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Luck versus Forecast Ability: Determinants of Trader Performance in Futures Markets*

Statistical techniques are used to demonstrate that the fortunes of individual futures traders are determined by luck, not forecast ability. Even though a large number of traders appear to exhibit significantly superior forecast ability, the investigation strongly supports three conclusions: there are fewer participants with significantly superior skill than expected if participants trade randomly, there are more traders exhibiting no skill than expected if participants trade randomly, and forecast ability is not correlated over time—superior forecasters in the early period are only average forecasters in the later period. Therefore it is luck that determines trader performance.

I. Introduction

The empirical evidence presented in this article lends little support for the hypothesis that futures traders possess the ability or skill to consistently earn positive profits. The statistical analysis utilizes the techniques introduced to study the performance of mutual and commodity futures fund managers (Jensen 1968; Kon and Jen 1978, 1979; Henriksson and Merton 1981; Merton 1981; Chang and Lewellen 1984; Henriksson 1984; Jagannathan and Korajczyk 1986; Cumby and Modest 1987). The most striking difference between this article and the previous studies is in the use of highly detailed daily transactions data on individual investors. On a daily basis the traders' ex ante predictions and ex post realizations are directly observed. Using this information and employing the nonparametric statistical procedures developed by Henriksson and

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Merton (1981, hereafter HM) and modified by Cumby and Modest (1987, hereafter CM), it is possible to determine the actual forecast ability of the individual traders.

Two different types of forecast ability or market timing are examined. The first type is called "consistent ability." A trader possessing this skill performs well because he is able systematically and consistently to predict the correct *direction* of future price movements. In other words, he establishes long (short) positions more often than not prior to an increase (decrease) in the futures price. The other type of forecast skill is called "big hit" ability. A trader possessing this ability is able to predict both the *magnitude* and the *direction* of price changes and will thus establish his largest positions (make his biggest bets) when the highest returns (largest absolute price movements) are anticipated.

II. Description of the Data Base

The data used in this article come directly from the Commodity Futures Trading Commission (CFTC) reports on the end-of-day commitments of large traders. In all futures markets, those traders, who either at the beginning or the end of a trading day hold commitments exceeding certain levels, must (as specified by CFTC regulations) report their trading activity, indicating their speculative and hedge, long and short positions separately for each contract maturity month.

Nine markets are analyzed covering the period from July 1, 1977, to December 31, 1981.[1] Included in this sample of nine markets are the three U.S. wheat markets. In the empirical analysis the positions held by individual traders in these three markets are aggregated.[2] The nine markets 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, and (9) 90-day T-bills traded on the International Monetary Market (IMM).

The motivation for participating in the futures market will likely differ for commercial and noncommercial traders.[3] Therefore, traders are categorized depending on the nature of the positions they report

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

2. This aggregation is appropriate since the contract specifications are all comparable. This is not true for any of the other closely related contracts such as live and feeder cattle.

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

TABLE 1 **Descriptive Statistics on Trader Profits and Average Net Position Values for All Markets Combined (in Millions of Dollars)**

	All Traders	Commercial Traders	Noncommercial Traders
Total	2,229	607	1,622
Position value:			
Mean	−1.04	−7.20**	1.26**
Median	.02	−1.84	.19
Standard deviation	30.43	52.99	14.26
Skewness	−16.82	−11.89	9.09
Kurtosis	440.48	167.08	191.72
Range	1,163.35	1,038.10	460.91
Profits:			
Total	1,046.78	763.40	283.38
Mean	.47**	1.26**	.17**
Median	.02	.01	.02
Standard deviation	6.16	10.93	2.68
Skewness	18.25	11.55	7.28
Kurtosis	541.33	195.37	161.81
Normality test[a]	.32**	.31**	.25**

[a] For the test of normality the Kolomogorov D-statistic is used.
** Significant at a 1% level.

(i.e., hedge versus speculative). Traders reporting only hedge positions over the full 4½-year period 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.[4]

For statistical reasons individual traders making less than 25 separate transactions are not included in the analysis. This results in the exclusion of 2,338 traders who were in Hartzmark (1984, 1987). Even so, the total number of traders analyzed is 2,229. The average number of transactions per trader ranges from 48 in the oats market to 483 in the live cattle market (see table 1).[5]

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

5. Transactions are defined as either purchases or sales. Tests for oats and pork bellies were performed in which an observation for each day the trader was in the market was used, not just observations when a transaction was made (i.e., even days when the change in position was zero were included). The results were similar, except there were many traders who made one or two transactions and simply held onto their position 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 were included in

The average net position value[6] held by commercial traders is substantially larger than the noncommercial position. This might be explained because commercial participants are less constrained by the rules limiting position size. In addition, the commercial traders hedge very large cash positions that have values that are directly related to the level of prices in the futures market. The very largest positions are net short on average, causing the size distribution of the individual positions to be negatively skewed. Commercial traders of interest rate futures hold much larger net positions than traders in the other commodities. As one would expect, a large proportion of the traders in the sample establish relatively small positions.

Hartzmark (1984, 1987) shows that the commercial traders earn the largest dollar profits. The one significant difference in the overall performance of the noncommercial traders examined in this article as compared with the results for the 4,567 traders reported in Hartzmark (1984, 1987) is that the aggregate profits of noncommercial traders are significantly different from zero.[7] In Hartzmark (1987) the returns to noncommercial traders are shown to be insignificantly different from zero. This indicates that the 2,338 traders discarded here are mostly noncommercial traders who earn small negative returns, on average. Therefore, if the selection criteria induces any bias, it is toward rejection of the luck hypothesis since the "noise" traders are removed.

In general, the return distributions in each market and for all markets combined are highly skewed and have large peaks around zero dollars (see table 1). Since the return distribution is a combination of the different position sizes and the price change distribution, a highly skewed return distribution is not evidence of certain traders possessing

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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 about the magnitude by which the price will increase. Conversely, 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.

6. The net position value is simply the dollar value of all long contracts minus the dollar value of all short contracts held by the individual trader on a given day. The average net position value is the average of the net position value for an individual trader over the period he is in the market.

7. 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. 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 equal zero). In addition, the opportunity cost of investing is quite small (Telser 1981; Hartzmark 1986).

skill. For example, in the interest rate markets the commercial traders are net short, on average. Furthermore, the commercial traders with the largest positions (in absolute value) are also net short. If negative price changes are observed (as they were over most of the period), then the returns from a naive strategy of buying a short position and holding it over the period would have offered significant positive profits. Moreover, the returns would be positively skewed since the largest traders in the interest rate markets (who are net short) would be the biggest winners. Noncommercial interest rate traders with their smaller net long positions would have small losses.

Overall, the general direction of the price movements and the varying magnitude of positions held by traders generate the profit distributions. In the following sections an empirical attempt is made to determine whether anything more than "riding the tide" explains the performances of the individual traders.

III. Statistical Methods Employed to Determine Forecast Ability

Testing for Consistent Ability

A statistical procedure introduced by HM and modified by CM is used to test for "consistent" forecast ability. To begin, the number of "correct" forecasts that each individual trader makes is observed. A trader is correct when he is long (short) and the subsequent price movement is up (down). A calculation can then be made of the probability of observing that number of correct predictions assuming forecasts are made randomly. To calculate these probability levels for each trader one needs to observe over the whole period (1) the number of correct predictions that prices fall (i.e., number of times the trader is short and the price goes down); (2) the number of upticks; (3) the number of downticks; and (4) the number of predictions made. With this information, a calculation can be made of the expected number of correct predictions when a trader is short.[8] The predicted and actual numbers of correct predictions are compared to determine if they are statistically different from each other. The magnitude of the difference and the associated significance level will indicate whether the individual trader possesses superior, inferior, or no forecast ability.

The statistical method introduced by CM is used in this article.[9] The binary variable $Z(t)$ will indicate the direction of the *actual* price move-

8. One can do all calculations using the same information and get identical results using the long positions as predictions.

9. The probability of correctly predicting the direction of the price movements is assumed to be independent of the magnitude of the subsequent price movements; therefore, using CM 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.

ment between time t and $t + 1$. The variable $Z(t)$ is equal to one if the price goes up (the dollar return, $R(t)$, is greater than zero), and $Z(t)$ is equal to zero otherwise. The binary variable $U(t)$ indicates the trader's prediction at time t. The variable $U(t)$ is equal to one if the trader takes a long position—indicating that he thinks the price is going up—otherwise, $U(t)$ is equal to zero. 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

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

Given observed positions and price changes, one can test directly whether the trader possesses forecast ability. When $Z(t)$ is independent of $U(t)$, then B equals zero and the trader possesses no forecast ability. If B is significantly greater than zero, the trader possesses superior forecast ability. If B is significantly less than zero, the trader possesses inferior ability.[10]

A logit equation is specified to determine the sign and magnitude of B. Because the standard errors and the degrees of freedom differ dramatically across traders, the relative magnitudes of the parameter estimates and the t-statistics examined alone cannot be used to make inferences about the ability of a single trader. The probability significance level associated with the parameter estimate, B, offers the necessary information to implement the analysis to follow.

Testing for Big Hit Ability

It is likely that a trader does more than simply predict the direction of price movements. He adjusts the magnitude of his position depending on the strength of his conviction. The tests for big hit forecast ability take into account both the magnitude of the trader's net position and the magnitude of the actual price change. Simply because the number of correct predictions an individual trader makes is not above some statistically significant level does not mean that the forecasts are poor. It may be the trader is better able to predict big price changes rather than small changes. To include this additional information the assumption that the magnitude of the price change is independent of the probability of a correct prediction must be relaxed.

To measure big hit ability CM assumes that the magnitude of the price change or dollar return, $R(t)$, depends linearly on the forecast, or, in other words, that the probability of a correct forecast is greater for larger price changes. In this article, because we have even more information than CM, it is assumed that $R(t)$ depends linearly on the net position held by the trader. Big hit ability is indicated if the trader holds

10. The HM test is equivalent to testing whether B is significantly different from zero.

his largest positions when there are the largest price movements in a favorable direction.

Two effects are being combined using this 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 larger the subsequent price change.

Define $LS(t)$ as the net position (long minus short contracts) at time t, such that $LS(t)$ is greater than zero if the trader is net long, and $LS(t)$ is less than zero if the trader is net short.[11] The regression equation combining the two effects is then

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

Testing whether the trader possesses big hit ability is identical to determining whether B' equals zero. If B' is significantly greater than zero, then, as before, the trader possesses superior ability. While if B' is significantly less than zero, the trader exhibits inferior big hit ability.

Deriving Forecast Coefficients from the Regressions

The magnitude of the parameter estimate alone gives little information about whether the individual trader possesses significant forecast ability. For example, observing B_i equal to 0.35 and B_j equal to 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 may also differ dramatically. Term B_i may be significantly different from zero, while B_j is not.

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

$$FC_i = (1 - \text{probability level}_i) \times (\text{sign of parameter estimate}_i).$$

For example, if the probability significance level from the logit or ordinary least squares (OLS) equation is 0.25 and B_i is equal to -0.90, then

$$FC_i = (-1) \times (1 - .25) = -0.75.$$

11. 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 on a spread.

Therefore, the range ($-1.0 <= FC_i <= 1.0$) encompasses the universe of traders: those with statistically significant inferior ability, those with no ability, and those with statistically significant ability.

The Expected Distribution of the Forecast Coefficients

Even in the case when profits are randomly generated one would expect to observe a certain proportion of individuals with forecast coefficients with extreme values (e.g., less than -0.90 or greater than 0.90). Therefore, observing forecast coefficients above 0.90 is not sufficient to indicate that there is significant forecast ability in the market as a whole.[12] Therefore, the null hypothesis to be tested is:

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

If the positive tail of the distribution of the forecast coefficients is fatter than expected, one can conclude that a greater than expected number of traders possess significant forecast 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 is a significant number of inferior forecasters. If both tails are thinner than expected, one of two conclusions can be reached: either (1) the standard errors of the regression parameters are somehow biased upward 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.

IV. Empirical Tests for Forecast Ability

Consistent Forecast Ability

Table 2 presents the descriptive statistics for the distributions of consistent forecast coefficients. The Kolomogorov D-statistic and the chi-square tests are used to determine whether the distributions are uniform.[13] If a trader always positions himself on one side of the market, a consistent forecast coefficient cannot be calculated.[14] Therefore, the number of traders having consistent forecast coefficients differs from the number having big hit coefficients. For example, nine of 48 oat

12. See Denton (1985) for a detailed application of this principle using a fair coin toss game.

13. 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).

14. In this case in which 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.

TABLE 2 Descriptive Statistics: Consistent Forecast Coefficients ($\times 10^{-2}$, except Traders and χ^2)

	Number of Traders	Mean Coefficient	Median Coefficient	Standard Deviation	Skewness	*D*-Statistic	χ^2 Statistic
Oats:							
All traders	39	−3.88	−2.58	51.55	7.62	13.53	1.90
Commercial	20	−10.58	−18.56	53.09	31.78	20.46	1.00
Noncommercial	19	3.17	−.91	50.32	−15.87	14.48	3.89
Wheat:							
All traders	308	−3.70	−.84	51.46	4.22	8.86	49.66**
Commercial	142	−5.31	−.84	52.78	1.71	9.62	34.90*
Noncommercial	166	−2.32	−.87	50.42	7.50	9.42	42.43**
Pork bellies:							
All traders	301	2.62	.66	55.96	−2.35	6.38	22.92
Commercial	26	15.13*	1.13	43.41	32.53	25.58*	17.08**
Noncommercial	275	1.44	.66	56.92	−1.01	5.71	23.84
Live cattle:							
All traders	425	4.45*	.65	55.66	−5.78	7.46*	56.84**
Commercial	82	−.65	−1.06	52.51	10.49	9.27	30.20*
Noncommercial	343	5.67*	.91	56.39	−9.77	8.19*	42.36**
Feeder cattle:							
All traders	151	2.80	.61	57.98	−8.02	7.62	37.48**
Commercial	48	5.32	6.91	55.19	−27.22	12.05	12.83
Noncommercial	103	1.63	−.60	59.47	−32	6.36	32.73*
T-bonds:							
All traders	411	3.18	.58	53.15	−7.25	6.72*	38.20**
Commercial	86	8.29	15.07	55.59	−18.58	8.29	10.28
Noncommercial	325	1.82	.00	52.49	−4.74	6.87*	40.85**
T-bills:							
All traders	354	−2.02	−1.26	53.60	8.49	5.32	20.24
Commercial	83	2.68	−1.12	52.12	9.91	7.68	16.71
Noncommercial	271	−3.46	−2.93	54.06	8.79	5.71	14.39
All markets:							
All traders	1989	1.21	.00	54.30	−.89	4.38**	122.85**
Commercial	487	1.16	−.64	52.99	−1.26	5.85*	51.36**
Noncommercial	1502	1.22	.00	54.74	−.78	4.34**	94.91**

* Significant at a 10% level.
** Significant at a 1% level.

traders have 25 or more transactions but hold net positions only on one side of the market. Comparing the "All Markets" category in tables 1 and 2 indicates that 240 traders take positions on one side only.

Across the markets the means of the forecast coefficients are almost always indistinguishably different from zero. Only the commercial traders of pork bellies show significant, positive forecast ability, on average. Given the selection procedures used to develop this sample, it is not necessary for the mean forecast coefficient to be zero. Many market participants are not included (i.e., scalpers and small traders).[15] If the large reporting traders represent an elite subset of successful survivors in the market, then one would expect a positive mean forecast coefficient. Alternatively, the large degree of turnover in these markets could explain negative average forecast coefficients. With constant exit and entry of traders possessing poor forecast ability (but who establish large positions and make at least 25 transactions), one would expect the mean forecast coefficient to be negative. If the mean coefficient is significantly positive or negative, the null hypothesis is rejected since implicit in each result is that traders have differing skills.

With the exception of the "All Markets" distribution (which is symmetric) the distributions are almost all negatively skewed. None of the observed standard deviations are significantly different from those expected from a uniform distribution spanning an interval from -1.0 to 1.0.[16]

The D-statistics indicate that uniformity is rejected in only one of seven markets for commercial traders and in only two of seven markets for noncommercial traders. The fact that uniformity is accepted in the individual markets and rejected for all markets combined is likely the result of the increased sample size and thus the increased precision of the test.

Figure 1 offers a clear illustration of why uniformity is rejected for "All Markets." The bars in this chart 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 in each interval if skill is uniformly distributed.

Uniformity is not rejected because there are more outliers than expected. On the contrary, it results because there are more traders with forecast coefficients close to zero than expected. The "All Markets" chart indicates that, if anything, there are more poor forecasters than

15. In most markets the combined holdings of the sample traders total more than 50% of the open interest.

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

expected. But again, it is the central portion that dominates. Only in pork bellies, live cattle, and feeder cattle are there more coefficients above 90% than expected from chance. In none of the individual markets does one observe more coefficients below negative 90% than would emerge from a random draw.

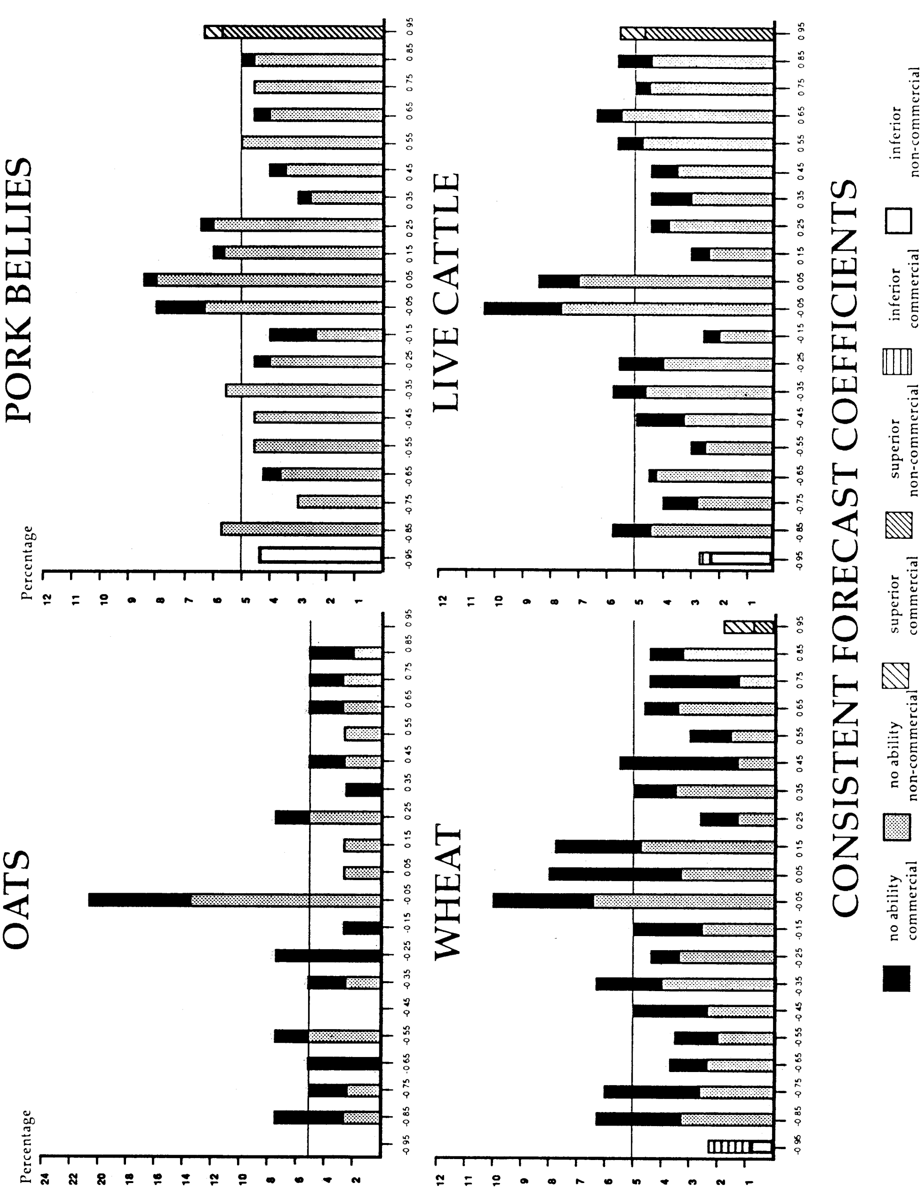
In general, examination of the *individual* markets shows that the forecast coefficients are randomly distributed. Therefore, the null hypothesis is supported. When all markets are combined, forecast ability appears nonrandom because of dependence among traders. If a substantial proportion of the traders in these markets 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.

Why traders with apparently 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 related markets. Therefore, the traders look like poor forecasters in a one-dimensional sense since they are losing money in the futures market. However, in a multidimensional approach, since there is a trade-off between profits and risks, the traders are actually increasing their expected utilities. If this is the case, one would expect to observe a significant difference between the performance of commercial and noncommercial traders. The commercial traders are more likely to use these markets to hedge their cash market price risks. They can "afford" to look like bad forecasters in the futures market since they will have the opposite performance 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 directly to reduce their price risks. Most academic studies have demonstrated that futures markets do not reduce systematic price risks (Dusak 1973; Bodie and Rosansky 1980; Baxter, Conine, and Tamarkin 1985; 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 forecast skill. The risk hypothesis as an explanation for the observed distributions forecast coefficients is not supported.

Big Hit Ability

To calculate the big hit forecast coefficients, all of the available information on individual positions and market price movements is used. The regression of the magnitude of the price change between time t and $t + 1$ on the size of the position at time t, indicates whether the


OATS
PORK BELLIES
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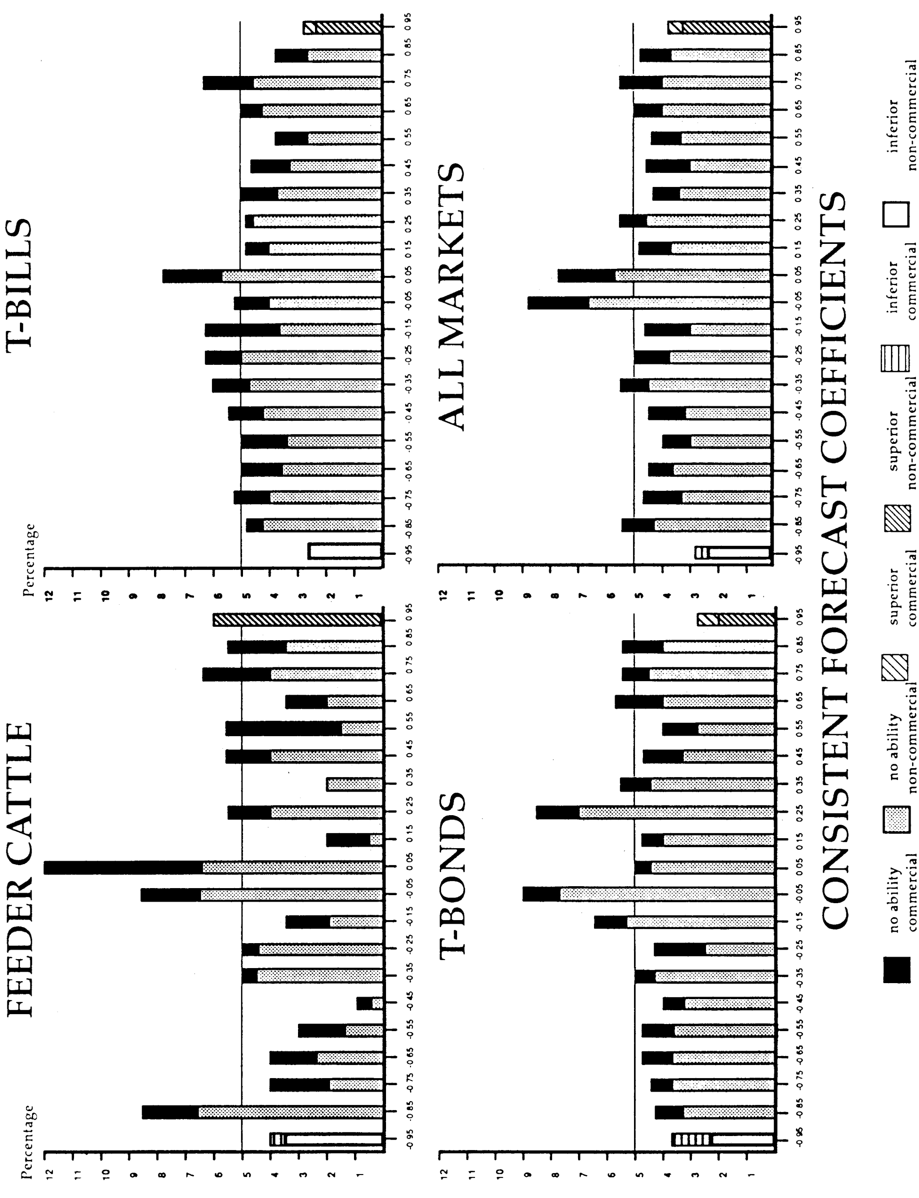


FIG. 1.—Consistent forecast coefficients

individual trader makes his biggest bets when he expects the largest price changes.[17]

The results of the big hit regressions are presented in table 3. One major difference between these and the consistent forecast coefficients is that three of the markets have significant negative mean coefficients for noncommercial traders. The mean coefficient for the noncommercial traders in "All Markets" is also negative and significant. Except for the oat market, all the signs on the means of the noncommercial distributions are negative.

In almost all of the markets the big hit distributions are positively skewed. The standard deviations are those expected from a uniform distribution. The *D*-statistics for the big hit forecast coefficients are similar to those for the consistent forecast coefficient distributions. One major difference is that the distributions for commercial traders are all uniformly distributed. 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" are shown. In the T-bond and feeder cattle markets there are more traders with forecast coefficients less than negative 90% than expected. In the interest rate markets it is interesting to note that there is a reduction of traders with superior big hit coefficients when compared to the consistent coefficients. This is somewhat surprising given the massive profits earned by the traders in these markets. However, given the observed large downward price trends over the period analyzed, it did not take a genius to earn large profits.

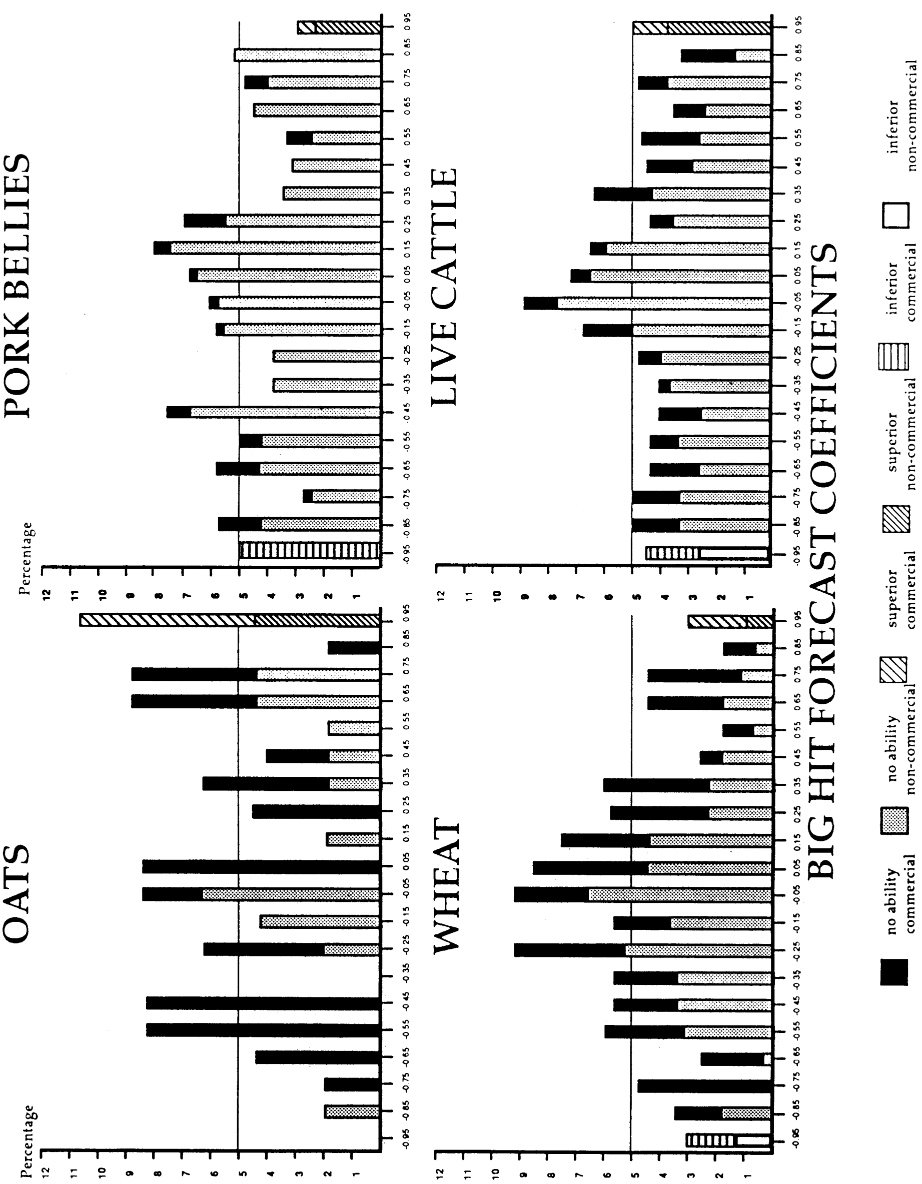
In the oats market, there are a large number of traders with big hit coefficients greater than 90% and the mean is positive and significant. This is in contrast to the consistent forecast results where no oats traders have coefficients greater than 90%. There are certain commercial traders who take their largest positions immediately prior to the biggest price moves. This may be the result of their possessing inside

17. An adjustment for heteroscedasticity is made to account for expected differences in the variance of the price changes over different time intervals. 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 trader's transactions, the square root of the number of days between each transaction is used as a weight in the adjustment procedure. There 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, few traders participate for long enough intervals for this type of heteroscedasticity to be a problem.

TABLE 3 Descriptive Statistics: Big Hit Forecast Coefficients ($\times 10^{-2}$, except Traders and χ^2)

	Number of Traders	Mean Coefficient	Median Coefficient	Standard Deviation	Skewness	*D*-Statistic	χ^2 Statistic
Oats:							
All traders	48	14.14*	7.91	54.72	−3.01	10.29	5.96
Commercial	27	6.81	−1.39	60.93	20.71	11.18	9.85*
Noncommercial	21	23.56*	7.98	45.22	−23.31	29.69*	14.00**
Wheat:							
All traders	341	−4.37*	−5.50	48.97	12.77	12.05**	63.52**
Commercial	168	−1.03	.97	53.74	6.50	8.17	20.33
Noncommercial	173	−7.62	−6.03	43.75	12.45	18.09**	69.89**
Pork bellies:							
All traders	342	−2.89	−.95	55.17	6.48	7.68*	30.28*
Commercial	28	−4.63	−2.34	59.52	22.94	13.55	1.64
Noncommercial	314	−2.73	−.95	54.86	4.94	7.59*	28.29**
Live cattle:							
All traders	483	−.95	−1.50	54.59	2.06	5.48	36.54**
Commercial	121	−2.58	−9.03	62.63	3.03	9.24	22.31
Noncommercial	362	−.41	−.32	51.71	2.92	8.08	55.24**
Feeder cattle:							
All traders	193	−3.28	−.69	56.96	−.73	6.99	24.10
Commercial	69	.28	.27	61.18	−3.62	5.52	6.22
Noncommercial	124	−5.25	−1.10	54.62	−1.26	10.89	27.61*
T-bonds:							
All traders	439	−2.48	−.78	51.25	−.27	10.21**	57.54**
Commercial	96	1.80	−.64	52.96	10.29	8.89	13.37
Noncommercial	343	−3.68	−1.09	50.78	−4.13	11.55**	57.06**
T-bills:							
All traders	383	−8.31**	−7.11	50.09	10.92	13.85**	63.42**
Commercial	98	−6.63	−8.28	53.76	12.67	9.63	17.51*
Noncommercial	285	−8.88**	−5.94	48.86	9.45	16.22**	62.30**
All markets:							
All traders	2,229	−3.21	−2.87	52.71	5.57	8.22**	171.44**
Commercial	607	−1.46	−3.91	56.76	7.03	3.92	16.29
Noncommercial	1,622	−3.87**	−2.66	51.11	3.91	10.13**	211.14**

* Significant at a 10% level.
** Significant at a 1% level.


OATS
PORK BELLIES
WHEAT
LIVE CATTLE
Percentage
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no ability commercial
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inferior commercial
inferior non-commercial

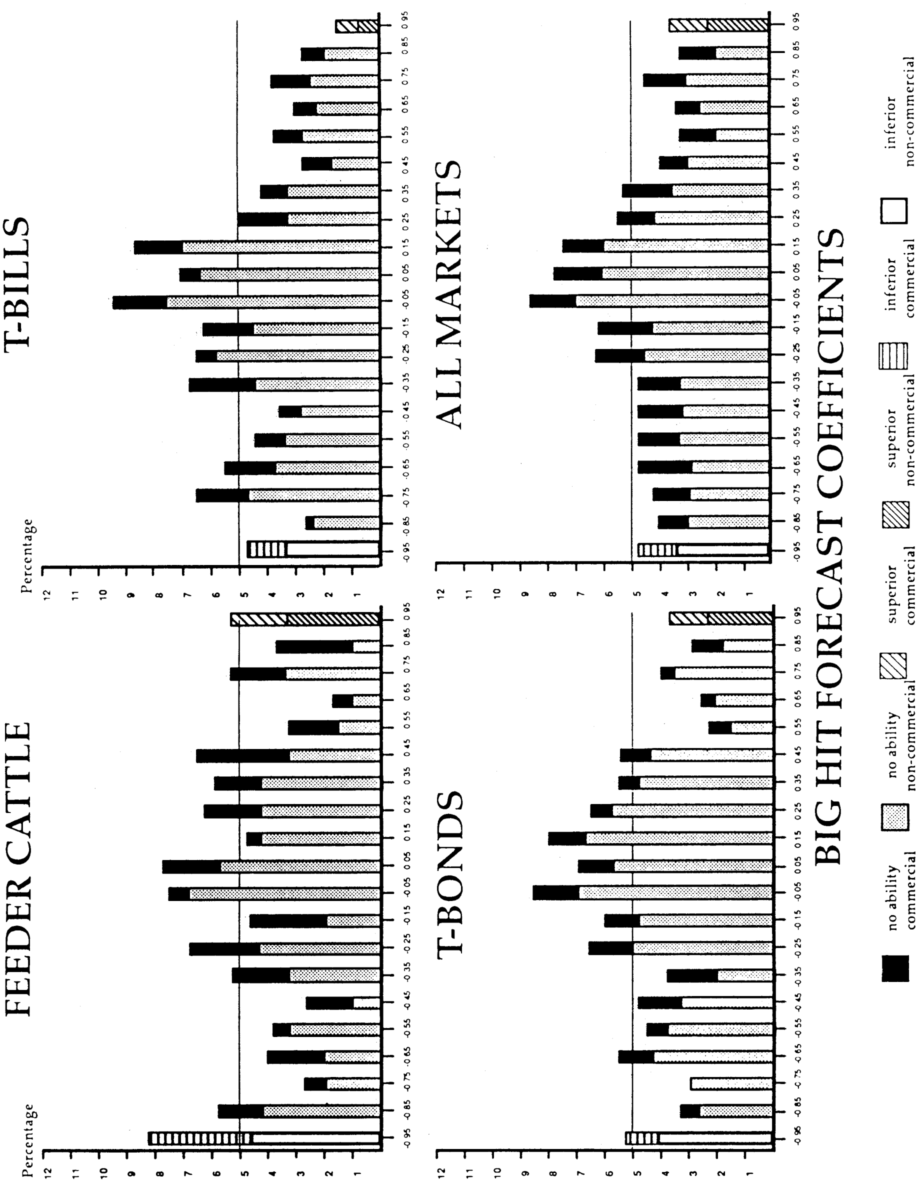

FIG. 2.—Big hit forecast coefficients

information or their hands-on grasp of the elements that drive the oat market. This is also consistent with selective hedging operations. Commercial traders may be hedging and consistently taking small losses on their futures positions (thus their negative consistent forecast coefficients). However, when they expect a major price move, they speculate in a big way by adjusting their position sizes accordingly.

Overall, figures 1 and 2 describe similar relationships between profit and performance. Coefficients bunching around zero result in the rejection of uniformity. If this bunching is due to a statistical anomaly, such as heteroscedasticity, one would expect that the bias would have its greatest impact on the big hit results where nonstationarity in price changes can have adverse effects on the efficiency of the big hit parameter estimates. However, this is not the case, and statistical anomalies do not appear to drive the results. There must be dependence across traders.

V. Ex Ante Tests of Forecast Ability

Do the traders who display superior (or inferior) forecast ability in an early period continue to demonstrate it in a later period? A significant positive relationship between performance in the two periods supports the skill hypothesis.

To analyze this intertemporal relationship, traders with at least 25 transactions in both an early and a later period are used. The early period extends from January 1, 1977, to September 30, 1979. The later period covers October 1, 1979–December 31, 1981.

Since the commercial traders are mostly hedging (by definition), it is unclear how to interpret the "life-cycle" results for the commercial group.[18] In the previous section this group was analyzed to serve as a benchmark with which to compare the performances of noncommercial traders. Since the results in the early period can now be used as the benchmark, I focus only on the performance of noncommercial traders.

Correlation Statistics

In table 4 three variables are correlated for each market to determine 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.

The correlations between dollar returns earned in the two periods are significant when all traders are pooled. For the individual markets the most puzzling result is in the live cattle market where the correla-

18. In an early period a commercial trader may perform well in the futures market and poorly in the cash market. In the later period he may have the opposite results. However, the trader may have met his goals in each period.

TABLE 4 Correlation Statistics across Periods

	All Traders			Noncommercial Traders		
	Return	Consistent	Big Hit	Return	Consistent	Big Hit
Oats	.89*	.01	.01	−.76*	.10	−.06
	26	18	26	9	9	9
Wheat	.23**	.23**	.01	−.18	.39**	.29*
	161	131	161	60	58	60
Pork bellies	.68**	.16	.22*	.15	.16	.26**
	117	99	117	103	88	103
Live cattle	−.58**	.04	−.10	−.05	.04	−.06
	151	126	151	104	96	104
Feeder cattle	.05	.16	.17	−.44*	.21	.18
	50	39	50	27	22	27
T-bonds	.08	−.06	−.13	.06	−.02	−.04
	72	64	72	47	42	47
T-bills	.33**	−.00	.13	.85**	.04	.13
	87	82	87	59	57	59
All markets	−.01	.10	.04	.20**	.12*	.12**
	664	559	664	409	372	409

NOTE.—The number of observations is below the correlation coefficient. Early period is July 1977–September 1979. Late period is October 1979–December 1981. Oats periods are January 1978–June 1979 and July 1979–December 1980.
* Significant at a 10% level.
** Significant at a 1% level.

tion is significant but negative.[19] For the noncommercial traders alone there are positive significant correlations only in the T-bill market and for all markets combined. In two markets the correlations are negative and significant. In general, for the noncommercial traders, it does not appear as if dollar performance in one period is positively related to dollar performance in the other period.

As for the forecast coefficients, there does not appear to be any strong correspondence between a trader's observed abilities in the first and second periods. For the noncommercial traders in the wheat markets there are some small significant correlations. In addition, there are significant correlations when all markets are pooled. Even so, these few significant correlations are quite low. Overall, the correlations provide little evidence in support of the skill hypothesis.

Traders Broken Down by Decile of Early Period Forecast Ability

In table 5 the individual early period forecast coefficients are divided up into deciles depending on their relative magnitudes.[20] For each

19. All types of questions have been asked about activity in the live cattle 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 one where prices trend upward, while in the later period the trend is slightly downward or flat.

20. Deciles for individual markets were also examined. The results were similar. In addition to the statistics presented in tables 5 and 6, average duration, size, and serial correlation measures were calculated. There are no significant differences in any of these

decile, the means of variables describing performance in the later period are calculated. Overall, traders participating during both periods have slightly positive and significant means of early period consistent forecast coefficients. One might expect traders remaining in the market for a second period would have done better than average in the first period, whether positive forecast coefficients are the result of skill or luck. Interestingly, this is not true for the big hitters where the early period mean forecast coefficient is not different from zero (see table 6). Overall, the second-half consistent forecast coefficient is zero, while the big hit average is negative.

Scanning across deciles it is clear that forecast ability regresses toward zero. Traders exhibiting superior skill in the first half appear to have average (or no) skill in the second half. Traders with inferior skill in the first half improve slightly in the second half.

Only for the traders in the top decile of the consistent forecast coefficients is there some weak evidence supporting the skill hypothesis. This decile is composed of traders who almost all have early period coefficients significantly different from zero at the 10% level. In the second half the significance levels fall, on average, but still remain slightly above the average for the group as a whole.

Other second-period measures of performance are less supportive for the group in the top decile of traders with early period superior consistent forecast ability. In the first half, 84% of these traders earn positive dollar profits (i.e., are successful). In the second half, this percentage falls significantly, to 65%. In fact, for the deciles where the early period consistent forecast coefficients are positive (i.e., deciles 5–10), the percentage of late period winners is always significantly below the percentage of early period winners. Furthermore, except for decile 6, the second-half percentages are all indistinguishably different from 50%. This is exactly what would be expected from random trading. Only in the bottom decile does this percentage increase significantly. The percentages of winners in the second half fall and approach 50% in the big hit forecast coefficients deciles 5–10 as well. This again is strong evidence supporting a regression to the mean or luck hypothesis.

The mean dollar profits earned in the first half by all the traders who remain in the market during the second period are significantly different from zero. This probably explains what induces the traders to remain in the market during the second period. However, in the second period the mean dollar profits are not different from zero. Scanning the

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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 averaged about -0.25. This suggests that current performance is negatively related to the past record.

TABLE 5 **Descriptive Statistics by Deciles of Early Period Forecast Coefficients, Rank by Early Consistent Coefficient (Profits in Millions of Dollars)**

Statistic	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
Consistent coefficient:											
First half	.10**	−.82**	−.59**	−.33**	−.14**	.03**	.19**	.38**	.58**	.76**	.91**
	(.03)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.10)
Second half	−.02	−.07	.05	−.18*	−.07	−.10	−.09	.00	.01	.10	.18*
	(.03)	(.09)	(.11)	(.08)	(.09)	(.09)	(.09)	(.10)	(.09)	(.10)	(.09)
Overall	.09**	−.57**	−.28**	−.28**	−.02	.01	.04	.26**	.36**	.57**	.79**
	(.03)	(.07)	(.08)	(.07)	(.08)	(.09)	(.07)	(.08)	(.08)	(.08)	(.05)
Overall big hit coefficient	−.04*	−.01	−.12	−.10	−.09	−.09	−.14*	.02	−.01	.11	.05
	(.02)	(.05)	(.08)	(.06)	(.06)	(.06)	(.06)	(.07)	(.07)	(.16)	(.07)
Profits:											
First half	.62*	−.07	.73	.38	.74*	.61**	.21	.67*	.57*	1.10**	1.26**
	(.10)	(.22)	(.53)	(.27)	(.31)	(.22)	(.21)	(.30)	(.25)	(.29)	(.29)
Second half	.15	−.30*	.46	.16	.25	.01	−.24*	1.08	−.25	−.21	.52
	(.14)	(.16)	(.30)	(.38)	(.35)	(.22)	(.14)	(1.09)	(.21)	(.28)	(.44)
% successful:											
First half	63**	30*	54	46	55	65*	76**	76**	68**	76**	84**
Second half	48	43	51	46	53	46	30	53	41	54	65

Note.—Standard errors are in parentheses.
* Significant at a 10% level.
** Significant at a 1% level.

TABLE 6 **Descriptive Statistics by Deciles of Early Period Forecast Coefficients, Rank by Early Big Hit Coefficient (Profits in Millions of Dollars)**

Statistic	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
Big hit coefficient:											
First half	.01	−.85**	−.53**	−.32**	−.16**	−.04**	.06**	.17**	.34**	.56**	.84**
	(.02)	(.02)	(.01)	(.01)	(.01)	(.00)	(.00)	(.01)	(.01)	(.01)	(.01)
Second half	.06**	−.13	−.25**	−.12	−.12*	.08	−.01	−.09	.09	−.08	.01
	(.02)	(.09)	(.08)	(.07)	(.07)	(.07)	(.08)	(.07)	(.08)	(.08)	(.09)
Overall	−.02	−.40**	−.30**	−.17**	−.09*	.09*	.03	.02	.16**	.19**	.30**
	(.02)	(.08)	(.06)	(.06)	(.05)	(.05)	(.06)	(.04)	(.05)	(.06)	(.09)
Overall consistent coefficient	.08**	.06	−.10	−.06	−.00	−.11	.01	.22*	.23**	.29**	.30**
	(.03)	(.09)	(.08)	(.09)	(.10)	(.10)	(.10)	(.10)	(.09)	(.09)	(.09)
Profits:											
First half	.64**	.90*	.92*	.81**	.09	.00	.46**	1.26*	.78**	.76**	1.50**
	(.10)	(.43)	(.48)	(.28)	(.20)	(.15)	(.16)	(.18)	(.24)	(.26)	(.54)
Second half	.04	.17	1.10	−.17	.27	−.03	−.03	.11	−.26	−.36	−.09
	(.14)	(.16)	(1.03)	(.23)	(.31)	(.13)	(.40)	(.16)	(.31)	(.26)	(.20)
% successful:											
First half	65**	63*	68**	59	54	59**	68*	46*	78**	78*	72**
Second half	47	51	41	51	44	29	51	59	49	37	45

Note.—Standard errors are in parentheses.
* Significant at a 10% level.
** Significant at a 1% level.

TABLE 7 Traders with Outlying Early Period Forecasting Coefficients

	First-Half Big Hit Coefficient				First-Half Consistent Coefficient			
Statistic	≥.8	≥.9	≤−.8	≤−.9	≥.8	≥.9	≤−.8	≤−.9
Number of traders	25	13	28	16	42	18	20	7
Number with same significance second half	3	2	5	1	6	1	4	1
Number with opposite sign second half	14	5	12	8	14	4	7	2
First-half coefficient	.90	.95	−.91	−.95	.90	.96	−.89	−.96
Second-half coefficient	−.02	.21	−.16	−.06	.13	.30*	−.16	−.38
Maximum second-half coefficient	.98	.98	1.00	1.00	1.00	1.00	.94	.94
Minimum second-half coefficient	−.99	−.76	−.92	−.91	−.99	−.93	−.94	−.94

* Significant at the 10% level.

big hit forecast coefficient deciles, one observes a dramatic decrease in profits during the second period 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.

Summarizing, the second-half performances of the traders with the lowest and highest early period big hit coefficients are indistinguishable. This is not quite true when the early period consistent forecast coefficients are ordered. In this case, the second-half coefficients, profits, and percentage of successful traders are all greater for the most successful early period forecasters than those for the other deciles.

Examination of the Early Period Outliers

It may be the case that only a small number of traders make up an elite subset of superior forecasters. Most traders may have no significant forecast ability, with only a few outliers consistently exhibiting skill. The traders with big hit and consistent early period forecast coefficients greater than 0.8 (in absolute value) are examined in detail in table 7.

There are 25 traders with early period big hit coefficients greater than 0.8.[21] If second-period forecast coefficients are determined by luck,

21. This is slightly less than one would expect from chance given that there are 409 traders who participate in both periods, and 10% of these (or 41 traders) should be in the interval from 0.8 to 1.0.

then 10% 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% 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 forecast coefficients should be symmetrically distributed and insignificantly different from zero (which they are). Overall, table 7 shows for the early period big hit outliers that the later period forecast coefficients look like they are generated by a stochastic process.

The same cannot be said unequivocally about the traders with outlying consistent coefficients. The number of outlying traders with the opposite sign in the second period is smaller than expected. At the same time it is not far enough away from the level expected by chance to offer strong evidence supporting the skill hypothesis. The mean second-period consistent coefficient for the 0.9 outliers is positive and significant. This corresponds with the results for decile 10 in table 5 but is still only weak support for the skill hypothesis.

VI. Conclusion

The empirical evidence presented in this article strongly supports the contention that the returns to traders of futures are randomly generated. The support for the luck hypothesis comes from two sources: (1) the observed distributions of forecast coefficients that are either uniform or peaked at zero; and (2) the fact that the abilities in the first period of both the superior and inferior traders regress toward the mean in the second period.

There are two questions emerging from the analysis presented here. 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. Second, it is not clear why these large reporting traders, a subset of all participants, earn significant positive returns. If the performances of all traders, whether large or small, are due to luck, one would not expect the large traders to consistently 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 little support for the hypothesis that futures traders holding large positions possess the ability to consistently earn profits. It does appear that commercial traders show slightly better forecast ability than noncommercial traders. These commercial participants are the traders with access to the most timely information that they may be able to profit from. This is dramatically displayed in the oats market, where commercial traders do not possess significant consistent forecast 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 forecast ability than expected. In the intertemporal analysis, there is some weak support for the skill hypothesis when observing the results of the very few superior outliers with consistent forecast ability. 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.

What motivates new traders to continually enter these markets and old traders to remain? A sophisticated investment strategy that results in persistent losses in one financial market? An "irrational" belief that they possess superior skill? The desire to gamble on their beliefs and the consumption they derive from the activity? These are important questions, the answers to which will provide insight in to the overall performance of futures markets.

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