Sorting Cattle with Accumulated Data: What is the Accuracy and Economics

Maro A. Ibarburu

and

John D. Lawrence*

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* Lawrence is a professor (jdlaw@iastate.edu) and Ibarburu is a graduate student (maro@iastate.edu), Department of Economics, Iowa State University. The authors gratefully acknowledge Tri-County Steer Carcass Futurity Program and Darrell Busby for the use of their data and Suzanne Schuknecht for her valuable work.

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Practitioner's Abstract

Increasingly feedlots are managing cattle as individual animals rather than on a pen level basis. As such it is possible to predict an optimal marketing date for each animal. This analysis evaluates the keep-or-sell decision at reimplant time for feedlots cattle approximately 80 days prior to the expected marketing date for the entire group. A model predicting the least profitable cattle in the pen was developed using individual animal data representing over 14,000 cattle fed in 12 Iowa feedlots. It was tested out of sample on an additional 5,000 head to determine the optimal cull rate at reimplant time. The expected profit of sorting and reselling the least profitable cattle was calculated for two different levels of imperfect information and were contrasted against each other as well expost profit. The analysis concludes that there is a potential advantage of predicting the least profitable animals in a pen and re-sell them as heavyfeeder-cattle. It also shows that individual animal identification and management provides additional information and accuracy to apply this practice.

Keywords: cattle, sorting, imperfect information, profit, individual animal identification

Introduction

Feedlots typically manage and market cattle as a group, but with national animal identification on the horizon the infrastructure will exist to manage individual animals to optimize their fullest profit potential. Feedlots typically process cattle individually at the start and approximately half way through the feeding period at re-implant time and collect or have the potential to collect data at that time if it were shown to improve economic decisions. In addition to production decisions, grid marketing evaluates and prices cattle individually and rewards higher quality grade cattle at slaughter. Premiums at slaughter are not the only determinant of profits as managers must also consider cost factors such as feed efficiency, average daily gain, and health treatments. The relative importance of these traits is impacted by input and output price relationships which in turn depends upon the season of the year when production and marketing occurs. Thus, identifying the most profitable animals to produce and when to market is a complex, but important, challenge for the producers. While new tools to manage individual animals are emerging, the question remains as to whether profits can be improved with additional information.

Trenkle (2000), Strohbehn (1999), Feuz (1998) identified the economic importance of individual animal management such as selling at a different time or to different grids that more closely match the cattle. Forristall, May, and Lawrence (2002) report that marbling may become a more important trait than gain or feed efficiency to feedlot profitability at some Choice-Select and cost of gain to selling price relationships. Brethour (2000) concluded that ultrasound estimates of marbling and backfat during the feeding period can be used to predict carcass merit and identified that the accuracy of carcass marbling projections improved as evaluation neared slaughter. Rouse et al. (2000) have evaluated using ultrasound on live cattle to sort cattle based on marbling for grid markets and some large commercial feedlots are using ultrasound as part of an automated sorting system. However, there are other factors besides marbling that determine the most profitable time to sell an animal, and these detection technologies can be costly particularly for smaller feedlots. For example, Busby et al. (2004) reported that animals requiring individual treatment for sickness had poorer feedlot performance than healthy cattle and were significantly less likely to grade Choice or better at slaughter. Koontz et al. (2000) evaluated the advantage of sorting cattle to different fed-cattle markets using ultrasound technology and growth curves and concluded that the returns of sorting are between $11 and $25 per head.

As mentioned above most feedlots handle cattle individually through a chute at least two times during the feeding period and have the opportunity to collect and utilize animal specific data. One such time is at the start of the feeding period when cattle are given an ear tag and growth promoting implant and are vaccinated if needed. The feedlot may also record individual animal data such as weight, hip height, and frame score as well. The second time individual animal data may be collected is when the feedlot administers a second implant (or third depending on the length of the feeding period), known as re-implant time approximately 70-80 days prior to slaughter[1]. Given animal specific information and market information is it possible to accurately develop a process to sort cattle earlier in the feeding period that will improve feeding profits for the entire pen?

The purpose of the study is identify if information readily available at re-implant time is sufficient to identify less profitable animals and if it is enough to improve feeding profits by eliminating the animals that are less profitable at that moment by re-selling them as feeder cattle. Specifically, the objectives are:

1. Determine if readily available information at placement and re-implant time can accurately identify cattle likely to receive premiums and discounts at slaughter.
2. Evaluate if the accuracy and advantage from such a prediction method are large enough to offset the added cost of sorting and less than optimal pen utilization at different sorting and reselling levels.

Data Description

Individual animal data representing nearly 20,000 cattle fed in 12 Iowa feedlots in 2002-2004 were analyzed for this project. The data representing two different time periods in the same feedlots were divided into two datasets (Table 1). The first was used for regression analysis to develop a prediction model. The model was evaluated out of sample on the second dataset representing similar cattle and feedlots from a different time period. The cattle were weighed each time they were worked through the chute and individual data were collected. The cattle were also sorted for slaughter based on professional judgment and sold on two or three different marketing dates. As a result there are relatively few over weight or over fat carcasses in the datasets.

The first dataset represents 14,735 heifers (28%) and steers (72%) sold between August 2002 and June 2004. The second dataset represents 5,188 heifers (30%) and steers (70%) sold between January 2002 and July 2002. The average live weight at placement and at slaughter,

[1] Growth promoting implants typically are effective for 60-90 days

days on feed, and the grading distribution were similar between the two data sets.

The datasets report variables for each animal measured at five different moments: Birth, Delivery (the time the animal enters in the feedlot), Start on feed (just after few days of warm-up in the feedlot), Re-Implant (when animal receives second implant) and Slaughter sort (when they are sorted for slaughter). Feedlot performance (average daily gain, health treatment and estimated feed efficiency[2]) and carcass data were also collected.

A profit regression was developed to calculate the expected returns for each animal given its feedlot and carcass information. Prices and costs were standardized to remove market variations on the estimation of the marginal effect of the variables in profit equation. The monthly average of 12 years (06/1992-06/2004) fed-cattle price (USDA, Agriculture Marketing Service) was used as the base price to calculate the profit. The monthly trend in price variability was calculated from the same dataset. The Choice-Select spread used for the analysis for each month is the average of 5 years (06/1999-06/2004) for each month and the source of information was the "National Carcass Premiums and Discounts for Slaughter Steers and Heifers" (USDA, Agriculture Marketing Service).

Representative feeder-cattle prices for each sex and weight range was developed based on the average of the monthly Auction Cattle Prices reported for Missouri, Kansas, and Oklahoma for 12 years (01/1992-12/2003) reported by USDA-Agricultural Marketing Service. For calculating the profits of the animals at re-implant time, the opportunity cost of the steer or heifer was its feeder cattle price at re-implant adjusted for weight and fleshiness. As discussed later, this assumes that the feedlot re-sells the animal in an auction market rather than feeding it to slaughter if it is sorted off. It assumes that they look fleshy and will receive a price discount that depends on the weight and season (Schroeder et al., 1988; Smith et al., 1998). The 3% commission of the auction barn was also discounted from opportunity cost of the cattle. For cattle fed to slaughter, a widely used grid was used to calculate the yield grade and quality grade premiums and discounts and weight discount for each animal (Table 2).

The average feed price in the dataset (0.00551 $/pound) was adjusted by a corn price monthly index and this price was multiplied by the estimated feed consumed by each animal. The corn price index was based on prices received by Iowa farmers, 2000-2004 (Iowa Agricultural Statistics). Cattle owners pay an overhead fee ($10.17/head) and carcass data collection ($7.95/head). Daily yardage (0.29 $/day) was used for calculating the total yardage for each animal. The interest rate used for the analysis was the average of the dataset (7% / year). Average trucking, insurance & checkoff cost were $8.14/head.

Procedures

The dataset was split by sex, therefore all the analysis are made and reported for steers and for heifers separately. Three logit regressions were run with the information available at re-implant time as the independent variables with the goal of better identifying the:

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[2] The Cornell Net Carbohydrate model (Fox, Sniffen, and O'Connor, 1988) is used to estimate individual animal feed efficiency based on pen feed usage and gain, individual animal gain and carcass composition based on yield grade.

- HQG (carcasses grading 2/3 upper choice or better),
- LQG (carcasses grading select or worse),
- LYG (yield grade 1 or 2).

The procedure was to estimate the change in the probability of producing a carcass with any of these characteristics when the variables measured in animals changed. There were too few animals that produced a heavy carcass or a yield grade 4 or 5 carcass making the results of the logit regression for these cattle inaccurate. The estimates from these regressions were used to calculate the fitted values for HQG, (LQG, and LYG for each animal.

The decision the producer faces based on the information available at re-implant time is whether to re-implant the animal and feed it to slaughter weight or sell it immediately at the local auction market as a feeder animal to reduce the expected losses from feeding that animal further. Eliminating the least profitable animals will improve the average profit on the entire pen, but the producer doesn't know for sure which animals are the least profitable and will make mistakes on the decision, these errors can wipe out the potential profit of this practice. This analysis assumes that the cattle identified as unprofitable to feed can be re-sold at auction at the average price for a given weight and a discount for fleshiness. This assumption relies on asymmetric information and its important corollary, "There's one born every minute."

Generalized linear regressions with two different levels of information were run to identify the effect of each of the characteristics measured in the animal on profit and to get beta estimates to use in further analysis. Regression 1 (R1) utilizes pen data plus individual animal information across time such as: individual average daily gain, number of individual health treatments, predicted weight at slaughter, and an estimate of carcass quality and yield grade at slaughter (HQC, LQC, LYG). Regression 2 (R2) uses pen average data measured across the time such as: group average daily gain, cost of preventive health treatments for the group and some individual data observed at re-implant time, but not the estimated quality and yield grades.

Regression 1:

$$\text{Profit} = \beta_0 + \beta_1\, SlaughteredSummer + \beta_2\, SlaughteredFall + \beta_3\, SlaughteredWinter + \beta_4\, OneIndTrt + \beta_5\, TwoOrMoreIndTrts + \beta_6\, ADG + \beta_7\, AdjFinalWt + \beta_8\, fittedHQC + \beta_9\, fittedLQC + \beta_{10}\, fittedLYG$$

Regression 2:

$$\text{Profit} = \beta_0 + \beta_1\, SlaughteredSummer + \beta_2\, SlaughteredFall + \beta_3\, SlaughteredWinter + \beta_4\, British + \beta_5\, Continental + \beta_6\, SomeIndicus + \beta_7\, GrHealthTrts + \beta_8\, DispScoreImpl + \beta_9\, ImplWt + \beta_{10}\, GrADG + \beta_{11}\, GrKillWt$$

where :

- *SlaughteredSummer* is a dummy variable that takes the value 1 if the animal was slaughtered in summer and 0 otherwise
- *SlaughteredFall* is a dummy variable that takes the value 1 if the animal was slaughtered in fall and 0 otherwise
- *SlaughteredWinter* is a dummy variable that takes the value 1 if the animal was slaughtered in winter and 0 otherwise
- *OneIndTrt* is a dummy variable that takes the value 1 if the animal received one

individual health treatment and 0 otherwise
- *TwoOrMoreIndTrts* is a dummy variable that takes the value 1 if the animal received two or more individual health treatments and 0 otherwise
- *AdjFinalWt* is the predicted individual live weight (lbs) at slaughter of the animal
- *ADG* is the individual average daily gain (lbs/day) of the animal
- *fittedHQG* is a dummy variable that takes the value 1 if the animal was predicted as producing a high quality grade carcass by the logit model and 0 otherwise
- *fittedLQG* is a dummy variable that takes the value 1 if the animal was predicted as producing a low quality grade carcass by the logit model and 0 otherwise
- *fittedLYG* is a dummy variable that takes the value 1 if the animal was predicted as producing a low yield grade carcass by the logit model and 0 otherwise
- *British* is a dummy variable that takes the value 1 if the animal has at least 75% British breed genes and 0 otherwise
- *Continental* is a dummy variable that takes the value 1 if the animal has at least 75% Continental breed genes and 0 otherwise
- *SomeIndicus* is a dummy variable that takes the value 1 if the animal has at least 25% Indicus breed genes and 0 otherwise
- *GrHealthTrts* is the average money spent in preventive health treatments ($/head) of the lot that the animal belongs to
- *DispScoreImpl* is a subjective measure of the wildness of the animal at re-implant time in a scale 1-6 where 1 is a quiet animal and 6 is very nervous
- *ImplWt* is the individual live weight (lbs) at re-implant of the animal
- *GrADG* average daily gain (lbs/head/day) of the lot that the animal belongs to
- *GrKillWt* average live weight (lbs/head) at slaughter of the lot that the animal belongs to

The optimal level to sort and re-sell at re-implant time was evaluated for three levels of information and following a three step process. The three levels of information include: R1 and R2 described above and actual ex-post data. The latter provides a value of perfect information. The estimated profit calculated with each of these levels of information was used for making the decision.

The decision threshold is the net return of selling the animal today versus feeding it to slaughter. When an animal is sold back into the auction market, there are additional costs that must be faced that were not included in the calculus for profit such as trucking to the auction market and less than optimum pen utilization, these are considered as the new cost associated with re-selling the animal:

New cost= truck to auction market + yardage[1]

1- To calculate the cost of less than optimum pen utilization, it was assumed that the yardage was paid on dollars per pen per day instead of dollars per animal per day

Some of the animals expected profit could be negative, but the costs associated with selling them into the auction market are higher than the cost of facing this individual animal negative profit. Therefore the rule for eliminating an animal from the lot is that the expected loss associated with keeping it must be higher than the expected cost associated with reselling it. Every animal whose expected profit is negative and is higher in absolute value than the additional costs faced if the animal is sold back into the auction market (New Cost) is eliminated from the group.

Therefore the rule for eliminating an animal is that Profit < 0 and |Profit| > New Cost

The net return of feeding all the animals to the slaughter weight and sold as the pen was actually managed was contrasted with the net return from sorting some cattle off at re-implant time. This "re-selling advantage" is defined as:

RSA= Net return with sorting – Net return without sorting

The RSA average and its standard error was calculated across all pens of cattle for three levels of information (Actual, R1, and R2). Therefore for each of the three levels of information we have a distribution of the advantage of this practice with respect of the actual practice of selling all the animals to the slaughter plant when they actually were sold.

The models R1 and R2 estimated using dataset one were also used to make sorting decisions on dataset two, an out of sample evaluation. In addition the results were subjected to two sensitivity analyses to determine first if the parameter estimates were stable and second determine if the optimal sorting threshold changes with economic conditions. Both factors were compared using a change of:

- 30% in the Choice-Select spread, quality premiums, yield grade premiums and discounts, and weight discounts
- 20% in the cost of gain
- 10% in the feeder and fed cattle base price moving together (because feeder and fed cattle prices are highly correlated)

Results

Logit Regressions

The prediction power of the logit model to predict high quality, low quality and low yield grade animals was somewhat low (Table 3). Only 58% of the animals predicted to produce a high quality carcass actually had a high quality carcass and 57% of the animals identified as producing a low quality carcass actually produced a low quality carcass. Breed type, sex and delivery season are the variables that affected quality and yield grade the most (Table 4). Animals that were at least 75% British breeds tend to have better quality but higher yield grade[3]. Animals that were at least 75% Continental breeds tend to have lower quality but lower yield grade. Animals that were at least 25% Indicus breeds produced low quality and high yield grade carcasses. Steers had lower quality than heifers but also lower yield grade. The animals that entered in the feedlot in spring were the ones with the worst quality grade but produced the lowest yield grade.

Profit Regressions

[3] Lower number Yield Grades are preferred to higher Yield Grades because they have higher lean meat yield.

When animals are identified individually, fitted LQG was the most important variable affecting profit followed by average daily gain and slaughter season. Weight at slaughter was an important predictor of profit in steers but not in heifers. Higher final weight and average daily gain led to higher profits. (Table 5)

The beta estimates for this profit regression were relatively stable to changes in cost of gain with the exception of the estimate for the effect of average daily gain on profit. The slope estimates were also relatively stable to grids premiums and discounts with the exception of the slope estimate for *fittedLQG* that is sensitive to changes in grids premiums and discounts. *SlaughterWinter* beta estimate is sensitive to changes in cattle prices in steers.

When individual records were not kept from one period to the next R2 the characteristics that explain profit the most at re-implant are *GrADG* and slaughter season in steers followed by *GrKillWt* and breed type. *GrKillWt* and slaughter season were the most important variables affecting profit on heifers followed by *GrADG*, *ImplWt* and *SomeIndicus*. A higher *GrADG* was associated with higher profit. Higher weight at re-implant led to lower profit. After adjusting for the individual weight at implant, a higher *GrKillWt* led to lower profits. The concentration of Indicus breeds affected profit negatively. (Table 6)

The beta estimates for this profit regression were relatively stable to changes in cost of gain, grids premiums and discounts, and to changes in cattle prices.

Heifers were shown to be more profitable than steers with a 99% confidence. Heifers' average profit (from re-implant to slaughter) was \$12.2/head while steers average profit (from re-implant to slaughter) was \$4.5/head.

When less information is available the goodness of fit of the profit regression decreases. It can be seen that going from the information available through individual animal identification to the information available without individual animal identification decreases the R^2 of the linear regression from 0.29 to 0.11 in steers and from 0.22 to 0.15 in heifers.

Sort and Re-sell Results

Identifying the least profitable animals at re-implant time and re-selling them in the auction market potentially increases the feedlot profitability. The percentage of animals that should be eliminated to maximize profit varied with sex. Using ex-post information this optimum was 21% for steers and 14% for heifers. (Table 7)

The optimum cull rate decreases when the degree of information decreases. Lower information was associated with lower expected value of the RSA and with higher variation of the RSA. For example for the case of steers, going from ex-post to R1 information drops the expected value of the maximum profit derived from re-selling animals from \$35/head to \$15/head because you do not re-sell as many unprofitable animals with less than perfect information and sell some that would have been profitable to keep. Going from R1 to R2 information drops the profit from \$15/head to \$12/head. For heifers the RSA with ex-post information is large (\$31/head) and also drops dramatically with R1 information (\$10/head). With R2 information the RSA is not different than zero with 90% confidence in the actual dataset. The results show that not all animals should be fed to slaughter.

The prediction models of grade at slaughter increased the sorting advantage as the benefit from predicted quality and yield grade over estimates without it. It stands to reason a better prediction would produce better results. Ultrasound technology to predict slaughter grade is commercially available for $4/head. Most feedlots use ultrasound to predict how long to feed an individual steer or heifer. Perhaps "no longer" should be a choice.

The normality assumption of the RSA distribution was tested and it is not normally distributed. The distribution is skewed to the right and the tails are wider than in a normal distribution. Therefore it is needed to rely on the central limit theorem to make confidence interval and hypothesis testing. This situation cause that the second dataset cannot be separated by sex because it has only 36 lots of animals and if they are separated, the central limit theorem may not apply.

Out of sample for both sexes

When less information is available much of the advantage is lost but some of this advantage ($5/head) remains in the out of sample analysis for the R1 method. The advantage of counting on individual animal identification information is much higher when the slope estimates from one dataset are used to sort animals out of sample. The RSA with R2 identification is negative but is not statistically different than zero. (Table 8)

This difference in the out of sample expected value of the RSA with and without individual animal identification is enough to cover the expenses of individual animal identification and keeping good records that are around $4/head. But the $5/head RSA is about equal to the cost of data making feedlots indifferent.

The expected value of RSA and the proportion to re-sell were sensitive to changes in the market conditions (please see figures 1 and 2). The high variation in the percentage of selection and the RSA is probably a consequence of the expected value of profit being close to zero, therefore a big proportion of the animals expected profit is close to the threshold value and small changes in prices shift them from being profitable to being unprofitable and vice versa

Conclusions

This analysis showed that there is a potential advantage of predicting the least profitable animals in a pen and re-sell them as feeder-cattle. Individual animal identification and management provides additional information and accuracy to apply this practice. More accurate and complete information led to a higher expected re-selling advantage and lower variation. It is worth noticing that there are other management alternatives that become available with individual animal identification such as accurately sorting each animal to be sold at the time his expected premiums for quality and yield grades are higher or to the grid that offer the best prices for it, but the advantage from this single practice is enough to cover the costs of individual animal identification.

It was also found that the estimates from one set of data had some prediction power in a second data set of similar cattle suggesting that the results can be applied in feedlots with similar management practices and where individual animal identification information is available. But this advantage was very small out of sample when the information is not perfect and therefore a better prediction of animal profitability is needed.

Sorting practices improved with increased information about the animal and compared to the rest of the group. Compared to expost information that made for the most profitable sort, the prediction models error was on the side of keeping an unprofitable animal rather than selling a profitable animal too soon. The RSA was nearly $5/head across both steers and heifers. Given that the average return to cattle feeding has been $6.6/head for this dataset the return is worth pursuing.

Practical implications

Obviously, removing the least profitable animals from the pen will improve the pen average. The challenge is how to identify the least profitable animals and to weigh the marginal net benefit of feeding them longer versus selling them immediately. Individual animal management and accumulated data can improve the prediction accuracy as can tools such as ultrasound. The second obvious statement is that if this practice become widely used, buyers of heavy feeder cattle will become aware of the risk of buying cattle that another person eliminated for being unprofitable. The effects on the market prices of generalizing this practice are a subject for further research, but if the average RSA is $5/head an additional $1/cwt price discount on feeder cattle will wipe out the advantage.

There is still a large difference between the expected RSA with perfect information and predicted RSA with individual animal identification. Important predictors of profit were the carcass quality and yield grade but they could not be predicted accurately with the information available. Therefore, further research incorporating genetic potential, past history, or ultrasound predictions of quality and yield grade may be very valuable. Further research may include also the decision of sorting to more than one market and selling the animals to the market that pays a higher final price for each animal or the decision of feeding more or less days to optimize the animal's profitability.

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Appendix

Table 1. Descriptive Statistics and Quality and Yield Grade Distribution of Two Datasets Representing Cattle Fed in 12 Iowa Feedlots 2002-2004

	dataset 1	dataset 2
Number of head	14,735	5,188
Percent steers	72	70
Average placement weight	651	650
Average slaughter weight	1,179	1,180
Days On Feed	169	166

		Prime		Upper 2/3		Lower 1/3		Select		Outliers		Total YG	
Dataset		1	2	1	2	1	2	1	2	1	2	1	2
Yield grade	1	0.1	0.0	3.5	4.2	30.2	31.5	50.9	48.1	15.3	16.3	8.5	6.1
	2	0.7	0.8	15.1	15.2	50.9	47.4	30.4	32.0	2.9	4.6	49.4	47.9
	3	2.5	3.3	31.0	28.2	52.1	51.7	13.8	14.9	0.7	1.9	40.4	44.4
	4&5	8.2	5.1	26.6	17.7	59.7	65.8	5.6	11.4	0.0	0.0	1.6	1.7
	Total QG	1.5	2.0	20.7	20.3	49.8	48.7	25.0	25.0	3.0	4.0	100	100

Source: Tri-County Steer Carcass Futurity, Lewis, Iowa

Table 2: Grid quality and yield grade premiums and discounts

		Quality Grade				
		Prime	Upper 2/3 Choice	Lower 1/3 Choice	Select	Outliers
Yield grade	1	5 + 8	5 + 4	5 + 0	5 + (Ch/Sel spread)	5 + ((Ch/Sel spread) -20)
	2	3 + 8	3 + 4	3 + 0	3 + (Ch/Sel spread)	3 + ((Ch/Sel spread) -20)
	3	0 + 8	0 + 4	0 + 0	0 + (Ch/Sel spread)	0 + ((Ch/Sel spread) -20)
	4	-15 + 8	-15 + 4	-15 + 0	-15 + (Ch/Sel spread)	-15 + ((Ch/Sel spread) -20)
	5	-25 + 8	-25 + 4	-25 + 0	-25 + (Ch/Sel spread)	-25 + ((Ch/Sel spread) -20)

Heavy or light weight carcass discounts: -$20

In each cell of Table 2, the first value is the yield grade premium and the second value is the quality grade premium.

Table 3: Percentage of correct predictions for the logit regressions

Predicted HQG	58.5	Predicted LQG	56.6	Predicted LYG	72.6
Predicted Not HQG	78.1	Predicted Not LQG	77.1	Predicted Not LYG	61.3
Total Predictions HQG	77.4	Total Predictions LQG	75.0	Total Predictions LYG	67.3

Table 4: Logit regression for predicting, HQG, LQG, and LYG carcasses

	HIGH QUALITY			LOW QUALITY			LOW YIELD GRADE		
Variable	Beta	P-value	Stand. Beta*	Beta	P-value	Stand. Beta	Beta	P-value	Stand. Beta*
Intercept	-1.91	0.00	0.00	-0.21	0.37	0.00	0.99	0.00	0.00
Male	-0.60	0.00	-0.13	0.69	0.00	0.10	0.84	0.00	0.19
British	0.80	0.00	0.19	-0.69	0.00	-0.11	-1.16	0.00	-0.29
Continental	-0.84	0.00	-0.12	0.80	0.00	0.08	1.35	0.00	0.21
SomeIndicus	-0.96	0.00	-0.11	0.90	0.00	0.07	-0.23	0.01	-0.03
DelFall	1.41	0.00	0.29	-1.11	0.00	-0.16	-0.45	0.00	-0.10
DelWinter	1.51	0.00	0.18	-1.01	0.00	-0.08	0.24	0.07	0.03
DelSummer	0.92	0.00	0.15	-0.67	0.00	-0.08	-0.37	0.00	-0.07
OneIndTrt	-0.08	0.29	-0.01	0.24	0.00	0.03	0.30	0.00	0.05
IndTrts	-0.46	0.00	-0.05	0.66	0.00	0.05	0.66	0.00	0.07
GrHealthTrts	0.05	0.00	0.07	-0.04	0.00	-0.05	-0.04	0.00	-0.07
AveDispScore	-0.15	0.00	-0.05	0.20	0.00	0.04	0.19	0.00	0.06
CondScore	0.13	0.00	0.04	-0.17	0.00	-0.03	-0.05	0.17	-0.02
WtAgeOnTest	-0.72	0.00	-0.15	0.37	0.00	0.06	0.09	0.09	0.02
ADGTestImpl	0.07	0.00	0.05	-0.09	0.00	-0.04	-0.06	0.00	-0.04

* Stand. Beta is the standarized beta, it is equal to: $\boxed{\hat{\beta}_i \times \frac{\hat{\sigma}_{x_i}}{\hat{\sigma}_y}}$

Table 5: Profit regression with individual identification and a predicted value for quality and yield grade

	HEIFERS			STEERS		
Variable	Beta	P-value	Stand. Beta*	Beta	P-value	Stand. Beta*
Intercept	-34.27	0.00	0.00	-166.14	0.00	0.00
SlaughteredSummer	-44.99	0.00	-0.18	-35.14	0.00	-0.12
SlaughteredFall	-40.26	0.00	-0.17	-42.10	0.00	-0.13
SlaughteredWinter	-10.76	0.00	-0.07	-28.99	0.00	-0.17
OneIndTrt	4.21	0.20	0.02	-6.36	0.00	-0.03
TwoOrMoreIndTrts	-5.38	0.24	-0.02	-21.40	0.00	-0.08
ADG	18.85	0.00	0.17	22.52	0.00	0.19
AdjFinalWt	0.01	0.46	0.01	0.11	0.00	0.16
fittedHQG	16.15	0.00	0.07	12.11	0.00	0.04
fittedLQG	-75.17	0.00	-0.29	-82.31	0.00	-0.34
fittedLYG	1.86	0.61	0.01	4.64	0.02	0.02
		R-square is: 0.22			R-square is: 0.29	

* Stand. Beta is the standarized beta, it is equal to: $\boxed{\hat{\beta}_i \times \frac{\hat{\sigma}_{x_i}}{\hat{\sigma}_y}}$

Table 6: Profit regression without individual animal identification

	HEIFERS			STEERS		
Variable	Beta	P-value	Stand. Beta*	Beta	P-value	Stand. Beta*
Intercept	363.56	0.00	0.00	107.00	0.00	0.00
British	-2.09	0.45	-0.02	2.58	0.17	0.02
Continental	-4.30	0.33	-0.02	-22.00	0.00	-0.10
SomeIndicus	-25.41	0.00	-0.11	-39.64	0.00	-0.14
SlaughteredSummer	-49.04	0.00	-0.22	-45.29	0.00	-0.15
SlaughteredFall	-34.79	0.00	-0.16	-64.44	0.00	-0.21
SlaughteredWinter	-0.54	0.87	0.00	-35.20	0.00	-0.21
GrHealthTrts	-1.39	0.02	-0.04	-0.71	0.00	-0.03
DispScoreImpl	-4.36	0.00	-0.05	-1.08	0.29	-0.01
ImplWt	-0.07	0.00	-0.14	0.04	0.00	0.06
GrADG	25.96	0.00	0.14	51.63	0.00	0.21
GrKillWt	-0.30	0.00	-0.22	-0.23	0.00	-0.14
	R-square is: 0.15			R-square is: 0.11		

* Stand. Beta is the standarized beta, it is equal to: $\boxed{\hat{\beta}_i \times \frac{\hat{\sigma}_{x_i}}{\hat{\sigma}_y}}$

Table 7: RSA for each sex under approach in dataset one

	STEERS		
Estimate	Perf. Info	R1	R2
RSA mean	35.2	14.7	11.7
RSA SE	4.1	3.7	6
% Resell	21.1	13.1	4.8
% Resell SE	1.8	1.7	2
	Type I	4.7	1.3
Error (%)	Type II	12.8	19.3

Type I error => Eliminate a profitable animal
Type II error => Keep an unprofitable animal

	HEIFERS		
Estimate	Perf. Info	R1	R2
RSA mean	30.7	10.4	7.7
RSA SE	5.2	4.5	5.6
% Resell	14.3	7.5	8.1
% Resell SE	2.2	1.8	4.5
	Type I	2.5	4.9
Error (%)	Type II	12.9	15.3

Type I error => Eliminate a profitable animal
Type II error => Keep an unprofitable animal

Table 8: Out of sample Re-seeling advantage

Estimate	Perf. Info	R1	R2
RSA mean	19.2	5.0	-4.4
RSA SE	2.5	2.1	2.7
% Resell	13.3	8.3	2.8
% Resell SE	2.3	2.3	1.7
Error (%)	Type I	3.3	2.9
	Type II	7.7	10.6

Type I error => Eliminate a profitable animal
Type II error => Keep an unprofitable animal

Figure 1: Sensitivity of the RSA to market changes

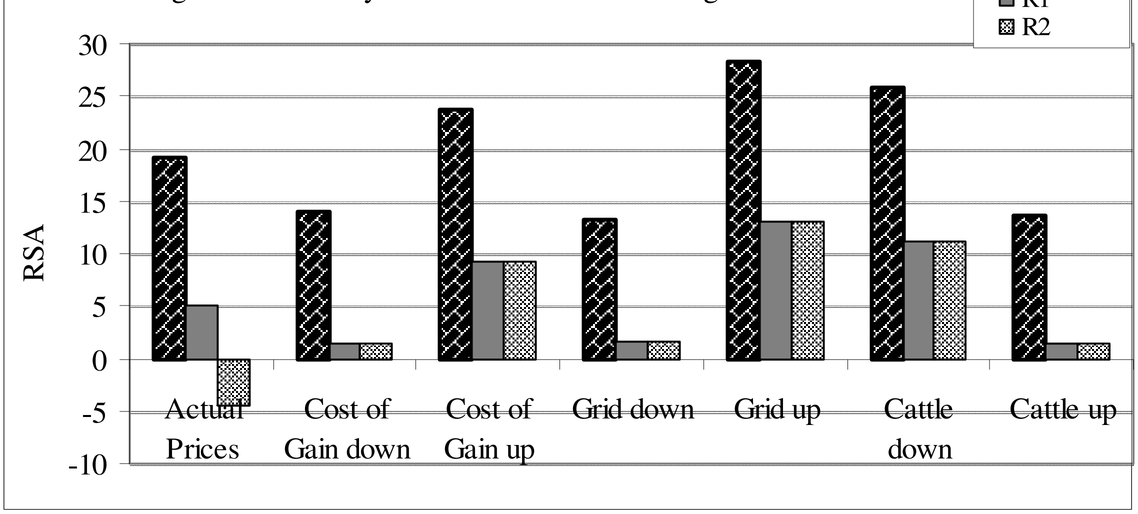

Figure 2: Sensitivity of the percentage of selection to market changes