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Optimal Marketing Decisions for Feeder Cattle under Price and Production Risk

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ABSTRACT

In many parts of the U.S., beef cattle production is a large sector of the agricultural economy, yet few of the cattle are stockered; instead the production is focused on cow-calf operations only. Restricting their operation to only the first phase of beef production may be limiting the cattle owners' profit potential. This paper examines the opportunities for operators to earn additional profit from stockering cattle. Using a representative risk-averse producer, a decision set with seven possible marketing strategies is evaluated for the optimal decision in a Bayesian framework which allows for price and production risk. We find that in many instances retaining the cattle for stockering is a superior decision when done in conjunction with specific hedging strategies utilizing options and futures contracts.

Key Words: *cattle, decision science, estimation risk, marketing.*
JEL codes: C6, D2, Q1

Nationwide, the beef cattle industry produces $15–20 billion of annual output, making it one of the top four agricultural commodities in terms of value. There are three phases in the cattle industry: cow-calf, stocking and feedlot operations. Cattle producers face decisions at several times when they must either sell the cattle or continue to feed them until they reach the next size class. The production of beef cattle is also one of the most significant sectors of the Southeast's agricultural economy, ranking fourth in an average year in agricultural income behind poultry, peanuts, and cotton, yet only about 25 percent of Southeastern cattle are retained for stockering. Thus a potential opportunity exists for Southeastern cattle producers to increase their farm income by increasing the role of stockering.

A stocker cattle producer faces two kinds of risk. One source is the market, which produces price variability, and the other one is production variability resulting from environmental conditions and production practices. The cattle industry is characterized by highly variable returns. According to McKissick and Ikerd, from 1950 to 1996 the net returns of winter stockering in Georgia ranged from −$9.28/cwt to $27.89/cwt, the net returns of the cow-calf plus winter stockering and yearling feeding ranged from −$47.14/cwt to $33.19/cwt (these results likely generalize well to the rest of the region). They also show that stocker operations seem to show an essentially random pattern of profit and loss between sharp market breaks regardless of whether cow-calf operations are in the profit or loss phase of the cycle.

In this paper we examine a set of seven

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marketing strategies in a search for optimal marketing decisions that balance the producer's desire for higher profits with an aversion for decisions that produce too much risk. The strategies range from simple (always sell calves in November or stocker through winter then sell in the cash market) to complex (stockering the cattle with put and call options used to reduce risk). These strategies are evaluated for a representative Georgia cow-calf operation for 1994 through 1996 and shown to be reasonably effective at helping producers choose optimal marketing strategies that can raise their profits without unduly burdening them with returns risk. To accomplish the evaluation of these marketing strategies, we implement a numerical Bayesian decision theory model to estimate the expected utility of profit of each strategy. The *ex ante* optimal choices are then compared to the *ex post* and some additional information and discussion is included. Specifically, we establish a method for finding the optimal marketing strategy under our production and price risk scenarios and also demonstrate that the Bayesian approach can produce the probability of achieving a selected level of profit under a particular strategy.

Theoretical Background

The expected utility model provides a single-valued index that ranks decision alternatives. Individual behavior in the face of risk can be described as if the individual maximized the expected utility of the risky outcome. Essentially, agents need to know the possible consequences of their choice, to have beliefs about the probabilities of these consequences of their choices, and to be concerned only with the consequences. When the selection of the optimal alternative is conditional on parameters that are unknown to the decision-maker (or modeler), there is an estimation risk problem.

Let x denote the vector of decision variables and let y denote a vector of random variables associated with the decision problem. The joint probability density function for y is denoted by $f(y|\theta)$, where θ is a parameter vector that characterizes this distribution. Let $\pi(y, x)$ denote the random return resulting from the decision, x; and let $U(\pi)$ denote the decision-maker's utility function. If θ is known to the decision-maker, then the decision-maker's objective function is represented by

$$(1)\qquad \max_{x\in X} E_{(y|\theta)}U[\pi(y, x)] = \max_{x\in X} \int_Y U[\pi(y, x)]f(y|\theta)\,dy$$

where E represents the expectation operator, X is the set of all possible decisions, and Y is the domain of y.

Two situations are included in estimation risk. The first one is when the functional form of $f(\cdot)$ is unknown; the second one is when the functional form of $f(\cdot)$ is known, but the value of parameter θ is unknown. In this study we will focus on the second case. With estimation risk, the expected utility value in the above equation depends on an unknown value of θ, so the problem cannot be solved as stated.

The Parameter Certainty Equivalent Method

The commonly employed method to solve the decision-making problem defined by equation (1) is to ignore the estimation risk. One simply replaces population parameter θ by a sample estimate of θ and makes decisions that are based on the resulting estimate of optimal behavior. This method is known as the *parameter certainty equivalent* (PCE) method (cf. Bawa, Brown, and Klein) or the "plug-in" method (Pope and Ziemer). The problem now becomes one of solving the following equation:

$$(2)\qquad \max_{x\in X} E_{(y|\theta=\underline{\theta})}U[\pi(y, x)] = \max_{x\in X} \int_Y U[\pi(y, x)]f(y|\underline{\theta})\,dy$$

where $\underline{\theta}$ is the sample estimate of θ. This approach has the advantage of simplicity, but it ignores estimation risk and is not consistent with expected utility maximization (Bawa, Brown, and Klein).

The Bayesian Method and Justification

Rather than replacing $f(y|\theta)$ by $f(y|\underline{\theta})$, where $\underline{\theta}$ is the sample estimate of θ, the Bayesian method considers all available information. Let $(S_1, \ldots, S_N)$ denote a sample from a distribution with likelihood function L, indexed by a continuous parameter θ, with prior density $p(\theta)$. Bayes' Theorem states that the posterior density for θ, $h(\theta|S_1, \ldots, S_N)$, which conveys all prior (non-sample) and all sample information about θ is given by:

$$(3) \quad h(\theta|S_1, \ldots, S_N) = \frac{L(S_1, \ldots, S_N|\theta)p(\theta)}{\int_\theta L(S_1, \ldots, S_N|\theta)p(\theta)\, d\theta}$$

In equation (3), the denominator does not depend upon θ, the posterior function is proportional to the product of $p(\theta)$ and $L(S|\theta)$:

$$(4) \quad h(\theta|S_1, \ldots, S_N) \propto L(S_1, \ldots, S_N|\theta)p(\theta)$$

Since parameters of the sort included in θ can rarely be observed, we can never be certain how well such a construct as a mean has been estimated or approximated. What are much more relevant, however, are observable quantities. Using a Bayesian approach we can solve the problem by integrating out the unknown parameters in the predictive density. The predictive density for y is given by

$$(5) \quad g(y) \equiv E_\theta[f(y|\theta)] = \int_\theta f(y|\theta)h(\theta|S_1, \ldots, S_N)\, d\theta$$

and the optimal decision is based on solving the following problem:

$$(6) \quad \max_{x \in X} E_{(y)} U[\pi(y, x)] \equiv \max_{x \in X} \int_Y U[\pi(y, x)]g(y)\, dy.$$

As pointed out by Bawa, Brown, and Klein, there are three reasons for employing a Bayesian method rather than the parameter certainty equivalent (PCE) method. First, the Bayesian method is derivable under a set of reasonable axioms. In contrast, the parameter certainty equivalent method has no axiomatic foundation (DeGroot, Chapters 7 and 8) and, at best, the PCE method is justified asymptotically when there is no estimation risk. The second is that the Bayesain method processes all relevant (sample as well as non-sample) information in terms of an entire distribution for θ via the predicative distribution. In contrast, the PCE method processes only sample information on θ by a single summary measure—the point estimate of θ. The third is that the Bayesian method has a minimum average risk or maximum average value for the specified prior (Berger, Chapter 4).

Related Previous Work

Analysis of estimation risk on decision making has been the focus of numerous investigations, both in the financial and agricultural economics literatures. Barry (1974) has shown that incorporating estimation risk into the decision framework will not change the efficient set, but doing so will change the expected utility-maximizing portfolio allocation for any given decision-maker. Dixon and Barry provided an empirical simulation of how incorporating estimation risk affects the optimal portfolio allocation in a three-asset example. Lence and Hayes (1994) have shown that the optimal futures position estimated by means of the PCE approach lacks normative value because it is generally suboptimal when there is uncertainty regarding the actual parameter values. They also provide a model that can be used to obtain an optimal futures position in the realistic situation where the decision-maker has sample information and prior beliefs regarding the relevant parameters. The Lence and Hayes (1994) model is based on a Bayesian decision criterion and nests both the theoretical model with perfect parameter information and the PCE formula.

Pope and Ziemer examined the effects of estimation risk in a stochastic dominance setting and found, using Monte Carlo techniques, that incorrect orderings were common under the PCE approach. They also found that the empirical distribution function was preferable to the PCE method when ordering discrete alternatives from sparse data sets. Collender examined the limitations of estimation risk on our ability to distinguish between the mean-variance characteristics of different portfolios.

Chalfant, Collender, and Subramanian analyzed the sampling properties of the land allocation vector obtained using the PCE approach in a mean-variance framework. They (CCS) showed that the PCE allocation vector is a biased estimator of the optimal allocation in the absence of estimation risk. CCS pursued this matter further and proposed an alternative allocation vector, also based on the sample mean vector and covariance matrix but featuring unbiasedness. They proved that the proposed allocation yields greater expected utility than does the plug-in allocation. By explicitly incorporating estimation risk, CCS improved on the PCE approach. Lence and Hayes (1995) reexamined the land-allocation problem in the presence of estimation risk. A Bayesian allocation rule based on the sample estimates of the mean vector and the covariance matrix of crop return was obtained. This land allocation rule was derived in a manner consistent with expected utility maximization and was therefore preferable to other criteria (e.g., plug-in, CCS rule, and an approximate Bayesian decision rule used by Bawa) for decision making in the presence of estimation risk. The allocation rule also yielded greater expected utility than did an allocation that is an unbiased estimator of the optimal land allocation in the absence of estimation risk.

In this study we take the Bayesian approach to handling the presence of estimation risk as superior. In applying this method we find that the integral in equation (10) is impossible to solve analytically. Therefore, we use a numerical approach to approximating the value of this integral (Dorfman; Tanner). The details of the numerical procedure will be reserved to the section on the data and strategies evaluated so as to make the description more concrete.

The Utility Function Chosen

To evaluate the different marketing strategies, a representative Georgia cattle producer is assumed to choose a strategy that maximizes the expected utility of profit, where *utility of profit* is defined as

$$(7) \qquad U(\pi) = -e^{-\phi\pi}$$

In the above utility function, ϕ is a constant absolute-risk-aversion coefficient which is defined as $\phi = -u''(\cdot)/u'(\cdot)$. Smaller values of ϕ imply less aversion to risk, with values generally being between 0.001 and 0.000001 (Cochran and Raskin), and with $\phi = 0$ equating to the risk-neutral case.

Babcock, Choi, and Feinerman showed that to determine a "reasonable" level of risk aversion one needs more information. The risk premium and the probability premium convey much more information than does the absolute-risk-aversion coefficient. For a binary gamble, let variable income $z = [h, -h; p, 1 - p]$ be a bet to gain or to lose a fixed amount h with probability p and $(1 - p)$, respectively. The following relations are derived for determining ϕ for a fair lottery game ($p = 0.5$) with a payoff of either win or lose:

$$(8) \qquad r_p(\phi, h) = \frac{\ln[.5(e^{-\phi h} + e^{\phi h})]}{\phi h}$$

$$(9) \qquad \phi = \frac{\ln[(1 + 2\rho)/(1 - 2\rho)]}{h}$$

where h is the wealth at risk (the gamble size) and r_p is the risk premium as a proportion of h with higher risk premia denoting greater risk aversion. For example, an individual willing to pay 90 percent of the potential loss in a gamble to eliminate the gamble would be characterized as extremely risk averse. The parameter ρ is the probability premium defined as $\rho = p - 0.5$, where p is the probability of gain such that the individual is indifferent to the choice between the fixed income and the risky one.

For this analysis of cattle marketing alternatives, we take the standard deviation of net returns for a representative producer as an ap-

Table 1. Matching the CARA Coefficient to the Risk and Probability Premia

	r_p	ρ
$\phi = 0.00005$	0.1715	0.0866
$\phi = 0.0001$	0.3247	0.1682
$\phi = 0.0002$	0.5471	0.3022

proximation for the gamble size; this yields $h = \$7000$. We set $\phi = 0.00005$, 0.0001 and 0.0002 to analyze the sensitivity of the simulation results to the risk-aversion coefficient. Further, to simplify the treatment of risk we assume cattle operators are only involved in the cattle business, or, equivalently, that they treat their cattle operations independently from any other activities (i.e., we are modeling enterprise risk, not whole farm risk). A farmer who grows crops with annual returns that are correlated with cattle returns might need to adapt the risk measure assumed here or otherwise adjust the optimization problem being solved. However, to incorporate these risks here we would have to assume the set of other commodities (both type and scale) that the farmer raises.

From equations (8) and (9) we get the value of r_p and ρ shown in Table 1. Under the three risk-aversion coefficients considered, a representative Georgia farmer is willing to pay \$1200, \$2273, and \$3830 to eliminate the market risk of a gain or loss of \$7000. These seem reasonable and results will be derived for these three risk-aversion levels.

For the utility function chosen in equation (7), if profit is normally distributed the expected utility of profit is simply

$$(10)\quad E[u(\pi)] = E(\pi) - (\phi/2)\mathrm{var}(\pi)$$

where $\mathrm{var}(\pi)$ is the variance of profits. The version of expected utility of profit shown in (10) will be used to select the optimal strategy in this study because normality of profits will be satisfied (at least approximately) due to the method used for simulation. The exact method of simulating the different strategies will be discussed in the next section.

Evaluating the Strategies

The Representative Producer

For the purposes of evaluating the marketing strategies with the optimization model, a representative Georgia cattle operation is created. The dominant Georgia stockering system of using temporary winter annual grazing for lightweight calves carried through the fall-spring period is selected. In Georgia, as in the Southeast generally, feeder calves are produced and sold as lightweight feeder cattle after weaning. The farm is assumed to have 100 acres available for pasture and other cattle-related operations.[1] The farm purchases (or retains) 131 steer calves in the first week in November and stockers the calves on mixed annual grazing, planted in late September and early October, and supplemental hay. The steer calves weigh 450 pounds per head or 58,950 pounds total at the start of stockering. The steers are assumed to gain an average of 300 pounds or 1.65 pounds per day, and to be ready for the feeder cattle market the first full week of May (an 181-day stockering period).

The Marketing Strategies

Since the establishment of the feeder cattle future options market in January 1987, cattle producers can use three markets to price cattle—the cash market, the futures market and the futures option market. A set of market strategies has been designed for the cattle owners to manage the risks. These strategies are most commonly used by the producers or recommended by the extension economists at The University of Georgia. The strategies are displayed in Table 2 arranged from the simplest to most complex. Strategy 1's approach of simply stockering and then selling the cattle

[1] There is no opportunity cost charged to the pasture for the winter if stockering is not undertaken. If no cattle are placed in the pasture, no winter forage is planted and those costs are saved, but the pasture has little other potential uses in winter as few cattle are stockered currently in the Southeast. Thus, the alternative is assumed to be an empty (or underused) pasture.

Table 2. Seven Marketing Strategies (November-May)

Strategy Number	Description
1	Cash market (sell next May)
2	Hedge, buy two future contracts (Nov.-May)
3	Buy two put option contracts (at-the-money)
4	Buy two put option contracts (out-of-the-money)
5	Buy two put option contracts (in-the-money)
6	Buy two put option contracts (at-the-money), sell two call option contracts (out-of-the-money)
7	Buy two put option contracts (out-of-the-money), sell two call option contracts (in-the-money)

Note: For put option contract:
at-the-money means the even dollar strike price closest to the relevant May futures price;
in-the-money means a strike price of $4 hundredweight higher than the at-the-money strike price;
out-of-the-money means a strike price of $4 per hundredweight lower than the at-the-money strike price.
For call option contract:
at-the-money means the even dollar strike price closest to the relevant May futures price;
in-the-money means a strike price of $4 per hundredweight lower than the at-the-money strike price;
out-of-the-money means a strike price of $4 per hundredweight higher than the at-the-money strike price.

for the May cash price makes no attempt to reduce risk, while the others all involve some type of hedging or risk-reduction component. Also note that the strategy of not stockering at all is an implicit option and will be considered in the results. The choice of a marketing strategy is affected by the producer's expectations concerning the future price level and by the producer's risk preferences. To properly model these expectations and the risk faced by the representative producer, we need to detail the effect of the various components of the seven marketing strategies listed in Table 2.

The result of any single hedging transaction can be represented as

$$(11) \quad \pi_f = p_{f,t-1} - p_{f,t} + C_{tc}$$

where π_f is the profit of the future market transaction, $p_{f,t-1}$ is the selling price of the future contract at time $t - 1$, $p_{f,t}$ is the buy price of the future contract at time t, for closing the contract opened at time $t - 1$. C_{tc} is the futures market transaction cost.

The result of a put option purchase transaction is

$$(12) \quad \pi_{op} = p_t - p_{t-1} - C_{tc}$$

where π_{op} is the profit of the option market transaction, p_t is the offset premium received (if any) from the put option resale at time t, p_{t-1} is the premium paid for the put option, and C_{tc} is the option market transaction cost.

The result of a put option purchase and a call option sale transaction is

$$(13) \quad \pi_{pc} = p_{p,t} - p_{p,t-1} - C_{p,tc} + p_{c,t-1} - p_{c,t} - C_{c,tc}$$

where π_{pc} is the profit of the option market transaction, $p_{p,t}$ is the offset premium received (if any) from the put option resale at time t, $p_{p,t-1}$ is the premium paid for the put option, $C_{p,tc}$ is the option market transaction cost for the put option purchases, $p_{c,t-1}$ is the premium received (if any) from the call option sale at time $t - 1$, $p_{c,t-1}$ is the offset premium (if any) paid for the call option, and $C_{c,tc}$ is the call option market transaction cost. These three equations underlie the profit simulations performed to evaluate the seven marketing strategies considered.

Simulating Production Risk

The key factor for analyzing the risk return trade-off analysis in the expected utility model is the probability distribution of the returns, which is the product of the price and the production less the variable cost. While the seven marketing strategies obviously pay considerable attention to price risk, cattle producers also face production risk. In the simulation described below, the weight gain of the cattle is taken as random based on the methodology described in this section. Because Georgia is a small part of the national production of beef and the weather-related reasons for the production risk are mostly local, we assume that the production risk is independent of the price risk.

The modeled stockering program on temporary winter annual grazing for lightweight calves is a period for cattle growing, not fattening. The main feed for cattle is forage. To simulate the cattle production output distribution we need historical data on the average daily gain(ADG) in lbs/head of stockering cattle. Unfortunately, there is no direct historical data for a specific winter stockering farm. However, a model has been established by the University of Georgia Animal Science Department for the relationship between forage production and the average daily weight gain of stocker cattle

$$(14) \quad ADG_t = \begin{cases} 1.65 + \dfrac{(f_{t,p} - f_{avg})/10}{181 \cdot 1.3}, & \text{if } ADG_t < 2.5 \\ 2.5 & \text{otherwise} \end{cases}$$

where ADG_t is the average daily gain in year t in lbs/head, and $f_{t,p}$ and f_{avg} are the forage production in year t and for the average year in lbs/acre, respectively. Average forage production is the average dry matter of rye forage in a 27-year performance test at the University of Georgia and the distribution of $f_{t,p}$ for any given year is taken to be a discrete distribution of the observable part of 27 annual observations (1971–1997), all treated as equally likely. In equation (14), 1.65 is the expected average daily gain (lbs) for a normal year, and the other part of the function represents a rule that for every additional 10 lbs dry rye forage matter the response is one pound of additional cattle weight gain; 181 is the total days of the stockering period, and 1.3 is the stockering rate (head/acre). Equation (14) also imposes a maximum average daily gain per head of 2.5 lbs regardless of the amount of forage matter.

Simulating Price Risk

For the first strategy (feeding until May and selling in the cash market), the random variable whose distribution must be estimated is the cash price on May 1. To do this, a simple linear regression model was developed to predict May 1 cash price on November 1. The May 1 cash price is modeled with a constant, the cash price from November (current), and the lagged May cash price (i.e., from that calendar year); thus all regressors are observable at the time the forecasts are needed. Assuming a normal distribution for the cash price (an assumption that is consistent with the estimated residuals of the regression model), forecasts are generated using the estimated regression model with the addition of a uniform prior distribution that is truncated to keep simulated May cash price between an upper and lower bound. These bounds are placed at plus and minus \$8/cwt of a central value equal to the current May futures price minus the five-year average basis. The regression used to generate the forecasts is re-estimated each period using data beginning in 1973 through the forecast time period, adding new observations as they become observable.

For the other strategies, the random variables to be forecast are the cash price on May 1 and the basis of the May feeder cattle futures contract (the difference between the May futures price and the May cash price). The basis is modeled as a discrete distribution based on data from 1973 to the forecast date with all points observable at the time of forecast taken as equally likely.

Simulating Expected Utility of Profits

Simulations are performed with and without production risk to evaluate the importance of production risk relative to that of modeling price risk. To compute the expected utility of profit from these strategies, the simulated values from the estimated distributions of May cash price, the basis, and weight gain are all combined using a formula for computing economic returns to generate a simulated distribution of profits. The evaluation of each strategy is based on 10,000 random draws from each of the appropriate distributions. To increase numerical approximation efficiency, antithetic replication (Geweke, 1988) is used for the cash price distribution—5000 draws plus the associated 5000 antithetic draws which are mirror images of the first 5000.[2]

The process goes step by step as follows. First, 10,000 random forecast values of the May cash price and the May basis are generated. Next, 10,000 May futures price forecasts are generated by subtracting the basis from the cash price. Then the at-the-money, in-the-money, and out-of-the-money put option premia and the at-the-money and out-of-the-money call option premia are calculated using the Black model. For simulations in which production risk is considered, 10,000 random values of daily gain are generated. Once we get the futures price and weight gain distributions we can get the distribution of returns in the futures and options markets. For the second strategy, to close the future market position, we need to buy two feeder cattle futures contracts back on May 1. For the third to the seventh strategies, at May 1, when the feeder cattle futures prices are higher than the strike price of the futures put option price or lower than the strike price of the futures call option price, the position is offset.

All of these random values are then used to compute 10,000 random profit values for each strategy accounting for the variable costs of production (assumed deterministic due to the limited randomness in costs such as feed, seed, fertilizer, etc.). The 10,000 profit values under each strategy are then used to calculate the expected value of profit and the variance of profit. Because these empirical values of profits are randomly generated from their distributions, the expected value and variance of profit can be calculated using the standard formulas for random samples (e.g., the expected value is the simple arithmetic average of the 10,000 random values). Also, because of the normality of the cash price forecasts and the empirical nature of the weight gain and basis predictive distributions, the simulated profit values appear consistent with an assumption of normality. This allows us to use the mean-variance form of the expected utility function in equation (10).

Empirical Results

Using the methodology and procedure described above, the seven strategies were evaluated for four November–May periods (1993–1994, 1994–1995, 1995–1996 and 1996–1997) using only information available on November 1 of the initial year. Each strategy was simulated two times, once considering both price and production risks and the other time considering only price risk. All results are implicitly measured relative to the strategy of no stockering since if no cattle are stockered profit and utility of profit over the following six-month period will be zero by construction.

The expected utilities of each strategy for each year are shown in Tables 3, 4, and 5 with each table containing results for one of the three representative risk-aversion coefficients specified earlier. A good decision of the expected utility model is one that is consistent with the decision-maker's expectations and preferences, not just a decision that works out well. A producer should choose the strategy that has the maximum expected utility in a given year. The choice of a marketing strategy is sensitive to risk preferences, so choosing an appropriate risk-aversion coefficient is critical to an optimal solution.

Table 3, the empirical results for ϕ = 0.00005, suggests that a Georgia cattle producer should choose Strategy 2 (a simple hedge) in the 1993–1994, 1994–1995 and 1995–1996 periods, and should choose Strategy 1 (cash market only) in the 1996–1997

[2] Antithetic replicates are "mirror" images of the original draws; that is, for each draw $b_{(j)} = b + \omega_{(j)}$ one also creates a draw $b_{(j)} = b - \omega_{(j)}$ on the opposite side of the mean value b. By increasing the symmetry of the draws around the mean, the accuracy of the numerical approximation is increased greatly.

Table 3. Expected Utilities of the Seven Strategies (ϕ = 0.00005)

	1993–1994		1994–1995		1995–1996		1996–1997	
	P	NP	P	NP	P	NP	P	NP
Strategy 1	−3074	−2881	−5484	−5548	−6304	−6399	11813	11848
Strategy 2	−1457	−1444	−3582	−3562	359	443	4676	4706
Strategy 3	−1908	−1743	−3756	−3728	−58	−13	8851	8711
Strategy 4	−2087	−2089	−3948	−3960	−968	−980	10304	10459
Strategy 5	−2395	−2358	−4235	−4180	−2425	−2638	11627	11557
Strategy 6	−1605	−1606	−3705	−3689	−478	−375	6661	6587
Strategy 7	−1662	−1574	−3863	−3593	−1026	−1014	6215	6053

NP means no production risks are considered, P means production risks are considered. The underlined value is the column maximum.

period. The results are consistent for both the simulations with and without production risk.

Table 4, the empirical results for ϕ = 0.0001, suggests that a Georgia cattle producer should choose Strategy 2 in the 1993–1994, 1994–1995 and 1995–1996 periods and should choose Strategy 1 in the 1996–1997 period. But for the 1994–1995 period, when production risk was not considered, the approach recommends choosing Strategy 7 (buying two out-of-the-money put options and selling two in-the-money call options).

Table 5, the empirical results for ϕ = 0.0002, suggests that in the 1993–1994 period a Georgia cattle producer should choose Strategy 6 (buy two at the money put options and sell two out-of-the-money call options) when both production and price risk are considered and choose Strategy 7 when only price risk is considered. In the 1994–1995 period, the producer should choose Strategy 2 when both production and price risk are considered, and choose Strategy 7 when only price risk is considered. In the 1995–1996 period, Strategy 2 should always be chosen. In the 1996–1997 period, Strategy 5 (buying two in the money puts) should always be selected. As risk aversion has increased, the optimal strategy varies more from year to year. This is because a more risk-averse producer will change strategies more quickly in search of risk-reduction benefits from the various futures and options strategies given changes in market conditions and perceived market risk.

To evaluate the effectiveness of this model, *ex post,* we need to compare the expected utility, $E(u(\pi))$, with the actual utility, $u(\pi)$. Since we cannot get the variance of the actual profit from a given strategy, the comparison is impossible. The closest approximation available is to compare the profit outcome to the choice of the model. *Ex post,* utility of profit equals the expected utility of profit, so there is some limited relevance to this comparison.

Table 4. Expected Utilities of the Seven Strategies (ϕ = 0.0001)

	1993–1994		1994–1995		1995–1996		1996–1997	
	P	NP	P	NP	P	NP	P	NP
Strategy 1	−4637	−4418	−7082	−7094	−7309	−7405	9856	9885
Strategy 2	−2672	−2641	−4650	−4644	−440	−359	3665	3713
Strategy 3	−3100	−2914	−4833	−4810	−849	−803	7364	7228
Strategy 4	−3311	−3277	−5076	−5086	−1735	−1763	8564	8724
Strategy 5	−3739	−3697	−5390	−5379	−3217	−3138	9795	9717
Strategy 6	−2739	−2759	−4751	−4702	−1260	−1155	5648	5571
Strategy 7	−2805	−2678	−4936	−4617	−1780	−1758	5201	5042

NP means no production risks are considered, P means production risks are considered. The underlined value is the column maximum.

Table 5. Expected Utilities of the Seven Strategies (ϕ = 0.0002)

	1993–1994		1994–1995		1995–1996		1996–1997	
	P	NP	P	NP	P	NP	P	NP
Strategy 1	−7764	−7419	−10280	−10187	−9320	−9417	5944	5961
Strategy 2	−5101	−5036	−6784	−6808	−2038	−1967	1644	1728
Strategy 3	−5482	−5256	−6987	−6975	−2431	−2384	4330	4236
Strategy 4	−5758	−5652	−7331	−7336	−3268	−3331	5084	5258
Strategy 5	−6429	−6376	−7898	−7776	−4801	−4677	6131	6037
Strategy 6	−5006	−5067	−6843	−6729	−2824	−2716	3620	3540
Strategy 7	−5092	−4941	−7084	−6664	−3288	−3245	3174	3020

NP means no production risks are considered, P means production risks are considered. The underlined value is the column maximum.

The actual profits that would have been earned by the representative producer under each of the strategies for these four years are shown in Table 6, along with the expected profits that would have been computed *ex ante*. This table shows that the strategy with the best profit outcome, *ex post*, was Strategy 2 for the first three periods and Strategy 1 for the fourth period. By comparing the results in Table 6 with the *ex ante* results in Tables 3, 4 and 5, we see that all the chosen strategies in Table 3 are the choices with best profit outcomes. In Table 4, for the 1994–1995 period when production risk is not considered, the best choice, Strategy 7, ranks fourth ex post in Table 3. In Table 5, the outcomes of five (out of eight) best choices are not the best *ex post* in Table 6.

The results also show that the optimal decision under appropriate risk aversion is different from that for a producer who is risk neutral (ϕ = 0). When the risk-aversion coefficient is set to zero, expected utility is a linear function of profit. Table 6 also shows the expected utility of risk-neutral results, the best choice *ex ante* for the 1993–1994 period would be Strategy 6 with the highest expected profit. Strategy 2, which ranks fourth *ex ante,* has the highest *ex post* profit. Also, we see that the results from Table 3, with the smallest degree of risk aversion, align perfectly with the *ex post* highest profit strategies. As risk aversion increases the correlation of optimal strategy with *ex post highest* profit decreases as one would expect. Finally, we note that the modeling or ignoring of production risk rarely had much impact on the optimal decision.

The Probability of Making a Profit

The results of a stockering production program are not like that of a binary lottery situation, win or lose. Each alternative has a range of possible outcomes; the profit or loss has a wide range of variation. At the beginning of production, the producer makes decisions based on expected utility of the outcomes. Producers have information accumulated through experience, technical knowledge,

Table 6. Expected and Actual Ex Post Profit (in $)

	1993–1994		1994–1995		1995–1996		1996–1997	
	exp.	act.	exp.	act.	exp.	act.	exp.	act.
Strategy 1	−1510	−5886	−3885	−10164	−5298	−13382	13769	11178
Strategy 2	−741	−2259	−2515	−5289	1157	−3713	5687	4207
Strategy 3	−717	−3302	−2679	−6053	732	−4298	10338	6557
Strategy 4	−863	−4557	−2820	−7261	−201	−5488	12043	9106
Strategy 5	−1050	−5845	−2881	−9139	−1633	−7761	13458	10668
Strategy 6	−472	−3515	−2659	−6497	303	−4902	7675	6171
Strategy 7	−519	−3547	−2789	−7167	−272	−5986	7229	5184

Table 7. The Estimated Probabilities of Certain Return Outcomes

	1993–1994			1994–1995			1995–1996			1996–1997		
	L	B	P	L	B	P	L	B	P	L	B	P
Strategy 1	53	10	37	65	9	26	76	8	16	4	3	93
Strategy 2	41	14	45	61	12	27	34	13	54	15	10	75
Strategy 3	45	12	43	61	11	28	37	14	49	6	5	89
Strategy 4	47	12	41	62	11	27	42	18	40	5	3	92
Strategy 5	49	12	39	62	10	28	57	12	31	4	3	93
Strategy 6	44	12	44	61	12	27	39	16	45	8	7	85
Strategy 7	45	11	44	61	13	26	44	16	40	9	8	83

L means a loss of more than \$1000, B means a return between \$−1000 to \$+1000, P means a profit of more than \$1000. All probabilities in percentage terms.

forecasts of revenue, and the cost, etc. However, development of appropriate probability estimates is a difficult task for farmers (Barry, 1984, p111). The Bayesian decision model used here simulates the production distribution and the price distribution of different strategies by combining the sample information and the subjective prior information; the resulting distribution of profits can then be used to calculate the probabilities of the different profit level shown in Table 7.

In the 1993–1994 period there is more than a 45-percent chance to make a profit of more than \$1000 following Strategy 2, with somewhat lower probabilities for the other strategies. Also we can see that the best strategy has the smallest probability of losing more than \$1000; this is consistent with the risk-aversion assumption. For the actual production process, in the first three production periods, the producer purchased the calves at a high price and sold the feeder cattle at a price lower than expected, so Strategy 2 of hedging was the best one. In the production period 1996–1997, the cattle producers faced a rising price; they sold the feeder cattle at a price higher than the price they paid six months ago. The model forecast this *ex ante,* showing that the farmer has a 93-percent probability of making more than \$1000, and suggested adopting Strategy 1 to take the advantage of the rising price.

Conclusions

Whenever economic analysis involves incorporating estimated parameters into theoretically derived decision rules, the optimal outcome will depend on the estimation procedure. Thus, an additional source of risk is the accuracy with which parameters are estimated. A Bayesian criterion procedure is consistent with expected utility maximization in the presence of estimation risk. It is justified by its foundation in reasonable axioms, using all relevant information, and having a minimum average risk or maximum average value for a specific prior.

Seven marketing strategies were designed for the producer at the beginning of the production period to correspond to different price movement expectations and risk preferences. If the price is expected to rise, Strategy 1 could be selected, cash sales only. If the price were forecast to fall, Strategy 2 could be selected, hedging to lock the price at a fixed level with the expected basis. Strategies 3 through 7 used options to set a floor or a fenced price, trading off between risk and return.

A Bayesian decision theoretic procedure was used to compute the expected utility of seven marketing strategies for four operating periods (1993–1994, 1994–1995, 1995–1996 and 1996–1997). Each strategy was simulated with and without production risk. The simulation showed that the results are sensitive to the prior information on price in May, the risk-aversion coefficient and the presence of production risks. An appropriate risk-aversion coefficient is important in selecting strategies that are truly consistent with producers' needs. The procedure also calculated the probability of different profit levels, which is difficult for farmers to do but is very useful information for them.

The results showed that in the production periods 1993–1994, 1994–1995 and 1995–1996, the forecast May cash prices are low because of the unfavorable time period in the production cycle, and, therefore, Strategy 2 (hedging) was selected as the optimal strategy. For the production period 1996–1997, the forecast May cash price was high, so Strategy 1 (simply sell in the cash market) was selected as the optimal one. The *ex post* analysis showed that the selected strategies usually had the best profit outcomes.

Future work might extend this approach to include treatment of uncertainty over functional form and the distribution of prices and stochastic production processes. Addressing these further sources of uncertainty would lead to even more robust management recommendations for cattle owners.

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