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Luck versus Forecasting Ability: Determinants of Trader Performance in Futures Markets

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**LUCK VERSUS FORECASTING ABILITY:
DETERMINANTS OF TRADER PERFORMANCE
IN FUTURES MARKETS**

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Working Paper No. 47

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LUCK VERSUS FORECASTING ABILITY:
DETERMINANTS OF TRADER PERFORMANCE IN FUTURES MARKETS

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ABSTRACT

Statistical procedures introduced by Henriksson and Merton (1981) and modified by Cumby and Modest (1987) are used to determine whether the returns to individual traders of futures are the result of luck or skill. Daily trading histories for over 1400 traders are used. A large number of these traders appear to exhibit statistically significant superior forecasting ability. However, there are fewer of these skillful predictors than one would expect in a game of chance where profits are generated by a stochastic process. In addition, it appears that there is dependence across traders since there is a greater than expected number of traders exhibiting no forecasting ability. It is suggested that this anomaly is due to traders following similar technical strategies and utilizing the same advisors and/or newsletters. Finally, when the sample is divided into two periods it is shown that individual forecasting ability regresses to the mean. In other words, the superior forecasters in the early period appear as average forecasters in the later period. Overall, it is concluded that returns to traders are the result of luck.

SECTION I — INTRODUCTION

Some economists contend that life is a lottery where the lucky firms, investors and workers earn relatively higher returns (Champernowne 1953; Gibrat 1931; Hardy 1940; Jencks 1972; Johnson 1977; Kalecki 1945). Others suggest that individual skills or investments in human capital are unequally distributed and that the most able among us earn the highest rewards (Becker 1964; Mincer 1974). In this paper detailed transactions histories of individual traders are analyzed to determine which factor, skill versus luck, plays a more important role in determining the distribution of winners and losers in futures markets. On the basis of the statistical tests employed in this paper one is unable to reject the notion that the returns to traders are generated by a stochastic process. The evidence supporting the skill theory is weak at best.

There are four reasons why economists will find the results of this study of importance. First, for the financial economist this study shows that strong-form market efficiency cannot be rejected. A small proportion of the traders perform extraordinarily well and appear to exhibit superior forecasting ability. However, there are no more of these "outliers" than a theory of chance would predict. In addition, when the sample is divided into two sub-periods the superior forecasters in the early period regress to the mean in the later period. This is consistent with strong-form efficiency since it shows that traders cannot continuously beat the market.

Second, since traders cannot be categorized as being either informed or uninformed the paradox of informationally efficient markets re-emerges as a puzzle (Grossman and Stiglitz 1980). Given the results in this paper, it appears unlikely that traders are able to earn normal returns on their information gathering and filtering costs. If this is true then one must ask

what motivates individuals to invest in costly information accumulation activities. Explaining why the commercial traders invest in information is straightforward.¹ These traders will receive information as a by-product of their cash market operations. They will use this information to jointly carry-out activities in the futures and cash markets. One would think that these traders would have their real advantage in the cash market where entry costs are significantly higher. Any profits or reduced risks that the futures market offers will be of residual benefit. Overall, the commercial traders will accumulate information and reveal it by both their cash and futures market activity. Given this jointness, they will not need to profit, on average, in the futures market. As a by-product of the trading of informed commercial traders the futures market will be informationally efficient.

It is less clear why noncommercial traders participate in a market where expected gains are non-positive. Hardy (1923) may be correct when he suggests that for speculators these market represent gambling opportunities.² Therefore, a more descriptive dichotomy than informed and uninformed speculators might be extremely lucky and the not-so-lucky speculators. If this is a gambling market one would expect to find it populated by a greater proportion of the risk-loving agents than found in the general populace. This is consistent with the observation that only a small proportion of all investors participate in these markets (say, as opposed to the securities markets) even though entry costs are quite low. Given that futures markets offer much fairer betting opportunities than any of the other legitimate alternatives it should not be surprising that many risk loving or risk neutral individuals are attracted to them. It is important to point out that this does not preclude commercial traders from utilizing these markets for legitimate hedging purposes. In fact, if there are an abundance of these risk

loving (or risk neutral) participants there is no need for any risk payments. Thus, commercial traders can hedge at zero or even a negative cost, possibly passing the savings on to consumers.

The issue of individual rationality is the third reason why economists should take note of the results presented in this paper. Even though the evidence does not allow us to infer that individuals act irrationally, it does cast some doubt on whether individuals act rationally. There are a significant number of survivors in the futures market who consistently lose money while exhibiting poor forecasting ability. This may be due to rational gambling, irrational behavior, or some other rational explanations.³ Unfortunately, from the empirical results presented in this paper one is only able to question the rationality assumption, not resolve whether it is a meaningful construct.

Of final importance to economists is whether these results can be generalized to goods and labor markets. In these other types of markets, specifically labor markets, it has been shown that individuals receive rewards that are commensurate with their abilities. This is not the case in futures markets. Superior forecasting ability is not rewarded in these information markets because informational externalities abound. Because of this free rider problem informed traders are unable to consistently appropriate gains from their investments in either acquiring predictive skills or gathering private information. This result should not be taken to imply that individuals will be unable to derive private benefits from their superior skills in normal goods and labor markets. In these markets externality and free rider problems are of minor consequence.

The statistical techniques used in this paper allow for the detection of two types of forecasting ability or market timing. I call the

first type "consistent ability." A trader possessing this type of skill performs well because he is able to systematically predict the correct direction of future price movements. This superior forecaster will take long (short) positions more often than not when the futures price subsequently rises (falls). The other type of forecasting skill I call "big hit" ability. A trader possessing this type of ability will take his largest positions (make his largest bets) when the highest returns are expected. He will be able to predict both the magnitude and the direction of price changes. This superior forecaster may make a large proportion of incorrect predictions about the direction of prices, however when he hits, he hits home runs. Tests for the existence of both of these types of forecasting ability are implemented using statistical procedures introduced by Henriksson and Merton (1981, hereafter HM) and modified by Cumby and Modest (1987, hereafter CM).

SECTION II — DESCRIPTION OF THE DATABASE

The data used in this paper come from the same source as Hartzmark (1984, 1987). In these papers the information on the trading decisions of the individual large traders is taken from Commodity Futures Trading Commission (CFTC) reports on the end of day commitments of large traders. In all markets, traders who, either at the beginning or the end of a trading day, hold commitments exceeding certain levels are required by the CFTC to report their trading activity with their speculative and hedge, long and short, positions in all contract maturity months.⁴

Daily dollar profits for each trader for each contract held are calculated by multiplying the end-of-day positions by the change in the settlement price between the current day and the following day.⁵ This is the same procedure used by the central clearinghouse to mark each trader's account

to the market price at the end of each trading session. The total dollar profits earned by the trader are then used to measure performance. A percentage rate of return is not used because this measure has little meaning as a performance measure in the futures market. Since the net supply of contracts in futures markets is zero, there is no meaningful way to determine the magnitude of total investment in the market (i.e., the denominator for any percentage rate of return would be zero).⁶ In addition, the opportunity cost of investing is quite small (Telser 1981b; Hartzmark, 1986).⁷

Nine markets are covered over the period July 1, 1977 to December 31, 1981.⁸ Included in this sample of nine markets are the three U.S. wheat markets. In the empirical sections these three markets are combined after the profits are calculated for the individual markets.⁹ The nine markets in the sample include:

- 1) Oats traded on the Chicago Board of Trade (CBT)
- 2) Wheat traded on the CBT
- 3) Wheat traded on the Minneapolis Grain Exchange (MGE)
- 4) Wheat traded on the Kansas City Board of Trade (KBT)
- 5) Pork Bellies traded on the Chicago Mercantile Exchange (CME)
- 6) Live Cattle traded on the CME
- 7) Feeder Cattle traded on the CME
- 8) U.S. T-Bonds traded on the CBT
- 9) 90 day T-Bills traded on the International Monetary Market (IMM)

The motivation for participating in the futures market will differ for commercial and noncommercial traders. Therefore, traders are categorized depending on the nature of the positions they report (i.e., hedging versus speculative). Traders reporting only hedging positions are classified as commercial traders (or pure hedgers). Traders reporting only speculative positions are designated as noncommercial traders (or pure speculators). For those traders who report both hedge and speculative positions, the confidential files kept by the CFTC are consulted to determine if the trader's business is directly related to the market for the underlying commodity. If

the trader is in a closely related business (e.g., farmer, government securities dealer, cattle breeder) he is placed in the commercial category.¹⁰

SECTION III — MARKET PRICE, SIZE AND RETURN DISTRIBUTIONS

THE DISTRIBUTION OF DAILY PRICE CHANGES

In Table 1 descriptive statistics on daily price changes are presented.¹¹ In all markets, except the interest rate markets, the mean and median price changes are not significantly different from zero. In the interest rate markets there are downward (upward) trends in prices (interest rates) over the whole period. In these markets, as well as for the other five, the proportions of upticks and downticks are close to 50 percent.

<<<INSERT TABLE 1 HERE>>>

The distributions are symmetric, but none are normal (using the Kolgomorov D-statistic).¹² There are various explanations for the nonnormality. First, price change distributions are generally observed to be leptokurtic (Fama 1976). Second, using dollar price changes imposes even greater problems than using percentage price changes because of nonstationarity in the series. Finally, a small number of spikes in the distributions are observed at various absolute price changes because the exchanges impose artificial constraints on the magnitudes of the allowable price movements.

THE DISTRIBUTION OF INDIVIDUAL TRADER SIZE

With a small number of observations on a particular trader it is impossible to implement the statistical procedures used later in the paper. Therefore, an individual trader has to make at least 25 transactions to be included in the analysis.¹³ Transactions are defined as either purchases or sales. It is assumed that a rational trader will alter his position (i.e., transact in the market) whenever he updates his forecast and makes a new

prediction. Therefore, it is implicitly assumed that if the trader retains the same exact position over a long period of time his price forecast has not changed, even if the price level has.¹⁴

The descriptive statistics of the average net position values of the large traders are presented in Table 2. There are various ways to measure the size of an individual futures trader (Hartzmark 1984). The average net position value is chosen because it offers the most information relevant for the analysis to follow.¹⁵ Besides indicating the magnitude of the positions held, it also indicates whether the trader is net short or long on average. To calculate this measure, the trader's daily long and short dollar position values are each individually aggregated across all maturity months. The aggregate short position is subtracted from the total long position to get the daily net position value. These daily observations are then averaged across all the days that the trader is in the market to derive the average net position value.

<<<INSERT TABLE 2 HERE>>>

The size distributions are presented for each market individually, as well as for all markets aggregated. When all markets are aggregated it is not clear how to deal with the few traders who are in more than one market. Should these traders be considered as one trading entity or not? For example, within a given firm, T-bill and wheat traders may or may not make independent trading decisions. One group may be involved in the investment and/or speculative decisions, while the other is responsible for the hedging programs. Given this ambiguity, many of the results are aggregated in two ways. Under the heading ALL MARKETS #1 it is assumed that all decisions within a given firm are made independently. Thus, firms participating in more than one market have multiple observations. In ALL MARKETS #2 it is assumed

that all decisions within a given firm are made in concert. Therefore, the statistics for a given firm are averaged across all seven markets.¹⁶ If a trader is designated commercial in one market and noncommercial in another he then falls into the Both Types category under ALL MARKETS #2.

Because 25 transactions are necessary to be included in the analysis, there are over 2000 fewer traders than in Hartzmark (1984, 1987). Even so, the total number of traders exceeds 1450. The numbers of traders of each type are given in col. 1 of Table 2. The range is from 48 in the oat market to 483 in the live cattle market.¹⁷

From col. 2 it is clear that commercial traders are net short on average. In every market but wheat and feeder cattle the mean position is significantly negative. The noncommercial traders are net long on average (except in pork bellies). These observations on the commercial and noncommercial traders are consistent with various theories describing the roles that speculators and hedgers play in these markets (Hieronymus 1977; Cootner 1960; Hicks 1978; Keynes 1930; Telser 1981a;).

The positions held by commercial traders are substantially larger than the noncommercial positions. Except in pork bellies and feeder cattle the range in position size is greatest for the commercial traders. They appear to hold the largest net long and net short positions. This might be explained because they are less constrained by the rules on speculative position limits. In addition, the commercial traders are hedging very large cash positions. The sign of the skewness of the distributions of the ALL TRADERS category is the same as that for the commercial traders. The very large net short positions of the commercial traders account for this negative skewness. As one would expect, a large proportion of the traders in the sample have relatively small positions. This is indicated by the large positive kurtosis coefficients.

It is obvious that the commercial traders in the interest rate markets are far and away the largest participants. The range on the net position size of commercial T-Bill traders is over \$1 billion. The next closest non-interest rate range is in the live cattle market.

THE DISTRIBUTION OF INDIVIDUAL RETURNS

In Table 3 it is shown that in dollar terms the commercial traders are the big winners. There is one significant difference in these results as compared to those reported in Hartzmark (1984, 1987). In this paper, when all noncommercial traders are aggregated, the mean profits are significantly different from zero. In Hartzmark (1987) the returns to noncommercial traders are shown to be insignificantly different from zero. Therefore, the 2000 traders discarded in this paper are mostly noncommercial traders who earn small negative returns, on average.

<<<INSERT TABLE 3 HERE>>>

Overall, the return distributions are highly skewed and have large peaks around zero dollars. Values of zero for the skewness and kurtosis statistics are expected if the distributions are normal. Using the Kolmogorov D-statistic nonnormality is detected in all but one case (noncommercial traders of oats).

The return distribution is a combination of the position size and price change distributions. Observing the sizes and the general price trends gives an idea of how well a naive strategy would have performed.¹⁸ For example, in the interest rate markets the commercial traders are net short, on average. The very largest commercial traders are also net short. The average price change is negative, therefore the returns from a naive strategy of buying a short position and holding it over the period would offer significant positive profits. In addition, one would expect that the returns would be positively

skewed since the largest traders in the interest markets (who are net short) would be the big winners. Noncommercial interest rate traders with their net long positions do not fair as well. In the cattle market where prices go up on average, the net short commercial traders perform poorly. Overall, the general direction of the price movements and the magnitude of the positions held generate the profits earned by an individual. In the following sections I attempt to determine whether it is anything more than "riding-the-tide" that explains the performances of the individual traders.

SECTION IV — STATISTICAL METHODS EMPLOYED TO DETERMINE FORECASTING ABILITY

TESTING FOR CONSISTENCY ABILITY

A procedure introduced by HM and modified by CM is used to test for "consistent" forecasting ability. First, one observes the number of correct forecasts that an individual trader makes. Being correct means that the trader is long (short) when the price goes up (down). Second, a calculation is made of the probability of observing a given number of correct predictions assuming that the trader makes his forecasts in a random fashion. The magnitude of the probability will indicate whether the individual trader possesses significant forecasting ability.

Since the probability of correctly predicting the direction of the price movements is assumed to be independent of the magnitude of the subsequent price movements HM are able to utilize non-parametric statistical techniques. A major benefit of this approach is that there is no need to rely on any of the equilibrium models of security valuation. This is especially helpful in a study examining futures markets since researchers still disagree on the appropriate model or market proxy to use.

To implement the HM procedure begin by defining the return from holding one long futures position as $R(t) = F(t+1) - F(t)$, where $F(t)$ is the

settlement price of a futures contract on day t . It is assumed that a rational investor will purchase a long position on day t if he expects $R(t) > 0$. If he expects $R(t) \leq 0$, then a short position will be held. Thus I define $U(t)$ as the binary indicator of the prediction that the trader makes at time t . Let $U(t) = 1$ if the trader predicts that the price is going up (he is long). Alternatively, $U(t) = 0$ if the trader predicts that the price is not going up (he is short). Therefore, there are four possible combinations of forecasts and realizations. The trader may predict that the price is going up (i.e., he is long) and he is right (it goes up) or wrong (it goes down). Alternatively, the trader may predict that the price is not going up (i.e., he is short) and he is correct (it goes down) or incorrect (it goes up).

Define $P_u(t)$ as the conditional probability of a correct forecast (made at time t) given that the observed price change is positive, $R(t) > 0$. In other words, this is the probability that the trader was net long at time t given that the price goes up between t and $t+1$. It is a proxy for the trader's skill to predict upticks. $P_d(t)$ is defined as the probability of a correct forecast given that $R(t) \leq 0$. This is the probability that the trader was net short at time t given that the price does not go up between t and $t+1$. It is a proxy of the trader's downtick skill.

Merton (1981) shows that the sum: $P_u(t) + P_d(t)$, is a sufficient statistic to indicate the overall degree of individual forecasting ability. If the sum of these two probability estimates equals one, the trader's forecasts are said to have no value. In other words, the trader has no forecasting ability. This is the case when the predictions the individual makes at time t are independent of the observed price changes between t and $t+1$. If the sum of the probabilities is greater than one then the trader possesses superior forecasting skills. A sum less than one indicates that the trader has inferior forecasting skill.¹⁹

The null hypothesis that HM put forward is simply that $P_u(t) + P_d(t) = 1$. In other words, traders have no ability to forecast price changes. To empirically test whether the sum is statistically different from one, confidence intervals must be calculated. To calculate these probability levels for each trader one needs to observe the number of correct predictions that prices fall (i.e., number of times the trader is short and the price goes down), as well as the number of upticks, downticks and total predictions made.²⁰ Given this information one determines whether the number of correct predictions when the trader is short differs significantly from the number expected given the total number of predictions and the total number of up and downticks. Since the number of correct predictions has a hypergeometric distribution one can use straightforward methods to determine statistical significance and an associated probability level of significance.²¹

An alternative statistical method introduced by CM offers the same results as the HM approach. CM shows the equivalence between the HM test and a likelihood ratio test. Because of this, the CM method makes it easier (computationally) to calculate a precise probability significance level associated with a given number of correct predictions.²²

The binary variable $Z(t)$ indicates the direction of the actual price movement between time t and $t+1$. It is equal to one if the price goes up ($R(t) > 0$), and zero otherwise. The log odds that an individual trader is long at time t and the price goes up between t and $t+1$ is given as:

$$\text{LOG}\left(\frac{\text{Pr}[Z(t) = 1]}{\text{Pr}[Z(t) = 0]}\right) = a + BU(t).$$

From this one can directly test whether the trader possesses forecasting ability. The HM test for determining whether the sum of the conditional probabilities is different from one is equivalent to testing whether B is

significantly different from zero. When $Z(t)$ is independent of $U(t)$ then $B=0$ and the trader possesses no forecasting ability. If $B > 0$ then the trader possesses superior forecasting ability. If $B < 0$ the trader possesses inferior ability.

A logit equation is run to determine the sign and magnitude of B . Because the standard errors and the degrees of freedom differ between traders it is difficult to interpret exactly what is implied by the relative magnitudes of the parameter estimates. The t -statistic will also not allow for comparisons across traders. Since the null hypothesis asks whether B differs significantly from zero the probability significance level associated with the parameter estimate, B , offers all the necessary information and therefore is used for the analysis that follows. How this probability level will be transformed into a meaningful measure of forecasting ability will be described in greater detail below.

TESTING FOR BIG HIT FORECASTING ABILITY

The test procedure described above does not make use of all the information that is available. The strength of the prediction, as proxied for by the magnitude of the trader's position size, is not included in the HM test procedure. In addition, the magnitudes of the actual price changes are excluded. To allow for the inclusion of this additional information CM extends the HM procedure. First, the authors relax the independence assumption. They suggest that the size of the $R(t)$, or the magnitude of the price change, is directly related to the probability of a correct prediction. Therefore, just because the number of correct predictions an individual trader makes is not above some statistically significant number does not mean that the forecasts have no value. It may be that the trader is better able to predict big price changes rather than small changes. In other words, he is

long (short) more often than not when there are very large upward (downward) price movements. Therefore, the trader has a higher probability of correctly predicting large price changes relative to small changes. In this way, the trader's small frequent losses would be more than offset by his large gains.

To measure this type of forecasting ability CM outlines a simple regression technique. It is assumed that $R(t)$ depends linearly on the forecast $U(t)$, or that the probability of a correct forecast is greater for larger price changes. In this paper, because we have even more information than CM it is assumed that $R(t)$ depends linearly on the net position held by the trader. Forecasting ability is indicated if the trader holds his largest positions when there are the largest price movements in a favorable direction.

Define $LS(t)$ as the net position (long minus short contracts) at time t , such that $LS(t) > 0$ if the trader is net long and $LS(t) < 0$ if the trader is net short.²³ Forecasting ability will be observed if $LS(t)$ is linearly related to $R(t)$. Two effects are being combined using this type of measure. First, we are determining whether the probability of correctly predicting the price change is linearly related to the size of the position. In addition, we are testing to see if this probability is greater the greater the subsequent price change. The regression equation that will combine these two effects is given as:

$$R(t) = a' + B'LS(t) + e(t).$$

Testing whether the trader possesses big hit forecasting ability is identical to determining whether $B' = 0$. If $B' > 0$ then, as before, the trader possesses superior ability. While if $B' < 0$, the trader is an inferior forecaster. It is also assumed that the error term, $e(t)$, is normally and independently distributed. As before, since the degrees of freedom and standard errors differ between traders, it is necessary to use the probability significance level in the tests for ability.

DERIVING FORECAST COEFFICIENTS FROM THE REGRESSIONS

To derive consistent and big hit forecasting coefficients for each trader the logit and the regression techniques mentioned above are used. The parameter estimates, t-statistics and probability significance levels are saved. Unfortunately, the magnitude of the parameter estimates gives little information about whether the individual trader possesses significant forecasting ability. For example, observing $B_i=0.35$ and $B_j=0.55$ does not indicate whether trader j is a better forecaster than trader i. Each trader is in the market for a different amount of time (i.e., the degrees of freedom are different) and the standard errors of the parameter estimates differ dramatically. Therefore, B_i may be significantly different from zero, while B_j is not. What is important then, is to determine the degree to which the parameter estimates are different from zero.

To derive comparable measures of ability across all traders the probability significance levels for each trader are transformed into forecasting coefficients (FC_i). These measures incorporate information on the parameter estimates, standard errors and degrees of freedom into one aggregate measure. In all tests that follow the forecasting coefficient for the i th trader is defined as:

$$FC_i = (1 - \text{PROBABILITY LEVEL}_i) \times \text{sign}(\text{PARAMETER ESTIMATE}_i).$$

For example, if the probability significance level from the logit equation is 0.25 and $B_i=-0.90$ then $FC_i=-0.75$ ($=-1 \times (1-.25)$). If $B_i=0.70$, with the same significance level as above, then $FC_i=0.75$ ($=1 \times (1-.25)$). Therefore, this measure takes on values ranging from -0.999 (for traders with inferior forecasting ability) to 0.999 (for traders with superior ability). Using the same transformation, a similar measure is calculated for each trader using the parameter estimate B_i and the associated probability level.

The Expected Distribution of the Forecasting Coefficients

Because there are a large number of traders in the sample one is unable to use individual forecasting coefficients to conclude whether there is significant forecasting ability in the market as a whole. Even in the case when profits are generated by a stochastic process one would expect to observe a certain proportion of traders with forecasting coefficients with extreme values (e.g., less than -0.90 or greater than 0.90). Using a fair coin toss game as an example will hopefully clarify any confusion on this point (see Denton 1985 for a similar approach).

Assume that 1000 players attempt to predict whether a coin will land heads or tails. Given that we are looking at the participants "forecasting ability" it is not necessary to have the players bet any money. Assume that the game goes on for a large number of periods or flips. Over time one will observe that a few participants are able to consistently predict the correct side of the coin. The forecasting coefficients for these superior players (calculated using the logit method described above) will be positive and approach 1.0 . On the other other side of the coin will be a similar number of participants who are consistently wrong with their "predictions." These players will have forecasting coefficients approaching -1.0 .

Forecasting coefficients can be calculated for each player after a large number of tosses. Statistical theory suggests that the nature of the distribution of individual forecasting coefficients from a game of chance will be uniform. In this case it will be uniformly distributed in an interval from -0.999 to 0.999 . In other words, one expects to observe approximately five percent of all players (or 50 individuals) with forecasting coefficients between 0.9 and 1.0 , or five percent between -0.9 and -1.0 , or five percent between any ten decimal point region. Can we conclude that traders in the 0.9

to 1.0 interval have superior forecasting ability since their B_i 's are significantly different from zero at a ten percent level? No. Assuming that the coin is fair, it would be absurd to conclude that there are inferior and superior coin toss predictors. Chance or luck generates these outliers.

If profits in the futures market are generated by a stochastic process than the distribution of individual trader forecasting coefficients should resemble that from the coin toss game. In this case the forecasting coefficients will be uniformly distributed across the interval from -0.999 to 0.999. Now the null hypothesis to be tested can be stated:

**Returns are generated by a stochastic process,
thus the individual forecasting coefficients are
uniformly distributed over an interval spanning
-0.999 to 0.999.**

If the positive tail of the distribution of the forecasting coefficients is fatter than expected, one can conclude that a greater than expected number of traders possess significant forecasting ability and the null hypothesis is rejected. By the same reasoning, if the negative tail of the distribution is fatter than expected, one can conclude that there are a significant number of inferior forecasters. If both tails are thinner than expected one can reach one of two conclusions: 1) the standard errors of the regression parameters are somehow upward biased causing the associated probability levels to be biased toward one; or 2) there is some dependence across traders. This latter explanation is plausible if the traders are communicating with one another or using similar trading strategies.

SECTION V -- TESTS FOR FORECASTING ABILITY

CONSISTENT FORECASTING ABILITY

Table 4 presents the descriptive statistics for the consistent forecasting coefficients. The Kolomogorov D-statistic and the Chi square tests are used to determine whether the distributions are uniform.²⁴ The number of traders having consistent forecasting coefficients differs from the number having big hit coefficients.²⁵ If a trader always positions himself on one side of the market, a consistency forecasting coefficient cannot be calculated.²⁶ For example, 9 of 48 oat traders have 25 or more transactions, but only hold net positions on one side of the market. Comparing the ALL MARKETS #1 (#2) category in Tables 3 and 4 indicates that 240 (150) traders are on only one side.

<<<INSERT TABLE 4 HERE>>>

The means of the forecasting coefficients are almost always indistinguishably different from zero. Only the commercial traders of pork bellies show significant, positive forecasting ability, on average. Given the nature of this sample it is not necessary for the mean forecasting coefficient to be zero. First, all market participants are not included (i.e., scalpers and small traders). In most markets the sample includes traders whose combined holdings total more than 50 percent of the open interest. If it is the case that these large reporting traders are the elite subset of successful survivors in the market then one would expect a positive mean forecasting coefficient. Second, given that there is a large amount of turnover in these markets there is a good reason why the means may be negative. If there is constant turnover of traders possessing poor forecasting ability (but who remain in for at least 25 transactions), one would expect the mean forecasting coefficient to be negative. In either of the two cases, the null hypothesis

is indirectly rejected since implicit in the arguments are that traders have differing skills.

The distributions are almost all negatively skewed, except the ALL MARKETS #1 distributions that are symmetric (the skewness coefficients are quite small). The kurtosis statistics are all very large negative numbers indicating that the distributions are flatter than a normal distribution. This is expected for a uniform distribution, however. The standard deviations are all insignificantly different from those one would expect to find from a uniform distribution spanning an interval from -1.0 to 1.0.²⁷

The D-statistic indicates that uniformity can be rejected in only one of seven markets for commercial traders and in two of seven markets for noncommercial traders. Using the Chi square test uniformity is rejected in three (four) markets for commercial (noncommercial) traders. When the coefficients are all combined, uniformity is rejected for both commercial and noncommercial traders. The fact that uniformity is accepted in the individual markets and rejected for all markets combined must be because of the increase in sample size and thus the increase in the precision of the test.

Figure 1 offers a clear illustration of why uniformity is rejected for ALL MARKETS. The percentage bar charts in this figure show the percentage of traders that are observed in each of 20 equal sized intervals. The midpoints of the intervals are indicated on the charts. For example, the 0.95 interval includes coefficients between 0.90 and 1.00. The horizontal lines represent the percentage of traders expected to be in each of the twenty intervals if the distribution is uniform.

<<<INSERT FIGURE 1 HERE>>>

Uniformity is not rejected because there are more outliers than expected. On the contrary, it is because there are more traders with forecasting

coefficients close to zero than expected. This is dramatically displayed for ALL MARKETS #2. Unfortunately, in this chart the forecasting coefficients are averaged for the 457 traders who are in more than one market. Therefore, one might expect that the central portion of the distribution would be fat. The ALL MARKETS #1 chart indicates that, if anything, there are more poor forecasters than expected. But again, it is the central portion that dominates. Only in pork bellies, live cattle and feeder cattle does one see more coefficients above a 90 percent level than expected from chance. In none of the individual markets does one observe more coefficients below -90 percent than a random draw would predict.

Overall, in the individual markets the forecasting coefficients appear to be randomly distributed. Therefore, the null hypothesis is supported. When all markets are combined forecasting ability appears non-random because of dependence among traders. CM offer a statistical explanation for this. They state that, "even if the assumptions under which the HM test is derived are valid, the test appears to have weak ability to identify successful predictive ability for small to moderate sample sizes." Therefore, it might simply be that given the number of transactions chosen as a cutoff point, the power of the test is so weak that probability levels are small.

An alternative explanation is based on how traders react to information. If a substantial proportion of the traders in these markets behave in a sheep like manner, we would see a bunching around zero. If the traders follow the same technical strategies or respond in unison to the suggestions made by the newsletters or advisory services one would observe such a bunching.

It is interesting to note that the distributions are symmetric or negatively skewed. This indicates that there are as many bad forecasters as good forecasters. If anything, there are more outliers with significant

inferior forecasting ability than superior ability. This is a curious result given that this sample is made up of large traders that remain in the market for a reasonable length of time. One would expect that these "survivors" would look better than the general population (i.e., randomly chosen individuals). Why traders with poor skills remain in these markets and achieve such large size is puzzling.

One often cited suggestion is that these poor forecasters are using these markets to offset risks they have in other markets. Therefore, the traders look like poor forecasters in a one-dimensional sense since they are losing money. However, in a two dimensional approach, when profits are substituted for reduced risks, they are gaining. If this is the case one would expect to observe a dramatic difference between the commercial and noncommercial forecasting coefficient distributions. The commercial traders are supposedly using these markets to hedge their price risks. Therefore, they combine speculation and hedging. They can afford to look like bad forecasters in the futures market, since they will be good forecasters in the cash markets, or at least reduce their overall business risks. The noncommercial traders do not have the same opportunities to use futures markets to reduce their price risks. Most studies have shown that futures markets do not reduce systematic price risks (Baxter, Conine and Tamarkin 1985; Bodie and Rosansky 1980; Dusak 1974; Ehrhardt, Jordan, and Walkling 1987; Elton, Gruber and Rentzler 1987). In general, there are no significant differences between the commercial and noncommercial distributions. If anything the noncommercial traders exhibit more poor forecasting skill. The risk hypothesis is not supported.

BIG HIT FORECASTING ABILITY

To calculate the big hit forecasting coefficients all of the available information on individual positions and market price movements is used. The

regression of the size of the position at time t on the magnitude of the price change between time t and $t+1$ indicates whether the individual trader makes his biggest bets when he expects the largest price changes.

An adjustment for heteroscedasticity is made to account for expected differences in the variance of the price changes. If it is assumed that daily price changes have a constant variance, then holding period price changes do not have a constant variance. Since there are usually several days between each of the traders' transactions the square root of the number of days between each transaction is used as a weight in the regression procedure.²⁸

The results of the big hit regressions are presented in Table 5. One major difference between these and the consistent forecasting coefficients is that three of markets have significant negative mean coefficients for noncommercial traders. The mean coefficient for the noncommercial traders in ALL MARKETS #1 is also negative and significant. Except for the oat market, all the signs on the means of the noncommercial distributions are negative.

<<<INSERT TABLE 5 HERE>>>

In almost all of the markets the big hit distributions are positively skewed. The kurtosis statistics are again large and negative. The standard deviations are also what one would expect from a uniform distribution ranging from -1.0 to 1.0.

The D-statistics for the big hit forecasting coefficients are similar to those for the consistent forecasting coefficient distributions. One major difference is that the distributions for commercial traders are all uniformly distributed (except for ALL MARKETS #2). In five of seven markets for noncommercial traders the distributions are not uniform.

Similar results hold for the Chi square tests. Only the oat commercial distribution is not uniform. Uniformity is rejected for all seven of the noncommercial distributions.

In Figure 2 the percentage bar charts for the seven individual markets and ALL MARKETS #1 and #2 are shown. In the T-bond and feeder cattle markets there are more traders with forecasting coefficients less than -90 percent than expected. In the interest rate markets it is interesting to note that there is a reduction of traders with superior big hit forecasting coefficients when compared to the consistent coefficients. This is somewhat surprising given the massive profits earned by the traders in these markets. On the other hand, given the observed price trends it did not take a genius to earn significant profits. It was unnecessary to make big bets to earn large rewards because there were such pronounced price trends.

<<<INSERT FIGURE 2 HERE>>>

It is clear why the mean forecasting level in the oat market is significantly positive. There are a large number of traders with big hit forecasting coefficients greater than 90 percent. This is in contrast to the consistent forecasting results where no oats traders have coefficients greater than 90 percent. This helps to explain why the oat return distributions are positively skewed. There are certain commercial traders who take their largest positions immediately prior to the big price moves. This may be the result of their possessing inside information or their hands-on grasp of the oats market. This is also consistent with selective hedging operations. These commercial traders may be hedging and taking consistent small losses on their futures positions (thus their negative consistent forecasting coefficients). However, when they expect a major price move, they become big speculators and adjust their position size accordingly.

Overall, Figure 2 tells pretty much the same story as Figure 1. It is the traders bunching toward zero that force us to reject uniformity. If this bunching is due to a statistical anomaly, such as heteroscedasticity, one

would expect that the bias would be greatest for the big hit forecasting coefficients. This is because non-stationary prices can have adverse effects on the efficiency of the big hit regressions, but play no role in the non-parametric tests using the logit equations. However, if anything the big hit results are more peaked around zero than the consistent results. For example, the number of big hit coefficients for ALL MARKETS #1 is above that expected from -0.25 to 0.35 and less than expected between 0.45 and 1.0. By contrast the consistent coefficients are greater in a much smaller interval between -0.15 to 0.05 and less than expected in both of the extreme outlying intervals. It appears as if there is some dependence across traders.

EXAMINATION OF THE OUTLIERS

Figures 1 and 2 graphically show the number of traders who have forecasting coefficients greater than 90 percent (in absolute value). Since these are the traders that appear to possess statistically significant skills it is worthwhile to examine them more closely. If returns are generated by a stochastic process, one would expect to observe approximately 5 percent of the total number of traders in each of the outlying intervals. In addition, one might expect that the percentage of total gains (losses) earned by the superior (inferior) forecasters would be around 10 percent.²⁹

Table 6 contains descriptive statistics on the traders with forecasting coefficients greater than or equal to 90 percent in absolute value. The percentage of traders who have consistent forecasting coefficients greater than 90 percent varies from zero percent (in oats) to 10.3 percent (in pork bellies). On the whole, it does not appear that there are a significant number of outliers with superior consistent forecasting skill. The same is true for inferior consistent forecasting skill as the coefficients vary from zero percent to 8.3 percent.

<<<INSERT TABLE 6 HERE>>>

It does not appear as if the superior forecasters earn substantially larger profits than expected. They earn 26 percent of the total gross profits in the wheat market, but only 1-2 percent of the gross profits in the interest rate markets. The percentages of losses to total gross losses are even smaller for the inferior traders. In fact, in the feeder cattle market the inferior traders earn positive profits. This is possible if these poor consistent forecasters are good big hitters.

If commercial traders act as pure hedgers, one would expect a greater proportion of commercial traders in the "inferior" outlying interval as compared to the "superior" interval. In addition, the proportion of superior (inferior) commercial traders should be lower (higher) than the proportion of commercial traders in the market as a whole. There is no support for these suppositions. In only two markets is the proportion of superior commercial traders less than the percentage of inferior commercial traders. In all but the wheat market, the percentage of inferior commercial traders is less than the percentage of commercial traders in the market as a whole. This constitutes some weak empirical support for the forecasting ability hypothesis, as one would expect that the commercial traders would be privy to more valuable information than the noncommercial traders. Their successful selective hedging strategies would show up in positive forecasting coefficients.

The results for the big hit and the consistent forecasting coefficients are quite similar. There are more than 5 percent of the traders with big hit coefficients less than -90 percent, except for oats. There are double the number of inferior traders relative to superior traders in three markets. Only in the oats market are there substantially more superior traders than

inferior traders. In two of the markets, the inferior traders earn positive profits (suggesting that they have consistent skill). The proportion of superior commercial traders is greater than the proportion of commercial traders in the market as a whole in all but the live cattle market. The proportion of inferior commercial traders is larger in four of the markets.

DOLLAR RETURNS BROKEN DOWN BY DECILES

To get a sense of the nature of the relationship between the dollar profits and forecasting coefficients Table 7 presents the dollar returns broken down by deciles. This was done for all seven markets. However, because the results were all similar, space is saved by only reporting the results for ALL MARKETS #1.

<<<INSERT TABLE 7 HERE>>>

There are between 220 and 226 traders in each interval. The proportions of commercial traders in the bottom and top deciles are significantly above the proportions in the other deciles. The proportion of commercial traders in the top decile is significantly above the the proportion in the bottom decile. Most of the big winners and losers are commercial traders. However, the commercial traders are most dominant in the big winner decile.

In cols. 3-5 averages of various forecasting ability measures are presented for the traders in each decile. For the most part, forecasting ability increases with the deciles. For consistent ability the bottom decile average coefficient is -0.213, while in the upper decile it is 0.319. The differences are statistically significant. The same is true for the big hit forecasting coefficients.

In col. 6 an average duration measure is presented. This indicates the average number of days a trader is in the market holding a nonzero gross position. A survival theory where the losers go bankrupt and drop out

suggests that losers should stay in the market for a shorter time than the winners. The data show that the biggest winners are in the market the longest amount of time, while the biggest losers are in the market the second longest amount of time. The difference between the two duration measures is statistically significant. Across all comparable intervals (e.g., second-ninth, third-eighth, etc.) it is clear that the duration measures of the successful participants are all greater than the losers. Therefore, it appears as if the losers do not "irrationally" remain in the market for as long as the winners.

In cols. 7 and 8 average size measures are presented. The biggest winners are the largest traders (in absolute value) and they also hold short positions, on average. The difference in the top and bottom deciles for the absolute net position value is only marginally significant. Examining all the other comparable intervals there does not appear to be any significant and systematic differences in these size measures.

The theory suggesting that performance is a stochastic process is supported by the results associated with time and size. One would expect that in a game of chance, that the largest traders and the participants that lasted the longest would be the biggest winners and losers. However, if performance is determined by a stochastic process one would not expect there to be any significant relationship between the forecasting coefficients and dollar returns. In Table 7, there does appear to be evidence indicating a linear relationship between dollar profits and ability.

SECTION IV — EX ANTE TESTS OF FORECASTING ABILITY

In the previous section evidence was presented supporting the luck hypothesis, in combination with the notion of dependence. An alternative method of testing for luck versus skill is to relate the individual's

observable characteristics, such as schooling, profession, number of years with trading experience, etc. to the forecasting coefficients or performance measures. A strong relationship would indicate that factors other than luck are important. Unfortunately, information on individual traders is not available.

Instead, a life cycle approach is used to determine if past performance can help predict future performance. The results for traders who have at least 25 transactions in both an early and a late period are examined to determine whether traders exhibit any noticeable consistency in their ability over time. The main question is: Do the traders who display superior (or inferior) forecasting ability in the early period continue to show it in the later period? If there is no relationship between performance in the two periods the luck hypothesis is reinforced.

To make this analysis a bit cleaner only the noncommercial traders are examined. Since the commercial traders are mostly hedging it is unclear how to interpret the results for this group. In the previous section they were analyzed and used as a benchmark with which to compare with the noncommercial traders. In this section the results in the early period are used as the benchmark.

CORRELATION STATISTICS

In Table 8 three Pearson correlation coefficients for each market are presented to see if there is a relationship between performance in the early and late periods. The correlations are given for all traders and for the noncommercial traders only. The dividing point between the sub-periods is October 1, 1979 (except for oats where it is July 1, 1979).

<<<INSERT TABLE 8 HERE>>>

When all traders are pooled there are significant correlations between dollar returns earned in the two halves. For the individual markets the most puzzling result appears in the live cattle market where the correlation is significant, but negative.³⁰ For the noncommercial traders alone there are positive significant correlations for T-bills and all markets combined. In two markets the correlations are negative and significant. In general, for the noncommercial traders it does not appear as dollar performance in one period is strongly related to dollar performance in the other period.

As for the forecasting coefficients, there does not appear to be any strong correspondence between a trader's observed ability in the first and second halves. For the noncommercial traders, especially in the wheat markets, there is some small significant correlations. In addition, there are significant correlations when all markets are pooled. Even so, these significant correlations are quite low. Overall, there is very little evidence supporting the skill hypothesis when examining the correlations.

TRADERS BROKEN DOWN BY DECILE OF EARLY PERIOD FORECASTING ABILITY

In Table 9 the individual early period forecasting coefficients are divided up into deciles depending on their relative magnitudes. For each decile, means of variables describing performance in the later period are calculated. In the left (right) half of Table 9 the deciles are for the early period consistent (big hit) forecasting coefficients. Overall, traders who spend two periods in the market have slightly positive and significant means of the early period consistent forecasting coefficients. One might expect that the survivors would have done better than average. Interestingly, this is not true for the big hitters where the early period mean is insignificantly different from zero. As for the second period, the results are worse for both types of ability measures. The second half consistent forecasting coefficient is zero while the big hit average is negative.

<<<INSERT TABLE 9 HERE>>>

Scanning the different deciles it clear that there is a regression to the mean in forecasting ability. Traders with superior skill in the first half appear to have average skill in the second half. Traders with inferior skill in the first half do slightly better in the second half. In essence, a mean reverting process is observed.

Only in the tenth decile for the consistent forecasting coefficient is there some weak evidence supporting the skill hypothesis. This decile is composed of traders who almost all have early period coefficients significant at the 10 percent level. In the second half the significance levels fall, on average, but still remain slightly above average.

Other second half measures of performance are less supportive for the group in the top decile of traders with early period consistent forecasting coefficients. In the first half 84 percent of these traders earn positive profits (i.e., are successful). In the second half, this percentage falls significantly to 65 percent. In fact, for the deciles where the early period consistent forecasting coefficients are positive (i.e., deciles 5-10) the percentage of early period winners is always significantly above the percentage of late period winners. In addition, except for decile 6, the second half percentages are all indistinguishably different from 50 percent. This is exactly what is expected from a game of chance. Only in decile 1 does this percentage increase significantly. The percentages of winners in the second half fall and approach 50 percent in the big hit forecasting coefficients deciles 5-10 as well. This is strong evidence supporting the regression to the mean or luck hypothesis.

The mean dollar profits earned in the first half by all traders is significantly different from zero. This probably explains why these traders

remain in during the second half of the period. The mean dollar profits are insignificantly different from zero in the second period. Scanning the big hit forecasting coefficient deciles one observes a dramatic decrease in profits in deciles 6-10. In fact, the traders in the top decile earn \$1.5 million, on average, in the early period and lose \$90,000, on average, in the later period. The results are similar for the consistent deciles as well. Significant positive profits earned in the first half turn into nonpositive profits in the second half.³¹

Comparing the second period performances of the top and bottom deciles one observes both similarities and differences. For the traders with the lowest and highest early period big hit forecasting coefficients, the second half performances are indistinguishable. This is not quite true when the early period consistent forecast coefficients are observed. The second half coefficients, profits, and percentage of successful traders are all greater for the most successful early period forecasters.

EXAMINATION OF THE EARLY PERIOD OUTLIERS

It may be the case that an elite subset of superior forecasters is composed of a small number of members. Therefore, a high percentage of the traders may have no ability, but a few who do consistently exhibit skill. The traders with big hit and consistent early period forecasting coefficients greater than 0.8 (in absolute value) are examined in Table 10. There is really nothing striking about Table 10. For example, there are 25 traders with early period big hit coefficients greater than 0.8. This is slightly less than one would expect from chance since there are 409 traders in both periods and 10 percent of these (or 41 traders) should be in the interval from 0.8 to 1.0. If second period forecasting coefficients are determined by luck then 10 percent of the 25 (or 2.5) traders should be lucky enough to have

coefficients above 0.8 in both the early and late periods. If luck determines the outcomes then 50 percent of the 25 (or 12.5) traders should have coefficients less than zero in the second period. And finally, if luck is important the mean forecasting coefficients should be symmetrically distributed and insignificantly different from zero (which they are). Overall, for the early period big hit outliers the later period forecasting coefficients look like they are generated by a stochastic process.

<<<INSERT TABLE 10 HERE>>>

The same cannot be said unequivocally about the traders with outlying consistent forecasting coefficients. As a percentage of the number of outlying traders the number of traders with the opposite sign in the second period is smaller. At the same time it is not far enough away from that expected by chance to offer important evidence for the skill hypothesis. The mean second period consistent forecasting coefficient for the 0.9 outliers is positive and significant. This corresponds with the results for decile 10 in Table 9. It is still only weak support for the skill hypothesis.

SECTION VI — CONCLUSION

The empirical evidence presented in this paper strongly supports the contention that the returns to traders of futures are generated by a stochastic process. Extremely lucky traders do well, while those less fortunate are made to pay. The support for the luck hypothesis comes from two sources: 1) the observed distributions of forecasting ability coefficients which are either uniform or peaked at zero; and 2) the fact that the superior and inferior traders regress toward the mean when comparing early and late period forecasting ability.

There are two questions left open from the analysis in this paper. First, it is not clear why there is a massive bunching of traders with no

ability. It is suggested that this dependence is due to the fact that many individuals use very similar trading strategies or information sources. There appears to be a widespread exchange of mediocre or worthless information. This information is probably in the public domain prior to trading and thus is already reflected in the price by the time the individual can act. Even so, traders act as if they believe this information to be their own. Second, it is not clear why these large reporting traders earn significant positive returns. If performance is due to luck, one would not expect the large traders to perform any better than the small traders. Yet in all studies to date the small traders are the big losers and the large traders are the big winners (Stewart 1949; Houthakker 1957; Rockwell 1964, 1977; Hartzmark 1984, 1987).

There is only weak support for the skill theories. It does appear that commercial traders show slightly more forecasting ability than noncommercial traders. These commercial participants are the traders with access to the most timely information and they may be able to profit from it. This is dramatically displayed in the oats market where commercial traders do not possess significant consistent forecasting ability, but demonstrate significant big hit ability. The commercial traders also make up a higher proportion of the biggest winners than one would expect if everything were random. There are also more commercial traders with superior forecasting ability than expected. In the ex ante analysis, there is some weak support for the skill hypothesis when observing the results of the very few superior outliers with consistent. They stand out, although without observing the underlying characteristics of this elite group it is impossible to determine if skill plays any part in determining performance.

An alternative, and maybe stronger, approach to testing for skill versus luck would have been to propose a null hypothesis stating that traders do possess forecasting ability. Unfortunately, it is impossible to determine what the distribution of forecasting coefficients would like in this case. First, we would have to determine the underlying characteristics of the distribution of forecasting skill. Next we would have to determine how this mapped into a distribution of forecasting ability. This would not be straightforward given that informational externalities abound in the futures market.

If returns are generated by a stochastic process then prices are either strongly efficient (reflecting all information) or totally inefficient (subject to the whims of the public psychology). In either case performance would be due to luck. It seems unlikely that the markets are driven by mass psychology. If this were the case there would not be a tight relationship between the cash and futures prices. This unstable basis would drive the commercial traders from the market and would destroy hedging opportunities. Yet, over the years commercial interest in futures markets has grown tremendously. Therefore, it appears to be the case that the price is indicating something of importance to this group. Unfortunately, this paper adds very little to the debate about whether speculators act to stabilize or destabilize prices.

The results for the noncommercial traders are puzzling. These traders do not have the opportunities to use these markets to reduce portfolio risks the way that commercial traders can use them. They have achieved a large size and remain large for a reasonable length of time. What motivates them to enter these markets? It is difficult to say. In general, one cannot say that these participants are irrational. It is likely that they enjoy the opportunity to

gamble on their beliefs. On the other hand, one must ask whether it is rational for so many sheep to be continuously led to the slaughter.

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FOOTNOTES

¹Commercial traders are those participants whose main line of business is focused on the underlying cash commodity.

²This notion of gambling is certainly consistent with strong-form efficiency.

³There are five alternative views of why traders are willing to participate in activities where expected gains are negative. First, traders may be willing to incur losses on their futures transactions because they are able to diversify or reduce their overall portfolio risks. Second, like MBA's or Ph.D.'s these losers may be paying for a "real life" education. In essence, they pay their fees to find out that they have failed to make good predictions. Third, certain groups of traders may simply make mistakes, exit, only to be replaced by more uninformed sheep. Because of significant search or learning costs new sheep are continually getting sheared. Fourth, traders may utilize stop-loss orders to transform trading into a lottery where big gains are possible, but the probability of substantial losses is small. This is reasonable if traders have a Friedman and Savage (1948) type utility function. And finally, institutional rules (e.g., tax laws) may offer traders incentives to make trades where expected returns are negative.

The first three explanations lack credibility. Most of the academic research suggests that futures trading offers little if any opportunity to reduce risks with diversification (Dusak 1974; Bodie and Rosansky 1981; Erhardt, Jordan and Walkling 1987; Elton, Gruber and Rentzler 1987). The second and third reasons make sense only if there are artificial restraints inhibiting the flow of information to potential traders. As a greater proportion of the population makes mistakes or "learns its lesson," the information about the lack of profitable opportunities should flow out to others. On the contrary, over time there has been a large growth in the speculative activity in the futures market.

⁴Actual fixed reporting levels and a detailed description of the large trader database are given in Hartzmark (1984) and McDonnell and Freund (1983). For a discussion of the modifications and extensions made to the original data see Hartzmark (1984). There are a total of 3.01 million daily observations on the positions that individual traders hold in each maturity month. There are 1.09 million observations in the database where, for each trader, the positions are aggregated across each maturity month on a daily basis.

⁵It is impossible to get transactions prices with which to calculate profits. However, given that most of the traders in this sample hold positions over long periods of time it is unlikely that using transactions prices will have a major effect on the results. In addition, the sample does not included day traders or scalpers.

⁶See footnote 8 in Hartzmark (1987) for a detailed discussion about using a CAPM framework for analyzing risk and return in a futures market.

⁷Margins are very small and can be posted in interest bearing notes.

⁸Data for oats runs from January 1, 1978 to December 31, 1980. Data for T-bonds runs from August 22, 1977 to December 31, 1981.

⁹This aggregation is appropriate since the contract specifications are all comparable. This is not true for any of the other closely related contracts.

¹⁰For a more detailed explanation of the decomposition see Hartzmark (1984, 1987). About 30 percent of all traders report both hedge and speculative positions. Of these traders, 49 percent are classified as commercial traders.

¹¹Each daily price change observation on each individual maturity month is used. Descriptive statistics for two alternative price change series were also calculated. These include: 1) the daily price changes of the nearby contract; and 2) a weighted average of all price changes on a given day (the weights are the open interest in the maturity month). In general, the results are the same. For the wheat markets, only the results for the CBT are presented.

¹²The Kolomogorov D-statistic is used to test for normality, unless there are fewer than 51 observations. In this case the Shapiro-Wilk W-statistic is used.

¹³Therefore, approximately 2000 of the traders that are included in Hartzmark (1984, 1987) are not included in the empirical results presented in this paper.

¹⁴Tests for oats and pork bellies were performed where all observations were used, not just observations when transactions were made. The results are similar, except there are many traders who made one or two transactions and simply hold onto them for more than 25 days. It does not seem appropriate to include these traders in the tests. In addition, the computer costs would grow out of sight if all observations are included in the statistical procedures. If a trader remains on the same side of the market after a transaction then it still counts as an update. For example, if the trader increases his long position from 100 to 300 contracts, or reduces his long position from 100 to 50 contracts I assume that he has made a new prediction that the price is going up.

¹⁵An example will describe the three possible measures. Assume that the trader holds 100 long contracts (at \$1.00 per contract) and 200 short contracts (at \$1.50 per contract). The net position value (NPV) is $\$100 - \$300 = -\$200$. The gross position value (GPV) is \$400 and the absolute net position value (ANPV) is \$200. Depending on what you want to show one measure may be more appropriate than the other. NPV is chosen because it gives a feel for the relative sizes of traders, as well as the side of the market they choose.

¹⁶ Instead of calculating the statistics for each market and then averaging across all seven markets I could have combined the daily net position values. Unfortunately, this is easier said than done and it is difficult to interpret. There is no longer a relevant price or contract. We can observe whether the trader is net long or net short in dollar terms. We can also observe the dollar profits earned. As will be apparent when the empirical tests are described, having only this information would not have allowed me to calculate the forecasting coefficients.

¹⁷ 463 traders are in one or more markets, with three traders in all seven markets. For these 463 traders, the "average" trader participates in 2.68 markets.

¹⁸ See Hartzmark 1984 for an implementation of such a strategy.

¹⁹ It is argued in HM that inferior skill has value since investors observing the traders predictions can simply reverse the perverse forecasts. However, HM studied mutual funds. In this study inferior skill remains perverse since the records used to determine the forecasting abilities are all confidential. Therefore, outsiders cannot use the information to improve their performance.

²⁰ One can do all calculations using the same information for the long predictions. The significance level for the sum of the conditional probabilities will be identical. One can see this since the information mentioned gives us the number of times the trader is long, as well as the number of times the trader correctly predicts that the price is going up.

²¹ For example, assume that a trader makes 50 transactions. Over the period the price goes down 35 times and up 15 times. The trader takes a short position 25 of the 50 times. What total number of correct predictions are necessary to reject the null hypothesis at the 99% confidence level? If the trader is short 22 times when the price falls the sum of $P_u(t) + P_d(t) = 1.43$. This is statistically different from 1 at a 99% confidence level. This significance region is derived assuming a hypergeometric distribution.

²² This is especially true if the trader makes only a small number of predictions. In addition, in the case when most predictions are one direction the CM technique is superior.

²³ For $LS(t)$ the number of contracts, not the dollar position value is used. This avoids any problems if price changes and price levels (which are part of the position value) are related. Net zero positions are excluded, even if profits are earned.

²⁴ The D-statistic is sensitive to departures in the shape of the actual distribution from uniformity. The Chi square goodness of fit test is better for finding any irregularities in the actual distribution (Sachs 1984).

²⁵ Therefore, the number of traders also differs from the number in Tables 2 and 3.

²⁶In this case where traders are always long (predicting the price is going up) or always short (predicting the price is going down) the hypergeometric distribution collapses into a binomial distribution. A unique maximum likelihood estimate using the logit procedure cannot be found.

²⁷The variance of a uniform distribution is $(a-b)^2/12$, where a and b are the endpoints.

²⁸There is one other source of heteroscedasticity that may be important, but is not corrected for in the regressions. In some of the markets (especially in T-bills and T-bonds) there are large changes in the daily variance of the price changes over time. Given the large number of regressions run and the fact that the traders were in for different periods, this cannot easily be adjusted for. However, as will be shown later there are very few traders who are in for long enough for this type of heteroscedasticity to be a problem.

²⁹I am implicitly assuming that traders with negative forecasting coefficients earn negative profits and traders with positive coefficients earn positive profits.

³⁰All types of questions have been asked about the performance of this market. It appears to be an anomaly. The results here support this. The negative correlation may also be due to price trends. The early period is where prices trend upwards, while the later period the trends are slightly downward or flat.

³¹Deciles for individual markets were also examined. The results were similar. In addition, to the statistics presented in Table 8 I calculated duration, size and serial correlation measures. There are no significant differences in any of these measures across the deciles. The correlations related past performance (cumulative profits up to and including month $t-1$) to current performance (profits in month t). Most correlations were about -0.25. This suggests that current performance is negatively related to the past record. On average, one would expect to observe this in a game of chance.

Table 1
DESCRIPTIVE STATISTICS: DAILY PRICE CHANGES
(in dollars per contract)

<u>Market</u>	<u>No. of Observations</u>	<u>Percent Upticks</u> ^a	<u>Percent Downticks</u> ^a	<u>Mean</u>	<u>Median</u>	<u>Std. Deviation</u>	<u>Skew- ness</u>	<u>Kur- tosis</u>	<u>D Sta- tistic</u> ^b
Oats	3655	47.6	48.7	0.98	0.00	125.38	-0.05	0.21	0.04**
Wheat	6792	47.9	47.9	0.10	0.00	282.02	0.07	1.85	0.06**
Pork Bellies	6614	48.3	48.8	-6.99	0.00	474.70	0.01	-1.04	0.05**
Live Cattle	9388	49.4	45.2	3.67	0.00	283.28	-0.14	-0.10	0.05**
Feeder Cattle	8886	48.7	44.5	2.30	0.00	328.47	-0.08	-0.46	0.05**
T-Bonds	12499	45.4	51.2	-37.00**	-31.25	657.76	0.11	1.36	0.07**
T-Bills	10431	46.2	50.3	-20.07**	-12.50	528.51	0.02	1.18	0.10**

** Significant at 1% level.

a. Percentages of upticks and downticks do not sum to 100% because of days with zero change.

b. Kolmogorov D statistics tests for normality of distribution.

Table 2
DESCRIPTIVE STATISTICS: AVERAGE NET POSITION VALUE
(in millions of dollars)

	Number of Traders	Mean	Median	Std. Devi- ation	Skew- ness	Kurtosis	Range
<u>Oats</u>							
All Traders	48	-0.40*	-0.11	1.31	-3.39	19.43	10.04
Commercial	27	-0.76*	-0.44	1.60	-2.91	13.61	10.04
Noncommercial	21	0.06	0.02	0.57	0.67	3.90	2.81
<u>Wheat</u>							
All Traders	341	-0.00	0.00	6.82	0.39	10.41	73.72
Commercial	168	-0.76	-0.99	9.35	0.51	4.91	73.72
Noncommercial	173	0.74**	0.11	2.42	1.42	3.20	14.53
<u>Pork Bellies</u>							
All Traders	342	-0.22**	-0.09	1.00	-0.64	4.09	8.57
Commercial	28	-1.04**	-0.71	1.44	-1.13	1.21	5.97
Noncommercial	314	-0.14**	-0.08	0.91	-0.13	3.51	7.29
<u>Live Cattle</u>							
All Traders	483	-0.38	0.43	7.58	-6.88	69.19	113.68
Commercial	121	-5.63**	-2.77	13.00	-4.35	23.29	103.24
Noncommercial	362	1.37**	0.90	2.87	0.93	8.37	32.48
<u>Feeder Cattle</u>							
All Traders	193	0.55*	-0.11	4.36	2.24	9.07	34.22
Commercial	69	0.05	-1.05	4.52	0.97	1.59	23.90
Noncommercial	124	0.83*	-0.00	4.27	3.15	14.21	34.22
<u>T-Bonds</u>							
All Traders	439	-2.72*	0.17	34.17	-13.98	249.61	758.61
Commercial	96	-15.47*	-2.22	68.34	-7.64	66.87	653.06
Noncommercial	343	0.85	0.27	11.80	1.03	87.81	260.77
<u>T-Bills</u>							
All Traders	383	-2.51	-0.25	62.68	-8.57	115.81	1163.35
Commercial	98	-20.74*	-6.59	110.47	-6.10	42.35	1038.10
Noncommercial	285	3.76*	0.18	31.00	4.77	43.69	460.91
<u>All Markets #1</u>							
All Traders	2229	-1.04	0.02	30.43	-16.82	440.48	1163.35
Commercial	607	-7.20**	-1.84	52.99	-11.89	167.08	1038.10
Noncommercial	1622	1.26**	0.19	14.26	9.09	191.72	460.91
<u>All Markets #2</u>							
All Traders	1450	-0.97	0.00	24.44	-20.07	600.38	919.70
Commercial	422	-5.36**	-2.01	42.72	-12.79	215.79	919.70
Noncommercial	995	0.92**	0.15	9.14	4.86	68.72	189.21
Both Types	33	-1.68	0.32	8.00	-4.02	19.49	47.47

* Significant at 10% level.

** Significant at 1% level.

Table 3
DESCRIPTIVE STATISTICS: RETURNS TO INDIVIDUAL TRADERS OF FUTURES
(in millions of dollars)

	Number of Traders	Total Dollar Return	Mean Dollar Return	Median Dollar Return	Std. Devi- ation	Skew- ness	Kurtosis	Test of Norm- ality ^a
<u>Oats</u>								
All Traders	48	10.13	0.21*	0.01	0.86	5.36	32.70	0.44**
Commercial	27	9.55	0.35	0.01	1.13	4.03	18.34	0.51**
Noncommercial	21	0.58	0.03	-0.00	0.13	-0.36	0.22	0.96
<u>Wheat</u>								
All Traders	341	83.20	0.24	0.01	5.70	8.37	112.64	0.31**
Commercial	168	75.83	0.45	-0.01	8.02	6.08	57.58	0.30**
Noncommercial	173	7.36	0.04	0.07	1.32	0.21	10.52	0.20**
<u>Pork Bellies</u>								
All Traders	342	101.43	0.30**	0.03	1.72	7.25	76.44	0.24**
Commercial	28	78.41	2.80**	0.99	4.85	2.54	7.71	0.71**
Noncommercial	314	23.02	0.07*	0.02	0.76	0.58	8.15	0.12**
<u>Live Cattle</u>								
All Traders	483	73.85	0.15	0.06	3.04	-1.57	36.86	0.21**
Commercial	121	-124.00	-1.02*	-0.49	4.99	-1.37	16.42	0.22**
Noncommercial	362	197.85	0.55**	0.17	1.86	3.51	23.25	0.21**
<u>Feeder Cattle</u>								
All Traders	193	113.86	0.59**	0.10	2.67	3.43	18.99	0.26**
Commercial	69	33.98	0.49	0.03	3.44	2.28	9.19	0.27**
Noncommercial	124	79.89	0.64**	0.13	2.15	5.41	38.33	0.26**
<u>T-Bonds</u>								
All Traders	439	534.01	1.22*	-0.05	11.61	12.75	208.49	0.37**
Commercial	96	571.66	5.95*	0.36	23.46	6.53	52.45	0.29**
Noncommercial	343	-37.65	-0.11	-0.09	3.43	8.68	122.56	0.28**
<u>T-Bills</u>								
All Traders	383	130.29	0.34	-0.00	4.34	4.60	67.51	0.29**
Commercial	98	117.96	1.20**	0.27	4.42	5.64	41.16	0.26**
Noncommercial	285	12.33	0.04	-0.02	4.28	4.36	80.73	0.32**
<u>All Markets #1</u>								
All Traders	2229	1046.78	0.47**	0.02	6.16	18.25	541.33	0.32**
Commercial	607	763.40	1.26**	0.01	10.93	11.55	195.37	0.31**
Noncommercial	1622	283.38	0.17**	0.02	2.68	7.28	161.81	0.25**
<u>All Markets #2</u>								
All Traders	1450	1046.78	0.72**	0.00	8.39	17.64	459.65	0.33**
Commercial	422	651.86	1.54*	-0.04	14.43	11.52	177.09	0.33**
Noncommercial	995	280.23	0.28**	0.02	2.96	7.52	117.78	0.26**
Both Types	33	114.69	3.48	1.16	12.35	2.12	6.24	0.73**

- a. For the test of normality the Kolomogorov D-statistic is used unless there are less than 51 observations, in which case the Shapiro-Wilk W Statistic is used.
* Significant at a 10% level. ** Significant at a 1% level.

Table 4
DESCRIPTIVE STATISTICS: CONSISTENCY FORECASTING COEFFICIENTS

(statistics $\times 10^{-2}$, except Traders and Chi square)

	Number of <u>Traders</u>	Mean Proba- <u>bility</u>	Median Proba- <u>bility</u>	Std. Devi- <u>ation</u>	Skew- <u>ness</u>	<u>Kurtosis</u>	D Sta- <u>tistic</u>	Chi Square <u>Statistic</u>
<u>Oats</u>								
All Traders	39	-3.88	-2.58	51.55	7.62	-96.31	13.53	1.90
Commercial	20	-10.58	-18.56	53.09	31.78	-89.56	20.46	1.00
Noncommercial	19	3.17	-0.91	50.32	-15.87	-70.98	14.48	3.89
<u>Wheat</u>								
All Traders	308	-3.70	-0.84	51.46	4.22	-93.62	8.86	49.66**
Commercial	142	-5.31	-0.84	52.78	1.71	-101.36	9.62	34.90*
Noncommercial	166	-2.32	-0.87	50.42	7.50	-86.66	9.42	42.43**
<u>Pork Bellies</u>								
All Traders	301	2.62	0.66	55.96	-2.35	-102.78	6.38	22.92
Commercial	26	15.13*	1.13	43.41	32.53	-29.82	25.58*	17.08**
Noncommercial	275	1.44	0.66	56.92	-1.01	-108.89	5.71	23.84
<u>Live Cattle</u>								
All Traders	425	4.45*	0.65	55.66	-5.78	-110.61	7.46*	56.84**
Commercial	82	-0.65	-1.06	52.51	10.49	-90.78	9.27	30.20*
Noncommercial	343	5.67*	0.91	56.39	-9.77	-113.39	8.19*	42.36**
<u>Feeder Cattle</u>								
All Traders	151	2.80	0.61	57.98	-8.02	-108.44	7.62	37.48**
Commercial	48	5.32	6.91	55.19	-27.22	-104.20	12.05	12.83
Noncommercial	103	1.63	-0.60	59.47	-0.32	-109.22	6.36	32.73*
<u>T-Bonds</u>								
All Traders	411	3.18	0.58	53.15	-7.25	-101.53	6.72*	38.20**
Commercial	86	8.29	15.07	55.59	-18.58	-114.67	8.29	10.28
Noncommercial	325	1.82	0.00	52.49	-4.74	-96.64	6.87*	40.85**
<u>T-Bills</u>								
All Traders	354	-2.02	-1.26	53.60	8.49	-108.49	5.32	20.24
Commercial	83	2.68	-1.12	52.12	9.91	-113.36	7.68	16.71
Noncommercial	271	-3.46	-2.93	54.06	8.79	-107.92	5.71	14.39
<u>All Markets #1</u>								
All Traders	1989	1.21	0.00	54.30	-0.89	-104.57	4.38**	122.85**
Commercial	487	1.16	-0.64	52.99	-1.26	-103.12	5.85*	51.36**
Noncommercial	1502	1.22	0.00	54.74	-0.78	-105.13	4.34**	94.91**
<u>All Markets #2</u>								
All Traders	1300	0.65	0.58	48.30	-2.99	-77.26	7.94**	189.57**
Commercial	334	0.36	0.99	49.89	-7.59	-90.94	7.96*	45.76**
Noncommercial	933	0.90	0.00	48.29	-1.20	-76.25	8.61**	139.60**
Both Types	33	-3.27	-1.10	28.81	-73.79	165.69	31.99**	31.70**

* Significant at a 10% level.

** Significant at a 1% level.

Table 5
DESCRIPTIVE STATISTICS: BIG HIT FORECASTING COEFFICIENTS

(numbers x 10⁻², except Traders and Chi square)

	Number of Traders	Mean Proba- bility	Median Proba- bility	Std. Devi- ation	Skew- ness	Kurtosis	D Sta- tistic	Chi Square Statistic
<u>Oats</u>								
All Traders	48	14.14*	7.91	54.72	-3.01	-120.31	10.29	5.96
Commercial	27	6.81	-1.39	60.93	20.71	-159.41	11.18	9.85*
Noncommercial	21	23.56*	7.98	45.22	-23.31	17.19	29.69*	14.00**
<u>Wheat</u>								
All Traders	341	-4.37*	-5.50	48.97	12.77	-64.68	12.05**	63.52**
Commercial	168	-1.03	0.97	53.74	6.50	-98.03	8.17	20.33
Noncommercial	173	-7.62*	-6.03	43.75	12.45	-20.90	18.09**	69.89**
<u>Pork Bellies</u>								
All Traders	342	-2.89	-0.95	55.17	6.48	-101.97	7.68*	30.28*
Commercial	28	-4.63	-2.34	59.52	22.94	-130.84	13.55	1.64
Noncommercial	314	-2.73	-0.95	54.86	4.94	-98.85	7.59*	28.29**
<u>Live Cattle</u>								
All Traders	483	-0.95	-1.50	54.59	2.06	-95.01	5.48	36.54**
Commercial	121	-2.58	-9.03	62.63	3.03	-140.88	9.24	22.31
Noncommercial	362	-0.41	-0.32	51.71	2.92	-73.64	8.08	55.24**
<u>Feeder Cattle</u>								
All Traders	193	-3.28	-0.69	56.96	-0.73	-97.24	6.99	24.10
Commercial	69	0.28	0.27	61.18	-3.62	-119.96	5.52	6.22
Noncommercial	124	-5.25	-1.10	54.62	-1.26	-81.91	10.89	27.61*
<u>T-Bonds</u>								
All Traders	439	-2.48	-0.78	51.25	-0.27	-76.55	10.21**	57.54**
Commercial	96	1.80	-0.64	52.96	10.29	-81.01	8.89	13.37
Noncommercial	343	-3.68	-1.09	50.78	-4.13	-76.69	11.55**	57.06**
<u>T-Bills</u>								
All Traders	383	-8.31**	-7.11	50.09	10.92	-77.32	13.85**	63.42**
Commercial	98	-6.63	-8.28	53.76	12.67	-100.02	9.63	17.51*
Noncommercial	285	-8.88**	-5.94	48.86	9.45	-68.23	16.22**	62.30**
<u>All Markets #1</u>								
All Traders	2229	-3.21	-2.87	52.71	5.57	-86.18	8.22**	171.44**
Commercial	607	-1.46	-3.91	56.76	7.03	-112.32	3.92	16.29
Noncommercial	1622	-3.87**	-2.66	51.11	3.91	-74.86	10.13**	211.14**
<u>All Markets #2</u>								
All Traders	1450	-1.29	-1.36	48.02	6.49	-63.03	10.42**	250.22**
Commercial	422	-0.80	-1.10	53.98	4.81	-98.19	6.60*	23.40
Noncommercial	995	-1.29	-1.30	45.74	6.07	-47.83	12.13**	260.34**
Both Types	33	-7.49	-3.98	32.44	29.73	-21.31	24.69*	22.61**

* Significant at a 10% level.

** Significant at a 1% level.

Table 6
DESCRIPTIVE STATISTICS: TRADERS WITH BEST AND WORST FORECASTING ABILITY
(returns in millions of dollars)

	Consistency ≥ 0.90				Consistency ≤ 0.90				Big Hit ≥ 0.90				Big Hit ≤ 0.90			
	Number of Traders	Total Return	% Commercial	Number of Traders	Total Return	% Commercial	Number of Traders	Total Return	% Commercial	Number of Traders	Total Return	% Commercial	Number of Traders	Total Return	% Commercial	
Oats	0 (0)	-	-	0 (0)	-	-	5 (20.8)	1.50 (12.0)	60.0 (56.3)	0 (0)	-	-	0 (0)	-	-	
Wheat	5 (2.9)	89.11 (26.0)	60.0 (46.1)	7 (4.1)	-17.93 (6.9)	71.4 -	10 (5.8)	3.09 (0.9)	70.0 (49.3)	10 (5.9)	-9.52 (3.7)	50.0 -	10 (5.9)	-9.52 (3.7)	50.0 -	
Pork Bellies	19 (10.3)	20.00 (11.8)	10.5 (8.6)	13 (8.3)	-4.99 (7.3)	0.0 -	10 (5.4)	19.80 (11.7)	20.0 (8.2)	17 (10.8)	-7.56 (11.1)	0.0 -	17 (10.8)	-7.56 (11.1)	0.0 -	
Live Cattle	23 (6.3)	47.74 (12.7)	13.0 (19.3)	11 (5.0)	-10.10 (3.3)	9.1 -	24 (9.2)	3.17 (0.8)	25.0 (25.1)	21 (9.5)	-12.09 (4.0)	38.1 -	21 (9.5)	-12.09 (4.0)	38.1 -	
Feeder Cattle	9 (8.3)	40.41 (23.3)	0.0 (31.8)	6 (7.1)	-6.24 (10.5)	16.7 -	10 (9.2)	4.74 (2.7)	40.0 (35.8)	16 (19.0)	3.14 (-5.3)	43.8 -	16 (19.0)	3.14 (-5.3)	43.8 -	
T-Bonds	11 (5.8)	9.91 (1.1)	27.3 (20.9)	11 (4.6)	51.42 (-15.2)	18.2 -	16 (8.1)	102.67 (11.76)	37.5 (21.9)	22 (9.1)	185.01 (-54.5)	18.2 -	22 (9.1)	185.01 (-54.5)	18.2 -	
T-Bills	10 (5.3)	5.59 (1.7)	20.0 (23.4)	9 (4.7)	-9.29 (4.7)	0.0 -	6 (3.1)	0.90 (0.3)	50.0 (25.6)	18 (9.3)	-8.43 (4.2)	33.3 -	18 (9.3)	-8.43 (4.2)	33.3 -	

Percentage in parentheses. Number is percentage of total gains (losses) for best (worst) forecasters for return and percentage of total traders for number of traders. For % Commercial, number is percentage of commercial traders in the market as a whole..

Table 7

DOLLAR RETURNS BROKEN DOWN BY DECILES, WITH ABILITY, DURATION
AND SIZE MEASUREMENTS FOR TRADERS IN EACH DECILE
(in millions of dollars)

<u>Decile</u>	<u># Traders/ % Commercial</u>	<u>Mean Dollar Return</u>	<u>Ability</u>	<u>Big Hit Fore- casting Level</u>	<u>Consistent Fore- casting Level</u>	<u>Days in Market</u>	<u>Net Dollar Position Value</u>	<u>Absolute Net Dollar Position Value</u>
First	221 46%	-3.97 4.65	0.975 (0.079)	-0.134 (0.542)	-0.213 (0.508)	470.55 (295.79)	1.62# (54.14)	21.57 (53.23)
Second	222 31%	-0.96 (0.48)	0.960 (0.090)	-0.198 (0.535)	-0.226 (0.506)	320.56 (230.26)	1.09# (13.93)	6.93 (13.60)
Third	225 29%	-0.40 (0.20)	0.961 (0.099)	-0.204 (0.522)	-0.198 (0.493)	256.99 (217.88)	0.66 (4.12)	3.93 (4.53)
Fourth	223 17%	-0.17 (0.08)	0.963 (0.100)	-0.070 (0.515)	-0.187# (0.491)	222.27 (173.71)	0.46# (4.52)	3.22 (4.66)
Fifth	226 15%	-0.04 (0.06)	0.982 (0.100)	-0.056# (0.464)	-0.088# (0.508)	215.79 (198.83)	-0.26# (3.44)	2.45 (3.67)
Sixth	222 18%	0.09 (0.07)	1.015# (0.106)	-0.000# (0.500)	0.073# (0.525)	213.75 (193.80)	0.54# (5.42)	3.35 (6.56)
Seventh	223 13%	0.25 (0.11)	1.025 (0.095)	0.025 (0.544)	0.142# (0.521)	259.61 (196.42)	0.19# (4.55)	3.49 (5.97)
Eighth	225 22%	0.55 (0.18)	1.022 (0.080)	0.110 (0.529)	0.167 (0.467)	319.69 (242.32)	-0.13# (9.75)	5.51 (9.71)
Ninth	222 31%	1.23 (0.44)	1.031 (0.074)	0.104 (0.480)	0.278 (0.487)	414.81 (266.10)	-0.58# (9.47)	7.21 (8.68)
Tenth	220 52%	8.19 (16.72)	1.032 (0.060)	0.104 (0.519)	0.319 (0.540)	641.84 (302.29)	-14.20 (76.34)	29.61 (85.89)

Number is NOT significant at 10% level. Ability is tested for being different from one. Dollar Returns, Forecasting Levels, and Net Dollar Position Values are tested for being different from zero.

Table 8
CORRELATION STATISTICS ACROSS PERIODS^a

	<u>All Traders</u>			<u>Non-Commercial Trader</u>		
	<u>Return</u>	<u>Consistent</u>	<u>Big Hit</u>	<u>Return</u>	<u>Consistent</u>	<u>Big Hit</u>
Oats	0.89* 26	0.01 18	0.01 26	-0.76* 9	0.10 9	-0.06 9
Wheat	0.23** 161	0.23** 131	0.01 161	-0.18 60	0.39** 58	0.29* 60
Pork Bellies	0.68** 117	0.16 99	0.22* 117	0.15 103	0.16 88	0.26** 103
Live Cattle	-0.58** 151	0.04 126	-0.10 151	-0.05 104	0.04 96	-0.06 104
Feeder Cattle	0.05 50	0.16 39	0.17 50	-0.44* 27	0.21 22	0.18 27
T-Bonds	0.08 72	-0.06 64	-0.13 72	0.06 47	-0.02 42	-0.04 47
T-Bills	0.33** 87	-0.00 82	0.13 87	0.85** 59	0.04 57	0.13 59
All Markets #1	-0.01 664	0.10 559	0.04 664	0.20** 409	0.12* 372	0.12** 409

Number of observations is below correlation coefficient.

a. Early period is 7/77-9/79. Late period of 10/79-12/81. Oats periods are 1/78-6/79 and 7/79-12/80.

* Significant at 10% level.

** Significant at 1% level.

Table 9
DESCRIPTIVE STATISTICS BY DECILES OF EARLY PERIOD FORECASTING COEFFICIENTS
(profits in millions of dollars)

Statistic	Rank by Early Consistent Coefficient										
	All Traders	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10
Number of Traders	372	37	37	37	38	37	37	38	37	37	37
1st Half Consistent Coefficient	0.10** (0.03)	-0.82** (0.01)	-0.59** (0.01)	-0.33** (0.01)	-0.14** (0.01)	0.03** (0.01)	0.19** (0.01)	0.38** (0.01)	0.58** (0.01)	0.76** (0.01)	0.91** (0.10)
2nd Half Consistent Coefficient	-0.02 (0.03)	-0.07 (0.09)	0.05 (0.11)	-0.18* (0.08)	-0.07 (0.09)	-0.10 (0.09)	-0.09 (0.09)	0.00 (0.10)	0.01 (0.09)	0.10 (0.10)	0.18* (0.09)
Overall Consistent Coefficient	0.09** (0.03)	-0.57** (0.07)	-0.28** (0.08)	-0.28** (0.07)	-0.02 (0.08)	0.01 (0.09)	0.04 (0.07)	0.26** (0.08)	0.36** (0.08)	0.57** (0.08)	0.79** (0.05)
Overall Big Hit Coefficient	-0.04* (0.02)	-0.01 (0.05)	-0.12 (0.08)	-0.10 (0.06)	-0.09 (0.06)	-0.09 (0.06)	-0.14* (0.06)	0.02 (0.07)	-0.01 (0.07)	0.11 (0.16)	0.05 (0.07)
1st Half Profits	0.62* (0.10)	-0.07 (0.22)	0.73 (0.53)	0.38 (0.27)	0.74* (0.31)	0.61** (0.22)	0.21 (0.21)	0.67* (0.30)	0.57* (0.25)	1.10** (0.29)	1.26** (0.29)
2nd Half Profits	0.15 (0.14)	-0.30* (0.16)	0.46 (0.30)	0.16 (0.38)	0.25 (0.35)	0.01 (0.22)	-0.24* (0.14)	1.08 (1.09)	-0.25 (0.21)	-0.21 (0.28)	0.52 (0.44)
% Successful 1st/2nd Half	63** 48	30* 43	54 51	46 46	55 53	65* 46	76** 30	76** 53	68** 41	76** 54	84** 65

Standard errors in parentheses.

* Significant at 10% level.

** Significant at 1% level.

(continued)

Table 9, continued

Statistic	Rank by Early Big Hit Coefficient										
	All Traders	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10
Number of Traders	409	41	41	41	41	41	41	41	41	41	40
1st Half											
Big Hit Coefficient	0.01	-0.85**	-0.53**	-0.32**	-0.16**	-0.04**	0.06**	0.17**	0.34**	0.56**	0.84**
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
2nd Half											
Big Hit Coefficient	-0.06**	-0.13	-0.25**	-0.12	-0.12*	0.08	-0.01	-0.09	0.09	-0.08	0.01
	(0.02)	(0.09)	(0.08)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.08)	(0.08)	(0.09)
Overall											
Big Hit Coefficient	-0.02	-0.40**	-0.30**	-0.17**	-0.09*	0.09*	0.03	0.02	0.16**	0.19**	0.30**
	(0.02)	(0.08)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.04)	(0.05)	(0.06)	(0.09)
Overall Consistent											
Coefficient	0.08**	0.06	-0.10	-0.06	-0.00	-0.11	0.01	0.22*	0.23**	0.29**	0.30**
	(0.03)	(0.09)	(0.08)	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)	(0.09)
1st Half Profits	0.64**	0.90*	0.92*	0.81**	0.09	0.00	0.46**	1.26	0.78**	0.76**	1.50**
	(0.10)	(0.43)	(0.48)	(0.28)	(0.20)	(0.15)	(0.16)	(0.18)	(0.24)	(0.26)	(0.54)
2nd Half Profits	0.04	-0.17	1.10	-0.17	0.27	-0.03	-0.03	0.11	-0.26	-0.36	-0.09
	(0.14)	(0.61)	(1.03)	(0.23)	(0.31)	(0.13)	(0.40)	(0.16)	(0.31)	(0.26)	(0.20)
% Successful 1st/2nd Half	65**	63*	68**	59	54	59**	68*	46*	78**	78*	72**
	47	51	41	51	44	39	51	59	49	37	45

Standard errors in parentheses.

* Significant at 10% level.

** Significant at 1% level.

Table 10

TRADERS WITH OUTLYING EARLY PERIOD FORECASTING COEFFICIENTS

<u>Statistic</u>	<u>1st Half Big Hit Coefficient</u>				<u>1st Half Consistent Coefficient</u>			
	<u>≥ 0.8</u>	<u>≥ 0.9</u>	<u>≤ -0.8</u>	<u>≤ -0.9</u>	<u>≥ 0.8</u>	<u>≥ 0.9</u>	<u>≤ -0.8</u>	<u>≤ -0.9</u>
Number of Traders	25	13	28	16	42	18	20	7
Number with same significance 2nd half	3	2	5	1	6	1	4	1
Number with opposite sign 2nd half	14	5	12	8	14	4	7	2
1st half coefficient	0.90	0.95	-0.91	-0.95	0.90	0.96	-0.89	-0.96
2nd half coefficient	-0.02	0.21	-0.16	-0.06	0.13	0.30*	-0.16	-0.38
Maximum 2nd half coefficient	0.98	0.98	1.00	1.00	1.00	1.00	0.94	0.94
Minimum 2nd half coefficient	-0.99	-0.76	-0.92	-0.91	-0.99	-0.93	-0.94	-0.94

* Significant at 10% level.

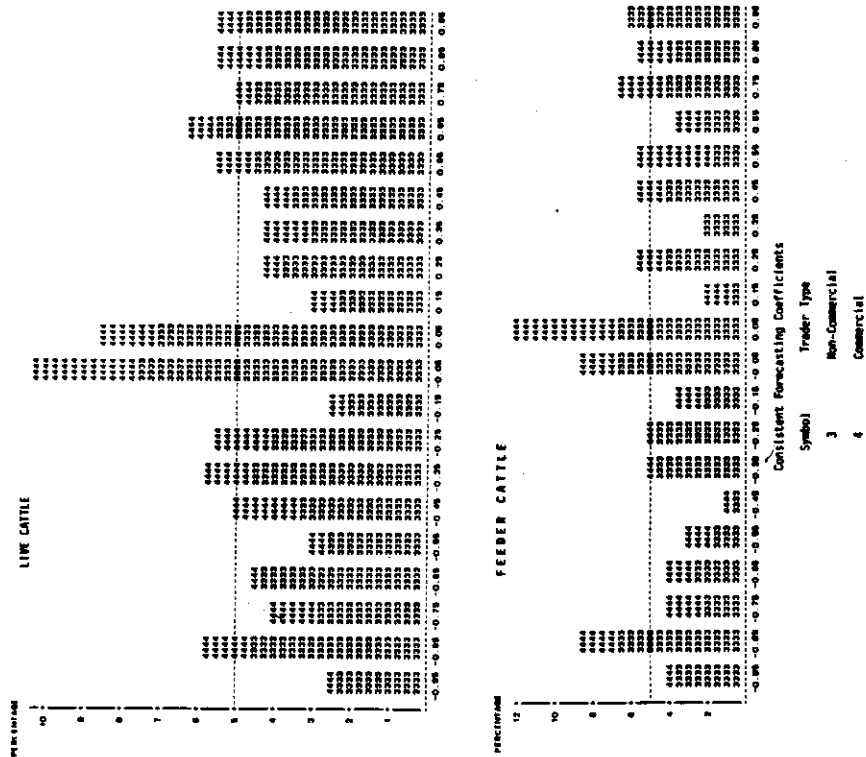
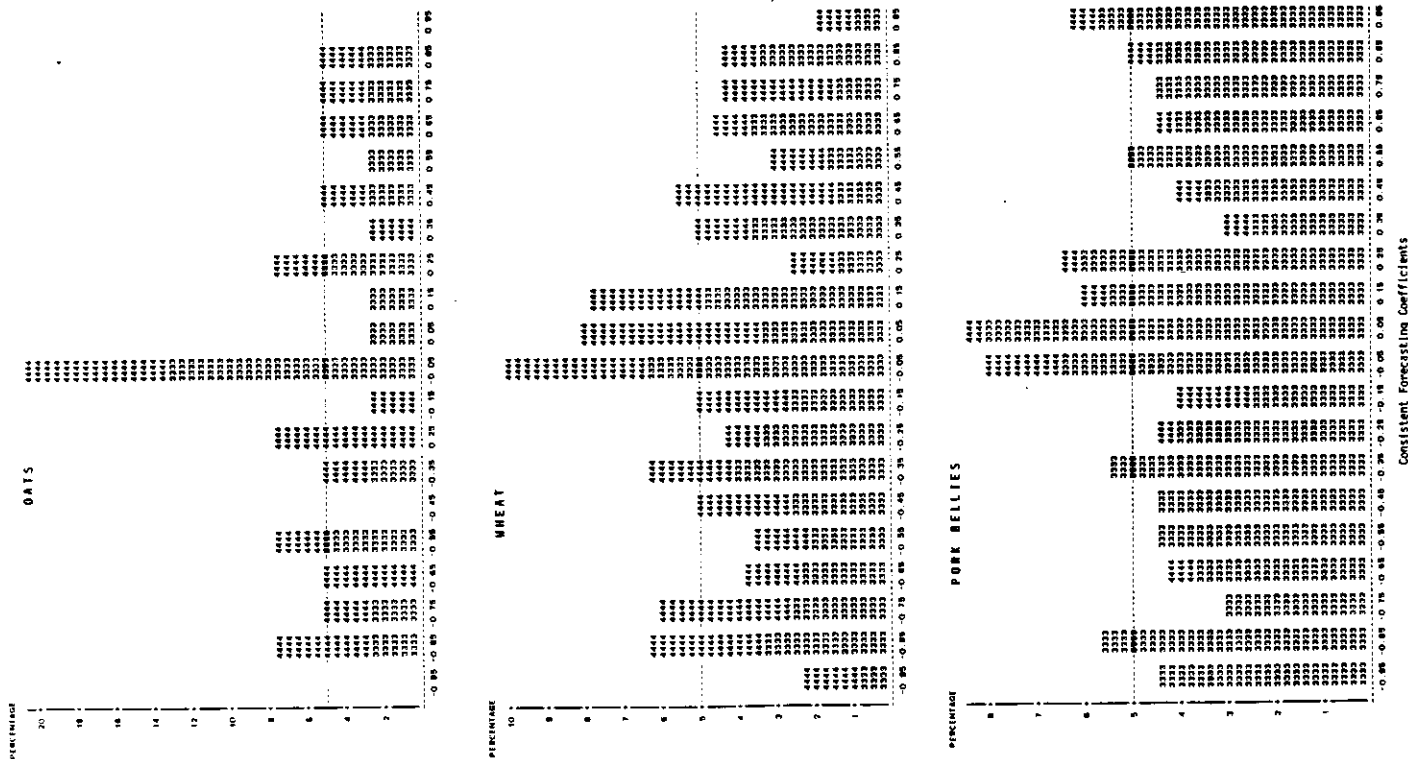


Figure 1 - Percentage Bar Charts
for Consistent Forecasting Coefficients

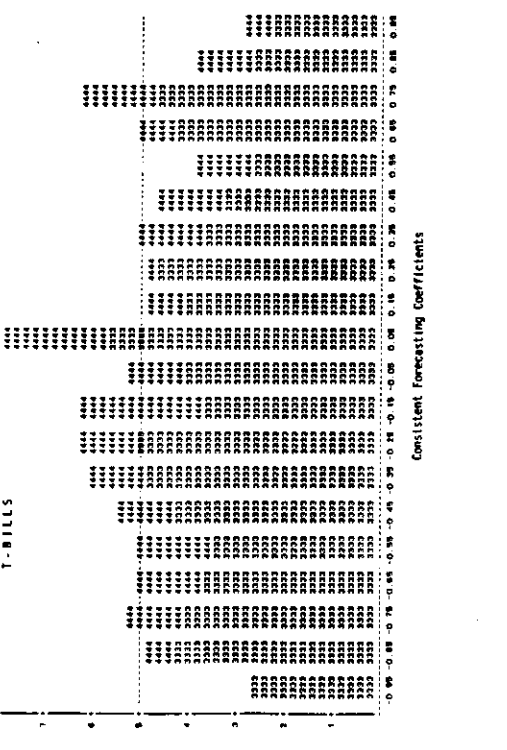
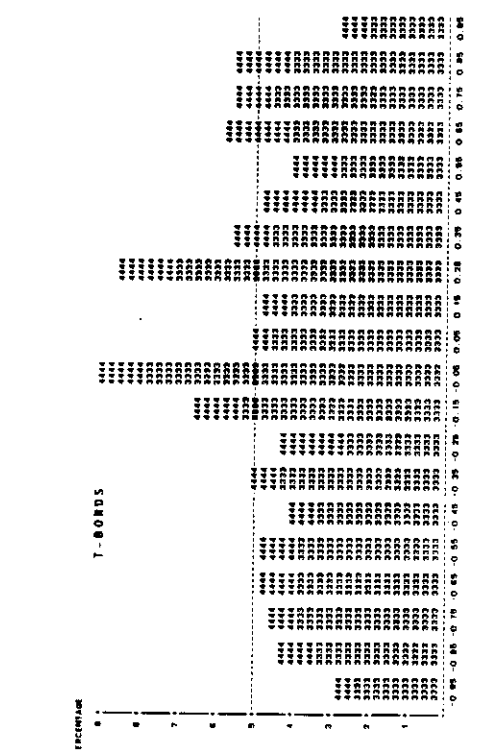
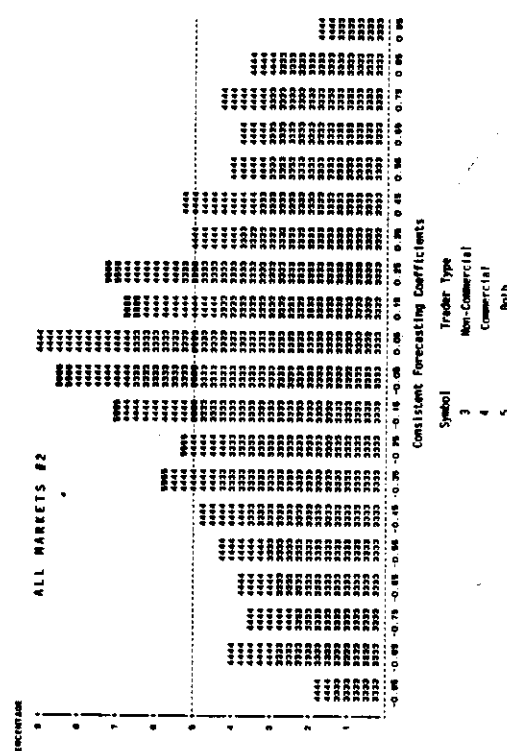
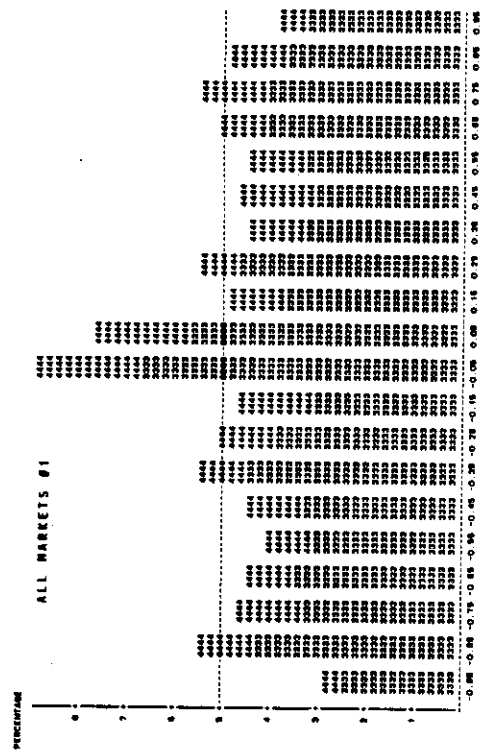


Figure 1 - Continued

Symbol
3
4
5

Trader Type
Non-Commercial
Commercial
Both

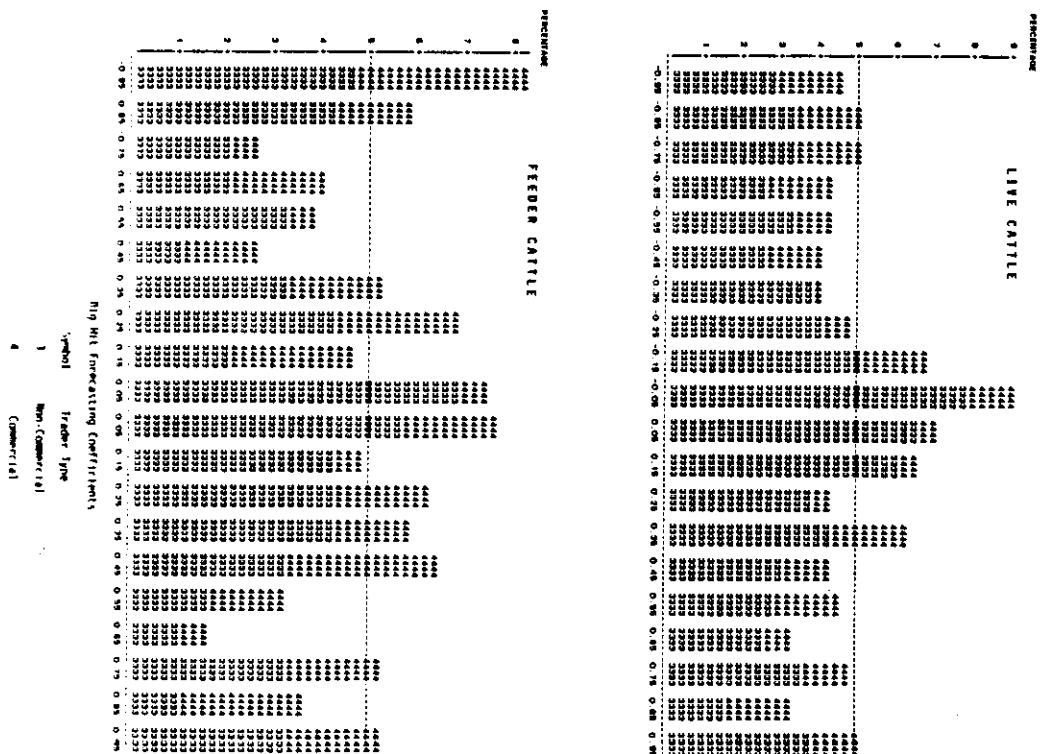
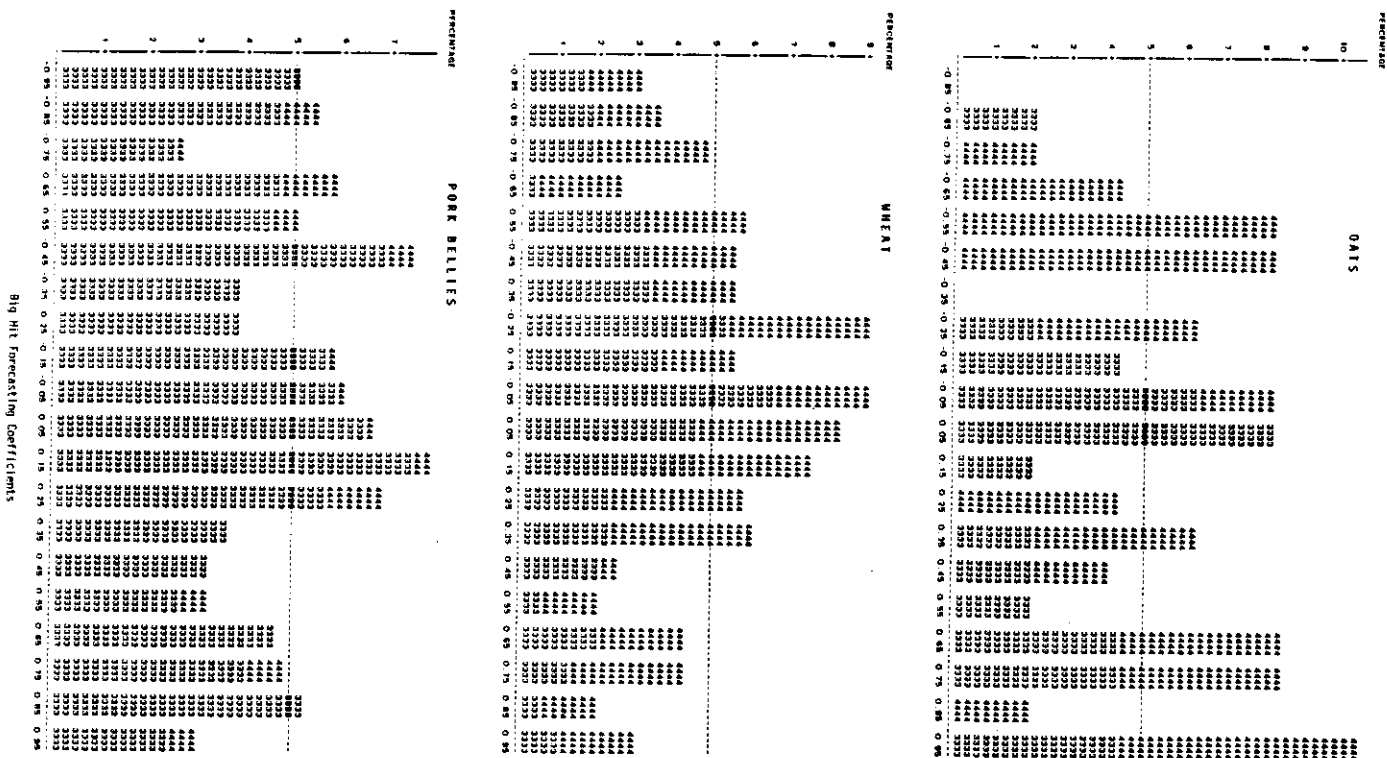


Figure 2 - Continued

