THREE ESSAYS ON AGRICULTURAL FUTURES TRADERS

BY

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ABSTRACT

This is a comprehensive study of the growth and impact of agricultural futures market traders. The growth of financial investment in commodities has introduced participants and raised both new questions and warranted revisiting old questions; these include the impact on commodity prices, the profitability of traders, and the existence of trading skill. To address these questions twelve commodity markets are chosen to capture the majority of agricultural trading on organized futures markets and encompass the agricultural commodity index trading activity. The data used are from the proprietary large trader database of the Commodity Futures Trading Commission (CFTC) that details individual trader end of day positions and covers the years 2000 to 2009.

The growth of index fund investment from $12 billion in 2002 to over $200 billion by 2008 initiated a debate on whether index funds are "too big" for the current size of commodity futures markets. Concerns emerged regarding their adverse effects on prices and volatility. The impact of the financial investment of index traders is analyzed using Granger Causality tests. The analysis investigates three different scenarios: (i) aggregated commodity index trader positions impacts on returns or volatility, (ii) changes in returns or volatility effects on aggregate commodity index trader positions, and (iii) disaggregated commodity index trader positions effects on contract returns or volatility during the roll period. Results show index traders do not have a widespread impact on returns or volatility and in some cases actually decrease volatility bringing stability to the marketplace. The futures markets have adjusted to the presence of the new financial participants and continue to provide price discovery and risk management. The results have important implications for the ongoing policy debate surrounding index investment; in particular, the results do not support limiting participation of index fund investors.

The returns to traders are analyzed to determine if a risk premium in agricultural futures markets exists, where hedgers pay speculators for protection against adverse price movements. The existence of a risk premium is often touted as a motivation factor for speculative trading. The long, passive index traders that emerged as major participants in 2004 and 2005 provide a natural experiment to determine if naïvely holding positions opposite of hedgers results in positive profits and thereby evidence of a risk premium. Even in the presence of increased prices and volatility that encourage the transfer of risk, no risk premium is found. CITs do not display evidence of receiving a risk premium by earning consistent positive returns but rather experience large losses in aggregate whereas noncommercial traders experience positive profits. The absence of a risk premium may occur because an infinitely elastic supply of speculative services results in the risk premium being bid to zero or the risk absorbing role is usurped by liquidity demands of index traders.

Finally, speculative, noncommercial traders are analyzed to determine if they persist in making profits or if profits are randomly generated. The study focuses on three important and representative commodities; corn for field crops, live cattle for livestock, and coffee for soft commodities. Two methods are used to analyze the persistent ability of traders to generate positive outcomes: (i) the first is the Fisher Exact test, a nonparametric two-way winner and loser rank contingency table analysis, and (ii) the second is the testing of trader by magnitude of profits using the rank of trader profits in the first period to identify top and bottom deciles. The results indicate that the top 10% of traders have substantial ability to persistently perform; this is about 5-8% more traders than identified in other studies of agricultural futures traders. The rigorous out-of-sample procedures used in this essay provide compelling evidence of the importance of skill in trader returns, and may help explain their continued presence in futures markets in the absence of a risk premium.

To everyone who helped make this possible. You know who you are.

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1. INTRODUCTION

The organized futures exchanges we see today developed gradually, emerging first as informal forward markets in the geographical marketing area for a commodity. Financing requirements grew apace with the increasing trade activity which motivated merchants to find buyers for their commodities on a forward basis. These early forward contracts were informal agreements between two parties and specified only quantity, price, and time of delivery. The need arose for more formal markets and multiple exchanges emerged in the second half of the nineteenth century. For example, in 1859 the Chicago Board of Trade was chartered and homogenous contracts were created specifying quality standards, size, delivery times, and margin rules that resulted in easy entry and exit of contracts and little default risk. Active futures markets emerged in other locations including the New York Cotton Exchange, New York Produce Exchange, Chicago Mercantile Exchange, and Chicago Produce Exchange. Today many of these exchanges have been consolidated or eliminated as business models and needs changed.

Since their inceptions, the growth of futures exchanges and the pace of product innovation have been phenomenal. In the 1960s the futures markets were limited to agricultural and metal products; today a variety of futures markets exists ranging across agricultural, credit derivatives, interest rates, energy, equities, environment, and foreign exchange contracts. In 1970 a mere 12.6 million futures contracts were traded on the principal commodity exchanges (Peck 1985), in 2009 the CME Group traded 2.2 billion contracts and ICE Futures traded 253 million contracts.

Commercial firms use futures markets for arbitrage, operational, and anticipatory hedging in an attempt to manage price risks inherent in commodity ownership. Following Peck (1985), the first commercial use is arbitrage; the most common example of an arbitrage hedging transaction focuses on seasonal storage of an agricultural commodity and the use of futures markets to secure a return to storage through a predictable change in relation between cash and futures prices. A second reason for commercial use of futures markets is operational; the futures markets are more liquid than the cash market and allow large commercial transactions to be priced quickly with minimal effect on prices. Firms can then search for specific grades or quantities in suitable locations. A third reason for the business use of futures is anticipatory hedging; a sale or purchase cannot be carried out today in the cash market so the hedger conducts the upcoming transaction in the futures market. This allows the commercial firm to buy or sell as market judgment dictates without the physical operation constraints.

Speculative (noncommercial) firms absorb the frequently unbalanced demands of commercial buyers and sellers and employ three forms of participation in futures markets: position trading, spreading, and market making. Position trading is accumulating a position based on the expectation of making a profit from price changes over time; this absorbs the imbalance between aggregate commercial buyers and sellers of futures contracts. Spread trading is taking opposite positions in two contract maturities to profit from the relative change in prices; this absorbs the future hedging needs of commercial buyers and sellers. Market making noncommercials trade in large volumes during the daily trading sessions and rarely hold positions overnight. They profit by 'scalping' fractions of a cent on trades and provide liquidity to the market by always being ready to buy or sell.

The commercial use of futures markets is the primary reason for their existence (Working 1954). When a futures contract market is not performing correctly or is perceived to be manipulated, a volley of complaints and comments ensue. Most recently, a world-wide debate has erupted about the price impact of the new ‘index fund’ speculators in commodity futures markets. A number of observers (e.g., Masters and White 2008) assert that buying pressure from index funds created a bubble in commodity prices during 2007-2008, which resulted in market prices far exceeding fundamental values and excess volatility. The bottom-line of this argument is that the size of index fund investment is “too big” for the current size of commodity futures markets. During this same time, non-convergence of cash and futures prices in corn, soybeans, and wheat markets became a major concern (Irwin et al. 2009), further fueling the controversy over speculation in commodity futures markets.

Based on these concerns, a number of bills have been introduced in the U.S. Congress to prohibit or limit speculation in commodity futures markets. The U.S. Senate Permanent Subcommittee on Investigations stated that “…there is significant and persuasive evidence to conclude that these commodity index traders, in the aggregate, were one of the major causes of “unwarranted changes”—here, increases—in the price of wheat futures contracts relative to the price of wheat in the cash market…Accordingly, the Report finds that the activities of commodity index traders, in the aggregate, constituted “excessive speculation” in the wheat market under the Commodity Exchange Act.” (USS/PSI 2009, p. 2). This and other research (e.g. Robles, Torero, and von Braun 2009, p.7) are used as justification for the passage of the Dodd-Frank Wall Street Reform and Consumer Protect Act that provides the CFTC with broad authority to set on-and-off exchange spot month, single maturity, and aggregate contract position limits in commodity markets in an attempt to prevent, “Excessive speculation in any commodity under contracts of sale of such commodity for future delivery…..causing sudden or unreasonable fluctuation or unwarranted changes in the price of such commodity, is an undue and unnecessary burden on interstate commerce in such commodity. …” (Dodd-Frank 2010). The concerns over speculation and manipulation facilitated the passage of unprecedented regulations on commodity derivate trading.

The provided background on the importance of the futures markets and the controversy surrounding them motivates further research of the role of commodity index traders and the functionality of these markets. The essays within will address two main questions, (1) with the introduction of commodity index traders, what is the impact on commodity prices and (2) what traders are making money and why? To address these questions 12 commodity markets are chosen to capture the majority of agricultural trading on organized futures markets and encompass the agricultural commodity index trading activity. The 12 markets include cocoa, coffee, cotton and sugar traded on the Intercontinental Exchange (ICE); corn, soybeans, soybean oil, and wheat traded on the Chicago Board of Trade (CBOT); feeder cattle, lean hogs, and live cattle traded on the Chicago Mercantile Exchange (CME); and wheat traded on the Kansas City Board of Trade (KBOT).

The end of day positions in the 12 markets for all "Large Traders", those traders required to report to the Commodity Futures Trading Commission (CFTC), are analyzed from 2000 to 2009. The propriety data is collected by trader at the end of each day and is used in this analysis. This important data set, called the Large Trader Reporting System (LTRS), is released in an aggregate form to the public each Friday, with reporting as of the previous Tuesday. The public looks to this data set called the Commitment of Traders Report (COT) to determine the proportion of open interest held by general trader groupings aggregated across maturities. This study utilizes the disaggregated data behind this public report to probe into the details behind the open interest by trader group and by individual trader.

Previous research on agricultural commodities has used the proprietary LTRS detailed data or the public COT aggregated data to analyze futures markets. Several studies have examined the relationship between large trader positions, including speculators, and subsequent commodity futures returns (e.g., Buyuksahin and Harris 2009; Brunetti and Buyuksahin 2009; Irwin and Sanders 2010b; Stoll and Whaley 2010). These studies generally do not find large trader positions cause prices but certain large trader categories do follow price changes. Another set of studies analyze if speculative traders make money due to a risk premium paid by hedgers to speculators for absorbing the risk hedgers offset in the market. The natural extension of this research is to discover if traders are skilled or lucky when earning profits (e.g. Houthakker 1957; Rockwell 1967; Hartzmark 1987, 1991; Leuthold, Garcia, and Lu 1994; Fishe and Smith 2010). The results are mixed but generally no risk premium is found and only a small portion of traders exhibit any consistent type of forecasting skill. The following three essays will continue this important research and help resolve some current and long standing debates.

The first dissertation essay is entitled, "**The Price Impact of Index Funds in Agricultural Futures Markets: Evidence from the CFTC's Daily Large Trader Reporting System.**" This essay analyzes agricultural commodity index traders to determine if their trading activity has impacted either returns or volatility in 12 different agricultural futures markets.[1] The data covers January 2000 to September 2009 detailing end of day positions for all traders. Granger Causality tests are used to assess casual relationships in conjunction with seemingly unrelated regression estimation. The analysis tests three different scenarios: (i) changes in returns or volatility cause aggregate commodity index trader positions (ii) commodity index trader aggregate positions cause changes in returns or volatility, and (iii) commodity index trader positions in individual maturities cause changes in returns or volatility during the roll period.

The motivation from this work stems from concerns about the influx of these index traders who passively buy agricultural futures and are non-responsive to the underlying market fundamentals. A Commissioner from the CFTC commonly calls these traders “massive passives”, indicating their large size in the marketplace and their inactive trading style.

The second dissertation essay is entitled, **“Returns to Traders and Existence of a Risk Premium in Agricultural Futures Markets.”** The purpose of the essay is to determine if a risk premium exists in futures markets where hedgers pay speculators for protection against adverse price movements. Hartzmark (1987) addressed this same question but his time period of study from 1977 to 1981 is limited and outdated. The current state of the futures markets is quite different today than in was in the late 1970s. The data for this study extends from January 2000 to September 2009 and covers 12 commodity markets. The profitability of aggregate trader groups is calculated using end of day positions and prices for individual commodities; these commodities are then grouped according to price patterns over the sample period into three groups including grains (corn, soybeans, soybean oil, and wheat contracts), livestock (feeder cattle, lean hogs, and live cattle) in addition to cotton, and soft commodities (cocoa, coffee, and sugar) except cotton. More importantly, long passive traders, called commodity index traders (CITs) emerged into the futures markets during 2004 and 2005 and provide a natural experiment to determine if naïvely holding positions opposite of hedgers results in positive profits and thereby evidence of a risk premium.

The third dissertation essay is **“Returns to Individual Traders: Skill or Luck?”** The purpose of this essay is to determine if noncommercial traders persist in making profits or if profits are randomly generated. This essay builds upon the work of the second essay, which identified noncommercial traders as the profitable category of traders. The data for this study extend from January 2000 to September 2009 and covers three important and representative commodities: corn for field crops, live cattle for livestock, and coffee for soft commodities. Two methods are used to analyze trader skill or persistence. The first is the Fisher Exact test, a nonparametric two-way winner and loser rank contingency table analysis. The second is the testing of trader by magnitude of profits using the rank of trader profits in the first period to identify top and bottom deciles. In this third essay, the analysis performs a stringent test with data spanning 10 years and across 3 main commodities to determine if past performance is predictive of future performance. Previous shortcomings are rectified by testing multiple investment horizons using both binary variables and magnitude of profit measures.

The dissertation contributes to the agricultural marketing literature by providing a unique insight into the trading activity of new commodity index trader entrants and a comprehensive assessment of trader profitability and skills. The results are interesting to regulators who have proposed restrictions on commodity index trading due to accusations of inflated price levels and increased volatility. Researchers who study the behavior of commodity traders and motivations of speculators find the profits and losses results contribute significantly to further understanding of the marketplace. The theoretical framework, data, methods to be employed, and results for each of the three dissertation essays follow.

2. THE PRICE IMPACT OF INDEX FUNDS IN AGRICULTURAL FUTURES MARKETS: EVIDENCE FROM THE CFTC'S DAILY LARGE TRADER REPORTING SYSTEM

2.1 Introduction

The idea of a long-only investment that tracks an index of commodity futures prices is not new (Greer 1978; Bodie and Rosansky 1980); however, monetary investment in such instruments was small until the early 2000's. The Commodity Futures Trading Commission (CFTC) estimates that index fund investment was only $12 billion in 2002 but increased to over $200 billion by 2008.[2] Index fund investors are attracted to commodity futures markets in search of risk premiums and portfolio diversification benefits (e.g., Gorton and Rouwenhorst 2006).

A world-wide debate has erupted about the price impact of these new 'index fund' speculators in commodity futures markets.[3] A number of observers (e.g., Masters and White 2008) assert that buying pressure from index funds created a bubble in commodity prices during 2007-2008, which resulted in market prices far exceeding fundamental values. Petzel (2009) argues that unleveraged futures positions of index funds are effectively synthetic long positions in physical commodities and represents new demand. If the magnitude of index fund demand is large enough relative to physically-constrained supplies in the short-run, prices and price volatility can increase sharply. The bottom-line of this argument is that the size of index fund investment is "too big" for the current size of commodity futures markets.

Based on these concerns, the U.S. Senate Permanent Subcommittee On Investigations probed index trading and their findings state that "…there is significant and persuasive evidence to conclude that these commodity index traders, in the aggregate, were one of the major causes of "unwarranted changes"—here, increases—in the price of wheat futures contracts relative to the price of wheat in the cash market…Accordingly, the Report finds that the activities of commodity index traders, in the aggregate, constituted “excessive speculation” in the wheat market under the Commodity Exchange Act.” (USS/PSI 2009, p. 2) This and other research (e.g. Robles, Torero, and von Braun 2009, p.7) are used as justification for the passage of the Dodd-Frank Wall Street Reform and Consumer Protect Act that provides the CFTC with broad authority to set on and off exchange spot month, single maturity, and aggregate contract position limits in commodity markets in an attempt to prevent, “Excessive speculation in any commodity under contracts of sale of such commodity for future delivery…..causing sudden or unreasonable fluctuation or unwarranted changes in the price of such commodity, is an undue and unnecessary burden on interstate commerce in such commodity. …” (Dodd-Frank 2010). The concerns over speculation and manipulation facilitated the passage of unprecedented regulations on commodity derivate trading.

In response to concerns about speculative behavior, several studies provide empirical evidence on the relationship between index traders and subsequent commodity futures prices. Gilbert (2009, 2010), Irwin and Sanders (2010b), and Stoll and Whaley (2010) analyze the impact of commodity index traders (CITs) on agricultural prices. These studies generally find that CITs do not have a significant impact on returns. Similarly, Brunetti and Reiffen (2010) and Irwin et al. (2011) study index trader position impact on spreads between the nearby and first deferred agricultural futures contracts during the “roll period” of index traders. The roll period is the interval of time when index traders must “roll” or change their futures positions from the expiring nearby contract to the first deferred contract; the roll involves exiting long positions in the nearby contract and entering long positions in the first deferred. Brunetti and Reiffen determine CITs contribute to decreased hedging costs with a modestly increasing affect on spreads whereas Irwin et al. determine that CITs have no affect on spreads during the roll period. Additional studies apply other methods that do not specifically rely on index fund positions. Tiang and Xiong (2009) conclude that index fund investing has an impact on commodity prices based on a trend towards increasing co-movement of futures prices for commodities included in popular investment indexes, such as the S&P GSCI Index™. Mou (2010) also studies the roll period and concludes the increased activity of index traders has caused a significant widening of spreads during this time.

Irwin and Sanders (2011) recently surveyed the literature surrounding the role of CITs in the commodity markets, weighing the evidence that CITs cause a price impact against the evidence that CITs do not artificially inflate prices. The authors call into question the data and methods used in the empirical studies finding evidence that commodity index investment impacts futures prices. Rather, they determine the evidence provided by the group of studies arguing against an impact is more robust and the CITs have no systematic influence on commodity futures prices.

While the weight of existing evidence tilts towards limited or no price impact of index funds, previous research is nonetheless subject to important data limitations. First, public data on CIT positions are only available weekly which limits the sample size and camouflages any impacts that may occur in periods less than a week. Second, public index trader data are not available prior to 2006 which does not include the most rapid position increases of CITs during 2004 and 2005 that is more probable to show the impact of index traders (Sanders, Irwin, and Merrin 2008).[4] Third, previous data are aggregated across all maturities which limit the ability to evaluate the market impact during the crucial index trader roll period. Thus far, matching prices with both the exiting of index trader position in the nearby maturity and entering of position into the first deferred contract has not been possible. Stoll and Whaley (2010) argue the roll period is more likely to exhibit an impact because the size of CIT position changes in roll periods is substantially larger than the size of position changes in non-roll periods.

Two important methodological issues have not been investigated in previous studies of CITs in agricultural futures markets. The first issue is due to uncertainty about how to categorize CIT positions. Specifically, CITs do not fit neatly into the hedger or speculative category which is the reason why the CFTC created a separate category for the reporting of index traders (2008b). Stoll and Whaley (2010) argue CITs cannot be classified as speculators because of the diversification motive of index investors. However, the actual motivation of investors in index funds is not precisely known, particularly in the case of exchange traded funds (ETFs).

The second issue is the roll period definitions used in previous studies. For example, Stoll and Whaley (2010) and Irwin et al. (2011) assume that the roll window is the fifth through ninth business days in the month before expiration, consistent with the traditional "Goldman Roll" definition. This definition of the roll window may exclude substantial amounts of rolling activity, particularly in light of CIT efforts to alter rolling strategies in order to lessen the liquidity costs (trade execution) of moving such large positions from the expiring nearby contract to the first deferred maturity.

The purpose of this paper is to analyze the price impact of long-only index funds in agricultural futures markets from January 2004 through September 2009, using disaggregated data from the CFTC's Large Trader Reporting System (LTRS). The data used in this study are not subject to previous limitations; the non-public CFTC database reports index trader positions on a daily basis and disaggregates positions by contract maturity. Furthermore, the data can reliably estimate CIT positions starting in 2004 to capture the period of their most rapid position growth. The commodity futures markets in this data set include corn, soybeans, soybean oil, CBOT wheat, KCBOT wheat, feeder cattle, lean hogs, live cattle, cocoa, cotton, coffee, and sugar. The previous methodological limitations are also addressed in this study including a test to determine if CIT positions changes react to past price movements and the definition of a data-dependent roll period.

This essay has three main parts. First, the hypothesis that aggregate CIT positions do not cause changes in price returns or volatility is tested. This tests if demand for long only commodity index portfolios impacts futures prices. Second, aggregate CIT positions are regressed on lagged returns and volatility measures to determine if CIT position changes are impacted by prices. Third, the analysis examines non-aggregated index trader positions in the nearby and first deferred contract maturities during the roll period. Limiting the specification to the roll period focuses the estimation on extreme changes in CIT open interest during a concentrated period of time. In all three parts, Granger causality tests are used to investigate whether a significant relationship exists between index trader position changes and commodity futures returns and volatility. Seemingly unrelated regressions (SUR) estimation is used to improve the power of statistical tests, and equality constraints are placed on the parameters not significantly different across equations. Additional cotemporaneous correlation tests are added to the roll period analysis to support the Granger causality tests. Overall, using both aggregated and non-aggregated positions in addition to the SUR estimation and daily data should provide the most powerful tests of CIT impact to date in agricultural futures markets.

2.2 Literature Review

A number of empirical studies test the impact of traders on prices and volatility in the futures markets, with a small portion directly assessing commodity index traders. In this literature review the focus is strictly on those empirical studies directly addressing commodity index traders and their potential impact on agricultural commodity market prices. The discussion of literature is in chronological order to demonstrate the progression of research through time.

Brunetti and Buyuksahin (2009) investigate speculators using the CFTC Large Trader Reporting System to test the hypothesis that speculative trading is destabilizing to the futures market. The five commodities studied include, NYMEX crude oil and natural gas, CME Eurodollar and mini-Dow, and CBOT corn. The sample period is January 2005 to March 2009 for all commodities except corn, which starts in August 2006. Swap dealer positions are used as a proxy for index fund investment. A vector autoregression (VAR) is estimated for each commodity to jointly test across trading groups to discover the direct effect of each group on returns or volatility, as well as the interaction of positions among groups. They provide evidence that speculative trading, including index investment, in futures markets is not destabilizing, and speculative trading activity reduces volatility levels.

Tiang and Xiong (2009) analyze the correlation of commodity futures returns with stock, bond, and dollar returns to determine if the financialization of commodities has increased correlation among commodities within the popular commodity indices, GSCI and DJ-AIG. The paper studies 28 commodities, four are energy, nine are grains, six are softs, four are livestock, and five are metals, from January 2, 1998 to March 2, 2009. They find that that correlation of commodity returns within indices increased starting in 2004; they attribute this increase to the existence of index investment. They find that along with the growth in investment, commodity prices have been increasingly exposed to market-wide shocks. The study highlights the increasingly important interactions between commodities markets and financial markets after than financialization of commodity markets.

Gilbert (2009) attempts to explain speculative influences on commodity futures prices by examining the price behavior in crude oil futures, three metals, and three agricultural futures from 2006 through 2008. He uses a test for bubbles created by Phillips, Wu, and Yu (2009) and finds evidence of bubbles in seven out of nine markets; the "bubble" days are concentrated in the summer of 2008. He also constructs a quantum index of commodity index investment using reported positions of index traders in 12 agricultural markets to approximate index investment in crude oil and metal commodities. This quantum index is used in Granger causality tests to determine if the index forecasts price changes. Results show index activity may impact prices in crude oil, aluminum, and copper but none of the agricultural commodities indicate index trader activity impacts prices.

Gilbert (2010) continues his investigation using monthly data from March 2006 to June 2009. He employs a CAPM type model and Granger causality analysis to establish the role of demand growth, monetary expansion, and exchange rate movements in explaining price movements over the period. He concludes there is modest evidence that the impact of index-based investment may have caused "bubble-like" commodity prices but acknowledges macro economic factors likely had a major impact on the food price increase in 2008.

Irwin and Sanders (2010a) calculate Workings T-index for speculation and employ bivariate Granger causality tests using lead-lag dynamics between index fund positions and futures returns (prices changes) or price volatility. Results show no convincing evidence that positions held by index traders impact market returns. For volatility, they do find larger long positions by index traders lead to lower market volatility but excessive speculation, as measured by Working's T-Index, is associated with greater subsequent variability in a few markets. Overall, these results do not support an argument that index funds cause inflation in commodity futures prices but does provide evidence that increases in index fund positions can lead to declining volatility.

Stoll and Whaley (2010) investigate commodity index positions and commodity futures prices to determine if commodity index investing is a disruptive force to markets. The study uses the Commodity Futures Trading Commission (CFTC) public Commitment of Traders Report (COT) from 2006 to 2009 for the cocoa, coffee, corn, cotton, KC wheat, soybean oil, CBOT wheat, crude oil, heating oil, natural gas, RBOB oil[5], feeder cattle, lean hogs, live cattle, gold, and silver. A linear regression is used to test if the number of nearby futures contracts rolled from one maturity to the next affects commodity returns; the roll effect is measured in the month before contract expiration from the fourth through ninth business days. Granger causality tests are used to determine the lead lag relationship between commodity index flows and returns. The authors argue that commodity index investment is not speculative, that commodity index rolls have little futures price impact, and that commodity index position changes do not cause futures price changes.

Mou (2010) specifically studies the roll activity of commodity index investors and the impact on commodity prices. The paper analyzes the change in spreads during the roll period over time and by comparing commodities that are both in and outside a commodity index. The paper studies 19 commodities involved in index investment from the agriculture, livestock, energy, and metal sectors and 18 commodities from similar categories that are not involved in index investment. Panel regressions are conducted to determine if the change in spreads during the roll period can be explained by an indicator variable if a commodity is in an index commodity, an indicator variable if a commodity is included in the Goldman Sachs Commodity Index on day *t*, and control variables for GDP and inflation. A second regression is computed including size of index investment relative to size of the market. Results find that spreads are widened by the increased participation of commodity index traders. Next, two simple trading strategies are devised to exploit this market anomaly; the strategies to “front run” the rolling activity proves to yield excess returns with positive skewness. The profitability decreases as the amount of arbitrage capital increases, measured as spread activity. Mou estimates that due to the price impact, index investor forwent on average 3.6% annual return and a 48% higher Sharpe ratio of the return.

Brunetti and Reiffen (2010) analyzed commodity index traders and hedgers in corn, soybeans, and CBOT wheat markets from July 2003 through December 2008 using the CFTC Large Trader Reporting System. They developed an equilibrium model of trader behavior for CITs and traditional short hedgers to determine if the cost of hedging has decreased in the presence of index traders. The empirical estimation employs a GARCH (1,1) model that regresses spreads between nearby and deferred contracts on index trader levels, a model derived measure of hedging activity in the cash market, and various dummy variables accounting for pre and post harvest contracts. They determine that hedging costs have decreased in the presence of index traders, consistent with the explanation that CITS are willing to take the opposite position from hedgers at lower prices than are traditional speculators. Within the same model, they also conclude that absolute levels of index trader’s positions are positively related to spread levels.

Irwin, Garcia, Good, and Kunda (2011) analyze if index funds are to blame for an increase in spreads and non-convergence in CBOT corn, soybean, and wheat futures contracts using data spanning from 1994 to 2010. First, the analysis tests if spreads in futures prices contributed to the lack of convergence. Second, the analysis investigates if index trading leads to expanded spreads and therefore caused convergence problems; the analysis uses weekly CFTC index trader positions data from 2004-2010. Results find that increases in spreads did contribute to the lack of convergence but fail to find that index traders significantly contributed to the increase in spreads.

Overall, previous research is mixed on the impact of index fund investment on commodity price returns and volatility but the majority of studies fail to determine that index traders significantly increase agricultural futures prices. Researchers widely agree that commodity index trader investment corresponds to the price increases in certain commodities during 2008 but actual causality is not established. The evidence regarding index traders impact on spreads is also mixed with Stoll and Whaley (2010) and Irwin et al. (2011) concluding index traders have no effect and Mou (2010) and Brunetti and Reiffen (2010) arguing index traders expand spreads. The study will join the debate using data from the detailed CFTC Large Trading Reporting System database.

2.3 CFTC Large Trader Reporting System

The CFTC Large Trader Reporting System (LTRS) is designed for surveillance purposes to detect and deter futures and options market manipulation (Fenton and Martinaitas 2005). Positions must be reported to the CFTC on a daily basis if they meet or exceed reporting levels. For example, the current reporting level in the corn futures contract is 250 contracts, or 1.25 million bushels. 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.[6,7] In recent years about 70% to 90% of open interest in commodity futures markets has been reported to the CFTC and included in the LTRS (CFTC 2010).

A weekly snapshot of the LTRS data is compiled in aggregate form and released to the general public as the *Commitment of Traders* report (COT). The COT pools traders into two broad categories (commercial and non-commercial), all contract maturities are aggregated into one open interest figure, and the report is released each Friday with the data as of the end-of-day on the preceding Tuesday. The COT report covers over 90 U.S. commodity markets and two versions are published: i) the *Futures-Only Commitments of Traders* report that includes futures market open interest only; and ii) the *Futures-and-Options-Combined Commitments of Traders* report that includes futures market open interest and delta-weighted options market open interest.

In response to industry concerns regarding commodity index fund positions, the CFTC changed the reporting system in 2007 by creating the *Supplemental Commodity Index Trader* (CIT) report that separates commodity index traders from the original commercial and noncommercial COT categories. CFTC staff engaged in a detailed process to identify index traders in the LTRS for inclusion in the new category. The process included screening all traders with large long positions in commodity futures contracts, analyzing futures positions to determine a pattern consistent with index trading, reviewing line of business forms (Form 40) to obtain more detailed information on their use of the market, and conducting an expansive series of phone and in-person interviews with traders. The CFTC acknowledges that the classification procedure was imperfect and that "…some traders assigned to the Index Traders category are engaged in other futures activity that could not be disaggregated….Likewise, the Index Traders category will not include some traders who are engaged in index trading, but for whom it does not represent a substantial part of their overall trading activity" (CFTC 2008a). While recognizing these potential problems, the CIT data are nevertheless widely regarded as providing valuable information about index trader activity in commodity futures markets.

The first weekly *Supplemental* report was published in January 2007 and provided aggregate futures and delta-adjusted options positions of CITs in 12 commodity futures markets:

corn, soybeans, soybean oil, CBOT wheat, KCBOT wheat, feeder cattle, lean hogs, live cattle, cocoa, cotton, coffee, and sugar. The CIT category was computed retroactively for 2006 to provide context for the initial release of the data in 2007.

As noted above, CITs are drawn from the original commercial and noncommercial categories in the LTRS. CITs from the commercial category are traders whose positions predominately reflect hedging of OTC transactions associated with commodity index investors seeking exposure to commodity prices following a standardized commodity index. CITs from the noncommercial category are mostly managed funds, pension funds and other institutional investors also seeking exposure to commodity price movements. Sanders, Irwin and Merrin (2008) show that approximately 85% of index trader positions are drawn from the long commercial category with the other 15% from the long non-commercial category. This implies that the bulk of CIT positions are initially established in the OTC market and the underlying position is then transmitted to the futures market by swap dealers (including both commercial and investment banks) hedging OTC exposure.

2.4 Commodity Index Trader Positions

Data on the positions of CITs are collected from the LTRS for the same 12 markets included in the weekly *Supplemental* report over January 2000 through September 2009. In contrast to the weekly data on CIT positions made public in the *Supplemental* report, CIT positions collected directly from the LTRS are reported on a daily basis, disaggregated by contract maturity month, and indicate if the position is in futures or options. The CIT classifications are applied retroactively from 2000 through 2005 to approximate CIT positions before the official CFTC index trader classifications began in 2006. This assumes that traders classified as CITs over 2006-2009 also were CITs previously in this period. Discussions with

CFTC staff indicate that CIT designations have changed little since the classification scheme was first constructed in 2006, which provides support for its retroactive application.[8]

The growth in CIT positions in commodity futures markets is pronounced during the 2000 to 2009 period. Table 2.1 provides a breakdown by year of the average daily net long open interest (long minus short contracts) held by CITs in the 12 markets. Note that these CIT futures positions are aggregated across all contract maturities and options positions are excluded. The general pattern is a small base of positions in 2000-2003, rapid growth during 2004-2005, and then a leveling off or more modest growth during 2006-2009. For example, the net long position of CITs in CBOT wheat increased from an average of 25,702 contracts in 2003 to 134,408 contracts in 2005, over a fivefold increase. The rapid growth in CIT positions is also apparent in CBOT wheat as a percentage of total open interest (long), which increased from 25% to 55% over the same time frame. There were some exceptions to this pattern. Growth in CIT positions in feeder cattle, live cattle, coffee, and cocoa was more linear from 2000-2009.

While there is some variation in the pattern across markets, the averages in table 2.1 clearly reveal that CITs became large participants in commodity futures markets during a relatively short period of time. By 2009, the lowest CIT percentage of total market open interest was 14% in cocoa and the highest was 52% in cotton. The average across all 12 markets in 2009 was 34%. Concerns about the price impact of index funds are understandable in light of the historic magnitude of this structural change in market participation. Some have termed this process the ‘financialisation’ of commodity futures markets (Domanski and Heath 2007).

Figure 2.1 provides daily detail on the growth of CIT positions for one of the most actively traded markets, the corn futures market.[9] Panel A displays the daily net long open interest in terms of number of contracts held by CIT traders for two categories: i) nearby and first deferred corn contracts combined, and ii) all other deferred corn contracts combined. Panel B displays the percent of total CIT open interest in all other corn deferred contracts. Separating positions into these two categories highlights any changes in the maturity of futures contracts held by CITs.

Total CIT open interest in corn was at a moderate level, between 25,000 and 50,000 contracts through the end of 2003, and then increased rapidly starting in early 2004, with a peak of more than 425,000 contracts in July 2006. CIT open interest leveled off and then declined thereafter in early 2009 with a subsequent rebound in late 2009. There is an increase in the importance of other deferred contracts in 2007, as reflected by the dark portion of panel A and the line in panel B. For example, about a quarter of CIT positions were held in longer maturity corn futures contracts in 2008. This is consistent with the much discussed trend of CITs spreading positions across more contracts in an effort to reduce trade execution costs (e.g., Meyer and Cui 2009). However, the magnitude of the increase in CIT activity for more distant contracts was less pronounced in several markets (soybean oil, feeder cattle, cocoa, coffee, and sugar).

Based on inspection of the data, other characteristics of CIT positions were identified. CIT traders bypass certain cotton, lean hogs, soybeans, and soybean oil contract maturities, presumably due to trading or liquidity costs considerations. These contracts are excluded in the later statistical analysis of price impacts.[10] It was also determined that CITs do not trade actively in options markets. The proportion of combined futures and delta-adjusted options positions represented by options has increased modestly over time, but it is unusual for options to make up more than 5% of the total. As a result only futures positions are used in the later statistical analysis. CIT traders are also interconnected across commodity markets; specifically, this data set contains 42 unique index traders with 33 traders in 10 or more markets and no traders in less than 5. Not only do they trade in similar commodities, but also trade in a similar long-only passive style.

A defining characteristic of CIT trading patterns is the "roll." Since commodity futures contracts have a limited life, CITs develop strategies to transfer (roll) long positions from an expiring contract to a later contract. The S&P GSCI Index™ is one of the most widely tracked indexes and the roll process for this index is described as follows:

> "The rolling forward of the underlying futures contracts in the excess return index portfolio occurs once each month, on the fifth through ninth business days (the roll period). As explained above, some of the underlying commodity contracts expire in the next month and thus need to be rolled forward. The simplest way to think of the process is as rolling from one basket of nearby futures (the first nearby basket) to a basket of futures contracts that are further from expiration (the second nearby basket). The S&P GSCI™ is calculated as though these rolls occur at the end of each day during the roll period at the daily settlement prices."[11]

The implication is that CIT trading ebbs and flows in specific contracts, as positions shift from one maturity to another. The nearby contract carries the majority of the open interest and the deferred contracts constitute the remaining positions.

Figure 2.2 presents an example of this "ebbing and flowing" for the 2007 calendar year in the March, May, July, September, and December corn futures contracts. Each contract expires roughly in the third week of the expiration month. The top solid black line in panel A represents the net long open interest aggregated across all contracts each business day. Total position size of CITs in corn was about 400,000 contracts at the start of the year, quickly declined to about 350,000 contracts, and then varied little from that level over the remainder of 2007. The "hills" below the total line show the composition of CIT positions on each day and clearly illustrate the pattern of rolling positions from contract-to-contract. Positions build up rapidly during the period when a contract is the nearest-to-maturity (nearby) and decline equally rapidly as the contract approaches expiration and positions are moved the next contract (first deferred) as shown in Panel B. Note that the pattern is somewhat different for the December 2007 “new crop” contract, with positions being held at some level in this contract for almost the entire year. Panel C shows the changes in the nearby and first deferred series are nearly mirror images[12]. Changes in the nearby are negative as traders rollout/exit their positions and changes in the deferred are positive as traders roll into/enter their new positions. Figure 2.2 highlights the importance of considering CIT positions in terms of both the rolling of *existing* positions from one contract to another and the change in aggregate *new net flows* into the investment category. This follows Stoll and Whaley’s (2010) argument that analyzing index investment in aggregate and by maturities is an important distinction.

2.5 Aggregate Index Positions Impacting Returns or Volatility

The directional relationship between CIT positions and prices can be tested two ways. The first, more controversial relationship is the influence of index positions on changes in prices. The second, less debated, directional relationship is the influence of changes in prices on index positions. The former is investigated first to determine if net flows of CITs and their demand for commodity investment have overwhelmed the market and systematically precede changes in returns or volatility. This directly tests the arguments of Masters and White (2008) and Petzel (2009) asserting that the “wave” index traders impacts prices and volatility in agricultural commodity markets. Aggregate CIT investment flows are used to test these relationships because aggregate positions represent the new investment decisions of index traders, not a simple shift of investment from one contract maturity to another (e.g. the roll period).

2.5.1 Methods

Hamilton (1994) recommends Granger tests to assess causal relationships between two time series using lead-lag variables. Granger causality tests reflect the basic idea that if event *X* causes event *Y* then event *X* should precede event *Y* in time. The independent variable is lagged CIT positions, the "*X*", and the dependent variable is returns or volatility, the "*Y*". Previous studies of large trader impacts in commodity futures markets (e.g., Buyuksahin and Harris 2009; Irwin and Sanders 2010b) use similar methods and specify returns as a function of lagged returns and lagged measures of trader participation. As is well-known, these tests require careful interpretation if the null hypothesis of no causality is rejected. A statistical correlation may be observed between *X* and *Y* when in reality an omitted variable *Z* is the true cause of both *X* and *Y*. Hamilton (1994, p. 308) suggest it is better to describe "Granger causality" tests between *X* and *Y* as tests of whether *X* helps forecast *Y* rather than whether *X* causes *Y*.

Equations 1 and 2 display the specification for testing CITs impact on returns and CITs impact on volatility as,

(1) $$R_t = \alpha + \sum_{i=1}^{m} \gamma_i R_{t-i} + \sum_{j=1}^{n} \beta_j X_{t-j} + \varepsilon_t$$

(2) $$V_t = \alpha + \sum_{i=1}^{m} \gamma_i V_{t-i} + \sum_{j=1}^{n} \beta_j X_{t-j} + Monthly\ Effects + v_t$$

where R_t is the daily return $[R_t = (\ln P_t - \ln P_{t-1})*100]$, X_t is a measure of CIT participation in the market, measures as both the change in position level and also percent change in position level, and V_t is volatility measured as both Parkinson estimate of volatility and implied volatility. Volatility is measured first by the Parkinson high-low estimator of daily nearby price volatility (annualized standard deviation) based on the difference between the daily high and low price

(Parkinson 1980). Implied volatility is also measured using option quotes on futures contracts and is supplied by CRB/Barchart. The method is described as,

> "This volatility is measured by entering the prices of options premiums into an options pricing model, then solving for volatility. The implied volatility value is based on the mean of the two nearest-the-money calls and the two nearest-the-money puts using the Black options pricing model. This value is the market's estimate of how volatile the underlying futures will be from the present until the option's expiration. " (Barchart/CRB, 2010).

Implied volatility is a widely accepted method of calculating forward looking volatility (e.g. Irwin 2010b, Hull, 2000, p. 255). *Monthly Effects* is a set of monthly dummy variables to allow for changing seasonal volatility (Egelkraut, Garcia, and Sherrick 2007); these dummy variables are only used if significant.

Following the convention in numerous studies, the nearby series for most futures markets is computed by rolling from the nearby contract to the first deferred contract on the last day of the month prior to the expiration month of the nearby contract. For instance, in February the nearest contract for corn is March. On the last business day in February the price series is rolled to May, the next nearest contract. Price and position changes are not calculated across contracts, so changes on a switching date correspond to the contract entering the series. Due to the nature of their contract expiration rules, cocoa, coffee, cotton, and sugar are rolled on the day following the 15th day of the month prior to the delivery month. For all variables, an augmented Dickey-Fuller test is used to determine stationarity. In every case, the test including a constant and trend rejects the null hypothesis of non-stationarity.[13]

Following Irwin and Sanders (2010b), the lag structure determined in the individual commodity regressions are used in a seemingly unrelated regression (SUR) system for 12 markets to increase statistical power. Using equations 1 and 2, the lag structure of the independent variables for individual markets is determine by minimizing BIC using an OLS search procedure with a maximum lag of m=5 and n=5. The SUR procedure incorporates cross-equation correlation of errors using a GLS estimator within Zellner's SUR framework (see Harvey, 1991, p 66). For example, corn and soybeans compete for the same acres to be planted, and grains are a major component to raising livestock. In addition to the efficiency gains from exploiting the correlation between residuals, Harvey also indicates constraints can be placed on parameters across contracts if those parameters are not statistically different from one another. First, all the commodities are tested in the general unrestricted SUR model. Second, a Wald test evaluates the null hypothesis that each parameter is equal across the markets, including α , each lag of γ, and each lag of β. If the null hypothesis is not rejected, then cross equation parameter restrictions are enacted. After the SUR system is estimated, the overall causality testing of $\sum_{j=1}^{n}\beta_j = 0$ can be determined using a F-test for each market separately (if all $\beta's$ are not restricted) and for the entire system across all 12 commodities, $\sum_{k=1}^{12}\sum_{j=1}^{n}\beta_{j,k} = 0$.

2.5.2 Results

The first set of Granger causality results using equation 1 test the null hypothesis that CIT positions do not cause returns. Aggregate CIT positions are either measured as a change in net positions or percent change in net positions of CITs. If the assertion that CITs drive up prices is true and CIT positions cause returns, then a necessary condition is for the estimated coefficients on CIT positions to be greater than zero and positive.

In table 2.2 the explanatory variable, change in CIT net positions, is used in a SUR system to test the null hypothesis that CITs do not impact returns. The minimum BIC lag structure *(m,n)* is (1,1) for all commodities except for live cattle and lean hogs which are (1,2) and (2,1), respectively. In this SUR system the cross-market restrictions are set for the intercept, α, which imposes the same intercept across all equations. The remaining unrestricted variables are allowed to vary across commodity markets. The third column test the null hypothesis that positions do not lead returns, $\beta_{j,k} = 0 \,\forall\, j$. Feeder cattle, lean hogs, and KCBOT wheat reject the null. The fourth column calculates the cumulative coefficient $\sum_{j=1}^{n} \beta_j$ and the fifth column calculates the p-value testing the null cumulative coefficient hypothesis $\sum_{j=1}^{n} \beta_{j,k} = 0$ for each commodity *k*. If only one lag is modeled, *n=1*, then no cumulative test is necessary; this is the case for all commodities in table 2.2 except for live cattle. Column six displays a one standard deviation impact of the explanatory variable which is calculated by multiplying a one standard deviation change in the positions by the cumulative coefficient from the fourth column. A one standard deviation change in positions, on average, is 1,000 contracts, with the largest being corn (2,760) and the smallest being feeder cattle (109). For example in lean hogs, a one standard deviation change in net positions is 747 contracts and the cumulative impact of a one standard deviation increase in positions would decrease returns by -0.13%.

The negative relationship between positions and returns holds for the other two significant commodities; in feeder cattle a one standard deviation increase in CIT positions decreases returns by -0.032% and in KCBOT wheat, a one standard deviation increase in positions decreases returns by -0.042%. The system wide tests at the bottom of the table show $\beta_{j,k} = 0 \,\forall\, j,k$ and cumulative coefficient $\sum_{j=1}^{n} \beta_{j,k} = 0$ to be significant at the 5% level with a negative cumulative coefficient overall (-0.0005).

Table 2.3 contains parallel results to table 2.2 but percent change in CIT positions is used as the explanatory variable instead of change in CIT positions. Using this measure, the null hypothesis is rejected for all commodities and the cumulative coefficients are negative and similar in magnitude to table 2.2. The average one standard deviation change in the explanatory variable is 1.6% across all commodities. For feeder cattle in table 2.3, a one standard deviation percent change in CIT positions (1.8%) would decrease returns by -0.035% compared to -0.032% in table 2.8. Not surprisingly, the system wide results for table 2.3 are significant and negative. Overall, table 2.2 and table 2.3 provide consistent evidence that an increase (decrease) in CIT positions is associated with subsequent decrease (increase) in commodity returns. Although this negative relationship between CIT positions and returns is small in magnitude, the results are in direct opposition to those proposed by individuals claiming CITs increased presence in commodity markets causes an increase in commodity prices.

The second set of Granger causality results use equation 2 to test the null hypothesis that CIT positions do not impact volatility in futures markets. CIT positions will again be measured as both change in open interest and percent change and volatility will be measured as both Parkinson's high-low estimator and implied volatility to represent realized and forward looking volatility. Overall four sets of results are provided. If CIT positions are followed by an increase in volatility and destabilize the market, than the impact coefficient will be positive; conversely if CIT positions are followed by a decrease in volatility because they provide liquidity and stabilization, then the impact coefficient will be negative.

In table 2.4 the explanatory variable, change in CIT net positions, is used in a SUR system to test the null hypothesis that CIT net positions do not impact realized volatility. The lag structure is (5,1) or (4,1) for all commodities. The CIT positions are all lagged once for each commodity and this lag is restricted to be equal across equations; therefore, all p-values are equivalent and no market rejects the null hypothesis. Predictably, the system wide test is also not significant. Despite the lack of significance, all cumulative impacts are negative indicating the CITs may have a small dampening effect on realized volatility.

The parallel results in table 2.5 use the explanatory variable, percent change in CIT net positions, in a SUR system to test the null hypothesis that percent change in CIT net positions do not impact realized volatility. The only significant test is the cumulative corn result indicating that a one standard deviation increase in percent of CIT positions would decrease annualized volatility by -0.7%. Based on this single significant commodity, the system wide SUR results are significant and negative.

Tables 2.6 and 2.7 directly relate to tables 2.4 and 2.5 but use implied volatility instead of realized volatility. Table 2.6 tests the null hypothesis that a change in aggregate CIT positions impacts implied volatility. None of the test results are significant and the null hypothesis cannot be rejected. Despite the lack of significance, all cumulative impacts are negative indicating the CITs may dampen implied volatility, corresponding with results in table 2.4. Table 2.7 tests the null hypothesis that percent change in CIT positions impacts implied volatility. Similar to the previous results, none of the coefficients are significant but all are consistently negative.

Overall tables 2.4-2.7 provide consistent evidence that aggregate CIT positions do not impact volatility. Furthermore, the negative coefficients indicate that if anything, CIT positions dampen volatility providing stabilization and liquidity to the markets. The conclusion is consistent with previous results by Irwin and Sanders (2010) and Brunetti and Buyuksahin (2009). Tables 2.2 and 2.3 provide some evidence that an increase in CIT positions my cause returns to decrease, in direct opposition of any argument that index traders cause increases in commodity prices due to increased investment.

2.6 Returns or Volatility Impacting Aggregate Index Positions

The previous section analyzes the influence of index positions on prices; this section will test the opposite directional relationship, the influences of prices on index positions. Similar to the previous section, tests are conducted on aggregate commodity index positions to determine if net flows of CITs are influenced by changes in returns or volatility. In this section, aggregate CIT positions are regressed on lagged returns and volatility to determine how positions react to changes in prices. The testing of index position reactions to prices provides insights into the motivation of the investors behind index funds.

2.6.1 Methods

Granger causality is employed in a similar, but opposite manner as in the method section 2.5.1. Granger causality tests if event *X*, returns or volatility, cause event Y, changes in CIT positions. Irwin and Sanders (2010b) use a similar methodology by specifying positions as a function of lagged positions and lagged returns.

Equations 3 and 4 display the specification for testing the impact of returns and volatility on CIT positions as,

(3) $$X_t = \alpha + \sum_{i=1}^{m} \gamma_i R_{t-i} + \sum_{j=1}^{n} \beta_j X_{t-j} + \varepsilon_t$$

(4) $$X_t = \alpha + \sum_{i=1}^{m} \gamma_i V_{t-i} + \sum_{j=1}^{n} \beta_j X_{t-j} + Monthly\ Effects + v_t$$

where variable definitions are identical to previous section 2.5. R_t is the daily return $[R_t = (\ln P_t - \ln P_{t-1})*100]$, X_t is a measure of CIT participation in the market represented as both the change in position level and also percent change in position level, and V_t is volatility measured as both realized volatility and implied volatility. *Monthly Effects* is a set of monthly dummy variables to allow for changing seasonal volatility; these dummy variables are only used if significant. The lag structure is determined by minimizing BIC using an OLS search procedure with a maximum lag of *m*=5 and *n*=5.

To increase statistical power, the 12 markets studied will be modeled together using a seemingly unrelated regression (SUR) consistent with section 2.5.2 and following Irwin and Sanders (2010b). In addition, constraints can be placed on parameters across contracts if those parameters are not statistically different to further promote efficiency. After the SUR system is estimated, the overall causality testing of $\sum_{i=1}^{n} \gamma_i = 0$ can be determined using a F-test for each market separately (if all $\gamma's$ are not restricted) and for the entire system across all 12 commodities, $\sum_{k=1}^{12}\sum_{j=1}^{n} \beta_{j,k} = 0$.

2.6.2 Results

The first set of Granger causality results using equation 3 tests the null hypothesis that returns do not influence CIT positions, $\sum_{i=1}^{n} \gamma_i = 0$. If the null hypothesis is rejected and returns impact CIT positions, then a relationship exists between returns and positions. The sign of the cumulative coefficient is potentially influenced by two competing forces. First is the rebalancing effect, this would create a negative relationship between prices and positions. When the price of a commodity within a portfolio increase, the number of contracts held in that commodity must decrease to maintain proper portfolio target weights. The second competing force is the trend following effect; this would create a positive relationship between prices and positions. When prices increase and the value of the commodity index increases, additional investors are attracted to the investment and CIT positions increase.

In table 2.8 the explanatory variable, change in CIT net positions, is used in a SUR system to test the null hypothesis that returns do not impact index positions. The minimum BIC lag structure *(m,n)* ranges from 1 to 5 for *m* and from 1 to 4 for *n*. In this SUR system the cross market coefficient restrictions are restricted for the intercept, α, and lag three of CIT positions, $\beta_{3,k} \forall k$. The remaining unrestricted variables are allowed to vary across commodity markets. The third column tests the null hypothesis that returns do not lead positions, $\gamma_{i,k} = 0 \forall i$. Eight out of the twelve commodities reject the null hypothesis at the 5% level and ten commodities reject the null hypothesis at the 10% level. The fourth column calculates the cumulative coefficient $\sum_{i=1}^{m} \gamma_i$, and the fifth column calculates the p-value testing the null $\sum_{i=1}^{m} \gamma_{i,k} = 0$ for each commodity *k*. If m =1, then the tests in column 3 and 5 are identical and are not repeated in column 5; this is the case for all commodities except for cocoa and soybeans. Column six is the one standard deviation impact calculated as a one standard deviation change in the explanatory variable (nearby futures returns) multiplied by the cumulative coefficient $\sum_{i=1}^{m} \gamma_i$. A one standard deviation change in returns is 1.8% on average over the 12 commodities. All cumulative impacts are positive; for example in lean hogs, a one standard deviation increase in returns of 1.5% will increase CIT positions by approximately 36 contracts, a relatively small increase in positions. The system wide tests at the bottom of the table show $\gamma_{i,k} = 0 \forall i, k$ and cumulative coefficient $\sum_{k=1}^{12} \sum_{i=1}^{m} \gamma_{i,k} = 0$ to be significant at the 5% level with a positive overall cumulative coefficient.

Table 2.9 contains parallel results using percent change in CIT positions as the independent variable. Using this measure, the null hypothesis is rejected for 6 out of 12 commodities at the 5% level and all cumulative impacts are positive. For example in soybeans, a 1.9% increase in returns will increase CIT positions by 0.19%. Across all commodities the increase in CIT positions from a one standard increase in returns would be 0.10%; although half of the coefficients are statistically significant, the overall effects are small. The system wide tests at the bottom of the table are significant and positive. Based on the small but positive impacts in table 2.8 and 2.9, trend following outweighs the rebalancing effect and provides evidence that index traders are not only passive, buy-and-hold traders, but are price-sensitive investors to some degree.

The previous results show that CITs positions have a positive relationship to past price movements; the same type of SUR test is employed to determine if CITs change positions in response to volatility. Prior to testing the expected relationship, if any, between CITs and volatility is negative. As volatility increases in a commodity, CITs may tend to decrease positions due to greater uncertainly brought on by the volatility that makes investment less desirable.

Equation 4 is tested using two measures of CIT positions, change in CIT positions and percent change in CIT positions, and two measures of volatility, realized volatility and implied volatility. Table 2.10 tests the null hypothesis that Parkinson's high-low estimate of realized volatility does not impact changes in aggregate CIT net positions. The lag structure (*m*,*n*) is highly varied across commodities and four coefficients are restricted during the SUR estimation including, intercept α , lag three of CIT positions $\beta_{3,k} = \beta_3 \forall k$, and lags three $\gamma_{3,k} = \gamma_3 \forall k$ and five $\gamma_{5,k} = \gamma_5 \forall k$ of volatility. None of the coefficients are significant although 11 out of 12 are negative indicating that as volatility increases (decreases) CIT positions decrease (increase). Not surprisingly, the overall system results are also insignificant with a negative cumulative coefficient. In parallel results, table 2.11 tests the null hypothesis that Parkinson's high-low estimate of realized volatility does not impact the percent change in aggregate CIT net positions. Consistent with previous results, the null hypothesis is not rejected in any situation and all cumulative coefficients are negative. No significant evidence exists that CITs change their positions in response to changes in realized volatility.

Next, both tables 2.10 and 2.11 are repeated in tables 2.12 and 2.13 using implied volatility instead of realized volatility. Table 2.12 tests the null hypothesis that implied volatility does not impact changes in CIT net positions. Five out of the twelve commodities are significant at the 5% level and all significant coefficients are negative. For example in cocoa, a one standard deviation increase in implied volatility of 8.2% causes a decrease in CIT positions of 19 contracts. The overall system coefficient is significant and also negative. Table 2.13's parallel results test the null hypothesis that implied volatility does not impact percent changes in aggregate CIT net positions. Only one commodity, cocoa, shows significance at the 5% level but this is only for the joint test and not the cumulative impact. For the system wide results, the joint test rejects the null hypothesis but the cumulative impact is not significant. Therefore, the system estimation does not reject the null hypothesis.

Overall, index positions have a small but positive relationship to past price movements indicating limited trend following behavior. Furthermore, index positions have a weak but inverse relationship to price volatility that is stronger for the measure of implied volatility than for Parkinson's volatility.

2.7 The Roll Period

In section 2.5, aggregate CIT position flows were used to test whether CITs impacted market prices, with limited evidence of significant results found. This is not entirely surprising since the average standard deviation of changes in aggregate CIT positions is only approximately 1,000 contracts and the average standard deviation of the percent change in positions is only 1.6%. The use of aggregate CIT positions measures the *new* net flows of CITs but does not capture the change in *existing* positions that occurs during the roll period (Stoll and Whaley 2010). The "roll" of the vast portion of *existing* index positions from one futures contract maturity to another before expiration represents the largest changes in CIT positions. During the conventional roll period, known as the Goldman Roll, the average standard deviation of positions changes is 3,300 contracts and average standard deviation of percent change in positions is 15%. Index traders concentrate their positions in the nearby contract because it closely replicates the cash market for the particular commodity in which they want long financial exposure. Every futures contract eventually approaches expiration and all traders either must close out their positions or make/take delivery; since index traders are not commercial traders and generally do not trade in the underlying cash market, they close out positions prior to expiration and invest in the next nearest to delivery contract. The impact of index funds on prices may be more evident during the roll period when large portions of existing CITs migrate to the next maturity than was otherwise evident from the much smaller changes in aggregate net flows of CITs.

Revisiting figure 2.2 panels A and B, the roll period is evident as CIT open interest in the nearest to maturity contract decreases and simultaneously the open interest in the first deferred contract increases. Panel C illustrates this further by displaying the change in CIT open interest in the nearby and first deferred contracts that peak during the rolling period; the two series are nearly mirror images of each other. Nearby open interest changes are negative as CITs exit their positions, and the first deferred open interest changes are positive as CITs enter new long positions. The aggregate positions in the top line of panel A mask this rolling behavior, providing the motivation for the second disaggregate test of specific CIT price impact.

Before proceeding with roll period tests, the question of how to precisely define the roll period has to be considered. The basic nature of the task is illustrated by figure 2.2, panel C, where the sizeable spikes in the changes in open interest associated with rolling activity is obvious. The main consideration is then what length of time should the roll period encompass or how wide of a spike should be considered? Most previous studies have identified the "width" as the Goldman Roll period spanning the fifth through ninth business day in the month before expiration (e.g. Stoll and Whaley 2010; Mou 2010; Irwin et. al 2011). The spike in the change in open interest definitely includes the conventional roll period, but there are numerous accounts in the financial press of index traders expanding the time frame in which they roll to mask trades, seek liquidity, or capture advantageous spreads. As Kemp (2010) reported in an article on the next generation of commodity investment strategies, "The most basic strategy enhancement, used by providers…….has been to offer index investors a more dynamic roll procedure."

The data available for this study are the first to be of sufficient detail to formally investigate the amount of position rolls both in and outside of the conventional Goldman Roll period. Figure 2.3 displays two different roll periods for the December 2004 and December 2008 corn futures contract maturities. The shaded box indicates the Goldman Roll period, the fifth through ninth business day in the month before expiration. The 25 business days before the Goldman Roll period and the 10 business days after are also displayed. The 2008 period shows a larger amount of the change in open interest occurring outside of the traditional Goldman Roll period than the 2004 maturity, this pattern also holds for the other commodities and maturities in this study. Based on this knowledge, a data dependent time roll time frame is formed which differs from previous studies using a preset roll period.

To determine a roll period that encompasses the bulk of CIT rolling activity, four different time frames are compared in figure 2.4; section 1 spans the entire 2nd month before the expiration month through business day 10 of the month before expiration, section 2 spans the 10th business day in the 2nd month before the expiration through business day 10 of the month before expiration, section 3 spans business days 1 to 10 of the month before expiration, and section 4 is the Goldman Roll period spanning business days 5-9 in the month before expiration.

Figure 2.5 displays the percentage of total roll activity over all commodities in each of the defined sections; for the purposes of this analysis, total roll activity is defined as the entire two months prior to the expiration month. Section 4 (Goldman roll) has approximately 65% of roll activity in 2004 but this has decreased over time to a little over 50% as CITs have increasingly distributed trading through time. Section 1 and section 2 both contain about 90% of the roll activity and section 3 averages about 75% of the total roll activity. Based on this analysis, the traditional Goldman roll period will not be used to define the period of roll days for this study; rather, section 2 will define the CIT roll period as it encompasses the majority of roll activity within the shortest time period. The second set of tests using specific maturities employs this definition of a roll period to test trader impact during the transfer period of positions from one maturity to the next.

2.8 Roll Impact Tests

In this section, tests are conducted to determine if the rolling of existing CIT positions from the nearby maturity to the first deferred contract impacts returns or volatility. Two different types of tests are conducted; first prices are regressed on CIT positions using Granger causality in a SUR system and second, a simple, straightforward contemporaneous correlation between positions and prices is tested.

2.8.1 Granger Causality Methods

Regressions for the Granger causality tests are specified in equations 5 and 6 as,

$$NR_t = \alpha + \sum_{i=1}^{m} \gamma_i NR_{t-i} + \sum_{j=1}^{n} \beta_j NX_{t-j} + \varepsilon_t \tag{5}$$

$$DR_t = \alpha + \sum_{i=1}^{m} \gamma_i DR_{t-i} + \sum_{j=1}^{n} \beta_j DX_{t-j} + \varepsilon_t \tag{6}$$

In equation 5 the nearby futures returns, NR_t, are regressed on lagged returns and a measure of CIT positions in the nearby futures contract, NX_{t-j}. This will capture the activity of CIT's exiting the nearby contract. Likewise, equation 6 captures the activity of CIT's entering the first deferred contract. The first deferred return, DR_t, is regressed on lagged returns and measure of CIT positions in the first deferred futures contract, DX_{t-j}. Equations 5 and 6 are then estimated as an SUR system to leverage the relationship between residuals using the same procedure described in the previous sections except that instead of a system across commodities, this system is run for each individual commodity.[14] Finally, this specification is flexible in that price impacts can differ between the nearby and first deferred contracts.

In addition to testing returns, SUR systems are also formed to test if CIT positions affect volatility as shown in equations 6 and 7 as,

$$NV_t = \alpha + \sum_{i=1}^{m} \gamma_i NV_{t-i} + \sum_{j=1}^{n} \beta_j NX_{t-j} + \varepsilon_t \tag{7}$$

(8) $$DV_t = \alpha + \sum_{i=1}^{m} \gamma_i DV_{t-i} + \sum_{j=1}^{n} \beta_j DX_{t-j} + \varepsilon_t .$$

In equation 7 the nearby volatility measure, NV_t, is regressed on lagged volatility and a measure of CIT positions in the nearby futures contract, NX_{t-j}. This will capture the activity of CIT's exiting the nearby contract. Likewise, equation 8 captures the activity of CIT's entering the first deferred contract. The first deferred volatility, DV_t, is regressed on lagged volatility and a measure of CIT positions in the first deferred futures contract, DX_{t-j}. Volatility is first tested as Parkinson estimator and then as implied volatility.

CIT positions in equations in equations 5 to 8 are defined as the change in open interest and as percent change in positions. The entire testing procedure will be 6 different equation systems, (i) returns regressed on changes in positions, (ii) returns regressed on percent change in position, (iii) Parkinson volatility regressed on changes in positions, (iv) Parkinson volatility regressed on percent change in positions, (v) implied volatility regressed on change in positions, and (vi) implied volatility regressed on percent change in positions. For each of these variables, an augmented Dickey-Fuller test is used to determine stationarity. In all cases, the test including a constant and trend rejects the null hypothesis of non-stationarity.

Data on CIT positions in nearby contracts and first deferred contracts are needed in order to estimate equations 5-8. As discussed above, the roll period, section 2, spans business day 10 or greater in 2 months before expiration to business day 10 in the month before the expiration month. For example, the March 2008 contract maturity roll period will span from mid January 2008 to mid February 2008. Similarly, the next maturity, May 2008 will span from mid March 2008 to mid April 2008. Any days between the roll periods are not included in the analysis, although, lags that occur prior to the defined roll period may be included as explanatory variables. The nearby and first deferred prices and positions that occur in the roll period windows are pooled together to construct a data series, but no data is lagged *across* roll period maturity windows.[15]

2.8.2 Granger Causality Results

Table 2.14 employs the SUR procedure on the roll period data to test the null hypothesis that CIT positions do not impact returns. Panel A defines the explanatory variable as change in CIT positions whereas panel B defines the explanatory variable as percent change in CIT positions. Column 2 is the minimum BIC lag structure (m,n) where m ranges from 1 to 2 and n ranges from 1 to 5. Column 3 is the joint coefficient test p-value for the SUR system. Column 4 is the system cumulative coefficient that is the sum of beta coefficients on lagged CIT positions, and column 5 tests if the cumulative coefficient is significantly different than zero. Columns 6 and 7 multiply the cumulative coefficient by a one standard deviation change in the nearby (column 6) and deferred (column 7) explanatory variable.

If CITs rolling activity impacts returns in the nearby contract as CITs “roll out”, this would be in the form of decreasing returns due to the selling pressure. Conversely, the impact in the first deferred contract would be in the form of increasing returns due to buying pressure. In both situations the relationship between CIT positions and returns would be shown in the results as a positive cumulative coefficient (column 4). The results can also be interpreted as CIT impact on the spread between the nearby and first deferred contract. If spreads widen, then nearby prices would decrease and/or deferred prices would increase. If spreads narrow, then nearby prices would increase and/or deferred prices would decrease. Spreads widening (narrowing) due to CIT positions is consistent with positive (negative) cumulative coefficient.

In table 2.14, the significant cumulative coefficients are grouped in the livestock markets, cocoa, cotton, and the wheat markets. All of the cumulative coefficients are negative, the exact opposite of the expected outcome if CITs widen spreads. For example in panel A for cotton, a one standard deviation decrease in nearby CIT positions would increase returns by 0.10%; likewise, a one standard deviation increase in deferred CIT positions would decrease deferred returns by -0.10%. The impacts are computed by multiplying the cumulative coefficient of -.000044 by the one standard deviation change in positions of 2,372 contracts in the nearby and 2,273 contracts in the deferred. The results are relatively consistent irrespective of modeling the explanatory variable as change in positions or percent change in positions.[16]

Why are CITs positions and returns moving in the opposite direction and contributing to narrower spreads? One possibility is that since CIT rolling patterns are so blatantly apparent, commonly called "sunshine trading" (Admati 1991; Brunnermeier 2005), where a large number of traders try to extract naïve rents from the CITs as they predictably change positions. These traders that anticipate CIT positions may, themselves, be influencing market prices. For the nearby contract, traders attempting to take positions opposite CITs aggressively place buy orders to attract CIT sell orders and thereby increase prices. For the deferred contract, traders attempting to take positions opposite CITs aggressively place sell orders to attract CIT buy orders and thereby decrease prices. Second, the common assumption that CITs would theoretically move the market because of their roll strategy often neglects that future markets are a zero sum game. Since CITs do roll prior to the expiration month, other traders on the short side are *also* rolling their hedges. This rolling strategy was not invented by index traders. Long before index traders were ever participants in the marketplace, hedgers rolled their position from one contract maturity to the next to maintain hedge positions. Therefore, position rolling strategies have long been common place in futures markets and by themselves unlikely to cause disruptions.[17]

Next the hypothesis that CITs rolling activity impacts volatility is examined for both realized volatility and implied volatility. If CITs impact realized volatility during the roll period, then both the nearby and deferred contracts would experience increases in volatility as index traders roll out of the nearby and into the deferred thereby causing rapid fluctuations in prices due to their trading activity.[18] In this scenario the cumulative coefficient would be negative for the nearby contract[19] and positive for the deferred contract. The direction of CIT impact on implied volatility is less clear as implied volatility is a forward looking measure.

The null hypothesis that CIT positions do not impact volatility during the roll period is tested using equations 7 and 8 in a SUR procedure; results are present in table 2.15 using realized volatility and in table 2.16 using implied volatility. In table 2.15, the null hypothesis that CIT positions do not impact realized volatility is consistently rejected for live cattle and lean hogs (column 5). The cumulative impacts for both the nearby and deferred series are positive for live cattle and lean hogs, and the impact tends to be larger when the percent change in CIT positions is the explanatory variable; this indicates that a one standard deviation percent change in positions may influence volatility more than a one standard deviation change in positions. For example, in table 2.15 panel A for live cattle a one standard deviation decrease (increase) in nearby (deferred) positions decreases (increases) annualized volatility by -0.14% (0.13%) where as in panel B for live cattle the corresponding estimate decreases (increases) annualized volatility -0.32% (1.32%) in the nearby (deferred) contract. During the roll period for live cattle and lean hogs, CIT positions precede movement in realized volatility by consistently decreasing volatility in the nearby contract and increasing volatility in the deferred contract in live cattle and lean hogs. As a whole the evidence is mixed and inconsistent across commodities and provides limited evidence that CITs impact realized volatility.

In table 2.16 the parallel null hypothesis that CIT positions do not impact implied volatility is tested. The commodities rejecting the null hypothesis include cocoa, cotton, feeder cattle, sugar, and wheat; the significant commodities are not consistent with table 2.15. Of the significant commodities both the nearby and the deferred cumulative impacts are the same sign, where five commodities have positive coefficients and one has negative. Therefore the majority of significant commodities indicate that as CITs exit nearby contracts they lead to decreased volatility and as CITs enter the first deferred contracts they lead to increased volatility. Across commodities, the potential impact (columns 6 and 7) appears to be larger for realized volatility in tables 2.15 (Parkinson's measure) and smaller for implied volatility in tables 2.16. This difference in magnitudes between volatility measures may occur because realized volatility is directly impacted by the roll trading behavior; conversely, the implied volatility is forward looking and the impact of roll period positions changes on future volatility of a contract is unclear.

Overall, the evidence is fleeting and insufficient to reject the null hypothesis that CIT positions do not impact volatility during the roll period, but if an effect exists it is more likely to be positively related to position movements and between 0.03 - 0.33% for a one standard deviation change in CIT positions and between 0.02 – 1.57% for a one standard deviation percent change in CIT positions. The surprising result of tables 2.15 and 2.16 is the positive coefficient for the nearby contract; this indicates that as CITs exit the nearby contract they are decreasing volatility. Less surprising is the positive coefficient in the deferred contract which indicates that as CITs enter the contract the volatility increases.

2.8.3 Contemporaneous Correlation Results

The Granger causality test results of the roll period provided little evidence that index traders materially influenced returns, spreads, or volatility during the roll period. An additional test is conducted that simply measures how two variables co-vary in a linear manner. A straightforward test of contemporaneous correlation between changes in CIT positions and prices is conducted for the data-defined, section 2 roll period and the traditional Goldman roll period. The Goldman roll period is added to the analysis because it represents the most concentrated period of roll activity. While this specification does not test causality, we argue this test provides additional useful information. In particular, a finding of no price or volatility impact using this basic analysis provides strong evidence against the hypothesis that index funds impact agricultural futures prices.

If CIT position changes are impacting returns, then the necessary (although not sufficient) contemporaneous correlation must be positive. A positive correlation coefficient would indicate that as index traders exit the nearby contract they decrease prices, and as index traders enter the first deferred they increase prices. By extension, the results can also be interpreted as CIT impact on the spread between the nearby and first deferred contract.[20] Spreads widening due to CIT roll behavior is consistent with positive correlation coefficient.

Table 2.17 displays the correlation between changes in CIT positions and returns and table 2.18 displays the correlation between percent change in CIT positions and returns for both section 2 and the concentrated Goldman roll period. Out of the 96 correlation coefficients across the two tables only 7 were significant at a 5% level, with 4 positive coefficients and 3 negative coefficients. Furthermore, the average correlation coefficients at the bottom of tables 2.17 and 2.18 only ranges between -0.01 and 0.04. The lack of evidence disproves the notion that index traders impact returns and does not provide evidence that index traders impact the spread between the nearby and first deferred contract during the roll period.

The next set of results test the correlation between change in index trader positions and volatility in four different ways. Tables 2.19 and 2.20 test the correlation between positions and Parkinson volatility measuring positions as both change in positions in table 2.19 and percent change in positions in table 2.20. Tables 2.21 and 2.22 test the correlation between positions and implied volatility measuring positions as both change in positions in table 2.21 and percent change in positions in table 2.22. If index traders are influencing volatility, then the expected correlation in the nearby contract is negative since as index traders exit the contract, volatility increases. The expected correlation in the deferred contract is positive since as index traders enter the contract, volatility increase.

For tables 2.19 and 2.20, 21 out of 96 correlation coefficients are significant. In the nearby, 8 out of 10 significant are negative. In the deferred, 1 out of the 11 significant are positive. Over all there is no widespread significant correlation between the commodities and realized (Parkinson) volatility. The average coefficients at the bottom of tables 2.19 and 2.20 range from -0.02 to 0.01 for the nearby and -0.01 to -0.09 for the deferred, further indicating the small correlation between realized volatility of prices and index trader returns. For tables 2.21 and 2.22 using implied volatility, 46 out of the 96 correlation coefficients are significant with a concentration in table 2.21 using change in positions. In the nearby, 1 of the 16 significant coefficients are negative. In the deferred, 1 of the 29 coefficients are positive. The evidence appears stronger that volatility decreased when index trader positions change; as CITs exit the nearby contract they decrease volatility (positive coefficient) and as CITs enter the deferred they decrease volatility (negative coefficient). The average coefficients at the bottom of table 2.21

and 2.22 range from 0.04 to 0.20 for the nearby and -0.07 to -0.31 for the deferred, providing further evidence that the change in CIT positions during the roll period dampens volatility.

Overall, the contemporaneous correlation results show no relationship between index trader positions and returns indicating the index traders are not causing an increase in spreads. The results agree with the Granger causality tests in table 2.14 that index trader positions are not increasing spreads during the roll period. The results differ in that the Granger causality tests find more significant negative relationship between prices and positions than do the contemporaneous correlation results.

The contemporaneous correlation between Parkinson volatility and index trader positions agree with the Granger causality tests in table 2.15, both find mixed signs across commodities with no broad based significance. The relationship between implied volatility and CIT positions is stronger for the contemporaneous correlation tests than for the Granger causality tests in table 2.16. The contemporaneous correlation between index trader positions and volatility is positive in the nearby contract and negative in the first deferred contract, indicating that index traders are dampening volatility in both the nearby and first deferred contracts. The implied volatility Granger results in table 2.16 find the same positive relationship in the nearby contract between positions and volatility for two commodities (sugar and feeder cattle) as tables 2.21 and 2.22. The analysis differs in that Granger causality results find a positive relationship in the deferred contracts in four commodities when the contemporaneous correlations results find a negative relationship. Despite these differences in the details, the weight of the evidence provided by the results dispels the notion that index traders are widening spreads, impacting prices, or increasing volatility during the roll period.

2.9 Summary and Conclusions

A world-wide debate has erupted about the price impact of long-only ‘index fund’ speculators in commodity futures markets. A number of observers assert that buying pressure from index funds impacted commodity prices during 2007-2008, which resulted in market prices far exceeding fundamental values. The purpose of this paper is to analyze the price impact of long-only index funds in commodity futures markets from January 2004 through September 2009. Daily positions of index traders in 12 markets are drawn from the internal Large Trader Reporting System used by the Commodity Futures Trading Commission (CFTC). The commodity futures markets include corn, soybeans, soybean oil, CBOT wheat, KCBOT wheat, feeder cattle, lean hogs, live cattle, cocoa, cotton, coffee, and sugar. Since index positions are available on a daily basis and disaggregated by contract the analysis is not subject to data limitations of previous studies.

Granger causality tests are used to investigate whether a significant relationship exists between index trader position changes and commodity futures returns and volatility. Seemingly unrelated regression (SUR) estimation is used to increase the power of statistical tests and equality constraints are placed on those parameters that are not statistically different across equations. The analysis is performed on both aggregate daily positions overall all maturities and on disaggregated nearby and first deferred contracts during the roll window of index traders. The use of aggregate positions attempts to determine if *new net flows* of index traders have an effect on futures prices; conversely, limiting the period of study to roll days using specific contract maturities focuses the estimation on extreme changes in *existing* open interest during a concentrated period of time.

As index driven financial products evolve they increasingly diversify their roll trading behavior; this may be driven by a desire to limit impact on the futures markets, camouflage trading activity, or ensure adequate liquidity for trades. For example, CIT roll activity has decreased in concentration over the sample period, and the percent of open interest change occurring during the Goldman roll period decreased from 65% to 50%. For this reason, the roll period used in this research is expanded beyond the traditional “Goldman roll” period to be defined as the 10th business day of the month two months before expiration through the 10th business day in the month before expiration. This expanded roll period captures approximately 90% of roll activity versus the 55% captured in the Goldman period.

The findings from this research on the impact of index funds indicate that an increase in aggregate CIT positions may *decrease* returns and may dampen volatility. This does not support the assertion that index traders contributed to price spikes in agricultural commodities due to increased investment. Second, an increase in returns tends to be followed by a small increase in aggregate CIT positions, and an increase in volatility tends to be followed by a decrease or no change in aggregate CIT positions. The results make clear that index traders may have limited reactions to changes in returns and volatility. Finally, tests analyzing the “roll period”, where CITs change the majority of their open interest, use both Granger causality methods and simple contemporaneous correlation coefficients. The contemporaneous tests find no relationship between returns and index positions. The Granger causality methods also find that index traders are not increasing spreads during the roll period although results show an opposite effect. Granger causality tests show returns in the nearby contract may *increase* as CIT positions decrease and returns in the deferred contract *decrease* as CIT positions increase into the contract leading to narrower spreads. The volatility results are mixed and small in magnitude across the methods and commodities. The contemporaneous correlation tests between changes in index positions and implied volatility had the greatest concentration of significant coefficients providing evidence that volatility decreases in the nearby contract as traders exit and volatility also decreases in the deferred contract as trader enter. Despite the differences in the details between the contemporaneous and Granger causality tests, the weight of the evidence provided by the results dispels the notion that index traders are widening spreads, impacting prices, or increasing volatility during the roll period.

Across all three testing methods using both aggregated and disaggregated index trader positions, it appears that CITs are not causing a major disruption to the futures market and in some cases actually decreasing volatility. In essence, the trader category is just another participant in the futures market that has changed the trader composition in the marketplace but has not undermined the fundamental price discovery function.

These conclusions from this essay are consistent with other research that use less frequent observations and a higher level of aggregation for index trader positions (e.g., Stoll and Whaley 2010) and most research on the effects of large trader positions on commodity market returns (e.g., Sanders and Irwin 2010b). The results of this study provide the strongest evidence to date that 'long-only' index funds have a minimal impact on commodity futures price movements. This has important implications for the ongoing policy debate surrounding index fund participation in commodity futures markets. In particular, the results provide no justification for limiting the participation of index fund investors. Since there is some evidence that index funds provide liquidity and dampen price volatility, limiting index fund positions may be harmful in that an important source of liquidity and risk-bearing capacity may be removed at a time when both are in high demand.

2.10 Tables and Figures

Table 2.1 Average Daily Net Futures Positions of Commodity Index Traders (CITs) in 12 Commodity Futures Markets, All Contracts, 2000-2009

	Year									
Market	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**
Panel A: Number of Contracts										
Cocoa	2,208	1,447	1,892	2,612	11,549	7,483	13,272	17,534	23,612	16,195
Coffee	2,728	1,475	2,867	6,916	21,735	23,114	33,862	42,716	54,434	38,165
Cotton	4,967	4,009	5,579	7,863	16,132	38,696	71,430	87,229	95,249	65,637
Sugar	12,898	10,059	17,659	23,497	61,931	98,672	136,135	230,434	309,598	180,138
Feeder Cattle	1	101	1,557	1,933	2,838	4,362	6,562	8,315	8,265	6,210
Lean Hogs	7,858	6,479	8,654	10,546	26,801	43,871	76,923	80,275	100,138	56,472
Live Cattle	22,360	12,779	12,067	13,941	33,118	52,931	86,152	112,310	128,549	90,465
Corn	28,732	30,217	48,209	53,656	117,364	233,142	393,954	357,482	358,979	289,860
Soybeans	6,509	4,920	9,563	28,279	36,692	76,884	114,591	147,449	143,982	122,437
Soybean Oil	-122	1	949	1,402	10,773	38,030	65,801	72,351	68,371	54,855
Wheat CBOT	20,178	18,704	21,439	25,702	56,682	134,408	195,194	185,341	165,968	151,227
Wheat KCBOT	5,591	5,777	7,921	9,543	14,971	18,210	25,480	31,372	26,156	26,178
Panel B: Percent of Total Open Interest										
Cocoa	2	1	2	3	11	6	10	12	16	14
Coffee	6	3	4	9	23	24	31	28	37	31
Cotton	8	6	8	10	20	37	45	41	43	52
Sugar	7	7	9	12	21	24	28	33	37	25
Feeder Cattle	0	1	12	11	17	17	22	29	27	27
Lean Hogs	16	15	26	25	34	43	48	44	47	42
Live Cattle	18	11	12	13	29	35	38	45	48	42
Corn	7	7	10	13	19	33	32	28	29	34
Soybeans	4	3	5	12	16	28	31	29	33	32
Soybean Oil	0	0	1	1	7	24	28	25	26	25
Wheat CBOT	15	14	19	25	37	55	45	46	48	49
Wheat KCBOT	8	8	11	16	22	20	18	24	26	29

Notes: Data for 2009 end on September 29, 2009. Positions of commodity index traders (CITs) are aggregated across all contract maturity months on a given day and exclude options positions.

Table 2.2 Granger Causality Test Results. Null Hypothesis: Change in Aggregate CIT Net Positions Do Not Cause Returns, January 2004 through September 2009

$$R_{t,k} = \alpha_{t,k} + \sum_{i=1}^{m} \gamma_{i,k} R_{t-i,k} + \sum_{j=1}^{n} \beta_{j,k} X_{t-j,k} + \varepsilon_{t,k} \text{ for each market, } k\text{, and time, } t$$

$X_t =$ Chg in CIT Positions

Market, k	m,n	p-value $\beta_j = 0, \forall j$	$\sum \beta_j$	p-value $\sum \beta_j = 0$	One StDev Impact
Cocoa	1,1	0.51	0.00009		0.034
Coffee	1,1	0.68	0.00005		0.021
Cotton	1,1	0.56	-0.00004		-0.024
Sugar	1,1	0.80	-0.00001		-0.023
Feeder Cattle	1,1	**0.04**	-0.00029		-0.032
Lean Hogs	2,1	**0.00**	-0.00017		-0.127
Live Cattle	1,2	0.89	0.00000	0.92	-0.002
Corn	1,1	0.26	-0.00001		-0.027
Soybeans	1,1	0.29	0.00003		0.032
Soybean Oil	1,1	0.26	-0.00004		-0.029
Wheat CBOT	1,1	0.05	-0.00003		-0.042
Wheat KCBOT	1,1	**0.02**	-0.00011		-0.042
		p-value $\beta_{j,k} = 0, \forall j,k$	Estimate $\sum\sum \beta_{j,k}$	p-value $\sum\sum \beta_{j,k} = 0$	
System		**0.00**	-0.0005	**0.036**	

Notes: The models are estimated across the K markets as an SUR system. The cross market coefficient restrictions not rejected by the Wald test are the intercepts. All intercepts are estimated as a single pooled parameter across all markets. Observations per commodity 1,447.

Table 2.3 Granger Causality Test Results. Null Hypothesis: Percent Change in Aggregate CIT Net Positions Do Not Cause Returns, January 2004 through September 2009

$$R_{t,k} = \alpha_{t,k} + \sum_{i=1}^{m} \gamma_{i,k} R_{t-i,k} + \sum_{j=1}^{n} \beta_{j,k} X_{t-j,k} + \varepsilon_{t,k} \text{ for each market, } k\text{, and time, } t$$

$$X_t = \text{Pct Chg in CIT Positions}$$

Market, k	m,n	p-value $\beta_j = 0, \forall j$	$\sum \beta_j$	p-value $\sum \beta_j = 0$	One StDev Impact
Cocoa	1,1	**0.00**	-1.97		-0.052
Coffee	1,1	**0.00**	-1.97		-0.029
Cotton	1,1	**0.00**	-1.97		-0.020
Sugar	1,1	**0.00**	-1.97		-0.025
Feeder Cattle	1,1	**0.00**	-1.97		-0.035
Lean Hogs	2,1	**0.00**	-1.97		-0.029
Live Cattle	1,1	**0.00**	-1.97		-0.025
Corn	1,1	**0.00**	-1.97		-0.023
Soybeans	1,1	**0.00**	-1.97		-0.025
Soybean Oil	1,1	**0.00**	-1.97		-0.057
Wheat CBOT	1,1	**0.00**	-1.97		-0.024
Wheat KCBOT	1,1	**0.00**	-1.97		-0.033
		p-value $\beta_{j,k} = 0, \forall j,k$	Estimate $\sum\sum \beta_{j,k}$	p-value $\sum\sum \beta_{j,k} = 0$	
System		**0.00**	-1.9712	**0.000**	

Notes: The models are estimated across the K markets as an SUR system. The cross market coefficient restrictions not rejected by the Wald test include the intercepts and first lag of CIT position measure. The coefficients are estimated as a single pooled parameter across all markets. Observations per commodity 1,447.

Table 2.4 Granger Causality Test Results. Null Hypothesis: Change in Aggregate CIT Net Positions Do Not Cause Parkinson Volatility, January 2004 through September 2009

$$V_{t,k} = \alpha_{t,k} + \sum_{i=1}^{m} \gamma_{i,k} V_{t-i,k} + \sum_{j=1}^{n} \beta_{j,k} X_{t-j,k} + Dum + \varepsilon_{t,k} \text{ for each market, } k, \text{ and time, } t$$

V_t = Parkinson High-Low Estimate X_t = Chg in CIT Positions

Market, k	m,n	p-value $\beta_j = 0, \forall j$	$\sum \beta_j$	p-value $\sum \beta_j = 0$	One StDev Impact
Cocoa	5,1	0.76	-0.00002		-0.008
Coffee	5,1	0.76	-0.00002		-0.009
Cotton	5,1	0.76	-0.00002		-0.012
Sugar	5,1	0.76	-0.00002		-0.046
Feeder Cattle	4,1	0.76	-0.00002		-0.002
Lean Hogs	4,1	0.76	-0.00002		-0.015
Live Cattle	4,1	0.76	-0.00002		-0.014
Corn	5,1	0.76	-0.00002		-0.053
Soybeans	5,1	0.76	-0.00002		-0.021
Soybean Oil	5,1	0.76	-0.00002		-0.015
Wheat CBOT	5,1	0.76	-0.00002		-0.028
Wheat KCBOT	5,1	0.76	-0.00002		-0.008
		p-value $\beta_{j,k} = 0, \forall j,k$	Estimate $\sum\sum \beta_{j,k}$	p-value $\sum\sum \beta_{j,k} = 0$	
System		0.76	-0.00002	0.765	

Notes: The models are estimated across the K markets as an SUR system. The cross market coefficient restrictions not rejected by the Wald test include the first lag of CIT position measure and fifth lag of the volatility measure. The coefficients are estimated as a single pooled parameter across all markets. Observations per commodity 1,447.

Table 2.5 Granger Causality Test Results. Null Hypothesis: Percent Change in Aggregate CIT Net Positions Do Not Cause Parkinson Volatility, January 2004 through September 2009

$$V_{t,k} = \alpha_{t,k} + \sum_{i=1}^{m} \gamma_{i,k} V_{t-i,k} + \sum_{j=1}^{n} \beta_{j,k} X_{t-j,k} + Dum + \varepsilon_{t,k} \text{ for each market, } k\text{, and time, } t$$

V_t = Parkinson High-Low Estimate $\quad$ X_t = Pct Chg in CIT Positions

Market, k	m,n	p-value $\beta_j = 0, \forall j$	$\sum \beta_j$	p-value $\sum \beta_j = 0$	One StDev Impact
Cocoa	5,1	0.82	0.90		0.024
Coffee	5,1	0.82	0.90		0.013
Cotton	5,1	0.82	0.90		0.009
Sugar	5,1	0.82	0.90		0.012
Feeder Cattle	4,1	0.82	0.90		0.016
Lean Hogs	4,1	0.82	0.90		0.013
Live Cattle	4,1	0.82	0.90		0.011
Corn	5,2	0.08	-59.29	**0.03**	-0.699
Soybeans	5,1	0.82	0.90		0.011
Soybean Oil	5,1	0.82	0.90		0.026
Wheat CBOT	5,1	0.82	0.90		0.011
Wheat KCBOT	5,1	0.82	0.90		0.015
		p-value $\beta_{j,k} = 0, \forall j,k$	Estimate $\sum\sum \beta_{j,k}$	p-value $\sum\sum \beta_{j,k} = 0$	
System		0.08	-59.29353	**0.03**	

Notes: The models are estimated across the K markets as an SUR system. The cross market coefficient restrictions not rejected by the Wald test include the first lag of CIT position measure and fifth lag of the volatility measure. The coefficients are estimated as a single pooled parameter across all markets. Observations per commodity 1,447.

Table 2.6 Granger Causality Test Results. Null Hypothesis: Change in Aggregate CIT Net Positions Do Not Cause Implied Volatility, January 2004 through September 2009

$$V_{t,k} = \alpha_{t,k} + \sum_{i=1}^{m} \gamma_{i,k} V_{t-i,k} + \sum_{j=1}^{n} \beta_{j,k} X_{t-j,k} + Dum + \varepsilon_{t,k} \text{ for each market, } k\text{, and time, } t$$

V_t = Implied Volatility X_t = Chg in CIT Positions

Market, k	m,n	p-value $\beta_j = 0, \forall j$	$\sum \beta_j$	p-value $\sum \beta_j = 0$	One StDev Impact
Cocoa	5,1	0.75	-0.000003		-0.001
Coffee	2,1	0.75	-0.000003		-0.001
Cotton	5,1	0.75	-0.000003		-0.002
Sugar	4,1	0.75	-0.000003		-0.008
Feeder Cattle	5,1	0.75	-0.000003		-0.0004
Lean Hogs	2,1	0.75	-0.000003		-0.003
Live Cattle	4,1	0.75	-0.000003		-0.002
Corn	1,1	0.75	-0.000003		-0.009
Soybeans	1,1	0.75	-0.000003		-0.004
Soybean Oil	3,1	0.75	-0.000003		-0.002
Wheat CBOT	3,1	0.75	-0.000003		-0.005
Wheat KCBOT	4,1	0.75	-0.000003		-0.001
		p-value $\beta_{j,k} = 0, \forall j,k$	Estimate $\sum\sum \beta_{j,k}$	p-value $\sum\sum \beta_{j,k} = 0$	
System		0.75	-0.000003	0.750	

Notes: The models are estimated across the K markets as an SUR system. Dummy variables for months are used. The cross market coefficient restrictions not rejected by the Wald test include the first lag of CIT position measure and may through October dummy variables. The coefficients are estimated as a single pooled parameter across all markets. Observations per commodity 1,447.

Table 2.7 Granger Causality Test Results. Null Hypothesis: Percent Change in Aggregate CIT Net Positions Do Not Cause Implied Volatility, January 2004 through September 2009

$$V_{t,k} = \alpha_{t,k} + \sum_{i=1}^{m} \gamma_{i,k} V_{t-i,k} + \sum_{j=1}^{n} \beta_{j,k} X_{t-j,k} + Dum + \varepsilon_{t,k} \text{ for each market, } k\text{, and time, } t$$

V_t = Implied Volatility $\quad X_t$ = Pct Chg in CIT Positions

Market, k	m,n	p-value $\beta_j = 0, \forall j$	$\sum \beta_j$	p-value $\sum \beta_j = 0$	One StDev Impact
Cocoa	5,1	0.94	-0.06		-0.002
Coffee	2,1	0.94	-0.06		-0.001
Cotton	5,1	0.94	-0.06		-0.001
Sugar	4,1	0.94	-0.06		-0.001
Feeder Cattle	5,1	0.94	-0.06		-0.001
Lean Hogs	2,1	0.94	-0.06		-0.001
Live Cattle	4,1	0.94	-0.06		-0.001
Corn	1,1	0.94	-0.06		-0.001
Soybeans	1,1	0.94	-0.06		-0.001
Soybean Oil	3,1	0.94	-0.06		-0.002
Wheat CBOT	3,1	0.94	-0.06		-0.001
Wheat KCBOT	4,1	0.94	-0.06		-0.001
		p-value $\beta_{j,k} = 0, \forall j,k$	Estimate $\sum\sum \beta_{j,k}$	p-value $\sum\sum \beta_{j,k} = 0$	
System		0.94	-0.063170	.	

Notes: The models are estimated across the K markets as an SUR system. Dummy variables for months are used. The cross market coefficient restrictions not rejected by the Wald test include the first lag of CIT position measure, January dummy variable, and may through October dummy variables. The coefficients are estimated as a single pooled parameter across all markets. Observations per commodity 1,447.

Table 2.8 Granger Causality Test Results. Null Hypothesis: Change in Returns do not cause Change in Aggregate CIT Net Positions, January 2004 through September 2009

$$X_{t,k} = \alpha_{t,k} + \sum_{i=1}^{m} \gamma_{i,k} R_{t-i,k} + \sum_{j=1}^{n} \beta_{j,k} X_{t-j,k} + \varepsilon_{t,k} \text{ for each market, } k\text{, and time, } t$$

$X_t =$ Chg in CIT Positions

Market, k	m,n	p-value $\gamma_i = 0, \forall i$	$\sum \gamma_i$	p-value $\sum \gamma_i = 0$	One StDev Impact
Cocoa	5,2	0.05	18.1	0.08	36.7
Coffee	1,2	0.05	9.8		19.5
Cotton	1,4	**0.03**	16.5		30.9
Sugar	1,2	0.22	33.3		68.1
Feeder Cattle	1,2	0.42	2.3		2.2
Lean Hogs	1,3	**0.02**	24.3		35.6
Live Cattle	1,3	**0.02**	30.9		30.9
Corn	1,3	**0.00**	132.1		266.0
Soybeans	2,2	**0.00**	117.7	**0.00**	220.1
Soybean Oil	1,3	**0.02**	21.4		39.7
Wheat CBOT	1,3	**0.00**	62.7		138.4
Wheat KCBOT	1,1	**0.00**	14.3		28.6
		p-value $\gamma_{i,k} = 0, \forall i,k$	Estimate $\sum\sum \gamma_{i,k}$	p-value $\sum\sum \gamma_{i,k} = 0$	
System		**0.00**	483.61	**0.0001**	

Notes: The models are estimated across the K markets as an SUR system. The cross market coefficient restrictions not rejected by the Wald test are the intercepts and lag three of CIT positions. All intercepts are estimated as a single pooled parameter across all markets. Observations per commodity 1,447.

Table 2.9 Granger Causality Test Results. Null Hypothesis: Change in Returns do not cause Percent Change in Aggregate CIT Net Positions, January 2004 through September 2009

$$X_{t,k} = \alpha_{t,k} + \sum_{i=1}^{m} \gamma_{i,k} R_{t-i,k} + \sum_{j=1}^{n} \beta_{j,k} X_{t-j,k} + \varepsilon_{t,k} \text{ for each market, } k\text{, and time, } t$$

X_t = Pct Chg in CIT Positions

Market, k	m,n	p-value $\gamma_i = 0, \forall i$	$\sum \gamma_i$	p-value $\sum \gamma_i = 0$	One StDev Impact
Cocoa	5,2	0.13	0.0013	0.06	0.2695
Coffee	3,1	0.24	0.0006	0.06	0.1191
Cotton	5,3	0.07	0.0001	0.83	0.0112
Sugar	1,2	0.70	0.0001		0.0123
Feeder Cattle	1,2	0.45	0.0003		0.0322
Lean Hogs	1,4	**0.03**	0.0003		0.0469
Live Cattle	1,4	**0.04**	0.0004		0.0350
Corn	1,3	**0.00**	0.0004		0.0785
Soybeans	2,2	**0.00**	0.0010	**0.00**	0.1926
Soybean Oil	1,4	0.15	0.0004		0.0723
Wheat CBOT	1,4	**0.00**	0.0004		0.0884
Wheat KCBOT	2,1	**0.00**	0.0012	**0.00**	0.2449
		p-value $\gamma_{i,k} = 0, \forall i,k$	Estimate $\sum\sum \gamma_{i,k}$	p-value $\sum\sum \gamma_{i,k} = 0$	
System		**0.00**	0.007	**0.00**	

Notes: The models are estimated across the K markets as an SUR system. The cross market coefficient restrictions not rejected by the Wald test are the intercepts and lag three of CIT positions. All intercepts are estimated as a single pooled parameter across all markets. Observations per commodity 1,447.

Table 2.10 Granger Causality Test Results. Null Hypothesis: Parkinson Volatility does not cause Change in Aggregate CIT Net Positions, January 2004 through September 2009

$$X_{t,k} = \alpha_{t,k} + \sum_{i=1}^{m} \gamma_{i,k} V_{t-i,k} + \sum_{j=1}^{n} \beta_{j,k} X_{t-j,k} + Dum + \varepsilon_{t,k} \text{ for each market, } k\text{, and time, } t$$

$V_t =$ Parkinson High-Low Estimate $\quad X_t =$ Chg in CIT Positions

Market, k	m,n	p-value $\gamma_i = 0, \forall i$	$\sum \gamma_i$	p-value $\sum \gamma_i = 0$	One StDev Impact
Cocoa	5,2	0.28	-0.56	0.23	-7.6
Coffee	3,3	0.05	-0.58	0.20	-7.4
Cotton	1,4	0.17	-0.80		-10.3
Sugar	3,2	0.49	-0.65	0.74	-9.3
Feeder Cattle	5,2	0.11	-1.11	0.08	-6.0
Lean Hogs	2,3	0.61	-0.92	0.33	-6.7
Live Cattle	1,3	0.25	-1.46		-7.9
Corn	1,3	0.91	-0.24		-3.4
Soybeans	2,2	0.95	-0.11	0.91	-1.5
Soybean Oil	1,3	0.37	-0.62		-8.0
Wheat CBOT	2,1	0.13	-0.24	0.82	-3.8
Wheat KCBOT	1,1	0.84	0.10		1.1
		p-value $\gamma_{i,k} = 0, \forall i, k$	Estimate $\sum\sum \gamma_{i,k}$	p-value $\sum\sum \gamma_{i,k} = 0$	
System		0.53	-9.034	0.23	

Notes: The models are estimated across the K markets as an SUR system. The cross market coefficient restrictions not rejected by the Wald test are the intercepts, lag three of CIT positions, and lag three and five of the volatility measure. All intercepts are estimated as a single pooled parameter across all markets. Observations per commodity 1,447.

Table 2.11 Granger Causality Test Results. Null Hypothesis: Parkinson Volatility does not cause Percent Change in Aggregate CIT Net Positions, January 2004 through September 2009

$$X_{t,k} = \alpha_{t,k} + \sum_{i=1}^{m} \gamma_{i,k} V_{t-i,k} + \sum_{j=1}^{n} \beta_{j,k} X_{t-j,k} + Dum + \varepsilon_{t,k} \text{ for each market, } k\text{, and time, } t$$

V_t = Parkinson High-Low Estimate $\quad X_t$ = Pct Chg in CIT Positions

Market, k	m,n	p-value $\gamma_i = 0, \forall i$	$\sum \gamma_i$	p-value $\sum \gamma_i = 0$	One StDev Impact
Cocoa	1,3	0.08	-0.00001		-0.0136
Coffee	3,1	0.08	-0.00001	0.46	-0.0127
Cotton	5,1	0.26	-0.00001	0.54	-0.0128
Sugar	2,2	0.20	-0.00001	0.33	-0.0143
Feeder Cattle	1,2	0.08	-0.00001		-0.0054
Lean Hogs	1,3	0.08	-0.00001		-0.0073
Live Cattle	1,4	0.08	-0.00001		-0.0054
Corn	1,3	0.08	-0.00001		-0.0141
Soybeans	1,2	0.08	-0.00001		-0.0133
Soybean Oil	1,4	0.08	-0.00001		-0.0130
Wheat CBOT	1,4	0.08	-0.00001		-0.0156
Wheat KCBOT	1,1	0.08	-0.00001		-0.0116
		p-value $\gamma_{i,k} = 0, \forall i, k$	Estimate $\sum\sum \gamma_{i,k}$	p-value $\sum\sum \gamma_{i,k} = 0$	
System		0.24	-0.000010	0.08	

Notes: The models are estimated across the K markets as an SUR system. The cross market coefficient restrictions not rejected by the Wald test are the intercepts, lag tow and three of CIT positions, and lag one of the volatility measure. All intercepts are estimated as a single pooled parameter across all markets. Observations per commodity 1,447.

Table 2.12 Granger Causality Test Results. Null Hypothesis: Implied Volatility does not cause Change in Aggregate CIT Net Positions, January 2004 through September 2009

$$X_{t,k} = \alpha_{t,k} + \sum_{i=1}^{m} \gamma_{i,k} V_{t-i,k} + \sum_{j=1}^{n} \beta_{j,k} X_{t-j,k} + Dum + \varepsilon_{t,k} \text{ for each market, } k\text{, and time, } t$$

$V_t = \text{Implied Volatility}$ $\quad X_t = \text{Chg in CIT Positions}$

Market, k	m,n	p-value $\gamma_i = 0, \forall i$	$\sum \gamma_i$	p-value $\sum \gamma_i = 0$	One StDev Impact
Cocoa	5,2	**0.00**	-2.28	0.05	-18.84
Coffee	3,3	0.31	-1.87	0.25	-11.99
Cotton	1,4	**0.04**	-3.79		-29.88
Sugar	1,2	**0.00**	-21.08		-160.79
Feeder Cattle	1,2	0.13	1.19		6.06
Lean Hogs	1,2	0.82	0.20		3.28
Live Cattle	1,3	0.13	-4.71		-20.78
Corn	5,3	**0.00**	-4.86	0.48	-42.19
Soybeans	1,1	0.14	-4.46		-35.88
Soybean Oil	1,3	0.18	-4.03		-23.63
Wheat CBOT	2,1	**0.00**	-9.52	**0.01**	-86.04
Wheat KCBOT	1,1	0.68	0.50		4.07
		p-value $\gamma_{i,k} = 0, \forall i,k$	Estimate $\sum\sum \gamma_{i,k}$	p-value $\sum\sum \gamma_{i,k} = 0$	
System		**0.00**	-48.94	**0.00**	

Notes: The models are estimated across the K markets as an SUR system. The cross market coefficient restrictions not rejected by the Wald test are lag three of CIT positions, and lag five of the volatility measure. All intercepts are estimated as a single pooled parameter across all markets. Observations per commodity 1,447.

Table 2.13 Granger Causality Test Results. Null Hypothesis: Implied Volatility does not cause Change in Aggregate CIT Net Positions, January 2004 through September 2009

$$X_{t,k} = \alpha_{t,k} + \sum_{i=1}^{m} \gamma_{i,k} V_{t-i,k} + \sum_{j=1}^{n} \beta_{j,k} X_{t-j,k} + Dum + \varepsilon_{t,k} \text{ for each market, } k, \text{ and time, } t$$

V_t = Implied Volatility X_t = Pct Chg in CIT Positions

Market, k	m,n	p-value $\gamma_i = 0, \forall i$	$\sum \gamma_i$	p-value $\sum \gamma_i = 0$	One StDev Impact
Cocoa	5,2	**0.00**	-0.00001	0.73	-0.0082
Coffee	3,1	0.57	0.00000	0.68	0.0000
Cotton	5,1	0.69	-0.00001	0.39	-0.0079
Sugar	1,2	0.28	-0.00001		-0.0076
Feeder Cattle	1,2	0.28	-0.00001		-0.0051
Lean Hogs	1,3	0.28	-0.00001		-0.0167
Live Cattle	1,4	0.28	-0.00001		-0.0044
Corn	1,3	0.28	-0.00001		-0.0087
Soybeans	1,2	0.28	-0.00001		-0.0081
Soybean Oil	1,3	0.28	-0.00001		-0.0059
Wheat CBOT	2,4	0.47	-0.00001	0.26	-0.0090
Wheat KCBOT	1,1	0.28	-0.00001		-0.0082
		p-value $\gamma_{i,k} = 0, \forall i, k$	Estimate $\sum\sum \gamma_{i,k}$	p-value $\sum\sum \gamma_{i,k} = 0$	
System		**0.02**	-0.000018	0.27	

Notes: The models are estimated across the K markets as an SUR system. The cross market coefficient restrictions not rejected by the Wald test are the intercepts, lag two and three of CIT positions, and lag one of the volatility measure. All intercepts are estimated as a single pooled parameter across all markets. Observations per commodity 1,447.

Table 2.14 Granger Causality Test Results for Roll Period Days. Null Hypothesis Change in Lagged CIT Positions do not Cause Returns, January 2004 through September 2009

Market, k	m,n	p-value $\beta_j = 0, \forall j$	Estimate $\sum \beta_j$	p-value $\sum \beta_j = 0$	One StDev Nearby Impact	One StDev Deferred Impact
Panel A SUR System *(lag)*		$NP_t = \alpha_t + \sum_{i=1}^{m} \gamma_i NP_{t-i} + \sum_{j=1}^{n} \beta_j NX_{t-j} + \varepsilon_t$			$DP_t = \alpha_t + \sum_{i=1}^{m} \gamma_i DP_{t-i} + \sum_{j=1}^{n} \beta_j DX_{t-j} + \varepsilon_t$	
Cocoa	1,5	**0.0001**	-2.6E-05	0.14	-0.022	-0.019
Coffee	1,5	0.86	-4.6E-06	0.20	-0.006	-0.006
Cotton	1,1	**0.0001**	-4.4E-05	**0.0001**	-0.104	-0.099
Sugar	1,4	0.49	-3.4E-06	0.16	-0.024	-0.021
Feeder Cattle	1,1	0.07	-2.2E-05	0.07	-0.007	-0.007
Lean Hogs	1,1	**0.002**	-1.3E-05	**0.002**	-0.039	-0.037
Live Cattle	1,1	**0.001**	-6.8E-06	**0.001**	-0.025	-0.022
Corn	1,5	0.63	-1.8E-06	0.09	-0.016	-0.015
Soybeans	2,1	0.70	-5.7E-07	0.70	-0.002	-0.002
Soybean Oil	1,1	0.56	-1.3E-06	0.56	-0.003	-0.003
Wheat CBOT	1,5	0.09	-4.1E-06	**0.04**	-0.021	-0.020
Wheat KCBOT	1,4	**0.001**	-3.5E-05	**0.02**	-0.034	-0.032
Panel B SUR System *(lag)*		$NP_t = \alpha_t + \sum_{i=1}^{m} \gamma_i NP_{t-i} + \sum_{j=1}^{n} \beta_j PNX_{t-j} + \varepsilon_t$			$DP_t = \alpha_t + \sum_{i=1}^{m} \gamma_i DP_{t-i} + \sum_{j=1}^{n} \beta_j PDX_{t-j} + \varepsilon_t$	
Cocoa	1,5	**0.0001**	-1.0E-02	**0.0001**	-0.234	-1.981
Coffee	1,3	0.85	2.1E-04	0.37	0.003	0.009
Cotton	1,3	**0.0001**	-1.2E-02	**0.0001**	-0.169	-0.297
Sugar	1,3	0.90	-3.8E-04	0.53	-0.005	-0.019
Feeder Cattle	1,1	**0.02**	-1.9E-03	**0.01**	-0.032	-0.094
Lean Hogs	1,1	**0.0001**	-1.0E-02	**0.0001**	-0.132	-0.356
Live Cattle	1,1	**0.0001**	-5.9E-03	**0.0001**	-0.074	-0.311
Corn	1,4	0.36	9.3E-04	0.15	0.011	0.011
Soybeans	2,4	0.89	1.3E-05	0.82	0.000	0.008
Soybean Oil	1,1	0.17	-3.8E-04	0.17	-0.010	-0.011
Wheat CBOT	1,5	0.06	-3.5E-03	**0.01**	-0.041	-0.045
Wheat KCBOT	1,3	**0.001**	-5.2E-03	**0.00**	-0.059	-0.270

Note: The results are presented for the system results only. Bold indicates significance at the 5% level. NP is nearby price return, DP is first deferred price return, NX is nearby change in CIT positions, DX is first deferred change in CIT positions, PNX is nearby percent change in CIT positions, and PDX is first deferred change in CIT positions. Observations vary by commodity due to differences in the number of maturing contracts, but each commodity has approximately 630 observations.

Table 2.15 Granger Causality Test Results for Roll Period Days. Null Hypothesis Change in Lagged CIT Positions do not Cause Parkinson Volatility, January 2004 through September 2009

Market, k	m,n	p-value $\beta_j = 0, \forall j$	Estimate $\sum \beta_j$	p-value $\sum \beta_j = 0$	One StDev Nearby Impact	One StDev Deferred Impact
Panel A SUR System *(lag)*	$NV_t = \alpha_t + \sum_{i=1}^{m} \gamma_i NV_{t-i} + \sum_{j=1}^{n} \beta_j NX_{t-j} + \varepsilon_t$			$DV_t = \alpha_t + \sum_{i=1}^{m} \gamma_i DV_{t-i} + \sum_{j=1}^{n} \beta_j DX_{t-j} + \varepsilon_t$		
Cocoa	1,5	**0.0001**	-1.4E-04	0.54	-0.115	-0.099
Coffee	1,5	**0.03**	1.2E-04	0.40	0.161	0.145
Cotton	1,1	0.61	2.0E-05	0.61	0.048	0.046
Sugar	1,2	0.08	2.7E-05	0.10	0.192	0.169
Feeder Cattle	1,1	0.51	7.8E-05	0.51	0.026	0.024
Lean Hogs	1,1	**0.01**	7.5E-05	**0.01**	0.221	0.211
Live Cattle	1,1	**0.002**	3.8E-05	**0.002**	0.138	0.126
Corn	1,1	0.39	6.0E-06	0.39	0.055	0.051
Soybeans	1,1	0.06	-3.0E-05	0.06	-0.130	-0.121
Soybean Oil	1,1	**0.02**	1.0E-04	0.21	0.225	0.216
Wheat CBOT	1,2	0.20	6.1E-06	0.66	0.032	0.030
Wheat KCBOT	2,4	0.07	1.3E-04	0.23	0.128	0.122
Panel B SUR System *(lag)*	$NV_t = \alpha_t + \sum_{i=1}^{m} \gamma_i NV_{t-i} + \sum_{j=1}^{n} \beta_j PNX_{t-j} + \varepsilon_t$			$DV_t = \alpha_t + \sum_{i=1}^{m} \gamma_i DV_{t-i} + \sum_{j=1}^{n} \beta_j PDX_{t-j} + \varepsilon_t$		
Cocoa	1,4	**0.0004**	-8.5E-03	0.51	-0.194	-1.642
Coffee	1,5	0.09	-1.3E-03	0.82	-0.018	-0.058
Cotton	1,1	0.58	-3.3E-03	0.58	-0.045	-0.080
Sugar	1,1	0.11	3.0E-02	0.06	0.430	1.510
Feeder Cattle	1,1	0.10	2.3E-03	0.10	0.040	0.115
Lean Hogs	1,1	**0.0003**	4.6E-02	**0.0003**	0.583	1.572
Live Cattle	1,1	**0.002**	2.5E-02	**0.0004**	0.316	1.321
Corn	1,5	0.90	-9.6E-03	0.46	-0.110	-0.108
Soybeans	1,1	0.63	1.3E-04	0.63	0.002	0.078
Soybean Oil	1,1	0.33	4.4E-03	0.33	0.115	0.125
Wheat CBOT	1,5	0.54	-1.6E-03	0.86	-0.019	-0.021
Wheat KCBOT	1,5	0.35	6.5E-03	0.17	0.074	0.339

Note: The results are presented for the system results only. Bold indicates significance at the 5% level. NV is nearby Parkinson volatility, DV is first deferred Parkinson volatility, NX is nearby change in CIT positions, DX is first deferred change in CIT positions, PNX is nearby percent change in CIT positions, and PDX is first deferred change in CIT positions. Observations vary by commodity due to differences in the number of maturing contracts, but each commodity has approximately 630 observations.

Table 2.16 Granger Causality Test Results for Roll Period Days. Null Hypothesis Change in Lagged CIT Positions do not Cause Implied Volatility, January 2004 through September 2009

Market, k	m,n	p-value $\beta_j = 0, \forall j$	Estimate $\sum \beta_j$	p-value $\sum \beta_j = 0$	One StDev Cumulative NX Impact	One StDev Cumulative DX Impact
Panel A SUR System *(lag)*	$NI_t = \alpha_t + \sum_{i=1}^{m} \gamma_i NI_{t-i} + \sum_{j=1}^{n} \beta_j NX_{t-j} + \varepsilon_t$			$DI_t = \alpha_t + \sum_{i=1}^{m} \gamma_i DI_{t-i} + \sum_{j=1}^{n} \beta_j DX_{t-j} + \varepsilon_t$		
Cocoa	1,1	**0.002**	3.9E-04	**0.0005**	0.333	0.286
Coffee	1,1	0.75	-8.0E-06	0.75	-0.011	-0.010
Cotton	1,1	0.79	-3.1E-06	0.79	-0.007	-0.007
Sugar	1,1	0.42	4.2E-06	0.42	0.030	0.026
Feeder Cattle	1,1	**0.01**	9.3E-05	**0.01**	0.031	0.029
Lean Hogs	1,1	0.39	1.4E-05	0.39	0.042	0.040
Live Cattle	1,1	0.22	5.6E-06	0.22	0.020	0.018
Corn	1,1	0.96	1.3E-07	0.96	0.001	0.001
Soybeans	2,1	0.72	1.7E-06	0.72	0.007	0.007
Soybean Oil	1,1	0.76	-4.8E-06	0.76	-0.011	-0.010
Wheat CBOT	2,1	0.93	-3.0E-07	0.93	-0.002	-0.001
Wheat KCBOT	1,1	0.08	4.8E-05	0.08	0.046	0.044
Panel B SUR System *(lag)*	$NI_t = \alpha_t + \sum_{i=1}^{m} \gamma_i NI_{t-i} + \sum_{j=1}^{n} \beta_j PNX_{t-j} + \varepsilon_t$			$DI_t = \alpha_t + \sum_{i=1}^{m} \gamma_i DI_{t-i} + \sum_{j=1}^{n} \beta_j PDX_{t-j} + \varepsilon_t$		
Cocoa	1,1	0.54	-1.2E-04	0.54	-0.003	-0.023
Coffee	1,1	0.75	3.3E-04	0.75	0.004	0.014
Cotton	1,1	**0.01**	-3.6E-03	**0.01**	-0.050	-0.087
Sugar	1,1	**0.04**	1.8E-03	**0.04**	0.025	0.089
Feeder Cattle	1,1	**0.01**	5.9E-03	**0.005**	0.104	0.302
Lean Hogs	1,1	0.71	6.6E-04	0.71	0.008	0.023
Live Cattle	1,1	0.34	3.7E-04	0.34	0.005	0.020
Corn	1,1	0.87	3.7E-04	0.87	0.004	0.004
Soybeans	2,1	0.69	2.1E-05	0.69	0.000	0.013
Soybean Oil	1,1	0.11	-2.5E-03	0.11	-0.064	-0.069
Wheat CBOT	2,1	0.47	-7.0E-04	0.47	-0.008	-0.009
Wheat KCBOT	1,1	**0.0001**	2.0E-03	**0.0001**	0.022	0.102

Note: The results are presented for the system results only. Bold indicates significance at the 5% level. NI is nearby implied volatility, DI is first deferred implied volatility, NX is nearby change in CIT positions, DX is first deferred change in CIT positions, PNX is nearby percent change in CIT positions, and PDX is first deferred change in CIT positions. Observations vary by commodity due to differences in the number of maturing contracts, but each commodity has approximately 630 observations.

Table 2.17 Correlation between Change in Index Traders Positions and Returns, January 2004 through September 2009

	Roll Period: Section 2 Contract		Roll Period: Goldman Roll Contract	
	Nearby	Deferred	Nearby	Deferred
Cocoa	-0.01	0.04	-0.05	-0.02
	(0.78)	*(0.33)*	*(0.52)*	*(0.85)*
Coffee	-0.01	0.02	-0.11	0.08
	(0.76)	*(0.67)*	*(0.2)*	*(0.34)*
Cotton	0.01	0.01	0.01	0.00
	(0.87)	*(0.89)*	*(0.89)*	*(0.97)*
Sugar	-0.04	0.05	-0.16	0.10
	(0.32)	*(0.28)*	*(0.07)*	*(0.31)*
Feeder Cattle	**0.08**	-0.07	0.11	-0.07
	(0.05)	*(0.06)*	*(0.08)*	*(0.29)*
Lean Hogs	0.02	0.05	0.12	0.04
	(0.64)	*(0.22)*	*(0.09)*	*(0.61)*
Live Cattle	0.06	-0.04	**0.19**	**-0.16**
	(0.11)	*(0.23)*	*(0.01)*	*(0.04)*
Corn	0.00	0.01	0.02	-0.04
	(0.93)	*(0.73)*	*(0.81)*	*(0.68)*
Soybeans	-0.04	0.05	-0.16	0.10
	(0.32)	*(0.28)*	*(0.07)*	*(0.31)*
Soybean Oil	-0.03	0.05	-0.02	-0.03
	(0.56)	*(0.22)*	*(0.85)*	*(0.77)*
Wheat	0.04	0.00	0.09	-0.04
	(0.37)	*(1)*	*(0.28)*	*(0.66)*
Wheat KS	0.02	0.01	0.16	-0.05
	(0.63)	*(0.74)*	*(0.05)*	*(0.58)*
Average Coefficient	0.01	0.01	0.02	-0.01

Note: The results display the Pearson Correlation coefficient and a p-value below each coefficient. P-values less than 0.05 are bold.

Table 2.18 Correlation between Percent Change in Index Trader Positions and Returns, January 2004 through September 2009

	Roll Period: Section 2 Contract		Roll Period: Goldman Roll Contract	
	Nearby	Deferred	Nearby	Deferred
Cocoa	0.00	0.02	0.04	**-0.16**
	(0.93)	*(0.62)*	*(0.62)*	*(0.05)*
Coffee	0.06	**0.09**	0.04	0.11
	(0.12)	*(0.03)*	*(0.64)*	*(0.19)*
Cotton	-0.07	0.03	-0.12	0.01
	(0.1)	*(0.51)*	*(0.22)*	*(0.93)*
Sugar	-0.05	0.04	-0.03	-0.02
	(0.27)	*(0.42)*	*(0.77)*	*(0.85)*
Feeder Cattle	0.06	0.05	0.03	0.09
	(0.1)	*(0.19)*	*(0.71)*	*(0.17)*
Lean Hogs	-0.02	0.04	0.05	0.04
	(0.58)	*(0.27)*	*(0.46)*	*(0.54)*
Live Cattle	0.01	0.04	0.06	0.13
	(0.7)	*(0.29)*	*(0.47)*	*(0.09)*
Corn	0.01	0.05	0.07	-0.01
	(0.8)	*(0.19)*	*(0.4)*	*(0.95)*
Soybeans	-0.05	0.04	-0.03	-0.02
	(0.27)	*(0.42)*	*(0.77)*	*(0.85)*
Soybean Oil	-0.05	0.02	**-0.19**	-0.03
	(0.29)	*(0.7)*	*(0.03)*	*(0.71)*
Wheat	0.01	0.06	0.12	-0.07
	(0.78)	*(0.15)*	*(0.16)*	*(0.4)*
Wheat KS	0.03	0.05	**0.19**	-0.05
	(0.42)	*(0.18)*	*(0.02)*	*(0.59)*
Average Coefficient	0.00	0.04	0.02	0.00

Note: The results display the Pearson Correlation coefficient and a p-value below each coefficient. P-values less than 0.05 are bold.

Table 2.19 Correlation between Change in Index Trader Positions and Parkinson Volatility, January 2004 through September 2009

	Roll Period: Section 2 Contract		Roll Period: Goldman Roll Contract	
	Nearby	Deferred	Nearby	Deferred
Cocoa	-0.03	-0.01	**-0.20**	0.15
	(0.46)	*(0.77)*	*(0.02)*	*(0.07)*
Coffee	0.04	-0.06	0.12	-0.15
	(0.32)	*(0.11)*	*(0.15)*	*(0.07)*
Cotton	0.06	-0.09	**0.37**	**-0.39**
	(0.19)	*(0.06)*	*(0)*	*(0)*
Sugar	**-0.11**	0.08	**-0.19**	0.17
	(0.02)	*(0.05)*	*(0.04)*	*(0.06)*
Feeder Cattle	0.05	-0.04	-0.08	0.02
	(0.18)	*(0.33)*	*(0.21)*	*(0.72)*
Lean Hogs	0.04	-0.01	0.08	-0.10
	(0.33)	*(0.81)*	*(0.25)*	*(0.17)*
Live Cattle	0.03	0.01	0.11	-0.13
	(0.36)	*(0.79)*	*(0.13)*	*(0.08)*
Corn	-0.05	-0.02	-0.04	-0.10
	(0.19)	*(0.66)*	*(0.67)*	*(0.22)*
Soybeans	**-0.11**	0.08	**-0.19**	0.17
	(0.02)	*(0.05)*	*(0.04)*	*(0.06)*
Soybean Oil	0.05	-0.08	**0.19**	**-0.26**
	(0.29)	*(0.05)*	*(0.03)*	*(0)*
Wheat	-0.06	-0.02	-0.03	-0.15
	(0.12)	*(0.64)*	*(0.71)*	*(0.08)*
Wheat KS	**-0.11**	**0.09**	**-0.17**	0.15
	(0.01)	*(0.03)*	*(0.04)*	*(0.08)*
Average Coefficient	-0.02	-0.01	0.00	-0.05

Note: The results display the Pearson Correlation coefficient and a p-value below each coefficient. P-values less than 0.05 are bold.

Table 2.20 Correlation between Percent Change in Index Trader Positions and Parkinson Volatility, January 2004 through September 2009

	Roll Period: Section 2 Contract		Roll Period: Goldman Roll Contract	
	Nearby	Deferred	Nearby	Deferred
Cocoa	0.00	-0.05	0.04	0.16
	(0.91)	*(0.26)*	*(0.6)*	*(0.06)*
Coffee	0.04	0.05	0.00	**-0.16**
	(0.28)	*(0.2)*	*(0.96)*	*(0.05)*
Cotton	-0.03	-0.03	0.08	**-0.21**
	(0.52)	*(0.48)*	*(0.39)*	*(0.02)*
Sugar	0.00	-0.03	0.03	-0.15
	(0.94)	*(0.54)*	*(0.72)*	*(0.11)*
Feeder Cattle	0.04	0.02	-0.07	0.04
	(0.3)	*(0.56)*	*(0.27)*	*(0.55)*
Lean Hogs	0.03	-0.06	0.04	-0.11
	(0.48)	*(0.1)*	*(0.55)*	*(0.11)*
Live Cattle	-0.01	0.02	-0.03	0.12
	(0.85)	*(0.6)*	*(0.66)*	*(0.11)*
Corn	-0.07	**-0.17**	-0.09	**-0.29**
	(0.07)	*(0)*	*(0.26)*	*(0)*
Soybeans	0.00	-0.03	0.03	-0.15
	(0.94)	*(0.54)*	*(0.72)*	*(0.11)*
Soybean Oil	0.03	**-0.11**	0.16	**-0.17**
	(0.53)	*(0.01)*	*(0.06)*	*(0.05)*
Wheat	-0.04	**-0.08**	0.00	**-0.30**
	(0.28)	*(0.05)*	*(0.98)*	*(0)*
Wheat KS	**-0.09**	0.00	-0.11	0.09
	(0.02)	*(0.99)*	*(0.18)*	*(0.28)*
Average Coefficient	-0.01	-0.04	0.01	-0.09

Note: The results display the Pearson Correlation coefficient and a p-value below each coefficient. P-values less than 0.05 are bold.

Table 2.21 Correlation between Change in Index Trader Positions and Implied Volatility, January 2004 through September 2009

	Roll Period: Section 2 Contract		Roll Period: Goldman Roll Contract	
	Nearby	Deferred	Nearby	Deferred
Cocoa	-0.01	**-0.13**	**-0.16**	-0.03
	(0.86)	*(0)*	*(0.05)*	*(0.69)*
Coffee	**0.14**	**-0.20**	**0.53**	**-0.56**
	(0)	*(0)*	*(0)*	*(0)*
Cotton	**0.13**	**-0.19**	**0.53**	**-0.54**
	(0)	*(0)*	*(0)*	*(0)*
Sugar	**0.09**	**-0.15**	0.10	**-0.28**
	(0.04)	*(0)*	*(0.26)*	*(0)*
Feeder Cattle	**0.14**	**-0.14**	0.01	-0.04
	(0)	*(0)*	*(0.89)*	*(0.52)*
Lean Hogs	0.00	**-0.08**	0.09	**-0.33**
	(0.92)	*(0.03)*	*(0.22)*	*(0)*
Live Cattle	**0.14**	**-0.16**	**0.55**	**-0.52**
	(0)	*(0)*	*(0)*	*(0)*
Corn	0.00	-0.05	0.08	**-0.19**
	(0.98)	*(0.17)*	*(0.37)*	*(0.02)*
Soybeans	**0.09**	**-0.15**	0.10	**-0.28**
	(0.04)	*(0)*	*(0.26)*	*(0)*
Soybean Oil	**0.12**	**-0.18**	**0.35**	**-0.41**
	(0)	*(0)*	*(0)*	*(0)*
Wheat	0.06	**-0.16**	**0.21**	**-0.38**
	(0.16)	*(0)*	*(0.01)*	*(0)*
Wheat KS	0.00	-0.06	0.07	-0.12
	(0.98)	*(0.12)*	*(0.42)*	*(0.14)*
Average Coefficient	0.07	-0.14	0.20	-0.31

Note: The results display the Pearson Correlation coefficient and a p-value below each coefficient. P-values less than 0.05 are bold.

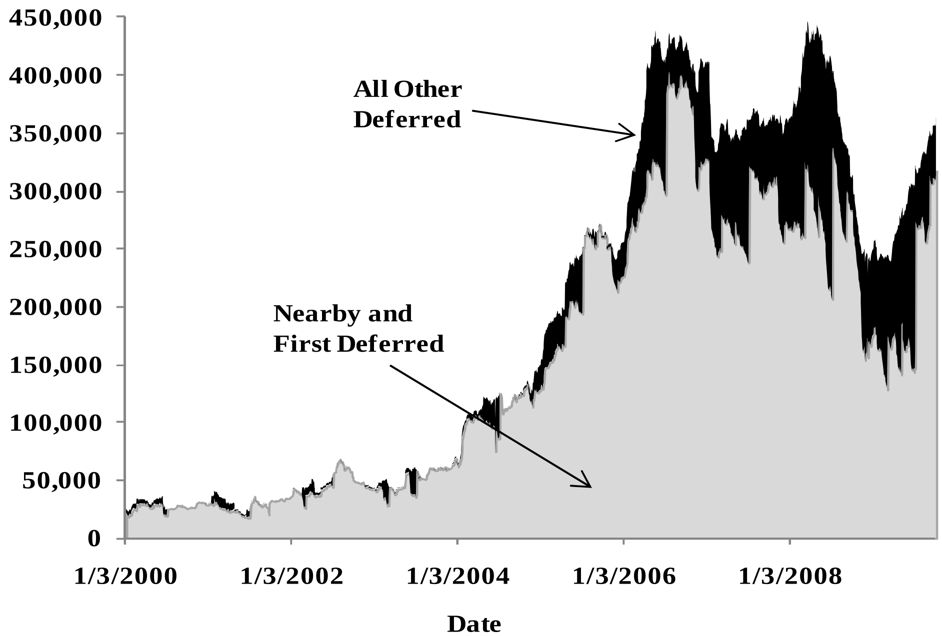
Table 2.22 Correlation between Percent Change in Index Trader Positions and Implied Volatility, January 2004 through September 2009

	Roll Period: Section 2 Contract		Roll Period: Goldman Roll Contract	
	Nearby	Deferred	Nearby	Deferred
Cocoa	0.04	-0.02	-0.07	0.12
	(0.3)	*(0.71)*	*(0.4)*	*(0.16)*
Coffee	-0.02	0.04	0.04	-0.06
	(0.69)	*(0.32)*	*(0.67)*	*(0.48)*
Cotton	0.01	-0.07	0.03	**-0.31**
	(0.77)	*(0.13)*	*(0.72)*	*(0)*
Sugar	0.08	-0.05	-0.01	-0.15
	(0.06)	*(0.24)*	*(0.92)*	*(0.11)*
Feeder Cattle	**0.14**	-0.01	-0.12	0.04
	(0)	*(0.74)*	*(0.06)*	*(0.5)*
Lean Hogs	0.02	**-0.08**	0.12	**-0.22**
	(0.67)	*(0.04)*	*(0.09)*	*(0)*
Live Cattle	0.04	-0.01	0.10	**0.18**
	(0.26)	*(0.77)*	*(0.21)*	*(0.02)*
Corn	0.00	**-0.14**	0.05	**-0.27**
	(0.99)	*(0)*	*(0.52)*	*(0)*
Soybeans	0.08	-0.05	-0.01	-0.15
	(0.06)	*(0.24)*	*(0.92)*	*(0.11)*
Soybean Oil	**0.09**	**-0.11**	**0.32**	-0.13
	(0.03)	*(0.01)*	*(0)*	*(0.13)*
Wheat	0.04	**-0.28**	0.15	**-0.52**
	(0.35)	*(0)*	*(0.07)*	*(0)*
Wheat KS	-0.01	**-0.09**	-0.02	**-0.17**
	(0.84)	*(0.03)*	*(0.8)*	*(0.04)*
Average Coefficient	0.04	-0.07	0.05	-0.14

Note: The results display the Pearson Correlation coefficient and a p-value below each coefficient. P-values less than 0.05 are bold.

Figure 2.1 Composition of Daily Net Long Open Interest of Commodity Index Traders (CITs) in the Corn Futures Market, January 3, 2000 - September 29, 2009

Panel A: Number of Contracts



Panel B: Percent of Position in All Other Deferred Contracts

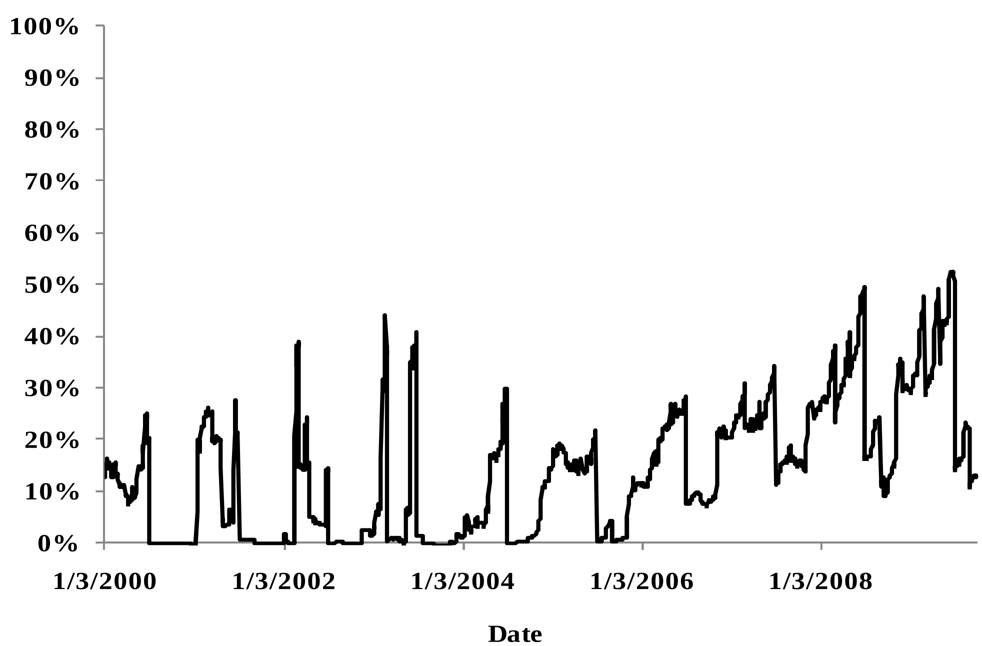
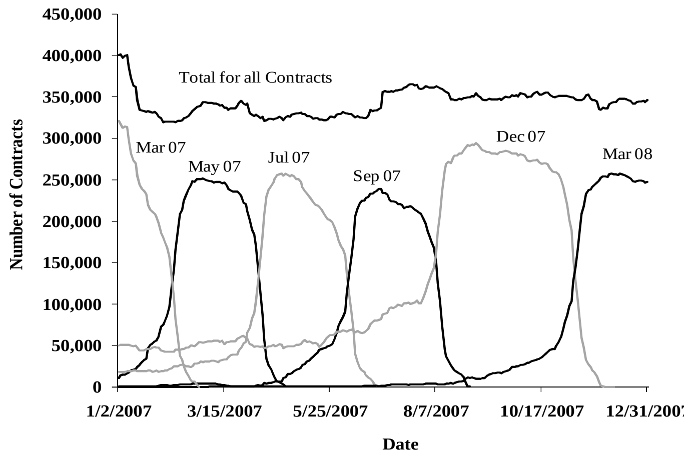
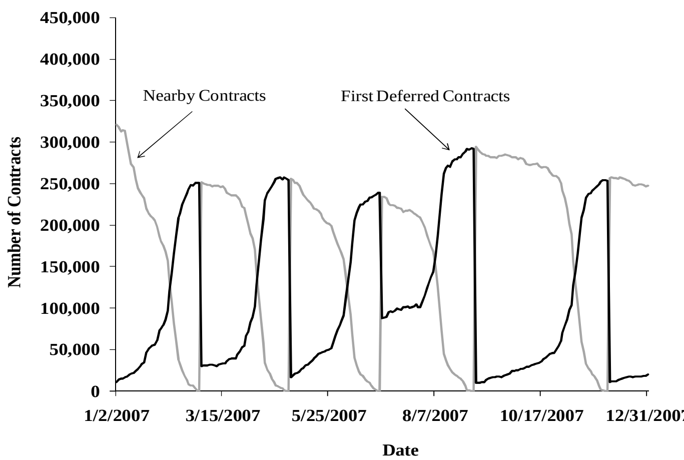


Figure 2.2 Level and Change in Daily Net Long Open Interest of Comm Index Traders (CITs) in Corn, January 2, 2007 - December 31, 2007

Panel A: Total and Contract-by-Contract Net Long Open Interest



Panel B: Nearby and First Deferred Contract Net Long Open Interest



Panel C: Change in Nearby and First Deferred Net Long Open Interest

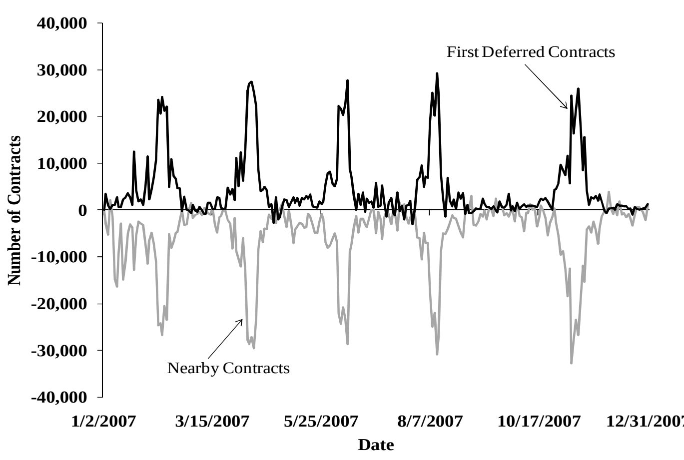


Figure 2.3 Commodity Index Trader Change in Open Interest Roll Pattern during the Goldman Roll, 25 Days Before and 10 Days After for Corn Futures Contract Maturities, December 2004 and December 2008

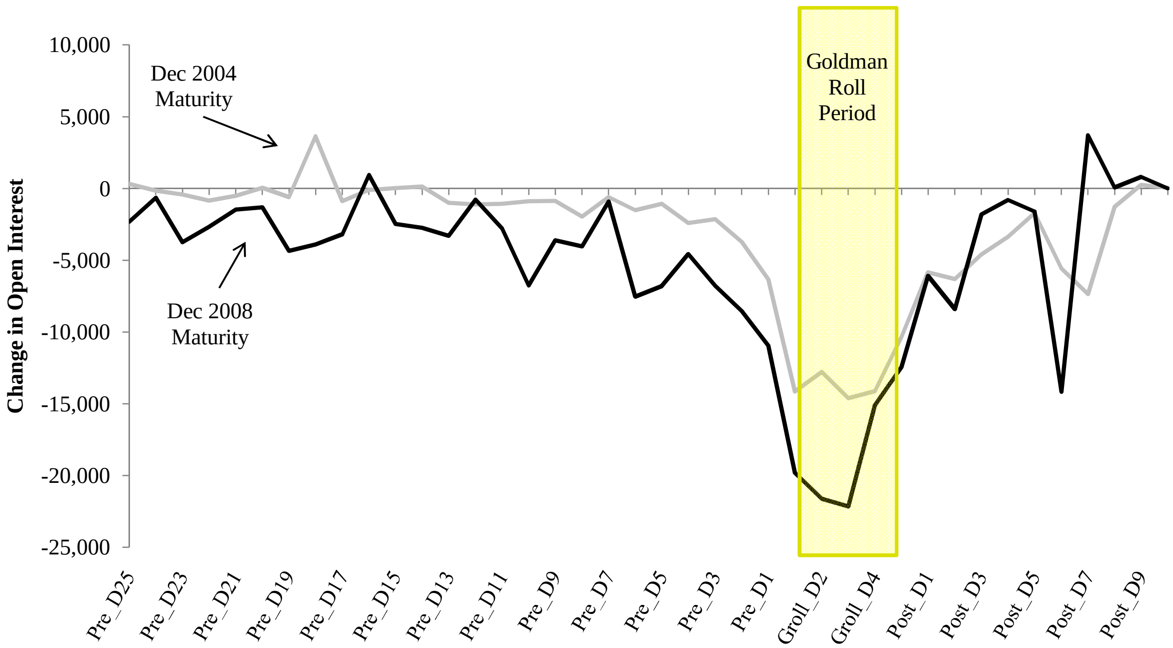


Figure 2.4 Defining the Commodity Index Trader Roll Periods

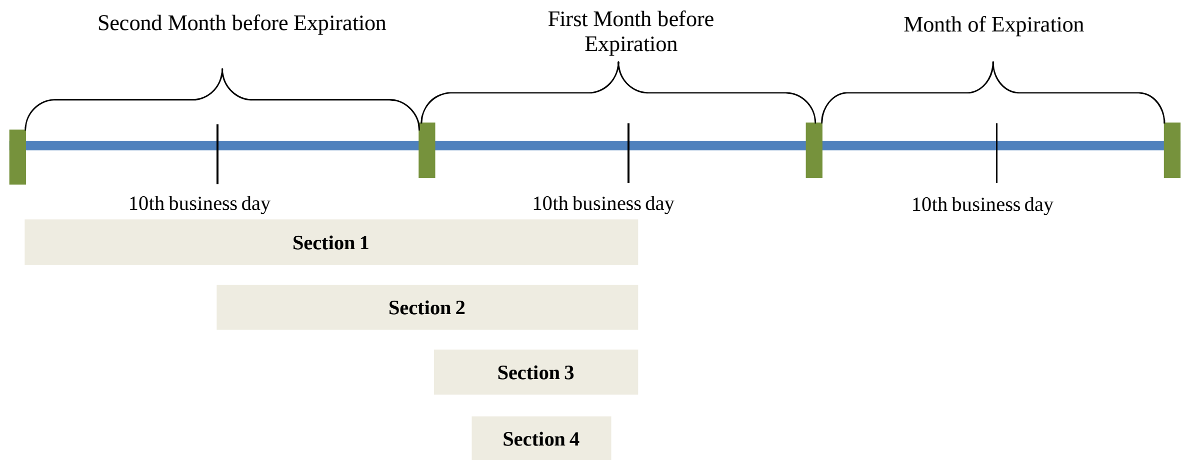
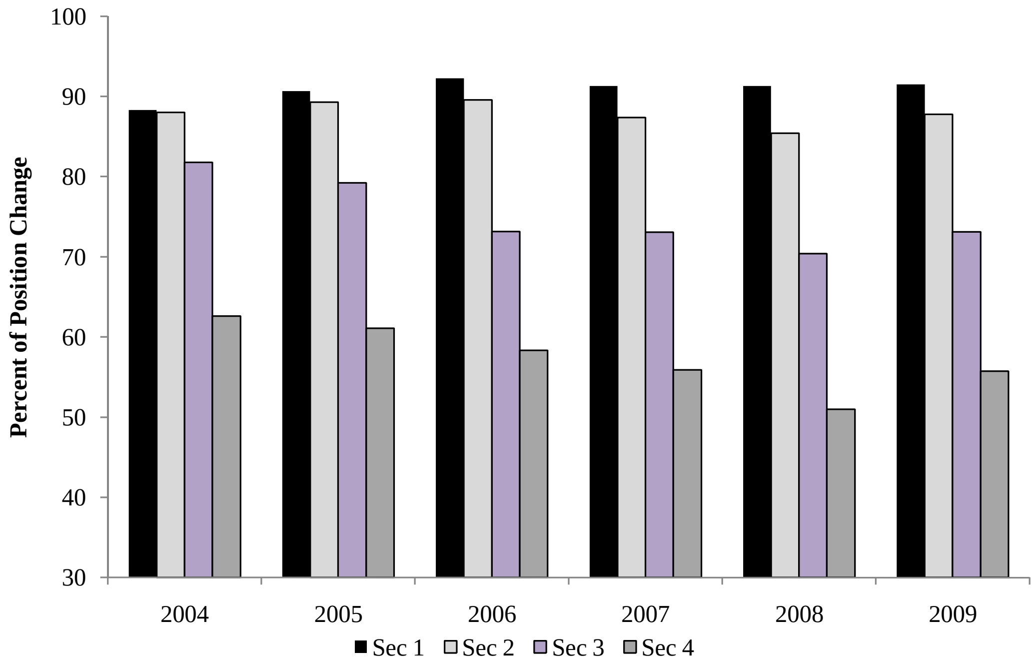


Figure 2.5 Percent of Roll Activity in Respective Periods, Average Over All Commodities and Maturities, 2004-2009



3. RETURNS TO TRADERS AND EXISTENCE OF A RISK PREMIUM IN AGRICULTURAL FUTURES MARKETS

3.1 Introduction

Important research in futures markets has been performed to assess the distribution and sources of trader returns. The Keynesian theory of normal backwardation was motivated by a desire to determine whether hedgers paid speculators for protection against adverse price movements. If the theory is true, speculators earn a positive return over time and hedgers earn a negative return as they pay speculators to reduce business risk. The risk premium is in the form of a bias in futures prices, whereby, “The quoted forward price, though above the present spot price, must fall below the anticipated future spot price by at least the amount of normal backwardation.” (Keynes 1930, pp.144)

Because of its central importance to understanding how futures markets function, the theory has raised considerable debate in the literature but has never been convincingly resolved (Telser, 2000). When testing for normal backwardation by calculating trader profitability, most early papers were hampered by infrequent observations and aggregation problems. This forced authors to make highly simplified assumptions about trading behavior. Nevertheless, Houthakker (1957) and Rockwell (1967) conclude that speculators can earn returns if they possess the skill to forecast price movements.

Hartzmark (1987, 1991) made significant contributions to the debate with daily data from 1977 to 1981 in nine markets by calculating the profitability of trader types. He finds no support for the presence of risk premium as commercial traders often obtained positive returns and later concluded that profits were primarily generated by luck. Leuthold, Garcia, and Lu (1994) followed Hartzmark’s work using more recent data from 1982-1990 from the frozen pork belly futures market. Leuthold et al. also find little evidence of risk premiums, but observed that the distribution of returns is not random. Large reporting traders generate significant profits, speculators are able to forecast profitably, and spreaders have less forecasting ability but are able to consistently identify the direction of market changes. Phillips and Weiner (1994) used a unique data set of forward market participants in the North Sea oil market in which participants face higher barriers to entry in the forward market than in the future markets. If a risk premium is to be uncovered, it would most likely exist in harder to enter markets rather than in more liquid futures markets where a risk premium could be eliminated by a large supply of willing speculators. Results of the study show no evidence of a risk premium, further supporting Hartzmark and Leuthold, Garcia, and Lu's findings. Dewally, Ederington, and Fernando (2009) investigated energy futures markets and find evidence that persistent profits among traders do exist, and that speculator profits are largely due to risk absorption services they provide. The debate continues. Recently, Fishe and Smith (2010) waded into the debate and argue against the theory that commercial hedgers pay a risk premium to speculators. Their results contradict the theory of normal backwardation finding liquidity demanders tend to be noncommercial traders and liquidity suppliers tend to be commercial firms. Brunetti and Reiffen (2010) find that hedging costs have decreased in the presence of index traders but do not calculate if index traders or speculators successfully profit from absorbing hedge trades.

The purpose of this essay is to contribute to the understanding of the distribution and sources of trader returns in futures markets, focusing on agricultural commodities in a time of changing market participants and price levels. During the sample period, agricultural commodity futures markets have experienced extreme changes in price levels and increased volatility which should enable us to effectively identify how returns to market participants change in risky situations. More importantly, the emergence of commodity index traders (CITs) into the futures markets during 2004 and 2005 provides a natural experiment to determine if holding positions opposite of hedgers results in positive profits. The emergence of CITs was encouraged by an influential study by Gorton and Rouwenhorst (2006) that finds futures prices rise over the life of a contract and passive long investors can earn a risk premium. Past studies using actual trader positions to test for the existence of a risk premium calculate profits of all noncommercial traders to determine if speculators actually earn a premium for absorbing risk. Testing all noncommercial traders mixes both an active trading strategy designed to leverage perceived skill and a passive trading strategy attempting to earn a risk premium opposite hedgers. The existence of CITs allows the disentanglement of these two strategies since CITs positions are opposite hedgers and passive in nature.

Although index funds maintain a passive strategy by using preset weights of commodities in portfolios, the motivation of the investors behind the funds is less clear. Aulerich (2011a) analyzes the positions of CITs to determine if they exhibit trend following behavior that differs from the assumption of passivity. The research finds that CITs do exhibit some limited tendencies to trend follow, where a one standard deviation increase in returns of 2% would encourage a maximum of 0.25% additional contract investment (and vice versa). This effect is minimal but does indicate that investors in index funds are not solely interested in earning a risk premium. In another caveat, CITs motivation for diversification would also cloud the strategy of strictly earning a risk premium. Following Gorton and Rouwenhorst (2006), commodities provide a hedge against inflation and are negatively correlated with equity and bond returns. Despite these imperfections, commodity index trader profits provide the clearest real time proxy to date for testing the strategy imbedded in the original normal backwardation theory.

This research uses daily disaggregated data from the non-public CFTC large trader reporting system from January 2000 through September 2009 for 12 agricultural commodity futures markets (cocoa, coffee, corn, cotton, feeder cattle, lean hogs, live cattle, soybeans, soybean oil, sugar, CBOT wheat, KS wheat). Daily profit is calculated for commercial, noncommercial, commodity index traders, and small traders. After analyzing aggregate returns by trader group, a temporal assessment of trader profits and positions over time is used to clarify findings. Next, a return on investment measure is computed, and profits are separated by days outside and inside the index trader roll period; the roll period is the time frame when traders move positions for the nearest maturity contract to the next nearest to maturity contract. The results from the additional tests support the conclusions from the aggregate results, which show that speculative noncommercial traders are indeed successful, earning approximately $7.9 billion whereas the hedging commercial traders experience a net loss of -$698 million. The small, nonreporting traders have net losses of -$366 million, consistent with previous beliefs that small traders are unskilled (Hartzmark 1991). Overall, no evidence of a risk premium is supported as CITs do not display evidence of receiving a risk premium by earning consistent positive returns but rather experience losses in aggregate of -$6.9 billion.

3.2 Literature Review

A number of empirical studies have attempted to study the existence of a risk premium in futures markets. The evidence is mixed as researchers use different data sets and techniques attempting to prove or disprove hedging pressure, normal backwardation, or a risk premium. This section first provides a review of research measuring the risk premium through calculation of trader's profits, the most direct method, and then reviews selected research employing alternate methods of risk premium detection that provide either direct or indirect evidence on the theory of normal backwardation. These include determining if risk premiums are functions of non-diversifiable risk and discovering the hypothetical profitability of positions opposite hedgers (hedging pressure).

3.2.1 Profit Calculations on Positions

Houthakker (1957) set out to determine if speculators could forecast prices by calculating the profits of hedgers, speculators, and small non-reporting traders. The analysis uses monthly data on trader positions for corn, wheat, and cotton from 1937 to 1947. Profits and losses by group are calculated by multiplying the end of month position by the monthly average futures price for the respective commodity. Results show long speculative positions to be profitable and short hedging positions to generate losses. The disentanglement of skill versus risk premium is attempted two ways. The first is a regression of net positions in each category on changes in prices, and the second is analysis of distributive skill. The regression results demonstrate that large speculators have skill and small traders do not. The distributive skill results reinforce the regression conclusions; large speculators are able to position themselves in shorter maturity contracts and incur positive profits by exploiting their knowledge of deliverable stocks. Small traders simply take the opposite side of short hedging positions and the opposite side of short speculative bets in order to profit from a risk premium. While both large and small speculators profit, the sources of profits differ; large speculators gain through distributive skill, while smaller speculators gain through a risk premium.

Rockwell (1967) considers whether returns by speculators are explained by normal backwardation or forecasting ability. Rockwell uses a similar method as Houthakker (1957) but covers a much broader sample of 25 markets for 18 years from 1947 to 1965. He splits the semimonthly data into large markets and small markets, large markets being both Chicago wheat and soybeans and New York cotton. He tests for normal backwardation by determining if a naïve speculator would earn profits by taking the opposite side of a the net hedger's positions. The evidence rejects the theory of normal backwardation, finding a naïve speculative strategy is not profitable. He then tests for basic versus special forecasting skills. Basic forecasting skills is tested by calculating a ratio of total value of long positions minus short positions divided by long positions plus short positions and the ratio multiplied by that rate of return for a single market. Special forecasting skill is a residual of aggregation of overall sets of markets minus basic forecasting skill. Results show that small traders exhibit a consistent negative special forecasting skill but large speculators consistently show both basic and special forecasting skill. He concludes that no significant evidence of normal backwardation exists and forecasting ability is the reason for speculative profits.

Hartzmark (1987) conducted ground-breaking research with daily position and price data from the CFTC to test the existence of a risk premium in futures markets. The study covers nine markets: oats, CBOT wheat, MGE wheat, KS wheat, pork bellies, live cattle, feeder cattle, T-bonds, and 90 day T-bills from July 1977 to December 1981. Daily profits for each trader for each contract held are calculated by multiplying end-of-day positions by the change in the settlement price between the current day and the following day. The results show that speculators in futures market do not earn significant positive profits and hedgers do not suffer significant losses. He infers that a risk premium implicit in the futures price is highly unlikely or the premium is masked by differences in price expectations.

Leuthold, Garcia, and Lu (1994) follow up to Hartzmark's work and examine the returns and forecasting ability of large traders in the frozen pork belly futures markets. The data used are from the same database as Hartzmark (1987) which is the CFTC's Large Trader Reporting

System and extends from 1982 to 1990. They calculate profits and search for skill using Cumby and Modest and Henriksson and Merton tests. The results show the distribution of profits over time is not random and all large reporting traders earn significant profits and small non-reporting traders experience losses. For a small subset of traders, significant profits are positively related to the traders' ability to forecast price behavior. The discovery of significant skill contradicts the notion that a large group of traders can make profits from risk premiums by naively positioning themselves opposite hedging traders.

Phillips and Weiner (1994) used unique data to analyze the existence of normal backwardation in the North Sea oil forward market. The data contain individual transactions rather than end of day positions and indicates the type of companies participating from July 1983 to December 1989. Profits and losses were computed by trader based on positions and the closing futures price. Results find no significant profits or losses and do not support the theory of normal backwardation. Given that entry into this forward market is far more costly than in futures markets, the absence of a risk premium in these results is even stronger evidence against the theory of normal backwardation. The analysis also tests for forecasting ability using HM non-parametric tests and is unable to detect forecasting ability among any of the nine trader types.

3.2.2 Non-diversifiable Risk in a Portfolio Context

Dusak (1973) examined the question of risk premium in a unique fashion using the Capital Asset Pricing Model and non-diversifiable risk. In this framework, the risk premium should depend not on the variability of prices but on the extent to which the variations in prices are systematically related to variations in the return on total wealth. She analyzed wheat, corn, and soybeans futures from 1952 to 1967 using semi-monthly data. The results indicate that average returns and portfolio risk are both close to zero during the sample period, providing evidence that a risk premium does not exist in the futures market.

Additional studies have been performed in an agricultural context using the portfolio approach; most indicate the absence of a risk premium except for Bjornson and Carter (1997) who find some evidence of a time-varying risk premium. They use a conditional asset pricing model on data from 1969 to 1994 to evaluate time-varying expected returns to holding commodity stocks under varying economic conditions. The expected return risk premia range from -0.03% to 0.03% of returns and does not support the theory of positive normal backwardation.

3.2.3 Hedging Pressure

Raynauld and Tessier (1984) approach the question of a risk premium in the futures market by using unrestricted regressions including pertinent variables selected from equilibrium and hedging models to explain risk premiums. The authors study corn, wheat, and oats markets from the third quarter of 1970 to the fourth quarter of 1981. In all three markets, risk premiums take on positive and negative values over extended periods. Therefore, empirical evidence provides no support for Keynes' normal backwardation theory that suggests futures prices are downward biased predictors of realized spot prices. Also, results do not support the hedging pressure hypothesis as the percentage of open interest held by reporting speculators and hedgers did not vary in conformity with the ex ante risk premium. For these reasons they were unable to empirically verifying the theory of normal backwardation.

Chang and Stevenson (1985) investigate the value of the risk-bearing function of speculators in the futures market in light of increased price volatility in the latter half of their sample period. The study scrutinizes the trading performance of small traders for corn, wheat, and soybean futures contracts in three sub-periods from 1951 to 1980 using a Henriksson and Merton (HM) methodology to assess small trader's timing ability. They find that small traders had ability in the last decade and attribute this to the extraction of a risk premium in more volatile futures markets.

Chang (1985) studied the theory of normal backwardation further using Henriksson and Merton's nonparametric procedure to test for market timing. The study uses corn, soybeans, and wheat semimonthly price quotes from July 1951 to June 1972 and monthly quotes from December 1972 to December 1980. The results show speculators are consistent winners in the futures markets and hedgers consistently lose money, providing evidence for normal backwardation. The evidence is inconsistent with the hypothesis that commodity futures prices are unbiased estimates of the future spot prices.

Wang (2003) studies the behavior and performance of speculators and hedgers in 15 U.S. markets to determine if positive feedback or contrarian styles are evident as well as the existence of hedging pressure (risk premium). The study analyzes 15 U.S. futures markets from October 1992 to March 2000, with monthly position data coming from the CFTC's public Commitment of Traders report. The determinants of trading decisions are tested by regressing the change in net position of a trader type on lagged Consensus index, futures returns, and set of common information variables. Market timing tests regress returns on lagged changes in net positions and a set of information variables. Results indicated that hedgers tend to engage in positive feedback trading, whereas speculators are contrarians. Speculators commonly outperform hedgers, but the market timing tests do not show that speculative traders have significant ability in predicting the market. In the absence of superior timing ability, the hedging pressure effects, not skill, are determined to be the source of speculative profits.

Bryant, Bessler, and Haigh (2006) investigate the existence of normal backwardation and the possibility that speculators or uniformed trader activity affects price volatility. The commodities analyzed are corn, crude oil, Eurodollars, gold, Japanese yen, coffee, live cattle, and S&P 500 from March 21, 1995 through January 8, 2003 using the CFTC's public Commitment of Traders (COT) report. They use the Fast Causal Inference (FCI) algorithm, developed in causality literature to infer causal relationships using observational data. Results show no evidence of normal backwardation and no evidence that activity by traders affects price volatility.

Dewally, Ederington, and Fernando (2009) study the existence of risk premia and if individual traders make profits attributed to information or luck. They use a proprietary data set of crude oil, gasoline, and heating oil from the CFTC's Large Trader Reporting System (LTRS) from June 1993 through March 1997. They estimate the analysis of variance (ANOVA) across 382 traders to test if the number of traders tending to make consistent profits or losses is more than one would expect due to chance. Then they test if futures prices tend to fall (rise) over time when hedgers on balance are long (short), if true this presents evidence that a risk premium exists. Results indicate that speculators earn profits primarily due to the liquidity and risk absorption services they provide hedgers.

Most recently, Fishe and Smith (2010) attempt to identify informed and liquidity traders in futures markets from a large group of 8,921 unique traders. The data used are from the CFTC's Large Trader Reporting System and extends from 2000 to mid-2009 covering the 12 commodities of crude oil, copper, corn, cotton, gold, heating oil, natural gas, silver, soybean oil, soybeans, sugar, and wheat. Instead of using the CFTC's classification of traders ex-ante, they analyze trader behavior and group them ex-post by trading actions. Traders are considered liquidity demanders if open interest moves with prices and is consistent with price changes. Traders are considered liquidity suppliers if their open interest moves with prices but is inconsistent with price changes. They find no evidence that commercial hedgers pay a risk premium to speculators. In fact, the results contradict hedging pressure theory, in that liquidity demanders tend to be managed money/hedge fund traders and liquidity suppliers tend to be commercial traders.

Brunetti and Reiffen (2010) analyzed commodity index traders and hedgers in corn, soybeans, and CBOT wheat markets from July 2003 through December 2008 again using the CFTC's disaggregated Large Trader Reporting System. They developed an equilibrium model of trader behavior for CITs and traditional short hedgers to determine if the cost of hedging has decreased or increased in the presence of index traders. The empirical estimation employs a GARCH (1,1) model that regresses spreads between nearby and deferred contracts on index trader levels, a model derived measure of hedging activity in the cash market, and various dummy variables accounting for pre- and post-harvest contracts. They determine that hedging costs have decreased in the presence of index traders, consistent with the explanation that CITs are willing to take opposite positions from hedgers at lower prices than are traditional speculators. Although Brunetti and Reiffen determine that hedging costs have decreased, they do not calculate if index traders or speculators successfully profit from absorbing hedge trades.

To conclude, the literature provides inconclusive evidence as to the existence of a risk premium. The most powerful evidence comes from profit calculations using daily end of day position data from the CFTC's Large Trader Reporting system. Previous studies using this type of data are dated or suffer from limitations on the number of commodities analyzed or the inability to disentangle naïve trading strategies from skill-based trading strategies. The emergence of CITs, which are basically long-passive traders (with the aforementioned caveats), provides the clearest proxy to develop an assessment of the original normal backwardation theory.

3.3 Data

The data for this study come 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.[21,22] 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.[23] The data provided in these reports usually cover 70-90 percent 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 himself 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 through more than one account, the CFTC is able to combine these accounts by trader and ownership level using 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 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 noncommercial from the information provided on 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 underlying business (e.g. producer, manufacturer, merchant, swaps dealer, etc.). If a trader does not meet the requirements for a commercial trader, they are then classified as a noncommercial 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 noncommercial 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).

Absent from the current From 40 is the sub-classification of Commodity Index Traders (CITs).   This category was created in response to industry concerns to separate out the passive long index traders from the original commercial and noncommercial categories to form a stand-alone category. CFTC staff engaged in a detailed process to identify index traders in the LTRS for inclusion in the new category. The process included screening all traders with large long positions in commodity futures contracts, analyzing futures positions to determine a pattern consistent with index trading, reviewing line of business forms (Form 40) to obtain more detailed information on their use of the market, and conducting an expansive series of phone and in-person interviews with traders. The CFTC acknowledges that the classification procedure was imperfect and that "…some traders assigned to the Index Traders category are engaged in other futures activity that could not be disaggregated….Likewise, the Index Traders category will not include some traders who are engaged in index trading, but for whom it does not represent a substantial part of their overall trading activity" (CFTC 2008a). While recognizing these potential problems, the CIT data are nevertheless widely regarded as providing valuable information about index trader activity in commodity futures markets.

This new commodity index trader category was first released publically in January 2007 as a *Supplemental* report coinciding with the CFTC's stalwart *Commitment of Traders* report (COT). The COT report pools traders into two broad categories (commercial and non-commercial) covering over 90 U.S. commodity markets, whereas the *Supplemental* CIT report only covers 12 agricultural futures markets: corn, soybeans, soybean oil, CBOT wheat, KCBOT wheat, feeder cattle, lean hogs, live cattle, cocoa, cotton, coffee, and sugar. The *Supplemental* CIT report covers a smaller number of markets because index traders in other markets are engaged in substantial amounts of non-index related trading activity which makes identification and segregation more difficult. The CIT category was computed retroactively by the CFTC for 2006 to provide context for the initial release of the data in 2007.[24] In this study, a longer retroactive application is applied from 2000 to 2006. This extended application assumes traders classified as CITs in 2007-2009 were also CITs in 2000-2006. The retroactive application is supported by both the fact that CIT's are passive net longs by definition without constantly changing strategies, and by discussions with CFTC staff which indicate that CIT designations have changed little since the classification scheme was first constructed in 2006.[25]

For this study, daily futures and delta adjusted positions from the LTRS cover the period from January 2000 through September 2009 for all 12 commodities in which CIT classifications exists.[26] The commodities studied are corn, soybeans, soybean oil, and wheat all traded at the Chicago Board of Trade (CBOT), cocoa, coffee, cotton, and sugar traded on the Intercontinental Exchange (ICE), feeder cattle, lean hogs and, live cattle traded at the Chicago Mercantile Exchange (CME), and wheat traded on the Kansas City Board of Trade. The traders are divided into the four broad categories established in the LTRS based on trading motivation; these include commercial, noncommercial, index, and nonreporting. Nonreporting traders are small traders not required to submit their positions to the LTRS because their holdings are under a pre-specified threshold; these small traders represent residual open interest not reported to the large trader reporting system at the CFTC. In this sample there are 23.6 million observations and 14,487 unique traders. The noncommercial group has the largest number of unique traders at 10,470, commercial has 3,975 and index has only 42 unique traders. The number of observations is greatest in the commercial group at 12.2 million, next is noncommercial with 10.6 million observations, and finally the CITs have 855,000 observations.

3.4 Trader Characteristics

Trader characteristics are analyzed to identify the position tendencies of traders both through time and across categories. The positions of CITs are shown to be net long opposite commercial trader positions where as noncommercial trader positions change between net long and net short. The long/short balance is important since futures markets are a zero sum game and for every winner there must be a loser and gains equal total losses. Furthermore, the CIT position characteristics are shown to provide a desirable real time proxy for testing the strategy imbedded in the original normal backwardation theory.

Traders best suited to test for the existence of a risk premium have two main characteristics, (i) positions opposite hedging traders and (ii) a passive strategy. As shown in table 3.1 (panel A) commercial traders are net negative for the vast majority of yearly average positions except for feeder cattle; feeder cattle commercial traders may include more long hedging feedlot operators who protect against rising input prices. From 2000 to 2009 the commercial position levels in the 12 commodities became increasingly larger negative positions. Conversely, CIT positions are net long and have increased long positions through the sample period (table 3.1, panel C) mirroring the increasing levels of net short positions by commercial traders. This key relationship between CITs and commercial trader positions satisfies the first requirement for testing the risk premium theory, positions opposite hedging traders. Second, following Gorton and Rouwenhorst (2006), the motivations for CITs trading are twofold, the desire for diversification affects and the ability to earn a risk premium. CITs attempt to accomplish this dual motivation by taking long positions in a basket of commodity futures contracts. As shown in table 3.1 (panel C) CITs are consistently net long unlike traditional speculators (panel B) that fluctuated between net long and net short since these noncommercial traders are speculative in nature and tend to exhibit considerable trend-following behavior or employ algorithmic trading strategies (Sanders, Irwin, and Merrin 2009). This key difference between the CITs and traditional noncommercial traders satisfies the second requirement for testing the risk premium theory, passive trading strategy. Although the index funds themselves are passive, the traders behind these funds do show a minimal amount of trend following behavior as shown in Aulerich (2011a).

To determine the magnitude of positions relative to total open interest, the percentage of both long and short open interest for the same groups of traders analyzed in table 3.1 are shown in tables 3.2 and 3.3, respectively. In table 3.2, commercial traders (panel A) have a decreasing proportion of long open interest but in 2009 still hold 21 percent of long open interest across commodities (down from 41 percent in 2000). Noncommercial traders (panel B) have a fluctuating but relatively steady proportion of long open interest at 31 percent across commodities and years. Commodity index traders (panel C) have an increasing proportion of long open interest, consistent with steadily increasing levels of open interest shown in table 3.1. The commercial traders have increasingly transferred long open interest to CITs thereby decreasing commercial percent of long open interest and increasing CITs proportion.

Table 3.3 documents the proportion of the market taking the short side opposite of those long side positions shown in table 3.2. Commercial traders (panel A) are a large and steady proportion of short open interest; indicating commercial traders position levels increase along with open interest. Noncommercial traders (panel B) percentage of short open interest is similar to that in long open interest, both a fluctuating but steady proportion of open interest. The average percent of short open interest held by noncommercial traders over all years and commodities is 27 percent, comparable to the 31 percent of long open interest. CITs in panel C hold a small portion of short open interest although this has increased slightly in 2008 and 2009 possibly due to swap dealers diversifying away from strictly servicing index traders or from the emergence of a greater number of actively managed commodity funds (Meyer 2009).

In total, CITs are well suited with positions opposite hedgers and a largely passive strategy to provide a natural experiment testing for the existence of a risk premium. The commercial traders hold a consistent net short position through the time period with a decreasing proportion of long positions. Opposite commercial traders, CITs increase long position levels and account for an increased proportion of long open interest in the market. The traditional speculators, noncommercial traders, hold positions fluctuating between net long and net short with relatively stable proportions of both long and short open interest.

3.5 Price Trend Characteristics

The movement of commodity prices from January 2000 to September 2009 is relevant to the profits and losses methodology due to the nature of trader's positions. For example, a downward trajectory in prices would favor commercial traders who tend to be net short; conversely, an upward movement of prices would favor index traders who are consistently net long. Over the time period of the sample there is no clear visual demarcation between stable price periods and unstable periods that apply to all commodities, but commodities can be placed into three groupings based on general price patterns.

The first group includes the grains (corn, soybeans, soybean oil, and wheat contracts). Price patterns for this group are relatively stable in the earlier portion of the data until large price increases in early 2007 and subsequent decreases in late 2008 and 2009; figure 3.1 demonstrates this pattern with corn. The second group is composed of the livestock commodities (feeder cattle, lean hogs, and live cattle) in addition to cotton. These commodity prices are relatively stable and fluctuate in a price channel as demonstrated by lean hogs in figure 3.2. The third group includes the soft commodities (cocoa, coffee, and sugar) except cotton. These prices had substantial and sustained price increases at the end of the sample period without subsequent declines, illustrated by cocoa in figure 3.3.

Within each of the three price groupings differences exist; the appendix includes the additional commodity price figures. In the grain grouping, all commodities began an upward trend prior to the start of 2007, but unlike the other commodities, corn moves in a “head and shoulders” pattern with two smaller price spikes flanking the large spike. In addition, corn, soybean oil, and to a greater extent soybeans had a small price spike in 2004, whereas wheat did not have a pronounced price increase. Within the second grouping, the price channel width is the smallest for lean hogs at 35 cents and largest for cotton at 60 cents. Lean hogs experienced a 20 cent drop and subsequent rebound in price at the end of 2002 which was not pronounced in the other commodities. The third group is the most volatile and diverse. From 2000 to 2001, coffee trended down, cocoa trended up, and sugar was relatively stable. Sugar and coffee experienced a small rally starting in mid-2005 that reversed in late 2006, whereas cocoa did not have such a rally. All commodities saw prices increases in 2009 without subsequent decreases. Despite the differences within the groupings, the different aggregations provide a constructive way to analyze the results.

Out of the 12 commodities analyzed, 8 had major price upswings of greater than 50 percent and only lean hogs experienced a price decline (table 3.4). From the analysis of price trends and trader positions, expected profits for CITs would be positive since CIT positions are typically net long and profits for commercial firms would be negative due to predominately net short positions. Noncommercial traders expected profits are more difficult to forecast due to the dynamic nature of their trading. These profit expectations are based on general price and position behavior; to test these generalizations, daily profits are calculated based on actual trader positions and prices.

3.6 Results

Daily profits for each trader for each 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* as shown in equation 1[27],

(1) $$\text{Trader Profit}_{i,t+1} = \text{End Day Position}_{i,t} \times \left(\text{Price}_{t+1} - \text{Price}_{t}\right).$$

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 consist 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 and to maintain consistency with previous work.[28]

3.6.1 Aggregate Profit Assessment

The profit and losses calculations (table 3.5) first report the results for all 12 commodities separately and then summarize the profits into the three groups of commodities specified in the *Price Trend Characteristics* section which include (i) row crops, (ii) livestock and cotton, and (iii) softs. Within each commodity and group, each measure is broken down by commercial, index (CITs), and noncommercial traders and the remainder of traders are classified as nonreporting.[29]

The calculated measures in table 3.5 first include a section of *net dollar returns* to provide overall position profits and losses. Net dollar returns are calculated in equation 1 by defining $\text{End of Day Position}_{i,t}$ as net positions (long- short). A positive CIT profit would support the existence of a risk premium. The total net dollar returns are tested for each commodity and category to determine if the mean returns are statistically different from zero. The standard t-test is first used and then the Wilcoxon rank test is employed in the presences of non-normality. The Wilcoxon rank test is a nonparametric signed rank test using the sign of differences between observations and median to determine statistical significance. All net profits of traders in a specific commodity and category are subtotaled first by day and then by monthly returns.[30] A star denotes the mean of daily returns is different than zero and an apostrophe denotes the mean of monthly returns is different than zero.

In the theory of normal backwardation, naïve speculators can position themselves opposite hedgers to earn profits. In direct contrast to this theory, CITs appear to transfer wealth to noncommercial traders where CIT's overall net dollar returns are -$6.9 billion and noncommercial are $7.9 billion. On the other hand, commercial traders lose a small -$7 million. CITs exhibit losses in 9 out of 12 markets, with a loss of -$752 million in row crops, -$6,433 million in livestock and cotton, and modest profits of $321 million in the soft commodity category.

Unlike CITs, noncommercial traders report positive profits in 9 out of 12 market with the majority of profits in row crops ($6.2 bil) and livestock ($1.8 bil) with small losses in softs. Commercial traders, on the other hand, report negative net profits in 5 out of 12 markets with losses in row crops (-$4.5 bil) and softs (-$517 mil) but large gains in livestock ($4.3 bil). The commercial results are the least conclusive about the profitability of traders, since unlike CITs and noncommercial traders where 9 out of 12 markets correspond in the direction of profitability, profits and losses of commercial traders vary across commodities. This difference may be due to hedgers having offsetting cash positions not represented in this data which limits visibility into their entire profit picture. Overall, the total net profit results do not support a risk premium; if a risk premium existed we would expect to see CITs earning profits and commercial traders experiencing futures market losses as they pay CITs for absorbing hedging risk.

In table 3.5, net profits are computed separately for when a trader is net long versus net short. In equation 1, net long (short) net dollar returns are calculated by defining $\text{End of Day Position}_{i,t}$ as the level of positions when a trader is net long (short) and zero when a trader is net short (long). These calculations are used to determine if a group is more successful as a net long or net short trader. If CITs are earning a risk premium, net long positions are expected to be profitable as these positions are opposite net short commercial hedgers. The results show positive profits when CITs are net short in row crops and livestock and negative when net long; counterintuitive to the expected outcome if CITs were earning a risk premium for taking long positions opposite hedgers. Although, consistent with CIT investment style, the largest portion of returns are generated when the trader is net long. Soft commodities on the other hand, do have returns consistent with a risk premium where net long positions earn $764 million and net short positions lose -$443 million. Soft commodities differ because these prices sharply increase at the end of the sample without a subsequent decrease whereby the long positions become profitable (appendix figures 7.1, 7.2, and 7.4).

The next section of table 3.5 calculates *gross dollar returns* to determine how closely the magnitude of gross losses and gains coincide; in equation 1, if $\text{Traders Profit}_{i,t+1}$ is positive then that trader's profit is included in gross gains, if $\text{Traders Profit}_{i,t+1}$ is negative then the trader's profit is included in the gross losses calculation. Gross gains minus gross loses equal net profits. If gross gains and gross losses are balanced it suggests that random elements may be a more important factor in determining the group's performance (Hartzmark 1987) and would be contrary to the theory of normal backwardation. Results of gross dollar losses and gains in columns four and five (table 3.5) are of similar magnitude totaling approximately -$317 billion and $310 billion for index traders suggesting that random elements are an important factor in determining profits and supporting the argument against a risk premium. Skewness and kurtosis of CITs profits is also considered; the theory of a risk premium would predict the distribution would be skewed to the right indicating the profits earned are more prevalent than predicted by a normal distribution. CIT profits results have a skewness of at -1.21 and kurtosis at 3.46, compared to the normal distribution with skewness of 0 and kurtosis of 3.[31] The profit distribution is slightly peaked with a kurtosis greater than 3 and skewed to the left indicating a longer left tail relative to the right. The departure from normality is contrary to the theory of a risk premium and indicates that more CITs earn negative returns than predicted by a normal distribution.

The *number of days* section in table 3.5 compares the number of days with net long positions compared to net short positions to view investment direction preferences of traders. Based on trading motivations, commercials are expected to have more net short days, CITs are expected to have more net long days, and noncommericals are expected to have roughly the same number of net long and short days. Consistent with expected investment behavior, index traders have over 400,000 net long days and only 10,000 net short days. Commercial traders are about 2 times more likely to be short than long and noncommercial traders are 1.5 times more likely to be long than short. The “split” between long and short days for commercial traders is less pronounced than for index traders (2 times versus 40 times) for a variety of reasons including i) commercials can be either long or short hedgers and ii) many commercials make trading decisions that are not strictly hedging but are more speculative in nature based on beliefs about the future.

Next, the *number of traders* section in table 3.5 first details the number of total traders, second reports the number of traders making a positive profit, and finally computes the percentage of profitable traders by simply dividing the number of traders with a positive profit by the total number of traders. A figure of approximately 50% would indicate profits are random among traders, over 50% would indicate more traders earn profits than losses, and below 50% would indicated the majority of traders in a group lose money. Both a significant portion of traders above or below 50% would indicate nonrandom profits. The theory of normal backwardation would predict the proportion of successful traders should be higher for CITs since they are earning a risk premium without the need for skill (Hartzmark 1987). Results in the final columns show that, in fact, the CITs have the *lowest* percentage of traders with positive profits at only 40% versus approximately 50% for commercial and noncommercial traders, contradicting the theory of normal backwardation. The majority of CITs experiencing losses may be caused by CITs paying commercial traders or noncommercial traders for liquidity.

3.6.2 Dynamic Profit Assessment

The aggregate profit results find negative CIT profits, indicating that a passive strategy opposite hedgers does not results in earning a risk premium. Positive profits would be predicted for net long CITs because all commodities, except for one, had higher prices at the end of the sample period than the beginning (table 3.4). In the soft commodity group, the positive net dollar returns ($321K) for index traders are anticipated as price trends in the latter half of the sample period increase without a subsequent decline (figure 3.3). The losses in the other two groupings (row crops, livestock and cotton) are unexpected as commodities had higher prices at the end of the sample period, except lean hogs (table 3.4). The counterintuitive profits of CITs spur the question, how did CITs experience such large negative returns? To answer this question two examples will examine detailed activity from the corn and lean hogs markets; these markets are chosen because they reflect the behavior of the row crops and livestock groupings. Softs are not highlighted because profits are positive, as expected based on price patterns, but the appendix covers each commodity in turn. The activity of lean hogs and corn will be examined by assessing net positions and cumulative profits of trader classifications over time to provide relevant insights into the presence of normal backwardation. This temporal view of profits allows an analysis of profit levels during various price patterns (e.g. increasing, decreasing, and stable) and ability to view the existence of a risk premium over time through CIT profits.

First, the temporal existence of a risk premium for corn is examined where prices increase and decrease substantially in 2008 and 2009 (figure 3.4, panel A).[32] The positions of the trading groups (panel B) increase for CITs rapidly during 2004 and 2005 while at the same time commercial traders became increasingly net short and noncommercial traders became more net long; the cumulative daily profits for these trading groups are presented in panel C. From 2000 to 2006 when corn prices appear to be mean–reverting, the profit patterns are similar to Hartzmark (1987) which contrasts with the theory of normal backwardation. Commercials experience gains and speculators experience losses; CITs experience losses to a greater extent than noncommercial traders. The profit distribution indicates commercial traders are paid by speculators to hedge risk. Only when prices spike precipitously (or are non-normal) does any evidence of normal backwardation emerge. CITs show positive profits during the price increase but not during the price decrease which indicates the profits have more to do with their long positions in an upward trending market than earning a risk premium during a volatile market for offsetting hedging risk for commercial traders. Additional insights may be seen from the 2008 period based on the peaks and valleys of profits during the period; figure 3.5 focuses solely on 2008 corn prices, CIT cumulative profits, and CIT net positions. Positions reached a high of 450,000 contracts in May 2008, less than two months before the all time high corn price of $7.60

per bushel at the beginning of July.   The CIT positions were at their highest levels as prices started to decrease; when prices rapidly declined, so did positions but over half of the positions rode the prices all the way down to the lows of \$3. The CITs profit decreased by approximately \$7.5 billion in the five months from July to November 2008. The pattern of positions and profits helps to explain the negative CIT profits in corn; CIT positions decreased more slowly than prices (partly due to CITs strategy as long passive traders) during the price spike and during periods of stable prices CITs did not earn a risk premium.

Second, the temporal existence of a risk premium in the lean hog contract is examined where prices (figure 3.6, panel A) over the sample period were not characterized by a historic price spike, as seen in corn, but CITs still lost -\$2.6 billion over the period. The positions of the trading groups (panel B) increased for CITs rapidly from 2004 into 2008 while at the same time commercial traders became more net short. At the end of July 2008 CIT positions peaked at 123,500 contracts and started a precipitous decline which correlated with an equally as abrupt reversion in commercial trader positions. The cumulative daily profits (panel C) were relatively stable until July 2008 where a divergence in trading group profits occurred. The divergence in July 2008 is not due to a historic price move, like in corn, but is more likely due to a change in the commodity marketplace. Since CITs participate across many commodity markets, the rapid deterioration of prices in commodities such as corn, wheat, and crude oil that make up a much larger portion of a commodity index (Aulerich 2008), triggered a decrease in CIT positions across all index commodities. Subsequently, CITs exited the lean hog contract reducing positions by almost 50% in 6 month; this is best shown in figure 3.7 that focuses solely on the 2007 to 2009 time period. The evidence of CITs earning a risk premium from absorbing risk is mixed prior to 2006 (figure 3.6, panel C) and is nonexistent thereafter as CITs profits continually decreased. The profitable commercial and noncommercial traders appear to be supplying CITs with liquidity as they exited the contract in droves, not the other way around. The lean hog market is relatively small and the rapid decline in CIT positions demanding liquidity resulted in CITs paying commercials and noncommercial traders to offset their positions. The pattern of positions and profits helps to explain the negative CIT profits in lean hogs; CITs did not earn a large risk premium from 2000-2006 and paid handsomely for the liquidity services provided to them by commercial and noncommercial traders from 2007-2009.

3.6.3 Normalization of CIT Profits

The net profit by category in table 3.5 can be unduly influenced by an influx of commodity index money during a single time period, such as CIT positions reaching maximum levels in 2008. In simple terms, a profit of $1 million produces different returns depending on an investment of $1 billion versus an investment of $10 billion.[33] For this reason, a return on investment measure normalizes profit by notional value to determine if profitability or size of invested dollars has changed over time. The cumulative monthly profit is divided by the month's average daily notional value to provide a return on investment over the sample period.[34] Equation 2 displays the return on investment as,

$$(2) \qquad \%\ \text{Profit}_t = \left(\frac{\text{Total Profit in Month}_t}{\text{Avg Daily Notional Value in Month}_t} \right) \times 100,$$

where the cumulative CIT profit in month t is divided the average daily notional value in month t.[35] Since a similar pattern emerges for individual commodities, results are aggregated over all commodities in figure 3.8 to show that CITs do not make consistent positively monthly returns, and the average monthly return on investment over the entire time period is -0.00024 percent. The average monthly return is of such a small magnitude because average daily notional value is of considerable size.   Regardless, evidence does not support consistent risk premiums earned by CITs over the sample period.

3.6.4 Roll Period Gains/Losses

Another possibility that may undermine the conclusion of no risk premium is the concentration of losses during the roll period. As shown in Aulerich (2011a), CITs change positions from nearest to maturity contract to the next nearest to maturity contract during a “roll period” which is typically concentrated at the beginning of the month prior to contract expiration. The transparent rolling trading strategy, called “sunshine trading” (Admati 1991; Brunnermeier 2005), may allow other traders in the market to front run or take advantage of the CITs predictable position rolling.[36] Trader losses during the roll period and gains outside the roll period would question the conclusion of the absence of a risk premium in the marketplace and may be evidence of front running by other trader types.

To address this possibility table 3.6 separates profits experienced during the roll period from outside the roll period.[37] In the last row, *All Markets*, the returns to CITs are negative both in and outside the roll period. Although, the losses are higher during the roll period despite the shorter time period it represents. Individual commodities and commodity groupings have mixed evidence with only 4 commodities with gains outside the roll period and losses during the roll period (coffee, sugar, CBOT wheat, KS wheat). In light of this evidence, CITs do not appear to only incur losses during the roll period and the existence of a risk premium is not supported.

Overall, the theory of Keynesian normal backwardation is rejected when commodity index traders’ (CITs) profits are examined as a natural experiment for testing the existence of a risk premium. Despite increasing price trends, CITs experience negative profits in 9 out of 12 commodities with total net loss of -$6.9 billion. The normalization of profits over time by investment size provides further evidence against the Keynesian theory of normal backwardation; CITs do not make consistently positive monthly returns and the average monthly return on investment is negative. Furthermore, CIT losses are not isolated to the roll period but rather are experienced both in and outside of the roll.

3.7 Summary

The debate over the existence of a risk premium is a central to understanding the functioning of futures markets. The Keynesian theory of normal backwardation (Keynes 1930) predicts that speculators earn a positive return over time and hedgers earn a negative return as they pay speculators to reduce business risk. The purpose of this research is to revisit the risk premium debate by employing the profits and losses methodology using Commodity Index Traders (CITs) as a natural experiment. The use CITs is not without shortcomings, since CITs show some trend following behavior, but the index traders provide the clearest proxy to test the profitability of positions that consistently trade opposite hedgers.

Unlike past research that tests all noncommercial traders together, entangling both an active trading strategy designed to leverage perceived skill and a passive trading strategy attempting to earn a risk premium, the CITs offer a natural experiment to actually calculate the profits earned for passively holding futures contracts in an effort to earn a risk premium. The dataset for this study is from the proprietary CFTC large trader reporting system database from January 2000 to September 2009 for 12 commodity futures markets providing one of the most comprehensive and detailed profit calculation studies to date.

Our findings reject the theory of Keynesian normal backwardation when commodity index traders' (CITs) profits are used to test for the existence of a risk premium. Despite increasing price trends, CITs experience negative profits in 9 out of 12 commodities with overall net loss of -$6.9 billion over the entire time period of 2000 to 2009. The normalization of profits over time by investment size provides further evidence against the Keynesian theory of normal backwardation; CITs do not make consistently positive monthly returns and the average monthly return on investment is negative. Furthermore, CIT losses are not isolated to the roll period but rather are experienced both in and outside of the roll time frame.

The findings are consistent with the research by Hartzmark (1987), who finds no evidence of a risk premium in agricultural markets, and by Phillips and Weiner (1994) which disprove the evidence of normal backwardation in the North Sea Oil forward market. Using more recent data, Fishe and Smith (2010) also find no evidence of a risk premium, although they apply different methods which use liquidity demand and supply analysis. In contrast to the conclusions in this essay, Dewally et al. (2009) use data from 1993-1997 and find evidence of a risk premium in three energy markets due to the absence of trader skill. Also, the passive commodity investment encouraged by the influential paper of Gorton and Rouwenhorst (2006) is not supported. Gorton and Rouwenhorst reported that a 5% risk premium could be earned by passively investing in commodities from 1959 to 2004. The results from this third essay and their study may differ for many reasons including, (i) the use of a different time period, (ii) the inclusion of 36 commodities across many sectors, or (iii) the use of simulated positions to calculate profitability.

The failure to find support for the Keynesian theory of normal backwardation in this essay may be explained by the speculative supply of services (with respect to expected dollar profits) being horizontal at a zero return (Hartzmark 1987). Thus, the risk premium will be bid to zero and the returns for bearing risk disappear. An alternative theory is that the risk absorbing role is usurped by the liquidity demands of the CITs. Fishe and Smith (2010) show that commercial traders are providers of liquidity, which runs contrary to previous beliefs (Working 1960). Possibly the emergence of CITs has altered the market structure; the liquidity provided by commercials is now more valuable to CITs than any risk absorption services offered by CITs to commercial traders.

This research argues against the theory of a positive risk premium, either constant or time varying, but cannot reject the idea of a time varying risk premium that changes between positive and negative values which in aggregate would be inconclusive and not inconsistent with this research. Additional questions are raised, specifically, do noncommercial traders really think of themselves as earning a varying risk premium? How do noncommercial traders experience substantial profits over the time period? This study rejects the theory of normal backwardation and provides motivation for further research examining the forecasting skill of the noncommercial traders.

3.8 Tables and Figures

Table 3.1 Average Daily Net Position by Trader Category in 12 Commodity Futures Markets for all Contract Maturities, 2000-2009

Commodity	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Panel A: Commercial Trader Number of Contracts										
Cocoa	-15,860	-1,637	2,497	17,552	-9,854	-18,064	-28,450	-61,432	-51,623	-38,068
Coffee	-5,585	-3,205	-14,439	-9,634	-38,817	-41,820	-41,487	-60,908	-70,411	-48,108
Cotton	-17,189	12,254	-21,313	-35,039	1,747	-40,011	-56,269	-108,453	-115,766	-72,073
Sugar	-39,270	-7,321	-55,218	-53,121	-110,363	-186,401	-193,763	-221,994	-417,904	-298,294
Feeder Cattle	2,522	2,882	-163	366	874	-1,941	-1,387	-2,298	-505	-1,581
Lean Hogs	-15,769	-8,710	-5,623	-9,566	-29,610	-29,084	-57,978	-63,597	-80,377	-29,041
Live Cattle	-20,497	-13,247	-27,331	-32,823	-40,394	-49,390	-65,776	-87,917	-94,598	-58,446
Corn	-54,692	-19,007	-67,214	-47,888	-127,954	-154,582	-443,079	-480,430	-455,991	-215,864
Soybeans	-45,680	-18,511	-47,297	-66,436	-39,404	-59,027	-67,703	-222,075	-184,688	-138,025
Soybean Oil	768	-9,249	-25,168	-42,642	-42,291	-50,753	-105,163	-142,974	-87,328	-51,000
Wheat CBOT	-32,454	-28,109	-32,729	-33,465	-45,195	-84,728	-146,862	-139,298	-118,669	-81,735
Wheat KCBOT	-15,826	-16,520	-15,030	-11,680	-15,806	-27,500	-64,839	-53,954	-29,649	-22,840
Panel B: Noncommercial Trader Number of Contracts										
Cocoa	-3,947	-4,598	-7,150	-20,874	-3,964	6,716	11,198	38,118	23,674	18,408
Coffee	-397	-4,638	3,234	-5,292	9,883	15,322	3,649	14,316	13,797	8,818
Cotton	7,760	-19,265	10,205	23,374	-19,039	-3,145	-19,507	11,005	13,510	2,639
Sugar	12,779	-7,598	15,453	11,353	22,166	61,126	42,611	-22,398	82,266	93,847
Feeder Cattle	5,054	2,882	-268	2,356	662	5,482	2,622	2,487	-59	-721
Lean Hogs	10,797	6,350	-1,087	1,389	8,597	-1,196	-3,311	-7,672	-12,366	-24,428
Live Cattle	9,449	10,483	17,757	25,014	13,062	16,161	8,819	4,632	-1,447	-14,664
Corn	45,209	8,211	22,533	7,343	50,248	-31,197	141,898	197,906	173,503	1,912
Soybeans	20,303	-5,487	27,148	34,897	4,667	2,354	-16,700	100,030	67,529	39,718
Soybean Oil	-6,884	1,266	10,649	28,146	21,282	5,067	32,494	59,437	11,849	-7,704
Wheat CBOT	-2,158	-3,683	3,118	6,487	-12,413	-41,772	-25,097	-18,574	-26,604	-52,910
Wheat KCBOT	4,305	1,442	1,887	2,088	1,132	11,576	42,041	29,182	11,981	1,846
Panel C: Commodity Index Trader Number of Contracts										
Cocoa	2,208	1,447	1,892	2,612	11,549	7,483	13,272	17,534	23,612	16,195
Coffee	2,728	1,475	2,867	6,916	21,735	23,114	33,862	42,716	54,434	38,165
Cotton	4,967	4,009	5,579	7,863	16,132	38,696	71,430	87,229	95,249	65,637
Sugar	12,898	10,059	17,659	23,497	61,931	98,672	136,135	230,434	309,598	180,138
Feeder Cattle	1	101	1,557	1,933	2,838	4,362	6,562	8,315	8,265	6,210
Lean Hogs	7,858	6,479	8,654	10,546	26,801	43,871	76,923	80,275	100,138	56,472
Live Cattle	22,360	12,779	12,067	13,941	33,118	52,931	86,152	112,310	128,549	90,465
Corn	28,732	30,217	48,209	53,656	117,364	233,142	393,954	357,482	358,979	289,860
Soybeans	6,509	4,920	9,563	28,279	36,692	76,884	114,591	147,449	143,982	122,437
Soybean Oil	-122	1	949	1,402	10,773	38,030	65,801	72,351	68,371	54,855
Wheat CBOT	20,178	18,704	21,439	25,702	56,682	134,408	195,194	185,341	165,968	151,227
Wheat KCBOT	5,591	5,777	7,921	9,543	14,971	18,210	25,480	31,372	26,156	26,178

Table 3.2 Average Daily Percent of Long Open Interest by Trader Category in 12 Commodity Futures Markets for all Contract Maturities, 2000-2009

Commodity	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Panel A: Commercial Trader Percent of Long Open Interest										
Cocoa	62	68	66	71	66	63	54	38	34	39
Coffee	48	48	43	39	25	24	23	25	24	26
Cotton	47	63	41	33	49	23	18	15	17	11
Sugar	53	58	46	45	30	27	31	30	23	30
Feeder Cattle	38	37	23	21	28	18	17	13	16	14
Lean Hogs	23	24	17	20	10	8	6	9	7	7
Live Cattle	31	35	20	19	20	16	13	9	8	14
Corn	42	44	39	39	35	27	19	23	23	23
Soybeans	24	36	31	28	33	25	22	18	19	20
Soybean Oil	50	49	41	43	41	28	22	25	31	30
Wheat CBOT	26	26	23	19	18	12	15	11	9	10
Wheat KCBOT	47	39	43	45	34	33	17	22	29	26
Panel B: Noncommercial Trader Percent of Long Open Interest										
Cocoa	17	21	23	18	15	22	28	43	42	39
Coffee	21	24	30	31	37	39	36	42	34	35
Cotton	27	12	33	42	20	26	26	34	30	25
Sugar	20	13	20	22	30	34	28	25	28	29
Feeder Cattle	41	40	32	42	31	47	42	39	41	33
Lean Hogs	40	36	28	34	35	35	34	35	34	33
Live Cattle	29	33	41	45	34	37	37	37	35	34
Corn	28	27	28	26	29	22	37	37	36	30
Soybeans	38	28	35	36	26	27	31	42	37	35
Soybean Oil	32	34	38	38	33	31	37	40	33	32
Wheat CBOT	30	32	33	34	28	22	30	33	29	28
Wheat KCBOT	18	21	18	18	21	28	46	38	29	26
Panel C: Commodity Index Trader Percent of Long Open Interest										
Cocoa	2	1	2	3	11	6	10	12	17	15
Coffee	7	3	4	10	24	25	31	28	38	34
Cotton	8	6	8	10	20	38	46	41	45	54
Sugar	7	7	10	12	21	24	29	35	41	31
Feeder Cattle	0	1	12	11	18	17	23	30	30	30
Lean Hogs	17	16	26	26	35	43	48	45	49	45
Live Cattle	18	11	12	13	29	35	39	45	49	42
Corn	7	7	10	13	19	33	32	29	30	35
Soybeans	4	3	5	13	17	29	32	30	33	34
Soybean Oil	0	0	1	1	8	25	29	26	27	27
Wheat CBOT	15	14	20	26	38	55	47	48	54	54
Wheat KCBOT	8	8	11	16	23	21	19	24	27	31

Table 3.3 Average Daily Percent of Short Open Interest by Trader Category in 12 Commodity Futures Markets for all Contract Maturities, 2000-2009

Commodity	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Panel A: Commercial Trader Percent of Short Open Interest										
Cocoa	76	69	63	52	74	78	75	79	68	72
Coffee	60	54	64	52	65	67	61	64	70	66
Cotton	73	45	71	74	46	61	55	65	67	68
Sugar	75	64	75	69	67	70	71	62	72	71
Feeder Cattle	26	20	25	19	22	24	22	22	15	20
Lean Hogs	53	44	33	41	47	36	42	45	45	29
Live Cattle	48	46	47	48	55	49	43	44	43	41
Corn	54	49	53	51	56	49	54	60	59	48
Soybeans	51	47	55	57	49	47	41	61	59	55
Soybean Oil	49	55	58	70	66	62	66	74	63	52
Wheat CBOT	50	47	51	50	48	47	49	45	42	36
Wheat KCBOT	68	61	63	63	59	61	63	63	57	52
Panel B: Noncommercial Trader Percent of Short Open Interest										
Cocoa	19	26	31	41	20	17	20	18	27	23
Coffee	22	32	26	38	27	25	32	33	27	28
Cotton	16	41	19	15	45	30	38	30	26	23
Sugar	13	18	13	18	23	20	19	29	18	16
Feeder Cattle	18	24	34	31	27	27	34	30	44	37
Lean Hogs	21	23	32	32	26	36	37	39	40	51
Live Cattle	22	25	24	23	23	27	33	36	36	41
Corn	19	25	24	24	21	27	26	22	23	30
Soybeans	26	32	22	21	26	27	36	23	23	26
Soybean Oil	37	34	31	20	21	27	25	20	29	36
Wheat CBOT	32	35	31	29	35	39	37	38	38	45
Wheat KCBOT	13	19	16	15	19	19	16	16	18	24
Panel C: Commodity Index Trader Percent of Short Open Interest										
Cocoa	0	0	0	0	0	0	0	0	1	1
Coffee	2	1	0	0	0	0	0	0	1	1
Cotton	0	0	0	0	0	0	0	1	2	2
Sugar	0	0	0	0	0	0	1	2	4	6
Feeder Cattle	0	0	0	0	0	0	0	0	3	2
Lean Hogs	0	0	0	1	1	0	0	1	2	3
Live Cattle	0	0	0	0	0	0	0	0	1	0
Corn	0	0	0	0	0	0	0	0	1	1
Soybeans	0	0	0	0	0	0	1	1	1	1
Soybean Oil	1	0	0	0	1	0	1	1	1	2
Wheat CBOT	0	0	1	1	1	1	1	2	5	5
Wheat KCBOT	0	0	0	0	0	0	0	0	1	1

Table 3.4 Price Summary for All Commodities, 2000-2009

Commodity	Low	High	StartPrice	EndPrice	PctChange	StDev
Cocoa ($/ton)	694	3275	830	3140	278	565.2
Coffee ($/lb)	43	168	117	128	10	29.2
Cotton ($/lb)	29	89	51	63	23	10.2
Sugar ($/lb)	4.8	25.4	6.1	25.4	316	3.5
Feeder Cattle ($/lb)	71	119	86	97	12	12.3
Live Cattle ($/lb)	59	109	70	86	23	10.2
Lean Hogs ($/lb)	30	81	56	50	-11	9.1
Corn ($/bu)	1.7	7.6	2.0	3.4	72	1.1
Soybeans ($/bu)	4.2	16.3	4.6	9.3	100	2.6
Soybean Oil ($/lb)	14	71	16	34	119	11.7
WheatCBOT ($/bu)	2.3	12.8	2.5	4.6	85	1.9
WheatKCBOT ($/bu)	2.7	13.4	2.7	4.8	74	1.9

Table 3.5 Performance Measures by Market and Trader Type for Futures and Options Positions (returns in million dollars) January 2000 to September 2009

Market and Trader Type	Net Dollar Returns: Total	Net Long	Net Short	Gross Dollar Returns: Total Losses	Total Gains	Number of Net Long Days	Number of Net Short Days	Number of Traders: Total	Positive earning $	Positive Return(%)
Cocoa										
Large Traders	1	1,820	-1,819	-64,013	64,014			1,457	793	54
Commercial	-82	1,095	-1,177	-41,060	40,978	51,790	67,057	191	106	55
Index	199	198	1	-3,774	3,973	27,992	945	35	29	83
Noncommercial	-116	526	-643	-19,179	19,063	130,148	82,193	1,231	658	53
Nonreporting	-1	-1,820	1,819	-64,014	64,013					
Coffee										
Large Traders	340 '	-3,093	3,434	-113,765	114,106			3,264	1402	43
Commercial	2,587 '	-878	3,464	-57,059	59,645	136,356	183,744	548	298	54
Index	-791	-844	52	-17,802	17,010	36,851	1,716	39	9	23
Noncommercial	-1,455 '	-1,372	-83	-38,905	37,450	289,824	186,025	2,677	1095	41
Nonreporting	-340 '	3,093	-3,434	-114,106	113,765					
Cotton										
Large Traders	170 '	-4,409	4,579	-95,439	95,609			2,645	1210	46
Commercial	2,195	-1,371	3,566	-49,847	52,041	115,922	119,112	465	213	46
Index	-1,925	-2,000	75	-20,583	18,658	37,146	930	38	11	29
Noncommercial	-100	-1,038	938	-25,009	24,910	251,251	166,210	2,142	986	46
Nonreporting	-170 '	4,409	-4,579	-95,609	95,439					
Sugar										
Large Traders	-553	5,635	-6,188	-163,905	163,353			1,618	824	51
Commercial	-3,022	1,903	-4,925	-94,424	91,403	77,528	114,784	358	156	44
Index	913	1,409	-496	-32,862	33,776	34,793	709	40	28	70
Noncommercial	1,556	2,323	-767	-36,619	38,174	163,699	101,948	1,220	640	52
Nonreporting	553	-5,635	6,188	-163,353	163,905					
Feeder Cattle										
Large Traders	53	16	37	-11,008	11,061			1,426	753	53
Commercial	51	91	-40	-3,507	3,558	56,505	87,941	553	296	54
Index	-74	-87	13	-1,931	1,857	25,426	852	30	9	30
Noncommercial	76	11	64	-5,571	5,646	77,707	59,028	843	448	53
Nonreporting	-53	-16	-37	-11,061	11,008					
Lean Hogs										
Large Traders	-304	-3,537	3,233	-57,752	57,448			1,697	903	53
Commercial	1,426	-23	1,449	-17,096	18,522	24,026	83,384	243	141	58
Index	-2,569	-2,605	35	-17,186	14,617	36,567	454	35	1	3
Noncommercial	839 * '	-909	1,748	-23,471	24,310	144,726	134,398	1,419	761	54
Nonreporting	304	3,537	-3,233	-57,448	57,752					
Live Cattle										
Large Traders	-245	-1,762	1,518	-73,466	73,221			2,337	1212	52
Commercial	664	155	509	-27,580	28,244	63,596	259,290	747	390	52
Index	-1,866	-1,864	-2	-18,047	16,182	37,592	269	39	4	10
Noncommercial	957 * '	-54	1,011	-27,838	28,796	178,339	132,856	1,551	818	53
Nonreporting	245	1,762	-1,518	-73,221	73,466					

Note: Since futures trading is a zero sum game, the nonreporting category is the residual from the large trader profits. * denotes if the mean of daily returns is different than zero and ' denotes if the mean of monthly returns is different than zero Significance is measured at the 5% level using the signed rank test due to non-normality.

Table 3.5 (continued): Performance Measures by Market and Trader Type for Futures and Options Positions (returns in million dollars) January 2000 to September 2009

	Net Dollar Returns			Gross Dollar Returns				Number of Traders		
Market and Trader Type	**Total**	**Net Long**	**Net Short**	**Total Losses**	**Total Gains**	**Number of Net Long Days**	**Number of Net Short Days**	**Total**	**Positive earning $**	**Positive Return(%)**
Corn										
Large Traders	4	-2,438	2,442	-356,521	356,525			4,996	2483	50
Commercial	100	-1,477	1,576	-183,849	183,949	312,529	602,144	1,401	676	48
Index	-1,622	-1,668	46	-66,426	64,804	40,891	489	39	9	23
Noncommercial	1,527	707	820	-106,246	107,773	429,969	364,010	3,556	1798	51
Nonreporting	-4	2,438	-2,442	-356,525	356,521					
Soybean Oil										
Large Traders	-160	1,218	-1,378	-93,095	92,935			1,427	723	51
Commercial	-716	506	-1,222	-51,681	50,964	73,402	82,405	278	127	46
Index	-30	-32	2	-11,864	11,835	22,711	1,191	36	15	42
Noncommercial	586	744	-158	-29,549	30,135	129,328	102,670	1,113	581	52
Nonreporting	160	-1,218	1,378	-92,935	93,095					
Soybeans										
Large Traders	665 *	11,155	-10,489	-295,348	296,014			4,505	2201	49
Commercial	-4,782 *	3,059	-7,841	-144,535	139,752	120,971	270,266	860	357	42
Index	2,514 *	2,546	-31	-53,572	56,086	39,151	511	41	27	66
Noncommercial	2,933 *	5,550	-2,617	-97,242	100,175	386,324	292,397	3,604	1817	50
Nonreporting	-665 *	-11,155	10,489	-296,014	295,348					
Wheat										
Large Traders	327	-739	1,066	-207,201	207,528			3,104	1539	50
Commercial	1,430	479	951	-70,140	71,570	64,204	170,492	501	254	51
Index	-1,562	-1,577	15	-63,289	61,726	40,564	1,541	40	9	23
Noncommercial	460	360	100	-73,772	74,232	242,413	255,840	2,563	1276	50
Nonreporting	-327	739	-1,066	-207,528	207,201					
Wheat KS										
Large Traders	65	1,156	-1,090	-61,650	61,715			1,332	589	44
Commercial	-547	453	-999	-35,162	34,615	80,340	139,147	427	181	42
Index	-52	-65	13	-9,203	9,150	27,785	523	30	11	37
Noncommercial	664	768	-104	-17,285	17,949	109,494	63,993	875	397	45
Nonreporting	-65	-1,156	1,090	-61,715	61,650					
Row Crops *(Corn, Soybean Oil, Soybeans, Wheat, Wheat KS)*										
Large Traders	902	10,352	-9,450	-1,013,815	1,014,717			15,364	7535	49
Commercial	-4,516	3,019	-7,535	-485,366	480,850	651,446	1,264,454	3,467	1,595	46
Index	-752	-796	44	-204,354	203,602	171,102	4,255	186	71	38
Noncommercial	6,170 *	8,129	-1,959	-324,095	330,265	1,297,528	1,078,910	11,711	5,869	50
Nonreporting	-902	-10,352	9,450	-1,014,717	1,013,815					
Livestock & Cotton *(Feeder Cattle, Lean Hogs, Live Cattle, Cotton)*										
Large Traders	-325	-9,692	9,367	-237,666	237,340			8,105	4078	50
Commercial	4,336	-1,148	5,483	-98,030	102,365	260,049	549,727	2,008	1,040	52
Index	-6,433	-6,555	121	-57,747	51,314	136,731	2,505	142	25	18
Noncommercial	1,772 *	-1,990	3,762	-81,889	83,661	652,023	492,492	5,955	3,013	51
Nonreporting	325	9,692	-9,367	-237,340	237,666					
Softs *(Cocoa, Coffee, Sugar)*										
Large Traders	-211	4,362	-4,573	-341,684	341,473			6,339	3019	48
Commercial	-517	2,121	-2,638	-192,543	192,025	265,674	365,585	1,097	560	51
Index	321	764	-443	-54,438	54,760	99,636	3,370	114	66	58
Noncommercial	-15	1,477	-1,493	-94,703	94,688	583,671	370,166	5,128	2,393	47
Nonreporting	211	-4,362	4,573	-341,473	341,684					
All Markets										
Large Traders	366	5,022	-4,656	-1,593,165	1,593,530			29,808	14,632	49
Commercial	-698	3,992	-4,690	-775,938	775,241	1,177,169	2,179,766	6,572	3,195	49
Index	-6,864	-6,587	-277	-316,539	309,675	407,469	10,130	442	162	37
Noncommercial	7,927 *	7,616	311	-500,687	508,614	2,533,222	1,941,568	22,794	11,275	49
Nonreporting	-366	-5,022	4,656	-1,593,530	1,593,165					

Note: Since futures trading is a zero sum game, the nonreporting category is the residual from the large trader profits. * denotes if the mean of daily returns is different than zero and ' denotes if the mean of monthly returns is different than zero Significance is measured at the 5% level using the signed rank test due to non-normality.

Table 3.6 Performance Measures by Market and Trader Type for Futures and Options Positions. Net Returns calculated by in/out of Commodity Index Roll period (returns in million dollars). January 2000 to September 2009

Market and Trader Type	Net Dollar Returns (All)	Net Dollar Returns (Not Roll)	Net Dollar Return (Roll)
Cocoa			
Large Traders	1	-59	60
Commercial	-82	-123	41
Index	199	171	28
Noncommercial	-116	-107	-10
Nonreporting	-1	59	-60
Coffee			
Large Traders	340	7	334
Commercial	2,587	315	2,272
Index	-791	4	-795
Noncommercial	-1,455	-312	-1,143
Nonreporting	-340	-7	-334
Cotton			
Large Traders	170	-54	224 *
Commercial	2,195	257	1,938
Index	-1,925	-670	-1,255 *
Noncommercial	-100	359	-459
Nonreporting	-170	54	-224 *
Sugar			
Large Traders	-553	-395	-157
Commercial	-3,022	-2,753	-269
Index	913	1,233	-319
Noncommercial	1,556	1,125	431
Nonreporting	553	395	157
Feeder Cattle			
Large Traders	53	-24	77
Commercial	51	51	0
Index	-74	-107	34
Noncommercial	76	32	44
Nonreporting	-53	24	-77
Lean Hogs			
Large Traders	-304	-199	-105
Commercial	1,426	718	708
Index	-2,569	-1,231	-1,338
Noncommercial	839 *	313 *	526 *
Nonreporting	304	199	105
Live Cattle			
Large Traders	-245	-243	-1
Commercial	664	593	71
Index	-1,866	-1,285	-580
Noncommercial	957 *	449 *	508 *
Nonreporting	245	243	1

Note: Since futures trading is a zero sum game, the nonreporting category is the residual from the large trader profits. A * denotes if the mean of daily returns is different than zero. Significance is measured at the 5% level using the signed rank test due to non-normality. Monthly significance is not measured since roll periods do not correspond to monthly time horizons. Net profits for inside and outside the roll period are not calculated for row crops, livestock, softs, and all markets since roll periods differ depending on commodities.

Table 3.6 (continued): Performance Measures by Market and Trader Type for Futures and Options Positions. Net Returns calculated by in/out of Commodity Index Roll period (returns in million dollars). January 2000 to September 2009

Market and Trader Type	Net Dollar Returns (All)	Net Dollar Returns (Not Roll)	Net Dollar Return (Roll)
Corn			
Large Traders	4	-151	155
Commercial	100	1,689	-1,589
Index	-1,622	-2,218	595
Noncommercial	1,527	378	1,149
Nonreporting	-4	151	-155
Soybean Oil			
Large Traders	-160	-29	-131
Commercial	-716	327	-1,044
Index	-30	-697	668
Noncommercial	586	341	245
Nonreporting	160	29	131
Soybeans			
Large Traders	665 *	161	504
Commercial	-4,782 *	-1,192 *	-3,590
Index	2,514 *	426	2,088
Noncommercial	2,933 *	927 *	2,006
Nonreporting	-665 *	-161	-504
Wheat			
Large Traders	327	326	2
Commercial	1,430	-660	2,090
Index	-1,562	799	-2,361
Noncommercial	460	187	273
Nonreporting	-327	-326	-2
Wheat KS			
Large Traders	65	31	34
Commercial	-547	-996	449
Index	-52	210	-263
Noncommercial	664	817	-153
Nonreporting	-65	-31	-34
Row Crops ***(Corn, Soybean Oil, Soybeans, Wheat, Wheat KS)***			
Large Traders	902	338	564
Commercial	-4,516	-832	-3,684
Index	-752	-1,479	727
Noncommercial	6,170 *	2,649	3,520
Nonreporting	-902	-338	-564
Livestock & Cotton ***(Feeder Cattle, Lean Hogs, Live Cattle, Cotton)***			
Large Traders	-325	-520	195
Commercial	4,336	1,619	2,717
Index	-6,433	-3,293	-3,140
Noncommercial	1,772 *	1,154	619
Nonreporting	325	520	-195
Softs ***(Cocoa, Coffee, Sugar)***			
Large Traders	-211	-448	237
Commercial	-517	-2,562	2,044
Index	321	1,407	-1,086
Noncommercial	-15	706	-722
Nonreporting	211	448	-237
All Markets			
Large Traders	366	-630	996
Commercial	-698	-1,775	1,077
Index	-6,864	-3,365	-3,499
Noncommercial	7,927 *	4,509	3,418
Nonreporting	-366	630	-996

Note: Since futures trading is a zero sum game, the nonreporting category is the residual from the large trader profits. A * denotes if the mean of daily returns is different than zero. Significance is measured at the 5% level using the signed rank test due to non-normality. Monthly significance is not measured since roll periods do not correspond to monthly time horizons. Net profits for inside and outside the roll period are not calculated for row crops, livestock, softs, and all markets since roll periods differ depending on commodities.

Figure 3.1 Nearby Prices for Corn Futures Contract, January 2000 - September 2009

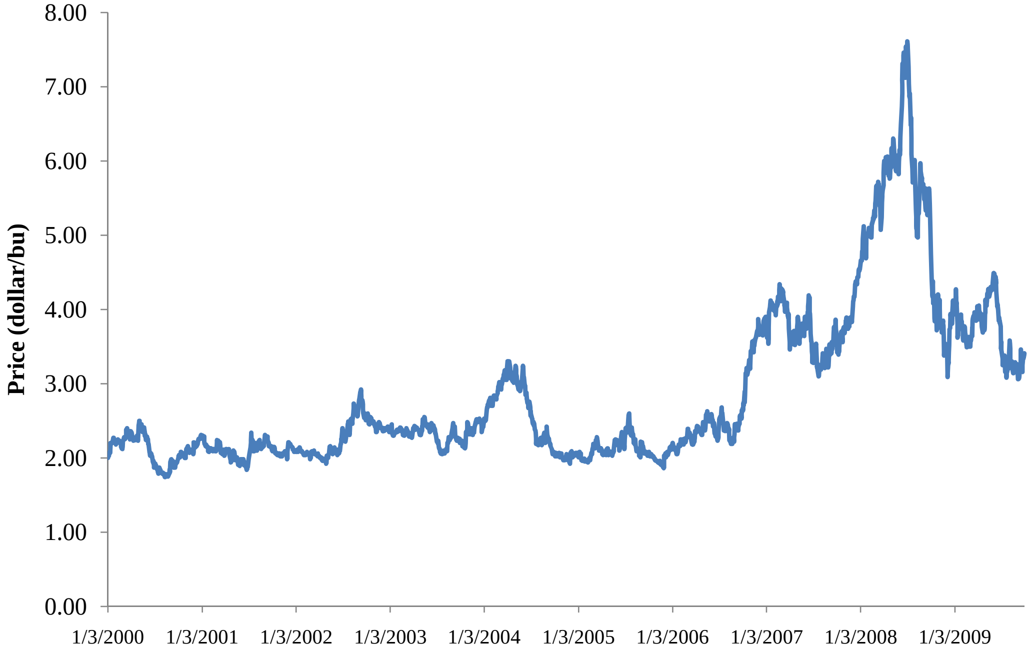


Figure 3.2 Nearby Prices for Lean Hogs Futures Contract, January 2000 - September 2009

Figure 3.3 Nearby Prices for Cocoa Futures Contract, January 2000 - September 2009

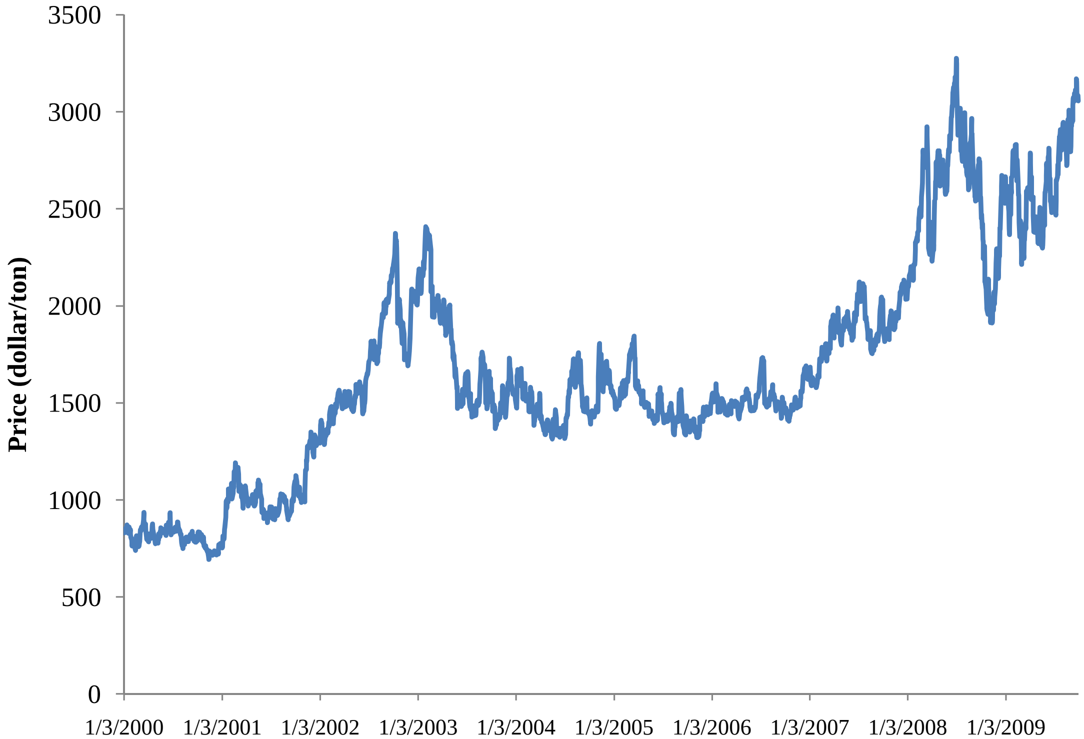
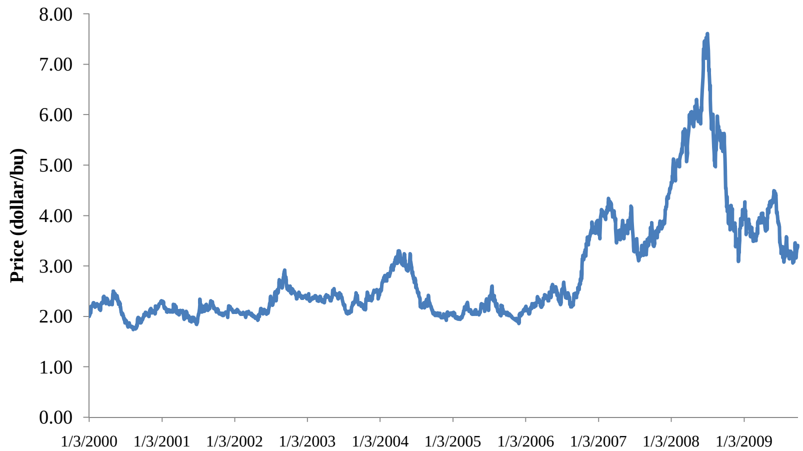
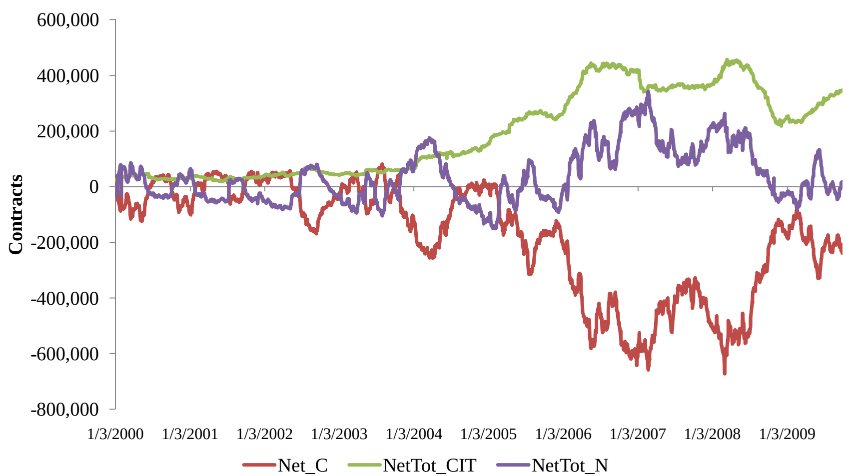


Figure 3.4 Futures Contract Prices, Positions, and Profits for Corn, 2000-2009

Panel A: Nearby Prices



Panel B: Net Positions



Panel C: Cumulative Daily Profits

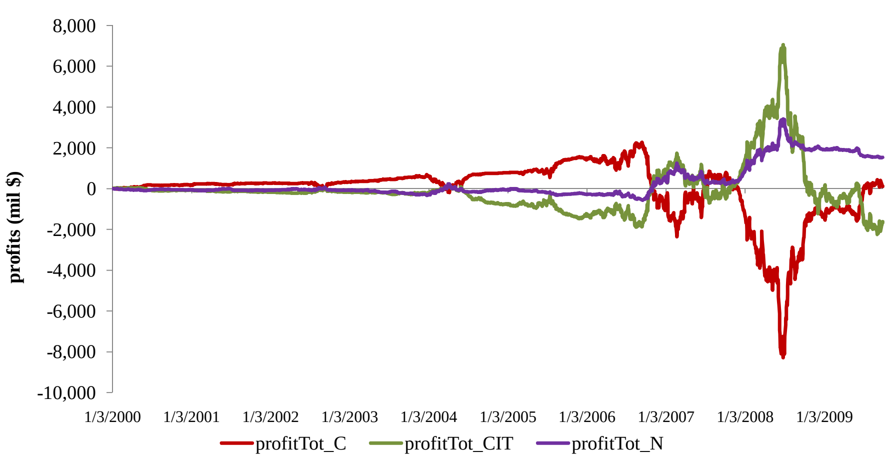


Figure 3.5 Commodity Index Trader Case Study of Corn Prices, Profits, and Positions, 11/2007 - 12/2008

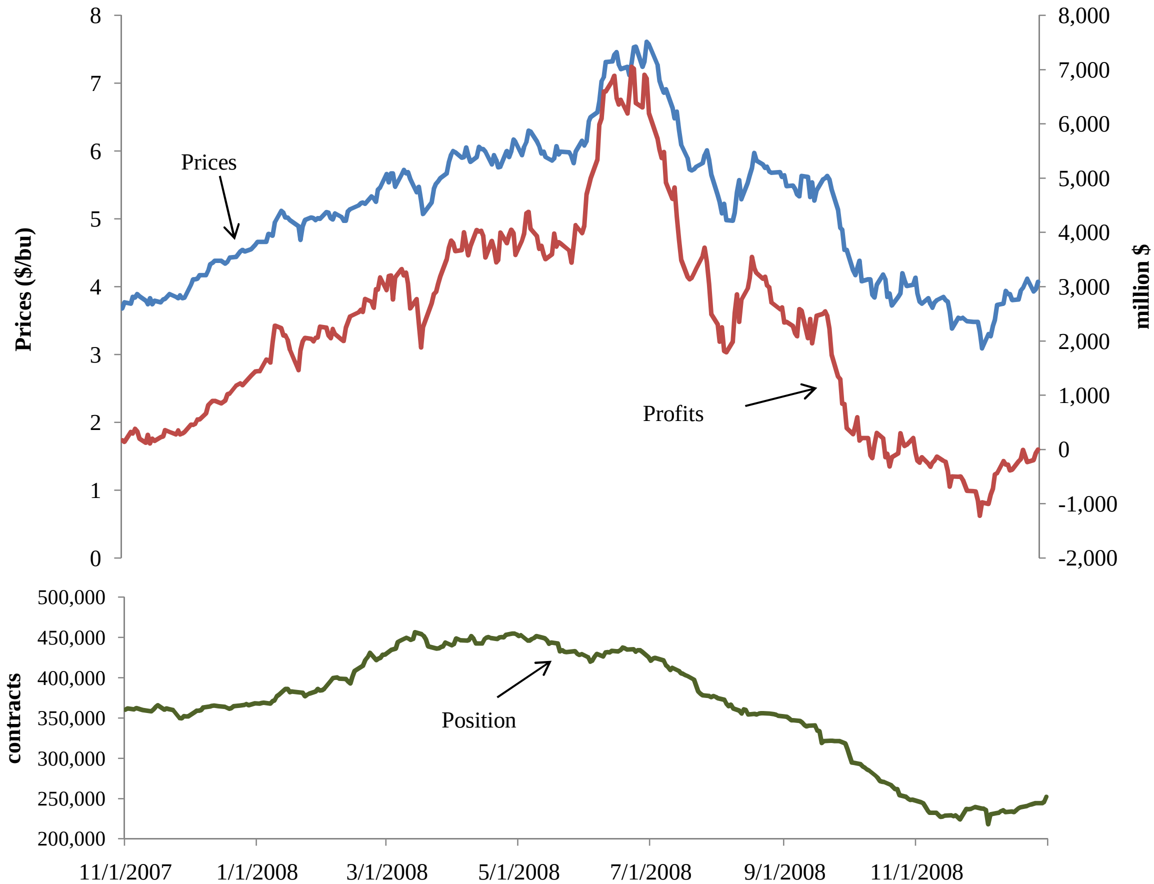
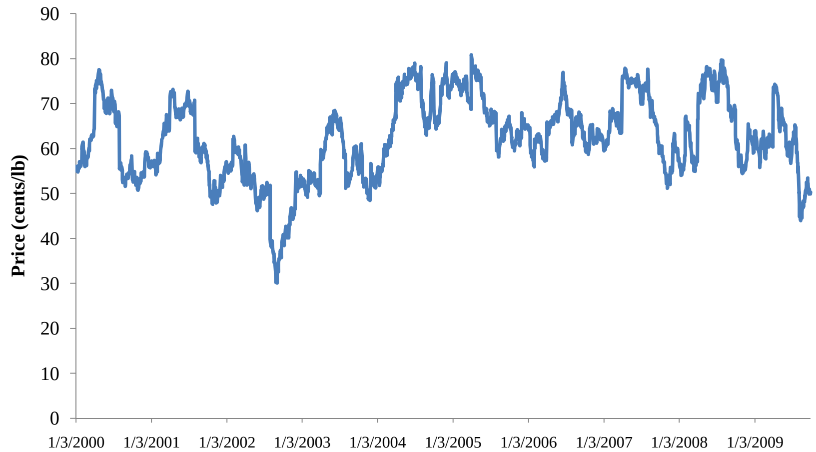
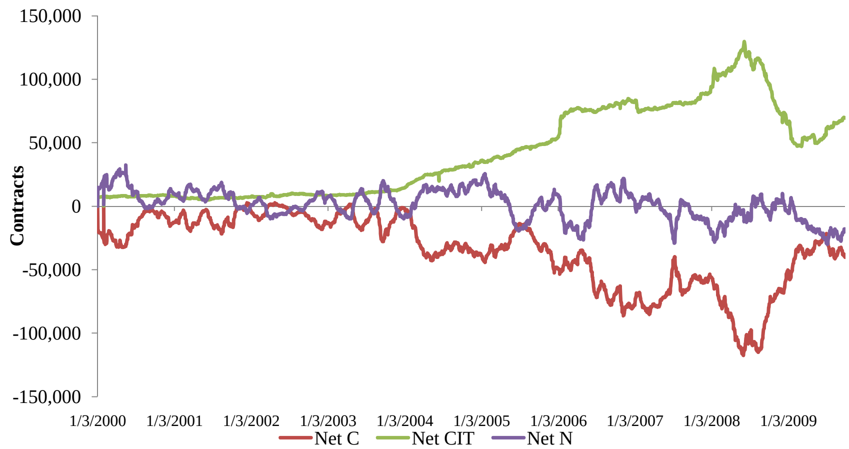


Figure 3.6 Futures Contract Prices, Positions, and Profits for Lean Hogs, 2000-2009

Panel A: Nearby Prices



Panel B: Net Positions



Panel C: Cumulative Daily Profits

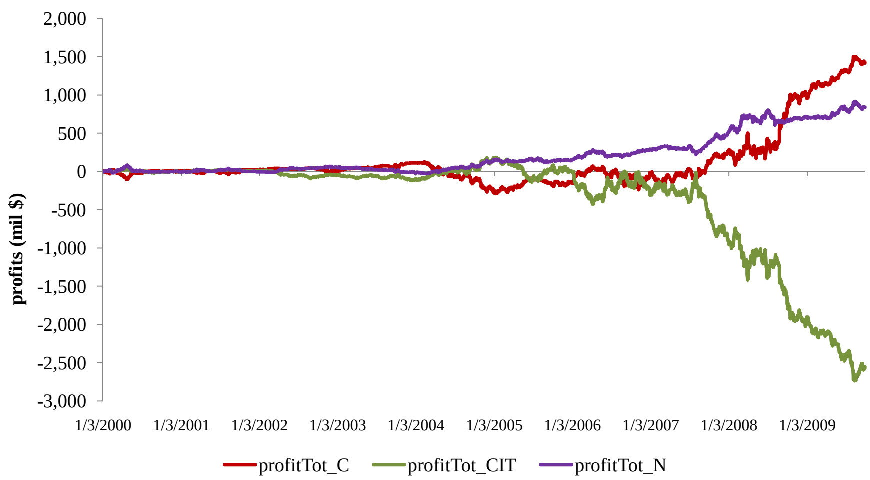


Figure 3.7 Commodity Index Trader Case Study of Lean Hog Prices, Profits, and Positions, 01/2007 - 09/2009

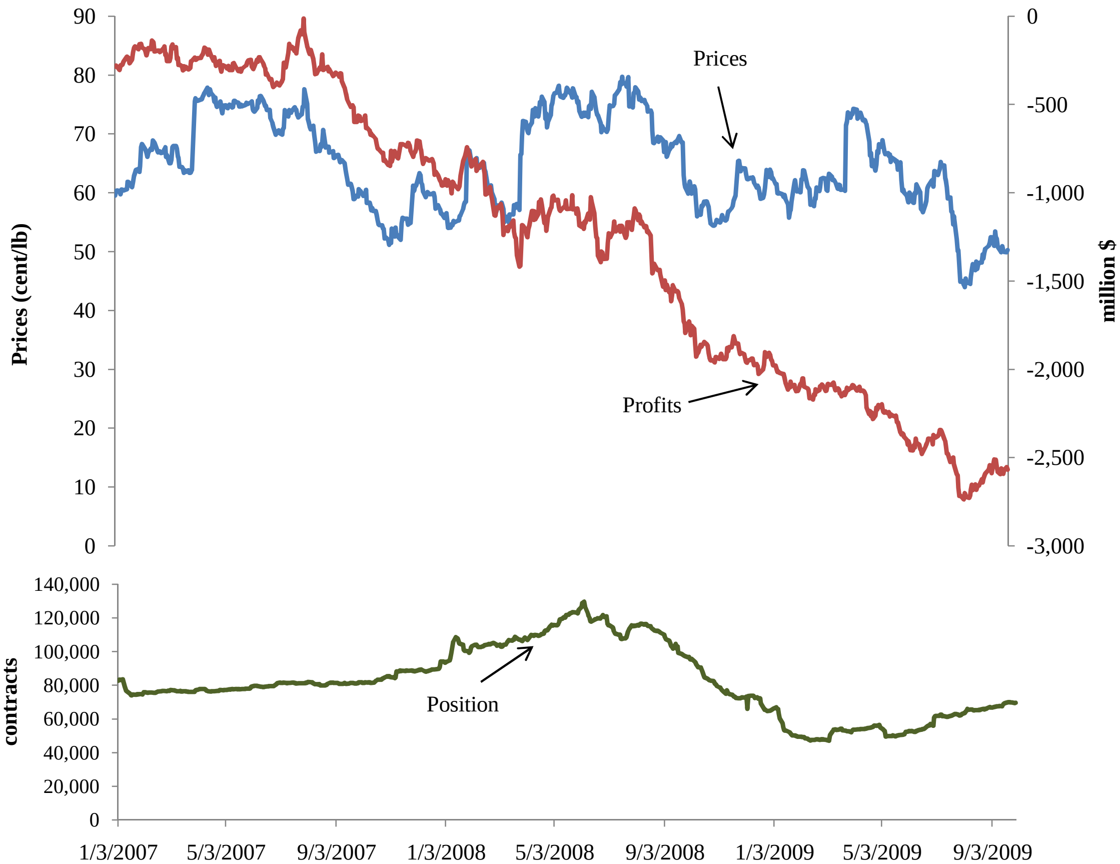
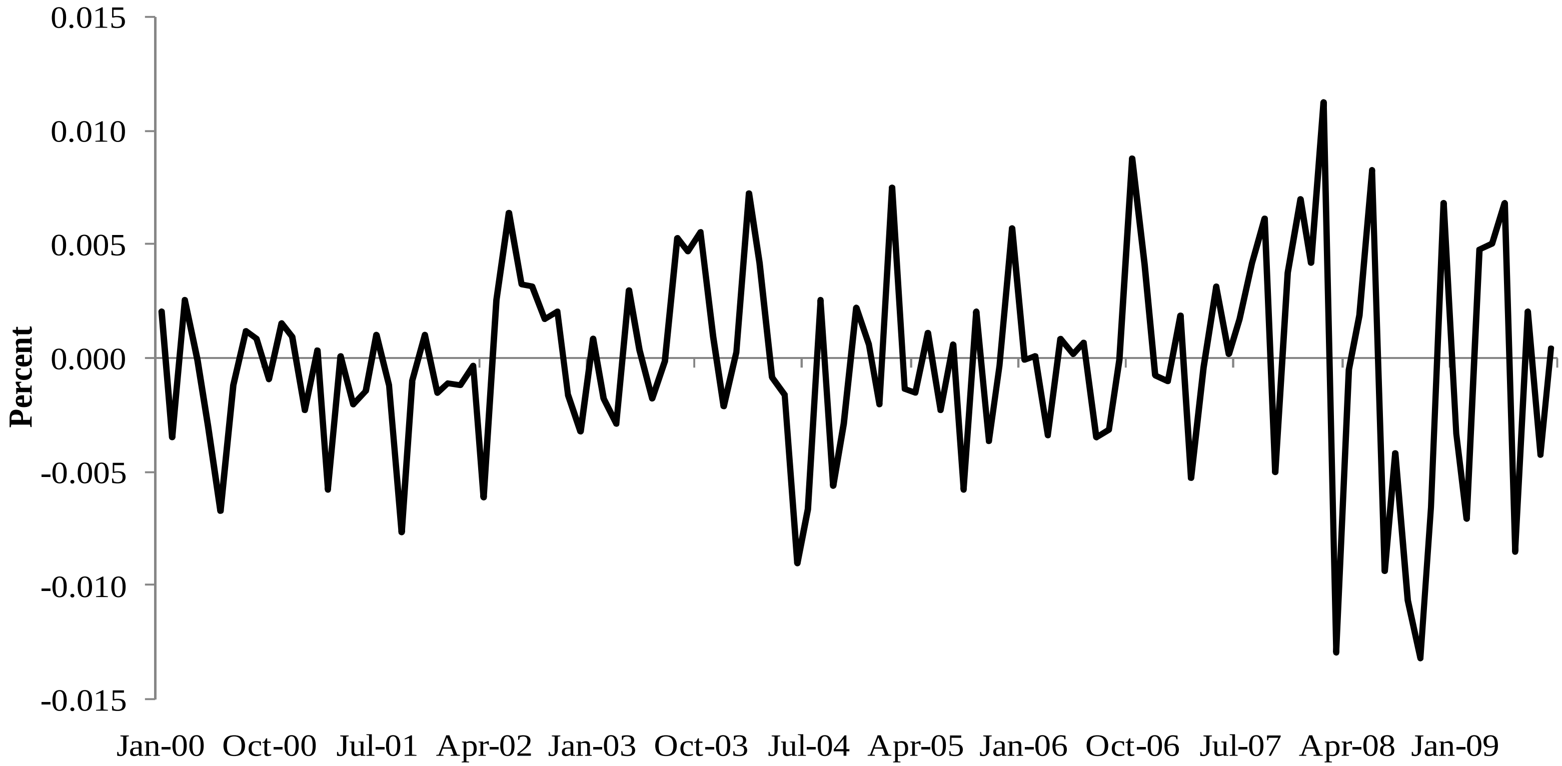


Figure 3.8 Commodity Index Trader Cumulative Monthly Profits as a Percent of Average Notional Value, All Commodities



4. RETURNS TO INDIVIDUAL TRADERS: SKILL OR LUCK?

4.1 Introduction

The persistent performance of financial market participants is important to both investors and observers of futures markets who want to know the basic question, can past performance predict future performance? The best example in recent history is the investing ability of Warrant Buffett, affectionately called the Oracle of Omaha for his persistent ability to earn money for his investors and subsequent ability to attract a large influx of investable dollars. This question of persistence can be examined in the context of portfolios and in the context of single market trader performance. Mahani and Bernhardt (2007) provide a model of individual trader behavior which provides an explanation for previous empirical regularities which are consistent with the notion that experienced speculators perform consistently well. Not all empirical research supports Mahani and Bernhardt's assertion and conclusions are mixed (e.g. Hartzmark 1991, Leuthold et al. 1994, Fishe and Smith 2010) calling into question the empirical regularities. The purpose of this paper is to provide an assessment of whether past trader performance is correlated with future performance. The findings should provide evidence relevant for the Mahani and Bernhardt model and permit a more comprehensive understanding of the market behavior and motivations of speculative traders.

The competing theories of why traders earn profits include existence of a risk premium, skill, or just plain luck (Keynes 1930, Hartzmark 1991). The risk premium or normal backwardation argument purports that speculators receive positive returns as compensation for risk while hedgers lose in the futures market by the amount of the risk premium. Numerous studies have tested this notion in the past (Hartzmark 1987, Leuthold et al. 1994, Aulerich 2011b) and with few exceptions previous evidence provides no support for the existence of a risk premium. Thereby, individual profits from trading stem from significant skill or possibly just luck. In this essay, trading profits are examined over multiple time horizons to determine if trading profits are systematically earned through skill or if they are randomly realized through luck.

The three most relevant research studies addressing the existence of individual trader skill in futures markets are Hartzmark (1991), Leuthold et al. (1994), and Fishe and Smith (2010).[38] Similar to this essay each of these studies use data from the CFTC Large Trader Reporting System database, focus on futures trader performance, and address agricultural futures markets. Hartzmark (1991) finds returns for large traders are generated randomly, Leuthold et al. (1994) find the distribution of returns over time is not random and the elite subset of traders examined have significantly positive profits from forecast skill, and Fishe and Smith (2010) find a small subset of traders has skill in determining the next day's price and a mostly non-overlapping subset of traders are skilled intra-day.

These three main studies attempt to evaluate individual futures trader performance but fall short of a comprehensive analysis. Hartzmark (1991) has a limited time horizon of 5 years and uses historical data from 1977-1981. Leuthold et al. (1994) attempt to follow up to Hartzmark but suffer from the use of only one commodity and restrict the analysis to the 50 largest traders and 20 largest spreaders. Fishe and Smith (2010) have sufficient time and scope using 10 years and 12 commodities but suffers from a (i) limited investment horizon of one day, (ii) no analysis of traders excluded from the study, and (iii) no analysis on the magnitude of profits. Finally, procedures used in previous studies have not asked a fundamental question regarding skill: do previous trader profits provide an indication of future profits? In a realistic context, this persistence criterion might be viewed as a more stringent test, and is similar to the standard applied to mutual funds and other institutions that seek to allocate funds for investors based on past performance records.

In this third essay, the analysis performs stringent tests with data spanning 10 years and across 3 representative commodities from row crop, livestock, and soft categories.[39] Previous shortcomings are rectified by testing multiple investment horizons using both binary variables and magnitude of profit measures. Since most traders included in the database are not day traders or high frequency traders their strategies may extend beyond the daily horizon used in most previous studies including Leuthold et al.(1994) and Fishe and Smith (2010). Therefore, we test for persistence using monthly, quarterly, and yearly horizons. Since not every trader is continuously active in the market, some traders are excluded in parts of the analysis. The systematic exclusion of traders can bias the results which makes analysis of excluded trader properties important. For this reason, summary statistics and discussion of the excluded traders are examined for the first time in the literature.

This essay builds on the work of Aulerich (2011b), which provides evidence against the theory of normal backwardation and identifies noncommercial traders as a profitable category of traders. In the absence of normal backwardation, the question then becomes how noncommercial traders earn profits. Are they just lucky or do they have significant skill? The study addresses this question and determines if noncommercial traders persist in making profits or if profits are randomly generated. Narrowing the study to noncommercial traders also removes potential noise caused by commercial traders, generally regarded as hedgers, who may have both hedging and speculative motives for trading and makes interpreting trading profits problematic. The noncommercial category from the same dataset used in Aulerich (2011a, 2011b) will be studied for corn traded on the Chicago Board of Trade (CBOT), live cattle traded on the Chicago Mercantile Exchange (CME), and coffee traded on Intercontinental Exchange (ICE) from 2000 to mid-2009. These three commodities are chosen to represent field crops, livestock, and soft commodities.[40] The source of the dataset is the CFTC Large Trader Reporting System database which consists of detailed non-aggregated end of day data. In the database, the number of unique traders in the noncommercial category for corn is 3,556, live cattle is 1,551, and coffee is 2,677.

Two methods are used to analyze trader skill or persistence. The first is the Fisher Exact test, a nonparametric two-way winner and loser rank contingency table analysis. The second is the testing of trader by magnitude of profits using the rank of trader profits in the first period to identify top and bottom deciles. A standard t-test or in the case of nonnormality, Wilcoxon signed-rank test is used to determine whether profits from the traders in these deciles differ in the next period. The tests have been widely applied in studies of investment performance (e.g., Malkiel 1995), and are viewed as an out-of-sample assessment of trader ability to consistently generate profits. Traders in the commodities are tested based on each trader's profitability level over monthly, quarterly, and yearly time horizons. Arguably the yearly 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 if traders not only show yearly persistence but also demonstrate skill in the shorter time horizons within a year. Large trading houses may be more focused on yearly results, but small traders need to survive through short-run adversity. The quarterly and monthly time periods can also be viewed as an indication of shorter-term risk in the market.

The Fisher Exact test results provide substantive evidence of persistence in rankings across the commodities and time horizons studied; the only period without statistically significant results is the monthly horizon for coffee. For the second method that determines the difference in profitability levels across deciles, the findings show the top 10% of traders have persistent skill. The results for shorter time horizons are stronger for corn than for live cattle and coffee. The shorter time periods are likely influenced by a high degree of volatility over shorter time periods where trader's fortunes are expected to fluctuate.

Overall, results indicate that noncommercial traders rank persistently through time and the top 10% of traders persistently make profits on a yearly time horizon. The evidence of persistence coincides with Mahani and Bernhardt's (2007) theoretical model that trader performance shows persistence. Additional empirical results find that 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 also coincide with Mahani and Bernhardt's model explaining that large, more active speculators outperform small, less active speculators.

4.2 Literature Review

The literature review addresses three different strains of the research: the performance of individual traders, mutual fund managers and hedge fund managers. Most relevant to this essay, individual trader research focuses on the actual trades of investors in stock or futures market investments. Conversely, mutual fund research focuses on the performance of the overall risk and return of a portfolio. Similar to mutual funds, hedge funds are evaluated on total portfolio performance, but unlike mutual funds, hedge funds are lightly regulated with higher barriers to entry and freedom to participate in less traditional investments. The various testing methodologies used in the mutual and hedge fund literature are more relevant to this essay than the actual results because this essay focuses on individual trader performance and not overall portfolio performance.

4.2.1 Individual Traders

The three most relevant research studies addressing individual trader performance in futures markets are Hartzmark (1991), Leuthold et al. (1994), and Fishe and Smith (2010). Similar to this essay each of these studies use data from the CFTC Large Trader Reporting System database, focus on futures trader performance, and address agricultural futures markets.

Hartzmark (1991) investigates the hypothesis that futures traders possess the ability or skill to consistently earn positive profits. Daily data on individual traders are used from the CFTC's Large Trader Reporting System (LTRS) from 1977 to 1981 for oats, wheat, pork bellies, live cattle, feeder cattle, t-bonds, and t-bills. Traders are divided into commercial and noncommercial categories. This was the first study to use the highly detailed daily transaction data on individual traders to investigate ex ante predictions and ex post realizations. He employs the nonparametric statistical procedure developed by Henriksson and Merton (1981) and modified by Cumby and Modest (1987) to determine individual trader forecast ability.

Two different types of forecast ability or market timing are examined. The first tests if a trader consistently predicts the correct direction of price movements. This skill is establishing a long position prior to an increase in futures prices and a short position prior to a decrease in futures prices. Two binary variables are defined, the first is equal to one if the price goes up and zero otherwise, and the second is equal to one if trader is long and zero otherwise. A logit equation is specified regressing the price movement binary variable on the position binary variable. The null hypothesis of no skill is rejected if the position coefficient is significant. The second test is called “big hit” ability. The test determines if a trader consistently predicts both the magnitude and direction of price changes. The skill establishes a long (short) position prior to an increase (decrease) in futures prices and adjusts the size of the position relative to the magnitude of the price move and thereby establishing larger positions when larger price moves are anticipated. To test for big hit ability, the price change is regressed on a trader’s net position; a coefficient significantly greater than zero indicates a trader with superior ability. Next, Hartzmark tests if a trader who displays superior (or inferior) forecast ability in an early period continues to demonstrate it in a later period. Hartzmark focuses this analysis solely on noncommercial traders from 1977 through September 1979 and tests if correlations between dollar returns earned in the two periods are significant. Deciles are then formed comparing coefficients across the first half and second half of the time period studied to determine if performance persists across time periods.

The study concludes that even though a large number of traders appear to exhibit significantly superior forecast ability he concludes that traders do not have skill. The entire investigation supports three conclusions, (i) there are fewer participants with significantly superior skill than expected if participants trade randomly, (ii) there are more traders exhibiting no skill than expected if participants trade randomly, and (iii) forecast ability is not correlated over time – superior forecasters in the early period are only average forecasters in the later period.

Leuthold, Garcia, and Lu (1994) follow up to Hartzmark’s work and examine the returns and forecasting ability of large traders in the frozen pork belly futures markets for a 9 year period. The data are from the CFTC’s Large Trader Reporting System and extends from 1982 to 1990. They calculate profits and use similar statistical methods as Hartzmark (1991), searching for consistent forecasting ability by first using Cumby and Modest and Henriksson and Merton type tests and second, by using a linear regression of returns on net positions to test for Big Hit ability. Compared to Hartzmark's 9 commodities and 5 years of data, Leuthold, Garcia, and Lu study one market but extends the analysis to 9 years. The analysis is restricted to the 50 largest traders and 20 largest spreaders; Hartzmark does not filter by these standards. This could be partially responsible for the difference in conclusions; Leuthold, Garcia, and Lu conclude that a small subset of traders have forecasting skill and Hartzmark concludes that profits are mostly earned randomly by traders. Furthermore, Leuthold, Garcia, and Lu only focus on frozen pork bellies, and Hartzmark's results isolated on frozen pork bellies do demonstrate significant, positive, consistent forecasting ability. The frozen pork belly market, in itself, is traditionally viewed as a small mature market trading a unique, semi perishable product. The market has been described as having a relatively higher level of "excess" speculation (Peck 1980). Based on these factors Leuthold's conclusion may not be broadly extended to other agricultural futures contracts.

Most recently, Fishe and Smith (2010) attempt to identify informed and liquidity traders in futures markets from a large group of 8,921 unique traders. The study does not specify how they define unique traders but does remove traders with less than 30 observations. The data used are from the CFTC's Large Trader Reporting System and extends from 2000 to mid-2009 covering the 12 commodities of crude oil, copper, corn, cotton, gold, heating oil, natural gas, silver, soybean oil, soybeans, sugar, and wheat. Instead of using the CFTC's classification of traders ex-ante, the authors analyze trader behavior and group them ex-post by trading actions. They use a daily binary measure of success to tests if traders are informed. First, the unconditional method is used to determine if the null hypothesis that a trader is successful half the time can be rejected and second, the Henriksson and Merton (1981) test is used, similar to both Hartzmark (1991) and Leuthold et al. (1994). They do not, however, take magnitude of profits into account in any testing procedures. The analysis differentiates between overnight informed traders using end of day positions with next day's prices and intraday informed traders using a 'triple test' procedure relating how position changes are compared to intraday price changes using close to close daily data. Fishe and Smith also differentiate between position profits and trading profits; position profits based on the level of open interest and trading profits based on the change in open interest. Results find that between 94 and 333 traders are informed about the next day's prices (depending on method) and 91 are informed intra-day. Both results are out of 8,921 observed traders, concluding 1% to 3.5% of traders are informed. They find no evidence that commercial hedgers pay a risk premium to speculators and find that liquidity demanders tend to be managed money/hedge fund traders and liquidity suppliers tend to be commercial traders. Using an inverse regression, trader characteristics are shown to offer strong predictive power identifying informed traders. These include, experience defined as average number of days with open interest, activity defined as days with change in open interest, size defined as number of contracts, average expirations held at one time, average net long positions, and average net short positions.

Overall, these three main studies attempt to evaluate individual futures trader performance but fall short of a comprehensive analysis. Hartzmark (1991) has a limited time horizon of 5 years and uses historical data from 1977 to 1981. Leuthold, Garcia, and Lu (1994) suffer from the use of only one commodity and restrict the analysis to the 50 largest traders and 20 largest spreaders. Fishe and Smith (2010) have sufficient time and scope using 10 years and

12 commodities but suffers from a (i) limited investment horizon of one day, (ii) no analysis of traders excluded from the study, and (iii) no analysis on the magnitude of profits.

Two addition relevant studies analyze individual traders, although they do not use CFTC position data, these include Coval (2005) and Mahani and Bernhardt (2007). Coval, Hirshleifer, and Shumway (2005) study the central question of whether all individual investors who earn profits on their trades are merely lucky or are indeed skillful. They use a dataset provided by a large discount brokerage firm on equity market trades placed by 115,856 accounts from January 1990 through November 1996. They use long term and short term risk adjusted measures to analyze profits. Results provide evidence that some individual investors are persistently able to beat the market and other individual investors systematically underperform. The difference in performance between the top and bottom deciles (10%) is tested and show persistent skill in these comparisons. The findings suggest investors' persistent abnormal performance is not derived primarily from trading on inside information and implies a potential violation of semi-strong form market efficiency.

Mahani and Bernhardt (2007) develop a theoretical model that helps explain trader performance in a dynamic context. This model shows how learning by rational traders reconciles several empirical regularities including, (i) cross sectionally, most individual speculators lose money, (ii) large speculators outperform small speculators, and (iii) performance shows persistence. They propose a rational, learning-based explanation allowing the authors to derive the effects of changes in parameters on the entry, exit, and performance of financial speculators. The model provides insight into the interaction between learning-from-trading and other elements of the financial markets. Their results show inexperienced traders initiate speculation on a small scale, trading off expected losses against the value of information generated by greater trading. Most inexperienced traders realize losses, conclude that they are unlikely to be skilled, and leave the markets; survivors expand their trades and make more profits.

4.2.2 Mutual Funds and Hedge Funds

The mutual and hedge fund literature is relevant to this analysis because similar methods can be used in the analysis of futures traders. The results themselves are less relevant because they pertain to an overall portfolio and compare to market benchmarks, unlike that of individual trader positions in a futures contract that lack an easy comparison. Therefore, the review of this literature will focus on the studies that highlight particular methods and will not be a comprehensive review of the mutual and hedge fund performance evaluation literature.

A common approach in analyzing the performance of fund managers is to test for persistence in fund returns, that is, whether past winners continue to produce high returns and past loser continue to underperform. Two widely-cited studies using this approach are Grinblatt and Titman (1992) and Carhart (1997).

Grinblatt and Titman (1992) analyzed the persistence of mutual fund performance using a dataset from 1974 to 1984. They develop a three-step procedure; first split the ten-year sample of fund returns into two five-year sub-periods. Second, compute the abnormal returns of each fund for each five year sub-period. Finally, estimate the slope coefficient in a cross-sectional regression of abnormal returns from the last five years of data on abnormal returns computed from the first five years of data. A significant positive t-statistic for the slope coefficient in this regression would reject the null hypothesis that past performance in unrelated to future performance and support the alternative hypothesis that past performance is positively related to future performance. They overcome the bias created by the highly correlated residuals resulting from funds with similar portfolios by developing a “time-series t-statistic”. The results of the tests show the differences in performance between funds persist over time and the persistence is consistent with the ability of fund managers to earn abnormal returns.

Carhart (1997) also developed a testing procedure to measure persistence in one year returns of mutual fund portfolios. Mutual funds are sorted on January 1 each year from 1963 to 1993 into decile portfolios based on their *previous* calendar year’s return. The portfolios are equally weighted monthly so the weights are readjusted whenever a fund disappears. Funds disappear primarily because of poor performance over several years; the average annual fund attrition rate is 3.6%. On average 2.2% per year disappear due to merger, 1% disappear because of liquidation, 0.1% because of self-selected means, and the remainder is unknown (Carhart 2002). Funds with the highest past one-year return comprise decile 1 and funds with the lowest comprise decile 10. The difference between top and bottom deciles is tested for significance to determine if traders’ performance persists from year to year. Results show that while the ranks of a few top and bottom funds persist, the year to year rankings on most funds appear largely random.

The other common approach is measuring “alpha” or the quantifiable amount a particular fund performs differently from a market portfolio. There are three common ways of modeling the alpha: CAPM is the Capital Asset Pricing Model described by both Sharpe (1964) and Lintner (1965), the Fama and French (1993) 3-factor model, and the Carhart (1997) 4-factor model.[41] The alpha approaches, although effective for mutual fund and hedge fund portfolio analysis, are not applicable to single market individual trader analysis. Rather in this third essay the analysis uses nonparametric ranking methods and comparison of profits across deciles similar to Hartzmark (1991) and Carhart (1997). These methods are appropriate to single market individual trader analysis because they do not relate to a market portfolio and can apply to both rankings of traders by profits and differences in profit magnitudes between top and bottom performing traders.

4.3 Data

The data for this study come from the Commodity Futures Trading Commission (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.[42,43] 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.[44] 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 himself 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 through more than one account, the CFTC is able to combine these accounts by trader and ownership level using 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 in the name of the first firm, but the first firm is than 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 removes any 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 noncommercial from the information provided on 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 underlying business (e.g. producer, manufacturer, merchant, swaps dealer, etc.). If a trader does not meet the requirements for a commercial trader, than they are classified as a noncommercial 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 noncommercial 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). For the purposes of research, noncommercial categories are commonly grouped into two groups, (i) managed money traders consisting of FCM's, IB's, CTA's, CPO's, and AP's, and (ii) floor broker traders consisting of FB's and FT's. Any traders classified as noncommercial 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.[45]

The sub-classification of Commodity Index Traders (CITs) was created by the CFTC in 2007 but is not a current category on Form 40. As explained in Aulerich (2011a, 2011b), CITs are passive long traders who invest based on a pre-specified index. This classification was created by staff within the CFTC and is composed of both commercial and noncommercial traders although CITs are typically separated from commercial and noncommercial traders to become a standalone category.

Broadly, the LTRS divides traders into the four categories based on trading motivation; these include commercial, noncommercial, index, and nonreporting. All of this daily data collected into the LTRS are released weekly to the public in variety of different reports including the Commitment of Traders report, Supplemental Commodity Index Trader report, Disaggregated Commitments of Traders report, and Traders in Financial Futures report.

For the purposes of this research, daily futures and options positions from the LTRS cover the period from January 2000 to September 2009 for 3 commodities.[46] The commodities are corn traded at the Chicago Board of Trade (CBOT), live cattle traded at the Chicago

Mercantile Exchange (CME), and coffee traded on the Intercontinental Exchange (ICE); these commodities are chosen to be representative of row crops, livestock, and soft commodity categories. The traders analyzed are exclusively from the noncommercial category of traders but exclude those who are defined as Commodity Index Traders (CITs).[47]

In this analysis the owner ID combined with the trader ID makes up the unique 'trader' identification used to isolate positions on a trader-by-trader basis. Table 4.1 displays summary statistics for each of the main LTRS categories and commodities by detailing the number of unique traders, overall profits, percent of profitable traders, the number of business days with open interest, and the average daily notional value per trader. The noncommercial 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); although noncommercial profits are reported at $1 billion, the losses are only present in coffee. The noncommercial coffee traders tend to be on average less profitable, less active, and smaller than noncommercial traders in corn and live cattle. This may be due to the international scope of coffee production and the difficultly in gathering and processing valuable information without direct involvement in the production and marketing of the underlying product, which may help explain the large profits to commercial coffee traders, although this is less clear for the commercial corn and live cattle participants. Commercial traders use the futures market for hedging[48] to offset a cash transaction in the course of business, and this creates limited sensitivity to profit or losses earned in futures markets. Data are not available on cash market activity so a commercial trader's total position profit and losses picture cannot be viewed. For this reason, commercial traders are not analyzed in this study. Commodity index traders are small subset of traders characterized by a buy and hold passive long strategy, this strategy is shown to be unsuccessful over the time period studied and consequently, this essay will not delve further into the source of these losses. Based on these previous arguments, the noncommercial traders will be the focal point of this research.

Focusing on the noncommercial trader section of table 4.1, the unique trader total of 6,102 is broken down further into the number of commodity markets in which a trader participates; a particular trader has the ability to participate in all three markets listed. The majority of participants are in one market, but 758 participate in two and 462 trade in all three. On average half of these unique traders are profitable over any computed cross section (daily, monthly, quarterly, or yearly). 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 noncommercial traders in corn are on average in the market 239 business days, a little less than a year, with an average notional value of $14 million per day. The live cattle noncommercial traders total 1,551, are in the market on average 217 business days, and have an average notional value of $11.5 million per day. The noncommercial coffee traders total 2,677, but on average have the least amount of active days at 184, and have the lowest average daily notional value at $6.6 million. The performance for noncommercial traders appears to be rather consistent with Mahani and Bernhardt's first two regularities: in a given cross-section the majority of individual speculators lose money (here approximately 50%); 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 (Aulerich 2011b), and essentially leave. To provide evidence for Mahani and Bernhardt's third assertion, that past performance predicts future performance, two testing procedures discussed in the following methodology section are implemented.

4.4 Methods

Two methods are used to analyze the persistent ability of traders: the first is the Fisher Exact test, a nonparametric two-way winner and loser contingency table ranking analysis, and the second is the difference in magnitude of profits between top versus bottom decile performing traders across adjoining periods. The tests have been widely applied in studies of investment performance (e.g., Malkiel 1995) and have the advantage of using information on both the ranking of traders and magnitude of trader profits. Traders in each commodity are tested based on returns over monthly, quarterly, and yearly time horizons.

4.4.1 Compute Profits

Daily profits for each trader for each 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.[49]

4.4.2 Non-parametric Winners and Losers 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 in the testing procedure is to create pairs of adjacent time periods, t and $t+1$ (e.g. 2000 and 2001, 2001 and 2002, 2002 and 2003). The second step is to form a sample of traders that actively trade in both *t* and *t+1*, any traders that are 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. 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. The fourth step is to repeat the ranking, sorting, and creation of winner and loser groups for the second period, *t+1*, based on profits. The fifth step is to 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 is discovered. The appropriate statistical test is the Fisher's Exact Test (Conover, 1999, pp.188-89), a nonparametric test that is robust to outliers, which may be important when analyzing the profitability of traders. 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 of the same length (e.g. yearly, quarterly, and monthly).

4.4.3 Top and Bottom Performance Deciles Test

While predictability may be limited or nonexistent across all traders, it may be possible for subgroups of traders to exhibit predictability, particularly in the context of "large" traders. For instance, persistence may exist at the extremes where top and/or bottom performing traders in one period may perform well in the next period but midrange traders do not exhibit persistence. In addition, the magnitude of performance differences of top and bottom performing groups can provide insights into the degree in which these two groups differ. This is the motivation for the second test of predictability that compares the magnitude of profits of top subgroups of traders to bottom subgroups across adjacent time periods.

The start of this testing procedure is very similar to the *Winners and Losers* test. First create the pairs of adjacent time periods, exclude any traders not in both periods, and then 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. Now 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 10^{th} decile of traders from period *t* performed in period *t+1*. Was the performance of these traders at the same level in the next period?   Compute the difference in the profit levels 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, than the null hypothesis can be rejected and the conclusion reached that traders persistently perform. 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.

These two tests analyze traders' profits by first testing the persistence in *ranking* of traders across pairs of adjacent time periods and second, by determining if the *magnitude* of profits is different between deciles of top and bottom performing traders.

4.5 Included and Excluded Traders

As explained in the methods section, in order to examine the forecasting ability of traders across time horizons a trader must be present in adjoining periods. For example if a trader is analyzed using a yearly time horizon in 2000 (*t*) and 2001(*t+1*), the trader would need to be present in both time periods. If a trader is not present in 2000 and 2001, than the trader is dropped from the analysis for this pair of time horizons. The trader only has to be in any two adjoining time horizons (*t, t+1)* to be included in the analysis, not in all time horizons of the dataset. Regardless, this leads to an analysis design were some traders are excluded. This relates to survivorship bias in mutual fund or hedge fund research because funds or traders that fail to have records (or sufficient records) in the period analyzed are dropped from the analysis. Fund survivorship bias occurs because a fund fails to exist and this normally happens when performance is poor and the fund is closed. Removing the funds with bad performance from the analysis would in turn place an upward bias on the performance results. On the other hand, individual traders who are removed from the analysis due to inactivity in period *t+1* may not always be due to performance. A trader could fail to be present in two adjoining periods because he has 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 also dealt with the excluded trader problem. Hartzmark (1991) only includes traders with 25 or more observations. Leuthold et al. (1994) includes the top 50 largest traders and top 20 largest spreaders. Fishe and Smith (2010) include traders with 30 or more observations. The impact of trader exclusion on results depends on the characteristic of the excluded traders.

Table 4.2 compares the included versus excluded traders by profitability, size of investment, and activity. One day of open interest per period is the minimum threshold for inclusion. The percentage of excluded traders is approximately 40%, 25%, and 16% using a yearly, quarterly, and monthly horizons, respectfully; these excluded traders are present in the first period (*t*) but drop out in the second period (*t+1*). The percentage is computed by taking the traders who were active in *t* but not in *t+1* (dropped out) divided by the total number of traders in period *t*.[50] The size of traders, measured by total absolute notional value, is smaller for the excluded trader group which averages just 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. For corn and live cattle the profitability of the excluded trader group vastly underperforms included traders, with losses from -$12 to -$400 million compared to included traders profits between $1 to $2 billion. This profitability comparison does not hold for coffee, where both included and excluded traders experience losses but the included traders losses are larger, approximately -$1 billion, and excluded traders loses are -$400 to -$150 million. As shown in table 4.1, the noncommercial traders in coffee lost to the commercial coffee traders who earn a positive $2.6 billion. 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 also support Mahani and Bernhardt's (2007) theoretical model that large, more active speculators outperform small, less active speculators.

Since the excluded traders are smaller, less active, and in general less profitable than included traders, both the ranking winners and loser test and the deciles tests (first and second methods) can potentially be affected. The exclusion of the traders with losses that are smaller in magnitude removes traders from mid to low-mid part of the distribution since the majority of these traders are not large enough to incur the magnitude of losses required to be in the very bottom of the distribution. For example if a trader starts trading in period *t* with a small amount of starter capital, discovers that he is not skilled and ceases trading during the same period *t*, then this trader would be excluded from the *t* and *t+1* analysis. In the ranking tests, removing observations from the middle of the trader ranking may make the top and bottom traders more distinct. For the deciles test, excluding the middle performing traders may make little difference when comparing only the top and bottom decile traders; although, the exclusion could increase the standard deviation of profits. The systematic exclusion of these traders could make finding persistence easier in the ranking tests but may have little impact on the deciles test. This scenario is partly addressed by using multiple time horizons to capture these types of traders. In table 4.2, the percent of excluded traders decreases from 40% in the yearly horizon to 15% using a monthly horizon, exemplifying the larger inclusion rates with the shorter observation periods. For example, if a trader is not in year *t* and *t+1*, he may be in the shorter quarterly or monthly horizon *t* and *t+1*. The high correspondence across the three different commodities indicates that traders behave similarly regardless of the commodity studied.

4.6 Results

The Winners and Losers contingency results in table 4.3 test the persistence in rankings 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 example the trader counts are significantly different than 50% and the null hypothesis that profits are randomly distributed is rejected. Out of all 9 comparisons of the yearly periods, a significant difference (at the 5% level) exists in 3 out of the 9 pairs for corn, 2 of 9 pairs for live cattle, and 4 of 9 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 on both quarterly and monthly time horizons for each commodity. Quarterly results span from quarter 1 in year 2000 through quarter 3 in year 2009, a total of 38 pairs. Monthly results span from January in year 2000 through September in year 2009, a total of 116 pairs. The individual groups of period results will not be displayed in a table due to space constraints, but the pooled results from all 9 conditional winner and loser tests are in table 4.4. These pooled 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 quarterly live cattle and monthly coffee where traders are split almost evenly between winners and losers. Overall the contingency table results support that traders show evidence of persistence in earning profits.[51]

The next set of results take 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. Table 4.5 displays the average profits for the out-of-sample periods (*t+1*) for each decile and the differences between top and bottom deciles over different time horizons. For example, in the live cattle yearly results the top decile is 10 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 5% level. If we expect traders to persist in earning profits then the top out-of-sample deciles should have greater average profits than the bottom out-of-sample deciles.

The yearly results for corn in panel A are not statistically significant but the top 10% of traders do show substantial skill, with an average profit of \$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 yearly 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%. Overall on a yearly 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 of $976,000 and $259,000, respectively. For live cattle, the quarterly results identify the top 10% is not greater than the bottom decile but is greater than deciles 9 through 2; in monthly results, the top decile is significantly greater than the bottom decile. For coffee, the quarterly losses appear symmetric around the middle decile with the greatest losses in the top and bottom deciles; in the monthly results, little evidence of persistent performance appears.

The variability of persistence evidence in the shorter horizons indicates either traders focus on a long term investment horizon and are less sensitive to intermediate period profits, or that quarterly and monthly results may be more difficult to reconcile in light of noise which exists due to random price patterns.[52] Overall the second set of results that take into account magnitudes of profits, provide conclusive evidence that the top 10% of traders show significant persistence in skill on the yearly horizon and support the conclusions of the first set of winner and losers rank contingency table tests.

4.6.1 Comparison of Method 1 and 2

Although the results from winner and losers 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 tests are yearly live cattle and coffee, quarterly corn, and monthly corn, live cattle, and coffee. The three non-matching tests are yearly corn, quarterly live cattle and coffee. The quarterly live cattle results find persistence for method 1 but not for method 2; 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 methods is pronounced for the quarterly coffee results; in the second method the difference between top and bottom deciles is an insignificant $10,000 but in the first method a statistically significant 52% of traders show persistence where as 48% do not. The disparity is also apparent in yearly corn results, for the second method the difference between top and bottom deciles is large but statistically insignificant at $357,000 compared to the first method showing a significant difference between traders exhibiting persistence (54%) and traders who do not (46%). The variation in statistical significance between the two procedures is likely reflective of the high degree of volatility during the period and as figures 4.1-4.3 will demonstrate, the extreme changes in deciles 1 and 10 ultimately make it difficult to differentiate between trading returns.

To help explain the results, figures 4.1-4.3 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 4.1-4.3, all the diagonals are greater than 10%, and many traders either stay in the same profit decile or move one decile up or down.[53] The tendency for traders to stay in or around their decile supports method 1 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 rank at 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.

These traders at the extremes may fall into one of two types, those who are skilled either superiorly or inferiorly 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 “flip flop” with the market. Persist performance in decile 10 encourages further participation through profits, but the continued performance of those in decile 1 is surprising since traders are continually earning negative returns. 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 of Hartzmark (1991), who argues profits are randomly distributed. The large shift in profits earned by the non-skilled traders is likely the volatility that creates differing statistical results in the decile tests, method 2. 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 yearly 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 yearly, live cattle quarterly, and coffee quarterly and monthly). In table 4.5, the significance of the tests is consistent across differences between the deciles studies

(10%, 20%, and 50%), but in light of the figures 4.1-4.3 the significance in the 20th and 50th percentiles is likely driven by the 10th percentile traders.

In general, the figures look similar across commodities indicating that traders perform similarly regardless of the market or time frame and allows for a visual assessment of the results presented by both statistical methods. The tendency for traders to remain in the approximately the same decile across periods helps explains results for method 1, the persistent ranking tests. Conversely, the drastic shifts in deciles 1 and 10 are likely the volatility that creates differing results for method 2, the decile tests.

4.7 Summary

The rigorous assessment testing if past trader profits can determine future trader performance, indicates a portion of traders do have the skill and the ability to persistently perform. The result help to explain why speculative traders continue to participate if no risk premium exists in the futures market (Aulerich 2011b). Traders are motivated by the ability to predictably perform and ability to expand trading when they determine themselves to have skill.

The contributions of this essay are threefold. First, to overcome previous time and scope limitations by using a dataset spanning ten years and across three main commodity contracts. Second, to test profits earned during monthly, quarterly, and yearly periods to account for investment horizons longer than a single day. Third, to focus solely on the profitable category of noncommercial traders that removes noise from commercial traders. Commercial traders are generally regarded as hedgers who may have both hedging and speculative motives for trading that makes profit interpretation problematic.

As shown in Aulerich (2011b), the noncommercial category is the most profitable earning $7.9 billion over 12 commodity markets and subsequently provides the speculative trader proxy to analyze in this essay. Data from the CFTC Large Trader Reporting System database is the same as used by Aulerich (2011a, 2011b) and spans from 2000 to mid-2009 analyzing corn traded on the Chicago Board of Trade (CBOT), live cattle traded on the Chicago Mercantile Exchange (CME), and coffee traded on Intercontinental Exchange (ICE) to represent field crops, livestock, and soft commodities.

Two methods are used to analyze the persistent ability of traders; (i) the first is the Fisher Exact test, a nonparametric two-way winner and loser contingency table analysis and (ii) the second is the testing of trader by magnitude of profits using the rank of trader profits in the first period to identify top and bottom deciles. A standard t-test or Wilcoxon signed-rank test is then used to determine whether profits from the traders in these deciles differ in the next period. The tests have been widely applied in studies of investment performance (e.g., Malkiel, 1995), and are viewed as an out-of-sample assessment of trader ability to consistently generate profits.

The first method's pooled results for the Fisher Exact tests show evidence of persistence in rankings across the commodities and time horizons studied. The annual, quarterly, and monthly results convincingly show that a portion of traders persistently rank among peers across time periods providing evidence that traders have trading skill. The second method tests the difference in profitability levels between top and bottom deciles. The annual results provide convincing evidence that the top 10% of traders persistently perform over the long term. Evidence from the quarterly and monthly performance horizons is strong for corn but more mixed for live cattle and coffee likely due to the high degree of price volatility during shorter time periods. Despite the mixed results for the shorter time periods, a subset of noncommercial traders convincingly demonstrate the ability to persistently perform.

Relating results back to previous research by Hartzmark (1991), Leuthold et al. (1994) and Fishe and Smith (2010) is somewhat challenging because they use different methods and time horizons. Despite these distinctions, this essay finds a larger portion of traders have skill in earning profits than previous studies. Harztmark finds that out of 1,622 noncommercial traders about 5% perform persistently, Leuthold analyzes 2% of traders out of 3,171 and finds them to have skill, and Fishe and Smith find 1% to 3.5% of traders are informed. This essay finds that the top 10% of traders have substantial ability to persistently perform relatively well. The rigorous procedures in this essay provide evidence of skill to explain why speculative traders continue to participate in agricultural futures markets. This emerges regardless of the sample, commodity, or method used, and supports the structure of the Mahani and Bernhardt model (2007) which is able to account for such a structure within a rational learning based model. What is still unknown is what trading strategies are used by successful traders? Do successful traders using technical trading rules? Fundamental commodity information? Some combination? The results from this paper provide evidence that skilled traders exist but are not able to determine the precise strategies used to earn persistent returns.

4.8 Tables and Figures

Table 4.1 Summary Statistics of Major Trader Categories, 2000 - 2009

	Commercial				**NonCommerical**				**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	0
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 indiviudal 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 4.2 Summary Statistics, Noncommerical Included versus Excluded Traders

	Time Horizon		
	Yearly *(obs=9)*	Quarterly *(obs=38)*	Monthly *(obs=116)*
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 4.3 Predictability of Trader Performance Based on Total Profits. Fisher Exact Test of Winner and Loser Categories between Adjacent Time Periods, 2000-2009

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

Table 4.4 Predictability of Trader Performance Based on Total Profits. Pooled Fisher Exact Test of Winner and Loser Categories between Adjacent Time Periods, 2000-2009

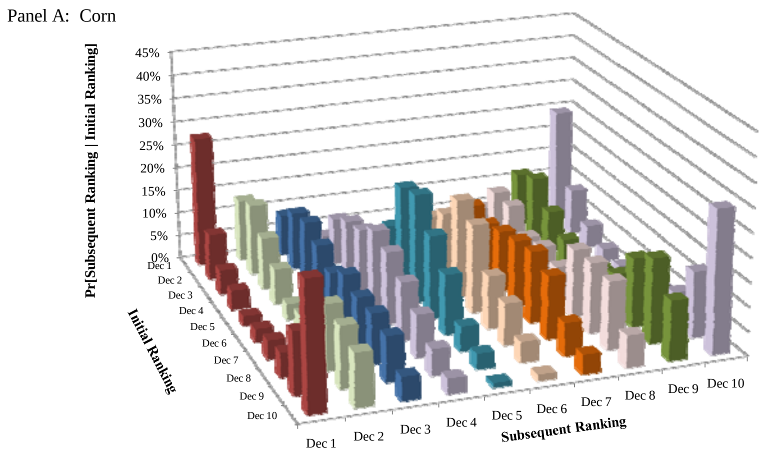
		Corn			Live Cattle			Coffee		
		Number of Traders		Two-Tail p-Value	Number of Traders		Two-Tail p-Value	Number of Traders		Two-Tail p-Value
Period		Winner *t+1*	Loser *t+1*	for Fisher's Exact	Winner *t+1*	Loser *t+1*	for Fisher's Exact	Winner *t+1*	Loser *t+1*	for Fisher's Exact
Annual (9 pairs)				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

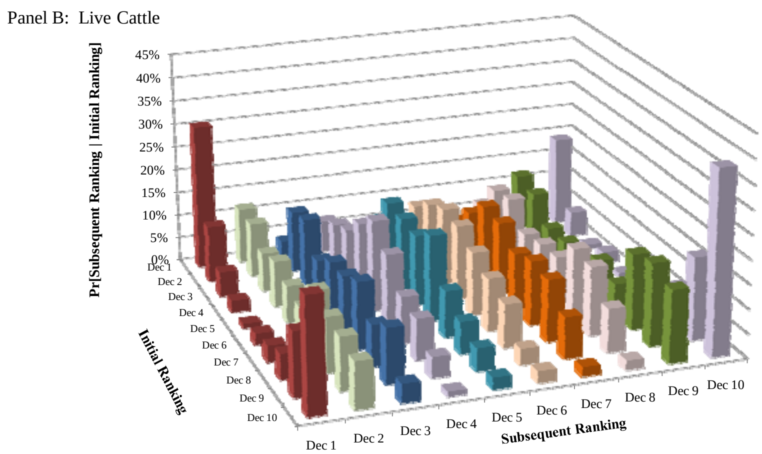
Table 4.5 Predictability of Trader Profitability Based on Groups of Adjacent Pairs of Time Horizons for, Corn, Live Cattle, and Coffee, 2000-2009

	Yearly (,000)							**Quarterly (,000)**							**Monthly (,000)**						
	Profits			Student's t		Signed Rank		Profits			Student's t		Signed Rank		Profits			Student's t		Signed Rank	
Decile	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																					
10 (best)	1143							795							226						
9	-36							173							52						
8	3							5							15						
7	53							40							22						
6	68							-1							4						
5	8							1							0						
4	-70							17							2						
3	80							-2							-11						
2	90							-71							-16						
1	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 Catte																					
10 (best)	3,482							529							420						
9	464							75							80						
8	319							115							17						
7	266							47							19						
6	351							29							15						
5	79							2							14						
4	36							14							5						
3	-79							83							20						
2	-195							10							15						
1	-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																					
10 (best)	-220							-431							-256						
9	-186							-95							-91						
8	-21							-56							-27						
7	-39							-24							-14						
6	-43							-34							4						
5	7							6							-13						
4	-43							-30							-4						
3	-298							-63							6						
2	-502							-106							-33						
1	-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: Decile 10 is the highest and decile 1 is the lowest. 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.

Figure 4.1 Contingency table of initial and subsequent annual performance rankings.
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.





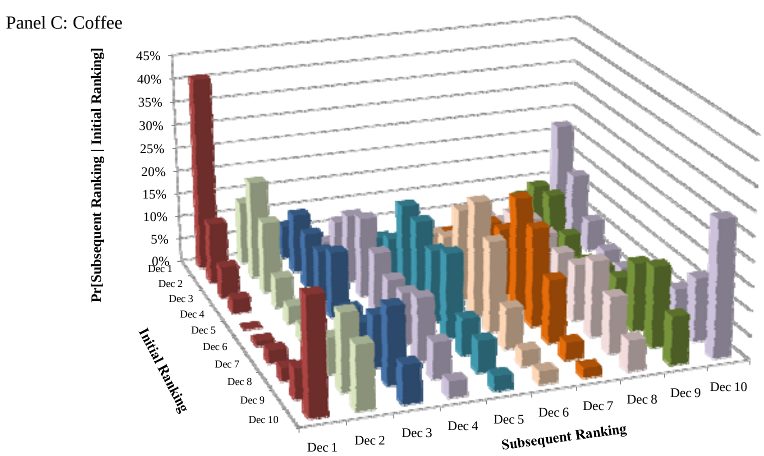
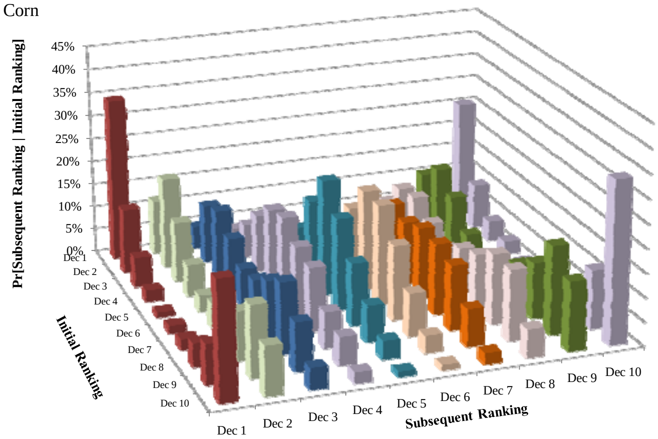
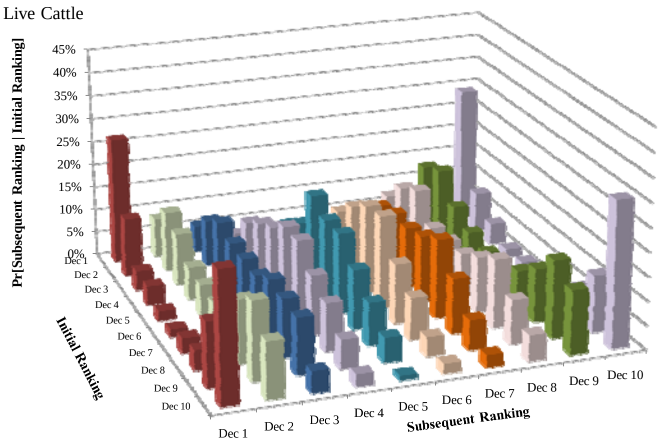


Figure 4.2 Contingency table of initial and subsequent quarterly performance rankings.
In each calendar year from 2000 to 2009,traders are ranked into decile portfolios based on one-year gross returns. These initial decile rankings are paired with the trader's subsequent one-year gross return ranking. 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

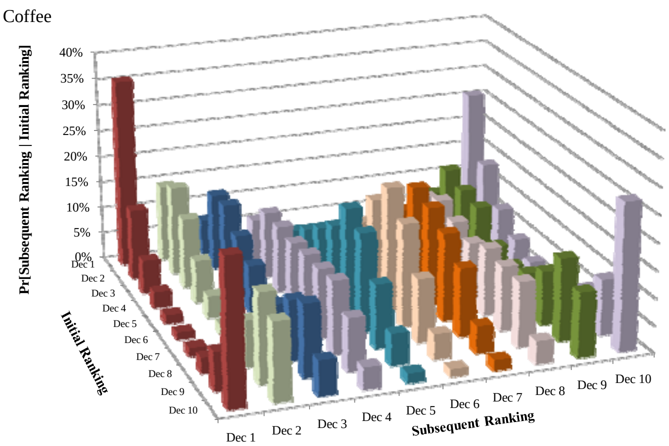
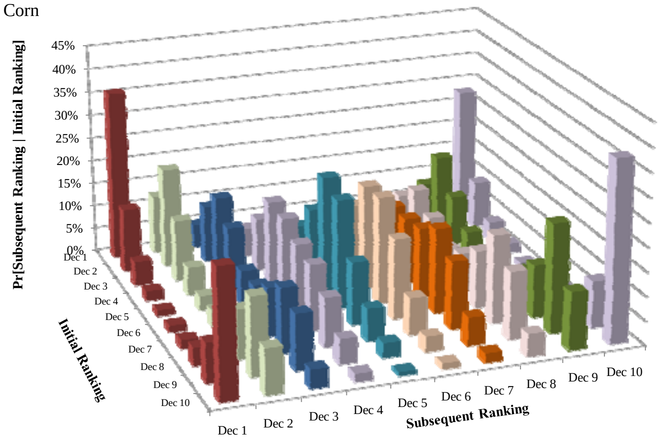
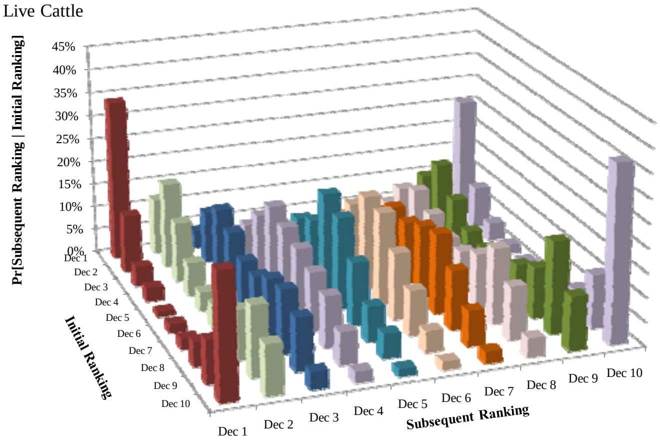


Figure 4.3: Contingency table of initial and subsequent monthly performance rankings.
In each calendar year from 2000 to 2009,traders are ranked into decile portfolios based on one-year gross returns. These initial decile rankings are paired with the trader's subsequent one-year gross return ranking. 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.

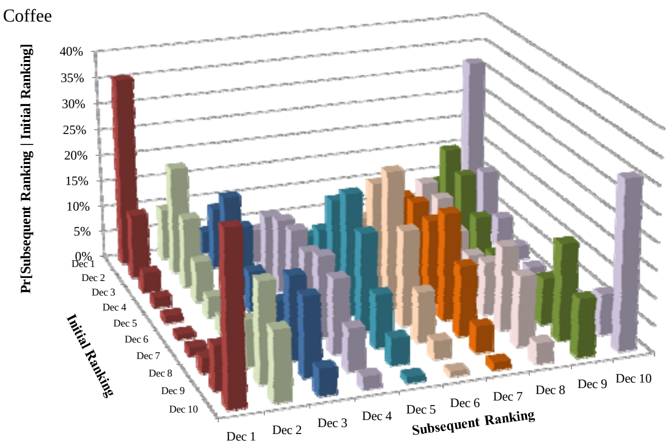
Panel A: Corn



Panel B: Live Cattle



Panel C: Coffee



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6. ENDNOTES

[1] The wheat traded on the Minnesota Grain Exchange is not included in commodity index funds.

[2] The source is the CFTC *Quarterly Index Investment Data* report found at: http://cftc.gov/marketreports/IndexInvestment/index.htm.

[3] In reality, a variety of investment instruments are typically lumped under the heading 'commodity index fund.' Large institutional investors, such as pension funds, may enter directly into over-the-counter (OTC) contracts with swap dealers to gain the desired long exposure to returns from a particular index of commodity prices. Some firms also offer investment funds whose returns are tied to a commodity index. Exchange-traded funds (ETFs) and structured notes (ETNs) have also been developed to make it easier for smaller investors to obtain commodity exposure in their portfolios. ETFs and ETNs trade on securities exchanges in the same manner as stocks on individual companies. See Engelke and Yuen (2008) and CFTC (2008b) for additional details.

[4] With the exception of Sanders and Irwin (2011), that utilizes weekly bank participation data as a proxy for index trader activity prior to 2006.

[5] RBOB stands for Reformulated Blendstock for Oxygenated Blending.

[6] 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.

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

[8] This assumption does not imply that the number of CIT traders is constant across the sample period. In fact, the number of CIT traders rises over time in parallel with the rise in aggregate CIT positions. For example, the number of CIT traders in corn increases from 7 in 2000 to 31 in 2008. Retroactive application of CIT classifications prior to 2006 could induce two types of misclassification error. First, CITs that traded between 2000 and 2005 but ceased operation sometime before 2006 would be excluded from the CIT category over 2000-2005. Second, traders classified as CITs over 2006-2008 would be incorrectly categorized as CITs over 2000-2006 if they changed their line of business at some point before 2006. Given the stability in CIT classifications over 2006-2008 the likelihood of either type of error is minimal.

[9] The patterns in the corn market are representative of those identified in other markets except where identified in the text. Similar figures for the other commodities are available from the author.

[10] CITs did not trade in the August and September soybean contracts, August, September, and October soybean oil contract, May lean hog contract, or October cotton contract.

[11] This material can be found at the following website: http://www2.goldmansachs.com/services/securities/products/sp-gsci-commodity-index/roll-period.html.

[12] Simple correlation between the two series is -0.94.

[13] Since non-stationarity tests have low power, Enders (1995) argues that rejection of the null with a constant and trend provides strong evidence that a series is stationary. Detailed results are available from the authors.

[14] In equation 5 and 6 the CIT position variable (NX_{t-j} or DX_{t-j}) is lagged one day, but it can be

argued that, CITs do not make decisions during the roll period that are based on expectation of futures returns which makes positions and prices exogenous. For this reason, equations 5 and 6 are also calculated without lagging CIT positions, where j=0 instead of j=1. The results were not markedly different from the results using lagged CIT positions and will therefore not be displayed.

[15] To clarify, the variables are lagged prior to removing the days outside the roll window. For example, returns on day t may be the independent variable and lag of positions on day $t-1$ may be the explanatory variable. If t is the first day of the roll period, then $t-1$ positions would not be in the roll period. In this estimation $t-1$ positions are still used in the estimation as the roll period definition is only applied to the independent variable t.

[16] Research conducted by Brunetti and Reiffen (2010) determines that the absolute level of index traders in the nearby contract increase spreads by they do not look at the absolute level of index traders in the deferred contract. Conversely, this methodology uses *changes* in index positions for both nearby and deferred contracts in an SUR system.

[17] Research done by Mou (2010) argues that commodity index traders do impact commodity spreads during the roll period but the methodology does not use actual index trader positions. Mou uses a yearly estimate of CIT investment value divided by average market value, unlike this essay that uses actual daily CIT positions by maturity during the roll period. Conversely, Irwin et. al (2011) finds that an increase in spreads occurs during the roll period even *before* index traders were major participants in the market place; they use data from 1995 to July 2010.

[18] This is slightly different than examining volatility when aggregate CIT positions are the explanatory variable. In this short roll period, the transfer of open interest from the nearby to first deferred would be expected to increase volatility in both contracts.

[19] Due to the negative position change the coefficient would also have to be negative. A negative position multiplied by a negative coefficient is positive overall impact on volatility.

[20] If spreads widen, then nearby prices would decrease and/or deferred prices would increase. If spreads narrow, then nearby prices would increase and/or deferred prices would decrease.

[21] Delta measures the rate of change in option value with respect to changes in the underlying asset price. Adjusting options positions by delta makes options positions comparable to futures positions in terms of price changes.

[22] The data does not include positions of day traders or scalpers since these participants seldom carry positions overnight.

[23] The reporting levels for the commodities in this paper include coffee and feeder cattle at 50 contracts, cotton, cocoa, live cattle, and lean hogs at 100 contracts, CBOT wheat and KS wheat at 150 contracts, soybean oil at 200 contracts, corn at 250 contracts, and sugar at 500 contracts.

[24] The CFTC released a new weekly Disaggregate COT report on October 20, 2009. The first iteration of the report covers 22 major physical commodity markets; on December 4, 2009, the remaining physical commodity markets were included. The Disaggregated COT report increases transparency from the legacy COT reports by separating traders into the following four categories of traders: Producer/Merchant/Processor/User; Swap Dealers; Managed Money; and Other Reportables. The new Disaggregated COT report does not break out Commodity Index Traders. In addition, the CFTC began another weekly report called Traders in Financial Futures

on July 22, 2010. The new report separates large traders in the financial markets into the following four categories: Dealer/Intermediary; Asset Manager/Institutional; Leveraged Funds; and Other Reportables.

[25] This assumption does not imply that the number of CIT traders is constant across the sample period. In fact, the number of CIT traders rises over time in parallel with the rise in aggregate CIT positions. For example, the number of CIT traders in corn increases from 7 in 2000 to 31 in 2009. Retroactive application of CIT classifications prior to 2006 could induce two types of misclassification error. First, CITs that traded between 2000 and 2006 but ceased operation sometime before 2007 would be excluded from the CIT category over 2000-2006. Second, traders classified as CITs over 2007-2009 would be incorrectly categorized as CITs over 2000-2006 if they changed their line of business at some point before 2006. Given the stability in CIT classifications over 2006-2009 the likelihood of either type of error is minimal.

[26] Both futures and options positions are used because they are closely linked and provide a comprehensive picture of a trader's exposure to the market. Aulerich (2011a) does not use options because index traders have little open interest in option markets as the majority of index funds invest solely in futures.

[27] The same profit methodology is implemented in Hartzmark (1987, 1991) and Leuthold (1994).

[28] Since commercial traders are more likely to be exchange members (with lower transactions costs), the dollar profits for the noncommercial traders would probably be reduced more than those of commercial traders if it were possible to include these costs (Hartzmark 1987).

[29] Since futures trading is a zero sum game, the nonreporting category is the residual from the large trader profits.

[30] Hartzmark (1987) used only monthly returns when calculating significance. This testing procedure also employs daily returns for robustness and to account for varying investment horizons.

[31] Skewness and Kurtosis is not reported in the table.

[32] The three series graphs for all commodities are provided in Appendix A.

[33] An inconsistent return on investment could be symptomatic of a shift in CIT objectives for investment.

[34] Using notional value is plausible when measuring CIT return on investment because CITs invest in an unleveraged manner. In practice CITs pay the required margin and invest the remaining value in low risk short term investments such as 3 month treasury bonds (Engelke 2008).

[35] Notional value is calculated as CIT open interest multiplied by both the contract size and settlement price summed over all maturities and commodities.

[36] This phenomenon may possibly only be seen with intraday data if any price distortions caused by the rolling traders dissipate before the trading day is complete. In this case, the end of day data would not capture this cost.

[37] The roll period is defined as the 10th business day and greater in 2nd month before expiration through business days 1 through 10 in month before expiration. The roll period is shown to encompass the greatest amount of roll activity with the shortest time period (Aulerich 2011a). These results are also calculated for another roll period called the "Goldman Roll" defined as the

5th through 9th business days in the month before expiration. The conclusions do not change substantially.

[38] The debate surrounding investment skill is also hotly debated in the analysis of mutual fund and hedge fund managers as these funds contend for investment dollars. Commonly, the studies try to determine if managers can persistently earn ‘alpha’ or a return beyond that of a comparable naïve benchmark (Merton, 1981; Zeckhauser, 1993; Carhart, 1997; Wermers, 2000; Kosowski, 2006). The various testing methodologies using in mutual fund and hedge fund literature are more relevant to this essay than the actual results because this essay focuses on individual trader performance and not overall portfolio performance.

[39] Row crops include corn, soybeans, soybean oil, CBOT wheat, and KS wheat. These are seasonal commodities that are heavily produced in the United States and are easily stored. Livestock includes lean hogs, live cattle, and feeder cattle. Livestock are non-seasonal production cycle and have little to no storage abilities. Soft commodities include cocoa, coffee, cotton, and sugar. These commodities are seasonal and storable but production is not focused in the United States.

[40] The commodities chosen have the largest number of traders in each respective category.

[41] CAPM is the Capital Asset Pricing Model described by both Sharpe (1964) and Lintner (1965). The CAPM approach is calculating the return on a portfolio in excess of the one month T-bill return regressed on excess return on the CRSP value-weighted portfolio of NYSE and Nasdaq stocks. The significance of the y-intercept, or alpha, determines if the fund performance differs from overall market performance.

The CAPM approach is modified in Fama and French (1993) into a 3 factor model. This model regresses the return on a portfolio in excess of the one month T-bill return regressed on excess return of a value weighted aggregate market proxy and value weighted factor mimicking portfolios for size and book-to-market equity. Carhart (1997) then expanded the 3 factor model into a 4 factor model by adding an additional regression variable, one year momentum on stock returns. The resulting regression is then return on a portfolio in excess of the one month T-bill return regressed on excess return of a value weighted aggregate market proxy and value weighted factor mimicking portfolios for size, book-to-market equity, and one year momentum on stock returns) by using his 4 factor model but apply a new bootstrap statistical technique that accounts for the complex non-normal distribution of mutual fund alphas, heterogeneous risk-taking by funds, and non-normalities in individual fund alpha distributions.

[42] 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.

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

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

[45] There are a small portion of traders that 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.

[46] Futures positions include delta adjusted option positions.

[47] As shown in the second essay, CITs fall outside the category of traditional speculators and are not profitable over the time period studied.

[48] Commercial traders may also use the futures market for speculative positions but must have a significant amount of hedging activity to be classified as a commercial.

[49] Since all of traders in this analysis are noncommercial traders, the differencing in transaction costs between traders is likely to be smaller than comparison across trader categories. For example, commercial traders are more likely to be exchange members and would possibly have lower transactions costs than non-exchange members.

[50] The absolute number of traders is calculated as the average number of unique traders per month, per quarter, or per year. Therefore the number of excluded and included traders is less for shorter time horizons (e.g. monthly is less than quarterly and quarterly is less than yearly).

[51] The contingency table results are also conducted on two additional measures of performance for robustness checks. In addition to profitability levels, total profit for a period is first normalized by average daily total notional value for the period and second by average net daily notional value. Two different notional value measures are used because spread traders notional value would be over represented by using total notional value but underrepresented using net notional value. Therefore, both measures are used for normalization of profits by investment size. Ultimately both measures produce similar results both to each other and the total profits measure reported in the main body of this essay.

[52] Outliers could also be a factor that makes it impossible to find consistent patterns in a statistical sense. Outliers are examined in this dataset by graphing individual trader profits in a

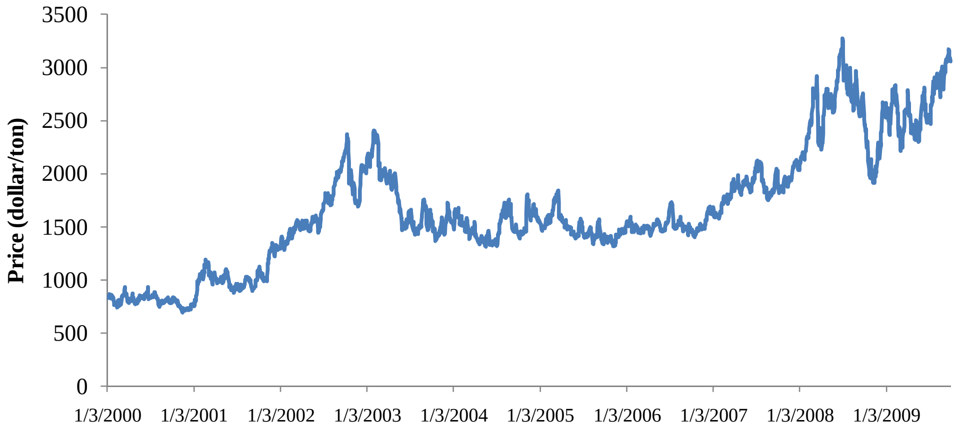
scatter plot with a trader performance in time *t* on the x-axis and time *t+1* on the y-axis. The biggest impact outliers that would bias findings in the direction of significance lie in the upper right corner of quadrants I and lower left corner of quadrant III, and outliers that would bias findings in the direction of not finding significance lie in the upper left corner of quadrant II and lower right corner of quadrant IV. Upon analyzing the scatter plots and stem and leaf plots, outliers do not appear to be a major concern in this analysis.

[53] This is more easily seen from the tables of underlying data which are not provided in this paper.

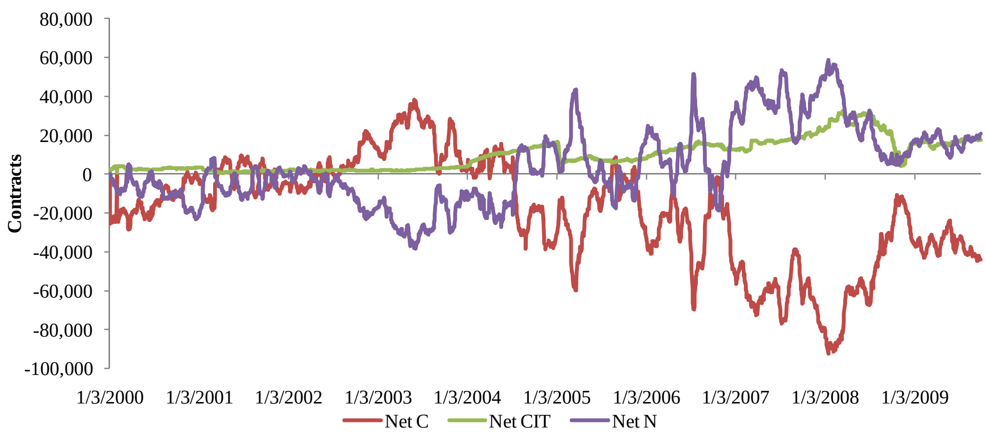
7. APPENDIX

Figure 7.1 Futures Contract Prices, Positions, and Profits for Cocoa, 2000-2009

Panel A: Nearby Prices



Panel B: Net Positions



Panel C: Cummulative Daily Profits

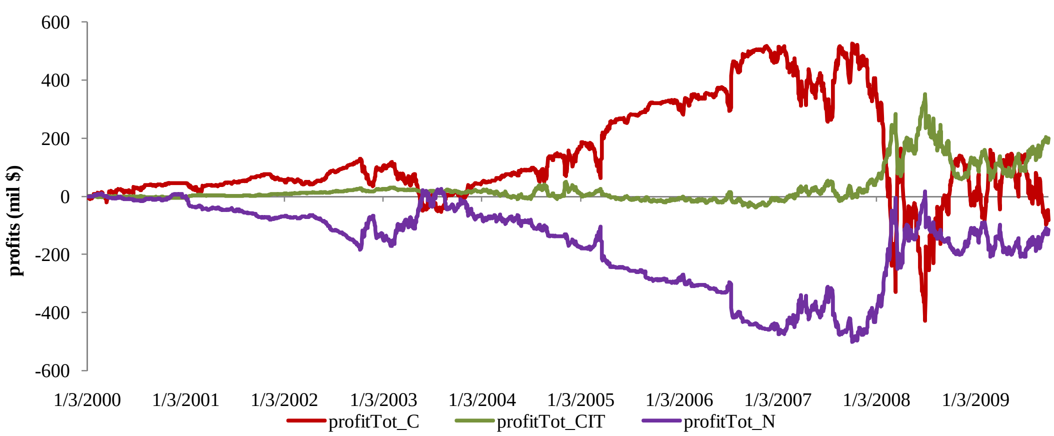
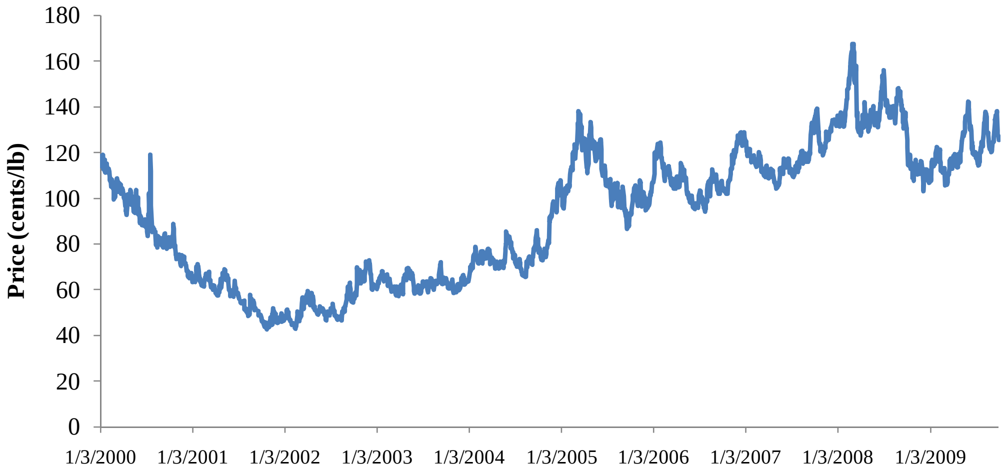
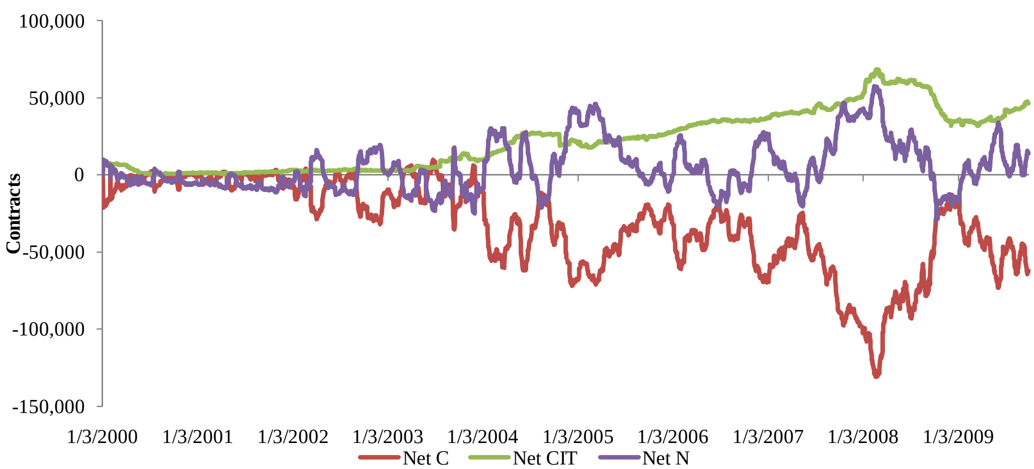


Figure 7.2 Futures Contract Prices, Positions, and Profits for Coffee, 2000-2009

Panel A: Nearby Prices



Panel B: Net Positions



Panel C: Cummulative Daily Profits

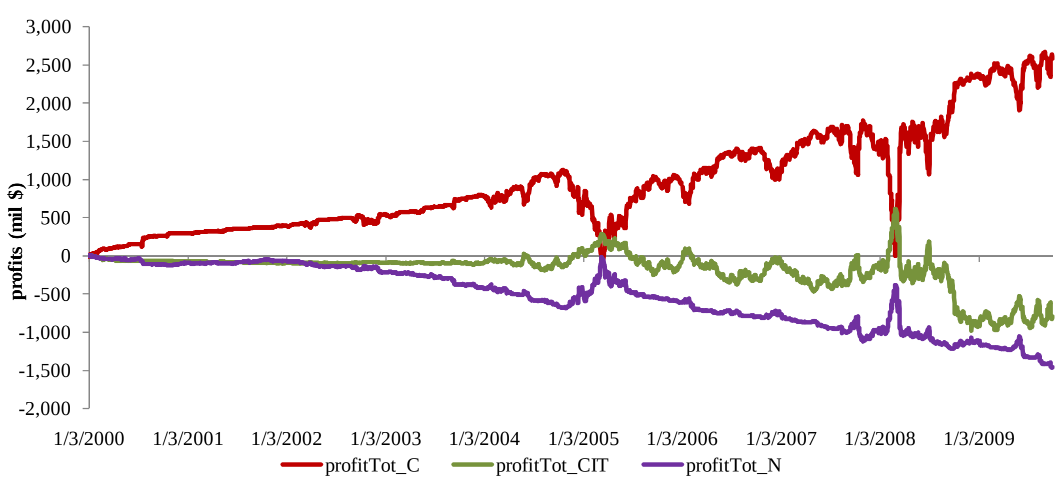
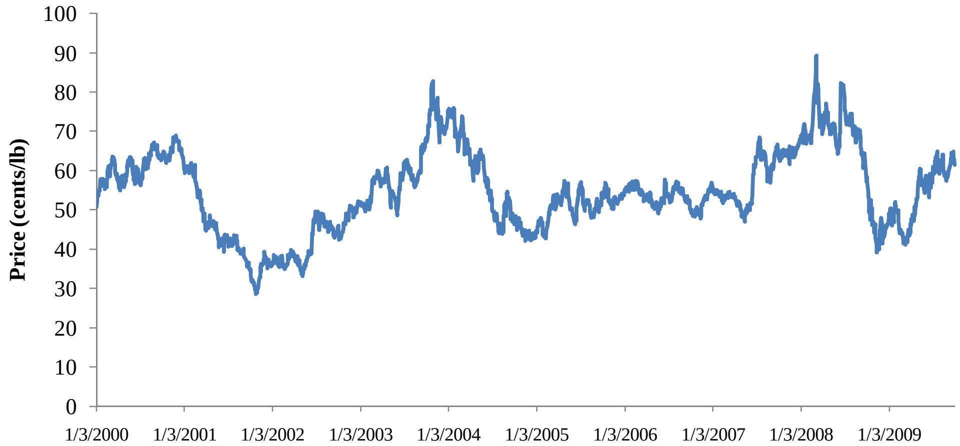
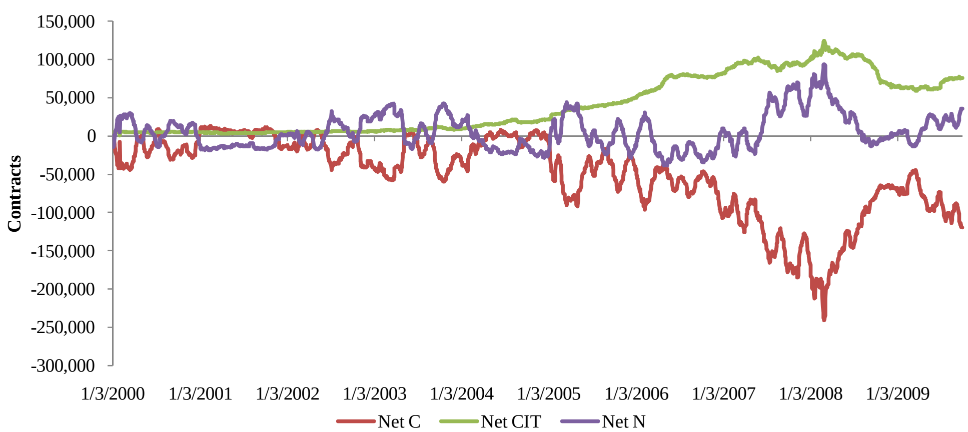


Figure 7.3 Futures Contract Prices, Positions, and Profits for Cotton, 2000-2009

Panel A: Nearby Prices



Panel B: Net Positions



Panel C: Cummulative Daily Profits

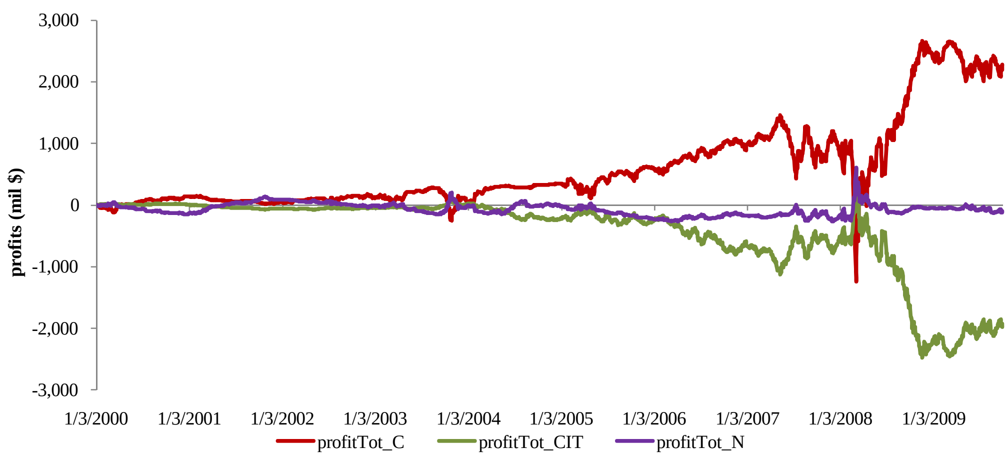
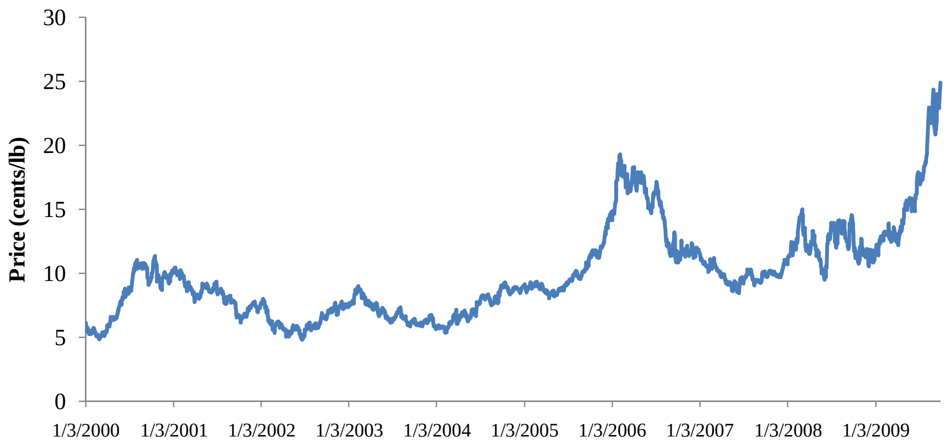
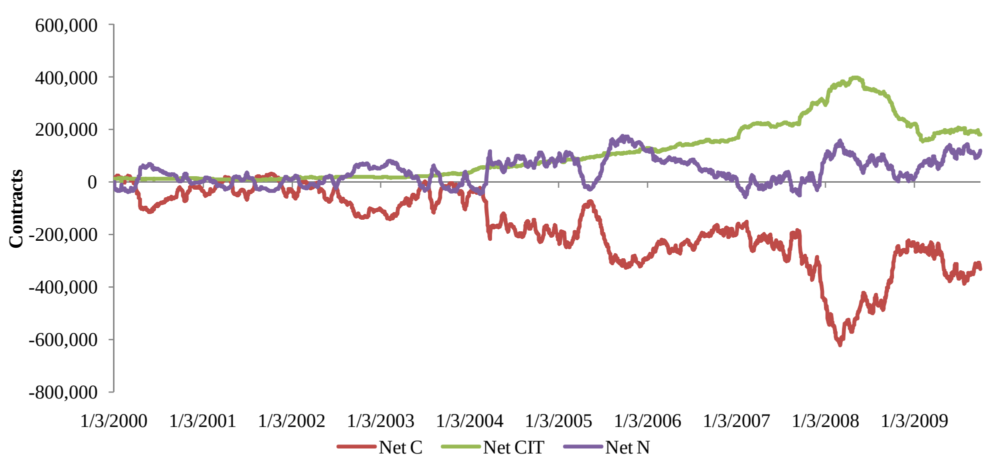


Figure 7.4 Futures Contract Prices, Positions, and Profits for Sugar, 2000-2009

Panel A: Nearby Prices



Panel B: Net Positions



Panel C: Cummulative Daily Profits

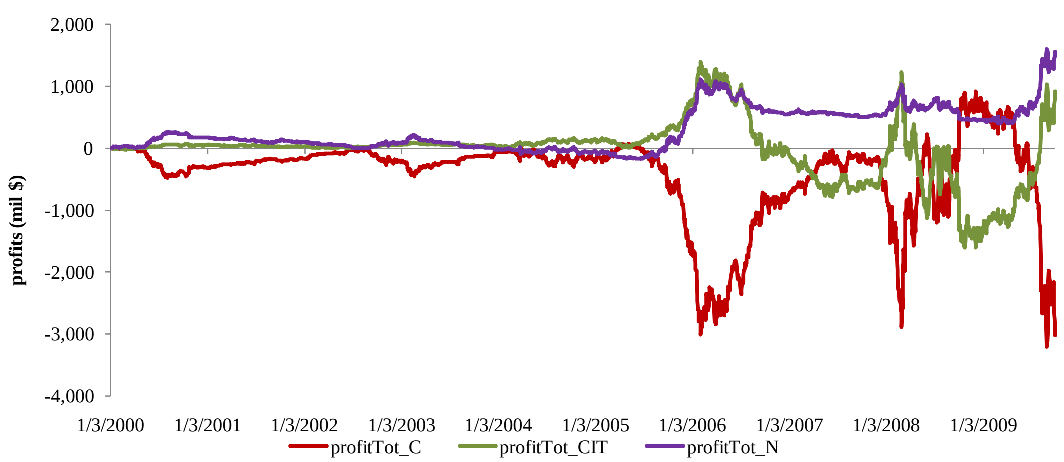
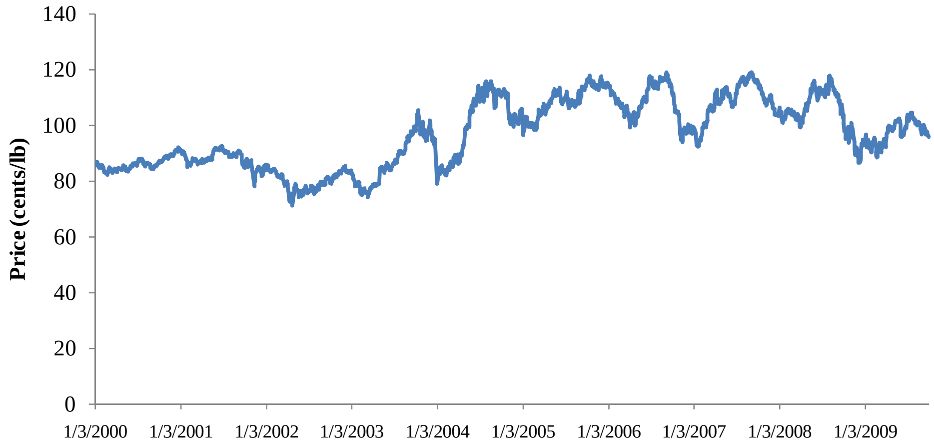
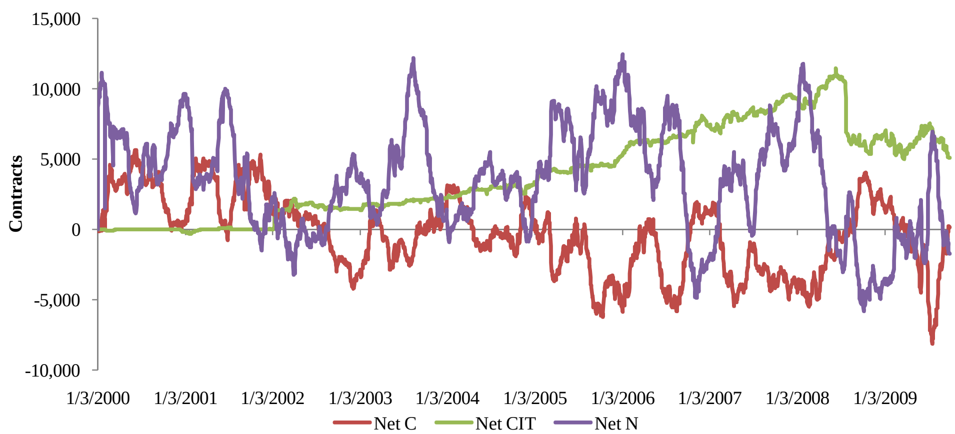


Figure 7.5 Futures Contract Prices, Positions, and Profits for FeederCattle, 2000-2009

Panel A: Nearby Prices



Panel B: Net Positions



Panel C: Cummulative Daily Profits

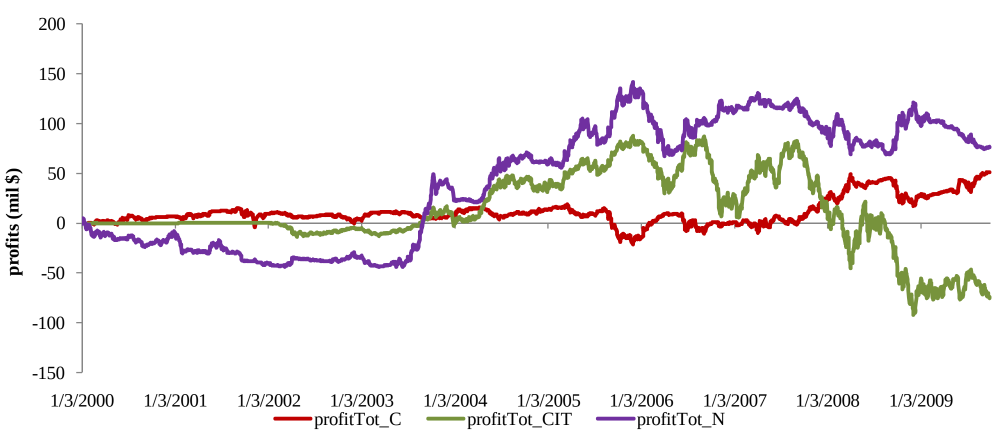
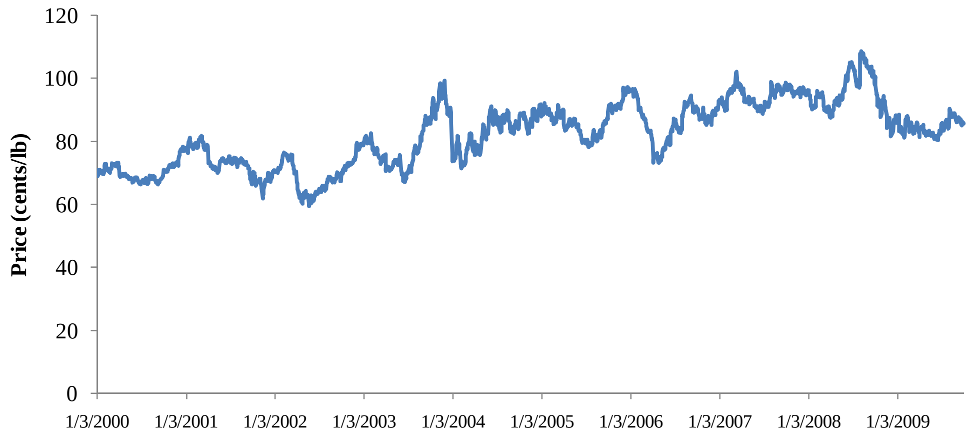
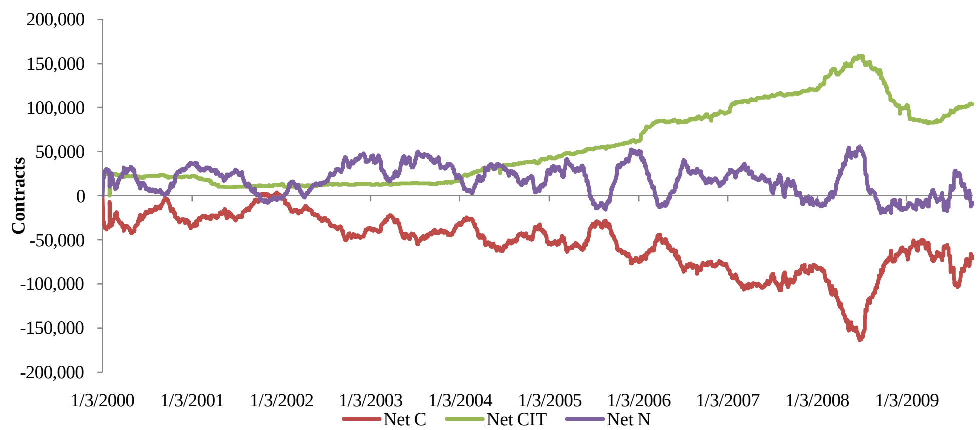


Figure 7.6 Futures Contract Prices, Positions, and Profits for Live Cattle, 2000-2009

Panel A: Nearby Prices



Panel B: Net Positions



Panel C: Cummulative Daily Profits

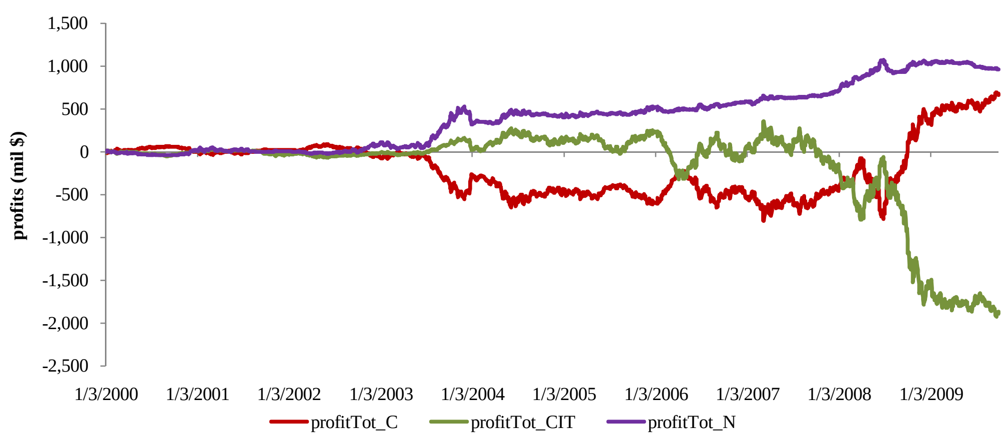
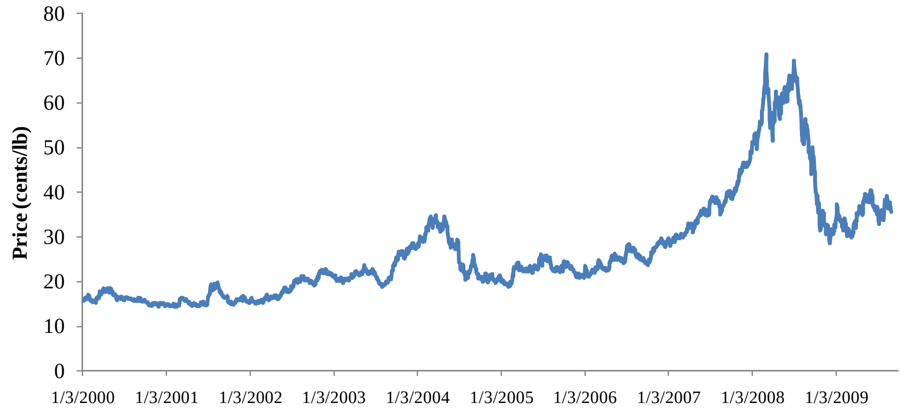
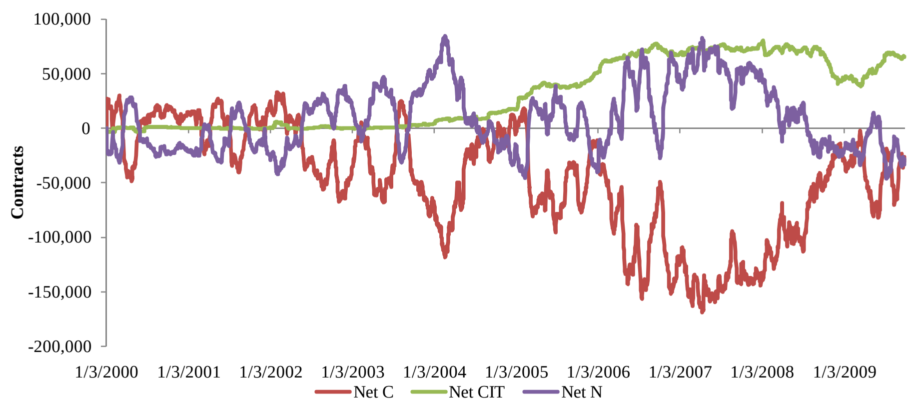


Figure 7.7 Futures Contract Prices, Positions, and Profits for Soybean Oil, 2000-2009

Panel A: Nearby Prices



Panel B: Net Positions



Panel C: Cummulative Daily Profits

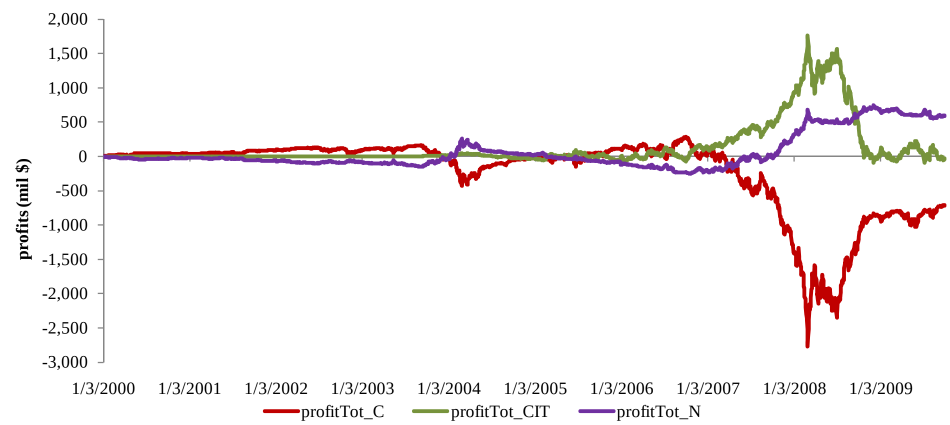
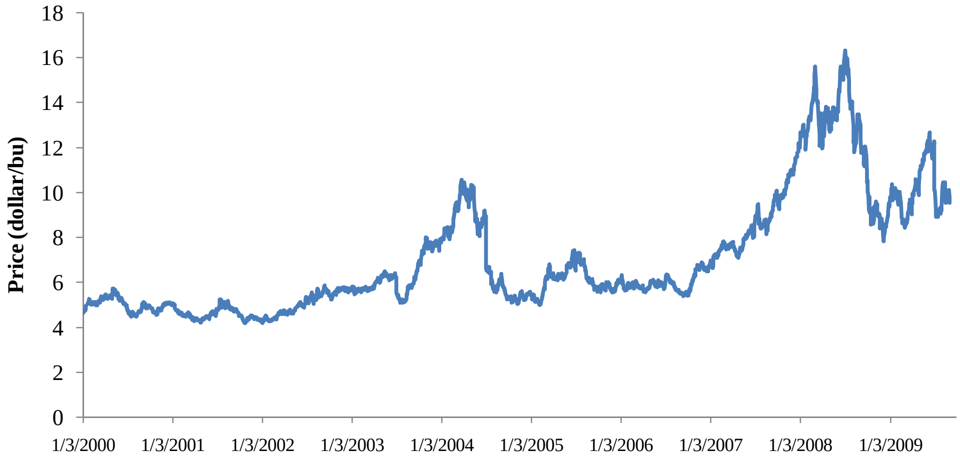
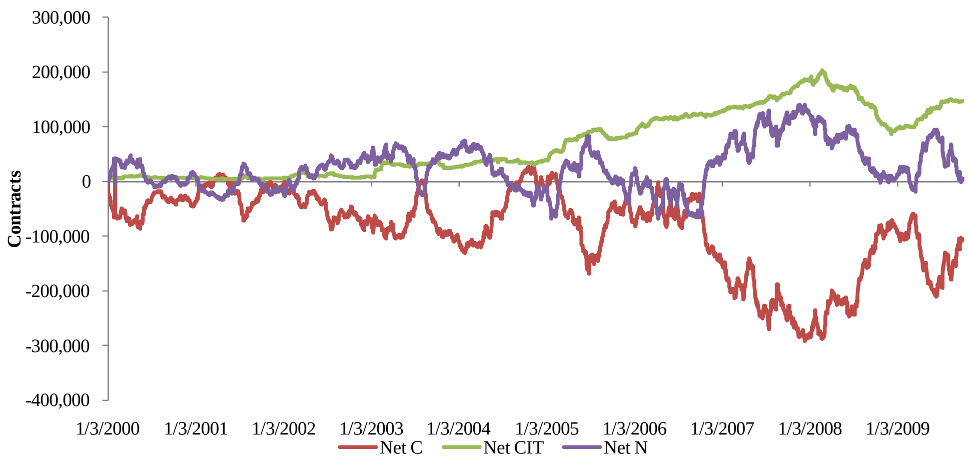


Figure 7.8 Futures Contract Prices, Positions, and Profits for Soybeans, 2000-2009

Panel A: Nearby Prices



Panel B: Net Positions



Panel C: Cummulative Daily Profits

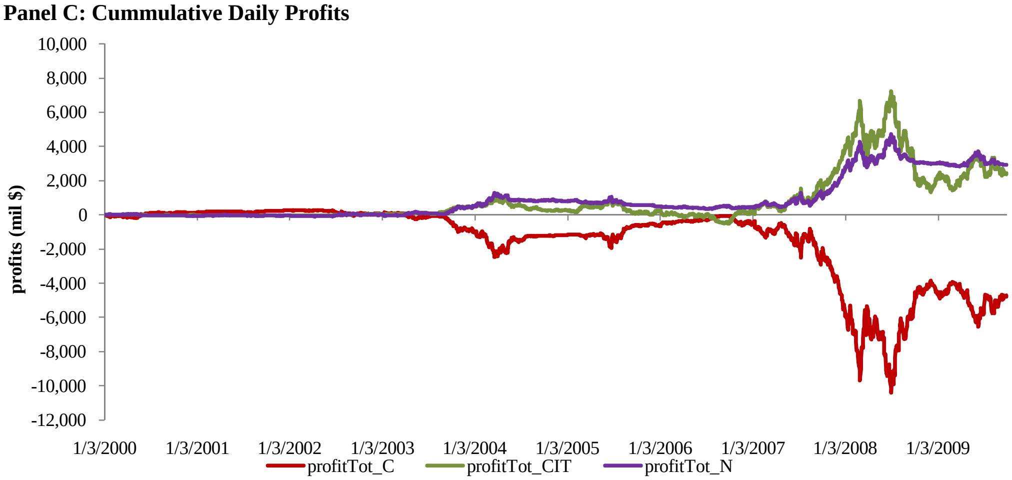
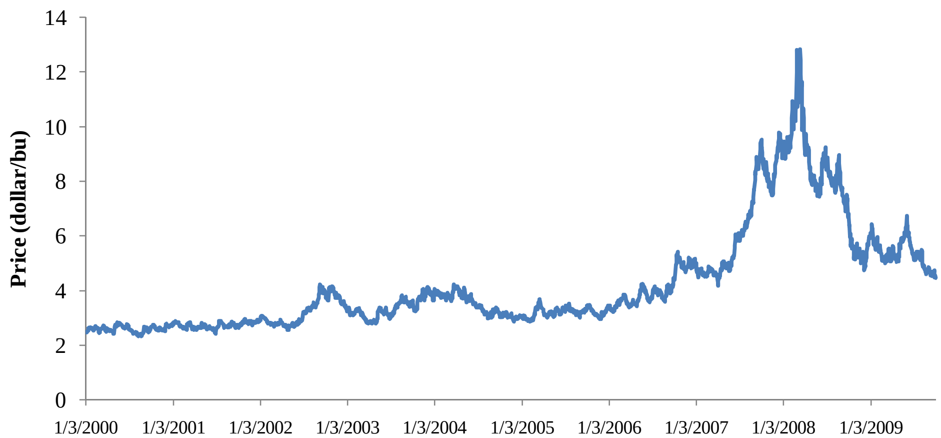
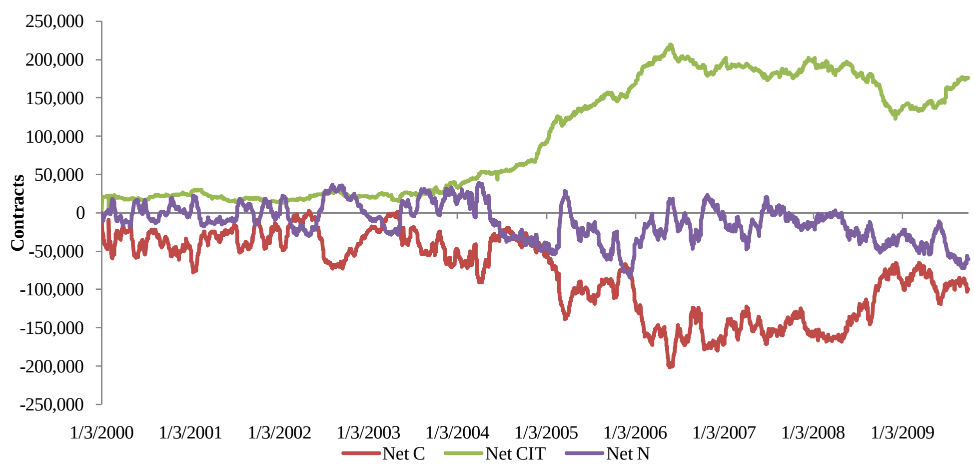


Figure 7.9 Futures Contract Prices, Positions, and Profits for Wheat CBOT, 2000-2009

Panel A: Nearby Prices



Panel B: Net Positions



Panel C: Cummulative Daily Profits

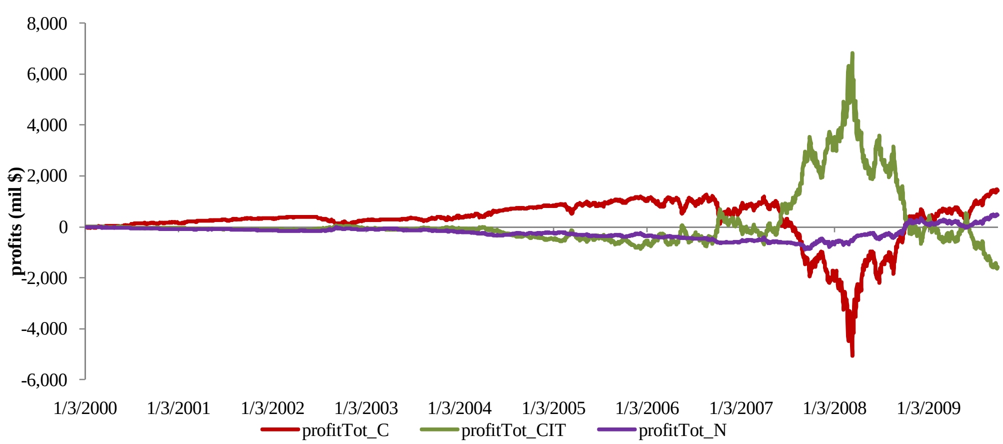
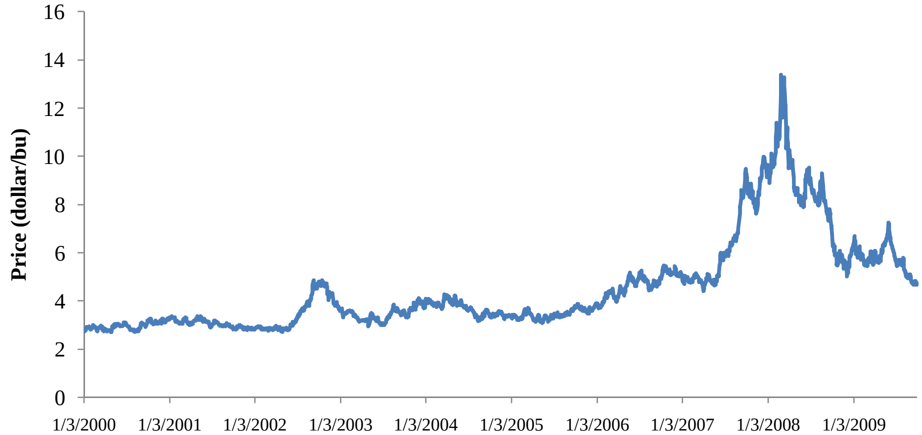
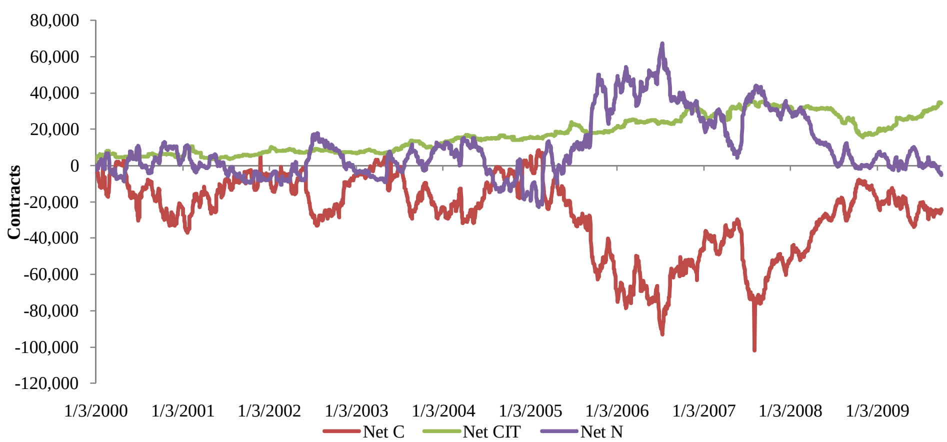


Figure 7.10 Futures Contract Prices, Positions, and Profits for Wheat KS, 2000-2009

Panel A: Nearby Prices



Panel B: Net Positions



Panel C: Cummulative Daily Profits