Impact of Hedgers and Speculators on the Effectiveness of the Price Discovery Process in Live Cattle Futures

Robert Murphy and Wayne D. Purcell

October 1995

SP-95-13

Research Bulletin 1-95

Department of Agricultural and
Applied Economics
Virginia Tech
Virginia Cooperative Extension Service
Virginia Tech and Virginia State
Virginia's Land-Grant Universities

Research Institute on Livestock Pricing
Virginia Tech
Blacksburg, VA 24061-0401

Impact of Hedgers and Speculators on the Effectiveness of the Price Discovery Process in Live Cattle Futures

Robert Murphy and Wayne D. Purcell*

October 1995

*Robert Murphy is employed in the Research Division, Chicago Mercantile Exchange, and is a former USDA Marketing Fellow, Agricultural and Applied Economics, Virginia Tech. Wayne Purcell is Professor of Agricultural and Applied Economics and Director of the Research Institute on Livestock Pricing at Virginia Tech.

Table of Contents

Introduction

It is generally recognized that the most important economic functions of futures markets are risk transfer and price discovery. The discovery of forward prices is an especially important function of futures markets for non-storable commodities such as livestock.

Price discovery is the process by which actual market prices converge to the price determined by the economic forces of supply and demand. In cash markets, the price discovery process ends when the buyer and seller reach a market-clearing or equilibrium price and the commodity changes hands. The same can be said of futures markets if the item transacted is interpreted to be the contract. Alternatively, if the transacted item is assumed to be the underlying commodity, then the price discovery process is technically not complete until the futures contract reaches maturity. From this perspective, the futures market spends months discovering the market-clearing price and the daily closing prices are just points in the market's movement toward an implicit but unknown equilibrium price.

Futures markets which perform the price discovery role efficiently are socially desirable for several reasons. Futures markets provide highly visible prices which can be used as information in the development of price expectations by producers and users of the commodity. Firms that utilize these prices are able to make better resource allocation decisions when futures prices are accurate reflections of true end-of-period supply and demand conditions. When new information is quickly and completely registered in market prices, the potential for over- or under-reaction by agricultural producers in the form of a supply response is reduced. The result is more stable commodity prices, better resource allocation, and a more efficient and effective commodity sector.

Problem Statement

Traders and potential traders in futures markets react to changes in their economic environment in many different ways. Those reactions will often involve changes in the traders' level of market participation, where participation refers to their willingness to act on price expectations. When particular trader groups decrease their presence in a futures market, the market is deprived of the information contained in their expectation of future prices. Conversely, increases in market presence will lend more weight to a given group's (or individual trader's) price expectation in the overall price discovery process.

Markets which attract traders who are willing and prepared to act on their expectations of price will perform the price discovery process better, especially if those expectations are based on a rich information base. Some traders may therefore be more valuable (socially) to the futures market than others, and this value may extend to broad groups of traders. If policies are enacted that adversely affect classes of traders and they respond to the policy by decreasing their futures market activities, information availability and quality may deteriorate in that market and the price discovery process is potentially damaged.

In order to properly evaluate a policy change, therefore, it is important to have information on the value to price discovery of the trader groups likely to be impacted. Little is known about the relative value of the market behavior of the various groups that trade live cattle futures. In recent years, changes in the tax policy of the Internal Revenue Service (IRS) caused many agricultural producers to reconsider using futures to hedge price risk. As a result of the 1988 Supreme Court decision in *Arkansas Best Corp. v. Commissioner*, IRS agents began to disallow ordinary deductions for losses incurred in futures trades that producers had theretofore considered to be hedging transactions. Losses generated by these hedging transactions had been treated as ordinary, not capital, losses. Because of the limited deductibility of capital losses, this policy change toward a more restrictive definition of a "hedge" increased a potential hedger's tax risk. As a result of this increased risk, some hedgers might leave the market, finding that the cost of managing their price risk with futures to be too high. A 1991 survey by Purcell found that the fear of having losses on futures positions considered as capital losses was an important factor affecting cattle feeders' decisions on participation in the cattle futures markets.

Changes in the trader composition in a futures market, regardless of whether it occurs purposefully or inadvertently, has the potential to change the information flow into that market and alter the price discovery process. The efficiency of the price discovery process in a futures market has important welfare implications for society. Prices originating in futures markets are sources of information to producers and users of the commodity.

Although some research has been undertaken to investigate the relationship between price changes in futures markets and positions held by certain groups of traders (Petzel; Rowsell; Yun), there has been no empirical effort to document the effect of different groups of traders on the price discovery process in these markets. Without such information, policy makers must rely on subjective estimates of the impacts of their policies on the inclination of various types of traders to participate and, thereby, on the price discovery process. Scientifically credible information on the impact of certain types of traders is needed to help guide policy and regulatory decisions in the futures markets.

Objectives

The overall objective of this research is to evaluate the contribution of several different types of traders to the price discovery process in the live cattle futures market. The specific objectives are:

1. to develop a conceptual model to describe the price discovery process in terms of the actions of identifiable market participants;

2. to develop a method to empirically measure the individual contributions of different trader groups to daily movements in live cattle futures prices;

3. to identify and analyze any structural interrelationships that might exist between the measures formulated in objective two;

4. to utilize the statistics developed in objective two and the relationships identified in objective three to simulate, *ex post*, changes in trader composition and assess how these changes impact prices in the live cattle futures market; and

5. to identify those trader groups, if any, whose market presence is consistently beneficial or detrimental to the price discovery process.

Theoretical and Empirical Issues

Futures markets provide a pricing system which helps society solve the problem of efficiently utilizing information not given in its entirety to any individual (Hayek). To perform this function, futures markets must collect information from all of the diverse individuals who possess it. The information collection process begins with the universe of all information. From this all-encompassing set, traders and potential traders in futures markets each select the subset of information that they consider useful for forecasting future prices.

Included in the universe of all information are the price expectations and market activities of other traders. Once all potential traders have identified the information they feel is most important to determining future prices (and feel that information is cost justified), they must then employ some method of condensing their information subset into a price expectation. This is accomplished through the use of some type of translating mechanism (TM). These TMs may be complex or simple, objective or subjective, unique or shared. Selection of the TMs, like choice of information subsets, is a subjective process. Once developed, however, the TM may be used in an objective manner to produce price expectations. This is the case where formula-type translating mechanisms such as econometric models are used to condense the information subset into a price forecast. Mathematically based technical trading rules are another example of an objective use of a TM.

Regardless of the nature of the TMs, all produce some price expectation. This price expectation is best represented, not as a single point, but as a function or a distribution that describes the trader's beliefs as to the likelihood of a wide range of prices. The TM condenses the information subset into a probability density function (PDF) for future prices.

Once traders have formed price expectations, they then face the decision of whether or not to act on that price expectation by taking a position in the futures market. The trader's willingness to act on a price expectation may be influenced by a number of variables such as the perceived accuracy of the price expectation, the degree of movement in prices indicated by the expectation (the profit potential), the existence of a cash position, the costs associated with participating in the futures market, and the risk preference of the trader.

The price expectation, when combined with the trader's willingness to act, results in trading behavior. Conceptually, it can be argued that the only thing that influences price is the trading behavior of the market participants. That trading behavior, of course, is a function of information, trader characteristics, and the analytical process--the TM--employed.

Whether or not a potential trader actually takes a futures position is dependent upon the expected costs and benefits of doing so. Since trading futures involves an action with uncertain outcomes, the expected utility model is an appropriate representation of the decision making process. The potential trader would be expected to take a futures position if the expected utility of market participation exceeded the expected utility of inaction.

E-V analysis was developed by Markowitz as a portfolio selection tool and extended to include risk-free assets by Tobin. The analysis is founded on the idea that risky prospects can be ordered based on the trade-off between expected value and variance of income. From these E-V sets, the E-V efficient frontier can be identified as the collection of all choices for which no other choice with the same expected value has a smaller variance. E-V analysis involves using decision maker preferences to select a risky action from among the choices on the E-V frontier.

The E-V approach can be derived from the more general expected utility (EU) maximization framework under some rather restrictive assumptions. Two sufficient assumptions for consistency between E-V choices and expected utility maximization are that the agent's utility function is quadratic (which implies that only the first two moments, the mean and variance, of outcome distributions are important in the decision process) or that the agent's outcome variable expectations are normally distributed. Figure 1 illustrates how optimal decisions are made in the E-V framework. Given some E-V efficient set of choices, the economic agent selects the choice that lies at the tangency between the E-V frontier and the highest EU indifference curve. A linear segment with slope identical to the slope of the E-V frontier at the tangency point can be extended to the expected value (E[y]) axis. This serves as an approximation to the unknown EU function. The point at which this segment intersects the E[y] axis is called the certainty equivalent (CE). Since they lie on the same indifference curve, the CE would give the decision maker the same expected utility as the optimal choice from the E-V frontier. Freund has shown that the slope of this segment will be $\lambda/2$ where λ is the agent's risk aversion coefficient.[1] Typically, the E-V analysis proceeds by defining the line segment in terms of the expected value and variance of the risky prospect under study, then maximizing the CE to find the optimal action. Comparative statics can then be used to study how the optimal action changes in response to important parameters in the problem.

For empirical work, the usefulness of the E-V model lies in its ability to closely approximate the results of the EU model. As an analytical tool, the relatively uncomplicated structure of the E-V model permits the relationships between variables to be easily studied. E-V models are therefore less important for their ability to measure empirically than for their ability to indicate the *direction* of movement in important variables as they respond to changes in elements of the decision making process (Robison and Barry).

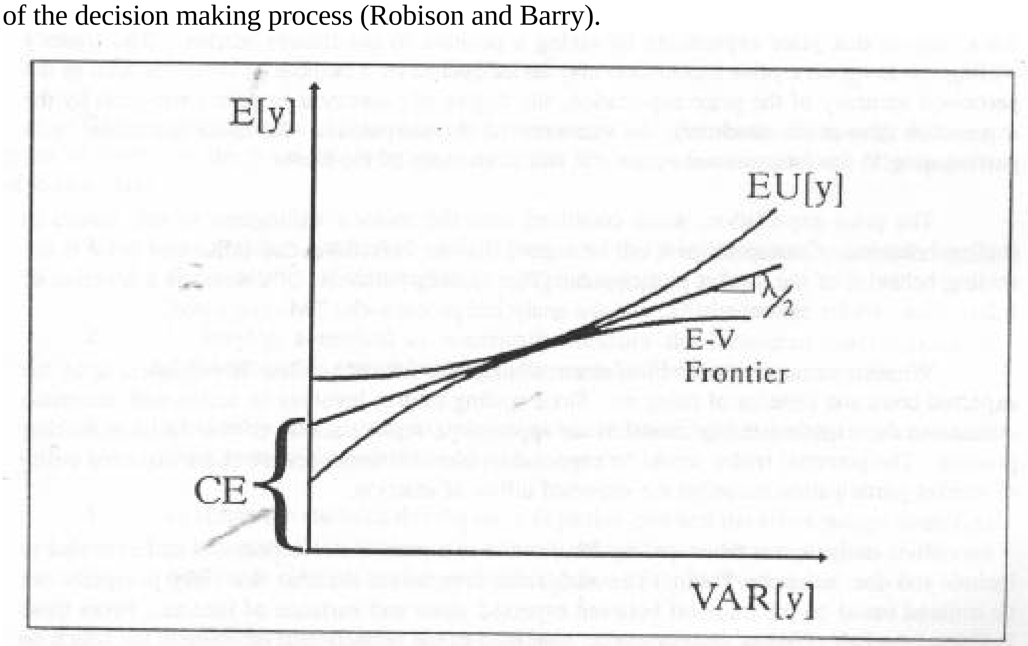

Figure 1. Graphical Representation of the E-V Model

[1]The risk aversion coefficient is defined as $-U''(y)/U'(y)$ where U is the decision maker's utility function which is expressed solely as a function of income, y (Pratt).

The analysis begins with the linear approximation to expected utility depicted graphically

$$CE = E[y] - \frac{\lambda}{2} VAR[y].$$

in Figure 1. Mathematically, this linear combination of risk and returns is expressed as: Here, y is the random variable representing the outcome of the risky action and λ is the risk aversion coefficient introduced by Pratt.

To utilize the CE concept to determine futures market participation, consider the situation where a potential trader has used his/her information subset and translating mechanism to arrive at a PDF in the current time period (t_0) for the futures price in a later time period (t_1). Assume that the trader's PDF or distribution of prices can be characterized by some mean value, f_1, and a random component, ε, where $\varepsilon \sim N(0, \sigma_\varepsilon^2)$. Also, let c_0 represent the current cash price and f_0 the current futures price. To simplify matters, assume that there is only one time period until contract maturity and that the futures price in t_1 converges to the cash price in t_1 so that there is no basis risk. The potential trader's profit function is:

$$\pi = (f_1 + \varepsilon - f_0)q_f - C(q_f, I) + (f_1 + \varepsilon - c_0)q_c$$

A cash position (q_c) may exist and any costs incurred in acquiring or producing the cash position are considered sunk; therefore, what is important to the trader is the change in the value of the cash position between periods. In the absence of production uncertainty and basis risk, futures decisions can be separated from production decisions (Anderson and Danthine). The first term in (2) represents revenues from any futures position (q_f) and is arranged so that $q_f > 0$ indicates long futures positions and $q_f < 0$ indicates short futures positions. The second term in (2) represents the cost of futures activity and includes not only the direct costs, commissions and interest on margins, but the cost of defining or developing the information subset and selecting the TM.[2] The third term is the change in value of the cash position. Because price in t_1 is uncertain, profit is a random variable.

The expected value of profit is:

$$E[\pi] = (f_1 - f_0)q_f - C(q_f, I) + (f_1 - c_0)q_c$$

$$VAR[\pi] = (q_f + q_c)^2 \sigma_\varepsilon^2 .$$

and the variance of profit is:
Therefore the CE of profit is given by:

[2]This cost function would not be of the usual type since the quantity variable, q_f, can take negative values. It would be as a usual cost function in the first quadrant and a mirror image of the usual cost function in the second quadrant. Derivatives of the cost function in the second quadrant should be interpreted as $\partial C/\partial |q_f|$.

$$CE = (f_1 - f_0)q_f - C(q_f, I) + (f_1 - c_0)q_c - \frac{\lambda}{2}(q_f + q_c)^2 \sigma_\varepsilon^2 .$$

The CE can then be maximized to find the optimal action. Choice variables in this analysis are the amount of effort exerted in defining the information subset and refining the translating mechanism (designated by I) and q_f. Consistent with the conceptual model, the decision process is a sequential one where the agent first determines the information effort and then forms the price expectation. Next, the quantity of futures is selected. Because the information effort is known at the time the futures decision is made, it can be treated as a constant. The decision maker must then choose the futures position, q_f, given the preselected information effort. Since q_f is the only choice variable, this

$$\frac{\partial CE}{\partial q_f} = (f_1 - f_0) - C_q - \lambda(q_f + q_c)\sigma_\varepsilon^2 = 0 \ .$$

involves setting $\partial CE/\partial q_f = 0$ as follows:[3,4]

The second partial derivative of CE with respect to the choice variable, q_f, is:

$$\frac{\partial^2 CE}{\partial q_f^2} = -C_{qq} - \lambda\sigma_\varepsilon^2 = \delta \ .$$

Since λ is positive for risk averse individuals and σ_ε^2 is positive, a sufficient condition for δ to be negative (making (6) a maximum) is $C_{qq} \geq 0$. A weaker condition would be $C_{qq} > -\lambda\sigma_\varepsilon^2$. The sufficient condition could very well hold with equality since C_{qq} measures the rate of change in non-information marginal costs of taking a futures position. These costs are commissions and interest on margins. For many traders, the additional cost of an additional futures transaction is constant, thus $C_{qq} = 0$. Assuming constant marginal transactions costs, the utility maximizing level of futures activity (q_f^*) is:

$$q_f^* = \frac{f_1 - f_0 - C_q}{\lambda\sigma_\varepsilon^2} - q_c \ .$$

---

[3]In order to use calculus in this analysis it is necessary to assume that the quantity of futures positions is a continuous variable. In reality, futures positions come only in fixed increments. For live cattle, each increment is equivalent to 40,000 lbs.

[4]Partial derivatives of this cost function are symbolized by subscripts immediately following C. For example, C_q is the first partial derivative of C with respect to q_f.

The characteristics of the trader's price expectation (mean, variance) in combination with his/her risk attitude determines the optimal price risk exposure ($q_c + q_f^*$). The futures position supplements the cash position to correct for any discrepancies between the fixed cash position and the optimal price risk exposure. If the cash position is larger than the optimal price risk exposure (in absolute value), then the optimal futures position will be in the direction opposite the cash position. This is the same as saying that part of the cash position is hedged to reduce overall price risk exposure.

The relationship between the optimal information set and the optimal futures position is recursive—the trader is free at any time to choose to use an alternative information set/translating mechanism which will lead to a new optimal futures position. Expanding the information subset or revising the translating mechanism has the potential to improve the price expectation. It is not unreasonable to assume that additional information effort will decrease the variability in the price expectation as well as increase costs.

The comparative static results from the E-V model (developed formally in *The Influence of Specific Trader Groups on Price Discovery in the Live Cattle Futures Market*, Murphy 1995) show that willingness to act on a given price expectation is:

1. positively related to the variance in the price expectation for hedgers, negatively related to the variance in the price expectation for speculators;

2. positively related to the size of the expected spread between the current and expected futures price for hedgers with short cash positions, negatively related to this spread for hedgers with long cash positions. For long speculators, willingness to act is positively related to the size of the expected spread between the current and expected futures price, and negatively related to the size of the expected spread for short speculators;

3. positively related to cash positions for hedgers and negatively related to cash positions for speculators[5];

4. positively related to transactions costs for hedgers and negatively related to transaction costs for speculators; and

5. indeterminant with respect to increased information gathering and translating effort.

Social Loss from Basing Production Decisions on Futures Prices

---

[5]A trader who holds a futures position in the same direction as an existing cash position has also been considered a speculator in the futures market by the IRS.

As suggested, futures markets perform an important social function by gathering information on future supply and demand from many diverse sources and consolidating this information into a single widely observable price. Agricultural producers have been found to use futures prices as a primary source of information (Gardner; Hurt and Garcia; Lance and Helmreich). When producers and users of a commodity rely on futures prices for economic decisions, the accuracy of futures prices as predictors of subsequent cash prices has resource allocation implications. Resource misallocation, and hence social loss, increases when futures prices are poor indicators of cash prices. This section examines two sources of loss that can occur from producers basing production decisions on futures prices. These are: (1) losses due to bias in futures prices, and (2) losses due to unpredictable noise in future supply or demand. Further, it is shown that producer risk aversion has the potential to cause some bias in futures prices. Cattle producers, specifically feedlot operators, are used as examples in illustrating these points.

Cattle finishing is a good example of an agricultural production process where the decision to produce is temporally separated from the realization of product prices. Feeder calves are placed in feedlots, fed a high-energy ration for four to six months, and emerge as finished cattle ready for slaughter. Feedlot operators must use expectations on future cash cattle prices when making the decision on how many animals to feed in a given time period.

Neoclassical economic theory renders the familiar result that when profit-maximizing producers operate in a competitive market, social welfare is maximized when producers operate at the minimum point on their average total cost (ATC) curve. At this point, all inputs are earning their marginal value product and no economic rents or losses are accruing to producers. In a competitive market, profit-maximizing producers will always seek to equate marginal cost with output price. In the cases where output price is uncertain but input costs are known, producers will choose to produce the quantity that equates marginal cost with their expectation of output price. In long- or short-run situations, deviations away from the minimum point on the ATC curve result in social loss.

Figure 2 illustrates how cattle placements based on an inaccurate futures price can cause social loss.[6] In this figure, the pareto optimal situation is represented by a price of P_E which would have feeders operating at the minimum of their ATC and result in Q_E produced in the total market. Assume D is future demand and S is the supply curve of cattle prior to the placement decision. Following the placement decision, the supply curve becomes S′.[7] The post-placement supply curve is much more inelastic than S, but it is not perfectly vertical since feeders may be able to make slight adjustments after placement that will affect the final quantity produced. At placement time, the futures market signals an inaccurate output price of P_{M-6}.[8] This causes individual producers to try and capture profits by producing q′ and fixes the post-placement supply curve at S′. When the cattle are ready for market, the market will clear at a price P_M and a deadweight social loss equal to the shaded triangle (*bcd*) will result.[9] The triangle represents the social welfare loss resulting from the over-allocation of resources to cattle finishing caused by the inaccurate price expectation given by the futures market.

The size of this welfare loss (L) can be measured as:

$$L = \frac{1}{2}(Q_M - Q_E)[(P_{M-6} - P_M) - (P_{M-6} - P_L)].$$

[6]This discussion is an adaptation of the argument put forth by Stein (1981).

[7]In reality, placements are spread over a period of several weeks. To simplify, it is assumed here that placements are determined at one point in time or, that the placements are those that occurred during the placement period while the futures market was signaling an average price of P_{M-6}.

[8]The subscript M-6 indicates six months prior to contract maturity.

[9]When Q_M is produced and sold for a price of P_M, producers suffer a welfare loss equal to the triangle *acd*. In this region, the value that producers put on the factors of production (represented by the supply curve, S) is greater than marginal revenue, P_M. Consumers realize gains equal to the triangle *abd* brought about by lower prices. Thus, the deadweight social loss is *bcd*.

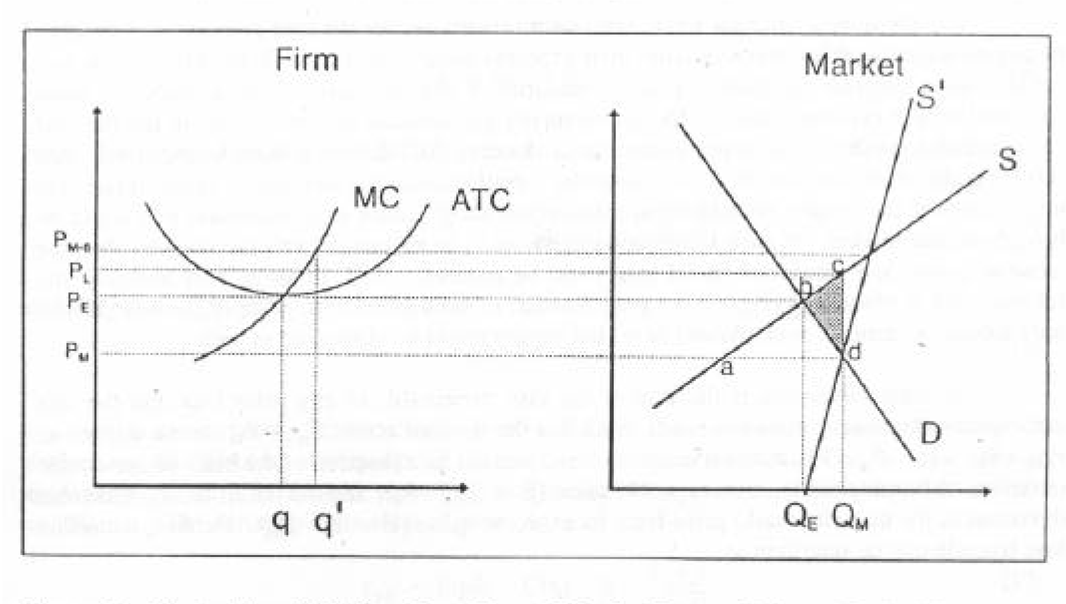

Figure 2. Illustration of Welfare Loss Due to Bias in Futures Price at Cattle Placement

$$\frac{(P_{M-6} - P_M)}{(Q_M - Q_E)} = b\,.$$

Next, define a line with constant slope b such that:
From this we get Q_M-Q_E = (P_{M-6}-P_M)/b. Plugging this into the expression for the welfare loss results

$$L = \frac{1}{2b}[(P_{M-6} - P_M)^2 - (P_{M-6} - P_L)(P_{M-6} - P_M)].$$

in:

$$L = \frac{1}{2b}[FE^2 - (P_{M-6} - P_L)\,FE].$$

Recognizing that P_{M-6}-P_M is exactly the forecast error (FE) of the futures price, we have:
When S′ is perfectly vertical, the difference P_{M-6} - P_L = 0 and the welfare loss is proportional to the squared forecast error. As S′ becomes more elastic, the welfare loss shrinks until it disappears at S′ = S. Here, b goes to infinity causing L to become zero. This only occurs where production can be easily altered after the initial production decision has been made. This, of course, is not the case with cattle feeding. Thus, the welfare loss in the live cattle market will be slightly less than proportional to the squared forecast error. The more vertical S′ is, the better the squared forecast error is as a measure of welfare loss from poor pricing signals offered by the futures market.

In the previously described situation, future supply and demand curves were assumed to be fixed. Welfare losses in this case are attributable to bias in the distant futures price. Bias occurs when the futures price, for whatever reason, systematically over- or under-predicts the subsequent cash price. Sustained trends in futures prices can be examples of price bias.

Next consider a situation where both future supply and/or demand possess some amount of noise—unpredictable deviations from their expected values. In Figure 3, the price of the live cattle futures contract six months prior to maturity is exactly equal to the equilibrium price indicated by the expected value of the future supply and demand curves. Noise in the demand for live cattle results in the end-of-period demand curve (D′) differing from its expected value (D). Again, there are social losses from the misallocation of resources. These losses are unavoidable if their exists no additional information about future supply/demand that could be brought to the market. If such information exists and can be enticed into the market, then the noise in prices and associated social loss could be reduced. Still, in an *ex post* analysis, the futures price at placement (P_{M-6}) was a poor forecast of subsequent cash price (P_M). For clarity, only stochastic demand was allowed here, but supply could be stochastic as well.

The total social loss is the sum of the loss attributable to any price bias and the loss associated with noise in futures prices. Note that the forecast error, P_{M-6} - P_M can be written as P_{M-6} - P_E + P_E - P_M. The forecast error can be expressed as a function of the bias, or systematic deviation of future price from its expected value ($B = P_{M-6} - P_E$), and the noise, or unpredictable deviation of the maturity (cash) price from its expected value ($U = P_E - P_M$). Further, the social loss triangle can be rewritten as:

$$L = \frac{1}{2b}[(B + U)^2 - (P_{M-6} - P_L)(B + U)].$$

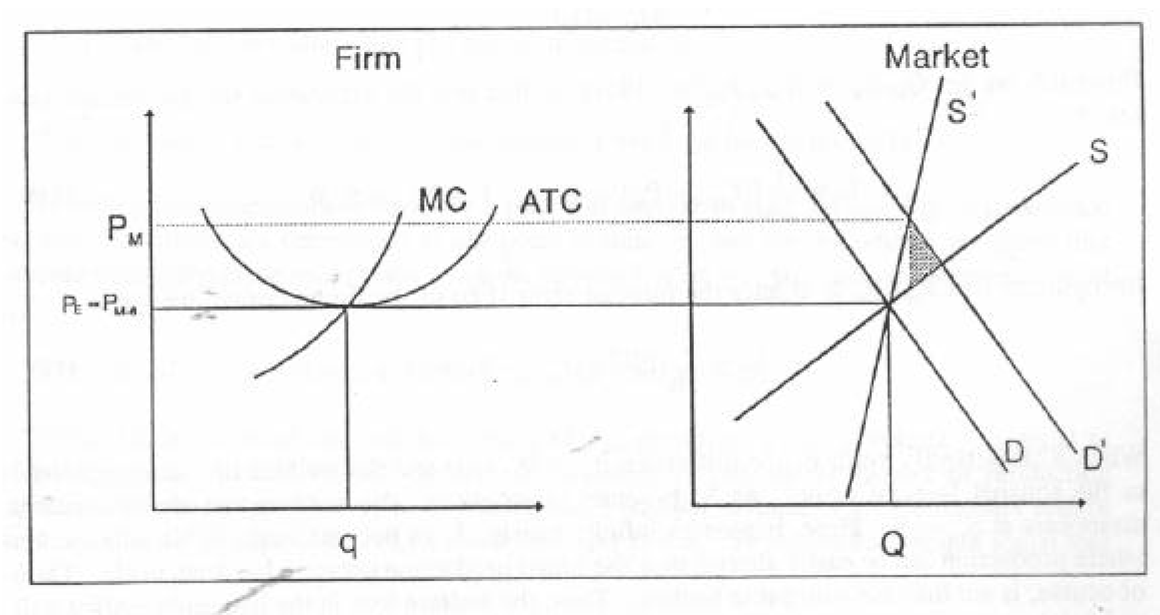

Figure 3. Illustration of Welfare Loss Due to Unpredictable Noise in Futures Prices

Up to this point, the risk attitude of the producer has been ignored. The cost and market curves used in the analysis reflect risk neutral producers. If producers are collectively risk averse, then this risk attitude can explain some of the bias and hence some of the social loss.

Risk is introduced with the aid of the certainty equivalent model. For the cattle producer

$$\pi = pq - C(q) - B$$

facing only price risk, the producer's profit function is:
where C(q) is the cost function and B represents fixed costs. Expected profit is given by:

$$E[\pi] = E[p]q - C(q) - B$$

$$\sigma^2(\pi) = q^2 \sigma_p^2$$

and the variance of profit is:
where σ_p^2 is the variance of the stochastic price variable. If the producer is using futures prices exclusively as a forecast of output price, then σ_p^2 is the variance of futures price. The certainty equivalent of profit is defined according to (1) with λ representing the Pratt risk aversion coefficient. The certainty equivalent of profit is:

$$\pi_{CE} = E[p]q - C(q) - B - \frac{\lambda}{2} q^2 \sigma_p^2 .$$

Setting the first derivative of π_{CE} with respect to q equal to zero defines the certainty equivalent maximizing condition for the risk averse producer:

$$E[p] = C'(q) + \lambda q \sigma_p^2 .$$

Since λ is positive for risk averse producers, the impact of price risk is to increase costs to producers. Figure 4 illustrates the shift that occurs in firm level cost curves under risk aversion and uncertain output price. There is also a corresponding shift in the market supply curve (from S to S_R).

If the futures price at placement time (P_{M-6}) is exactly tangent to the minimum point on the risk neutral ATC curve, risk averse producers will produce quantity q_R resulting in market quantity Q_R which will clear the market at price P_M. The risk aversion of cattle producers has caused fewer than the pareto optimal number (Q*) of cattle to be placed. Also, the quantity-restricting effect of risk aversion has caused the futures price at placement to be a poor forecast of end-of-period cash price (P_M). From the point of view of the risk averse producer, the placement-time futures price was

$$L = \frac{1}{2b}[(B_R + B_O + U)^2 - (P_{M-6} - P_L)(B_R + B_O + U)]$$

biased downward. It is clear that risk aversion itself can introduce a certain amount of biasedness into the futures price. Thus, the previous expression for bias in (13) can be divided into the sum of bias stemming from risk aversion (B_R) and bias from other sources (B_O). The social loss function can be rewritten as:
Figure 4 indicates that as the variance of the futures price decreases, the risk averse cost curves collapse to the risk neutral cost curves and the source of bias from risk, B_R, goes to zero. Reducing the variance of futures prices is also a reduction in the noise, U. Thus, it is apparent that futures

price series with smaller variances reduce social loss on two fronts: pure noise and bias due to risk aversion.

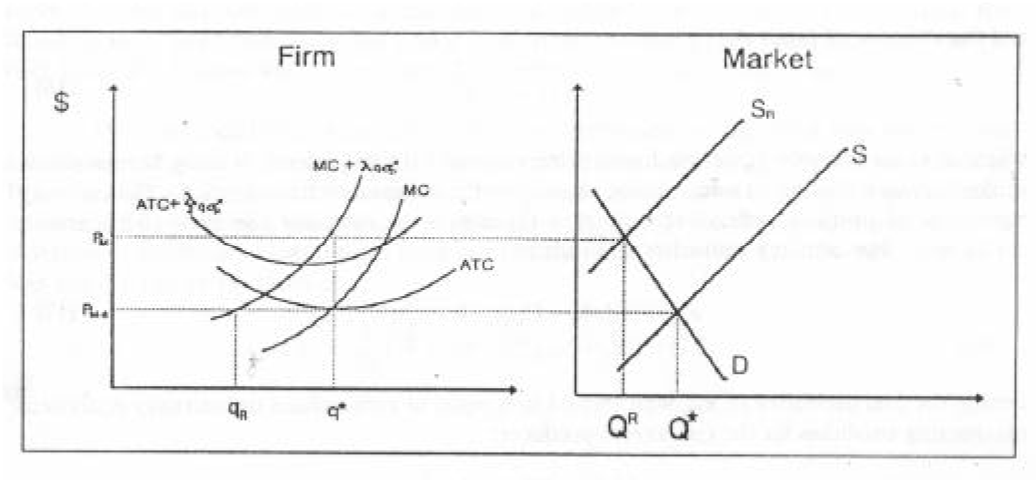

Figure 4. **Illustration of How Producer Risk Aversion Can Introduce Bias into Futures Price**

It has been shown, then, that when producers rely on futures prices as forecasts of subsequent cash prices, the variance of the futures price series is important in determining the social loss that occurs as a result of resource misallocation. Figure 5 presents some potential paths that futures price may take over the life of the contract. Path C is a result of biased prices, path B is an unbiased price path with a large variance, and path A is an unbiased price path with a smaller variance. From the preceding discussion, social loss under path A would likely be smaller than under either B or C. The perfect price path would be one that collapsed to the final settlement value and remained there for the life of the contract. Price risk would be completely eliminated as would be all social loss arising from price risk. Of course, this ideal scenario would never occur because the futures market would disappear as there would be no price risk and no incentive for traders to participate. It is apparent, however, that socially more desirable futures price paths are those that stay nearer the final settlement value over the life of the contract.

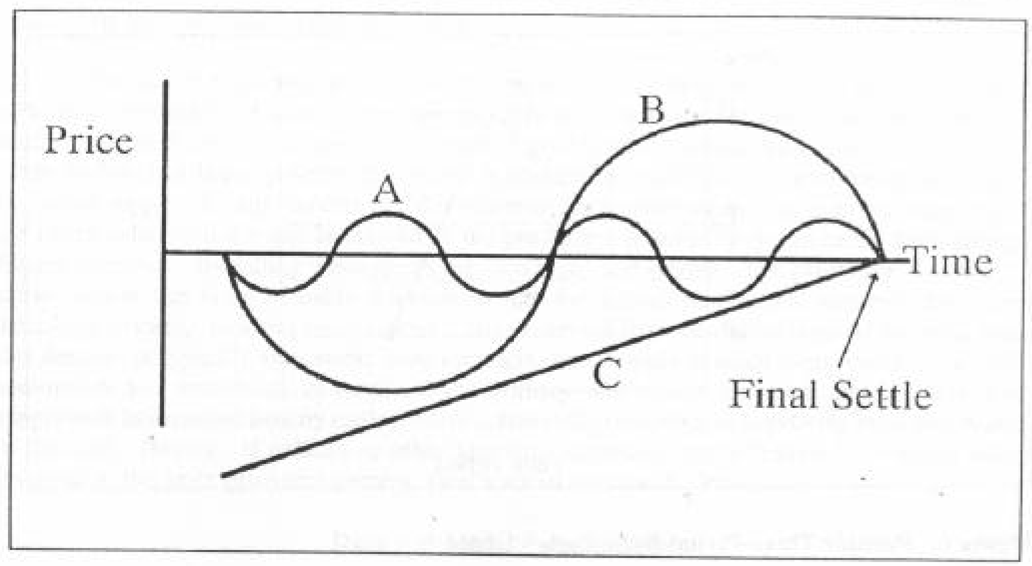

Figure 5. Potential Paths for Futures Prices

Price discovery is the process by which the market "learns" the true value of a commodity as indicated by supply, demand and the structure of a market. In cash fed cattle markets, the price discovery process can be a public auction, private negotiation, or even a predetermined formula. The price discovery process is repeated for each unit of the commodity, usually a pen of finished animals, and has a distinct beginning and end. In futures markets, the transacted item is a contract for future delivery. All contracts traded are identical. Because all contracts are identical, it is proper to view each trade as part of the larger price discovery process for the commodity defined by the contract. The process is completed when the futures price arrives at (or converges to) the cash price at maturity.

How well a futures market performs the price discovery function can be measured by how closely the prices generated during the process reflect the true value of the commodity. Price paths with smaller deviations around the final settlement value indicate a more efficient price discovery. More efficient price discovery implies reduced social loss from economic agents basing decisions on futures prices.

Consider the three-period situation depicted in Figure 6 where prices rise from t_0 to t_1 and then fall from t_1 to t_2. At time t_0 the trader forms expectations on prices in t_1 and t_2. Given accurate expectations (i.e., expectations consistent with the eventual realized prices), the profit-maximizing behavior for the trader will be to go long at t_0 and then adjust the position so that he/she is net short at t_1. In this way, the trader "captures the peak" in prices. From a social prospective, however, prices in t_0 are "too high" relative to their final settlement price in t_2 and the socially optimal behavior for the trader is to go short at t_0 and increase the short position at t_1. Thus, there is a possible divergence between profit-maximizing trading behavior and the socially optimal trading behavior with respect to price discovery.

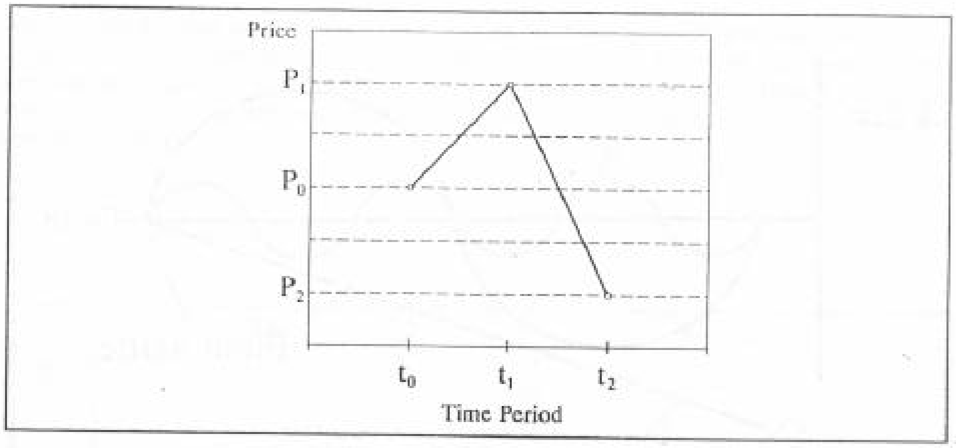

Figure 6. Possible Three-Period Price Path

This leaves one to question why prices rose in the intermediate time period, t_1. On the whole, all of the other traders in the market had t_0 price expectations on the true value of the commodity greater than P_0. These expectations were, of course, incorrect. These incorrect expectations reflect the limitations of trader information subsets and/or translating mechanisms.

One way that trader information subsets may be limited is if large numbers of traders hold no private information about commodity supply/demand and rely solely on publicly available information. Since public information is a subset of all information, this is a situation where a large number of traders share the same information subset. If these traders process information similarly, then changes in public information invoke similar changes in expectations and can cause large movements in price. Public information may, at times, produce price expectations out-of-line with the true value of the commodity.

This raises the potential for another type of trading behavior. If large numbers of traders react exclusively to changes in public information, then some traders will find profit from predicting the reaction of other traders to emerging public information. These traders will profit from correct prediction of other trader behavior regardless of whether the other trader behavior is in the best interest of price discovery. This is the case in Figure 6. Even though a trader may hold a price expectation that suggests the price in t_0 is "too high", it is still profitable for him/her to take a long position in order to profit from the incorrect expectations of the other traders in the market. This long position is detrimental to price discovery because the trader is, for the moment, ignoring the information that is important to society (the value of the commodity) and focusing instead on predicting and reacting to the behavior of other traders.

Private information can give those traders possessing it an advantage over other traders who rely solely on public information. This creates a potential for profit and is what motivates firms to develop accurate information on future conditions before it becomes widely available to the public. Two different types of private information may be developed: information about future supply/demand conditions, or information about the probable content of future public information and the likely reaction of traders to it. The former type of private information is far more beneficial to the price discovery process than the latter which may be detrimental to discovering the true value of the commodity.

The cost of developing private information is lower for those involved in the commercial trade in a commodity. Cattle feeders operate daily in the markets for live cattle inputs (feeder cattle, feed components) and are able to observe production conditions first-hand. This places cattle feeders in a better position than most to assemble accurate private information on future live cattle supply. If cattle feeders use this information to detect when futures prices stray from the likely value of live cattle at the end of the production process, they can profit from taking futures positions. By selling when prices are "too high" and buying when prices are "too low," cattle feeders can bring valuable information into the futures market and improve the price discovery process. Demand for slaughter cattle is derived from consumer demand for meat and this demand is typically very stable over the short-run. Supply is much more variable for this commodity and uncertainty in supply is the primary source of price uncertainty. Thus, the supply-side information held by cattle feeders is especially important to improving price discovery in live cattle futures. If policies or other restraints discourage cattle feeders from being fully involved in the price discovery process, then a social cost can be incurred.

Data and Model Specifications

The unique data set used in this study was provided by the Commodity Futures Trading Commission (CFTC). It consists of 261,172 observations on the individual accounts of traders whose position at the end of a daily trading session exceeded the minimum limit for mandatory reporting in live cattle futures. This minimum limit was 100 contracts during the time period covered by the data, 1983-1987. These are the data that have formed the basis for the CFTC's *Commitment of Traders Report* that was published monthly until 1994 when more frequent reports were initiated.

Each daily position reported in this data set was classified by the CFTC at the time of collection as either commercial or noncommercial. To assume that the commercial designation reflects the positions of hedgers would require a definition of what constitutes a hedge and knowledge of the trader's cash position. Since data on cash positions do not exist and there are considerable differences in opinion as to what constitutes a hedge (Purcell, Locke and Hudson), it is safer to assume only that traders holding futures positions classified as commercial had some cash position in cattle. Noncommercial designations were assigned to the positions of traders who had no cash position in cattle, i.e., speculators.

Coded account numbers were used by the CFTC to prevent identification of individual traders. In addition to the coded account number, each observation in the data set included the date of the position, the maturity month and year of the contract, geographic location of the trader (by state), and the number of long and short positions held. Price information was collected and added to this base data set. Daily closing prices on all futures contracts traded between January 1983 and December 1987 were included. A computer program was written to check the futures prices for errors (for correct chronological order and to ensure that price changes were within permissible daily limits). The prices were then matched to each observation in the CFTC data set according to date and contract month. The daily change in price was also added to the CFTC data set.

For this study, it was decided that individual traders (accounts) should remain in the same trader group for the entire period of the analysis. With respect to the data, this meant that each unique account code was assigned membership in a single trader group and all observations associated with that account code and appearing anywhere in the data set were considered a part of the assigned trader group.

All accounts that were only associated with observations identified in the data set as not being those of individual traders were grouped together. This grouping included the accounts of commodity pool operators, commodity trading programs of future commission merchants, and house positions. This group is referred to as the "funds/other" trader group. As would be expected, all of the observations related to the accounts in this group were classified as noncommercial, or speculative, positions. Next, accounts for which every observation in the data set was classified as commercial were grouped together. Likewise, individual accounts for which every observation was classified as noncommercial (speculative) were grouped together. These two groups, consisting of pure commercial accounts and pure speculative accounts, are referred to as the commercial and noncommercial groups, respectively.

To allow for differences based on the size of the trader (as measured by open contracts held) the commercial and noncommercial groups were split into subgroups. The basis for this subdivision was the average open position (AOP) of the account over the entire period of the study. An account's AOP is the total number of open positions associated with the account divided by the number of observations for that account.

The mean AOP was used as the dividing point in each group, with the commercial mean AOP=161 contracts and the noncommercial mean AOP=134 contracts. All accounts possessing an AOP less than the mean were placed in one subgroup and all accounts with AOP larger than the mean in another. For references purposes, these groups are referred to as the medium and large (commercial or noncommercial) groups, respectively.

One other group arises from the data. Small traders (those who hold less than 100 contracts) hold the positions necessary to balance the net positions of all of the accounts in the CFTC data set. By summing net positions across the five trader groups identified from the CFTC data and reversing the sign, the net positions of the small trader group can be calculated. Thus, all of the traders in live cattle futures over the period of the analysis can be classified into one of six groups: large commercials, medium commercials, large noncommercials, medium noncommercials, funds/other traders, and small traders.

Table I lists the number of accounts that fall into the first five trader groups as calculated from the CFTC data. The actual number of small traders is unknown, but it is unnecessary for the analysis. All that is important for the analysis is the net position of small traders, and this could be determined.

Development of Price Pressure Measures

The ultimate data measure required for the models is a statistic to record the amount of pressure exerted on price by each of the trader groups. The discussion so far has focused on the analysis of the raw CFTC position data to produce daily net positions for six specific trader groups. Changes in these net positions, together with observed changes in price, hold information about changes in the collective price expectation of each group.

To help illustrate the development, the price pressure calculations for one observation from the data set are presented. Daily net positions of each trader group can be symbolized as NP_{it} where the i subscript represents the trader group and t is a time period subscript. Table II gives the net positions of each of the trader groups in the December 1984 live cattle contract for two days in late

October, 1984. From the initial raw data given in Table II, the changes in net positions (ΔNP_{it}) are calculated and are also presented in Table II. Here, negative numbers indicate that a particular trader group has become "more short" or "less long" during the trading day and positive numbers indicate the opposite.

Table I. Number of Accounts in Each of the Five Trader Groups Constructed from the CFTC Data Set.

Trader Group	Number of Accounts
Large Commercial	149
Medium Commercial	228
Large Noncommercial	285
Medium Noncommercial	386
Other Traders	137
Total:	1,185

Next, the net position changes are used to calculate fractions which represent the percentage

$$I_{it} = \frac{\Delta NP_{it}}{\sum_i \left|\Delta NP_{it}\right|} \ .$$

of new net positions for that day attributable to each of the trader groups. For reference purposes, these fractions are called initial fractions (I_{it}) and are calculated as:
The number of new net positions is simply the sum of the absolute values of the changes in net positions across all trader groups. The new net positions are "new" in the sense that they are new to a particular group--they are positions that did not exist for that group at the end of the previous trading session. New net positions may arise from a shuffling of existing open positions between groups (e.g., offsetting an existing position) or they may result from the opening of new positions. Thus, the new net positions referred to here are not synonymous with new open interest. They are simply devices to measure the net activity in the market for a particular trading session.

Using these initial fractions, the daily price change is divided among the six trader groups to produce an initial measure of price pressure, IP_{it}, where $IP_{it}=I_{it}\cdot\left|\Delta P_t\right|$. Table III presents these calculations for the sample observation. Since the initial fractions necessarily sum to zero, the initial price pressure measures also sum to zero. The absolute value of the daily price change is used in these calculations because the direction of the price pressure is communicated by the sign on the initial fraction.

The next step in the procedure involves dividing the price change among only those groups

[10]Abbreviations for each of the trader groups are defined in the table. These abbreviations are used extensively in the remainder of this bulletin without further reference.

$$S_{it} = \frac{\Delta NP_{it}}{\sum_i \left|\Delta NP_{it}\right|} \quad i \in \text{mover groups}$$

that had net position changes corresponding to the direction of the price change. These groups are referred to as "mover groups." For example, if the direction of the price change is up, the mover groups for that observation are those possessing positive (more long or less short) net position changes. This step in the calculations acknowledges the fact that since the observed price change was in a particular direction, the groups whose net positions changed in a way consistent with that change must have exerted, in sum, more pressure on price than did the groups whose net positions moved contrary to the direction of price. Allocating the price change to mover groups for a observation begins with the calculation of supplemental fractions. These fractions are derived in the same fashion as the initial fractions, except that only the mover groups are part of the calculation. The supplemental fractions (S_{it}) can be represented by:

Table II. Net Positions, Change in Net Positions, Settlement Prices, and Change in Price For Two Observations on the December 1984 Live Cattle Contract

	First Observation	Second Observation
Date:	10/29/84	10/30/84
	----- Net Position ----- (Number of Contracts)	
Trader Group:		
Large Comm (LC)	-682	-634
Med. Comm. (MC)	377	368
Large Noncomm. (LN)	886	1266
Med. Noncomm. (MN)	266	451
Funds/Other (OTH)	-1713	-1723
Small Traders (ST)	866	272
	----- Change in Net Position ----- (Number of Contracts)	
Trader Group:		
Large Comm (LC)		48
Med. Comm. (MC)		-9
Large Noncomm. (LN)		380
Med. Noncomm. (MN)		185
Funds/Other (OTH)		-10
Small Traders (ST)		-594
Settlement Price ($/cwt):	63.92	64.22
Price Change ($/cwt.):		0.30

The denominator in this fraction is the total number of new net positions attributable to the mover group(s). Because this number is half of the total new net positions, the supplemental fractions will be double the initial fractions.

Table III. Calculation of Initial, Supplemental and Total Price Pressure Measures for the December 1984 Live Cattle Contract on 10/30/84.[a]

Total New Net Positions: 1226 contracts

Mover New Net Positions: 613 contracts

$|\Delta P|$: 0.30 \$/cwt.

	Initial Pressure[b] $IP = I \bullet |\Delta P|$	Supplemental Pressure $SP = S \bullet |\Delta P|$	Total Pressure $TP = IP + SP$
Trader Group:			
LC	$.0117 = {}^{48}/_{1226} \bullet 0.30$	$.0235 = {}^{48}/_{613} \bullet 0.30$	.0352 = .0117+.0235
MC	$.0022 = {}^{9}/_{1226} \bullet 0.30$	$.0044 = {}^{9}/_{613} \bullet 0.30$	.0066 = .0022+.0044
LN	$.0929 = {}^{380}/_{1226} \bullet 0.30$	$.1860 = {}^{380}/_{613} \bullet 0.30$	.2789 = .0929+.1860
MN	$.0452 = {}^{185}/_{1226} \bullet 0.30$	$.0905 = {}^{185}/_{613} \bullet 0.30$	.1357 = .0452+.0905
OTH	$-.0025 = {}^{-10}/_{1226} \bullet 0.30$	0 (NMG)	-.0025 = -.0025+0
ST	$-.1453 = {}^{-594}/_{1226} \bullet 0.30$	0 (NMG)	-.1453 = -.1453+0
Totals:[c]	0.00	0.30	0.30

[a]Symbols as follow: ΔP=Price Change, IP=Initial Pressure, I=Initial Fraction, SP=Supplemental Pressure, S=Supplemental Fraction, TP=Total Pressure, NMG=Not a Mover Group.
[b]Units for pressure measures are \$/cwt.
[c]May not add due to rounding.

The supplemental fractions are then used to divide the price change among the mover groups to form the supplemental price pressure measure, SP_{it}. This relationship is similar to the initial fraction calculation in that $SP_{it} = S_{it} \cdot |\Delta P_t|$. This calculation is carried through for the examples in Table III. Again, the absolute value of the price change is used because the sign on the supplemental price pressure is conveyed by the supplemental fraction. Finally, the initial and supplemental price pressure measures are summed to arrive at a total measure of price pressure for each of the trader groups, TP_{it}.

By construction, the total price pressures summed across all of the trader groups gives the exact daily price change. This is necessary in order that the change in price can be described solely as a function of the market activity of the six trader types. There will always be some positive (buying) and some negative (selling) pressure on price at each observation. The price pressure modeling process was applied first to the observations in the data set for the December 1984 live cattle contract. Figures 7 and 8 plot the total price pressure measures for the large commercial and large noncommercial trader groups over the life of this particular contract.

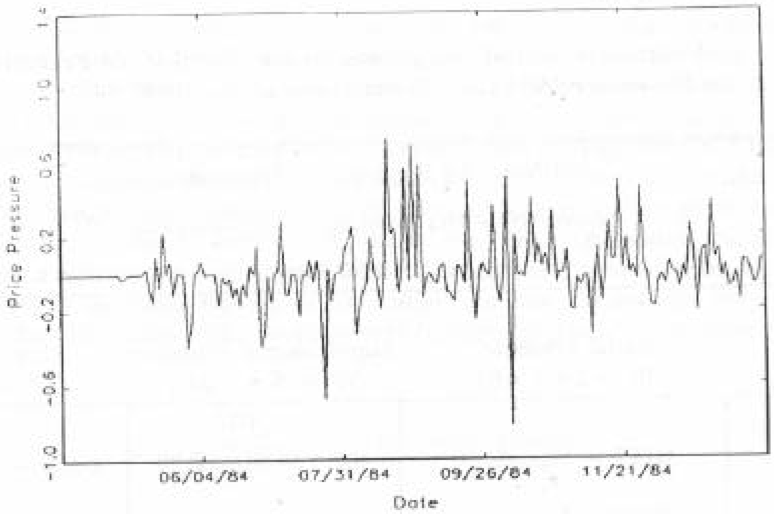

Figure 7. Large Commercial Price Pressure for the December 1984 Live Cattle Contract

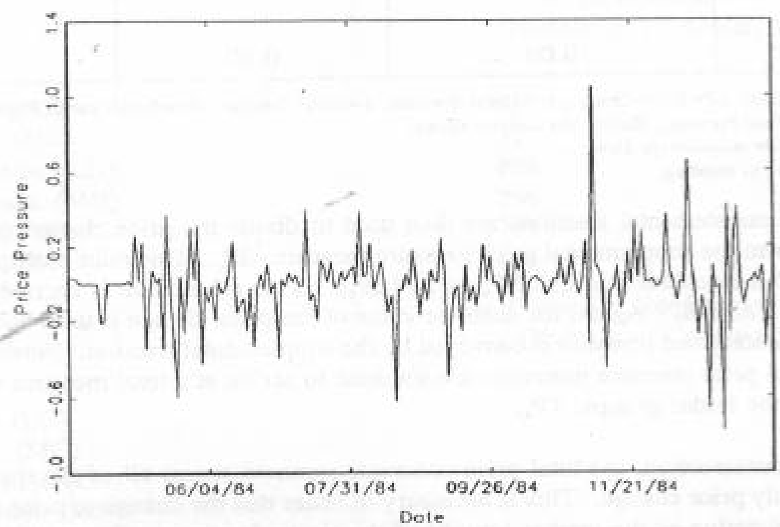

Figure 8. Large Noncommercial Price Pressure for the December 1984 Live Cattle Contract

Implicit in the way this measure is calculated is the assumption that every futures trade by a particular trader group in a given trading session has equal impact on price pressure. In reality, it is likely that individual traders engage in trades at different price levels, at different times within the day, and with different temporal characteristics. Thus the pressure exerted by trades originating from different individuals should and probably does vary. However, since the model calls for aggregation over all traders in a group, generalizing to give all trades by that group some equal, or average, weight does not affect the analysis. Differing contributions by individual traders would only be important if the analysis focused on individual traders rather than groups of traders.

On those infrequent occasions when there is no change in price from the previous day's close ($\Delta P = 0$), all of the $TP_{it} = 0$. This occurs even though there may be as many as six nonzero ΔNP_{it}'s. Theoretically, $\Delta P = 0$ could result from summing nonzero TP_{it}'s so long as the positive TP_{it}'s were equal in value to the negative TP_{it}'s. There are an infinite number of values the six TP_{it} could take and still sum to zero. The constraint assumed by this process is that all $TP_{it} = 0$. Although this price pressure modeling process may not be ideal in all respects (such as when $\Delta P = 0$), it does provide a rule than can be applied consistently to each observation to arrive at an objective price pressure measurement.

The primary objective of this modeling effort is to simulate price paths that reflect a live cattle futures market with a different mix of traders from the mix that was historically observed. These simulated price paths, along with the trader mix that produced them, can then be evaluated for their effect on the price discovery process. The general idea is to postulate a model where prices behave in a manner consistent with the actual live cattle futures market (e.g., price limits are enforced, closing price for day t + 1 is equal to the closing price on day t plus the price change on t + 1). Changes are then allowed in the price pressure of one or more trader groups (which mimics changes in their market presence) so that simulated daily price changes (and thus simulated daily prices) are developed. These simulated prices, when viewed as a time series, are a simulated price path.

All of the simulation models are quadratic programming models designed to minimize an objective function that defines the MSE of the price series. MSE is simply the mean squared deviation of each observation in the price series from the final settlement price ($MSE = \Sigma_t [Price_t - Price_{final}]^2/N$). There are a number of advantages to specifying the simulation model in this manner. By minimizing, or even simply reducing, the MSE of a price series, the price discovery process is improved. It was shown in an earlier section that the social loss from poor price discovery is nearly proportional to the squared forecast error of distant futures prices. The MSE used here represents that squared forecast error. Examining how the trader mix was changed in order to accomplish a MSE reduction provides information on the relative value of each trader group to the price discovery process. A programming model has the advantage that it generates dual values (shadow prices) which reflect the marginal value of each trader group to minimizing MSE, and hence to the price discovery process. Also, by formulating the model as one that optimizes a specific objective function, the model chooses the optimal trader mix and thus is able to avoid arbitrary specification of changes in trader mix.

Ten different models were specified. Although the models are all variations of the same general concept, each one provides different information on the contribution of the six trader groups to the price discovery process in live cattle futures. Each model is applied to the price pressure data on each of the 24 futures contracts. Some of the models are specified so that a change in trader mix holds for the entire period that the contract is traded (200 trading days) and some models permit the contract life to be divided into 10 subperiods (of 20 trading days each) with a different trader mix allowed in each subperiod. The subperiod models are designed to investigate how trader group influence on price evolves as the contract approaches maturity. Model 1 is presented below to help clarify what was done in the analytical process. Table IV provides details on the characteristics of each model and the purpose for which each was designed. Table V presents descriptions of the symbols used in the mathematical representation of the models which follow.

MODEL 1

$$\text{Min}\ \ MSE = \frac{1}{N}\sum_{t}(PRICE_t \quad PRICE_{200})^2 \tag{1.1}$$

$$\text{subject to:}$$

$$PRICE_t = PRICE_0 + \sum_{g}(\sum_{t=1}^{t} PP_{tg} + (PPCT_g \quad 1)\ k_g \sum_{t=1}^{t} PP_{tg}) \tag{1.2}$$

$$PRICE_{200} = ENDPR \tag{1.3}$$

$$PRICE_t \quad PRICE_{t1}\ \text{ge}\ 1.50 \tag{1.4}$$

$$PRICE_t \quad PRICE_{t1}\ \text{le}\ 1.50 \tag{1.5}$$

$$PPCT_g = 1 \tag{1.6}$$

$$MSE,\ PRICE_t\ \text{GE}\ 0 \tag{1.7}$$

The objective function of Model 1, and of all the models, defines MSE as the sum of squared deviations of the 200 daily prices from the final or true value divided by the number of observations. This is simply a measure of dispersion of actual or simulated futures prices around the "true" price. Because smaller values of MSE are more desirable from a price discovery prospective, this objective function is minimized.

The constraints require the final simulated price to equal the final historical price. This is important to the realism of the model. Any simulated price series should be expected to converge at maturity to the same price the historical series shows. In essence, then, the model is constrained to begin and end in the same place as the historical series. The path that it chooses to follow between these two points need not, of course, be the same as the historical price path.

If all the $PPCT_g$ variables are restricted to unity, the simulated price series arising from Model 1 will be identical to the historical price series. While this will not generate an optimal trader mix, these six constraints will have shadow prices associated with them. These shadow prices will indicate how the MSE will respond to a one unit increase of any of these constraints. That is, the shadow price associated with a particular constraint will convey the marginal value of increasing a particular group's market presence *from its historical level*. This information measures a particular group's influence and potential influence on price discovery.

Table IV. Distinguishing Characteristics and Purposes for the Ten Model Specifications

Model Number	Sub-periods	Distinguishing Characteristic	Purpose
1	No	All price pressures held at historical levels	Generate shadow prices to indicate relative influence of each group over life of contract.
2	Yes	All price pressures held at historical levels	Generate shadow prices to indicate relative influence of each group in each subperiod.
3	No	All price pressures allowed to vary simultaneously	Determine optimal trader mix over life of contract.
4	Yes	All price pressures allowed to vary simultaneously	Determine optimal trader mix by subperiod.
5 - 10	Yes	Only one trader group's price pressure is allowed to vary from historical in each model (Model 5 = LC Model 6 = MC Model 7 = LN Model 8 = MN Model 9 = OTH Model 10 = ST)	Determine optimal market presence of a particular group in each subperiod, *ceteris paribus*.

Table V. Symbol Definitions for the Mathematical Representation of the Models

Symbol:	Description:
Known Parameters:	
$PRICE_0$	Historical beginning price for a futures contract; the price 201 trading days before the contract expired.
ENDPR	Historical final settlement price for a futures contract.
PP	Historical price pressure calculated using methods detailed in a previous section.
k	Price pressure multiplier that captures intergroup response effects for a particular futures contract.
N	Number of trading days in a contract, N=200.
Variables:	
MSE	Mean Squared Error
PRICE	Simulated Daily Price
PPCT	Percentage of historical price pressure for non-subperiod models.
PCT	Percentage of historical price pressure for sub-period models.
Subscripts:	
t	trading day; t = 1 to 200.
g	trader group; g = 1 to 6;
p	sub-period; p = 1 to 10;
j	single trader group allowed to vary in Models 5-10.

Model 2 is identical to Model 1 except that it is a subperiod model. Instead of the choice variables being indexed over trader group only, they are indexed over trader group and subperiod (p). Each subperiod consists of 20 trading sessions with subperiod 1 being the first 20 daily trading sessions and subperiod 10 being the last 20 trading sessions. The expression labeled (1.2) in Model 1 is replaced with 10 comparable constraints, one for each of the 10 subperiods.

Model 1 had six choice variables, but Model 2 has 60. In Model 1, the change in market presence for any particular group (indicated by $PPCT_g$) will be in effect for the entire life of the

[11]Econometric techniques were used to estimate the contemporaneous response of each group's price pressure to changes in each of the other group's price pressure. These relationships were summarized in the form of price pressure multipliers which indicate the total impact on price of a one-unit change in a group's price pressure when all other group responses are taken into account. Average K_g levels for this study were: K_{LC}=.59, K_{MC}=1.11, K_{LN}=.90, K_{MN}=1.71, K_{OTH}=.79, K_{ST}=.51.

contract. Model 2 is considerably more flexible with each group being allowed a different market presence in each subperiod. The primary reason for specifying subperiod models is to study how trader groups influence price discovery at different points in the life of the contract. For Model 2, this means that the shadow prices arising from the 60 constraints will be examined to determine how each group's marginal contribution to MSE changed as time passed and the maturity date approached.

Model 3 is a non-subperiod model very similar to Model 1. It's distinguishing feature is that trader group market presence is no longer constrained to its historical value. Expression (1.6) in Model 1, which forces a trader group presence to its historical value, is replaced by two expressions which constrain a trader group's presence to no less than 80 and no more than 120 percent of historical levels. This is the first model in which an optimal trader mix is generated and the first for which the simulated prices arising out of the model differ from the historical prices.

Although the decision variables in this model are allowed to vary, some bounds must still be imposed upon them. Without bounds, a trader group could be removed from the market entirely ($PPCT_g = 0$) or its market presence increased to infinity. Neither situation is reflective of what might be expected from a real-world market response to a policy change. Further, removing a very large portion of any trader group or increasing the presence of a group to a very large degree would likely entail liquidity effects not accounted for by the present model. Because the models used in this study ignore any liquidity effects of changes in market presence by the various trader groups, the models are probably most accurate for relatively small alterations in price pressure. For these reasons, it was decided that the market presence of any trader group should not be allowed to change by more than ±20 percent. In addition to the optimal trader mix provided by the solution to this model, these constraints will provide shadow prices for any trader group whose optimal market presence is 80 (or 120) percent of its historical value. These shadow prices indicate the marginal value of additional decreases (increases) in that group's price pressure. For $0.8 < PPCT_g < 1.20$, the shadow prices will be zero.

Model 4 is the sub-period version of Model 3. This is the most flexible of all the models. Not only are the decision variables allowed to vary from unity, they can take different values in each of the 10 subperiods. Because of its high degree of flexibility, this model is expected *a priori* to be the one that produces the simulated price path with the smallest MSE. The model will render 60 optimal levels of market presence, one for each trader group in each time period. In addition, the 120 constraints employed will provide shadow prices for any PCT_{pg} for which these constraints are binding at the optimal solution. For trader groups that were beneficial to the price discovery process in a particular subperiod, a $PCT_{pg} > 1$ would be expected.

Models 5-10 are subperiod models designed to evaluate the effect on prices of a change in only one trader group's market presence while holding the remaining five group's price pressure at their historical levels. These models allow the study of optimal market presence for individual trader groups without distortion from simultaneous changes in market presence by other groups. These models could also be used to study the effect on prices of a specific change in market presence by a particular trader group. For example, if a policy maker determined that a policy might be expected to increase the market participation of a specific trader group by τ percent, then the appropriate model (from Models 5-10) could be used and the average price pressure of the group of interest over all 10 subperiods restricted to τ percent more than the historical average for that group. Then the model could be solved to generate a simulated price path and a MSE value associated with that price path. If this MSE was smaller than that from Model 1 or Model 2 (historical MSE), then the policy, had it been in effect, would have improved price discovery.

Results

Table VI gives the descriptive statistics for the six historical price pressure series. All 4,800 observations (24 futures contracts x 200 observations per contract) are included in these calculations. The small trader group possesses the largest positive mean price pressure and the large commercial group has the most negative mean. All of the mean values fall very close to zero, indicating that all of the groups, with the exception of the small traders, seem to exhibit roughly equal amounts of positive and negative pressure over time. The small trader group appears to be more prone to positive pressure.

Table VI. Descriptive Statistics for the Price Pressure Measures by Trader Group for All 24 Futures Contracts

Trader Group	Mean	Std. Dev.	Min.	Max.	Skewness	Kurtosis	N
LC	-0.008	0.295	-2.220	1.906	-0.559	12.167	4800
MC	0.001	0.170	-1.940	1.935	-0.654	27.182	4800
LN	-0.003	0.319	-2.250	2.250	-0.171	13.094	4800
MN	0.000	0.120	-1.364	1.296	-0.356	29.882	4800
OTH	-0.001	0.275	-2.250	2.220	-0.302	18.315	4800
ST	0.018	0.385	-2.243	2.250	0.091	10.448	4800

The small trader group also exhibits the most variation in price pressure as indicated by the standard deviation. The medium noncommercial group's price pressure varies the least with the standard deviation being only about one third of the value associated with the small trader group.

The skewness and kurtosis coefficients calculated from the sample data are also reported. These are important in detecting departures from normality in the distribution of the price pressure data. Variables whose distribution is normal are characterized by skewness equal to zero and kurtosis equal to 3.0. All trader groups other than the small trader group show price pressure distributions slightly skewed in the negative direction. All of the sample kurtosis coefficients are very large compared to what would be expected from normally-distributed data. Using the Bera-Jarque test, which jointly tests for skewness different from zero and/or kurtosis different from 3.0, the null hypothesis of normality was rejected at the 0.01 level for all of the price pressure samples.

To check for the possibility of contemporaneous linear dependencies among the price pressures of different trader groups, the correlation matrix of these six variables was calculated. Small trader price pressure is negatively correlated with the price pressure of all five other trader groups. This is not unexpected since the small trader group is the group that takes positions that balance all of the large trader positions. There appears to be no linear relationship between the price pressure of the two large trader groups, but there is a significant positive linear relationship between the pressure series of the two medium groups.

Another important descriptive statistic is one that measures the average overall pressure of each trader group. The mean of the price pressures does not adequately capture this characteristic because the negative and positive values tend to cancel one another. A better statistic which accounts for, and gives equal weight to, both positive and negative price pressure, is the mean of the absolute value of price pressure. These statistics were calculated for each contract month and are presented in Table VII. The overall market presence of each group (as measured by the amount of price pressure exerted) is conveyed by these data. The table indicates that market presence and influence varies from contract to contract for all trader groups, but the relative size of the statistic between groups changes very little.

Average market presence, measured here by the mean absolute value of price pressure, is influenced by three factors: 1) the number of open positions the group is responsible for, 2) the degree of agreement between individual traders within a group with respect to changes in position direction, and 3) the frequency with which a trader group is a mover group. It is hard to determine precisely the relative importance of these three factors in explaining the differences in average market presence listed in Table VII. One clue is given by the fact that the large commercial and large noncommercial groups are responsible for more total open positions than the medium commercial and medium noncommercial groups and the average market presence of the large groups is greater than that of the medium groups. This suggests that the first factor, number of open positions, dominates the second and third for these trader group definitions and data.

Price response to changes in the trader group mix is dependent upon trader group market presence. Prices will be influenced more by a one percent change in the price pressure of a group with a large market presence than the same percentage change in the price pressure of a group with lesser market presence. Therefore, it will be important to remember the differences in market presence indicated by Table VII when interpreting the results of the simulation models.

The General Algebraic Modeling System (GAMS) was used to code all of the models used in this study. Each of the 10 models was solved using the price pressure data from each of the 24 contracts resulting in a total of 240 model solutions.

Model 1 Results

The six decision variables in Model 1 shown on page 21 are the variables used to alter market presence, $PPCT_g$. All other model variable values depend on the value taken by these six variables. The values of the six decision variables were fixed at unity by the constraints employed. This means that the simulated prices will be exactly equal to the historical prices as defined by the sum of the price pressure parameters, PP_{tg}.

This model was solved for all 24 futures contracts individually. The most interesting results of this model are the shadow prices generated by the six constraints from (1.6) in Model 1. Basically, these shadow prices give the impact on MSE of doubling the presence of the trader group corresponding to each constraint represented by (1.6).

Table VII. Means of the Absolute Value of Price Pressure by Trader Group for Each Futures Contract

	---------- Trader Group ----------					
Contract	LC	MC	LN	MN	OTH	ST
Dec 83	0.138	0.054	0.161	0.041	0.091	0.246
Feb 84	0.198	0.068	0.182	0.034	0.101	0.214
Apr 84	0.171	0.082	0.150	0.073	0.087	0.215
Jun 84	0.129	0.076	0.138	0.043	0.104	0.191
Aug 84	0.095	0.047	0.111	0.056	0.085	0.175
Oct 84	0.125	0.032	0.122	0.026	0.103	0.162
Dec 84	0.106	0.046	0.117	0.025	0.093	0.166
Feb 85	0.122	0.039	0.166	0.016	0.070	0.141
Apr 85	0.118	0.048	0.158	0.032	0.083	0.182
Jun 85	0.141	0.064	0.141	0.038	0.139	0.194
Aug 85	0.172	0.089	0.134	0.050	0.113	0.236
Oct 85	0.169	0.113	0.155	0.040	0.135	0.223
Dec 85	0.207	0.093	0.198	0.049	0.148	0.265
Feb 86	0.236	0.089	0.230	0.043	0.165	0.302
Apr 86	0.258	0.087	0.247	0.073	0.126	0.342
Jun 86	0.235	0.118	0.223	0.025	0.183	0.330
Aug 86	0.213	0.101	0.259	0.039	0.210	0.328
Oct 86	0.180	0.076	0.259	0.039	0.194	0.349
Dec 86	0.210	0.086	0.206	0.048	0.158	0.283
Feb 87	0.142	0.044	0.205	0.033	0.159	0.254
Apr 87	0.151	0.068	0.183	0.047	0.132	0.209
Jun 87	0.140	0.061	0.169	0.045	0.146	0.202
Aug 87	0.128	0.042	0.146	0.049	0.136	0.215
Oct 87	0.156	0.076	0.169	0.078	0.139	0.191
Overall Average:	0.164	0.071	0.176	0.043	0.129	0.234

Table VIII lists the shadow prices by trader group for each futures contract included in the study. Within a particular futures contract, the largest negative shadow price identifies the trader group doing the most to keep prices near the final settlement price and the trader group associated with the largest positive shadow price is doing the most to cause prices to differ from the final settlement price. In those contract months where there are no negative shadow prices, marginally increasing the presence of *any* trader group would increase MSE. In these situations, the smallest positive shadow price indicates the group that would do the *least harm* to the objective function for an equivalent marginal percentage increase in market presence.

Table VIII reveals that the property of being most beneficial to price discovery (largest negative shadow price or smallest positive shadow price) belonged to the large noncommercial group in seven contracts (29%), the small trader group in seven contracts (29%), the large commercials in six contract months (25%), funds/other traders in two contracts (8%), and the medium commercial and medium noncommercial groups in one contract each (4%). These shadow prices are important because they signal the marginal contribution of each trader group to minimizing MSE *as measured at the historically observed prices and levels of market participation.* Thus, these results provide an *ex-post* measure of the relative value of these groups to the price discovery process in the live cattle futures market.

Table VIII. Shadow Prices for Each Trader Group for Each Contract from Model 1 With Intergroup Response Effects Included

	---------- Trader Group ----------					
Contract	LC	MC	LN	MN	OTHER	ST
December 1983	6.62	5.67	19.07	19.66	3.78	-13.21
February 1984	34.11	-10.09	51.96	-1.78	-6.20	-21.00
April 1984	23.83	-8.51	9.19	-3.96	-0.45	-18.31
June 1984	0.58	1.84	1.69	-0.12	-0.34	0.89
August 1984	-0.69	0.92	-0.87	-0.15	-1.50	6.17
October 1984	-4.29	-0.15	-2.58	1.79	-0.50	2.77
December 1984	1.07	2.29	8.00	-3.92	2.33	-6.86
February 1985	-4.20	0.68	5.51	0.82	0.45	1.20
April 1985	4.79	0.49	-36.54	5.13	5.31	10.61
June 1985	0.39	-4.44	20.36	-6.84	0.79	0.55
August 1985	-18.42	-9.40	17.87	-2.46	-3.55	22.15
October 1985	4.92	5.41	5.95	0.65	7.09	1.04
December 1985	1.44	5.97	2.63	4.84	10.89	2.52
February 1986	-22.27	-2.51	0.47	5.01	4.93	3.87
April 1986	-5.35	9.03	-11.98	0.96	4.39	-2.54
June 1986	-8.73	-2.40	1.75	-0.31	-2.12	19.39
August 1986	26.67	-6.31	-8.43	-2.71	43.36	-13.61
October 1986	-3.80	-8.07	-24.54	-4.21	44.43	18.97
December 1986	25.18	-2.63	-4.78	1.98	3.74	-3.74
February 1987	17.64	-7.01	3.39	12.60	42.88	-74.34
April 1987	26.89	17.04	-64.63	8.05	14.55	-15.48
June 1987	54.39	-10.43	48.99	-1.64	10.31	-37.97
August 1987	17.66	-1.68	-22.89	-4.16	-9.24	-8.55
October 1987	9.57	-16.18	-34.77	-33.19	22.04	-5.99

Shadow prices, averaged across all contracts, are used as an indicator of the marginal value of each trader group to price discovery over the entire four-year study period. In accordance with the mean shadow prices given in Table IX, the six trader groups can be ranked according to their marginal value in improving price discovery in live cattle futures from 1983 to 1987. A ranking in order of most beneficial to most detrimental would give:

1. Small Traders
2. Medium Commercial

3. Large Noncommercial
4. Medium Noncommercial
5. Large Commercial
6. Funds/Other Traders.

Table IX. Average Shadow Prices Across All 24 Futures Contracts for Model 1 With Intergroup Response Effects Included

	----------Trader Group----------					
	LC	MC	LN	MN	OTH	ST
Avg. Shadow Value	7.833	-1.687	-0.632	-0.165	8.225	-5.478
Sig. Test[a]	3	2	1	2	4	2

[a]Number of significant differences (α=.05) between the corresponding element and the remaining elements in the row.

The results of tests for significant differences are presented in a compact manner in the bottom line of Table IX. This row gives the number of times the null hypothesis (equality of means) was rejected (α = .05) when comparing the mean in the line directly above with the five remaining means. A value of five in this row would mean that the particular mean was found to be significantly different from all other means. Any value less than five indicates the null hypothesis was not rejected in some of the comparisons. Although it is not explicit, it should not be difficult to determine which pairs rejected the null. For instance, the small trader mean was significantly different from two other means on the row. A rational inference would be that those two means were the two furthest from the small trader mean, namely the large commercial mean and the funds/other trader mean. This method of reporting the results of statistical tests for differences was devised to reduce the volume of test results but still provide a method for adequately judging the results of individual comparisons.

Some general observations can be made from examining the data in Table VIII. First, the magnitude of the shadow prices for the two medium groups is generally much smaller than those of the remaining four groups. The two medium groups apparently have relatively less market presence when compared with the four other groups (Table VII). This restricts the two medium group's potential for having either a large positive or a large negative influence on MSE. Another characteristic of the results in Table VIII is that there are very few near-zero shadow prices. Near-zero shadow prices indicate that the corresponding trader group had a near-optimal market presence, historically. Thus, gains in price discovery appear to be possible from changes in the market presence of all of the trader groups.

Model 2 Results

Model 2 was identical to Model 1 except that the inclusion of subperiods raised the number of decision variables (PCT_{pg}) to 60—one for each trader group in each of 10 subperiods. Each subperiod consists of 20 trading sessions and corresponds to approximately one month in chronological time. Essentially, the Model 2 results are the Model 1 results, but with more detail.

The large number of shadow prices generated by Model 2 (1,440) require the use of summary statistics to facilitate interpretation of the results. Table X lists the mean shadow prices for each trader group by subperiod. A period-by-period listing of the most helpful and most harmful trader groups with respect to price discovery is as follows, where 1 = the first 20 day period and 10 = the 20 day period ending in contract maturity:

Subperiod	Most Helpful	Most Harmful
1	LN	LC
2	ST	OTH
3	ST	LN
4	ST	OTH
5	ST	LC
6	ST	OTH
7	ST	LC
8	LN	ST
9	LN	OTH
10	LC	LN

The small trader group appears to behave in a manner that tends to reduce MSE of the price series up until three calendar months prior to maturity. Large noncommercial interests do the most to restrict price dispersion from that point up until the last twenty trading days. In the last 20 trading sessions, it is the large commercial interests that do the most to bring price toward its true value. This result would be expected. It is the actions of hedgers who can deliver cattle under the futures contract that move the futures toward the cash market in the last trading days.

The four larger trader groups (LC, LN, OTH, ST) all take turns at being the group most harmful to prices with the funds/other group having the largest number of observations in that category (4). In the last 20 daily trading sessions, it is the behavior of the large noncommercial traders that tends to be most harmful to discovery of the true value of the commodity. These traders are closing out speculative positions during the delivery period of the futures. The absence of either medium trader group from this list is due, perhaps, to their smaller overall market presence.

One apparent pattern in Table X is that the magnitude of the shadow prices seems to be reduced for all groups as maturity approaches. This is consistent with the observation that as maturity approaches, prices tend to fluctuate nearer the final value. Because there is less overall deviation from the final value in the last few subperiods, there is less opportunity for any group to influence price dispersion as compared with earlier subperiods.

The lower section of Table X gives the results of pair-wise tests for differences in the means listed in the top of the table. These tests are administered in the same manner as those for Model 1 and the results are reported in the same fashion. The row-wise significance tests indicate the number of rejections of the null hypothesis (that means are equal) between the corresponding mean in the upper portion of the table and the remaining five means on that row. Similarly, the column-wise significance tests indicate the number of rejections between the corresponding mean in the upper portion of the table and the remaining nine means in that column.

Model 3 Results

This model is a non-subperiod model identical to Model 1 except that the six decision variables ($PPCT_g$) are no longer constrained to unity. Instead, the decision variables, which represent the degree of market presence of each trader group, are constrained to lie between 0.8 and 1.20. The solution to this model provides an optimal trader mix for each futures contract. This solution also provides values for the simulated price variables ($PRICE_t$) which differ from the historical prices and represent the price path that would be expected had the optimal trader mix been present in this market.

Table X. Average Shadow Prices Across All 24 Futures Contracts for Model 2 With Intergroup Response Effects Included

	---------- Trader Group ----------					
Subperiod	LC	MC	LN	MN	OTH	ST
1	3.158	-1.617	-3.495	-0.034	1.000	1.294
2	2.054	-1.062	0.335	-0.406	2.894	-1.756
3	-0.633	0.826	1.849	-0.141	0.700	-1.939
4	0.473	0.521	0.717	0.124	1.216	-0.237
5	1.526	-0.418	0.490	0.266	0.862	-1.142
6	0.397	0.527	-0.402	0.568	2.395	-0.795
7	1.104	-0.152	0.257	-0.242	-0.739	-1.067
8	-0.163	-0.274	-0.382	-0.309	-0.264	0.212
9	-0.009	-0.021	-0.064	-0.034	0.158	-0.037
10	-0.074	-0.017	0.063	0.043	0.003	-0.011
Subperiod	Row-wise Significance Tests[a]					
1	2	4	0	3	2	1
2	1	2	0	1	3	1
3	1	1	3	1	0	2
4	0	0	0	0	0	0
5	2	1	0	0	0	1
6	0	1	1	1	2	3
7	4	1	1	1	1	2
8	1	1	0	1	0	3
9	0	0	0	0	0	0
10	2	1	1	2	0	0
Subperiod	Column-wise Significance Tests[b]					
1	3	7	0	0	4	2
2	4	5	0	0	4	0
3	2	5	4	0	0	4
4	0	2	0	0	3	0
5	4	1	0	0	0	0
6	0	2	1	2	4	2
7	3	1	0	2	6	4
8	4	2	1	4	4	3
9	4	2	1	2	4	2
10	4	3	1	4	5	3

[a]Number of significant differences (α=.05) between the corresponding element and the remaining elements in the same row.
[b]Number of significant differences (α=.05) between the corresponding element and the remaining elements in the same column.

Table XI lists the optimal values of the decision variables for each trader group in each contract month. If a group's trading behavior was working to increase MSE, then the model will reduce that group's market presence and its new market presence (as indicated by the value of the decision variable, $PPCT_g$) will be less than its historical value. On the other hand, the optimal solution will include market presence larger than the historical presence for those groups whose trading behavior worked to reduce MSE. Many of the optimal values reported in Table XI are equal to either the upper or lower bounds placed on them. In these situations, the binding constraints yield shadow prices which have the same interpretation as those in the previous models. In those instances where the optimal value falls between 0.80 and 1.20, the shadow price of an increase in the RHS of one of these constraints is zero, since the constraint is not binding. Shadow prices corresponding to the binding constraint (or zero if neither the upper nor lower bound is binding) are reported in parentheses below the optimal values of the decision variables in Table XI.

Table XI. Optimal Percentage Changes in Group Price Pressure and Shadow Prices by Contract for Model 3 With Intergroup Response Effects Included.[a]

	---------- Trader Group ----------					
Contract	LC	MC	LN	MN	OTH	ST
Dec. 83	0.80	0.80	0.80	0.80	0.80	0.86
	(4.51)	(6.14)	(11.89)	(12.94)	(4.48)	(0.00)
Feb. 84	0.80	0.80	0.80	1.17	0.91	0.87
	(20.49)	(4.87)	(24.81)	(0.00)	(0.00)	(0.00)
Apr. 84	0.80	1.04	0.80	0.98	1.20	0.96
	(16.16)	(0.00)	(8.56)	(0.00)	(-0.41)	(0.00)
Jun. 84	0.93	0.80	0.96	1.20	1.09	0.80
	(0.00)	(0.35)	(0.00)	(-0.07)	(0.00)	(1.41)
Aug. 84	1.20	0.80	0.80	0.91	0.80	0.82
	(-0.00)	(0.22)	(0.45)	(0.00)	(1.03)	(0.00)
Oct. 84	1.20	1.20	0.80	0.80	1.06	0.80
	(0.00)	(-0.22)	(0.78)	(0.99)	(0.00)	(0.47)
Dec. 84	0.80	1.05	0.80	0.80	0.86	1.20
	(1.71)	(0.00)	(2.71)	(5.34)	(0.00)	(-0.21)
Feb. 85	1.13	0.80	0.80	0.80	0.80	1.14
	(0.00)	(0.17)	(0.61)	(0.01)	(0.18)	(0.00)
Apr. 85	0.80	0.96	1.08	0.80	0.80	0.80
	(4.08)	(0.00)	(0.00)	(3.18)	(2.60)	(6.21)
Jun. 85	0.80	1.10	0.80	1.20	0.93	0.83
	(0.35)	(0.00)	(21.09)	(-6.94)	(0.00)	(0.00)
Aug. 85	0.99	1.03	0.80	1.03	0.88	0.80
	(0.00)	(0.00)	(15.40)	(0.00)	(0.00)	(7.92)
Oct. 85	0.80	0.90	1.07	0.88	0.80	0.80
	(6.61)	(0.00)	(0.00)	(0.00)	(2.27)	(3.01)
Dec. 85	0.80	0.80	0.97	0.83	0.80	0.80
	(1.44)	(1.91)	(0.00)	(0.00)	(16.32)	(0.30)
Feb. 86	1.03	0.89	0.80	0.80	0.80	0.90
	(0.00)	(0.00)	(2.51)	(4.53)	(4.67)	(0.00)
Apr. 86	0.94	0.80	0.98	0.80	0.92	0.82
	(0.00)	(2.48)	(0.00)	(3.19)	(0.00)	(0.00)
Jun. 86	0.95	0.80	0.80	1.20	0.94	0.80
	(0.00)	(2.60)	(4.03)	(-0.19)	(0.00)	(6.73)

Table XI continued	LC	MC	LN	MN	OTH	ST
Aug. 86	0.85 (0.00)	0.92 (0.00)	0.97 (0.00)	1.03 (0.00)	0.80 (23.80)	0.80 (10.90)
Oct. 86	0.94 (0.00)	0.82 (0.00)	0.99 (0.00)	0.80 (5.74)	0.80 (24.14)	0.80 (13.10)
Dec. 86	0.80 (15.68)	1.00 (0.00)	1.00 (0.00)	0.83 (0.00)	1.03 (0.00)	0.80 (2.55)
Feb. 87	0.80 (13.13)	0.80 (6.85)	0.95 (0.00)	1.13 (0.00)	0.80 (11.48)	0.97 (0.00)
Apr. 87	0.80 (29.82)	0.80 (18.88)	0.95 (0.00)	0.80 (3.73)	0.80 (5.14)	1.20 (-3.68)
Jun. 87	0.80 (32.37)	0.80 (5.15)	0.80 (35.75)	1.05 (0.00)	0.80 (7.33)	0.96 (0.00)
Aug. 87	0.80 (9.23)	1.20 (-1.39)	1.12 (0.00)	1.04 (0.00)	0.80 (0.50)	0.96 (0.00)
Oct. 87	0.80 (5.93)	0.80 (4.31)	1.03 (0.00)	1.08 (0.00)	0.80 (17.89)	1.20 (-1.66)

[a]Shadow prices in ().

The mean optimal values and mean shadow prices for Model 3 are given in Table XII. All of the average optimal values are less than 1.0 indicating that, on average, reduction in the market presence of all groups improves the price discovery process. This says that price could have moved from its beginning value to its final value with less involvement by all of the groups along a price path characterized by smaller dispersion around the final price. The implication of this is that all of the groups, to some extent, are involved in creating unnecessary "blips" in the price path during the life of the futures contract.

A ranking of the trader groups from least to most harmful to price dispersion as indicated by the optimal values for Model 3 is:

1. MN
2. ST, MC
3. LN
4. LC
5. OTH.

Again, the relatively smaller historical market presence of the two medium trader groups could be largely responsible for their lesser influence on price dispersion.

Table XII. **Average Optimal Values and Average Shadow Prices Across All 24 Futures Contracts for Model 3 With Intergroup Response Effects Included**

	----------Trader Group----------					
	LC	MC	LN	MN	OTH	ST
Avg. Shadow Value	0.890	0.905	0.903	0.949	0.876	0.905
Sig. Test[a]	1	0	0	2	1	0
Avg. Shadow Value	6.730	2.180	5.358	1.352	5.060	1.960
Sig. Test[a]	3	3	3	3	3	3

[a]Number of significant differences (α=.05) between the corresponding element and the remaining elements in the row.

The mean shadow prices listed in Table XII are all positive indicating that the lower bound on $PPCT_g$ was often binding. These shadow prices are less informative than those of Models 1 and 2 because they indicate the marginal value of an increase in market presence from the values these decision variables take in the optimal solution of Model 3. Since this trader mix is a postulated one and did not actually occur, the shadow prices do not provide information on the historical value of any group to price discovery. Instead, they indicate only the marginal value of a group should the optimal trader mix be present. Row-wise statistical tests, conducted in the same manner as for the previous models, are also listed in Table XII.

Model 4 Results

Table XIII presents a summary of optimal values for PCT_{pg} by giving the average optimal value for this variable across all 24 futures contracts for each trader group along with the row-wise and column-wise tests for differences in these means. Likewise, Table XIV gives the average shadow prices from Model 4 for each trader group in each subperiod.

From Table XIII it can be seen that in every subperiod except subperiod nine, one or more of the trader groups has an average optimal value greater than one. These groups, on average, must have engaged in market behavior during that subperiod that did more to improve price discovery in the market than to harm it. Two patterns immediately observable in this table are the relatively large optimal values associated with the small trader group through the seventh subperiod and the relatively small optimal values belonging to the funds/other trader group in nearly every subperiod. These results are consistent with the findings of the previous models.

Table XIII. Average Optimal Values Across All 24 Futures Contracts for Model 4 With Intergroup Response Effects Included

	---------- Trader Group ----------					
Subperiod	LC	MC	LN	MN	OTH	ST
1	0.985	1.033	0.961	0.967	0.900	0.977
2	0.917	1.060	1.024	0.891	0.933	0.997
3	1.018	0.959	0.891	0.933	0.973	1.023
4	0.976	1.039	0.970	0.967	0.941	1.023
5	0.950	1.016	0.974	0.953	0.996	1.008
6	1.030	0.925	0.946	0.950	0.955	1.003
7	0.975	1.006	0.984	0.947	0.931	1.034
8	1.000	0.990	0.885	0.930	0.880	0.984
9	0.913	0.900	0.958	0.946	0.926	0.955
10	0.942	0.997	0.956	1.001	1.000	0.958
Subperiod	Row-wise Significance Tests[a]					
1	1	2	0	2	4	1
2	3	3	3	3	2	2
3	2	0	3	2	1	2
4	0	1	0	0	2	1
5	0	0	0	0	0	0
6	3	2	1	1	0	1
7	0	0	0	1	1	2
8	2	2	3	0	3	2
9	0	0	0	0	0	0
10	0	0	0	0	0	0
Subperiod	Column-wise Significance Tests[b]					
1	0	2	2	1	3	0
2	3	3	3	3	0	0
3	2	2	5	0	2	0
4	0	3	2	1	0	0
5	1	2	2	0	2	0
6	4	5	1	0	1	0
7	0	2	2	0	0	2
8	2	1	7	0	4	0
9	3	7	1	0	0	1
10	1	1	1	1	2	1

[a]Number of significant differences (α=.05) between the corresponding element and the remaining elements in the same row.
[b]Number of significant differences (α=.05) between the corresponding element and the remaining elements in the same column.

Table XIV. Average Shadow Prices Across All 24 Futures Contracts for Model 4 With Intergroup Response Effects Included

	---------- Trader Group ----------					
Subperiod	LC	MC	LN	MN	OTH	ST
1	1.766	-0.921	-0.303	-0.028	0.576	0.247
2	0.967	0.062	0.712	0.223	0.666	0.134
3	-0.167	0.081	0.805	-0.348	0.132	-0.095
4	0.246	0.029	0.330	0.127	0.524	-0.046
5	0.237	0.029	0.237	0.147	0.039	0.068
6	-0.076	0.052	0.192	0.055	-0.043	0.223
7	0.129	0.274	0.307	0.036	0.500	-0.042
8	0.286	0.286	0.986	0.499	0.478	0.082
9	1.017	0.797	0.242	0.517	0.427	0.117
10	0.803	0.679	0.168	-0.134	0.506	1.657
Subperiod	Row-wise Significance Tests[a]					
1	2	3	0	3	2	0
2	0	0	0	0	0	0
3	1	1	4	1	1	0
4	0	0	0	0	0	0
5	0	0	0	0	0	0
6	3	1	1	0	0	1
7	1	1	1	1	3	3
8	0	0	1	0	0	1
9	2	2	2	0	0	2
10	1	1	1	3	0	2
Subperiod	Column-wise Significance Tests[b]					
1	2	9	0	3	2	0
2	2	2	0	3	1	1
3	2	2	4	4	0	1
4	1	3	0	0	1	1
5	2	4	1	1	2	1
6	7	4	1	2	5	1
7	5	4	0	2	2	1
8	2	2	0	5	1	1
9	6	8	1	5	0	1
10	3	4	1	3	0	8

[a]Number of significant differences (α=.05) between the corresponding element and the remaining elements in the same row.
[b]Number of significant differences (α=.05) between the corresponding element and the remaining elements in the same column.

This model is the most flexible of all the models. By allowing the decision variables to take different values in every subperiod for each group, this model generates many more feasible points than the previous models. Consequently, MSE at the optimal solution for this model should be smaller than for any other model in the study.

The results generated by this model would probably be impossible to achieve in reality. It is doubtful that any policy change could exogenously induce the wide variety of alterations in trader mix called for by the optimal solution to this model every 20 trading sessions. Rather, this model is useful in that it illustrates the maximum potential price discovery gains if policy makers could be given absolute control over trader mix in the live cattle futures market. If this maximum potential gain is small, then it can be concluded that attempts to improve price discovery through alterations in trader mix are of limited value. If the potential gain is relatively large, however, this suggests that significant gains in price discovery can be achieved from policy-induced alterations in the trader mix.

Results from Models 5-10

Models 5-10 are subperiod models somewhat more restricted than Model 3 or Model 4. In these models, the market presence of only one trader group (per model) is allowed to vary while all other groups are held at their historical market presence. In this way, the changes in optimal market presence of the group of interest can be evaluated in isolation from the other groups.

A trader group's historical trading behavior was either helpful or harmful in reducing the MSE of a price series, and this fact does not change between models. If a trader group was found to be harmful to MSE in one model (and thus its market presence reduced by the optimizing algorithm) the same general result will occur in all other models. What differs between models is the degree of interaction between groups in reaching the constrained minimum of the objective function. In Models 5-10, the optimal values of the decision variables follow the same general pattern of their counterparts in Model 4, but may assume somewhat different values because of the additional restrictions.

Table XV provides the average optimal values and Table XVI gives the corresponding average shadow prices across all 24 futures contracts for these models. In Table XV, the first column represents the optimal values in each subperiod of the variable $PCT_{p,LC}$ because, in Model 5, the large commercial group was the only group allowed to have market presence different from its historical level. Model 6 allowed only $PCT_{p,MC}$ to vary and values reported in the second column of this table apply only to the medium commercial group. The same pattern is followed through to the last column which lists the results of Model 10, the model where only the small trader group was allowed to vary.

The results are similar to those of Model 4, for reasons cited above, but a general trend toward larger optimal market presence can be seen in the individual group models (Models 5-10). Average optimal values greater than one are associated with the small trader group in seven of 10 subperiods. The majority of average optimal values are less than one for the other five trader groups. Optimal values from these five models exhibit no particular patterns as maturity approaches.

MSE Comparisons

Table XVII presents the MSEs for all 10 models and the results of the tests for differences in MSE (Ashley, *et al.)*. The MSEs from Models 1 and 2 are identical and equal to the MSE of the historical price series since both of these models produce a simulated price path equivalent to the historical price path. From Table XVII it can be seen that the smallest MSE for every futures contract is associated with Model 4. This was expected since Model 4 is the most flexible, a subperiod model where all of the market presence variables are allowed to vary simultaneously. For all contract months, the second best reduction in MSE is provided by Model 3, a non-subperiod model that allows all decision variables to vary simultaneously. Among the single-group models (Models 5-10), the group responsible for the largest reduction in MSE differs considerably across futures contracts.

Table XV. Average Optimal Values Across All 24 Futures Contracts for Models 5-10 With Intergroup Response Effects Included

	---------- Trader Group ----------					
Subperiod	LC	MC	LN	MN	OTH	ST
1	0.984	1.066	0.967	0.967	0.928	0.995
2	0.942	1.066	1.027	0.884	0.918	1.013
3	1.040	0.936	0.917	1.000	0.967	1.026
4	0.991	0.993	1.005	0.917	0.979	1.024
5	0.969	0.996	0.981	0.975	1.009	0.969
6	0.967	0.992	0.952	0.956	1.002	1.023
7	0.983	0.930	0.983	0.999	0.992	1.082
8	1.032	1.027	0.933	0.989	0.931	1.012
9	0.970	0.919	0.958	0.962	0.956	1.042
10	0.986	0.995	0.991	1.039	0.994	0.955
Subperiod	Row-wise Significance Tests[a]					
1	1	4	1	1	1	0
2	2	3	3	3	3	2
3	2	2	3	1	0	2
4	1	1	1	4	0	1
5	0	0	0	0	0	0
6	0	0	1	0	0	1
7	1	2	1	2	1	5
8	2	2	3	1	4	2
9	1	1	1	1	1	5
10	0	0	0	1	0	1
Subperiod	Column-wise Significance Tests[b]					
1	0	7	0	2	2	1
2	2	7	3	8	4	1
3	4	3	4	2	0	0
4	0	3	2	4	0	0
5	1	3	0	1	3	2
6	1	4	1	2	3	1
7	0	4	1	2	2	5
8	1	3	2	2	4	1
9	1	7	0	2	0	2
10	0	3	1	5	2	3

[a]Number of significant differences (α=.05) between the corresponding element and the remaining elements in the same row.
[b]Number of significant differences (α=.05) between the corresponding element and the remaining elements in the same column.

Table XVI. Average Shadow Prices Across All 24 Futures Contracts for Models 5-10 With Intergroup Response Effects Included

	---------- Trader Group ----------					
Subperiod	LC	MC	LN	MN	OTH	ST
1	1.744	-1.189	0.058	-0.074	0.798	-0.343
2	0.392	-0.240	0.496	0.407	1.183	0.037
3	0.010	0.540	0.577	-0.560	0.171	-0.193
4	0.482	-0.087	0.019	-0.034	0.564	-0.286
5	0.089	0.263	0.072	0.289	-0.038	-0.410
6	0.118	0.011	-0.129	0.278	-0.381	0.272
7	0.169	0.438	0.751	0.035	0.408	-0.136
8	0.205	-0.149	2.336	0.201	0.623	-0.089
9	1.055	0.525	0.428	0.087	0.608	-0.236
10	1.027	0.419	0.741	-0.147	0.229	0.820
Subperiod	Row-wise Significance Tests[a]					
1	3	3	0	3	3	2
2	0	2	0	1	2	1
3	0	2	2	2	0	2
4	1	0	0	0	1	2
5	1	1	0	1	0	3
6	1	1	0	1	3	0
7	0	1	0	1	0	0
8	0	3	3	2	1	1
9	2	2	1	2	1	4
10	1	1	0	3	0	1
Subperiod	Column-wise Significance Tests[b]					
1	2	9	0	1	2	0
2	0	6	0	5	2	0
3	1	4	2	5	0	0
4	0	2	1	0	1	1
5	2	3	2	2	2	1
6	2	5	2	1	6	0
7	1	4	0	1	1	0
8	0	6	3	2	1	0
9	4	5	0	2	1	1
10	0	4	0	3	0	3

[a]Number of significant differences (α=.05) between the corresponding element and the remaining elements in the same row.
[b]Number of significant differences (α=.05) between the corresponding element and the remaining elements in the same column.

Table XVII. Mean Squared Errors (MSEs) for Each Model for Each Contract With Intergroup Response Effects Included[a]

				---------- Contract ----------				
Model#	Dec. 83	Feb. 84	Apr. 84	Jun. 84	Aug. 84	Oct. 84	Dec. 84	Feb. 85
1	40.98	41.31	39.91	2.32	1.48	2.22	7.27	1.51
2	40.98	41.31	39.91	2.32	1.48	2.22	7.27	1.51
3	32.40*	30.12*	33.97*	1.78*	0.85*	1.30*	4.97*	0.48*
4	19.98*	18.86*	24.96*	0.98*	0.40*	0.57*	2.91	0.33*
5	39.30*	37.33*	35.24*	2.06*	1.36	1.31	6.93*	1.07
6	38.61*	38.19*	36.26*	1.99*	1.20*	2.05	6.46*	1.32*
7	36.90*	35.81	36.70*	1.87*	1.26	1.53*	5.56*	0.71*
8	37.56	40.76	37.79*	2.18*	0.90	1.85*	6.46	1.42*
9	38.67*	39.86	39.11*	1.93*	1.16*	1.82*	6.12*	1.09*
10	34.04*	39.04	37.91*	1.80*	0.90*	1.87*	6.29	1.40
				--------- Contract ---------				
Model#	Apr. 85	Jun. 85	Aug. 85	Oct. 85	Dec. 85	Feb. 86	Apr. 86	Jun. 86
1	31.44	86.88	92.48	12.39	12.67	18.75	13.02	12.83
2	31.44	86.88	92.48	12.39	12.67	18.75	13.02	12.83
3	23.96*	80.96*	84.99*	9.80*	8.14*	16.17*	11.79*	9.84*
4	13.79*	62.33*	65.29*	6.55*	3.47*	10.08*	4.03*	4.76*
5	28.87*	86.81*	88.70	12.19	11.67*	16.37*	10.12*	11.41
6	29.85*	83.95*	90.56*	12.06*	10.81*	18.52	12.09*	11.89*
7	25.22	81.11*	88.85	11.51*	11.73*	15.13*	11.84*	11.73*
8	29.67*	84.27	89.51*	12.37	11.73*	18.44*	11.86*	12.80*
9	27.95*	79.58*	91.86*	12.03*	10.10*	16.91*	12.49	12.62*
10	27.66*	83.27	88.53*	11.00*	10.30*	17.98*	11.50	11.96*
				---------- Contract ----------				
Model#	Aug. 86	Oct. 86	Dec. 86	Feb. 87	Apr. 87	Jun. 87	Aug.87	Oct. 87
1	20.41	47.56	14.71	67.59	103.88	96.84	36.57	53.89
2	20.41	47.56	14.71	67.59	103.88	96.84	36.57	53.89
3	12.26*	38.12*	10.63*	60.70*	91.08*	78.91*	32.31*	46.49*
4	5.72*	24.85*	5.19*	40.25*	61.89*	62.85	27.23*	31.88*
5	18.23*	45.46*	12.31*	62.04*	97.35*	83.00*	34.07	50.67*
6	20.25*	45.62	13.57*	66.01*	99.98*	94.46*	36.22	49.04*
7	19.00	44.24*	11.99*	64.75*	84.61*	85.65*	32.46*	47.27
8	20.26*	46.77*	13.79	66.27*	102.06*	96.52	35.97*	50.71
9	17.27*	42.88*	13.15*	62.86	102.95	93.37*	34.12*	48.15*
10	20.27*	41.01	12.65*	60.49	99.29	92.89*	33.46	53.25*

[a]Asterisks indicate statistical difference (α=.05) from the historical MSE.

Table XVIII lists the percentage reduction in MSE from the historical MSE (given by the MSE for Model 1 or 2) for each of the eight models where the trader group market presences were allowed to differ from their historical level. All of the percentage reductions are positive indicating that all models were able to find an optimal trader mix that produced a better price path than the historical from a price discovery perspective. The largest reduction in MSE was the 77.94 percent reduction associated with the Model 4 solution in the February 1985 contract. The smallest reduction in MSE was the 0.09 percent reduction produced by Model 5 in the June 1985 contract.

Table XVIII. Percent Reduction in MSE from Historical MSE for Each Model in Each Contract Month

				---------- Contract ----------				
Model #	Dec. 83	Feb. 84	Apr. 84	Jun. 84	Aug. 84	Oct. 84	Dec. 84	Feb. 85
3	20.94	27.09	14.89	23.18	42.51	41.23	31.61	68.49
4	51.26	54.34	37.46	57.70	73.01	74.15	59.94	77.94
5	4.12	9.63	11.69	11.09	8.43	40.82	4.66	29.33
6	5.80	7.56	9.14	14.29	18.96	7.49	11.08	12.95
7	9.97	13.32	8.02	19.34	14.91	31.17	23.49	52.97
8	8.34	1.35	5.31	5.91	39.61	16.64	11.12	6.08
9	5.65	3.53	1.98	16.79	22.00	17.73	15.80	27.81
10	16.94	5.51	5.00	22.14	39.47	15.83	13.38	7.27
				--------- Contract ---------				
Model #	Apr. 85	Jun. 85	Aug. 85	Oct. 85	Dec. 85	Feb. 86	Apr. 86	Jun. 86
3	23.79	6.82	8.09	20.91	35.69	13.76	9.46	23.32
4	56.14	28.26	29.40	47.18	72.57	46.26	69.05	62.89
5	8.17	0.09	4.08	1.61	7.85	12.70	22.28	11.11
6	5.07	3.37	2.08	2.69	14.68	1.24	7.17	7.33
7	19.78	6.64	3.92	7.13	7.35	19.35	9.06	8.60
8	5.61	3.01	3.20	0.23	7.37	1.66	8.92	0.26
9	11.08	8.40	0.66	2.94	20.29	9.83	4.02	1.68
10	12.02	4.15	4.27	11.26	18.71	4.11	11.66	6.80
				---------- Contract ----------				
Model #	Aug. 86	Oct. 86	Dec. 86	Feb. 87	Apr. 87	Jun. 87	Aug. 87	Oct. 87
3	39.92	19.85	27.75	10.21	12.33	18.52	11.64	13.73
4	71.98	47.75	64.74	40.46	40.42	35.10	25.55	40.84
5	10.70	4.42	16.32	8.22	6.29	14.29	6.84	5.97
6	0.78	4.10	7.75	2.34	3.76	2.45	0.95	8.99
7	6.95	6.99	18.51	4.20	18.55	11.55	11.25	12.28
8	0.74	1.68	6.32	1.95	1.76	0.33	1.64	5.90
9	15.42	9.84	10.63	7.00	0.90	3.58	6.69	10.65
10	0.72	13.79	14.01	10.51	4.42	4.08	8.50	1.19

There is considerable variation in the degree of MSE reduction each model was able to attain across the 24 futures contracts. Table XIX summarizes the data in Table XVIII providing the average, minimum and maximum percentage reductions in MSE for each of the models in the study. Using the average reduction in MSE as a guide to model success in generating improved prices, Model 4 performed the best followed by Model 3. Among the six models that allowed only one trader group's market presence to vary at a time, performance can be ranked as follows where 1 = best performance:

1. Model 7 (Large Noncommercial)
2. Model 5 (Large Commercial)
3. Model 10 (Small Traders)
4. Model 9 (Funds/Other Traders)
5. Model 6 (Medium Commercial)
6. Model 8 (Medium Noncommercial)

Trader group value to the price discovery process is not measured directly by this ranking since the direction of the change in market presence required to produce smaller MSEs differs between groups. This listing ranks the trader groups for potential to impact prices through marginal increments in market presence. In general, these models rank the groups according to the mean of the absolute values of price pressure (Table VII) except for the small trader group. According to Table VII, the small trader group has the largest historical market presence, yet it is only ranked third in potential for impacting prices. It is important to note that, averaging over all subperiods in all contracts, the small trader group model (Model 10) is the only model where the optimal solution calls for increased market presence by the trader group in order to reduce MSE.

Table XIX. Average, Minimum and Maximum Percentage Reduction in MSE from Historical MSE for Each Model

	----------Model Number---------							
	3	4	5	6	7	8	9	10
Average Reduction in MSE	23.57	52.68	10.86	6.75	14.39	6.04	9.79	10.66
Minimum Reduction in MSE	6.82	25.55	0.09	0.78	3.92	0.23	0.66	0.72
Maximum Reduction in MSE	68.49	77.94	40.82	18.96	52.97	39.61	27.81	39.47

Intergroup Response Effects

An important aspect of this study, stated in objective 3, was to identify and include trader group interrelationships in the modeling process. All results presented to this point, as noted in the table titles, included or allowed for intergroup effects. All models were re-formulated so that the price definition constraint in the programming models ignored the intergroup response effects. The models were then re-optimized over all contract months.

The optimal values of the decision variables in all models do not differ greatly regardless of whether intergroup responses are included or not. The magnitude of the shadow prices associated with constraints on the decision variables are considerably different, however. In general, the shadow prices from models which include intergroup responses tend to be smaller for the LC, LN, OTH, and ST groups and larger for the MC and MN groups. The relative ranking of these shadow prices is virtually undisturbed by omitting the intergroup response effects, however. This general pattern of different shadow price magnitudes, but unaffected relative rankings between groups, permeates the results of all the models.

Overall, omission of intergroup responses tended to produce results that overstated the ability of an altered trader mix to improve the price discovery process. The influence of ignoring intergroup responses on the simulated price series was small, however.

Summary and Conclusions

The overall objective of this research was to evaluate the contribution of different types of traders to the price discovery process in live cattle futures. Previously, very little quantitative analysis on this subject has been available to policy makers. Price discovery performed by futures markets is an important social function and policy makers need to consider the impact of their actions and policies on the effectiveness of this process.

This work was based on a conceptual model that describes the way information is incorporated into futures prices. In this model, traders are the conduits through which information passes on its way to discover prices. At the extreme, traders are faced with the universe of all information that might be relevant to the price of a particular commodity. Traders must select and condense this information into an expectation on future prices. Much of the social value that traders supply in the form of aiding price discovery is accomplished through this selection and condensation process.

The elements of the conceptual model that are of the most interest, different trader information subsets and related translating mechanisms, are largely unobservable and thus difficult to measure. However, trading behavior, which depends heavily upon these two elements, is observable. In order to make some inference as to the value of the unobservable traits for particular types of traders, a quantitative measure that combined trading behavior with observed price movements was constructed. The resulting index was an estimate of the net pressure that a particular group of traders exerted on prices during a given trading session. Trading behavior data were obtained from the CFTC's reporting trader database which facilitated the identification of six specific groups of traders in live cattle futures: large commercials, medium commercials, large noncommercials, medium noncommercials, funds/other traders and small (nonreporting) traders.

Price pressure measures were formulated so that, taken together, they totally explained the daily change in price. This was consistent with the conceptual model which stipulated that the only thing that impacts price in a futures market is the trading behavior of market participants. Any outside event that influences price must be filtered through the behavior of traders.

Price discovery performance was measured by the mean squared error (MSE) of the futures price series around the final settlement value in the price series for each contract. Since futures prices converge to the cash price at maturity, the final settlement price represents the true value of the commodity—the value that the futures market had been working to discover across its trading life. The MSE, being a measure of the dispersion of prices around this true value, was a suitable loss function to use in evaluating the futures price series as a price discovery vehicle.

A price simulation tool was constructed in the form of quadratic programming models that minimized the MSE of a hypothetical price series resulting from altering the historical market presence of the six trader groups. These programming models were constrained to behave according to exchange regulations. In addition, interrelationships between the price pressure measures for the six groups were modeled and estimated via econometric methods from the price pressure data. These interrelationships were then characterized by price pressure multipliers constructed from the econometric parameter estimates. The price pressure multipliers were included in the programming models to capture the indirect effects (responses from other groups) of changes in any group's market presence.

Some variations of the programming model held trader group market presence at historical levels so that the simulated price series would be identical to the historical price series. Shadow prices from these models were useful in quantifying the relative influence of each group of traders on MSE, and hence, on price discovery. Other variations of the programming model allowed the optimization algorithm to select an optimal trader mix that differed from the historical mix. Results from these models were further indication of the price discovery value of each group's behavior and gave an indication of the size of the price discovery improvements attainable through changes in the trader mix.

In other versions of the model, market presence was allowed to vary for one group at a time in order to study the price discovery value of each group's trading behavior in isolation from the remaining groups. In another modification, the life of the futures contract was divided into ten 20-day intervals with each group allowed a different level of market presence in each subperiod. This alteration was designed to expose any patterns in trader group influence on price as the contract approached maturity. Finally, all of the models were reformulated to exclude the intergroup response effects. Comparison of results between the two sets of models allowed evaluation of the importance of including intergroup responses in the models.

This research found that, on average, small traders are the most beneficial to price discovery in live cattle futures and that large commercial traders do the most harm to the price discovery process. These results are somewhat surprising and counter-intuitive since small traders have long been assumed to be poorly-informed traders in futures markets and large commercial traders, with their close connections to the cash industry, could be the best informed. There are, however, two conclusions that can be drawn from the theoretical parts of this work that may explain these unexpected findings.

First, theoretical arguments show there can be a divergence between profit maximizing trader behavior and what is socially desirable from a price discovery prospective. In general, traders who are most beneficial to price discovery are those that form accurate long-run expectations of the commodity's value. Traders that seek profits by neglecting the long-run value of the commodity in favor of reaping profits from successful prediction of short-run price fluctuations can be detrimental to price discovery. Small traders, being farther removed from the activity in the pits, would seem to be at a disadvantage when it comes to accurately predicting the trading activity of others. Instead, small traders might do better to focus on detecting long-run supply-demand imbalances in price relationships. This is exactly the type of trading behavior that improves price discovery.

Those very close to the activity in the pits, the funds/other group and large commercial traders, might find profit in predicting short-run price fluctuations caused by the trading activities of others. If they are moving in and out of the market, attempting to capture the peaks or valleys in prices while temporarily neglecting long-run price expectations, the behavior of these traders is detrimental to price discovery. Technical trading systems, often used by these types of traders, typically give little consideration to long-run price expectations.

Second, to help understand why large commercial traders might not foster efficient price discovery, it must be recognized that hedgers and speculators can be expected to behave very differently. The E-V analysis indicated that the willingness to take a position in the futures market depends upon, among other things, whether the trader is a hedger or speculator. Even with identical price expectations, hedgers and speculators will exhibit differing trading behavior. This justifies segregating traders with respect to commercial status in order to evaluate which group of traders might be more beneficial to price discovery.

One of the most important conclusions that arose from the E-V analysis is that when the variance of the price expectation increases, hedgers seek to increase their futures positions while speculators seek to decrease futures positions. This means that hedgers will have a larger market presence when they are least sure of the direction that prices will take. In contrast, when speculators become more unsure of the direction of prices, they bow out of the market. A rush of futures activity by commercial interests may signal deteriorating price expectations, but a rush of activity by speculators indicates greater confidence in their assessment of future prices.

From a theoretical point of view, the presence of a cash position can interfere with the expression of price expectations through trading behavior. In fact, the presence of a cash position results in an asymmetry with respect to willingness to act in futures markets. When the expected direction of price change is in a direction favorable to the cash position, the commercial trader has *less* incentive to take a futures position than one who has no cash position. Indeed, when price levels are expected to increase and the commercial firm is long in the cash commodity, any long trade in futures would be seen as speculative by the IRS, and futures losses would not be deductible. When the price expectation is in the direction opposite the preferences of the cash position, the commercial trader therefore has *more* incentive to act in the futures market than would a noncommercial trader. These asymmetries may balance out if the number of commercial traders with long cash positions approximately equals the number of traders with short cash positions, but this is often not the case. And as suggested earlier, asymmetrical taxation policies, such as those spawned by *Arkansas Best*, give commercial traders, such as cattle feeders, an even larger predisposition toward futures positions that are opposite their cash positions. Thus, on the whole in this market, there is a greater tendency to react to declining price expectations than rising price expectations among commercial traders. This cannot be good for effective price discovery. Speculators do not suffer from these asymmetries in their willingness to take a futures position.

The argument that a close connection with the cash trade provides commercial traders with superior fundamental information and their extensive experience makes them better at interpreting this information may indeed be valid. However, it is possible that these advantages are negated by short-run profit maximizing behavior, the hinderance to balanced price expectation transmission caused by cash positions, and the tax treatment of trade in futures by commercial firms.

Models 1 and 2 were designed to measure the historical value to price discovery of the six trader groups. The results of these models indicate that price discovery value is highly variable for all groups. When the results are viewed on a contract-by-contract basis, each group has some contract months where it was helpful to price discovery and some months where its trading activities were harmful to price discovery. *Thus, the most important conclusion of this research is that no specific trader group consistently outperformed the others in facilitating price discovery in the live cattle futures market.* The strongest pattern observed was that the funds/other trader group most frequently exhibited detrimental trading behavior with respect to price discovery.

Although the results vary widely by contract, on average over the four year period of this study, the behavior of small traders did the most to restrict price divergence from the true value of the commodity. The funds/other group and large commercials behaved in such a way that they did the most to keep price away from its true value. The preceding discussion about attempts toward profitable prediction of short-run price fluctuations may explain these findings.

Both the large and medium noncommercial groups had similar average shadow prices over the four year period. Both were slightly negative and of similar magnitude. (Negative shadow values indicate that increases in the associated group's market presence will reduce the objective function, MSE, which improves price discovery.) Two conclusions arise from these results: (1) the average impact on price discovery of noncommercial traders is independent of the size of the trader and, (2) *on average, speculators do more to restrict price dispersion in the live cattle futures market than to promote it.* This is in opposition to the periodic claims of producer groups and others who believe that speculators destabilize live cattle futures prices.

The results from the subperiod model designed to measure the historical value of trader groups to the price discovery process (Model 2) are also highly variable from contract to contract. On average, the small trader group is the most beneficial to price discovery until 60 days before maturity. From 20 to 60 days to maturity, large noncommercials are the most beneficial group and within 20 days to maturity, the large commercials help price discovery the most. As maturity approaches, the long-term becomes the short-term and traders must be more aware of supply/demand fundamentals and formulate their price expectations accordingly. When driven to consider end-of-period fundamental conditions, apparently the large noncommercials and commercials are more capable than the small trader group in forming accurate expectations, on average. The subperiod model results support the hypothesis that both large commercial and large noncommercial traders neglect long-term price expectations when maturity is far in the future. Also, it is not surprising that large commercial traders help price discovery the most in the delivery month since they are in the best position to take or make delivery and because the potential for delivery has reduced the presence of other traders in the final trading sessions.

In general, solutions from the model formulations which solve for the MSE-minimizing optimal trader mix strongly reiterate the information that was revealed by the shadow prices in the models where trader presence was constrained to historical levels. If a group's trading behavior tended to increase (decrease) price dispersion, then that group's market presence was reduced (boosted) in the optimal trader mix.

The optimal mix results provided an indication of the size of the price discovery benefits obtainable from altering the mix of traders. This was measured by the amount of reduction in MSE that resulted from having an optimal trader mix over the life of the contract instead of the historical mix. For the most flexible model, this reduction averaged 53 percent suggesting that if policy makers had complete control over the mix of traders, welfare losses might be cut in half. Of course, policy makers have nothing approaching this type of control over trader mix. The models which allowed manipulation of only one trader group at a time produced more modest but important 6 to 15 percent MSE reductions, on average.

Direct manipulation of trader mix to obtain even the small price discovery improvements would be exceedingly difficult if not impossible. This would require a policy that would change the market presence of an individual trader group in each subperiod, raising it in some subperiods and lowering it in others.

The simulation models that generate optimal trader mixes would be useful for establishing upper and lower bounds on the price discovery effect that could be expected from a trader mix change. This would require policy makers to specify how trader mix is expected to change in response to a new policy or to changes in an existing policy.

Since the simulated prices are affected by response effects between groups, it would be important to include these when doing policy analysis of the price effects of altering the trader mix. With respect to establishing the relative importance of the six trader groups to the price discovery process, however, this research found that including intergroup response effects made little difference in group rankings.

Policy Implications

Realistically, the only trader mix alteration that policy makers could hope to purposefully induce in futures markets would be to change the participation level of a single, targeted group of traders. This research suggests that this type of trader mix alteration can produce gains in price discovery over the long-term. The short-term effect of any change in trader mix is difficult to predict. These results provide information that should be considered even for policy changes not directly targeted at price discovery improvement.

Policy should not be formulated to discriminate against small traders with the aim of improving price discovery. Finding ways to lower the cost of futures activity to small traders could lead to long-run gains in market efficiency and price discovery.

There are valid reasons for avoiding policy that discourages commercial activity in agricultural futures markets. The cash positions of commercials give them much more incentive to be active in the futures market specific to their commodity and thus helps to ensure the survival of that market as well as improve its liquidity. With a futures market in existence, society reaps resource allocation benefits. In the live cattle futures market, however, large commercial trader contribution to the price discovery process is not a good argument for encouraging greater participation by these traders. Large commercial traders are often found to increase the price dispersion around the final closing price.

This research found very different price discovery effects for two different classes of speculators. Individual customer speculators, those included in the large and medium commercial groups, were found to improve price discovery, on average. The funds/other group, also primarily speculators, was found to interfere with the efficient conducting of the price discovery process. Recalling that the funds/other group included transactions of commodity pool operators and the program trades of futures commission merchants, it is understandable that this group might be shorter-sighted in its price expectation formation. Policy makers should bear in mind that any policy increasing the market presence of these types of traders will likely carry negative price discovery consequences.

The question of how the price discovery process would be influenced if cattle feeders were fully involved in the price discovery process is not completely and fully answered by this research. To the extent cattle feeders are careful to adopt only short positions in live cattle futures, the only position the IRS would have ruled to be a hedge in the 1980s, cattle feeders' trading activities would likely have been included in the medium or large commercial groups. These groups were not the most impressive in their contribution to the price discovery process, perhaps because of the asymmetry in positions and the restrictions imposed by IRS tax policy. To the extent that cattle feeders were involved in trades that were not strict short hedges (such as buying distant live cattle futures vs. placing cattle when the distant futures only offers large negative feeding margins), the cattle feeders' trades would likely have been in the medium or large noncommercial groups or even the small trader group. Taking such futures positions would typically be seen as an alternative to placing cattle when only negative margins are being offered, and the number of futures traded would more nearly reflect a fractional part of the feedlot capacity. The 1991 survey by Purcell suggested that roughly 50 percent of cattle feeders do consider such (non-hedge) trades and do participate more fully in the price discovery process, but usually at relatively small levels. When the findings in this study are combined with the conceptual and theoretical support to get all possible private sector (including firm-level proprietary) information into the price discovery process, a case can be made for policies to encourage cattle feeders to be fully involved in the price discovery process. More research on this issue and the revenue implications (to IRS) of a policy to encourage cattle feeder participation is, it would appear, sorely needed.

Literature Cited

Anderson, R. W. and J-P. Danthine. "The Time Pattern of Hedging and Volatility of Futures Prices." *Review of Economic Studies* 50(1983):249-266.

Ashley, R., Granger, C. W. J, and R. Schmalensee. "Advertising and Aggregate Consumption: An Analysis of Causality." *Econometrica* 48,5(1980):1149-1167.

Freund, R. J. "Introduction of Risk into a Programming Model." *Econometrica* 24(1956):253-263.

Gardner, B. L. "Futures Prices in Supply Analysis." *American Journal of Agricultural Economics* 58(1976):81-85.

Hayek, F. A. "The Use of Knowledge In Society." *American Economic Review* 35(1945):519-530.

Hurt, C. A. and P. Garcia. "The Impact of Price Risk on Sow Farrowings, 1967-78." *American Journal of Agricultural Economics* 64(1982):565-568.

Lance, G. C. and D. P. Helmreich. *Marketing Practices for Six Agricultural Commodities Produced in Southwest Georgia*. University of Georgia Agricultural Experiment Station Research Report No. 369, 1980.

Markowitz, H. "Portfolio Selection." *Journal of Finance* 7(1952):77-91.

Murphy, R. D. "The Influence of Specific Trader Groups on Price Discovery in the Live Cattle Futures Market." Unpublished Ph.D. Dissertation, Department of Agricultural and Applied Economics, Virginia Tech, Blacksburg, VA, January 1995.

Petzel, T. E. "A New Look at Some Old Evidence: The Wheat Market Scandal of 1925." *Food Research Institute Studies* 18(1981):117-128.

Pratt, J. W. "Risk Aversion in the Small and in the Large." *Econometrica* 32(1964):122-136.

Purcell, W. D. "IRS Policy on Hedging vs. Speculation: Possible Implications to Market Efficiency and Price Discovery in Cattle Markets." in *Pricing and Coordination in the Consolidated Livestock Markets*, W. D. Purcell, ed., Research Institute on Livestock Pricing, Blacksburg, VA, 1991.

Purcell, W. D., Locke, R. L. and M. A. Hudson. "Taxes and Hedging: A Review of Selected Court Cases." MB319, Department of Agricultural Economics, Virginia Tech, June 1984.

Robison, L. J. and P. J. Barry. *The Competitive Firm's Response to Risk.* New York: Macmillan, 1987.

Rowsell, J. B. "Composition of Traders in Live Cattle Futures Contracts: Behavior and Implications to Price Discovery." Unpublished Ph.D. Dissertation, Department of Agricultural Economics, Virginia Tech, Blacksburg, VA, July 1991.

Stein, J. L. "Speculative Price: Economic Welfare and the Idiot of Chance." *Review of Economics and Statistics* 63(1981):223-232.

Tobin, J. "Liquidity Preference as a Behavior Toward Risk." *Review of Economic Studies* 25(1958):65-86.

Yun, W. C. "Tax Treatment of Trade in Cattle Futures: Possible Implications to Market Efficiency and Price Stability." Unpublished M.S. thesis, Department of Agricultural Economics, Virginia Tech, Blacksburg, VA, March 1992.