to a specified endpoint.

Hypotheses to Be Tested

Information related to leptin gene has been positively linked to many of the traits that cattlemen and feedlot operators presently use to determine the best feeding and marketing strategies. Thus, data should be evaluated to determine the extent of variations in profitability across different leptin genotypes and the explanation for these differences. The following hypotheses will be tested:

1. Unconditional mean profits and revenues are unaffected by leptin genotype.
2. Differences in mean profits and revenues are unaffected by leptin genotype, holding constant observable traits at placement.
3. Using leptin genotype information for selection will not increase profits.
4. Using leptin genotype information to sort animals and choose the optimal number of days to feed them will not increase profits.

CHAPTER IV

METHODOLOGY

Overall Description

Two simulations were conducted. The first, a static simulation, evaluated the profitability of the set of cattle on the dates in which they were actually slaughtered given a set of price and cost assumptions. In the second, a dynamic simulation, the optimal number of days on feed is determined, and profitability is compared across genotypes at their optimal days on feed.

Data Description

The data set contains observable carcass information from 1,668 head of beef cattle fed in twenty-six pens in the same commercial feedlot from August to November 2004. Entry weights and ultrasound readings to determine backfat thickness were recorded at placement. Also, a hair follicle was obtained from each animal to identify genotypic information. Additional weight and ultrasound measures were taken for the animals up to three more times prior to harvest. At slaughter, marbling score, quality grade, yield grade, and hot carcass weight data were collected.

To analyze genetic variation in the leptin gene, geneticists investigate single nucleotide polymorphisms or SNPs, which are variations in the DNA sequence when a single nucleotide (A, T, C, or G) in the genome sequence is altered. For example, a SNP might change the DNA sequence AAGGCT to ATGGCT. Schenkel et al. (2005) found two particular variations in the genome sequence found to influence leptin production and they serve as the focus of this analysis: UASMS2 and EXON2. Both contain two alleles (C and T) and can either be homozygous (e.g., CC or TT) or heterozygous (CT). Thus, there are three possible outcome combinations for each SNP (CC, TT, or CT) making nine possible genotypes available for analysis. Three of the genetic types occurred with very low frequencies in the population, so cattle of these genotypes were pooled into an "other" group. For simplicity, these genotypic categories will be referred to as type1 through type7 in the remainder of this study where type1 = (EXON2-CC;UASMS2-CC), type2 = (EXON2-CC;UASMS2-CT), type3 = (EXON2-CC;UASMS2-TT), type4 = (EXON2-CT;UASMS2-CC), type5 = (EXON2-CT;UASMS2-CT), type6 = (EXON2-TT;UASMS2-CC), type7 = (all other EXON2, UASMS2 combinations).

Table 1 reports summary statistics by genotype. As shown by the table, most of the cattle were of the type4 or type5 genotypes. Together, these two types comprised of almost 48% of the cattle in the sample. Only twenty-nine cattle, or 1.7%, were of "other," type 7 genotypes. For almost every variable reported in the table, the hypothesis that the means are equivalent across all seven genotypes is rejected at the P=0.05 level of significance or higher. Although only comprising of 1.7% of the sample, type7 cattle tended to be the fattest, having higher marbling scores 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 scores and type4 had the lowest yield grade. Type1 cattle had the highest average placement weight. Indeed, the fact that

Table 1. Summary Statistics: Means by Genotype

Variables	Genotype							
	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 by 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	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	2.50	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
Estimated Dry Matter Intake (lbs)	2955.63	2953.08	2828.24	3021.44	2912.89	2969.96	2977.06	<0.01
Live Weight at Slaughter (lbs)	1245.08	1213.50	1168.55	1229.90	1206.58	1213.35	1238.45	<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]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 an animal to a constant backfat at slaughter.

genotype differs in both input variables, such as placement weight, and output variables, such as yield grade, makes it difficult to determine the extent to which the variations in the outputs are a result of the differences in genotype by simply looking at the means.

Due to interest in calculating the profit for each of the observed animals in the data set, several considerations must be made. To eliminate any market variations that occurred over time, it is assumed that all animals faced equivalent market prices. Weekly dressed weight prices are reflective of the five-market weighted average by the USDA-AMS for the end of 2002 and beginning of 2003 and are used in grid pricing calculations. The base grid price is calculated as:

$$GRIDP = DRESSP + SPREAD \cdot CHOICE \tag{5}$$

where *GRIDP* is grid based price, *DRESSP* is dressed weight cash price, *SPREAD* is the choice-to-select price spread and *CHOICE* is the plant average percent choice or the percentage of the data set grading choice. Weekly grid premiums and discounts were obtained from the USDA-AMS National Carlot Meat Report or “Blue Sheet” for the year of 2004. The average premiums and discounts reported from various packers to the USDA-AMS over this time were used to formulate a “base grid.” Furthermore, to determine sensitivity of the results to the grid structure, two additional grids were constructed: a “quality grid” where differences in the quality grade premiums and discounts were more pronounced and a “yield grid” where differences in yield grade premiums and discounts were made more pronounced. The specific prices used in the analysis are located 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 across steers and heifers for use in the analysis. Additional costs are reflective of commercial feedlot budgets published in the Kansas State University Farm Management Update for 2003. Additional per day yardage costs are $0.05, and fixed costs consist of veterinarian and processing costs.

Table 2. Price Data Used in Static and Dynamic Simulation Analyses

	Grids		
Grid Components	**Base[a] ($/cwt)**	**Quality ($/cwt)**	**Yield ($/cwt)**
Base Price[b]	$118.00	$118.00	$118.00
Quality Grade Adjustment			
Prime	$8.29	$10.00	$8.29
Choice	$0.00	$0.00	$0.00
Select	-$8.72	-$15.00	-$8.72
Standard	-$18.25	-$25.00	-$18.25
Yield Grade Adjustment			
1.0 - 2.0	$2.93	$2.93	$3.25
2.0 - 2.5	$1.67	$1.67	$2.00
2.5 - 3.0	$1.24	$1.24	$1.50
3.0 - 3.5	-$0.08	-$0.08	-$0.08
3.5 - 4.0	-$0.08	-$0.08	-$0.08
4.0 - 5.0	-$13.70	-$13.70	-$14.25
> 5.0	-$18.04	-$18.04	-$18.50
Carcass Weight			
< 500 lbs.	-$21.69	-$21.69	-$21.69
500 - 550 lbs.	-$14.98	-$14.98	-$14.98
950 - 1000 lbs.	-$7.44	-$7.44	-$7.44
> 1000 lbs.	-$18.04	-$18.04	-$18.04

[a]Prices in base grid reflects the averages of grid premiums and discounts reported by the USDA/AMS for year 2004.

[b]Grid base price is calculated based on the formula: Grid Base Price = (dressed weight cash price) + [(Choice-to-Select price spread) x (plant average percent Choice)], where price is assumed to be $114.43 which is reflective of the five market weighted average as reported by USDA/AMS for late 2002 and early 2003.

Table 3. Cost Data Used in Static and Dynamic Simulation Analyses

Cost Variable			Cost
Feeder cattle Prices ($/cwt)[a]			
0 lbs.	to	349 lbs.	$112.32
350 lbs.	to	399 lbs.	$110.63
400 lbs.	to	449 lbs.	$107.54
450 lbs.	to	499 lbs.	$102.08
500 lbs.	to	549 lbs.	$97.77
550 lbs.	to	599 lbs.	$94.42
600 lbs.	to	649 lbs.	$91.07
650 lbs.	to	699 lbs.	$90.39
700 lbs.	to	749 lbs.	$88.20
750 lbs.	to	799 lbs.	$86.56
800 lbs.	to	849 lbs.	$84.27
850 lbs.	to	899 lbs.	$81.82
900 lbs.	to	949 lbs.	$78.88
950 lbs.	to	.	$77.60
Cost of Feed (dry matter basis $/ton)[b]			$117.65
Additional Per-Day Costs ($/head/day)[b]			$0.05
Fixed Cost ($/head)[b]			$8.00
Interest Rate (%)[b]			8.00%

[a]Average steer and heifer western Kansas feeder prices as reported by USDA/AMS for 2003.

[b]Costs are reflective of costs reported in the Kansas State University Farm Management Update for 2003. Additional per day costs are yardage costs and fixed costs consist of veterinarian and processing expenses.

Procedures

Static Marketing Simulations

The first step in the analysis of the data was to determine whether revenue and profit differ across leptin genotypes. As a first step profits were calculated for the time that each animal was actually marketed in order to avoid difficulty in predicting output characteristics had the animal been harvested sooner or later than their actual slaughter date.

Per-head revenues were determined for each of the three grids by

$$REV = DW \cdot GRIDP + ADJ \tag{6}$$

where *REV* is per-head revenue, *DW* is dressed weight in lbs., *GRIDP* is grid price in \$/lb. and *ADJ* is the adjustment for appropriate premiums or discounts. Per-head costs (*COST*) were calculated by

$$COST = r \cdot FEED + (WT \cdot P)(1 + (i / 365))DOF + FC \tag{7}$$

where *r* is the cost of feed in \$/lb., *FEED* is feed intake in lbs., *WT* is equal to placement weight in lbs., *P* is feeder cattle price in lbs./\$, *i* is the interest rate/365, *DOF* is the number of days on feed, and *FC* is the additional fixed costs per head.

Per-head profit is simply the difference in revenue and cost per-head. ANOVA tests were conducted to determine whether the mean per-head revenues and profits differ across genotypes. Comparing mean revenue and profit across genotype provides insight regarding the use of genotype information that feeders may want to implement in their purchasing decisions to avoid less profitable genotypes and identify animals that may be more profitable to feed. If so, producers and feeders can conclude that variation exists among different leptin types.

A simple comparison of the means across genotypes does not control for differences in easily observable traits at purchase, such as placement weight and frame score. Therefore, it obscures the fact that feeders can observe characteristics about the cattle they are buying. Therefore, to determine if differences in profitability persist after controlling for other measurable characteristics, it is necessary to use econometric modeling to conduct a conditional analysis. By controlling measurable or observable traits, we can determine whether variations in profits and revenues persist across genotypes or if they are simply due to phenotypic differences. The explanatory variables and each of the genotypes will be used to estimate both mean revenue and profit independently.

The general econometric models, π for profit and *REV* for revenue, are

$$(8)\ \pi = \beta_0 + \beta_1 WT + \beta_2 BFAT + \beta_3 FRAME + \beta_4 DOF + \beta_5 STEER + \beta_6 BFMETHOD + \sum_i^7 \alpha_i type_i + e$$

$$(9)\ REV = \beta_0 + \beta_1 WT + \beta_2 BFAT + \beta_3 FRAME + \beta_4 DOF + \beta_5 STEER + \beta_6 BFMETHOD + \sum_i^7 \alpha_i type_i + e$$

where *WT* is placement weight, *BFAT* is ultrasound backfat at placement, *FRAME* is frame score at placement, *DOF* is days on feed, *STEER* is a dummy variable for sex of the animal (1=steer, 0=heifer), *BFMETHOD* is a dummy for backfat method (1=feedlot used ultrasound to attempt to feed animal to a constant backfat at slaughter, 0=otherwise), and *type* is a dummy for each distinct genotype.

Due to the cross sectional dataset that was used, multicollinearity and heteroscedasticity were suspected to be potential problems while normality was assumed asymptotically. Correlation coefficients and auxiliary regressions were calculated and no problems with multicollinearity were found. None of the correlations were greater than 0.8, and the R^2 from each of the auxiliary regressions were less than 0.80 indicating that little of the variation in each of the independent variables was explained by the others. A lagrangian multiplier test was conducted to test for heteroscedasticity within the model that could affect the standard errors and variance and lead to false hypothesis rejections.

Based on the test results, the null hypothesis of constant variance of the error terms was rejected. Therefore, the choice of regression procedure was to use maximum likelihood estimation, and the error variance was estimated from the data using the exponential functional form to correct the errors and to efficiently estimate the effects of the input variables on per-head revenue and profit. Also, in order to test the model specification a regression specification error test (RESET) was conducted in SAS. The test estimates the model to obtain predicted values of the dependent variable, and then includes a specified form of the predicted values in the model to test the significance of higher order terms or to determine the validity of a linear model specification. The linear model was concluded to be adequate.

Dynamic Marketing Simulations

Realizing that the simulation described above is a straightforward approach to determining the value of leptin genotype information, it is likely not the best method of capturing the full value of knowing leptin genotype for multiple reasons. First, as discussed previously, it may be profitable to sort or select cattle on the basis of genotype. Also, highest profits may be achieved by feeding certain genotypes longer or shorter than others. For example, a genotype that deposits fat quickly needs to be marketed earlier than others in order to avoid incurring yield discounts and unnecessary feed costs. In order to address this issue a second, dynamic, simulation was conducted using the repeated measures of the sample cattle to determine the optimum number of days on feed for each genotype.

Each of the 1,668 head of cattle in the sample had up to three additional weight and ultrasound measures prior to harvest. In total, 5,025 observations were used. However, although carcass level data were collected at the actual day harvested for each animal, marbling score, quality grade, yield grade, dressed weight, and dry matter intake were not taken at the various points of re-measurement in the sample and must be calculated.

In order to calculate quality grade, a key variable affecting profitability, quality must be determined on the day each animal was re-measured. While quality grade has a discrete outcome, prime, choice, select, or standard, it is based on intramuscular fat. 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=high Choice; and 70-79=Prime. Brethour (2000) proposed the following equation to model marbling growth:

(10) $$mbs_t = I + kt^m$$

where I, k, and m are parameters, mbs_t is marbling score at time t, and t is days on feed. Using two data sets, Brethour estimates I at 3.10 and 3.39, k at 0.000214 and 0.00000000123642, and m at 1.55 and 3.42. This model, appropriately scaling for difference in the way marbling was measured, was then used to "backcast" the marbling score at each point that the animal was reweighed. After a bit of algebra, it can be shown that marbling at time t (mbs_t) is equal to

(11) $$mbs_t = \exp(\log(\exp(\log(-(-mbs_T + I)/k) - (dof_T - dof_t))m)k) + I$$

where mbs_T is marbling score at slaughter, dof_T is number of days on feed at slaughter, mbs_t can be the marbling score at any time t during the feeding period, and dof_t is the day on feed when re-measurement was conducted. Using both sets Brethour's estimates from equation (10), mbs_t is calculated for each animal in the present data set and the average of the two estimates is utilized in the analysis.

The yield grade of a carcass was calculated as

$$YG_t = 2.5 + (2.5(Bfat_t)) + (0.2(kph) + 0.0038(DW_t) - 0.32(REA_t) \tag{12}$$

where $Bfat_t$ is ultrasound backfat taken at points of re-measurement, and where kidney, pelvic, and heart fat in this dataset was fixed at the individual animal level over the entire feeding period. Dressed weight, or hot carcass weight, is simply calculated by multiplying the animal's dressing percentage by the animal's weight.

Finally, in calculating profits, costs must be considered. Dry matter intake must be calculated for each animal as a function of the number of days the animal has been on feed before the measure was taken. Although the data set contains an estimate of dry matter feed intake, it is an estimate of total dry matter intake. In order to calculate dry matter intake at any particular day on feed, the simulation employs a well known and widely used dry matter intake model. The study uses the dry matter intake equation reported in the National Research Council's Nutrient Requirements of Beef Cattle, utilized in work such as Tedeschi, Fox, and Russell (2000) and in the Cornell Net carbohydrate system. However, instead of simply including the weight at time t, an average was taken of the weight at placement and the weight at time t, labeled $AVGWT$. The model is

$$DMI_t = \begin{bmatrix} (0.96(AVGWT \ / 2.2))^{0.75}((0.2435(NE_{ma})) - \\ (0.0466(NE_{ma}{}^2) - 0.0869)) / NE_{ma} \end{bmatrix}(EBF) \tag{13}$$

where DMI_t is the average dry matter intake per day up to time t, NE_{ma} is the net energy value of the diet for maintenance (Mcal/kg), and is set at the value of 2.0 in the simulations. *EBF* is the empty body fat adjustment factor which takes the following values: 1.0 when $EBF<23.8$; 0.97 when $23.8<EBF<26.5$; 0.90 when $26.5<EBF<29.0$; 0.82 when $29.0<EBF<31.5$, and 0.73 when $EBF\geq 31$. Because *EBF* is not provided in the data set, it is estimated by the equation provided in Perry and Fox (1997)

(14) $$EBF_t = (((0.351(0.89(0.96(WT_t/2.2))) + 21.6(YG_t) - 80.8)/(0.89(0.96(WT_t/2.2)))100).$$

Finally, cumulative dry matter intake at time t is simply given by

(15) $$Cumulative\ DMI_t = DMI_t(DOF_t).$$

Econometric modeling is again used to regress the input variables on grid profit. In the static analysis, both revenue and profit calculations were included in order to ensure that the cost assumptions were accurate and that the revenue and profit results seemed to provide similar conclusions. As these assumptions seem to be adequate, they again will be used here, and for a lack of confusion, only regressions on profit were included. Due to the repeated observations for each animal and each pen, it was necessary to consider the need to model differences in behavior across animals. That is, the error term associated with the model is comprised of both an overall error term and an individual specific error term.

For the random effects model, PROC MIXED was used in SAS to model the effects on per-head grid profit of the input variables, dummy variables for genotype, and interactions between the inputs and days on feed and the inputs and genotype. The most general model appeared as follows:

$$
\begin{aligned}
\pi = {} & \beta_0 + \beta_1 WT + \beta_2 BFAT + \beta_3 FRAME + \beta_4 DOF_t + \beta_5 DOF_t^{\,2} + \beta_6 STEER + \\
& \beta_7 BFMETHOD + \sum_1^7 \alpha_i type_i + \sum_1^7 \lambda_i type_i (WT) + \sum_1^7 \delta_i type_i (BFAT) + \\
& \sum_1^7 \gamma_i type_i (FRAME) + \sum_1^7 \eta_i type_i (DOF_t) + \sum_1^7 \kappa_i type_i (DOF_t^{\,2}) + \\
& \sum_1^7 \nu_i type_i (BFMETHOD) + \sum_1^7 o_i DOF_t (WT) + \sum_1^7 \varpi_i DOF_t (BFAT) + \\
& \sum_1^7 \rho_i DOF_t (FRAME) + \sum_1^7 \omega_i DOF_t (BFMETHOD) + e
\end{aligned}
\tag{16}
$$

where *WT* is placement weight, *BFAT* is ultrasound backfat at placement, *FRAME* is frame score at placement, DOF_t is days on feed at time *t*, DOF_t^2 is a quadratic term for days on feed at time *t*, *STEER* is a dummy variable for sex of the animal (1=steer, 0=heifer), *BFMETHOD* is a dummy for backfat method (1=feedlot used ultrasound to attempt to feed animal to a constant backfat at slaughter, 0=otherwise), and *type* is a dummy for each distinct genotype. F-tests were then conducted to determine the significance of each included variable or set of variables in predicting profit in the model and the resulting p-values are shown in Table 4.

Table 4. Results of F-tests for Most General Model Specification

Tested Variables	P-Values		
	Base Grid	Quality Grid	Yield Grid
Placement Weight (β_1=0)	<.0001	0.0008	<.0001
Ultrasound Backfat at Placement (β_2=0)	0.6407	2.0920	0.3096
Frame Score at Placement (β_3=0)	0.0004	0.0295	0.0006
Days on Feed at time *t* (β_4=0)	<.0001	<.0001	<.0001
Days on Feed at time *t* Squared (β_5=0)	<.0001	<.0001	<.0001
BF Method (β_6=0)	0.0979	0.2165	0.2680
Steer (1=steer, 0=heifer) (β_7=0)	0.0319	0.0029	0.0074
type ($\alpha_1=\alpha_2=\alpha_3=\alpha_4=\alpha_5=\alpha_6=\alpha_7=0$)	0.3516	0.3083	0.3545
Placement Weight * type ($\lambda_1=\lambda_2=\lambda_3=\lambda_4=\lambda_5=\lambda_6=\lambda_7=0$)	0.1301	0.3253	0.2825
Ultrasound Backfat at Placement * type ($\delta_1=\delta_2=\delta_3=\delta_4=\delta_5=\delta_6=\delta_7=0$)	0.2286	0.4784	0.3721
Frame Score at Placement * type ($\gamma_1=\gamma_2=\gamma_3=\gamma_4=\gamma_5=\gamma_6=\gamma_7=0$)	0.4196	0.4172	0.4953
Days on Feed at time *t* * type ($\eta_1=\eta_2=\eta_3=\eta_4=\eta_5=\eta_6=\eta_7=0$)	0.0036	0.0250	0.0203
Days on Feed Squared at time *t** type ($\kappa_1=\kappa_2=\kappa_3=\kappa_4=\kappa_5=\kappa_6=\kappa_7=0$)	0.0009	0.0166	0.0124
BF Method *type ($\nu_1=\nu_2=\nu_3=\nu_4=\nu_5=\nu_6=\nu_7=0$)	0.1961	0.3721	0.2369
Placement Weight *DOF ($o_1=o_2=o_3=o_4=o_5=o_6=o_7=0$)	0.4718	0.3502	0.2277
Ultrasound Backfat at Placement * DOF ($\varpi_1=\varpi_2=\varpi_3=\varpi_4=\varpi_5=\varpi_6=\varpi_7=0$)	0.2848	0.1385	0.1337
Frame Score at Placement * DOF ($\rho_1=\rho_2=\rho_3=\rho_4=\rho_5=\rho_6=\rho_7=0$)	0.3685	0.6424	0.2824
BF Method * DOF ($\omega_1=\omega_2=\omega_3=\omega_4=\omega_5=\omega_6=\omega_7=0$)	0.1699	0.4240	0.4273

It was decided to include all linear effects in the model despite their insignificance, and all other variables that were significant at the P=0.05 level or better were also included. This process was repeated and the resulting F-tests are located below in Table 5. The results of these tests led to the final model specification which consisted of all linear variables, a quadratic term for days on feed, dummy variables for genotype, and interaction variables between genotype and both days on feed and days on feed squared. The final model is shown as:

(17) $$\pi = \beta_0 + \beta_1 WT + \beta_2 BFAT + \beta_3 FRAME + \beta_4 DOF_t + \beta_5 DOF_t^{\,2} + \beta_6 STEER + \beta_7 BFMETHOD + \sum_1^7 \alpha_i type_i + \sum_1^7 \eta_i type_i (DOF_t) + \sum_1^7 \kappa_i type_i (DOF_t^{\,2}) + e.$$

Heteroscedasticity problems were then considered by using an auxiliary regression to regress the explanatory variables on the residuals with a resulting R^2=0.00.

Table 5. Results of F-tests for Final Model Specification

Tested Variables	P-Values		
	Base Grid	Quality Grid	Yield Grid
Placement Weight (β_1=0)	<.0001	<.0001	<.0001
Ultrasound Backfat at Placement (β_2=0)	0.0106	0.6544	0.1755
Frame Score at Placement (β_3=0)	<.0001	<.0001	<.0001
Days on Feed at time *t* (β_4=0)	<.0001	<.0001	<.0001
Days on Feed at time *t* Squared (β_5=0)	<.0001	<.0001	<.0001
BF Method (β_6=0)	0.1019	0.0350	0.0915
Steer (1=steer, 0=heifer) (β_7=0)	0.0217	0.0085	0.0101
type (α_1=α_2=α_3=α_4=α_5=α_6=α_7=0)	0.6642	0.8692	0.5518
Days on Feed at time *t* * type (η_1=η_2=η_3=η_4=η_5=η_6=η_7=0)	0.0030	0.0231	0.0172
Days on Feed Squared at time *t** type (κ_1=κ_2=κ_3=κ_4=κ_5=κ_6=κ_7=0)	0.0007	0.0142	0.0094

In order to capture the value of implementing genotypic information into decision making, the final model was then used to determine the optimum days on feed for each of the genotypes. To determine which was the most optimal day on feed, grid profits were maximized by choosing days on feed. This can be shown as:

(18) $$\frac{\partial \pi}{\partial DOF} = \beta_4 + \sum_1^7 \eta_i type_i + [2DOF(\beta_5 + \sum_1^7 \kappa_i type_i)] = 0\,.$$

Then optimal grid profits were predicted for each of the three grids using the optimal days on feed. Again, the consideration that leptin genotype could affect both input and output variables was undertaken, and optimal grid profits were predicted and compared a second time using the overall mean levels of the data set. Finally, in the interest of capturing the full value of leptin genotype knowledge, and addressing the implications to sorting, selection, and marketing mentioned throughout this paper, grid profits were re-predicted multiple times using different assumptions. The value of information for sorting cattle into homogeneous groups and feeding them to their economically optimal end point is determined by comparing the predicted profits when all cattle are marketed at their genotypic optimum and the estimated profit derived from determining a mean optimal days on feed in which to market all genotypes alike. Furthermore, the value of information for selection is determined by comparing profits when only the most profitable genotype is marketed at its optimal days on feed and the profits derived from marketing all cattle at their genotypic optimum days on feed.

CHAPTER V

FINDINGS

Static Simulations

Table 6 shows mean profits and revenues for each genotype at the actual day they were marketed. Table 7 reports the results of the static simulations when controlling for other factors. The hypotheses that the mean per-head profits and revenues are equivalent across genotypes are rejected at the P=0.05 percent level of significance or better for all three grids.

Regardless of the grid investigated, type1 cattle generated the highest revenue and type4 generated the highest profit. There are a variety of ways to measure the value of information. The means can be used to rank the genotypes according to profits, or another way is to compare the profit of the best and worst performing genotypes. Differences in profit between type4 and type3 cattle is over $20/head for all three grids, and differences in revenue between type1 and type3 cattle is over $60/head for all three grids. These differences are economically large and the revenue difference is almost twice the amount reported in previous studies that estimated the increase in revenue obtainable from feeders choosing the best marketing method for each animal (Schroeder and Graff 2000).

Table 6. Summary of Static Simulations

Outcomes	Genotype							
	type1	type2	type3	type4	type5	type6	type7	P-value[a]
Base Grid								
Mean Revenue ($/head)	896.48	879.38	834.49	892.43	862.33	869.28	881.19	<0.01
	(96.56)[b]	(99.92)	(108.35)	(102.14)	(103.25)	(105.58)	(104.20)	
Mean Profit ($/head)	48.76	49.29	34.20	54.56	38.60	41.77	39.09	<0.01
	(65.93)	(60.03)	(64.13)	(65.69)	(61.49)	(71.94)	(61.26)	
Quality Grid								
Mean Revenue ($/head)	868.15	852.89	806.42	865.61	833.23	843.64	860.65	<0.01
	(101.87)	(109.52)	(113.24)	(109.69)	(110.33)	(114.38)	(110.15)	
Mean Profit ($/head)	20.43	22.81	6.14	27.75	9.50	16.14	18.55	0.02
	(77.43)	(72.36)	(75.55)	(78.58)	(73.26)	(84.37)	(72.46)	
Yield Grid								
Mean Revenue ($/head)	897.88	880.9	835.97	893.91	863.65	870.35	881.75	<0.01
	(96.64)	(100.10)	(108.53)	(102.52)	(103.49)	(106.10)	(104.75)	
Mean Profit ($/head)	50.17	50.82	35.82	56.05	39.92	42.85	39.65	<0.01
	(66.58)	(60.35)	(64.79)	(66.29)	(62.01)	(72.68)	(62.25)	
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]P-value associated with an ANOVA test that the means are equivalent across types.
[b]Numbers in parentheses are standard deviations

While these results suggest significant economic value of genotypic information for selection, differences in placement weight, ultrasound backfat at placement, frame score, and days on feed, may explain much of the differences in revenue and profits. To investigate the impact of the input variables on calculated profit and revenue, Table 7 reports the regression results where per-head profit and revenue is regressed on input characteristics and dummy variables for genotypes.

Table 7. Effect of Genotype on Revenue and Profit Controlling for Other Factors in Static Simulation: Maximum Likelihood Estimation (N=1,668 in each regression)

Independent Variables	Revenue			Profit		
	Base Grid	Quality Grid	Yield Grid	Base Grid	Quality Grid	Yield Grid
Intercept	80.95 **	47.17	81.09 **	-110.53 **	-144.32 **	-110.39 **
	(23.86)[a]	(29.38)	(23.99)	(20.73)	(27.00)	(20.90)
Placement Weight	0.93 **	0.91 **	0.93 **	0.18 **	0.16 **	0.18 **
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)
Ultrasound Backfat Measure at Placement	-475.39 **	-394.81 **	-485.34 **	-310.85 **	-230.28 **	-320.81 **
	(66.44)	(75.91)	(66.91)	(58.24)	(69.34)	(58.82)
Frame Score at Placement	-15.46 **	-13.08 **	-15.40 **	-13.80 **	-11.47 **	-13.76 **
	(2.00)	(2.32)	(2.01)	(1.79)	(2.12)	(1.81)
Days on Feed	2.04 **	2.04 **	2.05 **	1.02 **	1.02 **	1.02 **
	(0.08)	(0.10)	(0.08)	(0.07)	(0.09)	(0.07)
Steer (1=steer, 0=heifer)	7.07	2.50	7.46	5.49	0.60	5.88
	(6.06)	(7.16)	(6.11)	(5.41)	(6.49)	(5.47)
Backfat Method[b]	2.82	7.35	2.52	2.31	6.85	2.01
	(5.96)	(6.96)	(6.01)	(5.31)	(6.39)	(5.38)
type1[c]	8.31	7.35	8.40	8.50	7.57	8.59
	(8.34)	(10.15)	(8.39)	(7.71)	(9.60)	(7.79)
type2[c]	14.94 **	15.36 *	15.05 **	12.12 *	12.56	12.23 *
	(7.20)	(8.80)	(7.23)	(6.55)	(8.41)	(6.59)
type4[c]	15.69 **	16.37 *	15.77 **	11.76 *	12.46	11.84 *
	(6.92)	(8.49)	(6.96)	(6.41)	(8.17)	(6.45)
type5[c]	3.83	3.08	3.72	1.41	0.69	1.30
	(6.73)	(8.29)	(6.77)	(6.23)	(7.98)	(6.28)
type6[c]	7.93	9.92	7.66	2.82	4.70	2.55

Table 7. Effect of Genotype on Revenue and Profit Controlling for Other Factors in Static Simulation: Maximum Likelihood Estimation (N=1,668 in each regression)

Independent Variables	Revenue			Profit		
	Base Grid	Quality Grid	Yield Grid	Base Grid	Quality Grid	Yield Grid
	(7.17)	(8.73)	(7.21)	(6.68)	(849)	(6.73)
type7[c]	7.46	14.62	6.79	-0.72	6.46	-1.39
	(14.90)	(17.59)	(14.96)	(12.23)	(17.26)	(12.30)
F-test[d]	0.0902	0.1640	0.0832	0.0684	0.2252	0.0589
R^2	0.62	0.51	0.62	0.23	0.13	0.22

Note: two(**) and one (*) asterisks represent statistical significance at the 0.01 and 0.05 levels, respectively.
[a]Numbers in parentheses are standard errors.
[b]Takes the value of 1 if feedlot operator attempted to feed animal to a constant backfat; 0 otherwise.
[c]Effects of all genotypes estimated relative to type3.
[d]P-values associated with F-tests to test the equivalence of profit and revenue for all genotypes after controlling for input characteristics

Table 7 reports the results of six different models where profit/head and revenue/head are estimated as a linear function of several input variables and dummy variables for genotype, type3 is omitted for comparison, and the asterisks indicate coefficients that are significantly different than zero according to individual t-tests. F-tests were also conducted for each model to test the equivalence of profits and revenues for all genotypes. For both base grid models and both yield grid models the null hypothesis could be rejected at the P=0.10 level or below, but the p-values for the quality grid profit and revenue tests were 0.2252 and 0.1640, respectively. Thus, for the quality grid models we fail to reject the hypothesis that after controlling for input characteristics, genotype influences profit and revenue.

It is important to compare both conditional (Table 7) and unconditional (Table 6) means across genotypes. While it may seem logical to only consider conditional mean differences relevant, it must be considered that the individual animal's genotype may also influence important input characteristics. Thus, genotype may be a single measure that could serve as a proxy for a variety of input variables. Beyond this, while ultrasound backfat is observable, it can be costly and time-intensive to acquire the data. Therefore, even if differences in ultrasound backfat at placement explain some of the variability in profits across genotype, genetic information may still be useful as a replacement for or supplement to ultrasound information.

The results indicate that many of the input variables are significantly related to revenue and profitability. For example animals with higher placement weights and lower backfat measures show higher profits and revenues. Type1 cattle have higher average placement weights and backfat measures as shown by Table 1, but the regression results suggest that it is these differences that contribute to the fact that type1 cattle tend to have the highest unconditional mean revenue because the dummy variable is not statistically significant at any reasonable level in the econometric models. Although differences in the input variables explain some of the differences in revenues and profits, significant differences remain for some genotypes. For example type2 and type4 cattle tend to exhibit consistently higher revenues and profits than type3 cattle, about $11-$12/head more profit and $15-$16/head more revenue, even when input variables are held constant. Differences in placement weight, backfat, frame score, days on feed, percent steer, and percent managed by the backfat method, only explain [(20.36 - 11.76) / 20.36] * 100= 42.24% of the difference in profits between type4 and type3 cattle on the base grid, where 20.36 is the unconditional mean difference as shown in Table 6 and 11.76 is the conditional mean difference as shown in Table 7. By comparing these results we can conclude that at least 57.76% of the variation in profits can be explained by leptin genotype, and this estimate may be low due to the possible effects of genotype on the input characteristics.

Dynamic Simulations

Table 8 reports the model used in the dynamic simulations. The estimated coefficients show the effect of each of the input variables and dummy variables for genotypes and interactions on per-head profits. An interesting note when considering the variables included in the model is the fact the there was no significant interaction between days on feed and ultrasound backfat. These findings indicate that ultrasound, while a predictor of profitability, does not provide information about how long to most optimally feed cattle. However, individual animal information can be used along with these model parameters to predict per-head grid profits for each animal on each grid.

Table 8. Effect of Genotype on Profit Controlling for other Factors in Dynamic Simulation: PROC MIXED Estimation (N=5,025 in each regression)

	Profit					
Independent Variables	Base Grid		Quality Grid		Yield Grid	
Intercept	-329.27	**	-401.11	**	-363.23	**
Placement Weight	0.2521	**	0.2665	**	0.2879	**
Ultrasound Backfat at Placement	-113.58	*	28.47		-67.52	
Frame Score at Placement	-12.27	**	-11.06	**	-12.19	**
Days on Feed (DOF)	5.20	**	5.20	**	5.05	**
Days on Feed Squared (DOF^2)	-0.0205	**	-0.0195	**	-0.0191	**
BF Method[a]	6.52		12.05	*	7.55	
Steer (1=steer, 0=heifer)	-9.95	*	-16.33	**	-12.52	*
type1[b]	15.17		1.61		10.18	
type2	10.51		-4.18		1.97	
type3	5.04		-10.89		-5.76	
type4	12.08		-2.09		4.21	
type5	6.47		-7.27		-1.51	
type6	8.07		-2.03		2.98	
DOF*type1	-1.2910	**	-1.4341	**	-1.2626	**
DOF*type2	-1.2125	**	-1.3436	**	-1.1849	**
DOF*type3	-0.8911	*	-1.0840	*	-0.8671	*
DOF*type4	-1.2363	**	-1.3189	**	1.1573	**
DOF*type5	-1.0506	**	-1.1889	**	-1.0321	**
DOF*type6	-1.3016	**	-1.4183	**	-1.2349	**
DOF^2*type1	0.0091	**	0.0102	**	0.0090	**
DOF^2*type2	0.0090	**	0.0101	**	0.0091	**
DOF^2*type3	0.0063	*	0.0082	*	0.0067	*
DOF^2*type4	0.0093	**	0.0102	**	0.0091	**
DOF^2*type5	0.0078	**	0.0091	**	0.0081	**
DOF^2*type6	0.0097	**	0.0107	**	0.0095	**

Note: two(**) and one (*) asterisks represent statistical significance at the 0.01 and 0.05 levels, respectively.

[a]Takes the value of 1 if feedlot operator attempted to feed animal to a constant backfat; 0 otherwise.

[b]Effects of all genotypes estimated relative to type7.

The summary results of the unconditional dynamic simulation, where the input variables, placement weight, backfat at placement, and frame score at placement vary by genotype for each animal, are found in Table 9. Broadly these results show that the optimal number of days on feed exceed the number of days the cattle were actually on feed prior to harvest. As seen in Table 1, on average genotypes were fed between 134 and 142 days on feed, while the simulations suggest much longer feeding times were most optimal for most of the genotypes. Given the statistical significance of days on feed, the quadratic term for days on feed, and all interactions including those variables, these findings are not unexpected, but could simply allude to differences in the economic conditions faced by the feedlot operators and the price and cost data used assumed in the simulations. Also, the estimated optimal profits reported in Table 9 greatly exceed the simulated profits reported in Table 4. This, too, is expected since it is the goal of the dynamic simulation to determine the most profitable length of time to feed the cattle. The differences in profits between these two simulations exemplify the economic value that can be captured by optimally choosing how long to feed cattle.

Table 9. Summary Results from Dynamic Simulation: Unconditional Analysis

	Genotype							
Outcomes	type1	type2	type3	type4	type5	type6	type7	P-value[a]
Base Grid								
Mean Optimal Profit ($/head)	101.91	98.20	68.72	111.42	91.14	104.96	83.85	<.0001
	(27.95)[b]	(25.98)	(24.07)	(26.50)	(25.56)	(25.59)	(24.84)	
Mean Optimal Days on Feed	171	172	151	177	163	180	127	<.0001
Quality Grid								
Mean Optimal Profit ($/head)	93.47	93.63	56.40	108.15	82.17	109.21	59.93	<.0001
	(32.36)	(29.65)	(25.30)	(30.16)	(82.17)	(109.21)	(29.20)	
Mean Optimal Days on Feed	202	205	182	208	193	216	133	<.0001
Yield Grid								
Mean Optimal Profit ($/head)	112.06	111.40	77.08	124.34	103.49	119.05	82.61	<.0001
	(31.95)	(29.40)	(26.68)	(30.14)	(28.82)	(29.11)	(28.35)	
Mean Optimal Days on Feed	187	192	168	194	182	197	132	<.0001

[a]P-value associated with an ANOVA test that the means are equivalent across types.
[b]Numbers in parentheses are standard deviations

The outcomes in Table 9 illustrate how profits change as animals are marketed closer to the optimal day on feed. For the base and yield grid, type4 cattle showed the highest level of profit at $111.42 and $124.34, respectively, while type6 cattle generated the highest profit on the quality grid at $109.21. Type3 and type7 are the worst performing genotypes with the greatest difference in profits being $52.81 between type6 and type3 cattle on the quality grid. One difference that is apparent across the static and dynamic simulations is that type6 cattle rank first or second in terms of profits across grids when marketed closer to their optimal endpoint. This could be due to the fact that type6 cattle need to be fed longer than other types to achieve optimal profits regardless of the grid chosen. It is also of interest to consider that type7 cattle were consistently one of the worst performing genotypes in the simulations, but were already being marketed the closest to their optimal genotype of all types of cattle. Even when marketed at close to the optimal days on feed, profits were lower than for other types of cattle who were marketed further from their optimal day on feed. Furthermore, for some types there may exist longer spreads in time that achieve higher profits, while for some being marketed only a few days from their optimum may have a more significant impact on profitability. This is further illustrated by looking at how profits changed over days on feed as shown in Figure 1.

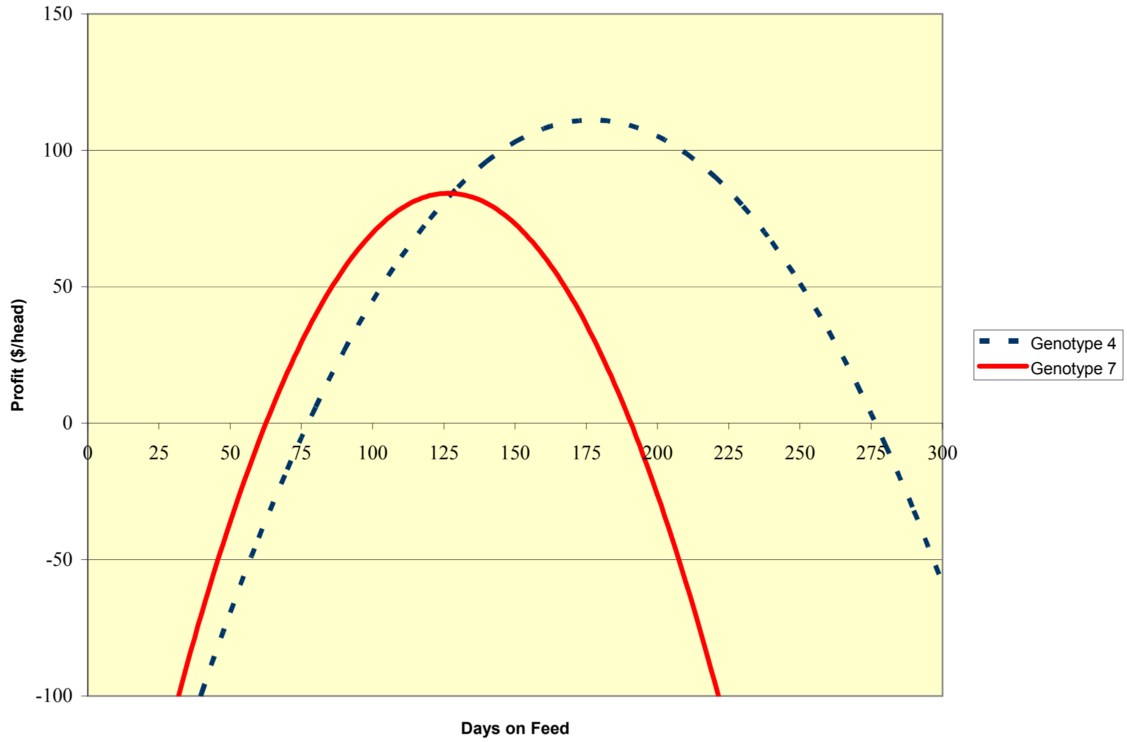

Figure 1. Profit by Days on Feed for Type7 and Type4 Cattle

Also shown by Table 9 are differences in grid sensitivity across genotypes. For example, for type2 cattle, the differences in profits between the base grid and quality grid was only about \$5/head, while for type7 cattle this difference was much larger at approximately \$23/head. It is also of interest that with the exception of type6 cattle, all of the genotypes generated lower profits when marketed on the grid rewarding quality than when marketed on the base grid. Therefore, there could exist incentives for producers and feedlot operators to consider each genotype's sensitivity to grid structure. For example, when facing grid structures rewarding quality grades, it is more desirable to produce and feed type6 cattle.

Table 10 displays the results of the conditional analysis where placement weight, backfat at placement, and frame score are set at constant, overall mean, levels for all genotypes. Due to no significant interaction of days on feed with the input variables in the model, the mean optimal days on feed for each genotype remains the same in both the conditional and unconditional analyses. Also, there is little variation in the rankings of the genotypes in the conditional and unconditional analyses. Type4 and type6 cattle still rank in the top two across all grids, while type3 and type7 are the worst performing genotypes.

Table 10. Summary Results from Dynamic Simulation: Conditional Analysis

	Genotype							
Outcomes	type1	type2	type3	type4	type5	type6	type7	P-value[a]
Base Grid								
Optimal Profit ($/head)	95.50	101.03	76.60	109.18	91.70	104.98	75.01	<.0001
	(5.63)[b]	(5.40)	(6.06)	(5.60)	(5.49)	(5.44)	(5.53)	
Optimal Days on Feed	171	172	151	177	163	180	127	<.0001
Quality Grid								
Optimal Profit ($/head)	85.23	96.32	66.48	105.65	83.35	108.92	49.40	<.0001
	(9.61)	(9.13)	(10.28)	(9.52)	(9.32)	(9.29)	(9.53)	
Optimal Days on Feed	202	205	182	208	193	216	133	<.0001
Yield Grid								
Optimal Profit ($/head)	104.1	114.25	86.77	121.79	104.37	119.08	72.49	<.0001
	(6.92)	(6.69)	(7.48)	(6.89)	(6.76)	(6.68)	(6.74)	
Optimal Days on Feed	187	192	168	194	182	197	132	<.0001

[a]P-value associated with an ANOVA test that the means are equivalent across types.
[b]Numbers in parentheses are standard deviations

Summaries of multiple unconditional dynamic simulations are found below in Table 11. If all cattle, regardless of genotype, were marketed on the base grid at 150 days, mean per-head profits are estimated at $92.87. Uniformly increasing days on feed to 170 days for the entire sample improves profits to $97.11/head, illustrating the economic gains to selling cattle closer to their optimum endpoint. If no genotypic information was available and all cattle had to be marketed on the same day, the predicted optimal number of days on feed would be 168 and the estimated profits would increase to $97.13/head. If all feedlots sorted cattle using genotypic information to market each genotype at its optimal end point, then per-head profits of $98.66 could be generated. However, if genotypic information was implemented into selection decisions and only the most profitable genotypes were fed and marketed optimally, results indicate that $111.41/head is obtainable.

Table 11. Profit from Various Marketing Strategies

	Mean Profit ($/head) from Unconditional Analysis		
Strategy	Base Grid	Quality Grid	Yield Grid
Market all Cattle at 150 days	$92.87	$66.90	$95.14
Market all Cattle at 160 days	$96.19	$75.69	$101.77
Market all Cattle at 170 days	$97.11	$82.52	$106.29
Market all Cattle Optimally without Genotype Information	$97.13	$91.19	$109.14
Market Each Genotype Optimally	$98.66	$93.70	$110.88
Market Only the Best Genotype Optimally	$111.41	$109.21	$124.34

By comparing these results from the base grid it is clear that profitability of cattle can be improved with the use of genetic information, and even greater spreads occur in profits on the yield and quality grids. Furthermore, while the value of using genotype information to sort cattle to feed them to their optimal end point is small ($98.66-

$97.13=$1.53), the increased profitability of using leptin genotype information for selection is at least $14/head ($111.41-$97.13=$14.28).

Further Sensitivity Analysis

The need for further sensitivity analysis is warranted due to the fact that previous model selection did not consider interactions between days on feed and the sex of the animal. As steers and heifers typically require different amounts of time on feed to reach an optimal endpoint, it is important to determine the significance of this relationship in the analysis. Also, attention is given to base price sensitivity in the grid using a price that more closely reflects the actual prices that producers and feedlot operators faced in 2004.

The average of the five market weighted average dressed weight price for steers and heifers, as reported by USDA/AMS for 2004, was $133.84. Using this figure as the base price in the grid, profits were recalculated. To select a final model, a general model was first estimated that contained all input variables including gender and dummy variables for genotype, while also containing all interactions between the inputs and days on feed, the inputs and genotype, and the inputs and the quadratic term for days on feed. F-tests were conducted to determine the joint significance of each set of variables in predicting profit. It was found that while interactions between days on feed and sex were insignificant, interactions between weight, backfat, and frame score and days on feed terms were significant in predicting profits. Table 12 contains the resulting model estimated using PROC MIXED in SAS.

Table 12. Effect of Genotype on Profits calculated with 2004 Base Price: PROC MIXED Estimation (N=5,025)

Independent Variables	Profit	
	Base Grid	
Intercept	-384.17	**
Placement Weight (WT1)	0.2765	**
Ultrasound Backfat at Placement (BFAT1)	199.75	**
Frame Score at Placement (FRAME1)	-2.38	
Days on Feed (DOF)	4.13	**
Days on Feed Squared (DOF^2)	-0.0044	
BF Method[a]	8.30	*
Heifer(1=heifer, 0=steer)	12.50	**
type1[b]	13.13	
type2	7.24	
type3	4.66	
type4	11.78	
type5	6.37	
type6	6.90	
DOF*type1	-1.0319	**
DOF*type2	-0.9352	**
DOF*type3	-0.6980	*
DOF*type4	-1.0654	**
DOF*type5	-0.9191	**
DOF*type6	-1.1691	**
DOF^2*type1	0.0070	**
DOF^2*type2	0.0070	**
DOF^2*type3	0.0047	*
DOF^2*type4	0.0079	**
DOF^2*type5	0.0067	**
DOF^2*type6	0.0087	**
DOF*WT1	0.0060	**
DOF*BFAT1	-4.9233	**
DOF*FRAME1	-0.2913	**
DOF^2*WT1	0.0000	**
DOF^2*FRAME1	0.0011	**

Note: two (**) and (*) asterisks represent statistical significance at the 0.01 and 0.05 levels, respectively

[a]Takes value of 1 if feedlot operator attempted to feed animal to a constant backfat; 0 otherwise.

[b]Effects of all genotypes estimated relative to type7.

It is interesting to note that no significant interaction was found between steer and days on feed. However, interactions between days on feed terms and variables which likely vary by the sex of the animal (e.g. weight and frame) were significant in predicting profits. Also, in contrast to previous results, the interaction between ultrasound backfat at placement and days on feed was statistically significant. Therefore, ultrasound backfat at placement may be helpful in determining the number of days in which to feed an animal depending on the base price used in the grid.

Table 13. Profits Calculated with 2004 Base Price for Various Marketing Strategies

	Mean Profit ($/head) from Unconditional Analysis
Strategy	Base Grid
Market all Cattle at 150 days	$165.38
Market all Cattle at 160 days	$160.90
Market all Cattle at 170 days	$153.02
Market all Cattle Optimally without Genotype Information	$166.50
Market Each Genotype Optimally	$175.00
Market Only the Best Genotype Optimally	$184.47

Again, multiple dynamic simulations were conducted and the summary results are found above in Table 13. When facing the adjusted pricing conditions used in this sensitivity analysis, the optimal number of days on feed for the data set declined from 168 days in previous analysis to 142 days. As seen in Table 13, marketing animals closer to their optimal day on feed at 150 days results in profits of $165.38, while it is clear that as animals are marketed further from their optimal days on feed profits decline. It remains clear that the profitability of cattle can be improved with the use of genetic information. Using the revised model and assumptions, the value of genotypic information for selection remains large and actually increases from about $12 to almost $18. That is, selling only the most profitable cattle, type4, versus optimally marketing all cattle without genotype information results in an increase in profits of $17.97 ($184.47-

$166.50= $17.97). Furthermore, the value of information for sorting and feeding cattle to their optimal endpoint is found to be much greater given the changed assumptions as it increased from about $1.50 to $8.50 ($175.00- $166.50= $8.50).

CHAPTER VI

SUMMARY & CONCLUSIONS

The objective of this paper was to determine whether leptin genotype information was related to individual-animal revenue and profit. Using a dataset of 1,668 commercially fed beef cattle, simulations were conducted for seven genotypic categories. In the static simulation, profits and revenues were compared across genotypes given the carcass characteristics of the animals at slaughter. Dynamic simulations were conducted using repeated carcass measures of the data set to predict the optimal number of days on feed for each of the genotypes, and profits at each genotype's optimum were compared across genotypes. Results in the static simulations revealed economically significant differences across genotypes. Type2 and type4 cattle generated the highest profit levels generating \$15.09/head and \$20.36/head more profit, respectively than the worst performing genotype, type3. Even after controlling for other observable factors, such as frame score and placement weight, the difference in profits from the best to worst performing genotypes was around \$12/head. The dynamic simulations revealed that feeding animals closer to their optimum number of days on feed drastically improved profitability for all genotypes. In the dynamic simulations type4 cattle continued to generate the highest profits on two of the grids, while type6 cattle had the highest profit on the other and surpassed type2 cattle regardless of the grid used. This result could be linked to the fact that type 6 cattle were not being marketed close to their optimal marketing date and require more days on feed. In this simulation, type4 cattle generated about $40 to $50 more per head than the worst performing genotype, type3, when marketed on the base and yield grids. On the quality emphasized grid type6 cattle outperformed type3 cattle by $52 per head. Consistently across grids, type4 and type6 cattle generated between $4 and $15 more per head than the next best performing genotype.

Several considerations are necessary when examining these results and their implications. First, as validated in further sensitivity analysis, these results are highly conditional on the model and grid base price assumptions. Not only do these assumptions appear to affect the magnitudes of the resulting values of information, but also affect model specification. Furthermore, the specific grid assumptions used in the analysis may be the cause of the lower value on the quality grid for most types of cattle. Also, variations may exist across genotypes in feed intake that would affect profitability, while in this analysis feed intake was calculated in the same manner for all genotypes. Little information was actually known about the cattle in the dataset. Therefore, it is not certain how representative the distribution of cattle used in the sample is, compared to the entire population of cattle in the world. These considerations lend to difficulty in applying these results broadly.

It is also important to consider these economic gains relative to the actual costs of testing the animals when thinking about these results and the potential for technology adoption. Currently the genetic profile, containing the two leptin markers used in this analysis and six others, is available at a cost of $37.50. Since the tests for leptin genotype are not offered for purchase on their own, but instead in a bundle of eight, we must consider the costs of only the leptin portion of the profile, although it could not be purchased in this manner. Since two of the eight markers identify leptin, the cost could be viewed as 25% of $37.50, or $9.38.

Overall, the results indicate that it may be important for producers to breed the right kind of cattle. The value of this information, as determined by this study, is that it will allow cattle producers to breed and purchase cattle of specific genotypes, while avoiding cattle with lower performing genetics. The econometric models can also be used to help determine the optimum days to feed an animal and the optimal grid on which to market cattle by genotype. Future work will be aimed at refining dynamic prediction equations used to estimate models of feed intake, which at present is identical for all genotypes. Considerations should be given in future research to the aggregate implications to producers adopting this technology. Additionally, this work showed that genotype was not only significantly related to output variables such as quality and yield grade, but was also possibly related to input variables such as placement weight, frame score, and backfat at placement. Future research might focus on the extent to which genotypic information can be used in lieu of collecting a variety of input measures, or substitute for more costly methods, such as ultrasounding. Also, interest may be found in determining the value of selecting for certain genotypes in cow-calf production.

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Candidate for the Degree of

Master of Science

Thesis: ECONOMIC VALUE OF LEPTIN GENOTYPE INFORMATION IN BEEF CATTLE

Major Field: Agricultural Economics

Biographical:

Education: Graduated as Valedictorian from Jay High School, Jay, OK in May 2001; received Associate of Science degree in Agriculture from Connors State College, Warner, OK in May 2003; completed 17 hours in Agricultural Economics at Texas A&M University; received Bachelor of Science degree in Agricultural Economics with a minor in Spanish from Oklahoma State University in August 2005. Completed the requirements for the Master of Science degree with a major in Agricultural Economics at Oklahoma State University in December 2006.

Experience: Raised on a farm near Jay, OK; employed by CNH Capital as a summer intern in summer 2002; employed by Department of Agricultural Economics at Oklahoma State University August 2005 to present.

Professional Memberships: Department of Agricultural Economics Graduate Student Association, American Society of Animal Science

Name: Andrea Beth Troyer Date of Degree: December, 2006

Institution: Oklahoma State University Location: Stillwater, Oklahoma

Title of Study: ECONOMIC VALUE OF LEPTIN GENOTYPE INFORMATION IN BEEF CATTLE

Pages in Study: 58 Candidate for the Degree of Master of Science

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Scope and Method of Study: Recent research developments in genetics have found variations to exist among mammals in the way they produce and react to leptin, a protein that works to control appetite and weight. These traits and others linked to leptin are highly important in commercial livestock production. Due to advances in technology, testing to determine an animal's genotype has become a relatively cheap and easy task. The purpose of this study is to determine the economic value that can be elicited from knowing differences in leptin genotype of beef cattle. The study implements static and dynamic market simulations to determine if variations in profitability and revenue exist across distinct genotypes in a set of 1,668 commercially fed beef cattle.

Findings and Conclusions: Results reveal significant differences in profitability across genotypes. The difference in per-head profit between the best and worst performing genotypes is over $20 in the static analysis and over $52 in the dynamic analysis.

ADVISER'S APPROVAL: Dr. Jayson Lusk