Speculation and Hedging in Corn and Soybean Futures Markets

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Abstract

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Recent spectacular increases in worldwide food prices has led some critics to assign blame for this phenomenon to speculators in commodity futures markets, especially index funds, for having caused increased price volatility in commodity futures and spot. This thesis addresses the question of whether speculation or hedging activity in the corn and soybean futures markets are responsible for increases in the futures price volatility in these markets. Theoretical reasons for each view are examined. In addition, this question is addressed empirically, while controlling for economic factors that may also affect futures price volatility. The effect of speculative and hedging activity in these futures markets upon the spot market price volatility is also studied. Since volatility may be caused by trading, but volatility may also attract traders, the empirical relationships are studied using Granger Causality tests. The empirical research is based on new and modified data on traders' positions made available by the Commodity Futures Trading Commission which allows for a more accurate classification of traders as speculators or hedgers. The results are inconsistent with previous empirical research that blames speculators for increases in agricultural commodity prices for both the spot and futures market. In contrast, the results show that hedgers tend to increase the volatility of corn futures' prices, thus lending support to the theory of hedging pressure. Only processors and merchants change their positions in the corn futures market upon increases in the futures price volatility, which indicates that this market is mainly used for hedging purposes while speculators in the soybean futures market tend to increase their positions in response to an increase in futures price volatility. Finally, the futures positions of no single trader category could be used to predict future price volatility movements across both markets, implying that traders are trend followers.

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Chapter 1 Introduction

In 2006, new and interesting headline news started appearing in major media sources all over the world. It did not involve threats of nuclear attacks, presidential elections, or major social revolutions; rather it was simply about the impact of rising food prices on household consumers, especially in developing countries. In June 2008, mass protests occurred in India, Mexico, Yemen and certain parts of Africa over the dramatic increase in grain prices that occurred since 2006. At the same time, children were marching in Egypt and Haiti to call attention to child hunger and malnutrition. Also, the FOA (Food and Agricultural Organization of the UN) announced that 36 countries are in crisis due to higher food prices and will require external assistance (World Bank, 2008). In developed countries food is a small portion of household consumption (10-15%), but in developing countries, it could reach 40% or more (Von Braun 2008). Large fluctuation in prices will have serious consequences in these countries and could lead to worldwide riots and threaten economical and political stability.

The drastic increase in food prices over the period 2006-08 coincided with large inflow of money in the commodity futures market by long-only commodity index funds. Index fund investment increased from $90 billion dollars in January 2006 to $200 billion dollars in December 2007 (Barclays 2007) mainly because influential studies proved that investing in long only commodity index funds would provide diversification benefits for portfolio managers (e.g. Gorton and Rouwenhorst 2006). Also, low transaction costs and liquid contracts made commodity futures very appealing for speculators and hedgers alike.

Due to the size and scope of commodity index funds transacting in the futures market, a worldwide debate erupted concerning their role in driving up commodity prices.

On one hand many economists and policy makers blamed index traders. They recommended position limits, and more transparency in commodity markets in order to limit speculation. In response to almost 4,670 comments provided by academics, traders, advisors, producers and futures market participants concerning the rapid increase of long-only investments, the CFTC (U.S. Commodity Futures Trading Commission) started publishing supplemental notes that broke down the position of index traders for all agricultural commodities in 2007. The report was labelled Commodity Index Traders report (CIT). Moreover, the CFTC announced in a meeting in September 2009 that it would provide more transparency to exchange traded futures by classifying traders into four different categories in the newly released DCOT report (Disaggregated Explanatory Notes) which are: 1) Swap Dealers (SD), who deal in commodity swaps and use the future markets to manage or hedge the risk of the swap transactions; 2) Money Managers (MM), who manage and conduct futures trading on behalf of investors; 3) Producers and Processors (PM), who have actual positions in the spot market and use the futures market in order to manage the risk of these positions and; 4) Other Reportable Traders (OR) who are not included in any of the above three categories but possess large enough positions to be classified as reportable traders.

If speculation is positively correlated with volatility, then it could be partially responsible for the rise of basic food prices worldwide.Although some level of speculation could be beneficial to the market since speculators provide liquidity, excessive speculation that increases volatility will have detrimental effects on producers. These producers face many risks in the production and marketing of these commodities.

The most important one is price risk, since it makes planning for long-term investment to increase yield or improve quality rather difficult. Usually large producers will use some sort of hedging as a mean of decreasing the variation in return. However, small and medium producers are less likely to hedge and are thus more vulnerable to price changes which could have detrimental effects on their production capacity and lead to huge decrease in the supply of agricultural crops. This leads to the question of whether speculation was one of the main reasons behind the last tremendous agricultural price spike or blaming speculators is just another historical misconception concerning traders who make mysterious gains through dealing in goods which they have no interest in producing or purchasing. This historical and social resentment towards the speculator is best described by an incident in the 1860's when traders on Wall Street sold gold short on rumours that the government would sell some of its surplus. This knocked down gold prices considerably and lead to Lincoln's famous quote: "I wish every one of them had his devilish head shot off." (Mc Clure 1879).

On the other hand, several studies rejected the hypothesis that speculators drove price increases in commodity futures and concluded that fundamental factors are the main drivers of higher prices. Recent price volatility in commodity futures could be explained using different factors such as the increase in demand by emerging countries, especially China and India, which enormously increased their consumption of commodities over the last decade and had a substantial 9% real GDP growth between 2000 and 2006 (Von Bauren 2008).

Another possible explanation is that the rise in food prices coincided with an enormous increase in commodity prices led by energy and metals (Gilbert 2010) which was similar to the 1973-1974 commodity price booms in the sense that it occurred in enormous world liquidity in futures markets resulting from huge US trade deficits and loose monetary policies.

Also, the demand for crops such as corn, soybean and feedstock used in bio-fuel production is a major contributor to the food prices increase (Rose-grant et al, 2008). The tradeoff of food versus fuel puts upward pressure on food prices and correlates agricultural commodity prices to that of oil.

The last fundamental factor that could explain the rise of agricultural prices is the depreciation of the US dollar which is the main currency of all commodity trading.

1.1 Research Objectives

After presenting a summary of the debate on what drives commodity prices, the following section presents the research objectives of the paper.

First of all, the impact of speculation on price movements in agricultural futures has been studied extensively in the literature. However, to our knowledge, the relation between the level of speculation and volatility in the corn and soybean futures market has not been studied extensively. All previous work has focused on the causal relation between the level of speculation and futures price movements.

Corn was chosen because it is the most widely produced feed grain in the United States, which produces 40% of the world's harvest. Corn is mostly used to produce corn oil, starch, beverages and fuel ethanol. In addition, the U.S. accounts for 20% of the world exports of corn. Soybean is the second most widely produced crop in the U.S. with a value of 38 billion dollars in 2009/10 and accounts for 90% of total U.S. oilseed production (USDA 2010). The significance of the two commodities implies that their prices would be closely followed by regulators, and producers. Also, derivatives on these commodities would be traded extensively and would be liquid.

- Our first objective is to study the relation between the volatility of the corn and soybean futures contracts and the level of speculation in each market using the new and modified Disaggregated Commitments of Traders (DCOT) data made available by the Commodity Futures Trading Commission (CFTC) which allows us to more accurately classify traders as speculators and hedgers for the period 2006-2010. In order to classify traders as hedgers or speculators, we will use the methodology of De Roon et. al (2000) and modify it in order to match the new classification we have for the DCOT data. We will use a class of stochastic processes known as generalized autoregressive conditional hetroscedasticity (GARCH) and exponential GARCH (EGARCH) in order to analyze causality for all the variables discussed in the paper.
- The second objective would be to test whether traders that are classified as hedgers have any impact on the volatility of the contracts. Hedgers have actual positions in the spot market and use the futures market in order to manage their risk. Speculative positions, unlike hedging positions, are limited by the CFTC in terms of how many net long or short contracts can be held on each exchange. However, hedgers can apply for exemptions and large producers place huge short positions in order to better manage their production risk. We believe that there could be a significant relation between hedging positions and changes in volatility of the two contracts. This provides a counter argument to the existing one.
- Third, we would test whether a relation exists between futures trading activities of speculators and hedgers and the volatility of the spot market. If such a relation exist,

then traders are partially responsible for increasing prices of basic commodities and diminishing the purchasing power of poor consumers, thus increasing worldwide income disparity and economic inequality. Also, we will test for the alternative hypothesis of whether the volatility of the spot market leads that of the futures.

- A multivariate model that controls for basic fundamental factors is used to test the above three objectives. Zellner's seemingly unrelated regression (SUR) is employed by pooling the two regressions together since it will lead to statistical accuracy especially when the error terms across the equations are correlated.
- Lastly, the new data allows us to test using a pooled Seemingly Unrelated Regression (SUR) whether or not each trader category could be used to predict the subsequent volatility of the two futures contracts in the sense that traders could be labeled as trend followers or contrarian traders.

1.2 Contribution, Hypotheses and Implications of The Research

The main contribution of the thesis is that it allows us to test whether speculation and hedging affect the spot and futures price volatility of corn and soybean. To our knowledge, this relation has never been studied before. Moreover, the more comprehensive and detailed DCOT data has not been used previously to test for hedging and speculation effects. We believe that the classification offers a superior procedure of classifying traders as hedgers or speculators.

Also, previous studies tend to test for causality using a bivariate model. We will use a multivariate model that includes the basic effect of supply and demand upon the spot market and cost of carry and convenience yield for the futures market. We believe that estimating the cost of carry and convenience yield are important because differences between contemporaneous spot and futures prices are explained using interest lost in storing a commodity, warehousing costs, shipping and insurance costs, and a convenience yield on inventory which will be modeled using an exchange option (Kocagil 2004).

Furthermore, the new data will allow us to examine whether each trader category in the new classification could lead to changes in the volatility of the contracts. Although the methodology used in this section is already discussed in Sanders et al. (2004), the new data allows us to further divide commercial and non-commercial classifications used in the COT report. As well, the period of 2006-2010 was characterized by more volatility in the spot market than the period 1992-99 which was used by Sanders et al. (2004).

Hypotheses

1. Speculation will lead to higher volatility in both markets. Although empirical results produce contradicting results, I would expect that speculation will lead to higher volatility during the period of study since it is characterized by large positions of swap dealers (discussed later in detail).
2. Hedging decreases the volatility of the spot market since it allows producers and merchants to transfer risk to other market participants.
3. Traders are trend followers thus hedgers will increase their short positions and speculators their long positions after volatility increases.

Implications

Our findings could have significant implications for consumers, practitioners and policy makers. If futures trading activity of speculators or hedgers are found to cause price volatility of our futures contracts and the commodities, then policymakers should try and devise ways to try and limit these effects since they lead to tremendous effects on household purchasing power throughout the globe. If speculation was found to be significantly related to spot price volatility, then policymakers could impose tougher trading restrictions or position limits. Also, if hedgers are partially responsible for the increase, then perhaps the CFTC should reexamine its classification procedure for traders and maybe require stricter rules for classifying traders as hedgers since some speculators might have the motive to classify themselves as hedgers in order to bypass trading restrictions.

Moreover, it would be very appealing to practitioners to know whether any of the four traders' categories have any significant predictive power and could signal market continuation or reversal and could be translated into profitable trading strategies. Also, if volatility tends to lead traders' positions in corn and soybean future contracts, then this will add support to the existing literature concerning that traders are trend followers.

Chapter 2 Literature Review

2.1 Link between speculation, hedging and price movements

The impact of speculation, principally long-only index fund investment, has been a hot debate in commodity research. It is commonly believed that speculative buying created a bubble and commodity prices far exceeded fundamental values over the period of our study. Before summarizing the bubble debate, we will start by reviewing earlier papers that dealt with the level of speculation in agricultural futures. Peck (1981) examined changes in the degree of speculation for corn, wheat and soybean using monthly data from 1974 to 1977. Her main finding was that increase in the trading range is related to a decrease in speculation. Peck used a monthly average of daily trading ranges as a measure of price variability and concluded that speculation has a large impact on market return.

The recent boom in commodity prices led to extensive research on the relation between the level of speculation and prices, in an attempt to provide evidence on the question of whether the sharp increases in prices were due to a bubble. Gilbert (2009) studied price movements in three agricultural (wheat, corn and soybeans) futures, metal (aluminum, copper and nickel) futures and crude oil futures for 2006-2008. Using Granger causality tests between lagged index fund investment and price changes, the author found a statistically significant relationship between the two for crude oil, copper and aluminum but weaker evidence for grain futures. However, his main results indicated that index funds' investments in futures lead to significant price changes in only 3% of the sample over the period 2006-2008.

Stoll and Whaley (2009) used weekly data to study the relation between long-only index fund investment and price changes for all 12 futures markets included in the COT report. Also, Granger causality tests indicated that commodity index investing did not cause any futures price movements.

Sanders, Irwin and Merrin (2008) studied the adequacy of speculation in agricultural futures contracts in the period 2004-2008. Their main finding was that Working's T, which is a measure of speculation first introduced by Working (1960) was still within its historical range and that the number of short hedging positions were increasing at a higher rate than long hedging positions. The authors inferred that long-only investments provided overall liquidity for hedgers and any limitation on the participation of index fund investors would lead to a major liquidity shock in the market.

Sanders and Irwin (2010) studied the impact of index and swap funds on commodity futures markets. They studied the relation between futures returns and traders' positions using cross-sectional tests rather than a regression analysis of time-series. Their study failed to find a relation between returns and traders' position. Empirical results provided little evidence that long-only positions affected returns in various commodity futures markets.

The most cited paper that blamed index traders for the recent boom in prices is that of Masters and White (2008). They found a correlation between large investment of index funds and price variation and blamed the tremendous increases in commodity prices on institutional investors'. They recommended regulatory actions in order to limit speculation through re-examining speculative position limits and eliminating index speculation. The U.S. Senate Subcommittee investigation related to the CBOT wheat futures market reached a similar conclusion as that of Masters and White in the sense that excessive speculation by index traders was one of the major reasons for the tremendous price fluctuation. They recommended restricting index traders to 5000 contracts, and conducting more investigations into the effect of index fund trading in other agricultural markets.

An alternative theory that could explain price movements would be that hedgers' positions might be correlated with movements in futures prices. Hedging pressure theory dates back to Keynes (1930). It focuses on risks that hedgers face due to market frictions such as high transaction costs or information asymmetries. Chang (1985) studied the extent to which net hedgers' and speculators' positions are related to price movements in agricultural futures contracts using monthly CFTC data. He found that both hedgers' and speculators' positions affect prices in the sense that prices rise on average in months in which speculators hold enormous long positions and hedgers hold short positions, and concluded that a risk premium for the level of speculating and hedging should be included in the futures prices.

In order to better determine the futures risk premium, De Roon et al. (2000) presented a model which implied that the futures risk premium depended on market and cross-market hedging pressure. Their main result was that the futures risk premiums in 20 futures markets classified into four different categories: financial, agricultural, mineral and currency were correlated with their hedging pressure variables constructed from the CFTC data. Hedging pressure had a significant effect on futures returns after controlling for market risk and price risk. An interesting result was that the authors found that hedging pressure effects were also significant in explaining the spot return for the corresponding markets.

2.2 Fundamental Factors

In an attempt to explain recent prices using fundamental factors, Cooke and Robles (2009) used a time series model to test for factors that affect agricultural commodities' prices. These factors included ethanol and biodiesel production, exports, and imports, prices of crude oil, and fertilizers, and the U.S. dollar-Euro exchange rates as a proxy for the U.S. dollar depreciation, as well as proxies for speculation.

Considering corn and soybean, the results indicated that while only oil prices were a significant factor for corn, for soybean, oil prices were significantly negatively related to prices, export and the U.S. dollar-Euro exchange rate were positively related to prices. The study used Granger causality to test for the effect of above factors on commodity prices.

Other papers dealing with the topic used graphs and theories to explain the factors that affected agricultural futures prices. The most cited ones are Abbott et al. (2008) and Mitchell (2008) which emphasized the effects of rising demand in countries such as China and India, increases in ethanol production, increased oil/fertilizer prices leading to higher costs of production for producers and devaluation of the U.S. dollar, since most commodities are priced in U.S. dollars. The Euro exchange rate seemed to have the dominant effect since only the U.S. and Europe used these two commodities for biodiesel and Europe imported 70% of the total U.S. corn exports.

Roach (2010) used a spline-GARCH model to test the relation between volatility and spot prices for six commodities. His sample included both corn and soybean markets and ranged from 1875-2009. The author claims that it is helpful to separate volatility patterns into low and high frequency components. High frequency volatility included weather and pest shocks and uncertainty about expected harvest while low volatility can be defined as changes in the level of price variability which persist for more than one year. His main result was that low frequency volatility is positively correlated across different markets. Also, U.S. dollar exchange rate variability and U.S. inflation volatility were the two variables that explained a large part of the rise in volatility since mid-1990s.

2.3 Relation Between Futures and Spot Markets

The issue of whether the introduction of futures markets lead to less variability in cash market prices is debatable. In an interesting article, Jacks (2007) argued that the introduction of futures markets would lead to lower commodity price volatility using a rational expectations model with storage and futures markets. The author showed that higher spot market volatility existed before the introduction of futures exchanges using indices for 16 major agricultural, and metals markets.

Antoniou and Holmes (1995) studied the impact of trading of the FTSE-100 stock index futures contract on the volatility of the spot market using daily closing prices for the period 1980-1991and reported that futures trading increased the volatility of the underlying spot market.

Darrat et.al (2002) studied the role of index futures trading upon spot market volatility for the S&P 500 using exponential GARCH (EGARCH) to model spot and futures price volatilities for the period 1987-1997. Their main finding was that futures trading did not lead volatility in the spot market; rather, there was strong evidence to support the alternative hypothesis that spot volatility led that of the futures market.

2.4 Traders' Positions

Sanders et al. (2004), using Granger causality tests and data from the CIT report, examined whether a relationship existed between traders' positions and market price movements for the following contracts: crude oil, unleaded gasoline and natural gas futures. Using traders' positions for 1992 to 1999, they found that positive futures returns led to an increase in noncommercial net positions in the following week, while long commercial positions decreased after a futures price increase. The interesting part in this paper is that they tested for the effect of non-reporting traders, for which the CFTC provide no information to whether their positions are for hedging or speculative purposes. They also focused on the idea that non-commercials were true speculators while commercial positions need not be for hedging alone. This point will be discussed in detail in the methodology section. Another major result was that traders' positions did not lead market returns and should not be used as an independent indicator of market returns.

Wang (2001) constructed a sentiment index based on traders' positions in six agricultural futures markets in order to study whether these positions could predict futures price movements. If a relation were found to exist, then this could be useful in timing the market. The sentiment index was constructed using total open positions and included net long open positions, and historical maximum and minimum aggregate positions. The author concluded that speculators' positions were a price continuation indicator, while hedgers' positions were contrary indicators.

Chapter 3: DATA

3.1 CFTC Data for Corn and Soybean Futures Markets

Traditional COT reports provide a breakdown of each Tuesday's open interest for markets in which 20 or more traders hold positions equal to or above the reporting levels established by the CFTC. Open interest is divided under reporting and non-reporting trader categories. Reporting traders' positions are divided into commercial long and short and non-commercial long, short, and spreading positions. Non- reporting traders' positions are divided into long and short positions. The COT has a major drawback in the sense that there is an incentive for speculators to try and classify their activity under commercial hedgers in order to bypass position limits (CFTC 2009).

In order to address these issues, the CFTC started publishing the Disaggregated Commitments of Traders (DCOT) report under which reporting traders' positions are classified under those of swap dealers, managed money, processor and merchants, and other reporting traders. Positions are divided into long, short and spreading. The last simply indicates that traders take long and short positions in the same contract but with different futures contract maturities. Swap Dealers (SD) are entities that deal in swaps for a commodity and use the futures markets to manage or hedge the risk of the swap transactions. Money Managers (MM) are engaged in managing and conducting futures trading on behalf of investors. Producers and Processors (PM) have actual positions in the spot market and use the futures market in order to manage their risk, while Other Reportable (OR) includes positions which are not included in one of the above three categories but are large enough to be reported. Weekly Data were collected from the U.S. Commodity Futures Trading Commission (CFTC) for the period of June 2006-

September 2010 for a total of 225 observations. This sample represents all available data that provides a better classification of traders.

3.2 Spot and Futures Price Data

Daily spot and futures prices for corn and soybean were collected from Datastream for January 2006 to September 2010. The following led to 1,230 observations. In order to match daily data with the weekly data provided by the CFTC, the two files were merged using Tuesday prices. For soybean spot prices, 5 daily observations were missing, of which only 1 was Tuesday prices. In order to adjust for that, the price of the day before was used as a proxy for Tuesday's price. The same procedure was used to adjust for two missing Tuesday corn prices.

Insert Figure 1

Insert Table 1

Figure 1 graphs weekly spot and futures prices over the period 2006-2008. From figure 1, it is apparent that most of the price increases occurred in the period 2006-08. Table 1, which provides characteristics of spot and futures prices, as well as other variables used in the analysis, shows that prices over this period were very volatile for both markets, with corn futures trading between 220 and 750 cents/bushel and soybean futures from 500 to 1,600 cents/bushel.

3.3 Convenience Yield and Storage Costs

Brennan (1958) and Tesler (1958) show that inventory owners have benefits from holding stores of a commodity, such as the ability to profit from temporary shortages of the commodity and to maintain a stable production process, which are not available to holders of futures contracts.

Gibson and Schwartz (1990) argue that this concept has been empirically shown to be one of the drivers of the relation between futures and spot prices for agricultural commodities. Another factor which influences future prices is the cost of carry, which includes storage costs, transportation costs, insurance and interest rates. The cost of carry model expresses futures prices as a function of spot prices:

$$F = (S + sc)e^{(r-c)t} \tag{1}$$

F: futures prices, S: Spot price, sc: storage cost and c: convenience yield, t represents the time to delivery of the futures contract.

Storage costs for both contracts are collected from the CME rulebook. These include a premium for insurance on the crops stored at authorized facilities. Barge rate data collected from the U.S. Department of Agriculture (USDA) are used as a proxy for weekly transportation costs. Three month T-bill rates from the Federal Reserve statistical releases are used to calculate interest forgone on storing the commodity.

In order to estimate the convenience yield associated with corn and soybean, we will use an exchange option model proposed by Kocagil (2004) which will be discussed in detail in the methodology part. The estimation requires two sets of future prices that are six months apart and are obtained from Datastream.

3.4 Other Control Variables

Economic factors that have been shown to affect spot prices are used as control variables in the spot volatility regression. These factors include net exports, oil prices and the Euro-U.S. dollar exchange rate.

Net Exports: Weekly data on the net shipment is collected for both markets from the USDA. Since the U.S is a major worldwide exporter of both commodities, the data collected are indicative of huge positive net exports. From Table 1, it is apparent that exports are huge, with corn exports being on average double the exports of soybean.

Oil: Average weekly crude oil spot prices collected from Bloomberg are used to control for the effect of oil and biodiesel production. Biodiesel production data is only available monthly and since there is a high correlation between oil prices and biodiesel production, we believe that oil prices could represent that effect. Also, oil is directly related to production and transportation costs. During the period of 2006-2008, oil prices fluctuated between 41.50 and 149.50 dollars a barrel.

Euro-U.S. dollar exchange rate: Since previous research showed that the depreciation of the U.S. dollar directly affected the prices of agricultural commodities, we will use the Euro-U.S. dollar exchange rate as a proxy for that depreciation. Daily exchange rates are collected from Bloomberg.

The sample consists of 1,230 observations for daily spot and future prices and 225 observations on traders' positions from the weekly CFTC report.

Chapter 4 Methodology

4.1 Calculation of Speculative and Hedging Indices

As previously mentioned, the speculative and hedging indices will be based on the theoretical model of De Roon et al. (2000) which used the COT data to examine hedging pressure in 20 futures markets. They defined hedging pressure as the difference between commercial short and long positions divided by the total positions of reporting commercials. The data is provided under reporting and non-reporting positions. Two issues arise when using the CFTC data. First, a major drawback of this analysis is to assume that all commercials are hedgers and all non-commercials are speculators. Also, we should match commercials and non-commercials positions to the new DCOT data. The CFTC provides supplemental notes that are used to construct hedging and speculative indices from reporting positions by using the following equation:

$$Hedgers = Commercials\ (COT) = Processors\ and\ merchants(DCOT) \tag{2}$$

$$\begin{aligned} Speculators &= NonCommercials + Index\ (COT) = Swap\ Dealers \\ &+ Managed\ Money + Other\ Reportable\ (DCOT) \end{aligned} \tag{3}$$

In September 2008, the CFTC launched a report on the characteristics of the swap dealer positions. They concluded that swap dealers correspond closely to index funds in agricultural futures (CFTC, 2008b) but not in metal or oil; thus there is minimum error in attributing index fund investment to swap dealers.

Also we will follow the methodology of De Roon et al. (2000) and use the percent net long positions held by non-commercials to represent the speculative index. Hedging and speculation are estimated by the following equations:

$$H_t = \frac{PMS_t - PML_t}{PML_t + PMS_t} \tag{4}$$

$$S_t = \frac{(SDL_t+MML_t+ORL_t)-(SDS_t+MMS_t+ORS_t)}{(SDL_t+MML_t+ORL_t)+(SDS_t+MMS_t+ORS_t)+2Spread\ (SD_t+MM_t+OR_t\ )} \tag{5}$$

$\mathrm{H_t}$ = Hedging index, $\mathrm{S_t}$ = Speculative index, PM = Processors and Merchants, SD = Swap Dealers, MM = managed money, OR = Other Reportable, (L) = Long and (S) = Short

A major concern is the method used to allocate the positions of non-reporting traders. In our methodology, we will follow the procedure of Sanders et al. (2008) and allocate the non-reporting traders' positions to swap dealers, managed money, processors and merchants, and other reportable traders, using their respective weights of total reporting traders.

Table 1 shows the mean for the hedging and speculative index constructed from equation 4 and 5. The degree of hedging is around 53% for soybeans and 50% for corn, while the degree of speculation is around 40% for both.

Insert Table 2

Table 2 is divided into three panels. Panel A shows the average position size by category. Managed money long positions are around three times as big as short positions. Processor and merchant positions are mostly concentrated in short positions while swap dealers have an enormous difference between average positions for long and short with short positions around 8,700 contracts and long positions around 327,000 contracts. This clearly indicates that compared to the CIT report, this category represents long only index investments.

Panel B provides the average position size by trader. We decided to include that in order to observe the significance of traders in each category. An interesting observation is that for managed money, other reportable, processor and merchant categories, the traders seem to have similar number of contracts for long and short. The major difference is in the swap dealers' category in corn futures, who hold on average 10 times more long contracts than short.

Panel C shows the percent of long and short positions for each category. Although the average swap dealer holds enormous positions, their overall percentage of long positions is not overwhelming. Based on the fact that swap dealers hold around 1% of all short positions, we can infer that this category is similar to long-only index investments and is classified as speculators. Also, as expected, traders classified as processors and merchants hold around 80 % of all short positions. However, this category holds 25% of total long positions which implies that processors and merchants may not be pure hedgers but rather tend to try to earn some profit by assuming long positions. Note that processors and merchants could apply for exemptions from speculative position limits on futures exchanges and thus a motive exists for traders to try and classify their activities under the category of processors and merchants. Also, the fact that processors and merchants hold most of the short positions and a significant part of the long positions could lend support to the fact that agricultural markets are mostly used for hedging purposes as Working

(1960) suggests.

4.2 Calculation of Convenience Yield and Storage Costs

A factor which influences future prices is the cost of carry which includes storage costs, transportation costs, insurance and interest rates. A series of assumptions will be made in order to estimate the cost of carry. First, we assume that all delivered grains are No.2 for corn and soybean, since delivering other grades is accepted by exchanges; however, it results in a premium or discount based on the quality delivered. Second, delivery on futures contracts will take place on the first trading day of the deliverable month for corn and soybean which will be used as a proxy in order to estimate storage days and cost. The daily storage cost includes a premium for insurance on the crops stored at authorized facilities. According to Irwin et al. (2009), 15 million bushels of corn and 10 million bushels of soybean are shipped monthly through the Illinois delivery facilities. Therefore, Saint Louis-Illinois facilities will be used as a proxy for the shipping destination, since these facilities account for most of the shipping certificates issued from the CME.

There are three methods of transporting corn and soybean which are: railroad, trucks and barge. The U.S. Grain Council (2008) estimates that barge transportation is the cheapest for exporting grains and provides easy access for 80% of U.S. corn production.

The USDA issues weekly barge rate quotes which represent the cost of transporting a short ton of grain from a specific origin to a destination. Several barge rate indexes exist, however, along the Mississippi River system, and the destination is not specified and could be anywhere between Baton Rouge and New Orleans, including South Louisiana. As of August 2005, these three ports served as a gateway for about 55 to 70 percent of all exported corn and soybean (North American Export Grain Association, 2006).

We will use the above barge rate index in order to estimate transportation costs. Storage costs = storage costs at authorized facilities + transportation costs + interest foregone

Storage costs are almost identical for corn and soybean with averages of 7.5 and 6.5 cents/bushel respectively.

Early theoretical work (Brennan, 1958) and empirical work (Fama and French, 1987) on the convenience yield assumed that shortage in the spot commodity would lead to a positive convenience yield and thus to an inverse relation between convenience yield and the amount of inventory. However, recent work implies that convenience yield could be modelled using a call option (Heinkel et al. 1990). Our method of estimating convenience yield is consistent with Heinkel et al. In order to estimate the convenience yield that accrues to owners who have benefits from holding the spot commodity, such as the ability to profit from temporary shortage and maintain a stable production process, the method used by Kocagil (2004) is employed.

First, assume that at time t a producer has to choose between selling now and waiting till time$(t+1)$. The decision is based on the expected future spot price and carrying costs. Thus, the inventory holding decision resembles a financial option. In order to decide whether to store the commodity or to sell it right away, Kocagil uses future prices that are five month apart. In our estimation, the following data was collected from Datastream and Bloomberg and it includes an intra commodity spread under which a trader is long one futures contract and shorts the other. The approach assumes a short position in the March contract and a long position in the September contract. Also, May-

December is used as a proxy for the intra commodity spread when the weekly futures price is for the delivery month of March or September. The daily convenience yield is estimated as the value of an exchange option where the holder has the right but not the obligation to exchange the spot commodity for a futures contract with a future delivery date.

The closed form solution for the exchange option can be represented as:

$$V_x = S_2 N(d_1) - S_1 N(d_2) \tag{6}$$

where: $d_1 = \frac{\ln\left(\frac{S_2}{S_1}\right) + (\sigma^2/2)T}{\sigma\sqrt{T}}$, $d_2 = d_1 - \sigma\sqrt{T}, and\ \sigma = \sqrt{\sigma_1^2 + \sigma_2^2 - 2\rho\sigma_1\sigma_2}$

$N(.)$ = cumulative normal distribution; T is the time to maturity and S_1 S_2 are distant and current future prices which follow a Brownian motion with volatilities σ_1, σ_2 and instantaneous correlation ρ. Note that the option value is independent of the interest rate. Basically, convenience yield is the value of exchanging the distant futures contract with a contract that has a shorter maturity.

Results of equation 6 are shown in table 1 which indicates that the convenience yield for corn is around 40 cents/ bushel which is 10% of the average corn future prices. For soybean, the convenience yield is around 8% of the average price.

4.3 GARCH Model to Estimate Conditional Variance

After calculating the speculative indices, we estimate the volatility of the futures contracts for the two markets using GARCH (1, 1) or EGARCH models, which are well known conditional variance models and are time series techniques used to model serial dependence in volatility. A first look at the data allows us to detect the presence of volatility clustering which is the first motivation for GARCH models. In order to test for this, we will conduct the Engle (1982) test on the residuals of the estimated model in order to test whether these classes of models are suited for our data. First, a linear model is used to estimate the residuals, which are then used to regress squared residuals on a constant and p lags of residuals. We chose a p-lag = 5 since it represents a weekly data of observations. All results from the Engle test on raw returns indicate that the GARCH families of models are suited for our data. The results are shown in table 3 for GARCH (1, 1). The mean and variance equations are represented below:

$$Mean\ Equation: Y_t = \log price\ change + \mu_t$$

$$Variance\ Equation: \sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{7}$$

The second equation indicates that conditional variance is the sum of three functions: a constant term α_0, an ARCH term from the previous period: u_{t-1}^2 and the last period forecast of variance σ_{t-1}^2.

GARCH (1, 1) imposes restrictions on parameters such that $\alpha_{i,}\ \beta_1 \geq 0\ and\ \alpha_1 + \beta_1 < 1$

4.4 E-GARCH Model to Estimate Conditional Variance

When any of these assumptions are violated, we will use EGARCH to model volatility. EGARCH was initially proposed by Nelson (1991) and could be represented as follows:

$$\log \sigma_t^2 = w + \beta_j \ln (\sigma_{t-j}^2) + \gamma_k \frac{\mu_t - k}{\sqrt{\sigma_{t-k}^2}} + \alpha_i \left[\frac{|\mu_t - i|}{\sqrt{\sigma_{t-i}^2}} - \sqrt{\frac{2}{\pi}} \right] \tag{8}$$

β_j: lagged Garch, γ_k: Lagged Arch and α_i: Asymmetry effect

The model has two major advantages over GARCH. First, log variance is used in a sense that parameters' values are not restricted to positive values as in GARCH. Also, the asymmetry effect measures the relation between volatility and returns in a sense that a negative relation between return and volatility will lead to a negative α (Brooks 2008).

A normal distribution for the error terms is assumed in estimating the GARCH model using maximum likelihood techniques. Since our data exhibits non- normality as seen from Bera- Jarque statistics provide in Table 1, and researchers on financial time series data found that the normality assumption is violated even after accounting for conditional heteroscedasticity, we will use the Quasi Maximum Likelihood (QML) proposed by Bollersev and Woolbridge (1992), under which the variance- covariance matrix estimated is robust to non-normality. The technique is similar to the method of maximum likelihood, except that the function which is maximized is not the log-likelihood function corresponding to any actual probability distribution, but is instead fit using generalized linear methods (GLM). Therefore, QML is consistent and asymptotically normally distributed and is a compromise estimation method although it is closer to maximum likelihood estimation than to the Generalized Method of Moments (GMM).

Since GARCH models are non-linear, QML is employed in order to estimate the residuals. Employing QML alters the estimated covariance variance matrix but does not affect the parameter estimates which are optimized using conditional likelihood functions which are calculated by maximizing the function below:

$$L = -\frac{T}{2}\log 2\,\pi - \,^{1}/_{2}\sum_{t=1}^{T}\log\left(\sigma_t^2\right) - \frac{^{1}/_{2}\,\sum_{t=1}^{T}\left(y_t - \mu - \,\theta\, y_{t-1}\right)^2}{\sigma_t^2}$$

Berndt et al. (BHHH, 1974) uses first derivatives of the likelihood function in order to optimize the log-likelihood function with respect to the parameter values at each iteration. We will employ the Marquardt method, a modified version of BHHH which calculates first and second derivatives thus better estimating optimal values. To ensure flexibility, we allow up to 12 weekly autoregressive lags. The number of lagged GARCH is estimated using the sign bias t-test. Results prove that no misspecification exists for any variable. Results for EGRACH model are found in table 4 and show that there is a positive effect of leverage in a sense that an increase in return will lead to an increase in volatility.

After estimating the parameters, the Ljung-Box test is conducted on the residuals in order to estimate whether a higher order autocorrelation exists at lag k=12.

Insert Table 3

Table 3 provides the parameters for the variables that satisfy the restrictions, as well as, the Log likelihood value from optimizing the equations. As we can see, six variables: oil spot, euro, soybean futures and spot, corn spot and futures provide a good fit for the model in equation 7 and satisfy all the restrictions for GARCH (1,1). As expected, all lagged GARCH coefficients are significant with large values and the sum of lagged squared error and lagged conditional variance is very close to unity implying that shocks to conditional variance will be persistent. No visible autocorrelation exists in the residuals for all variables, as measured by Ljung Box test statistic.

Insert Table 4

Table 4 shows the parameter estimates for the EGARCH model. α_i shows that the ARCH term is significant for most variables. The relation between volatility and return is negative and highly significant as measured by γ implying that an increase in volatility leads to a decrease in return.

As a robustness test, we will use exponentially weighted moving average instead of all the EGARCH volatilities estimation and run all regressions again. The results on the parameter estimates are not provided in this thesis since they are not significantly different.

4.5 Unit Root Tests

After calculating the conditional volatility for all the variables included, we conduct a unit root test on each set of data. A unit root tests whether $\emptyset = 1$ in the following equation:

$$y_t = \emptyset\, y_{t-1} + u_t \tag{9}$$

Where y_t: each variable in turn $u_t: error$

$\emptyset = 1$ implies that the data contains a unit root. Now, if a unit root does exist for any variable, then the observations are non-stationary, and we run a cointegration test on the errors terms to examine the long run relationship between the errors terms for the two variables. Only stationary models will be used to make accurate estimates and interpretations. For example, if the model is non-stationary, then the t test statistic will not follow a t-distribution and inferences about p-values will be inflated.

A unit root test is conducted using an Augmented Dickey Fuller (ADF) time series regression and Kwaitkowski et al. test (KPSS). ADF uses p lags of the dependent variable. The issue in this test is that there is no clear consensus on how to determine the number of lags. We will use the Akaike information criterion in order to estimate the number of lags. Using lags of y_t will absorb any dynamic structure present in the dependent variable to ensure that u_t is not correlated.

In econometrics, a long run relationship implies that the variables have converged to some long term value and thus it is impossible to conclude whether several variables will have a long term relationship. Different critical values are used, since the residuals have been constructed from a set of coefficient estimates and the sampling estimation error in those coefficients will alter the distribution of the t-statistic. We will use the critical values proposed by Dickey-Fuller.

KPSS is assumed to be stationary under the null, and uses residuals from the OLS regression of y_t on the exogenous variable x_t. Lag length for KPSS are calculated using the Newey- West (1994) automatic bandwidth selection method. Brooks (2008) argues that failure to reject the null could be due to insufficient information or because the null was correct. A solution to this would be to use a stationary test (KPSS) and a unit root test (ADF). For the results to be robust, we should reject HO (ADF), do not reject HO (KPSS) or vice versa. Table 3 and 4 shows that all variables are stationary on the basis of ADFF and KPSS and thus we can confidently proceed with testing our hypotheses using our main model.

4.6 Seemingly Unrelated Regression (SUR)

In order to test our hypotheses, we can estimate our model using OLS. However, the error terms across markets are correlated for the equations for any two variables and since we have similar variables in both equations, the power of the test could be increased by modeling the equations below as a system of seemingly unrelated regressions. SUR was introduced by Zellner (1960) and it accounts for hetroscedasticity and correlation in the error terms. It is a generalization of OLS for a multi-equation model. The first step in SUR is to compute an initial OLS regression to compute residuals which are used to estimate the cross equation covariance matrix. The second step is to estimate the parameter based on the estimated error from the first equation using feasible GLS which provides the best unbiased estimation of the parameters. SUR estimates the following model:

$$\mathrm{VFR_t} = \beta_0 + \beta_1\mathrm{(L)VSR_t} + \beta_2\mathrm{SC_t} + \beta_3\mathrm{CY_t} + \beta_4\mathrm{H_t} + \beta_5\mathrm{S_t} + \mathrm{u_t} \tag{10}$$

$$\mathrm{VSR_t} = \Psi_0 + \Psi_1\mathrm{(L)VFR_t} + \Psi_2\mathrm{Oil_t} + \Psi_3\mathrm{NX_t} + \Psi_4\mathrm{Euro_t} + \Psi_5\mathrm{H_t} + \Psi_6\mathrm{S_t} + \varepsilon_t \tag{11}$$

(L)VFR : (Lagged)Volatility of Futures, (L)VSR: (Lagged) Volatility of Spot, SC: Storage Cost
CY: Convenience Yield S: Speculative Index H: Hedging index NX: Net Export Oil: oil spot Prices
Euro: Euro/US dollar exchange rate.

As we already mentioned, the above equation allows us to test the relation between the volatilities of corn and soybean futures contracts and the level of speculation and hedging using the new and modified DCOT data. Also, we will be able to determine if futures trading activities leads to an increase in the volatilities of the contracts and thus are partially responsible for the increase in worldwide prices.

In the next section, we will explain the methodology for checking whether each trader category is useful in predicting subsequent market volatility.

4.7 Granger Causality

Most research, that tries to test whether a relation exists between traders' positions and return on the contracts, uses a bivariate Granger causality. Granger causality tests how much of Y could be explained by previous values of Y and then observe whether the explanatory power improves by adding lagged values of X. We will test for two way causation. The method could be represented by the following equations:

$$PNL_t = \alpha + \beta_i \, PNL_{t-i} + \gamma_j VFR_{t-j} + \varepsilon_t \tag{12}$$

$$VFR_t = \emptyset + \varphi_{\,i} VFR_{t-i} + \varphi_j PN_{t-j} + \varepsilon_t \tag{13}$$

PNL_t: $position\ of\ trader\ by\ category$, VFR_t : $Volatility\ of\ future\ return$

Although the purpose of our paper is to examine whether speculation and hedging affects the volatility of commodity futures, we will examine whether an opposite relation exist between volatility and speculation. If volatility leads speculation, then this could be explained by the fact that speculators tend to prefer more volatile markets in which potentially higher returns could be obtained. The first equation tests whether volatility leads traders' positions by testing the null hypothesis that volatility does not lead changes in positions ($\gamma_j = 0 \ \forall \ j$) . We are interested in examining how each group of traders change their positions related to changes in volatility of the contracts. The second equation tests whether movements in traders' positions are useful in predicting changes in the contracts' volatilities. If they are, profitable trading strategies could be developed for the two contracts. However, this is beyond the scope of this research and our aim is just to provide insights about the relation between volatilities of the contracts and traders positions.

Wang (2001), Sanders et. al (2004), and (Irwin et al. 2010) studied the relation between traders' futures positions and return for commodities and suggested estimating each equation across markets in order to increase the power of the test. This is done by using a procedure similar to that described in the previous section. We will follow the same methodology as described in the previous section, but positions will be divided between PM, SD, OR and MM. The data for each trader category is used to test our hypothesis using seemingly unrelated regression adjusted for hetroscedasticity. An issue would be to choose an appropriate lag for the model and we choose the one that minimizes the Akaikie information criterion using lags=8 for $i\ and\ j$.

Chapter 5 Empirical Results

5.1 Effect of Speculative and Hedging Activities on Contracts' Volatilities

Insert Table 5

Insert Table 6

The results of the analysis of equations 10 and 11 shown in table 5 which allows us to study the impact of Hedging and Speculating Indices simultaneously on corn spot and futures. First of all, the lagged volatility of spot prices is highly significant and positively correlated to the futures market volatility in both corn and soybean markets. An explanation would be that investors tend to hedge volatile spot prices through increasing their trading in the futures market which is consistent with De Roon et al. (2000) and Darrat (2002) who found evidence that hedging volatile spot markets involves cross-market hedging. We do not assume that our results are representative of all agricultural commodities since we only tested two markets. The fact that lagged futures returns increases spot volatilities for both markets is contradictory to our hypothesis that futures markets allows efficient transfer of risk between participants. Our result does not give a clear answer to the question of whether spot price volatility or futures price volatility destabilizes the other. However, we can conclude that both volatilities for corn and future are highly integrated and thus move in the same direction mainly because these markets are linked by the actions of arbitrageurs.

The volatility of storage costs for corn futures is highly significant and is the only variable that explains changes in volatilities. This could be due to the fact that the costs of storing corn depends on barge rates and most importantly on interest forgone (opportunity cost) on the investment in the corn. The volatility of the convenience yield does not affect that of corn futures prices, mainly because the volatility of the convenience yield tends to be very small when compared to the volatility of the other factors. The volatilities of net exports and the Euro-U.S. dollar exchange rate are not significant. The only control variable which is statistically significant is the volatility of oil for both corn and soybean spot price volatility as shown in Tables 5 and 6. This is in line with expectations, since oil prices affect production input costs, transportation costs and the demand for bio-fuel production. Our results for the corn market for the effect of the volatility of fundamental factors upon the volatility of spot prices are similar to that of Cooke (2009) who found that only oil prices are significant of all the basic supply and demand factors affecting the corn market.

In addition, the rise and fall in agricultural prices over the period 2006-08 was parallel to the sharp swings in crude oil prices over the same period. Therefore, it could be that the more heavily traded and followed crude oil market could have led to major fluctuations in prices of agricultural commodities. Gilbert (2010) provided a similar argument in the sense that tremendous increases in food prices coincided with an enormous increase in commodity prices led by energy and metals.

The major part of this research is to test whether speculation and hedging in both markets affect the volatilities of spot and futures prices. First, the speculative index constructed decreases the volatility of corn futures and is positively related to that of the spot market. However, both results are insignificant. This adds to the empirical evidence which indicates that speculators are not responsible for the last food price crisis and thus speculative trading by swap dealers, managed money and other reportable traders has no effect on volatilities, which is identical to the results of Stoll and Whaley (2009) concerning the relation between speculation and futures returns. This could be due to the fact that speculators have position limits set by exchanges and thus their trade impact is minimal. Also, this rejects the argument that greedy investors are to be blamed for price increases and are indirectly responsible for putting downward pressure on household consumption all over the world. Moreover, this lends support to the fact that speculators facilitate hedging needs by providing liquidity and transfer of risk from producers and merchants. Our results contradict the common belief among producers and policy makers that speculators in futures markets destabilise the volatility of spot prices and are indirectly responsible for decreasing social welfare increasing economic disparity. Although blaming speculators is appealing to societies and policymakers, our empirical results provide support to the classical view that speculators make prices more efficient.

On the other hand, hedgers' positions tend to affect both spot and futures price volatilities for the corn market. Our hedging index tends to be positively related to futures price volatility and negatively related to the spot price volatility (Table 5). The fact that a positive relation exists between hedging and the volatility of corn futures prices implies that hedgers in this market put pressure on volatility through increasing their hedging demand when volatility increases. This could be explained by the fact that traders classified as producers and merchants hold 82 % of the total short positions and thus they tend to hedge volatile spot markets through increased involvement in the futures market. This result is similar to Bessembinder (1992) and De Roon et.al (2000), who found that hedging demand is an important determinants for future returns.

One interesting result is that changes in hedgers' positions decrease the volatility of the spot market, which implies that hedgers' trading improves liquidity in the spot market and rejects the hypothesis that future markets destabilize prices and volatility of the spot market. For the corn market, we can conclude that the futures market allows efficient transfer of risk for producers and merchants, which allows them to hedge their positions efficiently and to decrease the volatility of the spot prices.

Hedging and speculative indices for the soybean market tend to be insignificant. The differences between the two markets could be due to the fact that the corn futures market is three times bigger than the soybean futures market, or the fact that position sizes by trader is much larger, especially for swap dealers and managed money (Table 2). Sander's et al. (2004) discussed this issue by stating that practitioners and researchers should be aware that empirical results using COT data in one market do not imply similar results in another. This leads to a major concern to be acknowledged in this paper which is the construction of our speculative indices as well as the classification of traders as hedgers or speculators. Based on the data provided by the CFTC and previous research, we can conclude that our classification and methodology is accurate. However, this does not eliminate the possibility that better classification, transparency and restrictions on traders will provide different results. Many hedgers speculate and many speculators hedge. There is no clear consensus on traders' behaviours in commodity markets, or the motivation for their trades. The fact that recent views on speculators tend to ignore classic research such as that of Working (1960) and Peck (1980), which states that all commercial firms speculate on market movements and price direction, is absurd. We tend to analyze our results taking into consideration the fact that producers and merchants tend to have huge long positions which is contradictory to the fact that these traders are expected to be pure hedgers. This point is acknowledged by the CFTC when it classifies traders by categories. We feel that classifying traders by categories is misleading and a better understanding of commodity markets is feasible if the CFTC classifies traders as hedgers and speculators by better monitoring the behaviour of traders.

5.2 Relation between Traders' Positions and Price Volatilities

Insert Table 7

As we already mentioned, the CIT data allows us to further divide traders into four categories. Although an extensive body of empirical work regarding the impact of traders on futures returns exists, there is no empirical work on traders' positions and market volatility for agricultural futures.

Although we used a multivariate model that includes control variables in the first part, we will only test for causality between volatility and traders' positions by using a bivariate model. The point in this section is to see how each traders group changes its positions relative to the futures price volatility and whether traders' behaviour impacts the volatility of the two contracts.

The results of the analysis of equations 11 and 12 are shown in table 7 which shows the results of the tests for causality using Granger causality. Sanders et al (2004) and Wang (2001) argued that estimating the model as an SUR system across markets will provide more robust results. In interpreting the results, we will only focus on categories where both the short and long positions are affected by the futures price volatility. Panel A of Table 7 tests whether futures price volatility leads traders' positions. It is interesting to observe if traders alter their positions based on changes in the futures price volatility. Hedgers should increase their short positions and speculators might increase their long positions or short positions in response to an increase in the futures price volatility.

Processors and merchants tend to decrease their long positions and increase their short positions after an increase in volatility for the corn futures market. This implies that the corn market is mainly used for hedging risk for producers in the sense that traders are mainly concerned with decreasing their exposure to risk. Also, processors and merchants are trend followers in a sense that they will increase their positions after volatility increases to face higher concerns of price swings.

Results for the soybean market are included in panel B of table 7. In this market, swap dealers both long & short and managed money long positions are positively related to volatility. These traders are also trend followers since speculators increase their positions in volatile markets in order to gain higher economic profit or because of a sense of over confidence that the market is turning in their direction. It should be noted that the period under study was characterized by a boom in prices.

There are two important points to note for Panel A: First, other reportable trading positions that are classified as speculative tend to decrease their long positions and increase their short positions with increases in the futures price volatility for corn, and increase their short positions for soybean, thus acting like hedgers in both markets. This could be due to the fact that these positions include those of some hedgers. However, if this is true, then those traders will try to be classified as hedgers in order to face fewer restrictions by exchanges. Another explanation would be that this class of traders are contrarian or negative feedback traders.

Second, processor and merchants tend to increase their long and short positions after an increase in futures price volatility for soybean market. The fact that traders in soybean future market increase their long positions could imply that hedgers might include some speculators. This could explain the difference in our results for the two markets and is an issue that requires further research since there is a chance that speculators might be classified as hedgers by exchanges. The results indicate that the corn futures market is mainly used for hedging while traders in soybean act differently. This could be due to the fact that the soybean market is much smaller and maybe would be easier to manipulate.

Panel B of Table 7 tests whether traders' positions lead volatilities. This is very important since it allows us to check whether traders' positions are useful in predicting future volatility in the market and could be used as an indication for agricultural futures market movement, as well as provide basic insights for developing profitable trading strategies based on their positions. Results for both markets indicate that all categories of traders have no predictive power concerning future changes in the futures price volatility.

Chapter 6 Conclusion

In this thesis, we test whether traders' positions classified as speculative or hedging, using new and modified DCOT data provided by the CFTC could explain changes in the price volatilities of corn and soybean futures contracts. Volatility was estimated using GARCH (1,1) and EGARCH models. Each model was tested using a SUR system and controlling for fundamental economic factors that affect volatility. Also, the effect of these different positions on the spot market is tested in an attempt to observe whether traders could be indirectly linked to the recent food crisis and inefficient distribution of food worldwide. Lastly, we study the impact of volatility on traders' positions and whether these positions could be used to predict market movements using Granger causality tests.

Our results contradict previous empirical research that blames speculators for increases in agricultural commodity prices for both the spot and futures market. However, we find that hedgers tend to increase the corn futures contract's price volatility, thus lending support to the theory of hedging pressure. Only processors and merchants change their positions in the corn futures market indicating that it is mainly used for hedging purposes while speculators in the soybean futures market tend to increase their positions after volatility increases. Finally, no trader category could be used to predict future volatility movements across both markets, implying that traders are trend followers.

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Figure 1: Corn and Soybean Spot and Future Prices

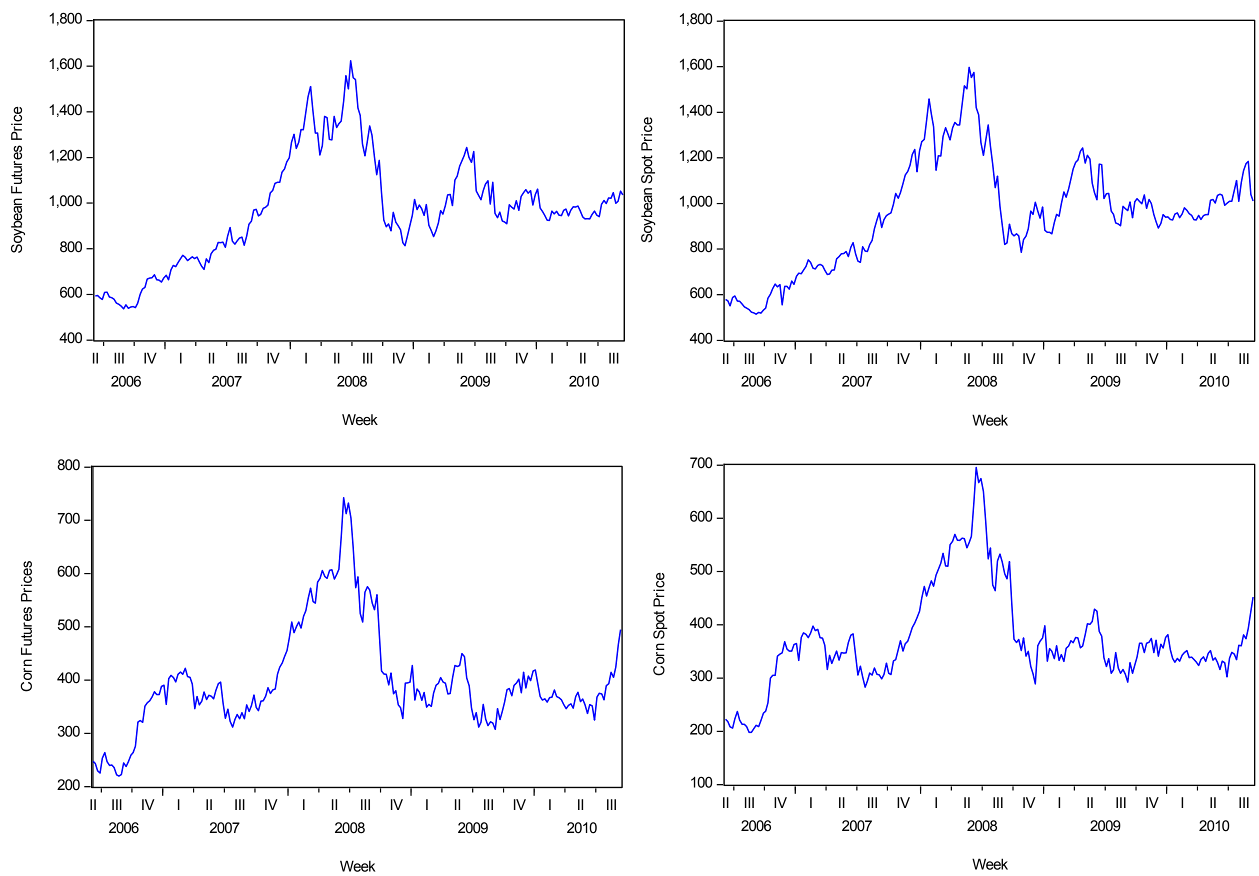

Table 1: Descriptive Statistics

The following table reports the descriptive statistics of all variables except traders' positions. Euro is the exchange rate for the euro in dollars/euro, oil represents oil spot prices in $/barrel, NX represents Net Export and is measured in tons, CY represents the convenience yield. All other variables are measured in cents/bushel.

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob.
Corn Spot	371.1027	351.5	695.5	198	91.96	1.012	4.51	59.62	0.001
Corn Futures	398.673	376.375	742.25	219.5	98.15	1.10	4.53	67.89	0.001
Soybean Spot	955.0456	952.75	1596.5	515	236.88	0.21	2.79	2.21	0.33
Soybean Futures	968.7946	965.5	1623	537	235.86	0.31	2.86	3.84	0.14
Oil Spot	79.21027	76.28	149.42	41.48	21.64	1.02	4.11	51.08	0.001
Euro	1.378162	1.35995	1.5922	1.19	0.09	0.48	2.32	12.98	0.001
NX Corn	851524.8	754436	4851059	8301	573513.8	2.52	15.37	166.47	0.001
NX Soybean	491927.5	382147	3046570	3144	393404	1.83	10.16	60.72	0.001
Storage Corn	7.55	7.12	18.15	0.59	4.25	0.38	2.28	10.31	0.005
Storage Soybean	6.45	5.82	17	0.59	3.76	0.54	2.56	12.98	0.001
CY Corn	41.91	36.7	135.38	1.55	27.03	1.12	4.58	76.19	0.001
CY Soybean	84.2	1.4	324.71	1.84	58.91	1.41	5.47	131.94	0.001
Hedging Soya	53.37%	56.14%	69.87%	20.14%	12.16%	-0.87	3.14	28.61	0.001
Hedging Corn	50.70%	51.79%	78.95%	25.55%	9.27%	-0.34	4.09	15.65	0.039
Speculation Corn	40.49%	41.28%	59.23%	17.48%	10.11%	-0.20	2.01	10.56	0.005
Speculation Soya	40.25%	43.31%	58.64%	9.68%	11.97%	-0.76	2.92	21.71	0.001

Table 2: DCOT Trader Data

The following table is divided into three different panels. Panel A represents the weekly average positions held by each category as classified by the CFTC. Panel B represents the weekly average positions by each trader group. Panel C shows the traders' positions as a percentage of total long or short positions held by all traders.

Panel A: Average position size by category

Market	Managed Money			Producers & Merchants		Swap Dealers			Other Reporting		
	Long	Short	Spread	Long	Short	Long	Short	Spread	Long	Short	Spread
Corn	198451.13	69618.37	72051.88	220522.71	628767.54	326738.01	8757.45	15374.74	114530.67	51957.88	87198.74
Soybean	85411.67	24959.96	30350.70	74916.72	240089.35	126440.48	3788.26	6354.86	35641.34	22240.73	34174.57

Panel B: Average position size by trader

Market	Managed Money			Producers & Merchants		Swap Dealers			Other Reporting		
	Long	Short	Spread	Long	Short	Long	Short	Spread	Long	Short	Spread
Corn	2159.36	2072.86	1153.47	1020.6	1718.98	15016.96	5131.15	1108.35	785.39	547.41	627.92
Soybean	1178.71	850.95	820.89	925.56	1690.50	6781.2	792.65	487.63	533.5	326.36	416.63

Panel C: Percent of Long and Short Positions

Long Positions

Market	Managed Money	Producers & Merchants	Swap Dealers	Other Reporting
Corn	23.13%	25.56%	37.97%	13.34%
Soybean	26.49%	23.24%	39.22%	11.05%

Short Positions

Market	Managed Money	Producers & Merchants	Swap Dealers	Other Reporting
Corn	9.17%	82.83%	1.15%	6.84%
Soybean	8.57%	82.48%	1.3%	7.64%

Table 3: Results of Estimation Using the GARCH Model

Parameters/z statistics

	Corn Spot	**Corn Future**	**Soybean Spot**	**Soybean Future**	**Oil Spot**	**Euro**
α_0	0.00033	0.001767	0.000215	4.64E-05	0.00016	0.00000818
	(0.984442)	(3.755456)**	(1.622841)	(1.156523)	(1.353319)	(1.560277)
α_1	0.109108	0.053443	0.158412	0.091459	0.097082	0.154533
	(2.02024)*	(1.321311)	(2.495691)*	(2.497829)**	(2.341082)**	(2.41473)*
β_1	0.795125	0.876001	0.758287	0.885105	0.849899	0.819112
	(5.857935)**	(8.415367)**	(8.351949)**	(17.64525)**	(12.35941)**	(13.44935)**
L	326.2907	334.7666	373.4023	403.5194	343.3847	630.9909
LB(12)	9.8043	12.699	7.2877	5.4478	7.0339	10.332
	(0.633)	(0.391)	(0.838)	(0.941)	(0.855)	(0.587)
ADF	-4.049208	-8.463075	-4.030593	-14.87346	-17.07127	-2.807986
P-value	(0.0014)**	(0.001)**	(0.0015)	(0.001)**	(0.001)**	(0.001)**
KPSS	0.180173	0.166722	0.199378	0.182286	0.44014	0.44014

Note: *Denotes significance at 5% level and **denotes significance at 1% level.

$Garch: \sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2$

z-statistics are in parentheses. $LB(12)$ is the Ljung-Box statistics to test for autocorrelation in the squared normalized residuals using 12 lags. L is the log-likelihood value for each estimation. ADF represents augmented Dickey Fuller test statistic to test for unit roots. KPSS represents Kwaitkowski et al. test statistic for unit root using Lagrange Multiplier.

Table 4: Results of Estimation Using The EGARCH Model

	Parameters/z statistics					
	NX Corn	**NX Soybean**	**Storage Corn**	**Storage Soybean**	**CY corn**	**CY soybean**
w	-0.189817	-1.736187	-0.001385	-0.088082	-0.964324	0.262312
	(-2.239239)*	(-2.998426)**	(-0.04134)	(0.5258)	(-5.968836)**	(1.472395)
β	-0.17324	0.357384	-0.289824	-0.15929	-0.045719	-0.083634
	(-1.508405)	(2.551342)**	(-5.170691)**	(0.2464)	(-0.468534)	(-1.850076)*
γ	-0.575152	-0.416646	-0.350399	-0.685644	-1.144507	0.446633
	(-3.50693)**	(-4.250639)**	(-4.257382)**	(-3.90785)**	(-1.144507)**	0.985126
α	0.959229	0.716023	0.985699	0.993851	0.5716	0.366526
	(52.998)**	(7.155872)**	(149.456)**	(71.72403)**	(13.16429)**	0.711625
L	336.064	250.6576	761.659	957.8272	457.0687	405.3969
LB(12)	48.831	34.564	3.1214	100.21	6.8801	51.421
	(0.0001)**	(0.001)**	0.21	(0.0001)**	0.23	(0.0001)**
ADF	-4.338021	-11.75474	-12.30239	-13.36873	-13.63453	-16.55567
P-value	(0.0005)**	(0.001)**	(0.001)**	(0.001)**	(0.001)**	(0.001)**
KPSS	0.158999	0.061789	0.13501	0.053923	0.241241	(0.040127)*

Note: *Denotes significance at 5% level and **denotes significance at 1% level.

EGARCH: $\log \sigma_t^2 = w + \beta_j \ln(\sigma_{t-j}^2) + \gamma_k \frac{\mu_t - k}{\sqrt{\sigma_{t-k}^2}} + \alpha_i \left[\frac{|\mu_t - i|}{\sqrt{\sigma_{t-i}^2}} - \sqrt{\frac{2}{\pi}} \right]$

z-statistics are in parentheses. $LB(12)$ is the Ljung-Box statistics to test for autocorrelation in the squared normalized residuals using 12 lags. L is the log-likelihood value for each estimation. ADF represents augmented Dickey Fuller test statistic to test for unit roots. KPSS represents Kwaitkowski et al. test statistic for unit root using Lagrange Multiplier.

Table 5: Iterative Seemingly Unrelated Regression (Corn):

Volatility of Corn Futures:

	Coefficient	Std. Error	t-Statistic	Prob.
β_0	-0.029392	0.005195	-5.657471	(0.001)***
(L)VSR	0.502953	0.014693	34.23127	(0.001)***
SC	0.23188	0.083018	2.793123	(0.0055)***
CY	0.005281	0.00384	1.375149	0.1698
S	-0.006823	0.013477	-0.506218	0.613
H	0.094508	0.014871	6.355017	(0.001)***

Volatility of Corn Spot:

	Coefficient	Std. Error	t-Statistic	Prob.
Ψ_0	0.097489	0.007339	13.28437	(0.001)***
(L)VFR	0.540944	0.043539	12.42438	(0.001)***
OIL	0.015775	0.008912	1.770045	(0.0774)*
Euro	-0.003532	0.010974	-0.321845	0.7477
NX	-0.000291	0.004197	-0.069391	0.9447
S	0.019363	0.019776	0.979124	0.3281
H	-0.151685	0.021712	-6.986399	(0.001)***

Note: *Denotes significance at 10% level, ** at 5% and ***denotes significance at 1% level.

Iterative SUR Model:

$$\mathrm{VFR}_t = \beta_0 + \beta_1(\mathrm{L})\mathrm{VSR}_t + \beta_2\mathrm{SC}_t + \beta_3\mathrm{CY}_t + \beta_4\mathrm{H}_t + \beta_5\mathrm{S}_t + u_t$$

$$\mathrm{VSR}_t = \Psi_0 + \Psi_1(\mathrm{L})\mathrm{VFR}_t + \Psi_2\mathrm{Oil}_t + \Psi_3\mathrm{NX}_t + \Psi_4\mathrm{Euro}_t + \Psi_5\mathrm{H}_t + \Psi_6\mathrm{S}_t + \varepsilon_t$$

Lagged values for volatility of spot and futures prices were estimated using Akaike's Final Prediction Error (FPR).

(L)VFR： Lagged Volatility of Futures Prices, (L)VSR: Lagged Volatility of Spot Prices, SC: Storage Cost

CY: Convenience Yield S: Speculative Index H: Hedging NX: Net Export Oil: Oil Spot Prices Euro: Euro/US dollar exchange rate.

Table 6: Iterative Seemingly Unrelated Regression (Soybean):

Volatility of Soybean Futures:

	Coefficient	Std. Error	t-Statistic	Prob.
β_0	0.013175	0.005015	2.627041	(0.0089)***
(L)VSR	0.644648	0.033016	19.52523	(0.001)***
SC	-0.01715	0.102697	-0.16699	0.8675
CY	0.111615	0.265926	0.41972	0.6749
S	-0.01075	0.022236	-0.48343	0.629
H	-0.00681	0.021771	-0.31276	0.7546

Volatility of Soybean Spot:

	Coefficient	Std. Error	t-Statistic	Prob.
Ψ_0	-0.01446	0.00674	-2.1453	(0.0325)**
(L)VFR	0.580944	0.043539	11.42438	(0.001)***
OIL	0.108609	0.031088	3.49366	(0.0005)***
Euro	-0.01729	0.039921	-0.43315	0.6651
NX	0.001459	0.00199	0.733312	0.4638
S	0.030406	0.030515	0.996439	0.3196
H	0.006917	0.03007	0.230018	0.8182

Note: *Denotes significance at 10% level, ** at 5% and ***denotes significance at 1% level.

Iterative SUR Model:

$$\mathrm{VFR}_t = \beta_0 + \beta_1(\mathrm{L})\mathrm{VSR}_t + \beta_2\mathrm{SC}_t + \beta_3\mathrm{CY}_t + \beta_4\mathrm{H}_t + \beta_5\mathrm{S}_t + u_t$$

$$\mathrm{VSR}_t = \Psi_0 + \Psi_1(\mathrm{L})\mathrm{VFR}_t + \Psi_2\mathrm{Oil}_t + \Psi_3\mathrm{NX}_t + \Psi_4\mathrm{Euro}_t + \Psi_5\mathrm{H}_t + \Psi_6\mathrm{S}_t + \varepsilon_t$$

Lagged values for volatility of spot and futures prices were estimated using Akaike's Final Prediction Error (FPR).

(L)VFR： Lagged Volatility of Futures Prices, (L)VSR: Lagged Volatility of Spot Prices, SC: Storage Cost

CY: Convenience Yield S: Speculative Index H: Hedging NX: Net Export Oil: Oil Spot Prices Euro: Euro/US dollar exchange rate.

Table 7: Granger Causality Test Using an SUR System

The following model is estimated across the two markets using an SUR system. The p-value is from the Wald chi-squared test of the null $\gamma_j = 0\ \forall_j$ in Panel A and $\varphi_j = 0\ \forall_j$. Rejection of the null indicates that volatility leads traders' positions in Panel A and traders' positions leads volatility in Panel B. The lag structure is selected by minimizing Akaikes Information Criterion. The sign indicates the impact of volatilities on trader's positions in corn and soybean markets.

$$PNL_t = \alpha + \beta_i\, PNL_{t-i} + \gamma_j VFR_{t-j} + \varepsilon_t$$

$$VFR_t = \emptyset + \varphi_{\ i} VFR_{t-i} + \varphi_j PNL_{t-j} + \varepsilon_t$$

Panel A: Volatilities Lead traders' positions

		SD (Long)	SD (Short)	MM (Long)	MM (Short)	OR (Long)	OR (Short)	PM (long)	PM (Short)
Corn	P-value	0.55	0.1650	0.4342	0.90	0.49	0.001	0.05	0.001
	Sign	+	-	+	-	+	-	-	+
Soybean	P-value	0.02	0.001	0.001	0.945	0.001	0.09	0.001	0.001
	Sign	+	+	+	+	-	+	+	+

Panel B: Traders' positions lead volatilities

		SD (Long)	SD (Short)	MM (Long)	MM (Short)	OR (Long)	OR (Short)	PM (long)	PM (Short)
Corn	P-value	0.87	0.70	0.829	0.91	0.76	0.72	0.82	0.87
	Sign	+	-	+	-	-	-	-	-
Soybean	P-value	0.92	0.91	0.92	0.81	0.84	0.93	0.82	0.88
	Sign	+	-	+	-	+	-	-	+