8-2015

Effects Of Noncommercial Open Interest On Corn And Soybean Futures Price Volatility

William Grady Ferguson
University of Tennessee - Knoxville, wfergus5@vols.utk.edu

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I am submitting herewith a thesis written by William Grady Ferguson entitled "Effects Of Noncommercial Open Interest On Corn And Soybean Futures Price Volatility." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Agricultural Economics.

Aaron Smith, Major Professor

We have read this thesis and recommend its acceptance:

Jim Larson, Kim Jensen, Dayton Lambert

Accepted for the Council:
Carolyn R. Hodges

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

Effects Of Noncommercial Open Interest On Corn And Soybean Futures Price Volatility

A Thesis Presented for the
Master of Science
Degree
The University of Tennessee, Knoxville

William Grady Ferguson
August 2015

ACKNOWLEDGEMENTS

I would like to thank Dr. Aaron Smith for his many hours of conversation and debate on agricultural futures markets and for his willingness to explore new research topics and methods. I would like to thank Dr. Roland Roberts for his enthusiasm and fastidious technical and literary critiques over the past several years. The contributions of my advising committee are appreciated, especially the technical guidance of Dr. Dayton Lambert. Outside the department, Dr. Hamparsum Bozdogan and doctoral candidate Tyler Massaro provided valuable insights and discussion in statistics. Lastly, I would like to thank doctoral candidate Jessica Welch for sharing her invaluable research style of impassioned pragmatism and her work ethic of concerted incrementalism.

ABSTRACT

Since the early 2000s a dramatic rise in institutional investment in agricultural futures markets has occurred. This rise may have caused an increase in price volatility, potentially resulting in added risk for farmers, agribusinesses, and consumers. Currently, regulators, hedgers, exchanges, and speculators lack information regarding how modern investments in agricultural futures markets affect short-term price volatility. The objective of this analysis is to examine the effect of institutional investment on short-term price volatility for corn and soybean futures markets. Using daily price data for corn and soybean futures from the Chicago Board of Trade (CBOT), several measures of price volatility – including differences, ratios, and measures of central tendency – are calculated and their results compared by Akaike's Information Criteria (AIC) and Schwarz Bayesian Criteria (SBC). Using the Commodities Futures Trading Commission's (CFTC) Commitments of Traders (COT) weekly Aggregated Futures and Options Combined report for corn and soybeans, a percent of open interest held by noncommercial traders is used to estimate movements in institutional investment. In order to account for the dependence of price on recent prices and the dependence of the variance of price on recent variances of price, a bivariate generalized autoregressive conditionally heteroskedastic (GARCH) model is used in this analysis. Portmanteau Q Tests and Engle's LM tests are used to justify this approach. We find for each model the effect of institutional investment on price volatility is positive and, for most models, statistically significant.

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CHAPTER I: INTRODUCTION

Agricultural commodities futures markets have long had two primary purposes: i) price discovery and ii) reducing the risk inherent in buying and selling commodities under changing market conditions. Through the futures and options markets, hedgers (or physical market participants) can reduce the uncertainty in return on investment. Hedging, as opposed to speculating, is the primary purpose of the agricultural futures markets (Arthur, 1966; p.230). Hedgers buy and sell commodity derivatives to protect against changes in the price of the physical commodity, while speculators buy and sell commodity derivatives for the purpose of earning money on the derivative. Speculators hold the critical role of providing liquidity, increasing the likelihood there will be a seller for every buyer and a buyer for every seller (Szafarz, 2012) and providing to the market more opinions regarding the most appropriate price. Speculators purchase or sell financial derivatives based on expectations of future prices accompanied by an equivalent, opposite, future transaction of the derivative. Speculators do this without offsetting activity in the underlying physical market (Kohlhagen, 1979; p. 323) and without the intention of owning the physical commodity. One category of speculators is institutional investment. While definitions for institutional investment vary, it can be very broadly thought of as a category comprised of large speculative traders.

While institutional investors have had a presence in agricultural futures markets since the markets' inception, the "financialization" of commodity futures is a relatively recent phenomenon in which the futures markets have become media for investment and traded similarly to debt and equity markets (Tang and Xiong, 2012; Buyuksahin and Robe, 2014). According to both studies, financialization of commodities has tied their price activity more strongly to those of equities. In recent literature it has become useful to address speculators as belonging to one of two categories: those that take only long positions and those that take long and/or short positions. Long-only speculators can take positions in a number of commodities, adjust the size of their longs to fit their forecasts, and many times make public the fund's weights by commodity (Irwin and Sanders 2011). Index funds are a common example of long-only speculators. Long-and-short speculators can take long and/or short positions, can take positions in a number of commodities, and generally do not make their compositions public (Irwin and Sanders 2011, p. 523). Hedge funds, commodity trading advisors (CTA), and Commodity Pool Operators (CPO) are of this category. Both long-only and long-and-short speculators are – in contract to physical market participants – subject to positions limits by the Commodities Futures Trading Commission[1] (CFTC, 2015b). Both long-only and long-and-short speculators can trade futures, options, over-the-counter (OTC) derivatives, and swaps. For this reason, either long-only or long-and-short speculators can affect short-term price volatility. *Institutional investment* is the moniker of large speculators of both varieties.

According to Barclay Capital estimates, institutional investors have dramatically increased shares of open interest (OI) and volume since the early 2000s (Sanders and Irwin, 2011; Tang and Xiong, 2012). Not only has total OI risen in corn and soybean markets over the 18 years considered (Figure 1) but the share of OI held by institutional investors has risen in corn (Figure 2) and soybeans (Figure 3). As articles such as Stoll and Whaley (2011) attest, times of dramatic price changes – especially price increases – seem to encourage more than the usual amount of attention on institutional investors. If a shift has occurred in the treatment of agricultural commodities markets away from the minimization of risk and price discovery toward the allocation of capital, several parties would hold an interest in it. Farmers and end-users (e.g.,

[1] A position limit is a ceiling on the number of contracts a trader can hold in a given commodity.

food processors and ethanol producers) would hold an interest in the risk management efficacy of a futures contract (Arthur, 1966); regulators, in an increased use of more opaque transaction methods (Stout 1999); exchanges, in the limits to jurisdiction over the type of instrument traded (Donohue 2014); and consumers, in the stability of food prices.

As of May 21, 2015, #2 yellow corn and #2 yellow soybeans traded on the Chicago Mercantile Exchange (CME) together comprised 53% of total agricultural commodities OI (CME Group, 2015). As the most frequently traded agricultural commodities on the CME, corn and soybean markets may provide a proxy for all commodities in the study of a shift in market treatment. It is reasonable to ask if institutional investment is affecting short-term price volatility because as of writing (May 21, 2015) it accounts for 49% of total OI in Chicago Board of Trade (CBOT) corn markets and 52% of the total OI in CBOT soybeans markets, using the CFTC Commitments of Traders (COT) *noncommerical* category as its proxy. The increase in these shares has coincided with the increase in short-term price volatility over the past 20 years. The causal mechanisms for this effect might be the increased linkages between commodities and equities, the larger trade denominations of institutional investors versus other trader types, and/or the market power afforded a trader type with such a large market share. The research objective of this paper is to discover whether the share of total OI held by institutional investors affects short-term price volatility. To accomplish this, regressions were constructed of several measures of price volatility on institutional investment's share of OI. Each regression's null hypothesis was that institutional investment had no effect. This paper contributes to the existing body of knowledge by using data of both before and after the early 2000s' rise in institutional investment's share of OI, by using more complete measures of futures prices, and by analyzing the data through a framework that accounts for both the autoregressive and the conditionally heteroskedastic natures of futures price.

CHAPTER II: LITERATURE REVIEW

Existing literature reflects concern over the effect of an increase in OI by institutional investors on commodities futures prices since the early 2000s (Sanders and Irwin 2011; Tang and Xiong 2012). Studies can be grouped into three broad types of investigation into institutional investment's effect on market prices: i) changes in future price value; ii) changes in futures price volatility; and iii) changes in cross-market price effects. The fourth and final subsection of the Literature Review describes the data used in existing literature.

Futures Price Value

The first broad type of investigation analyzes whether institutional investment is causing futures prices to overestimate the fundamental value of commodities and includes examinations into the nature and history of bubbles (Gilbert, 2010; Capell-Blancard and Coulibaly, 2011). The idea that futures prices are experiencing increases as a result of an inundation of investment money was championed by Michael Masters in his testimony before the U.S. Senate Committee on Homeland Security and Governmental Affairs (2008) and his testimony before the CFTC (2009) and Masters and White (2014). While Masters' and Masters and White's claims have not been widely accepted by the academic community (Sanders and Irwin 2012; Buyuksahin and Robe 2014), debate continues over both methods and results. Sanders and Irwin's (2012) review concludes that while some studies find in favor of Masters (2008) most find against it. In addition, studies using the Granger causality test, such as Irwin, Sanders, and Merrin (2009), fail to find a causal link between institutional investment and overvaluation of futures. Acharya, Lochstoer, and Ramadorai (2013, p. 442) state, "Limits on the risk-taking capacity of speculators imply that aggregate producer hedging impacts futures prices adversely from the producers' perspective." Sanders, Boris, and Manfredo (2004) find speculative traders' (hedging traders') net long positions are positively (negatively) correlated with positive price changes, though they find traders' position lag price changes.

Futures Price Volatility

The second broad type of investigation includes studies into changes in futures price volatility. These studies address the issues of how quickly and in what magnitudes futures prices rise or fall.

The effect of hedge funds on futures price volatility is addressed by Holt and Irwin (2004) through data of futures prices and both hedge funds and commodity trading advisors (CTA), both of which take long and/or short positions. Their data were collected from a six-month period during 1994, approximately 10 years before the rise in institutional investment's presence. The study concludes that when funds are profitable (which in aggregate they were, over the six-month period) they decrease market volatility by trading on valuable private information.

Chang, Pinegar, and Schachter (1997) address short-term price changes resulting from large speculative traders. The data used were from trades occurring between 1983 and 1990, well before the increase in institutional investment. Hamilton and Wu (2015) use current data but exclude hedge funds, CTAs, CPOs, and all other long-and-short speculators. A study contemporary to Hamilton and Wu's (2014) was performed by Miffre and Brooks (2013) via the use of portfolio mimicry, the reconstruction of a portfolio to study its behavior under different market conditions. They analyze price volatility over varying time periods, comparing volatility of price within the intervals of one-month, three-months, six-months, and one-year. Approaching the issue of price volatility from a purpose of analyzing a method of investing, as they do, calls for a model that changes a portfolio's holdings in response to changes in the price of individual commodities futures. If, alternatively, the research interest is in examining the short-term price changes of a market, a more appropriate method is to hold the portfolio's holdings constant throughout the period of analysis.

Gilbert and Pfuderer (2014) find that while there is no Granger causality of investment on price, there is instrumental variable contemporary causality of investment on price, especially if only index funds are considered. DeLong et al. (1990) find that the price volatility in the stock market is increased due to positive feedback trading, a dynamic possibly attributable to institutional investment. Liu et al. (2014) find a causal relationship: bullish and bearish news of equal magnitudes cause market price adjustments of different magnitudes. Kristoufek and Vosvrda (2014) find the corn futures markets are of average efficiency among a group of 25 energy, metal, and agricultural commodities, using the Efficiency Index introduced by Kristoufek and Vosvrda (2013).

The issue of whether speculation stabilizes prices is also approached from a theoretical perspective. If all agents are rational and have the same information, Hart and Kreps (1986) show that speculation can, but not necessarily will, lead to less stable prices. The results are equally applicable to futures markets as they are to physical markets. While the implication of their findings is that further regulation on speculation is not necessary, they conclude that the assumptions necessary to allow their model to stabilize prices are far stronger than those that allow for the possibility of speculation not stabilizing prices. From their research the theoretical results of speculation on price stability are not clear. However, the conclusion reached by Barber, Lee and Odean (2014) that institutional investors are profitable allows researchers to make an important assumption about stability, articulated by Friedman (1953, p. 175), "People who argue that speculation is generally destabilizing seldom realize that this is largely equivalent to saying that speculators lose money, since speculation can be destabilizing in general only if speculators on the average sell when the currency is low in price and buy when it is high."

Cross-market Price Effects

Both of the two broad types of investigation outlined above build on the prerequisite to institutional investment's involvement, the financialization of commodities, a relatively recent phenomenon in commodities markets described by Irwin and Sanders (2012) and Tang and Xiong (2012). The financialization of commodities and commodities' subsequent inclusion as an investable asset class has widened the investment opportunities for fund managers. Cross-market spillover of price volatility illustrates the fund managers' new investment opportunities. That the increase in financialization of commodities coincides with the increase in inter-market price correlations suggests that money managers are increasingly considering commodities a substitute for traditional investments, such as debt and equities (Tang and Xiong, 2012). The effect of cross-market linkages on how institutional investors affect agricultural price volatility is still largely under academic development.

One approach to examining institutional investment's effects on price dispersion from the perspective of fund managers is to compare the behavior of the prices of traditional investment classes to the prices of the emerging investment classes. Tang and Xiong (2012) find evidence for the spillover of oil's price volatility into non-oil commodities' price volatility around the increased oil price volatility of 2008. Crucial to the conceptual framework of this paper, they find institutional investors cause oil and non-energy markets to become more correlated, particularly in commodities markets included in either the Standard and Poor's Goldman Sachs Commodities Index or the Dow Jones-UBS Commodities Index.

While their research emphasizes the investment implications, it provides an anchoring point for investigation into institutional investment's effects. Investigations into the correlation between price movements of agricultural commodities markets and of equities markets such as those by Buyuksahin and Robe (2014) are similarly particular to the literature on investment strategies. Buyuksahin and Robe (2014), while informing research on institutional investment's effects on market efficiency, do not address a potential causal relationship between the proportion of OI held by institutional investors and price volatility in a single commodity market.

Data in Existing Literature

The CFTC'S COT report has been used by Sanders, Boris, and Manfredo (2004). Specifically, they used the COT category of noncommercial traders to proxy for speculation. The Commodity Index Traders (CIT) report, a supplement to the COT, was used by Capelle-Blancard and Coulibaly (2011) and Tang and Xiong (2012). The latter article uses net long positions in each commodity to proxy for index trading. Net long positions calculated from the managed money category of the CIT report, along with rare daily institutional investors' position data, are used by Holt and Irwin (2004). The CIT report was the original title for the Supplemental Commitments of Traders (SCOT) report, which is used by Hamilton and Wu (2015) and Stoll and Whaley (2011); under each name it suffers largely the same problems as the COT report. Holt and Irwin (2004) compare CIT and non-public data of rare daily institutional investment positions across 13 markets to daily price data across the same markets. While they focus on precisely the type of data needed to address short-term changes in futures prices resulting from institutional investors' presence, their definition of speculation and their time period of observation do not allow their work to answer the proposed research question. They define speculators only as hedge funds and CTAs, excluding long-only speculators like index and pension funds, which comprise a significant portion of OI, volume, and public concern (Holt and Irwin, 2004; CFTC, 2014). More significantly, the CFTC data they use cover only a six-month period in 1994 (April 4, 1994 to October 6, 1994).

Chang, Pinegar, and Schachter (1997), which use data of the change in long positions and the change in short positions and data of large speculator volume from the CFTC's '01' data, suffer the same problem as Holt and Irwin (2004): both studies use data periods that pre-date the financialization of commodities, the dramatic rise in percent of noncommercial OI and volume in commodities markets, and the subsequent increasing cross-market linkages among commodities, equities, and debt. The distinction between the pre- and post-early-2000s time periods is important because noncommercial traders had very low shares of OI and volume before the early 2000s (Sanders and Irwin, 2011; Tang and Xiong, 2012), and as studies on the increasing role of cross-market price linkages suggest (Tang and Xiong, 2012; Buyuksahin and Robe, 2014), the behavior of today's managed money may be substantively different from the managed money of 20 years ago.

Sanders and Irwin (2012) use CFTC's Index Investment Data (IID), which disaggregates the long and short positions of each firm. The COT report calculates only net long positions disaggregated by firm. They state their preference for the IID report as due to the confidence placed in it by their personal contacts in the CFTC and investment banks and the confidence placed in it by "a well-known private firm that has been tracking such investments for more than a decade." However, IID only began to be assembled and released in 2008 and was for a time reported only quarterly.

Three primary data constraints exist regarding short-term changes in price and short-term changes in noncommercial OI: i) COT categories do not exclusively and exhaustively capture hedging and speculating activities, ii) the data precede the rise of noncommercial OI, and iii) the frequency of data on noncommercial OI is less than daily. Existing literature that focuses on institutional investment does not focus on agricultural commodities data, post-financialization data, or either.

CHAPTER III: DATA AND METHODS

Data for our analysis were obtained from two sources: the CFTC and the CME. The CFTC's COT Futures-and-Options Combined reports from 1995 to 2013 provided weekly OI for corn and soybeans by firm type. Daily corn and soybean settlement prices for futures contracts at the CME were collected, and a single daily weighted average price was estimated for each commodity. The following three subsections outline the CFTC data, the CME data, and the GARCH framework used in our study.

CFTC's COT Futures-and-Options Combined Reports

In order to make claims about intra-daily or daily changes in institutional investors' presence, a study would need to include trade-level data of all – or at least one – institutional investors. In such a study, the analysis could measure the change in price volatility after a single, particular trade. This is the approach of Granger Causality. Because such data is not publicly available it may be necessary to take a step back, view the relationship of institutional investment and price volatility on a larger time scale, and ask how short-term price volatility before the rise of institutional investment differs from short-term price volatility after the rise. This is the approach of structural analysis. However, without being able to identify an a priori causal mechanism for a structural change, this element of the conceptual framework with the greatest scientific integrity may be to assume a smooth effect over time and choose data and models accordingly.

The CFTC'S COT reports are released weekly and provide a breakdown of each Tuesday's OI for future contracts in which 20 or more traders hold positions equal to or above the reporting levels[2] established by the CFTC (CFTC, 2015a). The COT reports list OI by firm

[2] Current reporting levels for corn and soybeans are 250 and 150 contracts, respectively.

type, as opposed to trading activity. Under the categories of the COT report, firm type can be commercial, noncommercial, or nonreportable and are determined by what the CFTC judges the general purpose of the firm to be. If the CFTC judges a firm to participate in the futures markets largely for the purpose of hedging physical market activities, it designates the firm as commercial. If the CFTC judges a firm to participate in the futures markets largely for another purpose, it designates the firm as noncommercial. Nonreportable firms are firms that maintain position limits below the reporting levels established by the CFTC. To clarify, a given firm can participate in multiple types of trading activities (i.e., hedging and speculation), but the COT assigns the firm a single designation (i.e., commercial or noncommercial). As such, a firm can use this limitation of the CFTC's reporting to obfuscate its type of trading, allowing it to avoid the burdensome regulations applicable to speculators (Sanders, Boris, and Manfredo, 2004). Sanders, Boris, and Manfredo (2004, p. 430) explain, "[B]ecause of the speculative position limits placed on noncommercials, there is some incentive for traders to classify themselves as commercials. Also, since cash positions for true commercials are unknown, their positions may be speculative in nature." In this analysis we use the COT noncommercial trader's category to represent institutional investment, recognizing that some traders classified as commercial or nonreportable may also be speculative.

The CFTC'S COT aggregated report – the version of the COT used in our study – divides noncommercial OI into long, short, and spread positions (Figures 4 and 5) and divides commercial and nonreporting OI each into long or short positions. Following Sanders, Boris, and Manfredo (2004), Equation 1 explains the total open interest as reported on the COT report:

(1) $$2(TOI) = [NCL + NCS + 2(NCSP)] + [CL + CS] + [NRL + NRS]$$

where

TOI is total OI as reported on the COT report;

NCL is the long OI positions held by noncommercial traders;

NCS is the short OI positions held by noncommercial traders;

NCSP is the spreading OI positions held by noncommercial traders;

CL is the long OI positions held by commercial traders;

CS is the short OI positions held by commercial traders;

NRL is the long OI positions held by nonreporting traders;

NRS is the short OI positions held by nonreporting traders;

A shortcoming of these metrics in the examination of institutional investment's effect on price volatility is that the category of noncommercial includes large, independent speculators as well as institutional investors. Data from weekly CFTC's COT reports from 1995 to 2013 were used to estimate noncommercial OI as a percentage of total OI (Equation 2). The date range was chosen to provide data before and after the rise in soybean and corn futures and options OI held by noncommercial traders.

(2) $$NCOI = 100 \cdot \frac{NCL+NCS+2*NCSp}{2*TOI}$$

where

NCOI is the percent of all open interest held by noncommercial traders;

NCL is the long open interest positions held by noncommercial traders;

NCS is the shorts held by noncommercial traders;

NCSp is the spreads held by noncommercial traders;

TOI is the total open interest as reported on the COT.

CME Corn and Soybean Futures Prices

Because futures contracts of a commodity are specified by particular delivery periods, there is not a single price for either corn or soybeans futures contracts for any given day. In order to capture as much information about price as possible, multiple contract months are considered. Particularly in examining the effects of institutional investment, considering multiple contract months can be beneficial because it may account for calendar spreads. Calendar spreads, also called simply *spreads*, often constitute a majority of institutional investment's position, as Figure 4 shows for corn and Figure 5 shows for soybeans. Daily corn and soybean futures prices from the CME, from 1995 to 2013, were used to estimate a single daily weighted average price for each commodity (Equation 3). For each commodity, the weighted average price reflects each futures contract's daily settlement price, weighted by the percentage of total OI for that futures contract. For example, if on February 10th the March corn contract constituted one third of all corn contracts' OI, the March contract's settlement price would contribute one third of the weighted average price for that day. Price data for each commodity and contract were collected from barchart.com for the last two years of each contract's life (372-454 trading days with an average of 405 trading days). If a contract were to be traded, say, three years prior to its expiration, the prices of the first year (the year furthest from expiry) would not be captured in the weighted average price. The total number of contracts included in any given day's weighted average price for corn is typically seven to 10 (minimum of one and maximum of 10) and for soybeans is typically eight to 14 (minimum of four and maximum of 14). Weighted average price is defined in Equation 3 and graphed in Figure 6.

(3) $$P_{c,s} = \sum_{i=1}^{L} SP_{c,s,i} \cdot \frac{OI_{c,s,i}}{TOI_{c,s}}$$

where

$P_{c,s}$ is the price for commodity *c* on day *s*;

$SP_{c,s,i}$ is the settlement price for commodity *c* for contract *i* on day *s*;

$OI_{c,s,i}$ is the open interest for commodity *c* for contract *i* on day *s*;

$TOI_{c,s}$ is the total open interest across all contracts for commodity *c* on day *s*;

L is the number of contracts being traded for commodity *c* on day *s*.

To more accurately depict the volatility in the change in price ($R_{c,s}$), shown in Figure 7, the absolute value of the change in price was taken (Equation 4 and Figure 8).

(4) $$absR_{c,s} = abs(P_{c,s} - P_{c,s-1})$$

where

$absR_{c,s}$ is absolute value of the average of daily changes in price for commodity *c* for day *s*;

$P_{c,s}$ is the average of daily prices for commodity *c* for day[3] *s*;

$P_{c,s-1}$ is the weighted average price for commodity *c* at the close of day *s-1*.

To determine the normalized change in price, the absolute value of $R_{c,s}$ was divided by the previous day's price (Equation 5 and Figure 9).

(5) $$absNR_{c,s} = \frac{absR_{c,s}}{P_{c,s}}$$

where

$absNR_{c,s}$ is the absolute value of the weekly change in price normalized by the price on day *s* for commodity *c* for day *s*;

[3] A week is not a trading week (i.e., Monday to Friday). It is the time interval covered by the CFTC'S COT report.

$absR_{c,s}$ is the absolute change in weighted average price for commodity c for day s;

$P_{c,s}$ is the price for commodity c for day s;

The third measure of price volatility was the standard deviation of a running five-day range (approximately one trading week) of the current and previous four days' settlement prices (Equation 6 and Figure 10).

(6) $$stdevP_{c,s} = \sqrt{\frac{1}{5}\sum_{i=0}^{4}(P_{c,s-i} - [\frac{1}{5}\sum_{j=0}^{4} P_{c,s-j}])}$$

where

$stdevP_{c,s}$ is the standard deviation of a running five-day range for commodity c on day s;

$P_{c,s-i}$ is the weighted average price for commodity c for day $s-i$ (i=0…4);

$P_{c,s-j}$ is the weighted average price for commodity c for day $s-j$ (j=0…4)

The above price values are then rolled up into weekly values in order to reconcile the difference caused by CFTC data being offered weekly. The rollup is achieved by way of a simple average of the daily price values into a single weekly price value. This method avoids the loss of data fidelity that would result from ignoring daily price values. A price volatility measure constructed with weekly price values is the ratio of weekly prices, given by Equation 7.

(7) $$Pratio_{c,t} = 100 \cdot \frac{P_{c,t}}{P_{c,t-1}}$$

where

$Pratio_{c,t}$ is the ratio of price on week t to the price on week $t-1$

$P_{c,t}$ is the weighted average price for commodity c for week t

The above-defined measurements of weighted average price will henceforth simply be called *price*. Because of this, the term *price* will refer to week-level data (the average of the settlement price for each day in the week). *Price volatility* will refer to a measure of the change in price by week. To achieve normality of residuals the price measurements may be transformed.

Generalized Autoregressive Conditional Heteroskedasticity (GARCH)

The generalized autoregressive conditionally heteroskedastic (GARCH) framework was introduced by Bollerslev (1986), who built upon the work of Engle (1982), who introduced the autoregressive conditionally heteroscedastic (ARCH) framework to deal with the vagaries of financial market data in statistical analysis. Specifically, the assumption of homoskedasticity (the non-constancy of residual distributions across time) often does not hold for financial data. There are times in financial markets filled with chaos and others of relative tranquility. This volatility clustering spoils the assumption of homoskedasticity. Engle's solution was to define the sample variance conditioned on past values of all variables in terms of past values of the error term. Bollerslev took the idea a step further by defining the error variance in terms of past error variances and past error terms. GARCH has been used in numerous studies to model prices in financial markets, including by Miffre and Brooks (2013) and by Beckmann and Czudaj (2014) in the investigation of agricultural futures price. A visual inspection of the change in price, the absolute change in price, and the absolute change in price normalized to current price levels suggest volatility clustering may be an issue for corn and soybeans futures for the years we considered (Figures 7, 8 and 9, respectively).

The stationarity of the measures of price volatility is tested by the Dickey-Fuller Unit Root Test. If non-stationarity is found, a moving average component would be incorporated into the regression equation. Serial correlation of price volatility is tested for by the Durbin Watson statistic. If serial correlation is found, an autoregressive component of an order(s) selected by Akaike's Information Criterion (AIC) or Schwarz Bayesian Criterion (SBC) is added to the model. Homoskedasticity is tested by the Portmanteau Q test and by Engle's LM test. If the assumption of homoskedasticity does not hold, a model that accounts for differences in variances over time is used. If autocorrelation and heteroskedasticity are found in price volatility, a GARCH framework that estimates parameters by maximum likelihood procedures is used to model the relationship between price volatility and institutional investment. Each GARCH model requires an order be specified, both for the autoregressive terms (p) and the conditional variance terms (q). In the style of Sanders, Boris, & Manfredo (2004), GARCH order is determined by comparing each model's AIC. All combinations of orders $p = \{1,2,3,4\}$ and $q = \{1,2,3,4\}$ are compared, representing up to one month of history. The order of the model that minimizes AIC is selected. The comparison is made for each commodity for each dependent variable. For robustness purposes, similar selections are made among GARCH orders using minimum SBC. If regressions of the above-defined measures of price volatility (Equations 4, 5, 6, and 7) result in residuals that are not normally distributed, transformations of price volatility measures are taken and the regressions re-run. For simplicity, the transformation of choice is a natural logarithm. If that fails to produce normally distributed residuals, investigations are expanded to other transformations. If multiple dependent variables in a single commodity produce normal residuals, AIC and SBC are again used to select the model of best fit so that a single model can be chosen to represent NCOI's relationship to institutional investment for each commodity. Computations are performed using SAS v9.3.

The autoregressive component in GARCH accounts for the dependence of each time period's dependent variable upon its previous value and follows the form

(8) $$y_{c,t} = f(y_{c,t-1,} y_{c,t-2}, \dots, y_{c,t-p}, h_{c,t-j}, \dots, h_{c,t-q})$$

where

y	is the measure of price volatility;
h	is the conditional variance of the residuals;
p	is the maximum number of autoregressive dependent variable lags;
q	is the maximum number of conditional variance lags;
c	is the commodity; and
t	is the week.

The conditionally variance component accounts for the dependence of each time period's error term upon its previous value(s) and follows the form

(9) $$\varepsilon_{c,t} = f(\varepsilon_{c,t-1,} \varepsilon_{c,t-2,} \dots, \varepsilon_{c,t-q}, h_{c,t-j}, \dots, h_{c,t-q})$$

where

ε	is the error of the mean equation;
h	is the conditional variance;
p	is the maximum number of autoregressive dependent variable lags;
q	is the maximum number of conditional variance lags;
c	is the commodity; and
t	is the week.

The mean equation is:

(10) $$y_{c,t} = \beta_{c,0} + \sum_{i=1}^{p} \beta_{c,i} y_{c,t-i} + \beta_{c,NCOI} NCOI_{c,t} + \varepsilon_{c,t}$$

where

y	is the measure of price volatility;
NCOI	is the percent of total OI held by noncommerical traders;
p	is the GARCH order;
c	is the commodity; and
t	is the week.

As presented by Bollerslev (1986, p. 309), the GARCH model incorporates for each commodity a mean equation error term, ε, and a conditional error variance equation, h_t given by:

(11) $$\varepsilon_t \mid \psi_{t-1} \sim \mathrm{N}(0, h_t)$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}$$

where

h_t	is the conditional variance of the residuals at time t;
q	is the order of the GARCH component;
p	is the maximum number of autoregressive lags of both the dependent variable and the conditional error variance;
ε_t	is the error of the mean equation at time t; and
ψ_t	is the total information set at time t.

$$p \geq 0, \qquad q > 0, \qquad \omega > 0,$$

$$\sum_{i=1}^{q} \alpha_i \geq 0,$$

$$\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1.$$

The unconditional variance equation is:

$$(12) \qquad \sigma_c^2 = \frac{\omega_c}{1 - \sum_{i=1}^{q} \alpha_{c,i} - \sum_{j=1}^{p} \beta_{c,j}}$$

where

ω	is the intercept of the error variance equation;
α	is the coefficient on the conditional variance terms;
β	is the coefficient on the autoregressive terms;
p	is the GARCH order;
q	is the ARCH order; and
c	is the commodity;

$$p \geq 0, \qquad q > 0, \qquad \omega > 0,$$

$$\sum_{i=1}^{q} \alpha_i \geq 0,$$

$$\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1.$$

CHAPTER IV: RESULTS AND DISCUSSION

In order to achieve normality of residuals, natural log transformations of price volatility measurements were made. The natural log was chosen over other transformations because of its simplicity. After including the transformations there were eight measures of price volatility: change in price, absolute change in price, natural log of absolute change in price, absolute normalized change in price, natural log of absolute normalized change in price, standard deviation of price (5-day, rolling), natural log of standard deviation of price (5-day, rolling), and natural log of the ratio of prices (current week's price divided by previous week's price). A variety of dependent variable transformations were tested because different applications of this study may require different measures of price volatility. Models were constructed for all orders GARCH(1,1) to GARCH(4,4) for the nine dependent variables. For soybeans, there were five dependent variables for which at least one GARCH order returns normal residuals; for corn, there was only one dependent variable with normal residuals (natural log of absolute normalized change in price). The order selection based on AIC agreed with the order selection based on SBC for all orders of normally distributed residual except for soybean's natural log of price ratio. Akaike's Information Criteria and SBC suggest different orders for soybean's natural log of price ratio because of the difference in how SBC and AIC discount goodness of fit by the number of parameters. Because soybean's natural log of price ratio has a model for AIC-selected order and a model for SBC-selected order, six soybean models were estimated even though there were only five soybean dependent variables with normally distributed residuals. Table 1 shows the models indicated by AIC and SBC for each dependent variable.

Dickey Fuller tests showed each measure of price volatility was stationary. Durbin-Watson tests showed autocorrelation existed in each price volatility time series (Table 2).

Durbin-Watson tests performed on the predicted dependent variables show autocorrelations persisted after the GARCH process. This is acceptable, as the GARCH process fits predicted values to physical values. Well-fitting predicted values are of similar shape to physical values. Portmanteau Q tests and Engle's LM tests indicated heteroskedasticity for all orders GARCH(1,1) to GARCH(4,4); see Table 3 for corn and Table 4 for soybeans. Q tests and Engle's LM tests run on predicted dependent variables indicated the GARCH process had sufficiently accounted for heteroskedasticity; see Table 5 for corn and Table 6 for soybeans. Table 7 reflects the results for all seven models (one corn model and six soybean models). As might be expected given the summary statistics presented in Table 8 and Table 9, all coefficients of institutional investment were positive, and most were statistically significant.

Interpretation of Mean and Conditional Variance Equations

All eight models returned positive effects of institutional investment on price volatility, and most effects were statistically significant. The overall best corn model was GARCH(2,3) for the dependent variable *natural log of the absolute normalized change in price.* The overall best soybean model is GARCH(2,3) for the dependent variable *change in price*. The two information criteria were in agreement for each model. The models' respective results (given above and in Table 7) reflect the best estimations of institutional investment's effect on price volatility. These results imply a one-percentage point increase in NCOI's share of total corn contracts is associated with a 2.75% increase in magnitude of day-to-day settlement prices for corn, even after accounting the rise in the price of corn over the 18-year period. Corn's NCOI coefficient is strongly significant, holding a p-value of less than 0.0001. The story in soybeans is less eye-catching: the NCOI coefficient for the best-fit model is not significant. Additionally, soybean's best-fit model shows a much more modest effect of an eighth of a cent per bushel increase for every percentage point increase in NCOI's share of outstanding contracts. The remainder of this section is a model-by-model breakdown of results for all models not discarded for non-normal residuals.

In corn markets, when measuring price volatility by the natural log of absolute normalized change in price, a one percentage point increase (decrease) in NCOI, the percent of total OI held by noncommercials, was associated with a 0.0275 increase (decrease) in corn price volatility, shown in Table 7; point-A. This effect was significant at p-value<0.0001. For this measure of price volatility, a GARCH(2,3) order was indicated by both AIC and SBC. The GARCH order selected indicates that price volatility was statistically significantly affected by the previous two weeks' price volatility (GARCH2, p-value=0.0524), and the conditional error variance was statistically significantly affected by the previous week's conditional error variances (ARCH1, p-value=0.0427.

In soybean markets, when measuring price volatility by the change in price, a one percentage point increase (decrease) in NCOI was associated with a 0.0014 cent/bu increase (decrease) in average daily change in settlement price (Table 7; point-B). This effect was not significant at the 10% level. For this measure of price volatility, a GARCH(2,3) order was indicated by both AIC and SBC. Price volatility was statistically significantly affected by the previous two weeks' price volatility (GARCH2, p-value<0.0001), and the conditional error variance was statistically significantly affected by the previous two weeks' conditional error variances (ARCH1, p-value<0.0001; ARCH2, p-value=0.0001).

In soybean markets, when measuring price volatility by the natural log of the five-day standard deviation in price, a one percentage point increase (decrease) in NCOI was associated with a 0.0585 increase (decrease) in price volatility (Table 7; point-C). This effect was significant at a p-value<0.0001. For this measure of price volatility, a GARCH(2,3) order was indicated by both AIC and SBC. Price volatility was statistically significantly affected by the previous two weeks' price volatility (GARCH2, p-value=0.0001). The conditional error variance was statistically significantly affected by the previous three weeks' conditional error variances but only at the 10% level (ARCH1, p-value=0.0798; ARCH2, p-value=0.093; ARCH3, p-value=0.9489).

In soybean markets, when measuring price volatility by the natural log of the absolute normalized change in price, a one percentage point increase (decrease) in NCOI was associated with a 0.0117 increase (decrease) in price volatility (Table 7; point-D). This effect was significant at a p-value<0.0001. For this measure of price volatility, a GARCH(2,4) order was indicated by both AIC and SBC. Price volatility was statistically significantly affected by none of the previous week's price volatility, but the conditional error variance was statistically significantly affected by the previous three weeks' conditional error variances (ARCH1, p-value=0.019; ARCH2, p-value=0.0699; and ARCH3, p-value=0.048).

In soybean markets, when measuring price volatility by the natural log of the absolute change in price, a one percentage point increase (decrease) in NCOI was associated with a 0.0245 increase (decrease) in price volatility (Table 7; point-E). This effect was significant above p-value<0.0001. For this measure of price volatility, a GARCH(2,4) order was indicated by both AIC and SBC. Price volatility was statistically significantly affected by none of the previous week's price volatility, and the conditional error variance was statistically significantly affected by the previous three weeks' conditional error variances (ARCH1, p-value=0.0014; ARCH2, p-value=0.1077; and ARCH3, p-value=0.0201).

When measuring soybean price volatility as the natural log of the soybean price ratio, a GARCH(3,3) order was chosen under AIC. Under this specification, the effect of NCOI was small and statistically insignificant (Table 7; point-F). Price volatility was statistically significantly affected by the previous three weeks' price volatility (GARCH3, p-value<0.0001), and the conditional error variance was statistically significantly affected by the previous week's conditional error variances (ARCH1, p-value<0.0001). A GARCH(3,1) order was indicated under SBC, resulting in a small and statistically insignificant effect of NCOI (Table 7; point-G). Again, price volatility was statistically significantly affected by the previous three weeks' price volatility (GARCH3, p-value<0.0001), and the conditional error variance was statistically significantly affected by the previous week's conditional error variances (ARCH1, p-value<0.0001).

CHAPTER V: CONCLUSION

It is possible to argue that a futures contract's fundamental price – the price determined by the supply and demand of each commodity – has undergone a change in the 18-year period, that it has become more volatile because of market participants' increased access to information by the climb to near-ubiquity of internet, cell phones, and social media. If that is the case, a more volatile nominal price may be neither a surprise nor a concern. Though, if either that is not the case or the increased pace of actionable intelligence has *decreased* price volatility, then greater uncertainty surrounding futures prices should beg the question of market stakeholders as to the cause. In any case, the increase in the dispersion of futures prices means holding futures contracts for any purpose – hedging or speculating – has become a riskier endeavor. Firms participating in agricultural futures markets might need to increase the speed with which orders are submitted in order to combat this risk.

Existing literature agrees that results presented in this study may underestimate noncommercial's effects because the COT's noncommercial category does not capture speculative activity undertaken by commercial firms, firms the CFTC judges to be participating future markets largely for the purposes of hedging physical market activities. A single firm can participate in both hedging and speculating activities, but – to all firms holding reportable positions – the CFTC assigns the firm a single designation: commercial or noncommercial. A firm can use this limitation of the CFTC to obfuscate its type of trading, allowing it to avoid the burdensome regulations on speculators (Sanders, Boris, and Manfredo, 2004). As Sanders, Boris, and Manfredo (2004, p. 430-1) point out, the silver lining for study like this one is that the incentive structure implies the noncommercial category is likely a fairly unadulterated representation of speculation. For this reason, there is an unambiguous implication that the true parameters may be larger than the estimates offered in this study.

This study could be improved by including control variables to the multivariate GARCH models. Variables like weather (e.g., those capturing the drought of 2012) and policy (e.g., those capturing the Renewable Fuels Standard) may further help to explain changes to price volatility. Indicator variables could be introduced to adjust the mean price volatility by year, controlling for time-trending unobserved factors. Additional indicator variables could be introduced to account for intra-year seasonality, like those caused by the differences in susceptibility of crop prices to weather at different times during the growing season. Another research direction would be to identify the causal mechanisms of institutional investment's effects on commodity futures markets. Such a direction may involve an adaption of Tang and Xiong (2012) and Buyuksahin and Robe (2014). Institutional investment's effects on the volatility of calendar spreads could also be examined. Because of the large portion of noncommercials' position in spreads, there may be effects particular to contango and backwardation.

If an increase in institutional investment's share of OI causes an increase in the variance of futures prices, then the most obvious question might be whether cash prices experience a similar increase in variance. An examination of the effects of institutional investment on basis levels within a GARCH framework may shed light on this relationship. Cash markets may experience the same alternating periods of calm and chaos that necessitate GARCH models and debase those which ignore heteroskedasticity. If futures prices are more volatile but basis levels are not, the effects of institutional investment may reach into physical commodities markets, as this would imply basis is not compensating for the fluctuations in futures prices. This question may be the most relevant to academics and practitioners, as it has the ability to depict today's futures market as either an unintentional gambling house or an enduring risk management- and price discovery-protectorate.

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APPENDICES

FIGURES

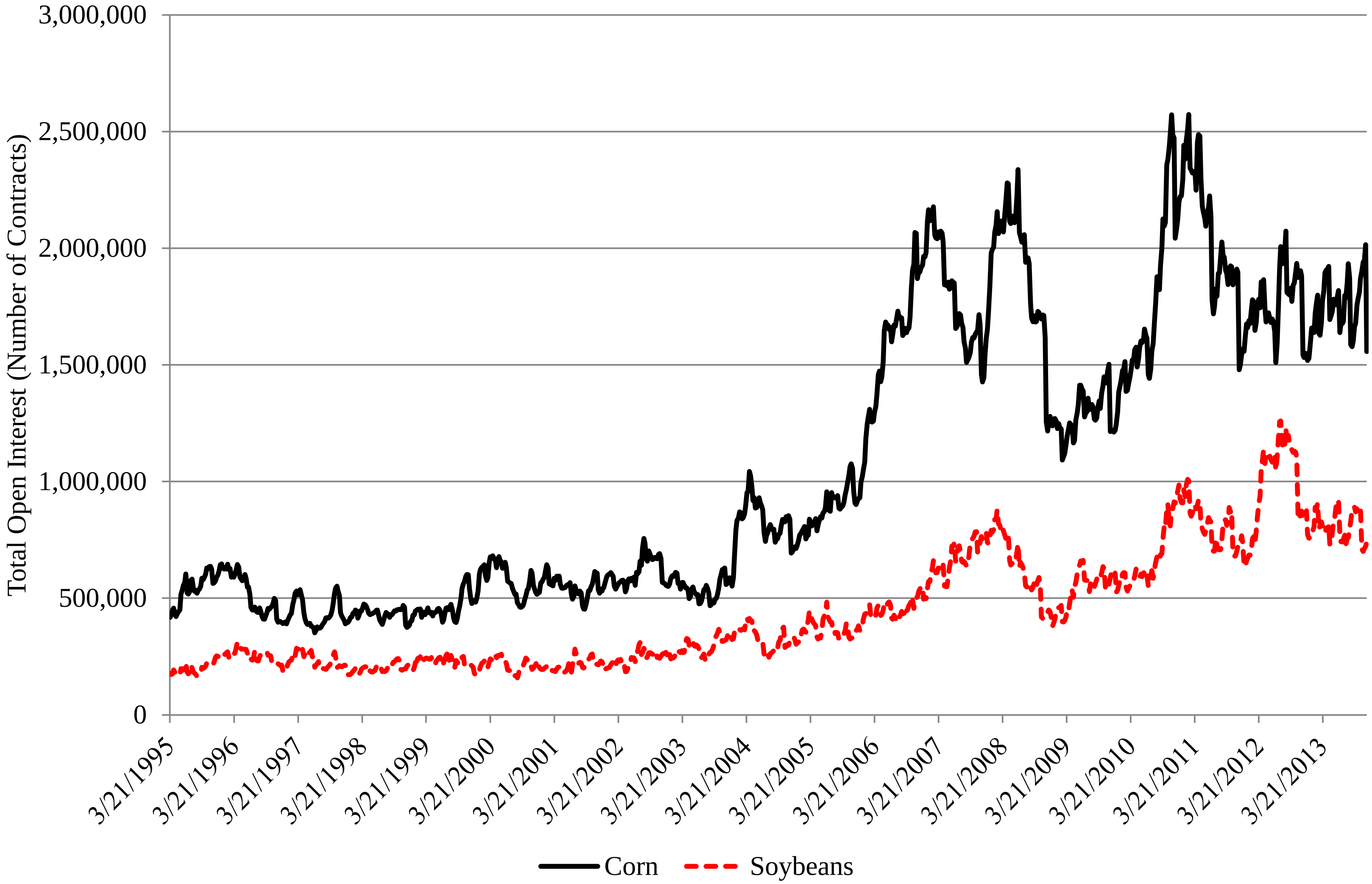


Figure 1. Total open interest for corn and soybeans from the CFTC's COT, Futures-and-Options Combined reports, 1995-2013

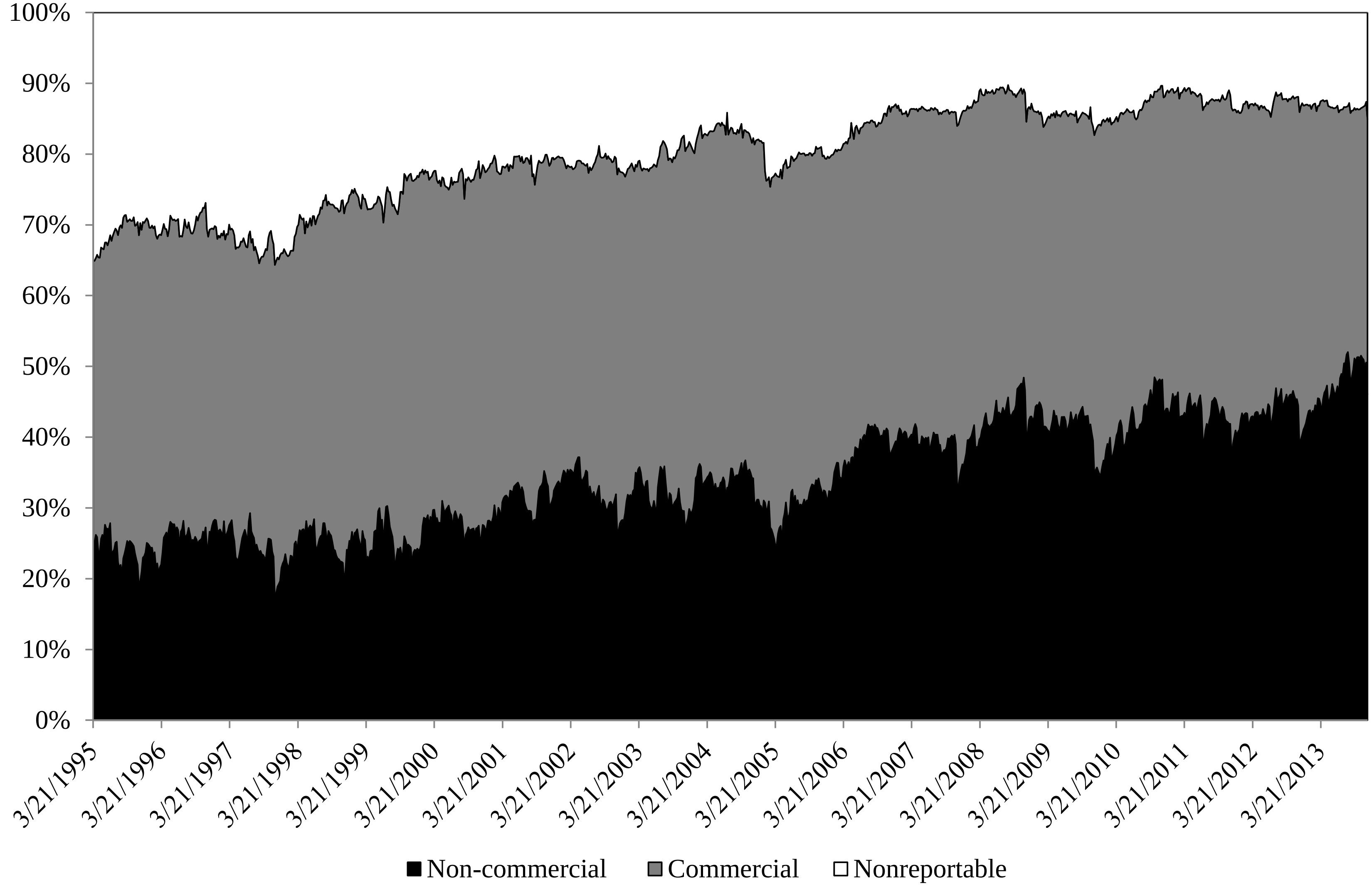


Figure 2. Share of total open interest for corn for noncommercial, commercial, and nonreportable traders from the CFTC's COT, Futures-and-Options Combined reports, 1995-2013

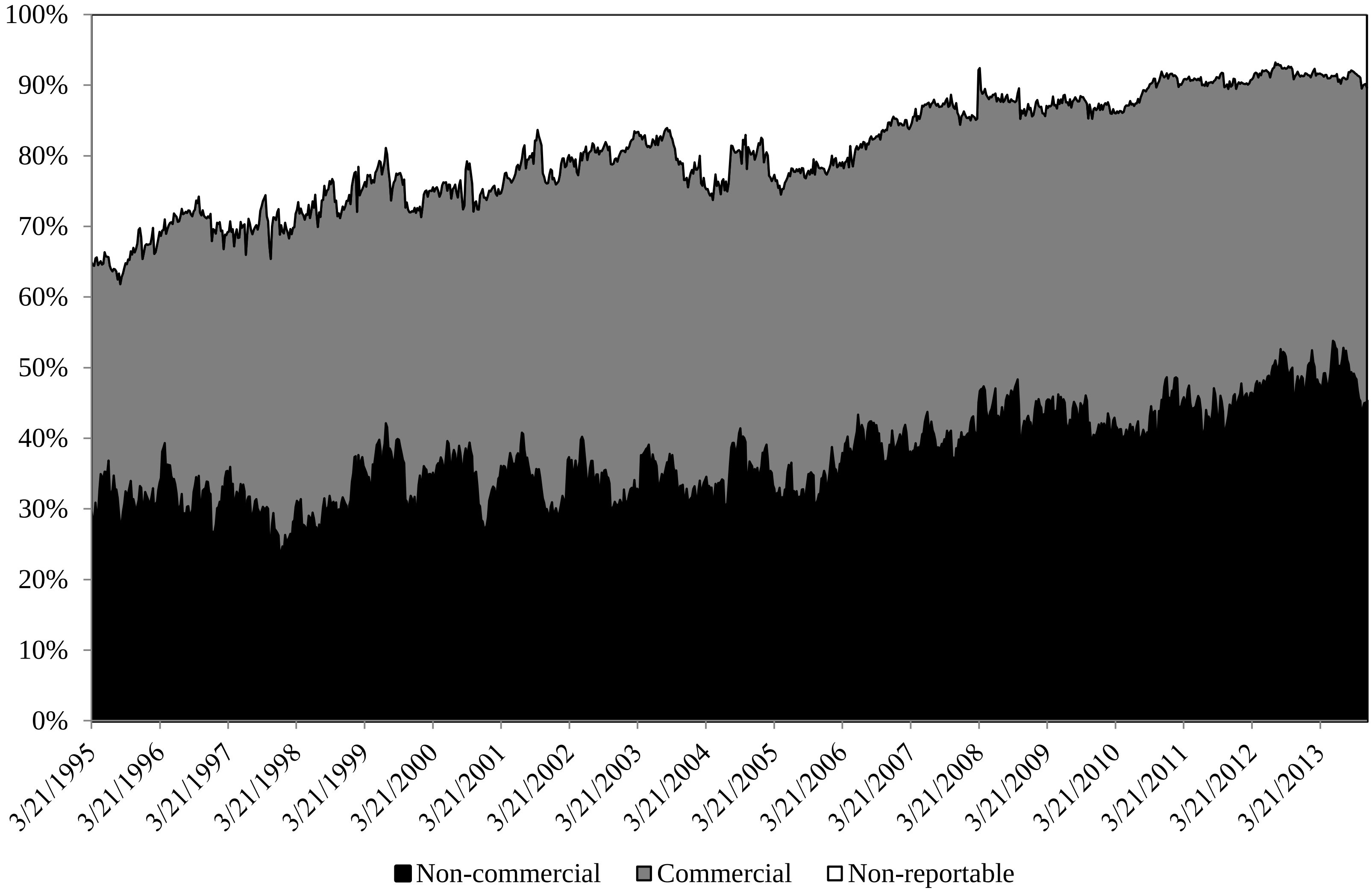


Figure 3. Share of total open interest for soybeans for noncommercial, commercial, and nonreportable traders from the CFTC's COT, Futures-and-Options Combined reports, 1995-2013

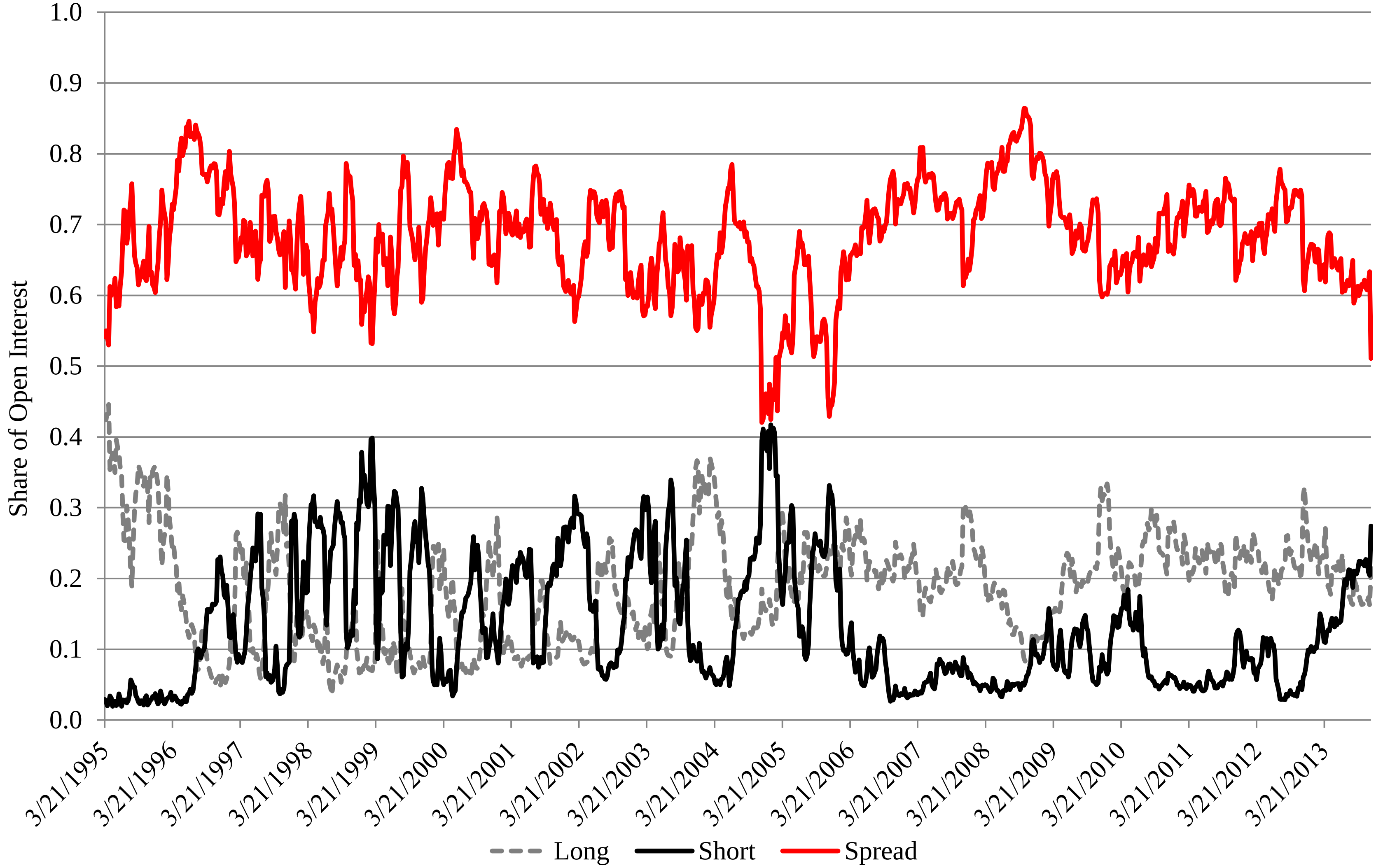


Figure 4. Share of corn total open interest for noncommercial traders by position from the CFTC's COT, Futures-and-Options Combined reports, 1995-2013

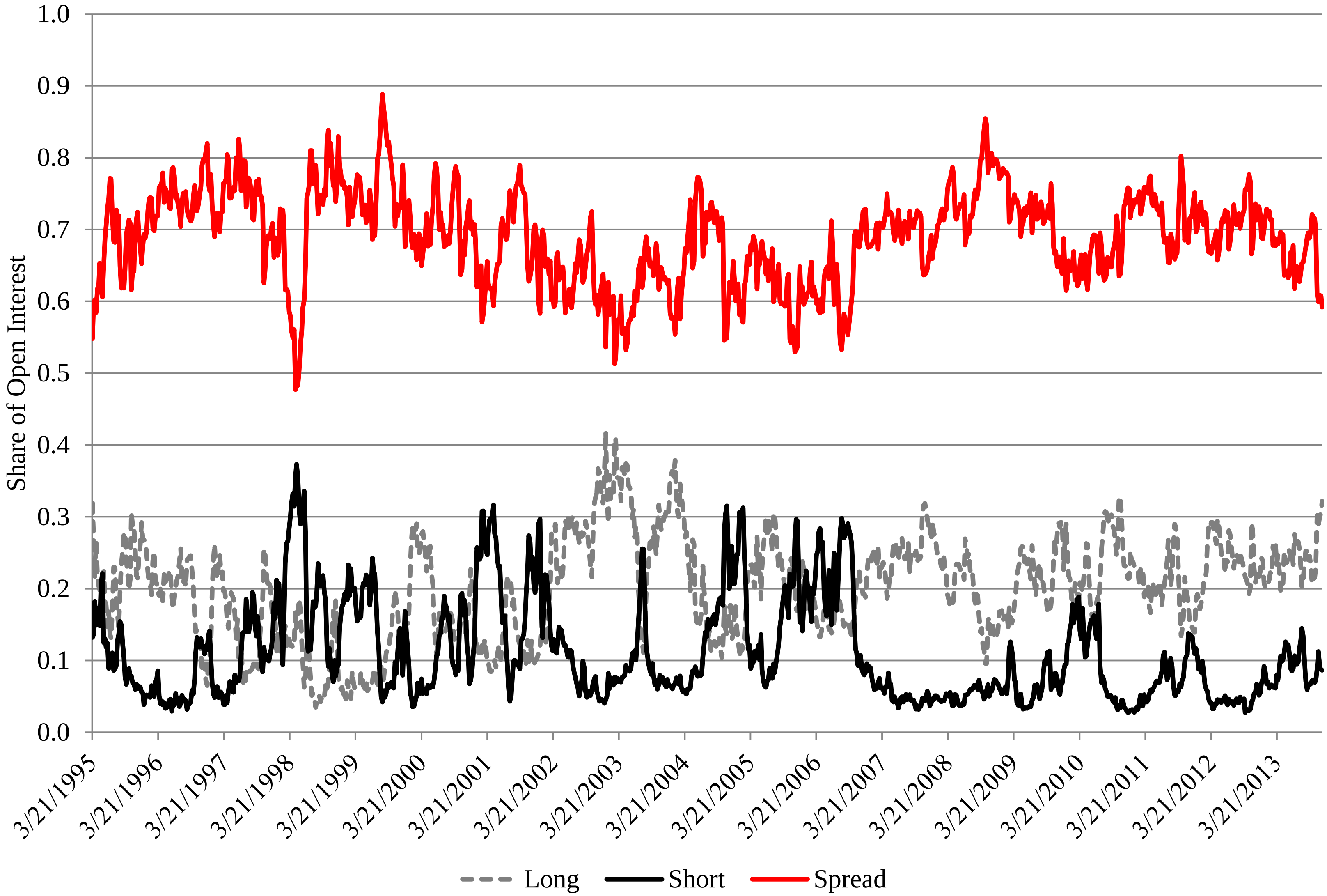


Figure 5. Share of soybean total open interest for noncommercial traders by position from the CFTC's COT, Futures-and-Options Combined reports, 1995-2013

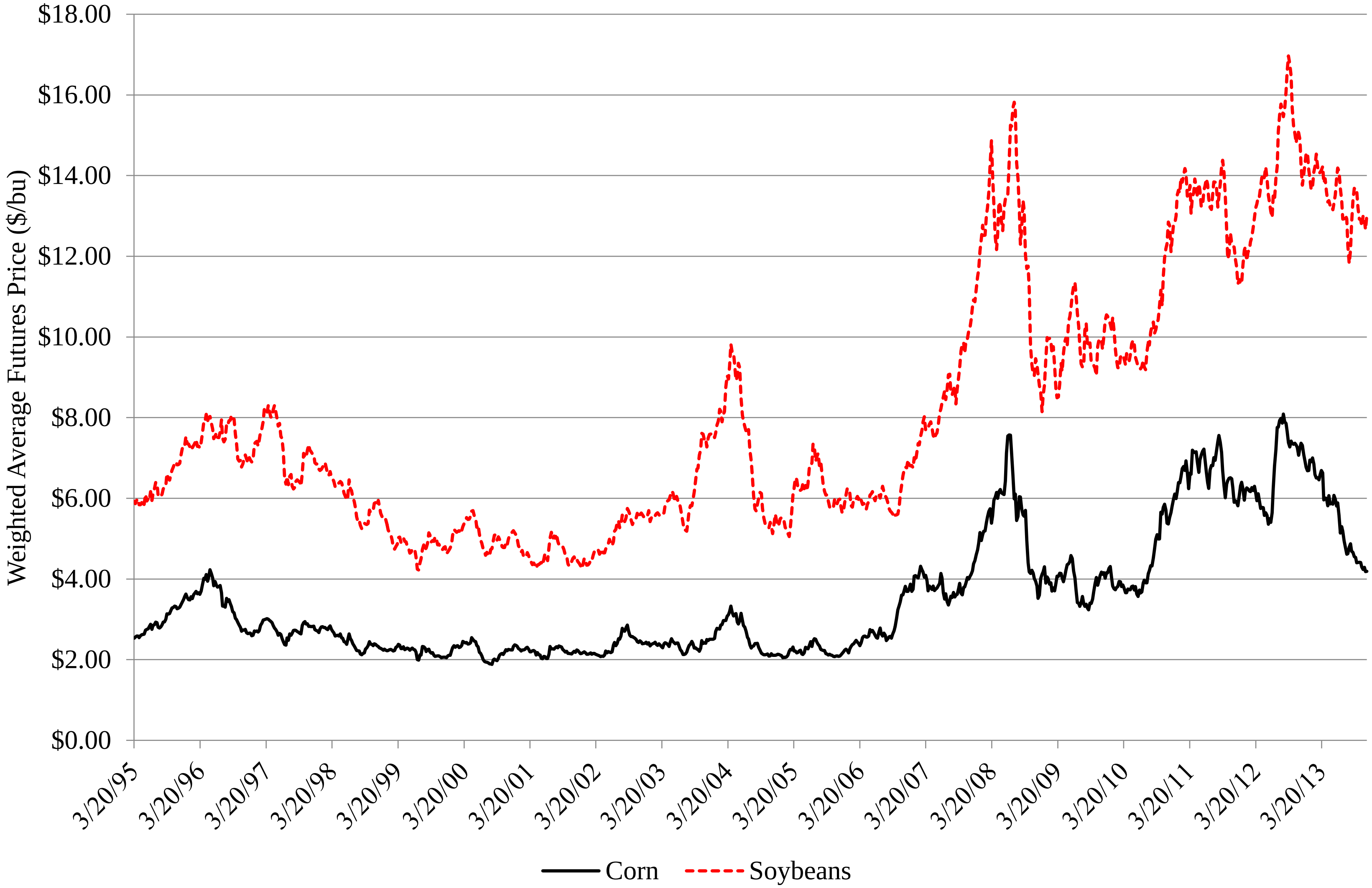
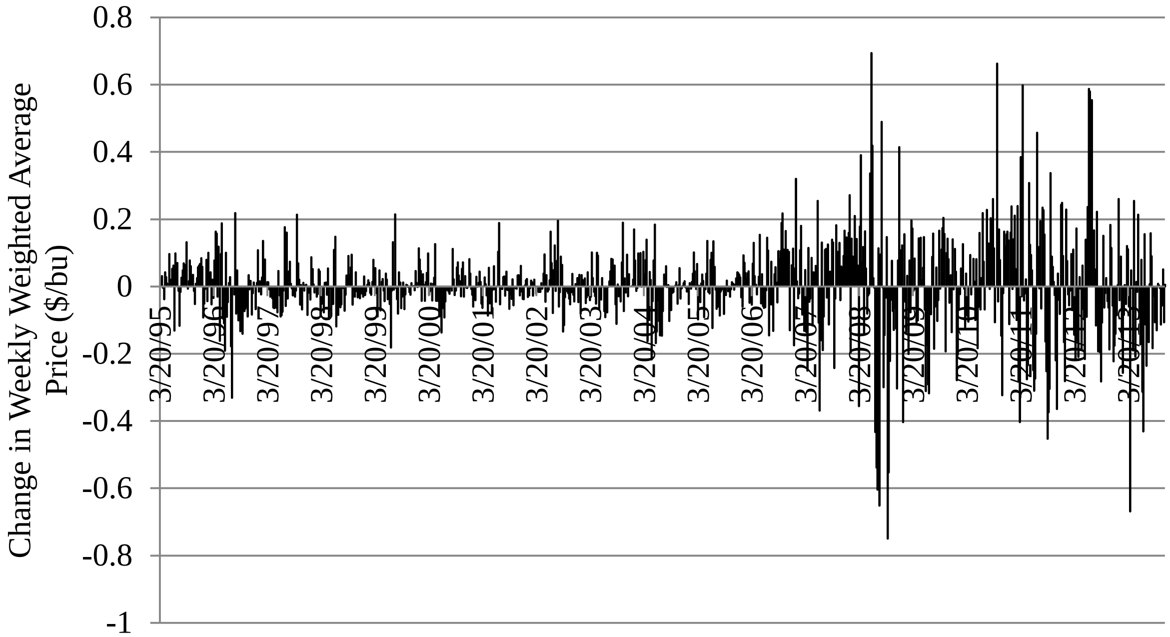


Figure 6. Weighted average corn and soybean futures price in dollars per bushel, nominal prices, Chicago Mercantile Exchange (CME), 1995-2013

Corn



Soybeans

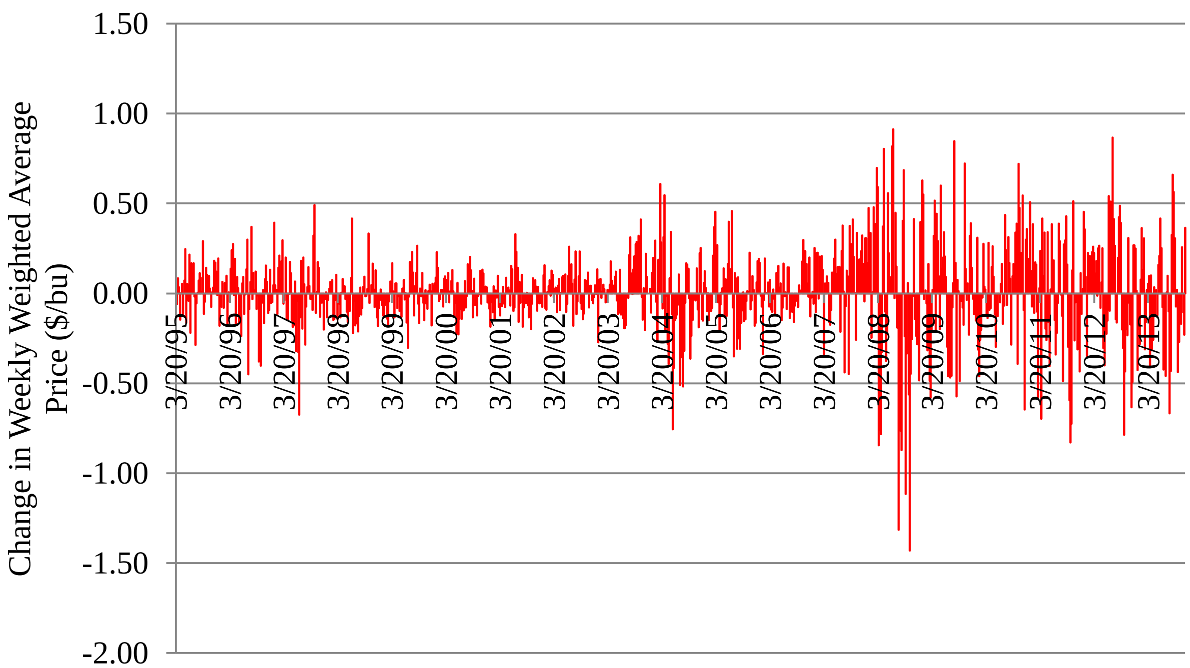
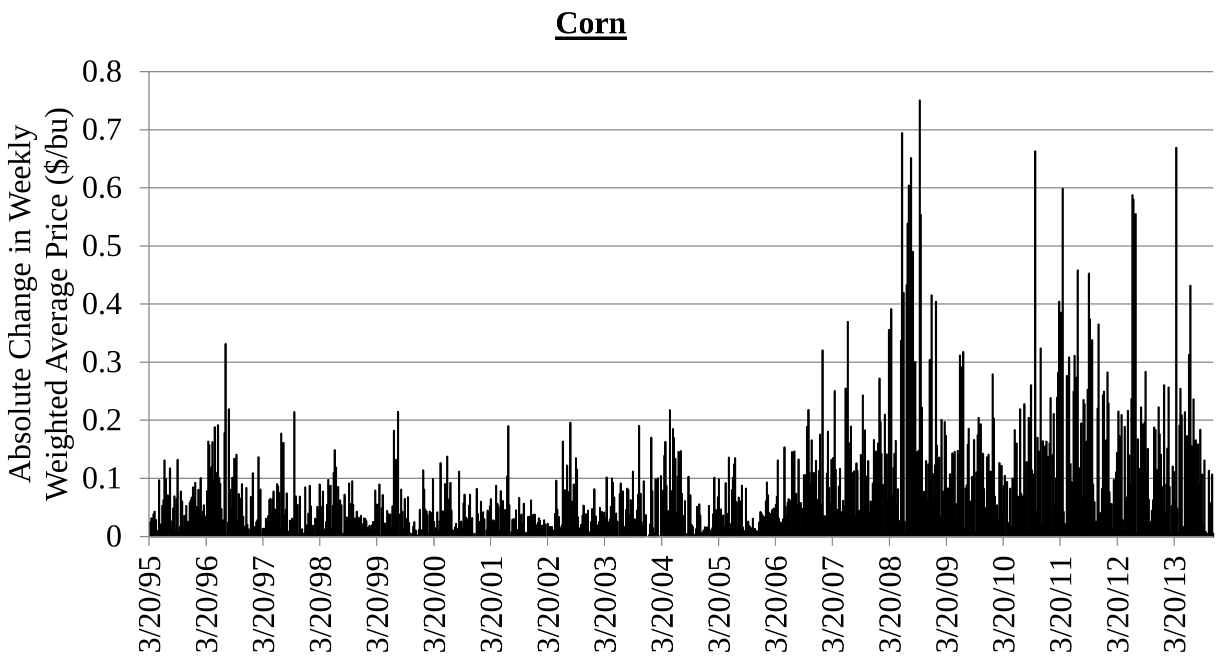


Figure 7. Change in weekly average weighted average price for corn and soybeans, nominal prices, Chicago Mercantile Exchange (CME), 1995-2013



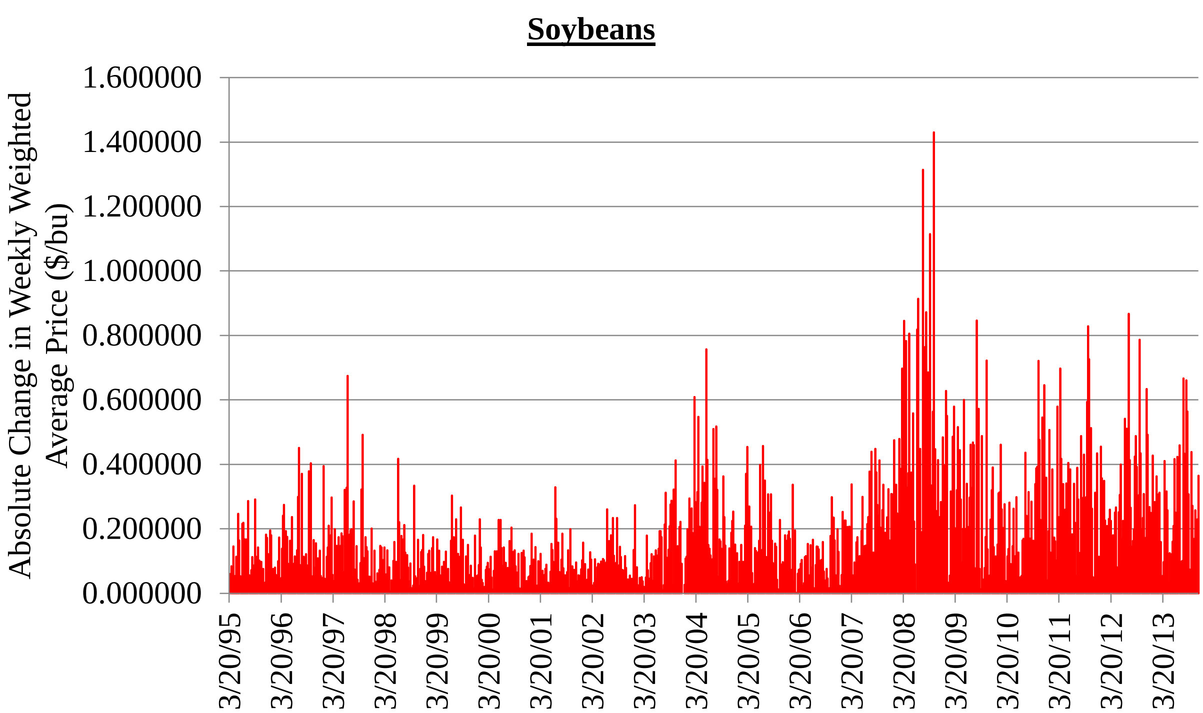
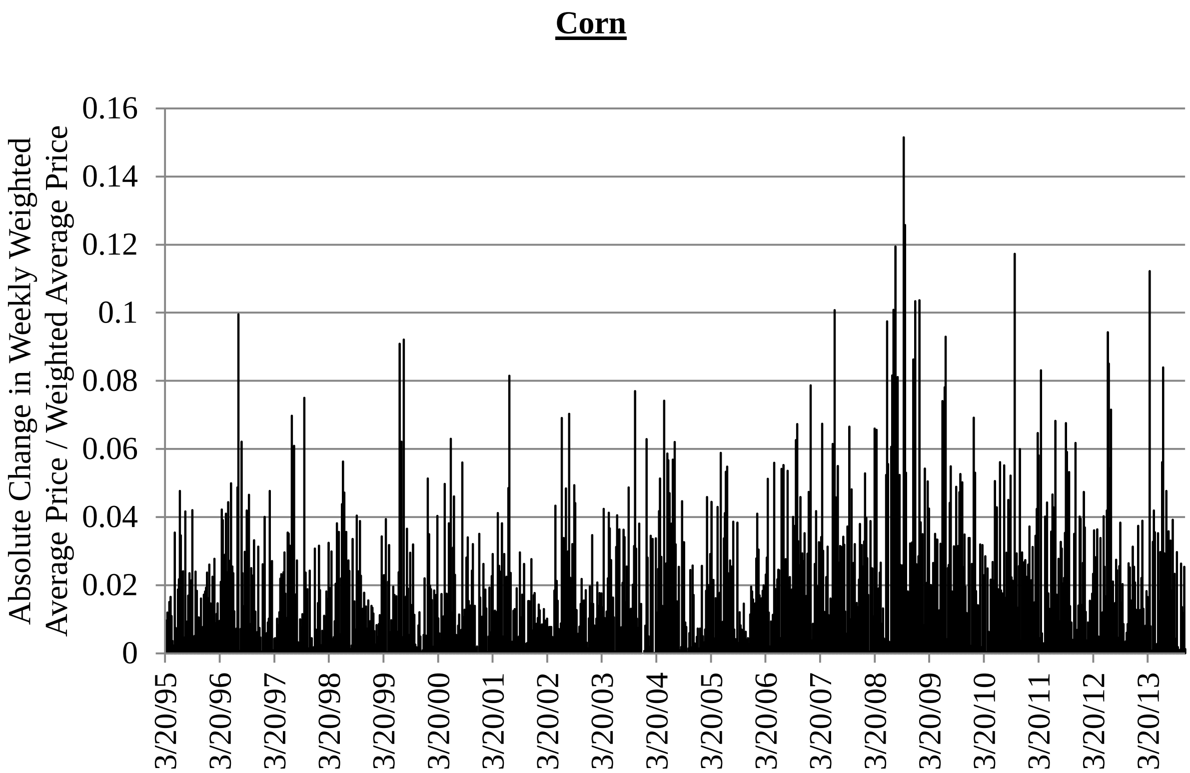


Figure 8. Absolute change in weekly average weighted average price for corn and soybeans, nominal prices, Chicago Mercantile Exchange (CME), 1995-2013



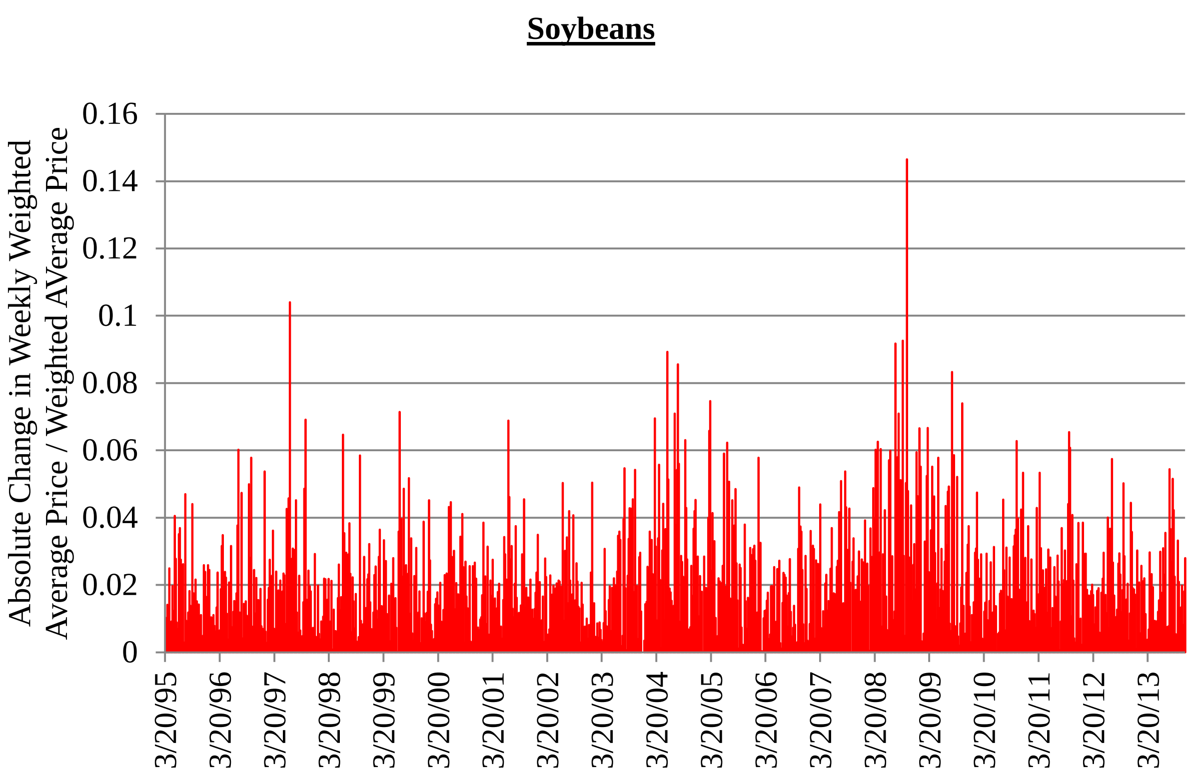


Figure 9. Absolute change in weekly average weighted average normalized price for corn and soybeans, nominal prices, Chicago Mercantile Exchange (CME), 1995-2013

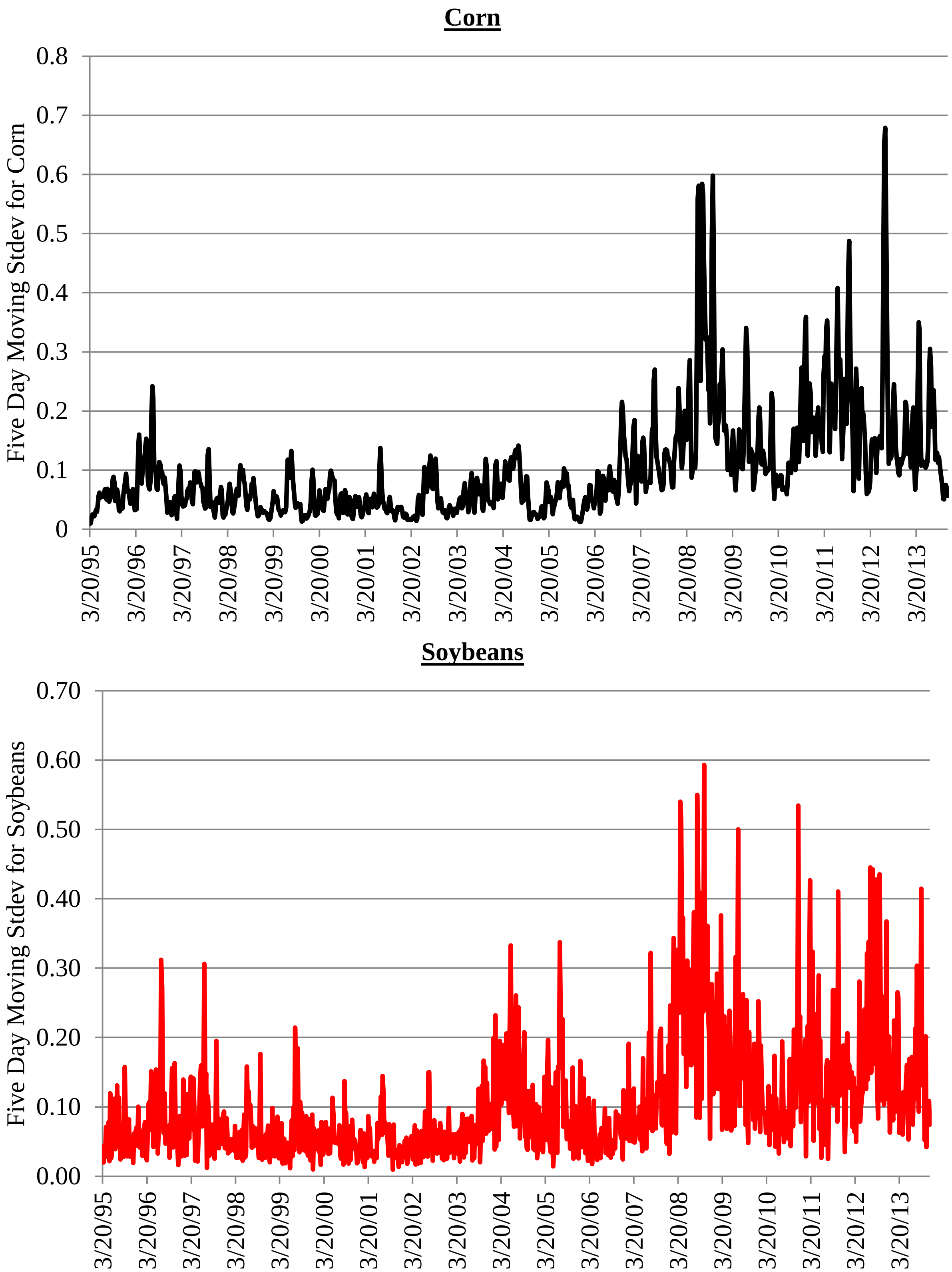


Figure 10. Five-day rolling standard deviation of weighted average price for corn and soybeans, nominal prices, Chicago Mercantile Exchange (CME), 1995-2013

TABLES

Table 1. GARCH order selection using minimum AIC and minimum SBC

	Order
Natural log of absolute normalized change in corn price	
AIC	GARCH(2,3)
SBC	GARCH(2,3)
Change in soybean price	
AIC	GARCH(2,3)
SBC	GARCH(2,3)
Natural log of the five-day standard deviation of soybean price	
AIC	GARCH(2,3)
SBC	GARCH(2,3)
Natural log of absolute normalized change in soybean price	
AIC	GARCH(2,4)
SBC	GARCH(2,4)
Natural log of absolute change in soybean price	
AIC	GARCH(2,4)
SBC	GARCH(2,4)
Natural log of soybean price ratio	
AIC	GARCH(3,3)
SBC	GARCH(3,1)

Table 2. Durbin-Watson Statistics by commodity and dependent variable

Order	DW	Pr<DW	Pr>DW
Natural log of absolute normalized change in corn price, corn			
1	1.2561	<.0001	1
2	1.3079	<.0001	1
3	1.3419	<.0001	1
4	1.4594	<.0001	1
Change in soybean price, soybeans			
1	1.3296	<.0001	1
2	1.9357	0.1582	0.8418
3	2.0056	0.5485	0.4515
4	2.0512	0.8067	0.1933
Natural log of the five-day standard deviation of soybean price, soybeans			
1	1.3639	<.0001	1
2	1.3456	<.0001	1
3	1.2992	<.0001	1
4	1.3532	<.0001	1
Natural log of absolute normalized change in soybean price, soybeans			
1	1.3007	<.0001	1
2	1.3652	<.0001	1
3	1.4084	<.0001	1
4	1.4101	<.0001	1
Natural log of absolute change in soybean price, soybeans			
1	0.994	<.0001	1
2	1.0644	<.0001	1
3	1.1004	<.0001	1
4	1.112	<.0001	1
Natural log of soybean price ratio, AIC order selection, soybeans			
1	1.3955	<.0001	1
2	1.9284	0.1322	0.8678
3	1.9333	0.1571	0.8429
4	1.977	0.3854	0.6146
Natural log of soybean price ratio, SBC order selection, soybeans			
1	1.3955	<.0001	1
2	1.9284	0.1322	0.8678
3	1.9333	0.1571	0.8429
4	1.977	0.3854	0.6146

Table 3. Q test and Engle's LM test for heteroskedasticity for natural log of absolute normalized change in price, corn

Order	Q	Pr > Q	LM	Pr > LM
1	11.5003	0.0007	11.3102	0.0008
2	20.6013	<.0001	18.1814	0.0001
3	26.9685	<.0001	21.8974	<.0001
4	27.423	<.0001	21.8998	0.0002
5	32.0975	<.0001	24.7438	0.0002
6	32.11	<.0001	24.9777	0.0003
7	35.0439	<.0001	26.7286	0.0004
8	36.3038	<.0001	27.0267	0.0007
9	36.3813	<.0001	27.5662	0.0011
10	36.9189	<.0001	28.8436	0.0013
11	37.2926	0.0001	29.4243	0.0019
12	37.3908	0.0002	29.6108	0.0032

Table 4. Q test and Engle's LM test for heteroskedasticity by dependent variable, soybeans

Order	Q	Pr>Q	LM	Pr>LM
Change in price				
1	64.5653	<.0001	64.4533	<.0001
2	106.989	<.0001	85.5876	<.0001
3	161.416	<.0001	110.0781	<.0001
4	257.249	<.0001	154.2817	<.0001
5	321.5691	<.0001	166.5508	<.0001
6	357.6477	<.0001	167.9935	<.0001
7	422.1173	<.0001	179.6159	<.0001
8	485.365	<.0001	185.5989	<.0001
9	517.4216	<.0001	185.5992	<.0001
10	552.693	<.0001	186.5524	<.0001
11	633.1296	<.0001	201.247	<.0001
12	672.4511	<.0001	201.2665	<.0001
Natural log of standard deviation (5-day)				
1	10.6598	0.0011	10.5421	0.0012
2	20.4797	<.0001	18.4226	<.0001
3	34.6705	<.0001	28.6501	<.0001
4	37.269	<.0001	29.1655	<.0001
5	39.825	<.0001	29.7911	<.0001
6	47.395	<.0001	33.8546	<.0001
7	47.4151	<.0001	34.302	<.0001
8	49.5859	<.0001	35.0406	<.0001
9	57.6066	<.0001	39.6309	<.0001
10	57.6127	<.0001	40.3165	<.0001
11	60.3243	<.0001	41.2271	<.0001
12	63.5578	<.0001	42.1506	<.0001
Natural log of normalized change in price				
1	23.4658	<.0001	23.0395	<.0001
2	39.9111	<.0001	34.0022	<.0001
3	49.6209	<.0001	38.209	<.0001
4	50.7243	<.0001	38.219	<.0001
5	52.395	<.0001	38.5582	<.0001
6	52.4314	<.0001	38.6947	<.0001
7	53.7976	<.0001	39.5735	<.0001
8	54.9912	<.0001	40.0666	<.0001
9	55.0181	<.0001	40.4444	<.0001
10	56.1571	<.0001	41.1083	<.0001
11	56.1672	<.0001	41.1559	<.0001
12	57.319	<.0001	41.9803	<.0001

Table 4 (continued). Q test and Engle's LM test for heteroskedasticity by dependent variable, soybeans

Order	Q	Pr>Q	LM	Pr>LM
Natural log of absolute change in price				
1	79.3848	<.0001	78.8151	<.0001
2	125.856	<.0001	98.6182	<.0001
3	169.5274	<.0001	113.2773	<.0001
4	195.3947	<.0001	116.409	<.0001
5	208.4113	<.0001	116.6599	<.0001
6	212.0692	<.0001	117.1857	<.0001
7	215.7084	<.0001	117.2244	<.0001
8	221.469	<.0001	118.4833	<.0001
9	223.8995	<.0001	118.5378	<.0001
10	227.179	<.0001	119.0917	<.0001
11	230.205	<.0001	119.3228	<.0001
12	236.6396	<.0001	121.1016	<.0001
Natural log of price ratio (AIC-selected order)				
1	25.3625	<.0001	25.363	<.0001
2	30.0521	<.0001	27.2677	<.0001
3	38.2995	<.0001	32.8333	<.0001
4	67.2455	<.0001	53.7107	<.0001
5	71.9837	<.0001	53.9738	<.0001
6	74.5697	<.0001	54.398	<.0001
7	82.5247	<.0001	57.5596	<.0001
8	94.8519	<.0001	61.3401	<.0001
9	105.0001	<.0001	64.7247	<.0001
10	117.3607	<.0001	69.3565	<.0001
11	126.9488	<.0001	70.9853	<.0001
12	135.0698	<.0001	72.0185	<.0001
Natural log of price ratio (SBC-selected order)				
1	25.3625	<.0001	25.363	<.0001
2	30.0521	<.0001	27.2677	<.0001
3	38.2995	<.0001	32.8333	<.0001
4	67.2455	<.0001	53.7107	<.0001
5	71.9837	<.0001	53.9738	<.0001
6	74.5697	<.0001	54.398	<.0001
7	82.5247	<.0001	57.5596	<.0001
8	94.8519	<.0001	61.3401	<.0001
9	105.0001	<.0001	64.7247	<.0001
10	117.3607	<.0001	69.3565	<.0001
11	126.9488	<.0001	70.9853	<.0001
12	135.0698	<.0001	72.0185	<.0001

Table 5. Q test and Engle's LM test for heteroskedasticity after GARCH process by dependent variable, corn

Order	Q	Pr > Q	LM	Pr > LM
Natural log of absolute normalized change in price				
1	1.0467	0.3063	1.045	0.3067
2	1.0884	0.5803	1.0749	0.5842
3	1.7948	0.6161	1.7646	0.6227
4	2.3062	0.6796	2.3479	0.6721
5	2.6318	0.7565	2.7283	0.7418
6	2.7849	0.8353	2.8477	0.8277
7	3.6149	0.8229	3.6739	0.8165
8	3.6297	0.8889	3.7322	0.8804
9	3.8154	0.9231	3.9112	0.9172
10	4.8898	0.8984	4.9472	0.8947
11	5.0615	0.9282	5.0965	0.9264
12	5.6408	0.9331	5.7698	0.9272

Table 6. Q test and Engle's LM test for heteroskedasticity after GARCH process by dependent variable, soybeans

Order	Q	Pr > Q	LM	Pr > LM
Change in price				
1	0.6058	0.4364	0.6046	0.4368
2	2.0245	0.3634	1.9744	0.3726
3	4.8811	0.1807	4.6343	0.2006
4	57.1989	<.0001	55.1612	<.0001
5	63.0455	<.0001	59.6479	<.0001
6	64.8414	<.0001	60.2814	<.0001
7	86.1468	<.0001	75.3271	<.0001
8	92.6688	<.0001	75.8613	<.0001
9	94.8135	<.0001	75.9101	<.0001
10	94.8776	<.0001	76.4384	<.0001
11	258.3	<.0001	196.75	<.0001
12	259.989	<.0001	196.771	<.0001
Natural log of the five-day standard deviation of price				
1	7.1673	0.0074	7.1588	0.0075
2	7.2102	0.0272	7.1592	0.0279
3	8.8169	0.0318	8.7471	0.0328
4	8.865	0.0646	8.9296	0.0629
5	8.9841	0.1097	9.0081	0.1087
6	10.0065	0.1244	10.066	0.1219
7	10.0352	0.1866	10.1588	0.1797
8	10.556	0.2281	10.7927	0.2137
9	11.6646	0.2329	11.507	0.2425
10	12.7722	0.2367	12.8705	0.231
11	12.898	0.3	12.9043	0.2996
12	13.049	0.3655	13.0838	0.363

Table 6 (continued). Q test and Engle's LM test for heteroskedasticity after GARCH process by dependent variable, soybeans

Order	Q	Pr>Q	LM	PR>LM
Natural log of absolute normalized change in price				
1	0.1067	0.744	0.1054	0.7455
2	0.4038	0.8172	0.3965	0.8202
3	0.4039	0.9394	0.3965	0.941
4	0.4353	0.9795	0.4313	0.9798
5	0.4694	0.9932	0.4638	0.9934
6	0.4929	0.9979	0.4839	0.998
7	0.5168	0.9994	0.5045	0.9994
8	0.5168	0.9998	0.5045	0.9999
9	0.5211	1	0.5082	1
10	0.5269	1	0.5138	1
11	0.5374	1	0.5236	1
12	0.5796	1	0.5631	1
Natural log of absolute change in price				
1	6.8161	0.009	6.7985	0.0091
2	11.4219	0.0033	10.532	0.0052
3	13.4058	0.0038	11.705	0.0085
4	13.5456	0.0089	11.7076	0.0197
5	13.6983	0.0176	11.7495	0.0384
6	13.6985	0.0332	11.7663	0.0674
7	13.7366	0.0561	11.8194	0.1067
8	13.7434	0.0887	11.831	0.1589
9	13.7564	0.1313	11.8496	0.2219
10	13.7564	0.1844	11.8497	0.2952
11	13.7637	0.2463	11.8557	0.3746
12	15.5701	0.2117	13.6342	0.3247

Table 6 (continued). Q test and Engle's LM test for heteroskedasticity after GARCH process by dependent variable, soybeans

Order	Q	Pr>Q	LM	Pr>LM
Natural log of price ratio, AIC order selection				
1	0.1816	0.67	0.1815	0.6701
2	0.185	0.9116	0.1854	0.9115
3	0.2154	0.9751	0.2167	0.9748
4	18.6075	0.0009	18.4735	0.001
5	18.6088	0.0023	18.4956	0.0024
6	18.6099	0.0049	18.4985	0.0051
7	18.9506	0.0083	18.7984	0.0088
8	20.4532	0.0088	19.1939	0.0139
9	21.2031	0.0118	19.9606	0.0182
10	21.4855	0.018	20.2138	0.0273
11	35.6499	0.0002	33.2698	0.0005
12	36.8876	0.0002	33.8984	0.0007
Natural log of price ratio, SBC order selection				
1	0.1842	0.6678	0.184	0.6679
2	0.1875	0.9105	0.1879	0.9103
3	0.2182	0.9746	0.2195	0.9744
4	18.7585	0.0009	18.6231	0.0009
5	18.7599	0.0021	18.6456	0.0022
6	18.7606	0.0046	18.6479	0.0048
7	19.1034	0.0079	18.9497	0.0083
8	20.6232	0.0082	19.3479	0.0131
9	21.3837	0.0111	20.1255	0.0172
10	21.6594	0.0169	20.3734	0.0259
11	35.8863	0.0002	33.4833	0.0004
12	37.1006	0.0002	34.0902	0.0007

Table 7. GARCH estimates by dependent variable and commodity

Variable	DF	Estimate	St Err	t value	P-value
Natural log of absolute normalized change in corn price, GARCH(2,3)					
Intercept	1	-0.9122	0.0781	-11.69	<.0001
NCOI	1	0.0275 (A*)	0.00222	12.37	<.0001
ARCH0	1	0.0862	0.0508	1.7	0.0898
ARCH1	1	0.1025	0.0506	2.03	0.0427
ARCH2	1	0.0467	0.0378	1.24	0.2163
ARCH3	1	0.0196	0.0682	0.29	0.7734
GARCH2	1	0.49	0.2526	1.94	0.0524
Change in soybean price, GARCH(2,3)					
Intercept	1	-0.0406	0.0343	-1.19	0.2359
NCOI	1	0.001359 (B)	0.00095	1.43	0.1525
ARCH0	1	0.000815	0.000399	2.05	0.0408
ARCH1	1	0.1955	0.0493	3.97	<.0001
ARCH2	1	0.0932	0.0243	3.83	0.0001
ARCH3	1	-0.061	0.0532	-1.15	0.2513
GARCH2	1	0.7672	0.0455	16.88	<.0001
Natural log of the five-day standard deviation of soybean price, GARCH(2,3)					
Intercept	1	-4.7903	0.1322	-36.24	<.0001
NCOI	1	0.0585 (C)	0.003434	17.04	<.0001
ARCH0	1	0.0816	0.0507	1.61	0.1077
ARCH1	1	0.0786	0.0449	1.75	0.0798
ARCH2	1	0.0654	0.039	1.68	0.093
ARCH3	1	-0.003683	0.0575	-0.06	0.9489
GARCH2	1	0.6601	0.1734	3.81	0.0001
Natural log of absolute normalized change in soybean price, GARCH(2,4)					
Intercept	1	-5.1383	0.094	-54.68	<.0001
NCOI	1	0.0117 (D)	0.002461	4.75	<.0001
ARCH0	1	0.1023	0.0346	2.96	0.0031
ARCH1	1	0.1211	0.0516	2.35	0.019
ARCH2	1	0.0898	0.0495	1.81	0.0699
ARCH3	1	0.111	0.0561	1.98	0.048
ARCH4	1	-0.0212	0.0439	-0.48	0.6294
GARCH2	1	0.2362	0.2022	1.17	0.2426
Natural log of absolute change in soybean price, GARCH(2,4)					
Intercept	1	-2.0974	0.045	-46.56	<.0001
NCOI	1	0.0245 (E)	0.001178	20.83	<.0001
ARCH0	1	0.0264	0.008339	3.16	0.0016
ARCH1	1	0.1929	0.0606	3.18	0.0014
ARCH2	1	0.0856	0.0532	1.61	0.1077
ARCH3	1	0.1479	0.0636	2.32	0.0201
ARCH4	1	0.0866	0.0679	1.27	0.2024
GARCH2	1	1.17E-07	0.2384	0	1

Table 7 (continued). GARCH estimates by dependent variable and commodity

Variable	DF	Estimate	St Err	t value	P-value
Natural log of soybean price ratio, AIC order selection, GARCH(3,3)					
Intercept	1	-0.1184	0.2145	-0.55	0.5809
NCOI	1	0.004662 (F)	0.005606	0.83	0.4056
ARCH0	1	0.1433	0.0512	2.8	0.0051
ARCH1	1	0.1577	0.0346	4.56	<.0001
ARCH2	1	0.0352	0.0254	1.39	0.1657
ARCH3	1	0.0323	0.0273	1.18	0.2366
GARCH3	1	0.6669	0.0684	9.75	<.0001
Natural log of soybean price ratio, SBC order selection, GARCH(3,1)					
Intercept	1	-0.1414	0.2211	-0.64	0.5224
NCOI	1	0.005257 (G)	0.005792	0.91	0.3641
ARCH0	1	0.097	0.037	2.62	0.0087
ARCH1	1	0.1391	0.0296	4.71	<.0001
GARCH3	1	0.7875	0.0455	17.29	<.0001

Note: ARCH terms are coefficients on autoregressive terms; GARCH terms are coefficients on conditional variance terms.

* Letters provide reference within the text.

Table 8. Summary statistics for corn and soybeans, percent of open interest for noncommercial, commercial, and nonreportable traders from the CFTC's COT, Futures-and-Options Combined reports, 1995-2013

Corn

	1995-2006				2007-2013				1995-2013			
	OI	NC	C	NR	OI	NC	C	NR	OI	NC	C	NR
Mean	665,486	29%	47%	24%	1,758,781	43%	44%	13%	1,070,701	34%	46%	20%
Min	351,111	17%	39%	13%	1,091,888	33%	35%	10%	351,111	17%	35%	10%
Max	2,067,296	42%	54%	36%	2,573,509	52%	51%	17%	2,573,509	52%	54%	36%
StDev	325,945	5%	3%	5%	321,717	3%	3%	1%	619,859	8%	3%	7%
Kurtosis	5.16	-0.30	-0.57	-0.96	-0.42	0.43	1.30	-0.54	-1.18	-1.15	0.37	-0.93
Skewness	2.29	0.37	-0.11	0.26	0.18	0.12	-0.74	-0.06	0.54	0.15	-0.27	0.50
Obs.	613	613	613	613	361	361	361	361	974	974	974	974

Soybeans

	1995-2006				2007-2013				1995-2013			
	OI	NC	C	NR	OI	NC	C	NR	OI	NC	C	NR
Mean	268,939	34%	42%	24%	731,969	44%	45%	11%	440,555	38%	43%	19%
Min	158,430	23%	29%	14%	379,052	36%	37%	7%	158,430	23%	29%	7%
Max	550,854	43%	52%	38%	1,259,806	54%	51%	16%	1,259,806	54%	52%	38%
StDev	81,679	4%	4%	5%	180,263	4%	2%	2%	257,452	6%	4%	8%
Kurtosis	0.71	-0.38	0.11	-0.50	0.19	-0.58	0.15	-1.20	-0.11	-0.72	0.78	-0.98
Skewness	1.18	0.01	-0.47	0.45	0.60	0.27	-0.19	0.15	0.94	0.29	-0.78	0.18
Obs.	613	613	613	613	361	361	361	361	974	974	974	974

OI Open Interest NC Noncommercial C Commercial NR Nonreportable

Table 9. Summary statistics for corn and soybean weighted average price, weekly returns, absolute weekly returns and percent change in absolute weekly returns, 1995-2013

Corn

	1995-2006				2007-2013				1995-2013			
	Price	Returns	Abs(R)	% Change	Price	Returns	Abs(R)	% Change	Price	Returns	Abs(R)	% Change
Mean	2.54	0.00	0.05	0.02	5.21	0.00	0.15	0.03	3.53	0.00	0.09	0.02
Min	1.88	-0.33	0.00	0.00	3.23	-0.75	0.00	0.00	1.88	-0.75	0.00	0.00
Max	4.23	0.22	0.33	0.10	8.09	0.69	0.75	0.15	8.09	0.69	0.75	0.15
StDev	0.45	0.07	0.05	0.02	1.32	0.20	0.13	0.02	1.56	0.13	0.10	0.02
Kurtosis	1.66	1.73	3.69	2.54	-1.27	1.88	4.07	3.64	0.14	6.37	10.51	4.78
Skewness	1.41	0.15	1.66	1.45	0.29	-0.12	1.83	1.64	1.14	-0.16	2.77	1.79
Obs	613	612	612	612	361	361	361	361	974	973	973	973

Soybeans

	1995-2006				2007-2013				1995-2013			
	Price	Returns	Abs(R)	% Change	Price	Returns	Abs(R)	% Change	Price	Returns	Abs(R)	% Change
Mean	6.01	0.00	0.12	0.02	11.68	0.02	0.27	0.02	8.11	0.01	0.17	0.02
Min	4.23	-0.76	0.00	0.00	6.76	-1.43	0.00	0.00	4.23	-1.43	0.00	0.00
Max	9.82	0.61	0.76	0.10	16.97	0.91	1.43	0.15	16.97	0.91	1.43	0.15
StDev	1.12	0.15	0.10	0.02	2.30	0.35	0.22	0.02	3.20	0.24	0.17	0.02
Kurtosis	-0.02	2.30	5.92	3.26	-1.03	1.19	3.85	5.84	-0.58	3.72	7.67	5.01
Skewness	0.66	-0.11	1.99	1.52	-0.12	-0.52	1.56	1.69	0.83	-0.50	2.24	1.65
Obs	613	612	612	612	361	361	361	361	974	973	973	973

OI Open Interest NC Noncommercial C Commercial NR Nonreportable

VITA

William Grady Ferguson is pursuing a Masters of Science in Agricultural and Resource Economics from the University of Tennessee. His interests are in the economics of trading in cash and futures markets for agricultural commodities. His research relies heavily on time series econometrics.