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Returns to Individual Traders in Agricultural Futures Markets: Skill or Luck?

by

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Abstract

Using individual trader data from the CFTC reporting system for the period January 2000 to September 2009, the paper investigates whether non-commercial traders in the corn, live cattle, and coffee futures markets persist in making profits. Two out-of-sample measures of skill—the Fisher Exact ranking test and a test to assess significant differences in the magnitude of profits of the top and bottom traders—are used to analyze trader’s ability to consistently perform well for monthly, quarterly, and annual time horizons. The findings identify significant persistence in rankings—traders in the top half of the profit distribution in a time period tend to stay in the top half in the next period. Differences in magnitude of profitability between the top and bottom deciles also provide support that persistent skill exists among the top 10% of traders. Detailed examination of annual rankings for those traders who were most continuously in the markets further reveals persistence in profits for a smaller subset of traders, and some indication of persistence in the face of losses.

Keywords: commodities, futures markets, non-commercial traders, persistence, profit

Introduction

The persistence of trading performance by futures market speculators is important to both investors and theories of futures markets. The basic question is: Does past market performance predict future performance? Mahani and Bernhardt (2007) provide an informative rational model of trader behavior that explains previous empirical regularities in speculative performance, and is compatible with the notion that more experienced, larger speculators perform consistently well. Key to their explanation of persistence is learning and self-selection by those futures traders who are adept at identifying profitable opportunities.

Investigations of trader behavior in futures markets focus on whether traders earn profits and the degree to which profits are explained by the existence of a risk premium, skill, or just plain luck. The risk premium or normal backwardation theory predicts that speculators receive positive returns as compensation for risk while hedgers lose in futures market by the amount of the risk premium. Numerous studies have tested this notion in the past (e.g., Dusak 1973, Hartzmark 1987, Kolb 1992), and with few exceptions there is limited evidence to support the existence of a risk premium. In the absence of a risk premium, individual trading profits stem from significant skill or possibly luck.

The three most relevant studies addressing individual trader skill in agricultural futures markets are Hartzmark (1991), Leuthold et al. (1994), and Fische and Smith (2010), each of which used data from the Commodity Futures Trading Commission’s (CFTC) Large Trader Reporting System (LTRS). Results from these studies are mixed. Hartzmark (1991) finds returns for large traders are generated randomly after conducting a battery of tests. Leuthold et al. (1994) report that the distribution of returns over time is not random and an elite subset of traders make significantly positive profits from forecasting skill. Fische and Smith (2010) also find a small

subset of traders has skill in determining the next day's price and a subset of traders are skilled intra-day.

While informative, these studies also have significant limitations. Hartzmark's (1991) sample is limited to five years and the data reflect a different market era (1977-1981). Leuthold et al. (1994) investigate one commodity and restrict the analysis to the 50 largest traders and 20 largest spreaders. Fishe and Smith (2010) have a large sample, 10 years and 12 commodities, but do not consider investment horizons of more than one day and provide no information on the magnitude of profits generated or traders excluded from the analysis. Finally, prior studies have focused on *in-sample* estimates of the correlation in performance measures, rather than *out-of-sample* estimates that are the standard in investment studies (e.g., Malkiel 1995). An out-of-sample measure is a more stringent test of the persistence of trader profits in agricultural futures markets.

In this research, we assess whether non-commercial traders in the corn, live cattle, and coffee futures markets display persistent profit-making ability over the January 2000 through September 2009 period. Two out-of-sample tests of persistent profit-making ability are used in the analysis. The Fisher Exact ranking test assesses in a non-parametric context whether traders in the top half of the profits distribution in a time period continue in the top half of the distribution in the next period. The second test is a paired *t*-test of the difference in the magnitude of profits between top versus bottom decile performing traders across adjoining periods. Both tests have been widely applied in studies of investment performance and have the advantage of using information on the ranking and magnitude of trader profits. Traders in each commodity are tested based on profit levels over monthly, quarterly, and annual time horizons.

The individual trader data is drawn from the CFTC LTRS, which consists of non-public end-of-day position data that is disaggregated by futures contract maturity. We focus on non-commercial traders, commonly referred to as speculators. This avoids potential problems associated with the use of commercial trader data. It is well-known that commercial traders (hedgers) have both cash and futures market positions and without knowledge of profits and losses in both markets it is not possible to reach definitive conclusions about their overall trading profitability. The number of unique non-commercial traders in these markets is 3,556 for corn, 1,551 for live cattle, and 2,677 for coffee.

Prior research has focused on short-term performance. Since most traders included in the database are not day traders or high frequency traders their strategies may extend beyond the daily horizon used by Leuthold et al. (1994) and Fishe and Smith (2010). As a result, we test for persistence using monthly, quarterly, and annual horizons. Arguably, the annual horizon is the most important from a standpoint of reporting and compensation, e.g. annual investment performance reports and year-end bonuses. The monthly and quarterly horizons are studied to include a larger percentage of traders and determine whether traders demonstrate skill in the shorter time horizons within a year. The quarterly and monthly time periods can also be viewed as an indication of shorter-term risk in the market.

Since not every trader is continuously active in the market, some traders are excluded in parts of the analysis. The systematic exclusion of traders could result in a sample selection bias, which makes analysis of excluded trader properties important. For this reason, summary statistics and

discussion of the excluded traders are provided. Finally, a detailed examination of annual rankings for those traders who are most continuously in the markets is undertaken. The analysis provides an opportunity to consider the consistent profit-making ability of individual traders most actively trading.

The findings across commodities and time horizons identify significant persistence in rankings—traders in the top half of the profits distribution in a time period tend to stay in top half in the next period. Differences in magnitude of profitability between the top and bottom deciles also provide support that persistent profit-making ability exists among the top decile of traders. The results for shorter time horizons are stronger for corn than for live cattle and coffee, and are likely influenced by a high degree of volatility over shorter time periods where trader's fortunes are expected to fluctuate. Detailed examination of annual rankings of those traders who were most continuously in the markets further reveals persistence in profits for a smaller subset of traders, but also some indication of persistence in the face of losses.

Data

The data are drawn from the CFTC Large Trader Reporting System (LTRS), which was designed for surveillance purposes to detect and deter futures and options market manipulation (Fenton and Martinaitas 2005). The LTRS database contains end-of-day reportable positions for long futures, short futures, long delta-adjusted options, and short delta-adjusted options for each trader ID and contract maturity.^{1,2} Traders who meet or exceed the reporting levels set by CFTC must report their positions on a daily basis. The reporting level can range from 25 contracts to over 1,000 contracts. The level for any given market is based on the total open positions in that market, the size of positions held by traders in the market, the surveillance history of the market, and the size of deliverable supplies for physical delivery markets. If at the daily market close, a reporting firm has a trader with a position at or above the CFTC's reporting level in any single futures or option expiration month, the firm reports that trader's entire position in all futures and options expiration months in that commodity, regardless of size.³ The data provided in these reports usually cover 70-90% of open interest in any given market (CFTC 2010).

When a trader surpasses the reporting level threshold, a reporting firm must file a Form 102 to identify each new reportable account and include the controlling traders of that account. The trader is then required to file a Form 40. Since traders frequently carry positions through more than one reporting firm and can control or have financial interest in more than one account, the CFTC is able to combine these accounts by trader and ownership level using the detail from these forms. For example, a diversified company can have a hedging operation and a separate speculative trading operation; these two operations would be assigned different trader ID's but the same owner ID.

In the case of an omnibus account, the process works in a similar fashion. An omnibus account is defined as an account between two brokerage firms where a number of individual customer accounts of one firm are grouped into a single account at the second firm. The account at the second firm is called an omnibus account and usually does not have individual details of each client. The second firm is required to report positions that are above large trader thresholds, which means that individual positions in the omnibus account are aggregated together and

reported by the name of the first firm, but the first firm is then required to report any large positions held by individual customer accounts and thereby relating the position back to the controlling trader. The LTRS system is designed to identify any double-counting from omnibus accounts and remove repetitive reporting.

In addition to ownership and trading control, classifications of traders are identified through the required filings. The trader is either determined to be a commercial or non-commercial from the information provided in the Form 40 filing. If a trader indicates they are engaged in bona fide hedging transactions, which classifies them as a commercial, then they are required to fill out Schedule 1 attached to Form 40 detailing their use of the futures markets for hedging. Upon satisfaction of the reviewing staff, the trader would then be considered a commercial trader and given a sub-classification based on his or her underlying business (e.g. producer, manufacturer, merchant, swaps dealer, etc.). If a trader does not meet the requirements for a commercial trader, they are classified as a non-commercial trader; which is commonly referred to as a speculator. Form 40 provides a section allowing the reporting trader to check a box indicating their registration under the Commodity Exchange Act; these non-commercial classifications include futures commission merchant (FCM), introducing broker (IB), associate person (AP) of an FCM, commodity trading advisor (CTA), commodity pool operator (CPO), floor broker (FB), and floor trader (FT). Non-commercial categories are commonly grouped into two groups, (i) managed money traders consisting of FCMs, IBs, CTAs, CPOs, and APs, and (ii) floor broker traders consisting of FBs and FTs. Any traders classified as non-commercial traders without a sub-classification are non-registered participants. These traders meet the CFTC reporting requirements due to trading size but do not have to register under regulation of the Commodity Exchange Act.⁴

The sub-classification of Commodity Index Traders (CITs) was created by the CFTC in 2007 but is not a current category on Form 40. CITs are passive long traders who invest based on a pre-specified index (Stoll and Whaley 2010). This classification was created by staff within the CFTC and is composed of both commercial and non-commercial traders, although CITs are typically separated from commercial and non-commercial traders to become a standalone category.

For the purposes of this research, daily futures and options positions cover the period from January 2000 to September 2009.⁵ The specific commodities analyzed are Chicago Board of Trade (CBOT) corn, Chicago Mercantile Exchange (CME) live cattle, and Intercontinental Exchange (ICE) coffee. These markets are representative of commodities from the crop, livestock, and soft categories and each has among the largest number of traders in their respective category. The traders analyzed are also exclusively drawn from the non-commercial category of traders but exclude those who are defined as Commodity Index Traders.

For each of the three markets, the owner ID combined with the trader ID makes up the unique 'trader' identification and it is used to isolate positions on a trader-by-trader basis. Table 1 displays summary statistics for each of the main LTRS categories by detailing the number of unique traders, overall profits, percentage of profitable traders, the number of business days with open interest, and the average daily notional value per trader. The non-commercial category has the largest number of unique traders at 6,102 followed by commercial category with 2,524 and

index trader category with 39. Total profits for this sample are highest for commercial traders (\$3 billion) and lowest for index traders (-\$4 billion). Non-commercial profits are reported at \$1 billion, with losses only present in coffee. The non-commercial coffee traders tend to be on average less profitable, less active, and smaller than non-commercial traders in corn and live cattle. This may be due to the international scope of coffee production and the difficulty in gathering and processing valuable information without direct involvement in the production and marketing of the underlying product. This may help explain the large profits to commercial coffee traders, although this is less clear for the commercial corn and live cattle participants. Commodity index traders are small subset of traders who use a passive buy-and-hold strategy, which was shown to be unsuccessful for the period studied.

Focusing on the non-commercial trader section of table 1, the trader total of 6,102 is broken down to identify in how many of the three markets a trader participates. The majority of participants are in one market, but 758 participate in two and 462 trade in all three. On average half of these traders are profitable over the time horizons (daily, monthly, quarterly, or yearly) considered. Traders participating in more than one market tend to be more profitable overall (except for coffee) although this is not true for the percentage of profitable traders. Each of the 3,556 unique non-commercial traders in corn are in the market an average of 239 business days, a little less than a year, with an average notional value of \$14 million per day. The live cattle non-commercial traders total 1,551 and are in the market an average of 217 business days and have an average notional value of \$11.5 million per day. The non-commercial coffee traders total 2,677, but average the least amount of active days, 184, and have the lowest average daily notional value.

The performance for non-commercial traders appears to be consistent with two regularities from Mahani and Bernhardt's model: in a given cross-section the majority of individual speculators lose money (here approximately 50% of the reporting non-commercial traders); and small, less active traders underperform while large, more active traders perform better. The appropriateness of the regularities is strengthened when it is noted that the LTRS system does not include extremely small traders who are often in the market for a short period, lose money, and essentially leave (Stewart 1949, Ross 1975).

Included and Excluded Trader Characteristics

In the analysis that follows, a trader must be present in adjoining periods to be included in the tests. For example, if a trader is analyzed using an annual time horizon, say 2000 (t) and 2001($t+1$), the trader needs to be present in both years. If a trader is not present in 2000 and 2001, the trader is not included in tests based on this pair of years. However, absence from the market in one year doesn't exclude the trader for the entire sample period, as the only requirement to perform the test is that information of trader activity must be available in the two adjoining time horizons ($t, t+1$). Regardless, the exclusion of some traders raises a possible sample selection bias analogous to that identified in the mutual fund or hedge fund literature where failing funds exit the database. Removing the funds with bad performance from the analysis can impart an upward bias on the performance results.

In our case, inactivity in either of two successive periods, which excludes traders from the analysis, may not always be due to performance. A trader may not appear in two adjoining periods because he or she decided to trade in a different commodity, fallen below the reporting threshold, temporarily ceased trading, or has permanently stopped trading for performance or other reasons. The barriers of entry and exit for an individual trader are much lower than for funds and consequently more entry and exit occur. Past researchers using this data source have defined their samples in different ways which excluded certain traders from the analysis. For instance, using daily observations for the period 1977-1981, Hartzmark (1991) only includes traders with 25 or more observations. Leuthold et al. (1994) include only the top 50 largest traders and top 20 largest spreaders to focus on the ability the largest traders to forecast price changes. Fishe and Smith (2010) include traders with 30 or more observations. Arguably, the impact of trader exclusion on results depends on the characteristic of the excluded traders.

Table 2 compares the included and excluded traders by profitability, size of market positions, and activity. One day of open interest per period is the minimum threshold for inclusion. The percentage of excluded traders across the three commodities is approximately 40%, 25%, and 16% for the annual, quarterly, and monthly horizons. The percentage is computed by taking the traders who were active in t but not in $t+1$ divided by the total number of traders in period t .⁶ The size of traders, measured by total absolute notional value, is smaller for the excluded trader group, averaging about ten percent or less of the size of the included trader group. The excluded traders are less active than included traders, measured as business days with open interest. The average number of open interest days per excluded trader is 50% or fewer days compared to an included trader.

Following Hartzmark (1987, 1991) and others, daily profits levels for each trader and contract are calculated by multiplying the end of day positions on day t by the settlement price change for the corresponding contract between the current day t and the following day $t+1$. The calculation assumes positions held at the end of day t are held throughout the trading day $t+1$ and all position adjustments occur at the settlement price on $t+1$. Since the data only consists of end of day positions, any profits of day-traders or scalpers who mainly trade intra-day are not included in the analysis. The profits do not account for commissions or margin requirements due to lack of available data, but since all traders are non-commercial the difference in transaction costs between traders is likely small.

For corn and live cattle, excluded traders lost between -\$12 and -\$400 million compared to profits between \$1 and \$2 billion for the included traders. This pattern of profitability does not hold for coffee, where both included and excluded traders experience losses. Further, included traders losses are larger, approximately -\$1 billion, while excluded traders losses are between -\$400 and -\$150 million. These losses by all non-commercial traders are consistent with the \$2.6 billion profits earned by commercials during the period (Table 1). Overall, the traders excluded from the analysis are smaller and less active compared to included traders. In the case of corn and live cattle, the excluded traders experience losses while included traders are profitable. These comparisons support Mahani and Bernhardt's (2007) theoretical model that large, more active speculators outperform small, less active speculators, but the descriptive information for coffee is less supportive in terms of performance.

Since the excluded traders are smaller, less active, and in general less profitable than traders included in subsequent tests, the findings of the tests must be interpreted in this light. The exclusion of the smaller traders with losses may remove traders from the mid to low-mid part of the profit distribution since the majority of these traders are not large enough to incur the magnitude of losses required to be in the lower tail of the profit distribution. To some degree, possible effects of excluding traders are mitigated by using different time horizons. As identified, the percent of excluded traders decreases from 40% at the annual horizon to 16% using a monthly horizon, with a high degree of correspondence across the three different commodities. Alternatively, if an upward bias is imparted by the exclusion of traders, this may simply reflect a market reality in which not all speculative traders succeed, but survivors increase their market activity, trade on a larger scale, and increase their average profitability as a result of a more informed understanding of markets and their trading environment (Mahani and Bernhardt 2007).

Winner and Loser Rank Test

The first test is a non-parametric two-way winner and loser contingency table analysis based on placing traders into winner and loser categories across adjacent pairs of time horizons. For a given commodity, the first step is to create pairs of adjacent time periods, t and $t+1$ (e.g. 2000 and 2001, 2001 and 2002, 2002 and 2003). Next, form a sample of traders that actively trade in both t and $t+1$, again implying that traders not in both periods are excluded. The third step is to rank each trader by profitability in t ; for example, the trader with the highest profit is ranked number one, and the trader with the lowest profit is assigned a rank equal to the total number of traders in the commodity in the given period.⁷ Then the traders are sorted in descending rank order, with the top half of traders considered winners and the bottom half of the traders considered the losers. Next, repeat the ranking, sorting, and creation of winner and loser groups based on profits in the second period, $t+1$. Finally, compute the following counts for the traders in the pair of adjacent time periods, winner t & winner $t+1$, winner t & loser $t+1$, loser t & winner $t+1$, and loser t & loser $t+1$.

Persistence is determined by whether the number of traders who are winners (or losers) in two consecutive periods is significant; conversely, if approximately the same counts of traders are found in each of the four combinations, then the null of random distributions of profits is not rejected and no persistence exists. The appropriate statistical test is the Fisher's Exact Test (Conover, 1999, pp.188-89), a nonparametric test that is robust to outliers. The Fisher's Exact test can be computed on each pair of adjacent time periods individually and then can be pooled to include all pairs of adjacent time periods with the same time horizon (e.g. annual, quarterly, and monthly).

The winners and loser contingency results in Table 3 test the persistence in rankings based on profit levels across groups of adjacent years (9 pairs) for corn, live cattle, and coffee and the pooled results from 2000-2009 are at the bottom of the table. As an example, consider the results for corn where 2001 is t and 2002 is $t+1$, of the 234 winners in 2001, 133 are winners and 101 are losers in 2002. Of the 234 loser in 2001, 101 are winners and 134 are losers in 2002. In other words, the conditional probability of a winner from 2001 repeating in 2002 is 57% (133/234) and conditional probability of a loser from 2001 repeating in 2002 is 57% (134/234).

These conditional probabilities are compared to the conditional probability expected of a random distribution of 50% (117/234), and in this case the null hypothesis that profits are randomly distributed is rejected. Out of all nine comparisons of the yearly periods, a significant difference (at the 5% level) exists in three out of the nine pairs for corn, two of nine pairs for live cattle, and four of nine pairs for coffee although some are marginally significant. For the pooled results, traders deviate from the random distribution (of 50%) with 53.5% (1436/2683) of traders exhibiting persistence for corn, 53.8% (562/1045) for live cattle, and 56.3% (863/1532) for coffee. The pooled tests have more power because of the increased number of observations; the results for corn, live cattle, and coffee reject the null hypothesis that profits are randomly distributed and support that notion that traders exhibit persistence in performance.

The conditional winner and loser ranking analyses are also tested for the quarterly and monthly time horizons for each commodity. Quarterly results span from quarter 1 in 2000 through quarter 3 in 2009, a total of 38 pairs. Monthly results span from January in 2000 through September in 2009, a total of 116 pairs. The pooled results are presented in Table 4. These results show widespread significance across all commodities and time periods. The only p-value larger than 5% is the monthly horizon coffee test of trader persistence with an 11% p-value. The italicized percentages below each quadrant count compares to the 50% expected under the null hypothesis of random distribution of profits. On average 53% to 54% of winners in t are also winners in $t+1$. The exceptions are in quarterly live cattle and monthly coffee results where traders are split almost evenly between winners and losers. Overall the contingency table results support that traders show evidence of out-of-sample persistence in earning profits.

Top and Bottom Performance Deciles Test

The second test takes into account the magnitude of profit differentials between top and bottom performing groups and allow for the possibility that top deciles of traders persist when other midrange traders do not. The starting point of this procedure is similar to the previous winner and loser test. First create the pairs of adjacent time periods, exclude any traders not in both periods, and rank traders in the first period by profits with the most profitable trader as number one. Then for a given commodity, sort traders by profits in the first period (t) and form deciles of traders based on this ranking. Next, use the deciles of traders formed in period t and compute how the same traders performed in period $t+1$. For example, take the best performing decile, decile 10, in period t and without resorting or re-forming groups of traders, determine how the 10th decile of traders from period t performed in period $t+1$. Then compute the difference in the profits between the top and bottom performing trader groups and test the null hypothesis that the difference between the trader groups is zero. If the performance for the top and bottom groups is significantly different than zero using a paired t -test, then the null hypothesis can be rejected and the conclusion reached that traders perform persistently. The paired t -test assumes a normal distribution and independent observations; when the normality assumption fails to hold, the nonparametric Wilcoxon Signed Rank test is used. Carpenter and Lynch (1999) recommend this test because it is well-specified and among the most powerful in their comparison of several predictability tests for mutual funds.

Table 5 displays the average profits for the out-of-sample periods ($t+1$) for each decile and the differences between top and bottom deciles for the different time horizons. For example, in the

live cattle annual results the top decile is 1 and is formed by ranking the profits for an in-sample period t (2000, 2001, ..., or 2008) and summarizing the profits of those same top decile traders in the out-of-sample period $t+1$ (2001, 2002, ..., or 2009). The average of all out-of-sample periods $t+1$ is \$3.5 million for the top decile and -\$208,000 the bottom decile. The difference between the top and bottom deciles is \$3.7 million which is significantly different than zero at the 1% level. The results also are presented for comparisons of the top and bottom 20% and 50%. If we expect traders to persist in earning profits then the top out-of-sample deciles would have greater average profits than the bottom out-of-sample deciles, and this would decline as we expand from the 10% to 50% comparisons.

The annual results for corn in panel A are not statistically significant, but the average profits for the top 10% is quite large at \$1.1 million. The lack of statistical significance is due to high profits in the bottom decile and not due to superior gains in the intermediate deciles. The large gains in the bottom decile may reflect successful loss-aversion behavior where losses in the prior period motivate traders to increase their risk taking to recoup losses. The annual results for both live cattle and coffee show substantial skill in the top 10%; the top traders in live cattle earn \$3.7 million more than the bottom, and the top traders in coffee experience \$2.6 million smaller losses than bottom 10%. These findings persist even when we expand the size of the deciles, but the differences in magnitude decline. Overall on an annual horizon, the top 10% of traders show a substantial persistence in performance.

The quarterly and monthly time horizon results are more varied. For corn, the top 10% of traders show significant skill at both the quarterly and monthly horizons with differentials of \$976,000 and \$259,000, respectively. For live cattle, the quarterly results identify the top 10% is not greater than the bottom decile; however, in monthly results, the top deciles are significantly greater than the bottom deciles. For coffee, the quarterly losses appear symmetric around the middle of the distribution with the greatest losses in the top and bottom deciles; in the monthly results, little evidence of persistent performance appears.⁸ The variability of persistence in the shorter horizons indicates that either traders focus on a long-term investment horizon and are less sensitive to intermediate period profits, and/or it may be more difficult to maintain profitable positions in the presence of short-term random events which occur in these agricultural markets.⁹ Overall, the second set of results that take into account magnitudes of profits, provide rather strong evidence that persistent skill exists among the top 10% of traders. This finding supports the conclusions of the first set of winner and loser rank contingency table tests.

Comparison of Test Results

Although the results from winner and loser ranking test and the top and bottom performing deciles tests generally support each other, differences in statistical significance exist in three out of nine scenarios. The six matching test results are annual live cattle and coffee, quarterly corn, and monthly corn, live cattle, and coffee. The three non-matching test results are annual corn, quarterly live cattle and coffee. The quarterly live cattle results find persistence for the first test but not the second; although the first method is statistically significant, economic significance is questionable because the difference between persistence and non-persistence is only 1%. The disparity between the first and second tests is pronounced for the quarterly coffee results; in the second the difference between top and bottom deciles is an insignificant \$10,000 but in the first a

statistically significant 52% of traders show persistence. The disparity is also apparent in annual corn results, where the difference between top and bottom deciles is large but statistically insignificant at \$357,000. The first test showed a significant difference between traders who exhibited persistence (54%) and those who do not (46%).

The variation in statistical significance between the two tests is likely reflective of the high degree of volatility during the period, and as Figures 1-3 demonstrate the extreme changes in deciles 1 and 10 ultimately make it difficult to identify significant differences in trading profits. Figures 1-3 display a contingency table of initial and subsequent annual, quarterly, and monthly performance rankings. A trader's initial ranking in period t is on the z-axis and subsequent ranking in period $t+1$ is on the x-axis. The y-axis is the probability of the subsequent ranking given the initial ranking. In a case where all profits are random and no persistence exists, each bar would be 10%. In a case where profits are not random and traders always rank exactly the same in every period, each bar on the diagonal (1/1, 2/2, ..., 9/9, 10/10) would be 100%. The actual results from the data appear somewhere in between these two extremes. In Figures 1-3, all the diagonals are greater than 10%, and many traders either stay in the same profit decile or move one decile up or down.¹⁰ The tendency for traders to stay in or around their decile supports the first test which finds that ranking persists among traders. Although this tendency is strong for deciles 2 through 9, the extreme rankings, decile 1 and 10, behave somewhat differently. A large portion of traders who initially rank in deciles 1 or 10 in period t either stay in the same decile or move to the opposite end of the performance spectrum in the subsequent period $t+1$. This pattern is demonstrated by the tall four corners across the figures; traders who initially are in decile 1 in period t are highly likely to be in decile 1 or decile 10 in period $t+1$ but less likely to be in intermediate deciles. Likewise, those traders who are initially in decile 10 in period t are highly likely to be in decile 10 or decile 1 in period $t+1$ but less likely to be in intermediate deciles.

The traders at the extremes may fall into one of two types, those who are highly skilled or severely challenged and continue to rank in decile 1 or 10, and those who possess no skill but take large risks and alternate between the top and bottom decile as their fortunes oscillate with the vagaries in the market. Persistent performance in decile 1 encourages further participation through profits, but the continued performance of those in decile 10 is surprising since traders are continually earning negative profits. Possibly the traders earning large negative profits are still exploring if they have skill or are compensating for losses with other investments. The traders alternating between success and failure are less surprising based on the arguments by Hartzmark (1991), who contends that profits are randomly distributed in agricultural futures markets. The large shift in profits earned by the non-skilled traders is likely the factor that creates differing statistical results in the decile tests. The impact becomes clear when analyzing the 4 corner percentiles and comparing the rankings that persisted (10/10 or 1/1) versus the drastic shifting rankings (10/1 or 1/10). When the extreme rankings 10/10 and 1/1 are larger than approximately 30% and the 10/1 and 1/10 shifts are approximately smaller than 25%, then the decile tests are significant (e.g. corn quarterly and monthly, live cattle annual and monthly, and coffee yearly). If the drastic shifts in deciles 10/1 and 1/10 are approximately equal to the other two corners of 10/10 or 1/1, then the decile tests are not significant (e.g. corn annual, live cattle quarterly, and coffee quarterly and monthly). In table 5, the significance of the tests is consistent across

differences between the deciles studies (10%, 20%, and 50%), but in light of the Figures 1-3 the significance in the 20th and 50th percentiles is likely driven by the 10th percentile traders.

Multi-Period Performance for Most Active Traders

It is natural to ask at this point if the performance persistence observed over the annual horizon extends to even longer horizons. To investigate this question we identify the number of times an individual trader is in the market, assess the number of times traders are consistently in the top half or bottom half of performance compared to their peers, and calculate average profits (losses) for traders who persist. The expectation is that the number of traders will decrease as the number of periods increases, and that average trader profits (losses) will increase the longer a trader perform well (poorly). However in contrast to profits, one would expect that large and somewhat persistent losses should drive rational traders out of the market.

To maintain trader confidentiality and enhance the analysis, the information is presented in several ways. Consistent with the notion of persistence, we focus on the data employed in the rankings and decile tests, and to make the analysis manageable we use annual observations. Information is provided in Figures 4 and 5 for all the data, and in Table 6 for a portion of this sample.¹¹ Figure 4 identifies for each market the number of annual pairs (adjacent years) a trader was in a market. There are nine pairs or temporal classifications which correspond to one less than the number of years in the full data set. Also, notice the annual pairs for an individual trader are not required to be continuous to be included. As an example of how to interpret the information, in the corn market there were 1,853 traders in one or more adjacent pairs of years, and 385 of these same traders were in the market in five or more adjacent years. This information is also presented in Table 6 (Panel A). Figure 5 provides information on the number of times or more a trader was in the top or bottom half of the profit distribution in the following year as a percent of the number of traders that were in the market for the same number or more adjacent years. For example, in the corn market, slightly more than 41% of the 1,853 traders that were in the market one or more adjacent years were also in the top half of the profit distribution the following year in one or more adjacent years. Similarly, slightly more than 12% of the 385 corn traders who were in the market in five or more adjacent years were also in the top half of the profit distribution the following year in five or more adjacent years. Table 6 provides similar information for a portion of these categories, but also includes average trader profits or losses for the entire period. Combined, the information permits a view of the performance of the traders most active in the market.

Several points emerge from the figures and table. First, slightly less than 50% of the traders in the three markets were active in adjacent years, affirming the ease of market exit and entry identified earlier. Second, the number of traders in adjacent periods declines rather quickly as the number of periods increase, but then begins to level off about at five or more adjacent year classification (Figure 4). At that point, there were 385 traders in corn, 144 traders in live cattle, and 193 traders in coffee that were in the market for roughly half of the sample period (Figure 4 and Table 6). The number of traders that were in the market for the entire period declines to 130 traders in corn, 47 traders in live cattle, and 41 traders in coffee. Third, the percentage of traders in the market for adjacent years who were also in the top of the profit distribution in the following year also declines. On a percentage basis, the pattern is similar for corn and live cattle

traders, reaching about 12.5% for those traders in five or more adjacent periods and roughly 2.5% for eight or more adjacent periods (Figure 5, Panel A). In terms of consistency, this pattern demonstrates that it is difficult for even large traders to always be in the top half of the profit distribution. The picture in coffee differs; the decline is sharper with only 4.0% (0.0%) of the traders in the market for five (eight) adjacent periods in the top half of the profits distribution the following year. Average total profits for these firms through the first five temporal categories offer a somewhat similar view (Table 6). Profits tend to increase for traders who persist in both the corn and live cattle markets, with profits in the live cattle market growing more rapidly and reaching \$36 million/trader. Average total profits initially also increase for traders in the coffee market, but then decline markedly for traders in five or more adjacent years.

Lastly, trader losses also exhibit a degree of persistence (Figure 5, Panel B and Table 6). On average across the markets, there were slightly more than 9% of the traders who were in the market for five or more adjacent years that were consistently in the bottom half of the profit distribution. On a percentage basis, the traders in the corn and live cattle markets exhibit similar patterns with the percentage of traders declining more rapidly than in the coffee market. Informatively, the percentage of traders in the corn and live cattle markets showing persistent losses in subsequent years is smaller than the percentage of traders exhibiting persistent gains identified earlier. For instance, nearly 7% (0.3%) of the traders in these markets for five (eight) adjacent years were in the bottom of half of the profit distribution the following year. This compares to the 12.5% and 2.5% of traders with gains identified earlier for the same temporal classification. For coffee, the story again differs from corn and live cattle, and even from the top half of the distribution for coffee. Here, almost 14% (2.0%) of the traders with five (eight) adjacent years were in the bottom half of the profit distribution the following year which is considerably larger than the percentages identified earlier in the top half of the distribution for the same temporal classifications. Average total losses for these firms through the first five temporal categories offer a somewhat different view (Table 6). Losses tend to increase for traders who persist in both the corn and coffee markets, with losses in the coffee market growing more rapidly and reaching \$32 million/trader. These average losses per trader in the coffee market far outstrip the average profits per trader identified previously in this market (Figure 5, Panel A). In contrast, average losses per trader in the corn market are less than average profits identified earlier. For traders in the live cattle market, average total losses initially increase, but level off at a magnitude that is considerably less than the average trader profits for this market.

Summary and Conclusions

Using individual trader data from the CFTC Large Trader Reporting System over January 2000 to September 2009, the paper investigates whether non-commercial traders in the corn, live cattle, and coffee futures markets persist in making profits. Given the limited evidence of risk premiums documented in these markets, persistent profit-making ability is an indication of skill. Two measures of skill—the Fisher Exact ranking test and a test to assess significant differences in the magnitude of profits of the top and bottom traders—are used to analyze trader's ability to consistently perform well for monthly, quarterly, and annual time horizons. The analysis is further supported by an investigation of the characteristics for excluded traders, and an investigation of the persistence of those traders that are most continuously in the markets.

Overall, the evidence from the individual tests and additional analyses support the notion of persistent profit-making ability for a small group of non-commercial traders, with some indication of persistence in the face of continued losses. The findings identify significant persistence in ranking—traders in the top 50 percent of the profits distribution in a time period tend to stay in upper half in the next period—in all three markets and time horizons. The results for corn, live cattle, and coffee reject the null hypothesis that profits are randomly distributed and support that notion that traders exhibit persistence in performance for the three horizons considered. On average 53% of winners in t are also winners in $t+1$.

Findings from tests of the differences in magnitude of profitability between the top and bottom deciles are somewhat mixed. The annual results for corn are not statistically significant, but average profit of the top 10% is quite large, \$1.1 million. The annual results for both live cattle and coffee show substantial skill in the top 10%; the top traders in live cattle earn \$3.7 million more than the bottom, and the top traders in coffee experience \$2.6 million smaller losses than bottom 10%. Quarterly and monthly results are varied. For corn, the top 10% of traders show significant skill at both the quarterly and monthly horizons, with average profit differentials reaching \$976,000 and \$259,000, respectively. For live cattle, the quarterly results identify the top 10% is not greater than the bottom decile, but monthly results find significant differences. For coffee, neither the quarterly nor monthly results provide evidence of persistent performance.

The variability of persistence results using this second testing procedure is likely a function of several factors. First, at shorter horizons traders may focus on a long-term horizon and are less sensitive to intermediate period profits, and/or it may be more difficult to maintain profitable positions in the presence of short-term random events which can occur in these agricultural markets. Second, at both short and long horizons, trader performance in the top and bottom deciles often changed dramatically such that the conditional probability of moving from the top to the bottom decile or vice versa appeared to be non-trivial. Despite these factors, evidence for persistent profit-making ability exists.

An investigation of the annual performance of traders most continuously in the market provides further insights into their persistent ability. The findings indicate that it is difficult for traders to always be in the top half of the profit distribution. Nevertheless, evidence emerges from the corn and live cattle markets that 12.5% (2.5%) of the traders who were in the market for five (eight) or more adjacent pairs of years were also in the top half of the profit distribution for five (eight) or more adjacent years. Average total profits also tended to increase for traders who persisted in both these markets, with profits in the live cattle market growing more rapidly and reaching \$36 million/trader. Traders in coffee market showed much less persistence in profit making with only 4.0% (0.0%) of the traders in the market for five (eight) adjacent periods in the top half of the profits distribution for five (eight) or more adjacent years. While average total profits initially also increase for these traders, they decline markedly with longer time in the market.

Evidence also emerges for persistence in the face of continued losses. On average across the markets, slightly more than 9% of the traders who were in the market for five or more adjacent years were consistently in the bottom half of the profit distribution. Traders in the corn and live cattle markets exhibit similar patterns with the percentage of traders showing persistence in the face of losses declining more rapidly than in the coffee market. Informatively, the percentage of

traders in the corn and live cattle markets showing persistent losses is smaller than the percentage of traders exhibiting persistent gains. For coffee, the story again differs, with almost 14% (2.0%) of the traders with five (eight) adjacent years also in the bottom half of the profit distribution the following year. Average total losses tend to increase for traders who persist in both the corn and coffee markets, with losses in the coffee market growing more rapidly and reaching \$32 million/trader for the entire period. These average losses per trader in the coffee market far outstrip the average profits per trader identified previously in this market. In contrast, average losses per trader in the corn market are less than average profits for traders with the same number of years in the market. For traders in the live cattle market, average total losses initially increase, but level off at a magnitude that is considerably less than the average trader profits for this market.

The differences in performance by traders most continuously in the market add insights. The unexpected findings in the coffee in part may be attributable to fact that commercial traders were highly profitable. Losses by all the non-commercial traders in the market were large and reflected the \$2.6 billion profits earned by commercials during the period. Despite some evidence of persistent profit-making ability, non-commercial traders may have been simply overwhelmed by informational and market advantages possessed by commercial traders. With regards to traders in the corn and live cattle markets, the weight of the evidence here points to persistence in profits for a subset of traders who are most active in the market, with smaller group of traders that persist in the face of losses.

How do our findings relate to the literature? Comparing our results to previous research in futures markets by Hartzmark (1991), Leuthold et al. (1994) and Fische and Smith (2010) is challenging because of the different methods and time horizons used. Hartzmark argues that profits are random for 1,622 non-commercial traders. Leuthold analyzes 2% of traders out of 3,171 and finds them to have skill, and Fische and Smith find 1% to 3.5% of traders are informed. Here, we also find a small subset with profit-making ability. The exact proportion is more difficult to identify with the ranking test results arguing for about 3% of skilled traders, and the decile tests suggesting a possible larger set among the top 10%. Results from the most active traders analysis point in the direction of a smaller of group of larger non-commercial traders that are able to make profits on a consistent basis in select markets. Regardless, our findings, using an arguably more rigorous measure—out-of-sample persistence in profit-making ability—are consistent with the notion that skill does exist as identified by Leuthold et al. (1994) and Fische and Smith (2011).

With regards to the work by Mahani and Bernhardt (2007), our finding that a small set of elite active speculative traders outperform less active speculators is consistent with the structure and implications of their rational learning-based model. Our empirical findings that excluded traders are smaller and less active compared to included traders also is supportive. However, our results that traders persist in the face of continued losses seem at odds with Mahani and Bernhardt's model and indeed rationality in its strictest sense. This finding, while not extensive in magnitude, may provide support for behavioral theories that explain outcomes in terms distorted expectations and overconfidence, risk-seeking, and loss aversion.

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Endnotes

¹ Delta is the change in option price for a one percent change in the price of the underlying futures contract. Adjusting options positions by delta makes options positions comparable to futures positions in terms of price changes.

² The data do not include positions of day traders or scalpers since these participants seldom carry positions overnight.

³ The reporting levels for the commodities in this paper include corn at 250 contracts, live cattle at 100 contracts, and coffee at 50 contracts.

⁴ A small number of traders report to the CFTC but are not required to do so. These commonly are entered into the database as non-classified since they have no Form 40 or Form 102 associated with the records.

⁵ Futures positions include delta adjusted option positions.

⁶ The absolute number of traders is calculated as the average number of unique traders per month, per quarter, or per year.

⁷ Return on investment for each trader also was calculated using the average daily total notional value as a rough gauge for investment. For instance, in a year t the total profit level earned by a trader in year t is divided by average daily notional value of investment during year t . In almost all cases, analyses using this measure produced similar findings to those reported in the text based on profits.

⁸ The decile results based on our measure of return on investment differed modestly from those calculated using profits. Both sets of results find 5 out of 9 tests are significant but one of the significant tests differs. Profit levels results find yearly live cattle to be statistically significant whereas return results find quarterly coffee results are significant.

⁹ Using scatter plots and stem and leaf plots, outliers which can make it difficult to find consistent patterns do not appear to be a major concern.

¹⁰ This is more easily seen from the tables of underlying data which are not provided in this paper, but are available.

¹¹ CFTC guidelines restrict the presentation of profits for categories with smaller than seven traders.

Table 1. Summary Statistics for Major Futures Trader Categories in Corn, Live Cattle, and Coffee, January 2000 - September 2009

	Commercial				NonCommercial				Commodity Index Trader			
	Corn	Live Cattle	Coffee	All Three Commodities	Corn	Live Cattle	Coffee	All Three Commodities	Corn	Live Cattle	Coffee	All Three Commodities
Number Unique Traders	1,401	747	548	2,524	3,556	1,551	2,677	6,102	39	39	39	39
Traders in 1 Market	1255	619	496	2,370	2445	712	1725	4,882				
Traders in 2 Markets	128	110	34	136	649	377	490	758				
Traders in 3 Markets	18	18	18	18	462	462	462	462				
Overall Profits (,000)	98,078	666,470	2,598,487	3,352,754	1,527,886	958,738	-1,454,846	1,030,837	-1,622,264	-1,865,625	-791,388	-4,279,277
Traders in 1 Market	623,541	618,608	1,883,580	3,125,729	337,872	86,462	-36,924	387,410				
Traders in 2 Markets	-248,907	163,091	278,167	192,351	446,372	561,873	-91,492	916,752				
Traders in 3 Markets	-275,109	-117,711	424,761	31,942	742,816	308,792	-1,326,222	-274,614				
Percent of Profitable Traders for Cross Section												
Daily	0.48	0.49	0.50	0.49	0.45	0.51	0.49	0.48	0.43	0.50	0.49	0.47
Monthly	0.50	0.52	0.53	0.52	0.51	0.53	0.47	0.50	0.49	0.46	0.44	0.46
Quarterly	0.54	0.52	0.56	0.54	0.51	0.54	0.45	0.50	0.36	0.46	0.41	0.41
Yearly	0.53	0.51	0.57	0.54	0.50	0.55	0.43	0.49	0.32	0.46	0.42	0.40
Traders in 1 Market	0.54	0.51	0.57	0.54	0.52	0.56	0.46	0.51				
Traders in 2 Markets	0.46	0.50	0.62	0.53	0.51	0.60	0.42	0.51				
Traders in 3 Markets	0.53	0.41	0.53	0.49	0.46	0.51	0.39	0.45				
Avg. Number of Business Days with Open Interest per Trader	655	442	585	561	239	217	184	213	1,062	971	989	1,007
Traders in 1 Market	646	392	573	537	200	126	136	154				
Traders in 2 Markets	682	645	692	673	228	216	171	205				
Traders in 3 Markets	1,127	929	737	931	456	357	379	397				
Avg. Daily Total Notional Value (,000) per Trader	13,970	6,578	11,516	10,688	13,970	11,516	6,578	10,688	165,111	94,997	51,356	103,821
Traders in 1 Market	10,180	6,958	4,772	7,303	10,180	6,958	4,772	7,303				
Traders in 2 Markets	20,064	12,449	5,848	12,787	20,064	12,449	5,848	12,787				
Traders in 3 Markets	25,465	17,778	14,095	19,113	25,465	17,778	14,095	19,113				

Note: Unique traders are the number of individual traders who participate on at least one day over the entire time period. Overall profits are total profits from 2000-2009. Percent of profitable traders for a cross section is the average percent of profitable traders per cross section of computer profits. Only the yearly cross section is broken down by trader in multiple markets. The average number of business days represents trader activity and is the average number of days with open interest. Mean daily total notional value per trader represent the size of a trader and is the average daily notional value per trader.

Table 2. Summary Statistics for Included versus Excluded Non-Commercial Futures Traders in Corn, Live Cattle, and Coffee, January 2000-September 2009

	Time Horizon		
	Yearly (<i>obs=9</i>)	Quarterly (<i>obs=38</i>)	Monthly (<i>obs=116</i>)
Corn			
Total Profits (,000)			
Excluded Trdrs	-94,851	-270,584	-395,160
Included Trdrs	2,003,651	1,884,074	1,954,539
Avg Daily Notional Value (,000)			
Excluded Trdrs	226,469,053	45,738,377	5,546,531
Included Trdrs	3,040,642,971	1,715,013,413	276,357,989
Avg Number Trdrs			
Excluded Trdrs	354	141	76
Included Trdrs	597	452	385
Pct Excluded Traders	37%	24%	16%
Avg Days in Market per Trdr			
Excluded Trdrs	44	19	8
Included Trdrs	119	42	17
Live Cattle			
Total Profits (,000)			
Excluded Trdrs	-44,016	-12,426	-68,296
Included Trdrs	1,073,398	1,003,430	1,042,140
Avg Daily Notional Value (,000)			
Excluded Trdrs	59,470,488	12,776,533	1,852,208
Included Trdrs	1,066,435,258	476,807,113	95,855,266
Avg Number Trdrs			
Excluded Trdrs	149	55	29
Included Trdrs	233	183	157
Pct Excluded Traders	39%	23%	16%
Avg Days in Market per Trdr			
Excluded Trdrs	36	16	7
Included Trdrs	119	42	17
Coffee			
Total Profits (,000)			
Excluded Trdrs	-154,684	-162,340	-407,451
Included Trdrs	-979,287	-1,160,054	-1,007,151
Avg Daily Notional Value (,000)			
Excluded Trdrs	88,003,359	15,010,363	1,672,534
Included Trdrs	917,243,091	456,024,778	84,910,035
Avg Number Trdrs			
Excluded Trdrs	273	96	47
Included Trdrs	341	266	228
Pct Excluded Traders	44%	27%	17%
Avg Days in Market per Trdr			
Excluded Trdrs	42	17	7
Included Trdrs	114	41	17

Note: Average is over each t period in each horizon studied.

Table 3. Winner and Loser Test Results for Non-Commercial Futures Trader Performance in Corn, Soybeans, and Coffee, January 2000 - September 2009

Period <i>t</i>	Period <i>t+1</i>	Corn				Live Cattle				Coffee			
		Number of Traders		Two-Tail p-Value for Fisher's Exact Test	Number of Traders		Two-Tail p-Value for Fisher's Exact Test	Number of Traders		Two-Tail p-Value for Fisher's Exact Test			
		Winner <i>t+1</i>	Loser <i>t+1</i>		Winner <i>t+1</i>	Loser <i>t+1</i>		Winner <i>t+1</i>	Loser <i>t+1</i>				
2000	2001	Winner <i>t</i>	122	111	0.35	Winner <i>t</i>	47	51	0.67	Winner <i>t</i>	64	41	0.00
		Loser <i>t</i>	111	122		Loser <i>t</i>	51	47		Loser <i>t</i>	41	65	
2001	2002	Winner <i>t</i>	133	101	0.00	Winner <i>t</i>	45	45	1.00	Winner <i>t</i>	56	58	0.90
		Loser <i>t</i>	101	134		Loser <i>t</i>	45	45		Loser <i>t</i>	58	57	
2002	2003	Winner <i>t</i>	135	118	0.15	Winner <i>t</i>	52	48	0.67	Winner <i>t</i>	93	36	0.00
		Loser <i>t</i>	118	135		Loser <i>t</i>	48	52		Loser <i>t</i>	36	94	
2003	2004	Winner <i>t</i>	133	145	0.35	Winner <i>t</i>	55	43	0.12	Winner <i>t</i>	109	73	0.00
		Loser <i>t</i>	145	133		Loser <i>t</i>	43	55		Loser <i>t</i>	73	109	
2004	2005	Winner <i>t</i>	149	161	0.38	Winner <i>t</i>	63	32	0.00	Winner <i>t</i>	111	95	0.12
		Loser <i>t</i>	161	149		Loser <i>t</i>	32	64		Loser <i>t</i>	95	112	
2005	2006	Winner <i>t</i>	164	154	0.43	Winner <i>t</i>	75	54	0.01	Winner <i>t</i>	107	99	0.49
		Loser <i>t</i>	154	165		Loser <i>t</i>	54	76		Loser <i>t</i>	99	107	
2006	2007	Winner <i>t</i>	214	146	0.00	Winner <i>t</i>	80	66	0.13	Winner <i>t</i>	131	94	0.00
		Loser <i>t</i>	146	215		Loser <i>t</i>	66	80		Loser <i>t</i>	94	132	
2007	2008	Winner <i>t</i>	217	159	0.00	Winner <i>t</i>	71	78	0.49	Winner <i>t</i>	111	91	0.06
		Loser <i>t</i>	159	218		Loser <i>t</i>	78	71		Loser <i>t</i>	91	111	
2008	2009	Winner <i>t</i>	169	152	0.18	Winner <i>t</i>	74	66	0.34	Winner <i>t</i>	81	82	1.00
		Loser <i>t</i>	152	170		Loser <i>t</i>	66	75		Loser <i>t</i>	82	82	
2000-2009 Pooled		Winner <i>t</i>	1,436	1,247	0.00	Winner <i>t</i>	562	483	0.00	Winner <i>t</i>	863	669	0.00
		Loser <i>t</i>	1,247	1,441		Loser <i>t</i>	483	565		Loser <i>t</i>	669	869	

Table 4. Pooled Winner and Loser Test Results for Non-Commercial Futures Trader Performance in Corn, Soybeans, and Coffee, January 2000 - September 2009

Period	Corn			Live Cattle			Coffee			
	Number of Traders		Two-Tail p-Value for Fisher's Exact	Number of Traders		Two-Tail p-Value for Fisher's Exact	Number of Traders		Two-Tail p-Value for Fisher's Exact	
	Winner $t+1$	Loser $t+1$		Winner $t+1$	Loser $t+1$		Winner $t+1$	Loser $t+1$		
Annual (9 pairs)										
2000-2009 Pooled	Winner t	1,436 54%	1,247 46%	0.00	562 54%	483 46%	0.00	863 56%	669 44%	0.00
	Loser t	1,247 46%	1,441 54%		483 46%	565 54%		669 43%	869 57%	
Quarterly (38 pairs)										
2000-2009 Pooled	Winner t	4,679 55%	3,906 45%	0.00	1,741 50%	1,720 50%	0.00	2,621 52%	2,415 48%	0.00
	Loser t	3,906 45%	4,702 55%		1,720 49%	1,757 51%		2,415 48%	2,640 52%	
Monthly (116 pairs)										
2000-2009 Pooled	Winner t	12,219 55%	10,091 45%	0.00	4,795 53%	4,255 47%	0.00	6,650 50%	6,548 50%	0.11
	Loser t	10,091 45%	12,281 55%		4,255 47%	4,856 53%		6,548 49%	6,707 51%	

Table 5. Decile Test Results for Non-Commercial Futures Trader Performance in Corn, Soybeans, and Coffee, January 2000 - September 2009

Decile	Yearly (,000)				Quarterly (,000)				Monthly (,000)												
	Profits		Student's t		Signed Rank		Profits		Student's t		Signed Rank		Profits		Student's t		Signed Rank				
	Avg $t+1$	StdDev $t+1$	Normal?	Statistic	P-value	Statistic	P-Value	Avg $t+1$	StdDev $t+1$	Normal?	Statistic	P-value	Statistic	P-Value	Avg $t+1$	StdDev $t+1$	Normal?	Statistic	P-value	Statistic	P-Value
Panel A: Corn																					
1 (best)	1143							795							226						
2	-36							173							52						
3	3							5							15						
4	53							40							22						
5	68							-1							4						
6	8							1							0						
7	-70							17							2						
8	80							-2							-11						
9	90							-71							-16						
10	785							-181							-33						
Top v Bottom 10%	357	3,739	yes	0.29	0.78	-1.5	0.91	976	8,406	no	0.72	0.48	111.5	0.11	259	5,222	no	0.53	0.59	699	0.05
Top v Bottom 20%	115	1,922	yes	0.18	0.86	-0.5	1.00	610	4,694	no	0.80	0.43	123.5	0.07	164	2,956	no	0.60	0.55	684	0.06
Top v Bottom 50%	67	844	yes	0.24	0.82	1.5	0.91	250	1,997	no	0.77	0.45	114.5	0.10	76	1,250	no	0.65	0.52	686	0.06
Panel B: Live Cattle																					
1 (best)	3,482							529							420						
2	464							75							80						
3	319							115							17						
4	266							47							19						
5	351							29							15						
6	79							2							14						
7	36							14							5						
8	-79							83							20						
9	-195							10							15						
10	-208							549							-79						
Top v Bottom 10%	3,691	3,485	yes	3.18	0.01	19.5	0.02	-20	3,599	yes	0.03	0.97	-21.5	0.76	499	2,890	no	1.86	0.07	628	0.08
Top v Bottom 20%	2,175	2,099	yes	3.11	0.01	19.5	0.02	23	1,977	yes	0.07	0.94	-11.5	0.87	282	1,707	no	1.78	0.08	622	0.00
Top v Bottom 50%	1,050	856	yes	3.68	0.01	19.5	0.02	27	830	yes	0.20	0.84	0.5	0.99	115	743	no	1.67	0.10	584	0.11
Panel C: Coffee																					
1 (best)	-220							-431							-256						
2	-186							-95							-91						
3	-21							-56							-27						
4	-39							-24							-14						
5	-43							-34							4						
6	7							6							-13						
7	-43							-30							-4						
8	-298							-63							6						
9	-502							-106							-33						
10	-2800							-465							-73						
Top v Bottom 10%	2,580	4,311	yes	1.80	0.11	12.5	0.16	33	3,308	no	0.06	0.95	26.5	0.71	-183	3,686	no	0.54	0.59	56	0.88
Top v Bottom 20%	1,448	2,435	yes	1.78	0.11	12.5	0.16	22	1,869	no	0.07	0.94	21.5	0.76	-121	2,127	no	0.61	0.54	50	0.89
Top v Bottom 50%	625	935	yes	2.01	0.08	13.5	0.13	3	800	no	0.03	0.98	20.5	0.77	-53	915	no	0.63	0.53	29	0.94

Note: Traders are ranked according to profits in period t and the profits for the same trader are calculated in $t+1$. Normality is tested, "yes" means the distribution is normal and Student's t -stat is used and "no" means distribution is non-normal and signed rank test is used.

Table 6. Multi-Year Performance of Non-Commercial Traders in Corn, Live Cattle, and Coffee, January 2000 - September 2009

Panel A: Total Number of Traders

	Zero or More Pairs of Years	One or More Pairs of Years	Two or More Pairs of Years	Three or More Pairs of Years	Four or More Pairs of Years	Five or More Pairs of Years
Corn	3,556	1,853	1,074	725	505	385
Live Cattle	1,551	743	420	300	206	144
Coffee	2,677	1,264	627	400	282	193

Panel B: Total Number of Traders in Top Half

	One or More Pairs of Years	Two or More Pairs of Years	Three or More Pairs of Years	Four or More Pairs of Years	Five or More Pairs of Years
Corn	766	332	157	91	48
<i>% of Tdrs</i>	41%	31%	22%	18%	12%
<i>Avg Total Pft (,000)</i>	3,630	6,503	8,020	7,411	8,402
Live Cattle	294	135	67	36	19
<i>% of Tdrs</i>	40%	32%	22%	17%	13%
<i>Avg Total Pft (,000)</i>	4,340	8,948	15,258	24,846	36,526
Coffee	598	180	62	23	7
<i>% of Tdrs</i>	47%	29%	16%	8%	4%
<i>Avg Total Pft (,000)</i>	103	2,254	2,919	5,589	448

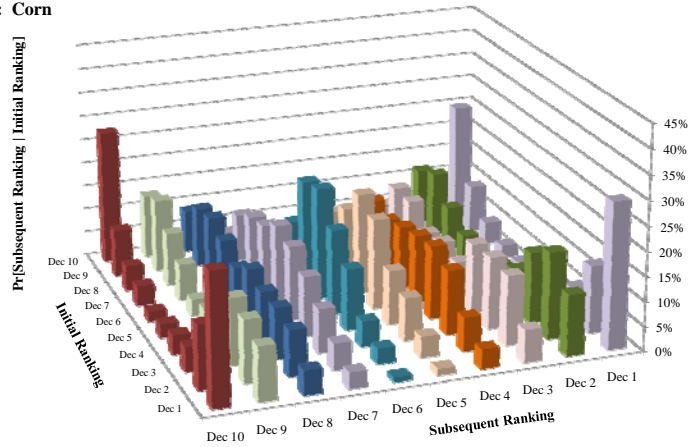
Panel C: Total Number of Traders in Bottom Half

	One or More Pairs of Years	Two or More Pairs of Years	Three or More Pairs of Years	Four or More Pairs of Years	Five or More Pairs of Years
Corn	896	317	124	59	29
<i>% of Tdrs</i>	48%	30%	17%	12%	8%
<i>Avg Total Pft (,000)</i>	-355	-1,493	-3,778	-3,790	-6,284
Live Cattle	359	118	55	20	9
<i>% of Tdrs</i>	48%	28%	18%	10%	6%
<i>Avg Total Pft (,000)</i>	75	-2,453	-3,743	-2,835	-2,348
Coffee	484	197	91	46	27
<i>% of Tdrs</i>	38%	31%	23%	16%	14%
<i>Avg Total Pft (,000)</i>	-3,464	-8,170	-14,850	-23,312	-32,205

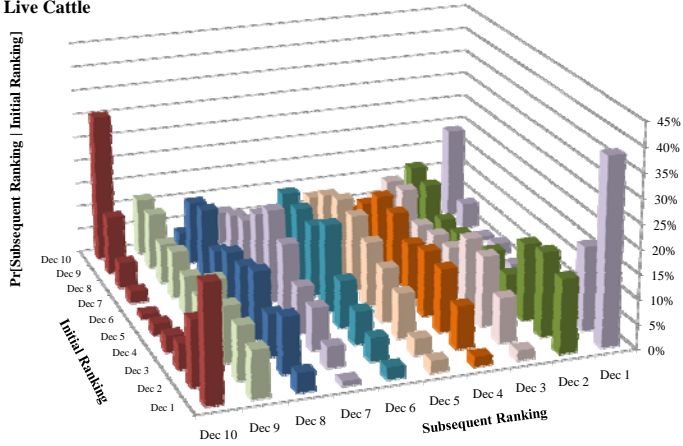
Note: Results are only shown for "five or more pairs of periods" to maintain trader confidentiality.

Figure 1. Contingency Table of Initial and Subsequent Annual Performance Rankings for Non-Commerical Futures Traders in Corn, Live Cattle, and Coffee, January 2000 - September 2009. In each calendar year from 2000 to 2009, traders are ranked into decile portfolios based on one-year gross returns. These initial decile rankings are paired with the trader's subsequent one-year gross return ranking. Traders that do not survive into the subsequent year are dropped from the analysis. The initial ranking is on the x-axis and the subsequent ranking is on the z-axis. The y-axis is the probability of the subsequent ranking given the initial ranking.

Panel A: Corn



Panel B: Live Cattle



Panel C: Coffee

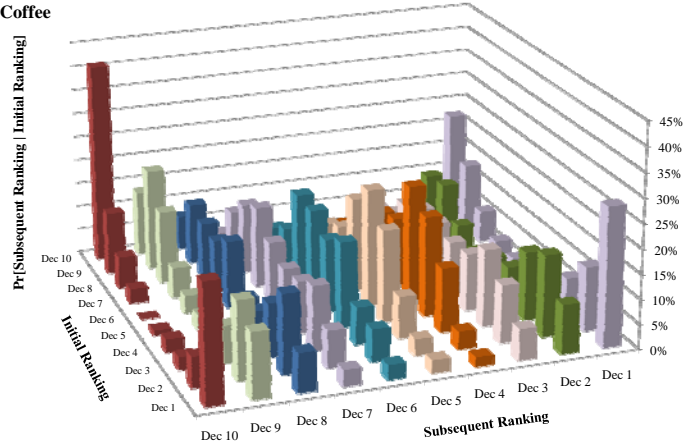
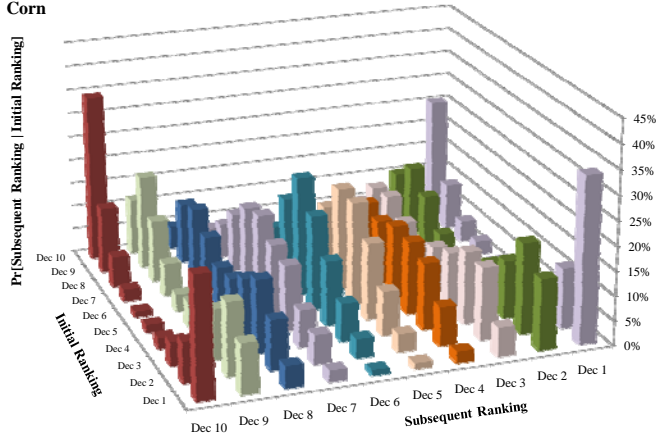


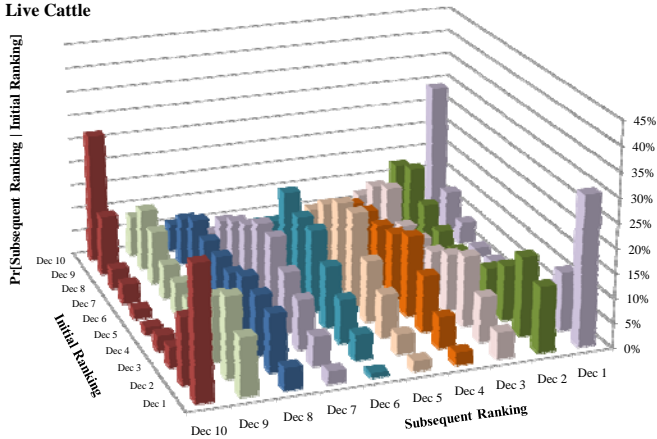
Figure 2. Contingency Table of Initial and Subsequent Quarterly Performance Rankings for Non-Commerical Futures Traders in Corn, Live Cattle, and Coffee, January 2000 - September 2009.

In each calendar year from 2000 to 2009, traders are ranked into decile portfolios based on one-year gross returns. These initial decile rankings are paired with the trader's subsequent one-year gross return ranking. Traders that do not survive into the subsequent year are dropped from the analysis. The initial ranking is on the x-axis and the subsequent ranking is on the z-axis. The y-axis is the probability of the subsequent ranking given the initial ranking.

Panel A: Corn



Panel B: Live Cattle



Panel C: Coffee

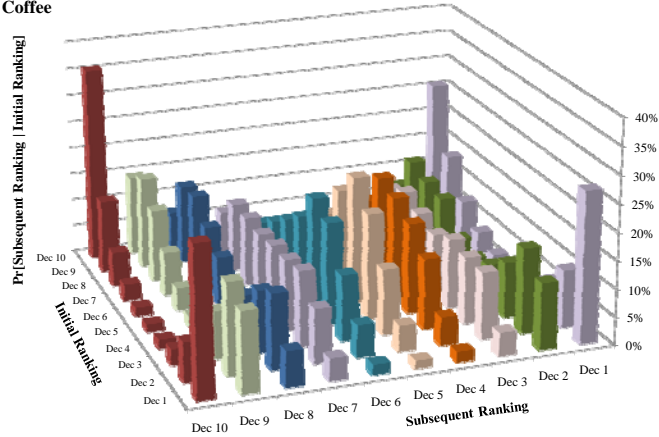
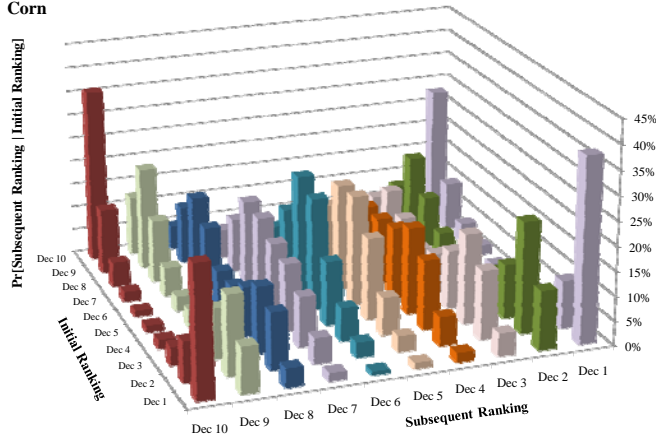


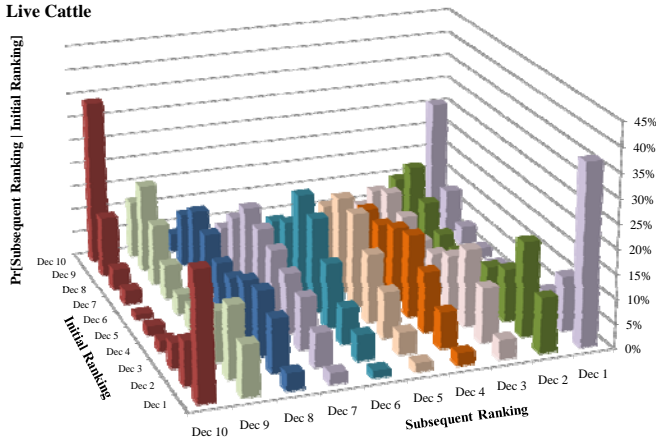
Figure 3. Contingency Table of Initial and Subsequent Monthly Performance Rankings for Non-Commerical Futures Traders in Corn, Live Cattle, and Coffee, January 2000 - September 2009.

In each calendar year from 2000 to 2009, traders are ranked into decile portfolios based on one-year gross returns. These initial decile rankings are paired with the trader's subsequent one-year gross return ranking. Traders that do not survive into the subsequent year are dropped from the analysis. The initial ranking is on the x-axis and the subsequent ranking is on the z-axis. The y-axis is the probability of the subsequent ranking given the initial ranking.

Panel A: Corn



Panel B: Live Cattle



Panel C: Coffee

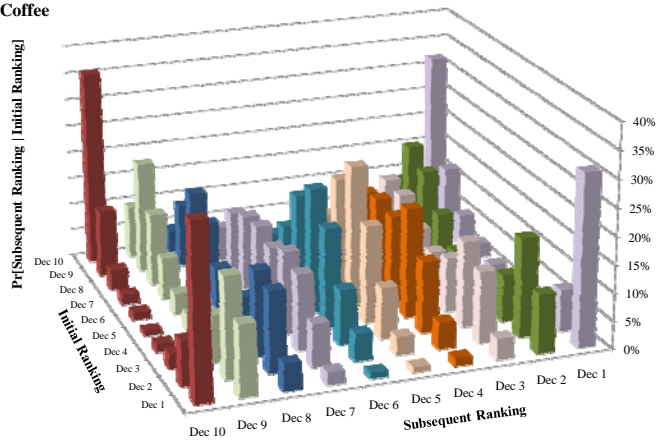


Figure 4. Total Number of Non-Commercial Futures Traders in Multiple Pairs of Years, Jan

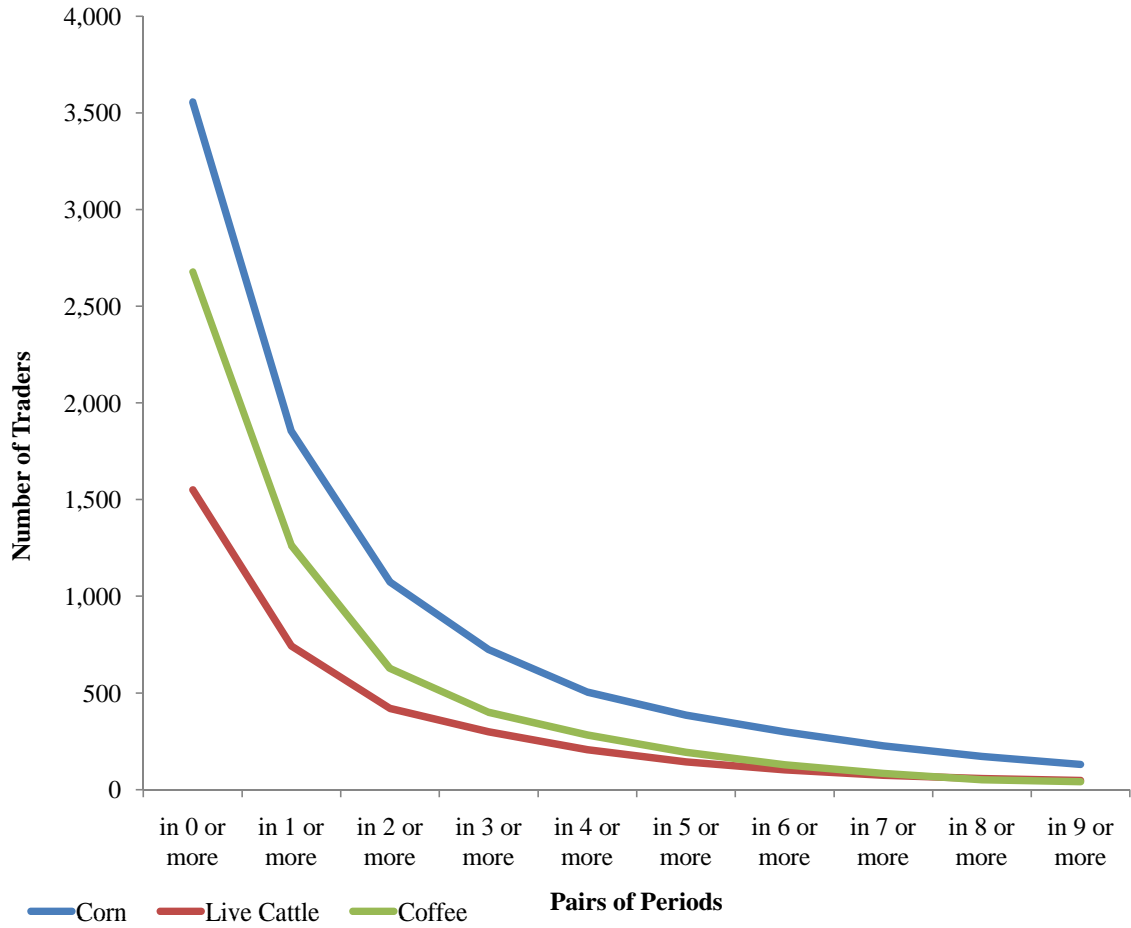
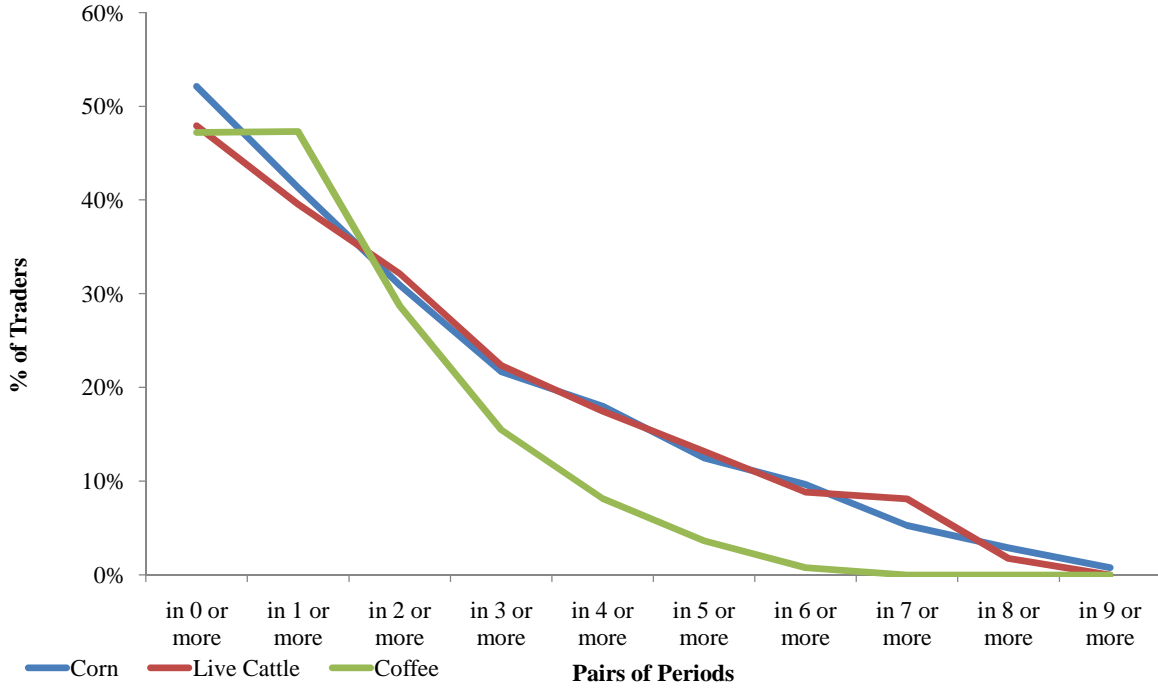


Figure 5. Percentage of Non-Commerical Futures Traders in Top and Bottom Half of Performance in Multiple Pairs of Years, January 2000 - September 2009

Panel A: Percentage of Traders in the Top Half of All Traders in the Grouping



Panel B: Percentage of Traders in the Bottom Half of All Traders in Grouping

