Determinants of Futures Price Volatility of Storable Agricultural Commodities: The Case of Cotton

by

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A Thesis

in

Agricultural and Applied Economics

Submitted to the Graduate Faculty
of Texas Tech University in
Partial Fulfillment of
the Requirements for
the Degree of

Master of Science

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December, 2014

ACKNOWLEDGMENTS

This thesis could not have been written without the guidance of my committee members Dr. Rahman, Dr. Knight and Dr. Chidmi. I am deeply obliged to you for your time and patience with me. Thank you.

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CHAPTER 1

INTRODUCTION

1.1 Background on the Issue

Agricultural commodity prices are susceptible to significant variability. Producers and buyers of agricultural commodities expose themselves to substantial price risk when they choose to deal in spot markets, i.e. the producers expose themselves to the risk of getting a price lower than what they expected and the buyers expose themselves to the risk of paying a price higher than what they expected when they choose to deal “on the spot”. Spot markets or cash markets of commodities are the markets where they are bought on the spot paying in full the currently prevailing price. Spot prices are determined by supply and demand conditions and are highly sensitive to various types of forces that affect commodity production and consumption. Bad weather conditions, changes in consumer preferences, political turmoil - any of these or many other factors can cause spot prices of commodities to take unprecedented turns (Investor's Business Daily, 2014).

Futures contracts are a way of protecting producers and users of commodities from the price risk of spot markets. Futures contracts are contractual agreements of buying or selling a standard quantity of a standard quality at an agreed price on a future date. Futures trading, in simple terms, can be thought of as entering into a contractual agreement at present involving a trade that is to be executed in future. Traders with opposing views of the future movement of prices engage in futures trading. Different degrees of risk preferences of the trading entities also motivate them to engage in futures trading for it allows transfer of risk from an entity that seeks to avoid risk at the cost of any profit that may have arisen due to any favorable price movement to an entity that is willing to accept the risk in the hope of making a profit resulting from a favorable price movement in the future (Cifarelli & Paladino, 2011). The homogeneity of futures contracts make them readily adaptable to be traded on organized exchanges that enable the traders to buy or sell the contracts with swiftness and ease (Johnson, 1960).

Futures contracts themselves are, however, vulnerable to significant price variability as the commodities underlying them. Figure 1.1 plots weekly changes in cotton spot prices and Figure 1.2 plots weekly changes in cotton futures prices. As can be seen from the figures, both price series display significant variability.

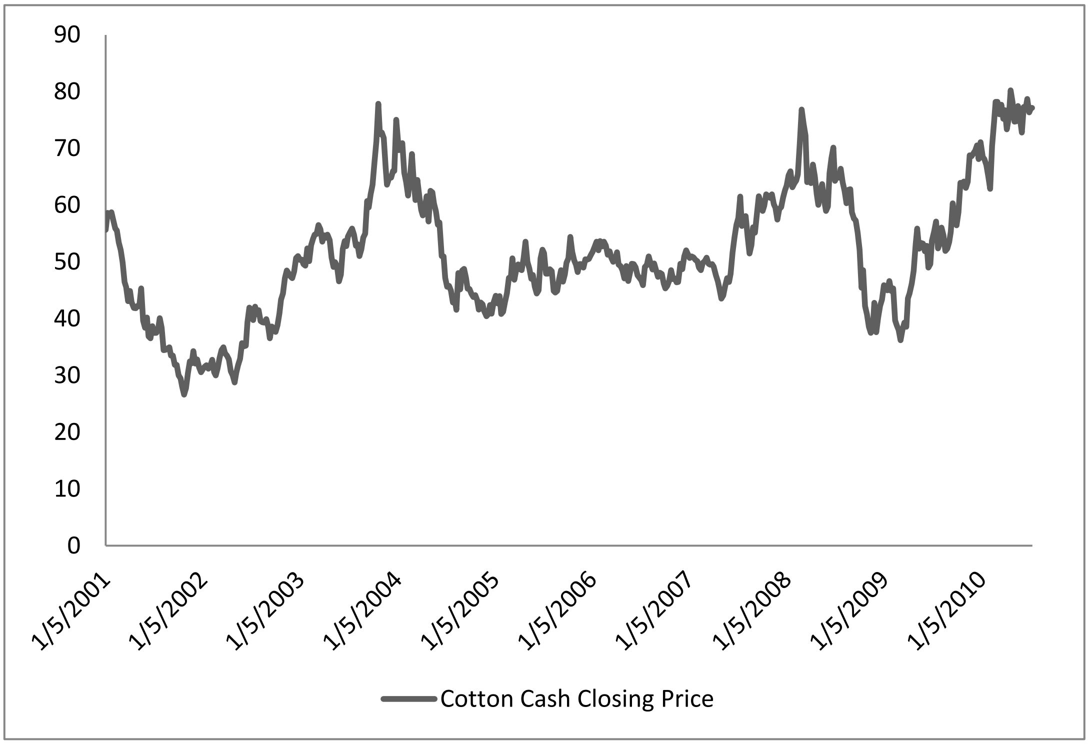

Figure 1.1: Weekly changes in cotton cash closing price

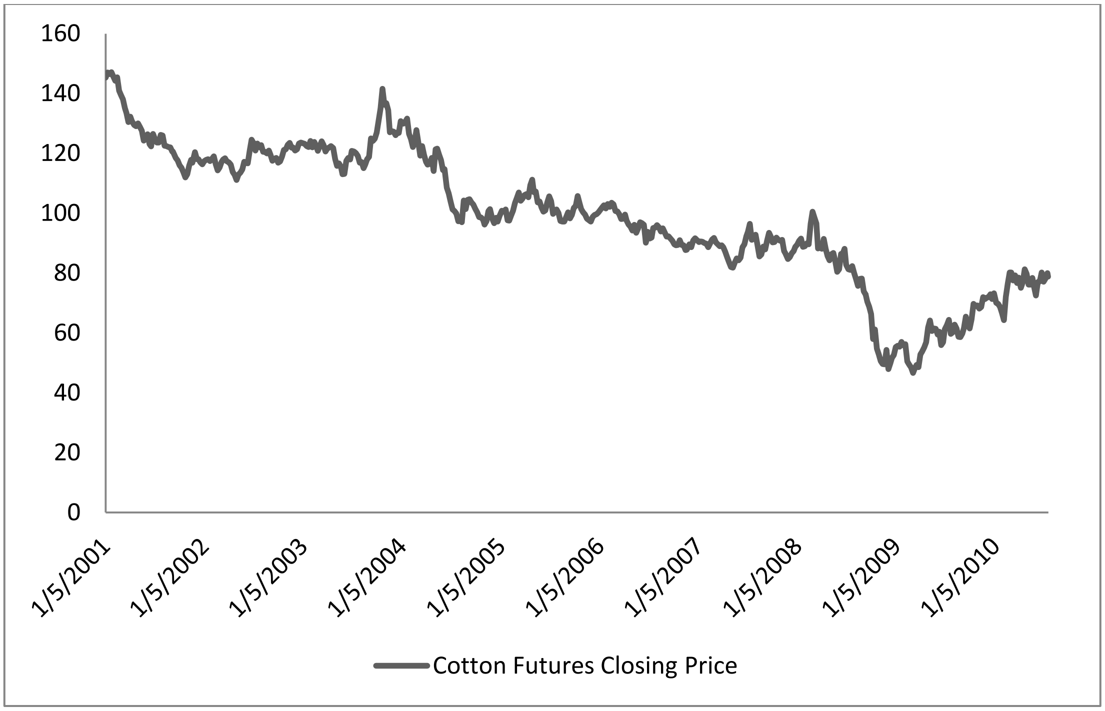

Figure 1.2: Weekly changes in cotton futures closing price

However, apart from the mean, the variance of futures prices may also change over time. Changes in the variance of prices is equally, if not more, important as changes in its mean. The variance of prices systematically fluctuate over time (Streeter & Tomek, 1992). The variance prices display over time is called volatility[1]. Algieri (2012) provides a succinct description of volatility:

> Volatility is a measure of the extent of the variability of a price or quantity that occurs on a day-to-day, week-to-week, month-to-month or year-to-year basis. The concept of volatility may be confused simply with rising prices; however, volatility can equally result in prices that are significantly lower than historical average levels. Technically, volatility measures how much a price changes either with regard to its constant long-term level, or to its trend. That is to say, volatility measures dispersion about a central tendency. In

[1] More generally, "volatility provides a measure of the possible variation or movement in a particular economic variable" (Tothova, 2011)

this respect, it is important to note that volatility does not measure the direction of price changes; rather it quantifies variation of prices around the mean. When price movements over a short period of time are extremely wide, we have "high volatility" (European Commission, 2009). Data with higher frequencies show higher volatility. Volatility diminishes when frequencies decrease. Annual data are less volatile than quarterly data; quarterly data are less volatile than monthly data.

Two measures of volatility are usually used- historical volatility and implied volatility. In simple terms, historical volatility can be conceptualized as a backward looking measure of volatility while implied volatility can be conceptualized as a forward looking measure of it. Historical volatility indicates the volatility of an asset in the past based on actual movements of recorded price over a past period. Implied volatility, on the other hand, indicates expectation of how volatile an asset will be in the future. Historical volatility reflects the resolution of past market conditions while implied volatility itself responds to current market conditions (Tothova, 2011). Figure 1.3 plots the historical and implied volatility of cotton futures prices. The volatility data are derived from Commodity Research Bureau (CRB) database.

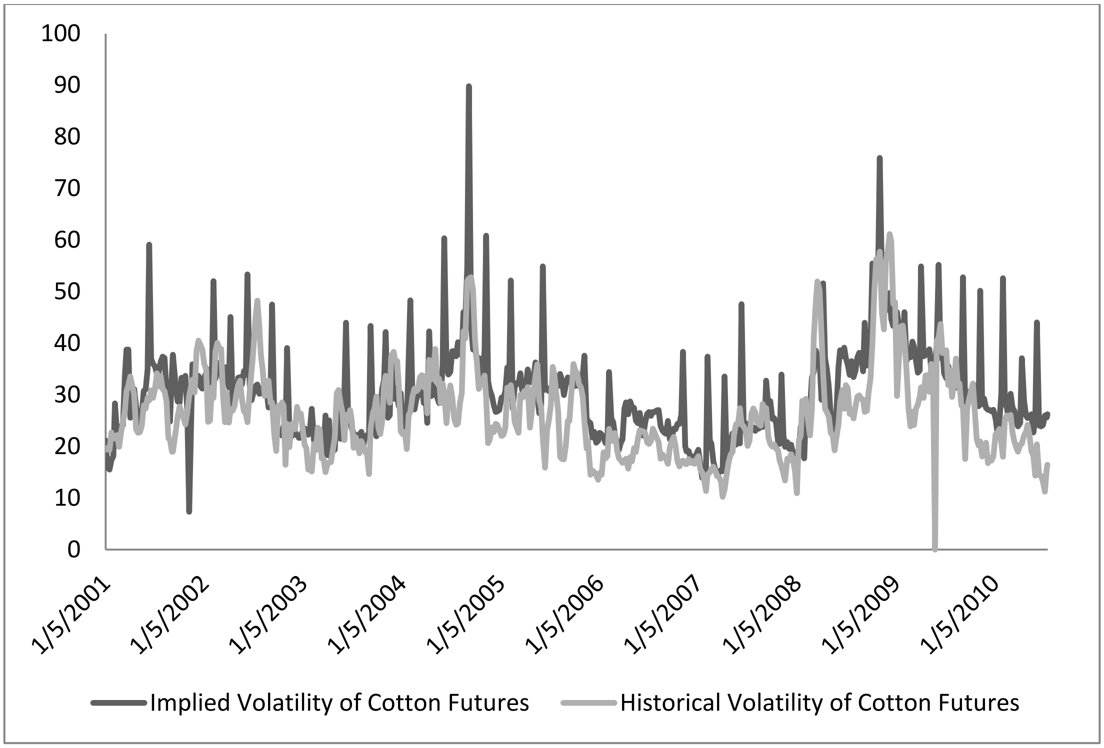

Figure 1.3: Historical and Implied Volatility of Cotton Futures

The historical volatility shown in Figure 1.3 is a measure of how volatile the cotton futures contracts have been for the 20 trading days prior to each observation date in the data series. It is an annualized standard deviation of price changes expressed as a percentage (CRB, 2014). The implied volatility shown in Figure 1.3 is "measured by entering the prices of options premiums into an options pricing model, then solving for volatility. The implied volatility value is based on the mean of the two nearest-the-money calls and the two nearest-the-money puts using the Black options pricing model. This value is the market's estimate of how volatile the underlying futures will be from the present until the option's expiration" (CRB, 2014).

Although popular measures like the Black model[2] (a variation of Black–Scholes option pricing model[3] that is used for valuation of options on futures

[2] Details of the model can be read in (Black, 1976).
[3] Details of the model can be read in (Black & Scholes, 1973).

contracts) or the basic Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model that does not account for the impact of any exogenous variable can produce volatility forecasts with rather limited data requirements, they cannot provide insight into the factors that cause prices to be volatile. Over the years, researchers have thus attempted to model the volatility of futures prices accounting for the effect of several exogenous variables. Identification of the factors affecting the price variability of futures contracts is important for agricultural policy makers, producers, commodity traders, and researchers (Goodwin & Schnepf, 2000). Streeter and Tomek (1992) draw some examples:

> The adequacy of the initial margin on a futures contract depends on the size of the margin relative to the volatility of prices. Thus, estimates of expected volatility are of interest to exchange committees charged with setting margins [e.g., Tomek (1985)]. Likewise, market participants who trade options on futures contracts require estimates of price volatility because prices of option contracts depend, in part, on the variability of the price of the underlying asset (futures contract). Market regulators also are concerned about the factors affecting the variability of prices and, especially, about how changes in market structure might influence price behavior.

Identification of factors underlying futures price variability can augment production and risk management decisions and aid in proper interpretation of a futures price time series (Karali & Thurman, 2010). This thesis empirically evaluates the factors that have been identified in the literature to be determinants of volatility of futures prices. The case in point is cotton futures.

Cotton futures are selected as the futures contract to be analyzed for two reasons.

First, no previous literature has analyzed the impact of exogenous variables on the volatility of cotton futures like this thesis intends to. So this adds an element of novelty to my work. Second, cotton is a crop of very significant economic importance. The National Cotton Council of America (2014) notes:

> Today, the world uses more cotton than any other fiber, and cotton is a leading cash crop in the U.S. At the farm level alone, the production of each year's crop involves the purchase of more than $5.3 billion worth of supplies and services. This stimulates business activities for factories and enterprises throughout the country. Processing and handling of cotton after it leaves the farm generates even more business activity. Annual business revenue stimulated by cotton in the U.S. economy exceeds $120 billion, making cotton America's number one value-added crop.

Further it has been noted that cotton generates over 400,000 jobs in the industry sectors from farms to textile mills (Osakwe, 2009).

For all these reasons proper modeling of the volatility of cotton futures prices makes a very important point of discussion.

1.2 Statement of the Problem

In economic terms cotton is a very important crop. The existence of a highly active cotton futures market provides a way to manage some of the price risk producers and users of cotton would have faced in the presence of only a spot market owing to the volatility of cotton cash price. However, the price of cotton futures is also very volatile. Proper anticipation of the volatility of cotton futures is vital for different groups of stakeholders (e.g. traders using cotton futures for hedging purposes, traders of options on cotton futures, exchange committees charged with setting margin on cotton futures, market regulators responsible for overseeing the cotton futures market). Nevertheless, in spite of the very high economic importance of cotton no prior literature has made an attempt to identify the factors influencing volatility of cotton futures prices. This thesis addresses this problem and aims to identify the factors that can aid in better understanding cotton futures price series.

1.3 Objectives

General Objective:

To empirically analyze how the volatility of cotton futures is affected by the factors hypothesized in the literature to impact the volatility of agricultural futures prices.

Specific Objectives:

1. Upon reviewing the literature, adopt a theoretical and empirical framework for analyzing cotton futures price volatility.
2. Collect data required for estimation of the empirical model and analyze the data.
3. Estimate the empirical model and explain the results.

1.4 Structure of the Thesis

The second chapter of the thesis presents the review of literature. The third chapter first presents the conceptual framework and then develops the empirical framework based on the conceptual skeleton discussed earlier. The fourth chapter discusses the data utilized; it elaborates how the data are collected, how the variables are constructed and also reports the descriptive statistics. The fifth chapter presents some preliminary statistical analysis and estimation of the main models of interest. The sixth chapter discusses the findings and draws implications. The seventh and final chapter concludes the thesis.

CHAPTER 2

LITERATURE REVIEW

2.1 Purposes behind Reviewing Literature

From obtaining a thorough understanding of the topic to identifying knowledge gaps that demand further investigation (Centre for Excellence in Teaching and Learning in Applied Undergraduate Research Skills , 2012) reviewing literature at the onset of any research serves several purposes. The specific purposes I sought to accomplish through reviewing literature are:

a. Reviewing the factors that have been identified to be determinants of volatility of futures prices in past literature.
b. Reviewing the ways volatility was measured in past literature.
c. Reviewing the approaches adopted in previous literature to model the impact of exogenous variables on the volatility of futures prices.

2.2 Review of the Factors Identified as Determinants of the Volatility of Futures Prices in Past Literature

Evaluation of the determinants of price variability of agricultural commodities has been the subject of a rich body of literature (Goodwin & Schnepf, 2000). Different authors have attributed futures price volatility to different factors. Following is a list of factors that have been argued in literature to be determinants of price volatility of agricultural commodities.

Time-to-delivery: In his 1965 seminal work Samuelson argued price volatility of futures contracts should increase as a contract approaches maturity, a phenomenon which later came to be termed in literature as *Samuelson effect*. The *Samuelson effect* can essentially be interpreted as the hypothesis that increasingly more information is available in the market about the underlying commodity as the future contract approaches delivery date (Anderson, 1985), and that the volatility of prices thus increase as the contract approaches maturity as a result of increasingly incorporating the newly available information. Different authors have investigated the *Samuelson effect* and found mixed results. Among others, Miller (1979), Castelino & Francis (1982), Milonas (1986)[4], Anderson (1985), Chatrath, et al. (2002), Karali and Thurman (2010) found evidence in its support while Grauer (1977), Hennessy and Wahl (1996), Streeter and Tomek (1992) found evidence against it. Rutledge (1976) found evidence supporting *Samuelson effect* in cases of silver and cocoa but rejected in the cases of wheat and soybean oil. Yang and Brorsen (1993) studied soybeans, oats, corn, coffee, soybean meal, wheat (Chicago), wheat (Kansas City), copper, gold (NY), palladium, platinum, silver futures and found evidence for time-to-maturity effect only for soybeans and oats. Goodwin and Schnepf (2000) found evidence supporting the phenomena in case of corn but not in case of wheat.

Seasonality: Seasonality is among the prime empirical characteristics that marks the difference of commodities from other conventional financial assets (like stocks, bonds) and is of particular significance in case of agricultural commodities with a seasonal harvesting pattern (Richter & Sørensen, 2002). Existence of strong seasonality in price volatility has been established in literature (Goodwin & Schnepf, 2000). Volatility for most agricultural commodities is specially seen to peak during summer months (Goodwin & Schnepf, 2000). Seasonality is observed to effect volatility in grain markets with volatility rising in the spring, peaking in July or August and declining through the end of the year (Streeter & Tomek, 1992). Sørensen (2002) studied the seasonal price patterns for corn, soybeans and wheat futures and found evidence that suggested that seasonal components for these commodities peak two to three months before the commencement of harvesting season. Anderson (1985) identified seasonality to be the most important predictor of changes in futures price

[4] Milonas (1986), however, argued that *Samuelson effect* only implies that numerous factors which influence price volatility becomes increasingly important as delivery date approaches Thus evidence in support of *Samuelson effect* essentially suggests that the impact of a vector of identified and unidentified variables increasingly increases as time to maturity nears. “Further research might identify the separate impact of each variable on price variability”, he opined.

variance. Choi & Longstaff (1985), Kenyon, et al. (1987), Streeter & Tomek (1992), Yang & Brorsen (1993), Hennessy & Wahl (1996), Goodwin & Schnepf (2000), Chatrath, et al. (2002) all found price volatility of the agricultural futures contracts that they studied to be significantly affected by seasons.

Level of inventory: Working (1933) is credited for originally proposing the Theory of Storage. The theory states that when inventory levels of a commodity are high its spot prices tend to be lower than futures prices (a situation referred to as 'contango') and volatility of spot and futures prices tend to be low and equal, whereas, when inventory levels of the commodity are low spot prices tend to be greater than futures prices (a situation referred to as 'backwardation) and volatility of spot prices and nearby futures prices are raised compared with the volatility of long term futures prices (Geman & Smith, 2013). According to theory of storage, cost of storage and spot price of a storable commodity should add up to its discounted expected price (Karali & Thurman, 2009). Physical inventories serve as a buffer to absorb shocks to price movements of storable commodities (Karali & Thurman, 2009). Hence, the return from holding commodities and the variance of the return can reasonably be expected to depend on the level of physical inventories and demand or supply shocks can be expected to attract smaller price responses when inventories are high. (Karali & Thurman, 2009). Goodwin & Schnepf (2000) , Karali & Thurman (2009) Karali & Thurman (2010), Perales (2010), Carpantier & Dufays (2012), Geman & Smith (2013) found evidence that supported theory of storage. In their study of corn, soybeans, Chicago wheat, Kansas wheat, and Minneapolis wheat futures prices Hennessy and Wahl (1996) did not find any inventory effects. Streeter and Tomek (1992), to their own surprise, found a positive relationship between levels of inventory and variability of soybean futures prices[5].

[5] Streeter and Tomek (1992) also found demand variables to have negative relationship and a variable representing total supply to have no significant relationship with soybeans futures price variability.

Growing conditions: Production of most agricultural commodities is fixed in the short-run and decidedly reliant on growing conditions (Geyser & Cutts, 2007). There is an established link between climate variability and agricultural commodity price volatility (Ash, et al., 2007). Brunner's (2000) analysis showed that El Niño-Southern Oscillation (ENSO) cycle has economically important and statistically significant effects on the volatility of commodity prices; one standard deviation positive change in ENSO is shown to cause 3.5 to 4 percentage points inflation in commodity prices. On inquiring the effect of rainfall and temperature on price volatility Hennessy and Wahl (1996) found that the combination of high temperatures-low rainfall increases volatility while the combination of high temperature-high rainfall tends to subdue it. Goodwin and Schnepf (2000) studied the impact of growing conditions on corn and wheat price variability and found it to have a significant negative impact in the case of corn futures price volatility; a negative relationship was also identified in the case of wheat futures but it was not statistically significant.

Trading volume: Cornell (1981), Grammatikos & Saunders (1986), Najand & Yung (1991) found evidence suggesting increased trading volume increases price volatility in futures markets.

Loan rates: Loan rate is a government program that welcomes voluntary participation from producers and promises its participants loan at a certain price regardless of the cash market price. Participants may forfeit their produce to the government and do not repay the loan if the cash prices remain below the sum of loan rate, and storage and interest costs. The program, in effect, tends to put a floor on the cash and futures prices near the loan rate but since producers are not mandated to participate in the program the floor is not absolute. The program serves to lessen downside price potential and thus futures price volatility should decrease as futures prices near loan rate (Kenyon, et al., 1987). Kenyon, et al. (1987) studied corn, soybean and wheat futures prices, three commodites for which the loan rate program exists, and found statistically significant evidence to support this contention.

Price levels: Works of Glauber and Heifner (1986); Kenyon et al. (1987); Streeter and Tomek (1992) have established that price levels are significantly, positively related to price volatility. Streeter and Tomek (1992), however, argued that price levels should ideally capture impacts of supply and demand conditions so discerning the effects of supply and demand variables from that of price levels on price volatility may be difficult if all these variables are included in the same analysis (Goodwin & Schnepf, 2000).

Speculative activity: Empirical analyses of the impact of speculation in futures price volatility have been approached differently but have offered similar conclusions mostly. Gray (1967) studied the Chicago, Kansas City and Minneapolis wheat futures markets and found that speculation has no price effect in markets with sufficient speculation but the price effect of insufficient speculation is sizeable. The Nathan Associates (1967) found that periods with unusually large price volatility tended to be associated with insufficient speculation. Ward (1974) studied frozen concentrated orange juice futures and found no evidence for price destabilizing effects of speculation. His results rather suggested speculation and price volatility is inversely, rather than directly, related. Rutledge (1978) studied fifteen commodity futures (wheat, corn, oats, live cattle, iced broilers, plywood, soybeans, soybean oil, soybean meal, silver, gold, deutsche mark, Japanese yen) and found evidence to reject the notion that speculation destabilizes prices. Petzel (1980) reexamined the accusations brought against speculators for causing the violent and unpredictable volatility of May 1925 wheat prices only to find no evidence to support the blame. Peck (1981) studied the role of speculation in wheat, corn and soybean futures markets and concluded they were ailed with inadequate amount of speculation that resulted in increased price variability. She concluded accusations of too much speculation in the future markets is unsubstantiated. In fact given her findings that increased speculation reduces price variability she opined that there was actually not enough speculation in the markets she studied relative to hedging activity. Streeter and Tomek (1992) analyzed soybean futures and found speculators to not dominate hedgers in a way that results in additional price variability. Their results showed price volatility tend to be smaller when speculation is larger relative to hedging.

Scalping activity: Scalping (and day trading) activity has been hypothesized in literature to effect futures price volatility (Goodwin & Schnepf, 2000). Scalpers operate at the shortest time horizon, oftentimes within a second, without holding any view as to where prices are going, rather buying or selling at moment's notice sometimes making only a fraction of a cent's profit on each contract (Büyükşahin & Harris, 2011). Scalpers make profit trading hundreds to thousands of contracts a day in this way. On the other hand day traders take their positions based on their expectations of where prices might be moving within minutes or hours (Büyükşahin & Harris, 2011). Day traders usually make larger profit per contract and trade smaller number of contradts a day than the scalpers, but like the scalpers close all their trading positions before the market closes for the trading day. Because these traders add liquidity to the market it is generally argued that their activities should contribute to lowering price volatility by decreasing bid-ask spreads (Goodwin & Schnepf, 2000); works of Peck (1981), Streeter and Tomek (1992), Goodwin and Schnepf (2000) have actually lent support to this contention. Brorsen (1991) however argued that scalping and day trading may augment price volatility by allowing prices to adjust to information more quickly. The overall relationship between scalping activity and price variability is, thus, unclear (Goodwin & Schnepf, 2000).

Market concentration: Market concentration is also hypothesized to be an determinant of price volatility. Prices may experience increased volatility if the activities of large traders restrain market liquidity or induce large price adjustments; nevertheless, the expected link between market concentration and price variability cannot be reasoned with certainly (Goodwin & Schnepf, 2000). Streeter and Tomek (1992) found that market concentration in both long and short positions tended to be positively related to price volatility. Goodwin & Schnepf (2000) found higher levels of market concentration in short positions to have a significant negative effect on price variability of wheat futures, but the effect to be not significant in case of corn.

2.3 Review of the Measures of Volatility Used in Previous Literature

Different authors measured volatility differently. Variance of the change in logarithms of prices was used to measure volatility by Milonas (1984), Anderson (1985), Glauber and Heifner (1986), Kenyon et al. (1987), Brorsen and Irwin (1987), Brorsen (1989), Streeter & Tomek (1992), Hennessy and Wahl (1996). Goodwin & Schnepf (2000) defined volatility to be the change in logs of weekly futures prices. Peck (1981) used monthly average of the daily trading range of nearby futures to measure volatility. Choi and Longstaff (1985) used standard deviation of the first difference of the logarithm of futures prices as their measure of volatility. Najand and Yung (1991) used the logarithm the price relative [i.e. $\ln(close_t/close_{t-1})$] to measure volatility.

2.4 Review of the Approaches Adopted to Study the Impact of Exogenous Variables on Volatility of Futures Prices in Past Literature

Different authors have modeled the impact of exogenous variables on volatility of futures prices differently.

Anderson (1985) tested for the effect of Samuelson hypothesis and state-variable-hypothesis (which states that the volatility of futures prices will be relatively high during periods when significant amounts of supply or demand uncertainty are resolved) in the volatility of wheat (CBOT, KC), corn, oats, soybeans, soybean oil, live cattle, silver and cocoa futures applying non-parametric and parametric tests. The non-parametric tests were conducted using the Benard and Van Elteren (1953) statistics[6] while the parametric tests involved both likelihood ratio tests based on least square estimates and Lagrange multiplier tests based on least absolute deviations

[6] Details about this can be read in (Benard & Van Elteren, 1953) and Appendix I of (Anderson, 1985).

estimates[7] of a linear model that sought to explain how the variance of futures prices were affected by Samuelson hypothesis and state-variable-hypothesis controlling for the effects of other factors that might be affecting the volatility of futures prices.

Goodwin and Schnepf (2000) used three different types of conditional heteroscedasticity models, namely multiplicative Conditional Heterescedasticity (CH) model of Harvey (1976), Autoregressive Conditional Heteroscedasticity (ARCH) model of Engle (1982) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) of Bollerslev (1986) to investigate the deterministic factors related to futures price variability. They investigated how growing conditions, seasonality, use-to-stocks ratio, speculation index, scalping activity, market concentration in short positions and time to maturity impact the intraseason price variability in corn and wheat futures markets.

Streeter & Tomek (1992) specified a regression model to study the impact of information flow effects, economic information effects and market structure effects on the volatility of soybean futures prices and estimated the parameters with ordinary least sqaures, feasible generalized least sqaures and non-linear least sqaures estimators.

Peck (1981) focused on studying the impact of speculation in the volatility of wheat, corn and soybean futures prices but also included three other explanatory variables in the regression model to capture the effects of flow of and certainty of new information and scalping activity on volatility of prices.

Glauber and Heifner (1986) regressed the volatility of soybean futures prices on monthly dummies, price level, quarterly interest rate for 6 month T-bills and total available supply for consumption in the next quarter.

[7] Details about this can be read in Appendix II of (Anderson, 1985).

Kenyon et al. (1987) sought to explain the volatility of soybean, corn, wheat, live cattle and live hog futures with seasonal, price level, quantity (production level), and loan rate (ratio of futures prices to loan rate) effects and estimated parameters of the model they specified with OLS.

Najand and Yung (1991) studied the how the trading volume impacts the volatility of T-bond futures using a GARCH model. They estimated their model parameters utilizing the maximum likelihood technique.

Yang and Brorsen (1993) also used a GARCH model to study how seasonality, day-of-the-week and time-to-maturity effects affect the volatility of corn, coffee, oats, soybean, soybean meal, wheat (Chicago), wheat (Kansas City), copper, gold, palladium, silver futures.

2.5 Contribution this Study Makes to the Existing Literature

This study adds to existing literature the identification of factors impacting the volatility of cotton futures-something that has not been previously addressed in any literature yet. The study differs from past literature in its analysis of the largest number of factors hypothesized to be related to the variance of futures prices. The framework developed in this thesis would be suitable to analyze determinants of futures price volatility of any other storable agricultural commodity.

2.6 Summary of the Chapter

This chapter reviews the literature on the topic addressed in this thesis. It is noted that researchers have differed in their approaches to studying the impact of exogenous factors on the volatility of futures prices and have considered different variables in their respective analysis. Time-to-delivery, seasonality, level of inventory, growing conditions, trading volume, price level, loan rate, speculative activity, scalping activity and market concentration in trading positions are identified in the literature to be determinants of agricultural futures price volatility. Researchers have also differed in the ways they have measured volatility. Variance of the change in logarithms of prices, changes in the logs of futures prices, average of the daily trading range of nearby futures, standard deviation of the first difference of logarithm of prices, logarithm the price relative are the different measures that have been used in literature to quantify volatility.

CHAPTER 3
CONCEPTUAL AND EMPIRICAL FRAMEWORK

3.1 Conceptual Framework

Econometric models reliant on the assumption of homoscedasticity, i.e. constant variance of error terms, are unsuitable for the empirical analysis conducted in this thesis since the variance of the error terms itself is of key interest. In the present analysis, weekly return on cotton futures is the dependent variable and the variance of the return represents the level of risk associated with it. Further, as can be confirmed with a simple visual inspection of Figure 3.1, like any other financial time-series data the dependent variable exhibits volatility clustering- the phenomenon of large changes in prices occurring in bunches rather than with equal spacing (Dueker, 1997). This means, that some periods (the expected value of error terms at some times is greater than at others) are riskier than others and that there is a degree of autocorrelation in the riskiness of the returns (Engle, 2001).

Given the data properties, empirical analysis is conducted using the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) framework of Engle (1982) and Bollerslev (1986). GARCH is the generalization by Bollerslev (1986) of the Autoregressive Conditional Heteroscedasticity (ARCH) model introduced by Engle (1982).

In an ARCH model conditional variance is allowed to change over time as a function of past squared errors. It derives its strength from the fact that the conditional means and variances can be jointly estimated using conventional models for economic variables (Najand & Yung, 1991).

Engle's ARCH regression model assumes that the mean of a random variable[8] y_t is given as $X_t ß$ (independent variables), a linear combination of lagged endogenous and exogenous variables included in the information set ϕ_{t-1} with $ß$ a vector of unknown parameters (Engle, 1982).

$$y_t \mid \phi_{t-1} \sim N(X_t ß, h_t)$$

$$y_t = X_t ß + \varepsilon_t \quad , \tag{1}$$

$$h_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i \varepsilon_{t-i}^{2} \quad , \tag{2}$$

where, h is conditional variance, ε is residuals, t denotes time and α_0 and α_i are empirical parameters determined by maximum likelihood estimation (Engle, 1982; Bollerslev, 1986; Khan, 2012)

Bollerslev (1986) generalized Engle's ARCH model to allow for more flexible lag structure. GARCH (p,q) regression model is given as follows:

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

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^{2} + \sum_{i=1}^{q} ß_i h_{t-i}^{2} \,. \tag{3}$$

In equation (3), p indicates the number of autoregressive lags included in the equation and q indicates the number of lags that are included in the moving average component of a variable (Engle, 2001). In equation (3) $p>0$ and $q\geq 0$. When $q=0$, the above specification reduces to a ARCH (p) process and when $p=q=0$, ε_t is simply white noise.

Following (Goodwin & Schnepf, 2000) the following specification of the GARCH model is estimated where Z_t is a vector of determinants of cotton's conditional price variability.

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^{2} + \sum_{i=1}^{q} ß_i h_{t-i}^{2} + Z_t \gamma \,. \tag{4}$$

[8] "Since the groundbreaking work of Haavelmo (1944), economic time series are considered to be realizations of stochastic processes. That is, each point of an economic time series is considered to be an observation of a random variable." - Engle, et al. (2008)

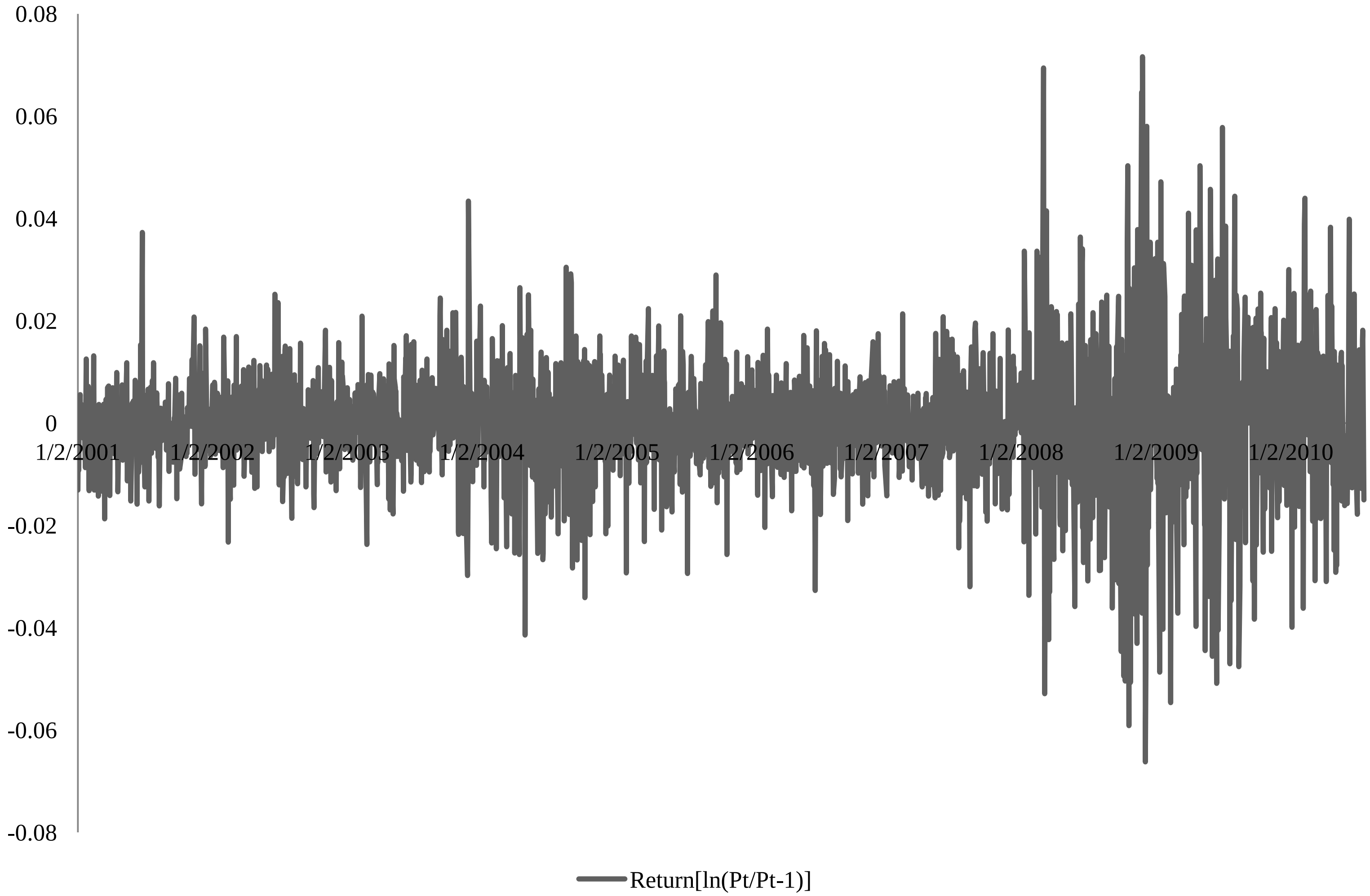

Figure 3.1: Returns of cotton futures

3.2 Empirical Model

Following Goodwin & Schnepf (2000) the mean of the returns in the GARCH (1,1) model has been allowed to be influenced by growing conditions relaxing the assumption of market efficiency which dictates returns should not be predictable.

Seasonal dummies, stocks-to-use ratio, growing condition index, a discrete indicator variable to indicate time of the year during which the growing condition data were available, lagged volume, price level, speculative index, scalping activity, market concentration in long positions and market concentration in short positions are included as explanatory variables in the variance equation specification of the GARCH (p,q) model.

Two of the variables identified in the literature to be determinats of agricultural commodity futures price volatility, time to matury and closing price to loan rate ratio, are not considered for analysis in this thesis. The reasons for exclusion of these variables needs explanation.

Goodwin and Schnepf (2000) argued:

> "In light of the significant seasonality apparent in the variance of agricultural product prices, it may be difficult, if not impossible, to distinguish time-to-maturity effects from patterns of seasonality when a single futures contract is examined. Time to maturity is essentially a linear trend variable when used in a model for a single contract. Thus, linear seasonality patterns cannot be distinguished from time-to-maturity effects."

Thus, Tuesday closing prices of nearby cotton futures, rolled over on the last day of contract expiration date are used in the analysis and single contracts are not separately considered so the model can better capture effects of seasonality, the time-to-maturity variable could not be included in the model.

The closing price to loan rate ratio variable has not been included in the model because the loan rate was fixed at 52 cents during the entire period studied so taking a ratio of the closing price and loan rate merely scaled the closing price level. The closing price to loan rate ratio variable was calculated nevertheless but on pripori analysis it was found to be highly correlated with the price level variable and so it was not included in the final model.

Thus, the final empirical model to be estimated is specified as follows:

$$y_t = X_t ß + \varepsilon_t \ , \qquad (5)$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^{\ 2} + \sum_{i=1}^{q} ß_i h_{t-i}^{\ 2} + Z_t \gamma \ , \qquad (6)$$

where, y_t = $\ln(P_t/P_{t-1})$.

X_t contains the intercept term and the growing condition index variable. Z_t contains seasonal dummies, stocks-to-use ratio, growing condition index, a discrete indicator variable to indicate time of the year during which the growing condition data were available, lagged volume, price level, speculative index, scalping activity, market concentration in long positions and market concentration in short positions variables.

3.3 Formation of Hypothesis

In this section, hypotheses regarding the expected relationship between the explanatory variables and the volatility of cotton futures are formed.

Seasonality is established in the literature to be significantly related to volatility of most agricultural commodity futures. However, the direction of that relationship in different parts of the year, positive or negative, is not uniform across commodities. Usually, cotton is planted in the second quarter of the year and harvested through late third quarter to the end of fourth quarter (National Agricultural Statistics

Service, 1997). Usual planting and harvesting dates of cotton by state appear in Table 3.1.

Table 3.1: Usual Planting and Harvesting Dates, by State [Table reproduced from (National Agricultural Statistics Service, 1997)]

State	**Usual Planting Dates**			**Usual Harvesting Dates**		
	Begin	**Most Active**	**End**	**Begin**	**Most Active**	**End**
AL	Apr 12	Apr 24 - May 24	Jun 6	Sep 22	Sep 20 - Oct 20	Dec 15
AZ	Mar 15	Apr 1 - Apr 30	May 15	Sep 15	Oct 10 - Nov 10	Dec 25
AR	Apr 24	May 1 - May 24	May 31	Sep 22	Oct 6 - Oct 30	Nov 24
CA	Apr 1	Apr 15 - Apr 30	May 15	Oct 1	Oct 15 - Nov 1	Nov 15
FL	Apr 1	Apr 15 - May 15	Jun 15	Sep 15	Oct 1 - Nov 1	Dec 1
GA	Apr 20	Apr 25 - May 25	Jun 5	Sep 20	Oct 5 - Nov 15	Dec 15
LA	Apr 17	Apr 26 - May 16	Jun 2	Sep 15	Sep 28 - Oct 20	Nov 13
MS	Apr 14	Apr 28 - May 28	Jun 9	Sep 15	Oct 6 - Nov 3	Nov 17
MO	Apr 25	May 5 - May 20	Jun 1	Sep 20	Oct 5 - Oct 30	Nov 20
NM	Apr 10	Apr 20 - May 10	May 20	Oct 10	Oct 25 - Nov 30	Dec 20
NC	Apr 21	May 1 - May 20	Jun 8	Sep 27	Oct 7 - Nov 15	Dec 15
OK	May 6	May 20- Jun 12	Jun 29	Oct 11	Nov 4 - Nov 29	Dec 15
SC	Apr 24	May 1 - May 20	Jun 1	Sep 23	Oct 15 - Nov 13	Dec 5
TN	Apr 25	May 5 - May 20	Jun 5	Sep 20	Oct 5 - Nov 1	Nov 25
TX	Mar 10	May 5 - Jun 6	Jun 30	Aug 10	Oct 1 - Dec 2	Dec 28
VA	Apr 10	Apr 20 - May 10	May 20	Sep 30	Oct 25 - Nov 25	Dec 10

Since concrete information about the new cotton supply is available during the third and fourth quarter of the year volatility of cotton futures should decrease at that time. Thus it is hypothesized:

H_1: Seasonality should significantly affect volatility of cotton futures with volatility decreasing in the third and fourth quarters of the year.

According to the theory of storage, higher levels of inventory should dampen the volatility of prices. The effect of inventory levels is captured in this study with the stocks-to-use ratio variable. It is hypothesized:

H_2: Stocks-to-use ratio should be negatively related to the volatility of cotton futures prices.

Owing to the short run fixed production levels of agricultural commodities, growing conditions send important signal to the markets about the commodities' short run availability. Better growing conditions should assure the market about stable short run supply and thus reduce price volatility. The effect of growing conditions is captured in this study with the growing condition index variable. It is hypothesized:

> H_3: Growing condition index should be negatively related to the volatility of cotton futures prices.

Najand & Yung (1991) quoted in their paper the Wall Street wisdom that, "It takes volume to make prices move." A positive relationship between volume and volatility of futures prices is well documented in the literature. It is hypothesized:

> H_4: Trading volume should be positively related to the volatility of cotton futures prices.

Price level has also been repeatedly found to be positively related with the volatility of futures prices in literature. It is hypothesized:

> H_5: Price level should be positively related to the volatility of cotton futures prices.

Speculative activity in the futures market has been empirically established to reduce volatility of prices in literature. The strength and success of futures markets depend on the generation of an adequate trading volume by hedgers and speculators so that establishment of futures positions without incurring any market entry or exit cost is facilitated (Ward, 1974). Speculative traders who do not have any exposure to the underlying commodity of concern play an essential role to ensure smooth functioning of futures markets. Speculation in the futures market is necessary for the proper effecting of hedging. Speculators provide the market with the much needed liquidity that is necessary to establish or terminate futures contracts immediately and thus eliminate transactionary risk from futures trading (Ward, 1974). Short hedgers cannot always find long hedgers willing to trade with them at the exact time or in the quantity they are willing to and so speculators enter the market to fulfill the hedging demands (Lehecka, 2013). The effect of speculative activity is captured in this study with the speculative index variable. It is hypothesized:

> H_6: Speculative index should be negatively related to the volatility of cotton futures prices.

Results have been mixed in the literature about the three other explanatory variables considered in this study. It has been argued that scalping activity should reduce volatility of prices for the active participation of scalpers in a market serves to reduce the bid-ask spread; a counterargument has been presented that scalping activity should increase volatility of prices for the active participation of scalpers allow new information to be quickly adjusted to prices. As noted in the second chapter of the thesis, Streeter and Tomek (1992) found that market concentration in both long and short positions tended to be positively related to price volatility while Goodwin & Schnepf (2000) found higher levels of market concentration in short positions to have a significant negative effect on price variability of wheat futures, but the effect to be not significant in case of corn. No specific hypotheses about the direction of relationship between these three explanatory variables and the volatility of futures prices are thus formed.

3.4 Summary of the Chapter

In this chapter the conceptual framework, empirical model and formation of hypotheses about the relationship between the explanatory variables and the volatility of cotton futures prices are discussed.

A GARCH (*p*, *q*) model is chosen for analysis because it properly accounts for the heteroscedasticity and volatility clustering the time series data of concern display and allows for simultaneous examination of both the mean and the variance of the time series. The variance of the time series is of primary concern in this analysis and the GARCH (*p*, *q*) model allows the variance to be influenced by exogenous variables whose effects are intended to be studied. Thus, in effect, this model allows examining how the exogenous variables affect the volatility of the time series of interest.

Seasonal dummies, stocks-to-use ratio, growing condition index, a discrete indicator variable to indicate time of the year during which the growing condition data were available, volume, price level, speculative index, scalping activity, market concentration in long positions and market concentration in short positions are the exogenous variables included in the variance equation of GARCH (*p*, *q*) model specification. It is expected that seasonality will significantly affect the volatility of cotton futures prices with volatility decreasing in the third and fourth quarter of year. Volume and price level are expected to positively affect the volatility of prices while the stocks-to-use ratio, growing condition index and speculative index variables are expected to affect it negatively. No prior expectation is formed about how the scalping activity and the market concentration variables are related to the volatility of cotton futures prices.

CHAPTER 4

DATA

4.1 Variable Construction and Data Sources

The dependent variable, return on cotton futures (y_t), is defined as the natural logarithm of Tuesday price changes of cotton futures, $\ln(P_t / P_{t-1})$. Tuesday closing prices of nearby cotton futures, rolled over on the last day of contract expiration date, collected from the Commodity Research Bureau (CRB) database are used. Prices of the futures contracts traded on the Intercontinental Exchange (ICE)[9] are used in the analysis. ICE futures contracts are an established benchmark and serve as the central global price discovery mechanism for cotton partly because of the importance of U.S. cotton production in the global market for textiles (Janzen, et al., 2012).

Next, construction of the variables included in Z_t, a vector of determinants of cotton's conditional price variability, in equation (6) is described.

To capture the effect of seasonality a variable S_t is included as the first explanatory variable in the model. Seasonal dummies D_{2t}, D_{3t}, D_{4t} are created for the first three quarters of the year respectively. No dummy is created for the first quarter as the model includes an intercept; the seasonal effect of the first quarter will be explained by the intercept itself. At any time period t only one of the seasonal dummies will equal 1 and all other will be 0. The variable S_t can thus be represented as,

$$S_t = \sum_{i=1}^{3} \gamma_i D_{it} . \qquad (7)$$

The second explanatory variable included in the model is stock-to-use ratio, SU_t. The motivation behind inclusion of this variable in the model is to capture the effect of level of inventory. Since ICE contracts are used by both U.S. and foreign cotton merchants, growers, and processors to manage price risk (Janzen, et al., 2012),

[9] ICE was previously known and New York Board of Trade.

world stock-to-use ratio is used as an explanatory variable in the model specified. Monthly measures of the variable are collected from United States Department of Agriculture's (USDA) World Agricultural Outlook Board's (WAOB) World Agricultural Supply and Demand Estimates (WASDE) reports and are interpolated to obtain the weekly measures.

The third explanatory variable included in the model is growing conditions index, GCI_t, which is designed to account for the effect of growing conditions on price volatility. The variable is developed following Goodwin & Schnepf (2000). During the growing season (i.e., from immediately after planting until harvest) National Agricultural Statistics Service (NASS) publishes a weekly measure of crop quality in which the proportion of the crop that falls into each of five condition categories: very poor, poor, fair, good, and excellent is reported. Using the proportions of crop in each category as weights and assuming a simple numerical scale, where 1=very poor…5=excellent, a crop quality index is first constructed taking weighted averages. For the non-growing portion of the crop year when the NASS assessments of crop quality are not reported the crop quality index is set at the mean value of the index over the entire period of study. A growing condition index is then developed to represent deviations from the mean value of the crop quality index such that the growing condition index variable had a value of zero during portions of the year when no information about crop progress was available and was positive (negative) when crop quality were above (below) average levels. Following Goodwin & Schnepf (2000) a discrete indicator variable having the value of 1 during periods when NASS reports were unavailable is also created and included as the fourth variable in the model. Goodwin & Schnepf (2000) did not find the variable to have any significant impact in any of the models they studied, so no priori expection about the signifance or direction of impact of this variable on cotton futures price volatility is formed.

Trading volume, V_t is included in the model as the fifth explanatory variables to test if it has any sizeable impact on price volatility. The volume data are collected from the CRB database.

A price level variable, PL_t, calculated as the average of daily closing prices for each week is included as the sixth variable in the model. Streeter & Tomek (1992) used a similar variable in their study but their measure reflected monthly, instede of weekly, price levels. As noted before, the price data are collected from the CRB database.

Working's (1960) speculative index, T_t, is included as the seventh variable in the model to capture the effect of speculative activity in the futures market on volatility. Working (1960) devised his speculative index as a direct measure of the amount of speculation that is in excess than the amount required to fulfill unbalanced short hedging demand in a commodity. The speculative index reveals how much more speculation is prevailing in the market than the minimum amount necessary to fulfill all long and short hedging demand, recognizing that long and short hedgers do not, and cannot, always possibly counterbalance each other even in markets where they hold positions in comparable magnitudes (Peck, 1980b). When there is just enough speculation in the market to equal hedging demand the speculative index has a minimum value of 1.00. If the speculative index has a value bigger than 1.00, say 1.45, it means there are 45% more speculative positions in the market than what is required to fulfill hedging needs (Lehecka, 2013). Working (1960) explained that this technically excess speculation is in fact economically necessary because in the absence of it a futures market will be one in which heavy short hedging induces extreme price depression[10]. The index is calculated based on the total number of long and short positions held by hedgers and speculators.[11]

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[10] Working (1960) drew the example of an imaginary futures market with no long hedging. In such a market, he noted, the amount of long speculation could exactly equal the amount of short hedging only if it were the case that the market also did not have any amount of short speculation. An absolute

If short hedging is greater than or equal to long hedging, Working's speculative index is calculated as

$$T = 1 + SS/(HL+HS) \qquad [\text{if } HS \geq HL], \tag{8}$$

where, *SS*=short speculation, *HS*= short hedging, *HL*= long hedging and *T* denotes Working's speculative index. If long hedging is greater than short hedging the index is calculated as

$$T = 1 + SL/(HL+HS) \qquad [\text{if } HL > HS], \tag{9}$$

where, *SL*= long speculation.

Prior to any further discussion a brief explanation of what is meant by headers and speculators would be useful. A trader, with actual physical exposure to the commodity either as a seller or a buyer, who enters into a futures contract preferring security of a predefined price to avert the risk arising from a fall (in the case of a seller) or rise (in the case of a buyer) of prices in the future is a hedger. A trader with actual physical exposure to the commodity entering into a futures contract only because he thinks locking in a deal at a predetermined price would benefit him for he expects the price to move in a direction (up or down) that is disadvantageous to his position (as a buyer or a seller) is essentially speculating but is still generally

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absence of short speculation could have only meant that prices are already so low that no speculator is willing to bet for the chance of prices getting any lower. In Working's (1960) own words, "The uncertainties of price appraisal being what they are, a price so low that *no* speculator thought it likely to go lower would assuredly be too low. Any futures market must have more speculation than the minimum technically necessary to carry the hedging, else it will be one in which heavy short hedging causes excessive price depression."

[11] Peck (1980) succinctly restated Working's (1960, p. 197) argument as to why it necessary to include both long and short positions held by hedgers and speculators by noting, "Net hedging is not the most useful view of the demands commercial users make on a market. Speculation is needed to offset both long hedging and short hedging. Only coincidentally are long and short hedgers sufficiently alike in date and amount to be offsetting, although increased balance increases the probability of such correspondence and differences in seasonal needs between long and short hedgers decreases this probability. The appropriate measure of minimum required speculation must at least begin with total hedging demand."

considered as hedger for the simple fact that objective identification of the intention of a trader for entering into a futures contract is essentially impossible.

A speculator, on the other hand, is considered to be a trader who does not have any physical exposure to the commodity as either buyer or seller and enters into futures contracts primarily with the intention of liquidating his position at any time before the delivery date and extracting a return from the intervening price change. Being an ideal platform of executing a speculative bet without having to take physical possession of the underlying commodity (and thus avoiding any transportation, storage and other similar costs involved) makes futures markets a lucrative park for the speculators.

Fagan and Gencay (2008) found that hedgers and speculators frequently assume opposing positions and that there is a strong negative correlation between their respective long positions (Cifarelli & Paladino, 2011). In practice, it must be noted however, it is extremely difficult to identify traders as hedgers or speculators as the mediation of futures exchanges, meant to standardize futures contracts, has made background information about individual traders opaque to public view (Schutter, 2010). Distinguishing hedgers from speculators in futures market is not a straight forward task (Büyükşahin & Harris, 2011).

CFTC addresses this issue by categorizing traders as commercials and non-commercials before they can trade on an exchange (Schutter, 2010). The weekly[12] COT report published by CFTC classifies reportable trading positions in two broad categories, commercial and non-commercial, and also provides records of non-reportable trading positions held by small traders. CFTC recognizes a commercial trader to be any trader who uses futures (or options) “contracts in a given commodity for hedging purposes, as defined in CFTC regulations. Commercial traders hold

[12] Weekly publication of the COT report started from 2000; prior to that it used to published less frequently (CFTC, 2014).

positions in both the underlying commodity and in the futures (or options) contracts on that commodity" (CFTC, 2012). On the other hand, a non-commercial trader, according to CFTC, is any trader who does not own the underlying asset or its financial equivalent. Non-commercial traders hold only positions in futures (or options) contracts (CFTC, 2012). Non-commercials traders are mostly financial entities (like hedge funds, mutual funds), floor brokers and traders who are not registered with the CFTC under the Commodity Exchange Act (Büyükşahin & Harris, 2011). CFTC also keeps and publishes record of non-reportable positions held by traders who do not meet the reporting thresholds set by the CFTC (usually small traders) (CFTC, 2012). The non-reportable positions are obtained by subtracting the reportable positions from the total open interest and the commercial/ non-commercial classification of the traders in this category are unknown (CFTC, 2014). A single trading entity cannot be classified as both a commercial and a non-commercial trader for the same commodity but can be identified differently for different commodities. To ensure accuracy and consistency of the classification Commission staff reserve the right to use judgment in re-classifying a trader based on additional information about the trader's use of the market should such information be available to them (CFTC, 2014)[13]. For the purpose of present discussions throughout this thesis traders

[13] Classification of poisition holders as non-commercial and commercial is useful but is incomplete in revealing the full picture of speculative activities taking place in the futures market as it has been long recognized hedgers also speculate (Tomek, 1981). Traders with a commercial interest in or an exposure the physical commodity in question traditionally are identified as hedgers and those without any exposure to the physical commodity are called speculators (Büyükşahin & Harris, 2011). Nevertheless, it is not uncommon to see tarders with an exposure to the physical commodity taking a view on the future movements of price and choosing to not hedge in the futures market (and thus in effect taking short positions; further, withholding downward pressure on futures prices and also signalling that prices are expected to go up) and thus acting like speculators (Büyükşahin & Harris, 2011). Further CFTC classification of commercial traders include swap dealers who do not have any exposure to the physical commodity in concern and primarily use futures market to hedge over-the-counter positions and usually take positions for commodity index funds that view commodities as a distinct asset class and thus are considered by some to be speculators (Büyükşahin & Harris, 2011). In the words of Sanders, et al. (2009) "the blanket categorization of speculators as wrongdoers and hedgers as victims of their actions is mistaken. Many hedgers speculate and some speculators also hedge. It is not clear that there is an easily identified "bad guy." Market dynamics are complex, and it is not easy to understand the interplay between the varied market participants and their motivations for trading."

categorized as commercial by CFTC are considered to be hedgers and traders categorized as non-commercial by CFTC considered to be speculators.

One methodical obstacle one needs to overcome when using Working's *T* index is deciding on how to treat the non-reporting traders. Working's *T* index suffers from the problem of lacking any guidance as to how to classify the non-reporting traders. Different authors have addressed this problem differently. Peck (1980) classified all non-reporting traders as speculators and thus created an upper bound for the speculative index. Leuthold (1983) classified all non-reporting traders as hedgers and thus created a lower bound for the speculative index. Both variations of the index are developed and tested for their efficacy separately in the model. All the data for calculating the speculative index is collected from the weekly Commitment of Traders (COT) report published by U.S. Commodity Futures Trading Commission (CFTC).

To account for the effect of scalping activity an eighth variable, $SA_{t,}$ is included in the model. Since no comprehensive data about the level of scalping is available a proxy for scalping activity is created following the literature. First the ratio of daily volume to open interest is calculated and then averaged for the week as a proxy of scalping activity. Goodwin & Schnepf (2000) used the same proxy for weekly scalping activity in their study while Streeter & Tomek (1992) followed the same procedure to measure scalping activity on a monthly basis. The data for calculating this variable are collected from the CRB database.

The ninth and tenth variables MCL_t and MCS_t, representing market concentration in long and short positions respectively, are included in the model to capture the effect of presence of large positions (regardless of whether they are held by hedgers or speculators) relative to total open interest. These variables are defined as the percent of total open interest in cotton futures contracts held by the four largest traders in long and short positions, respectively, as reported in the COT reports published by CFTC. Streeter & Tomek (1992) used the same variable in their study.

4.2 Descriptive Statistics

The analysis is conducted on weekly data observed over the period January 02, 2001 to July 13, 2010. Table 4.1 reports the summary statistics of the variables studied in the thesis. As can be seen in the table, return, stocks-to-use ratio, growing condition index, price level, speculative index, market concentration in long positions and market concentration in short position variables have an approximately symmetric distribution[14]. Volume and scalping activity variables are highly positively skewed. The speculative index variable has a mean value of 1.1995 which means that, on average, the market has had 20% more speculation than the amount needed to completely absorb hedging.

Table 4.1: Summary Statistics of the Variables Studied

Variable	**Mean**	**Standard Deviation**	**Skewness**	**Maximum**	**Minimum**
Return	-0.0016	0.0286	-0.3348	0.1001	-0.1401
Stocks to Use Ratio	0.4365	0.0544	-0.0363	0.5777	0.3229
Growing Condition Index	0.0060	0.1358	0.3062	0.4963	-0.4937
Volume	6.1900	7.3844	1.8601	51.0680	0.0010
Price Level	98.7855	22.6942	-0.3101	148.2075	46.7900
Speculative Index	1.1995	0.0739	0.2904	1.3944	1.0696
Scalping Activity	0.3049	0.3811	2.8603	2.3824	0.0067
Market Concentration in Long Positions	0.2219	0.0561	-0.2542	0.3450	0.1080
Market Concentration in Short Positions	0.3338	0.0875	-0.2287	0.5110	0.1300

[14] A perfectly symmetrical distribution has skewness=0. However, an exact zero value of skewness is rare in real world data. Interpretations are drawn in this thesis following Bulmer (1979)'s suggested rule of thumb that a distribution is highly skewed is skewness is less than -1 or greater than +1, a distribution is moderately skewed if skewness is between −1 and −½ or between +½ and +1, a distribution is approximately symmetric if skewness is between −½ and +½.

4.3 Data Analysis

Time series data that have changing means and variances are identified as as non-stationary (Hamilton, 1994) Non-stationary time series tend to cause estimation, inference and forecasting problems in empirical modeling (Maradiaga, et al., 2013). . To free empirical analysis of time series data of the problems that may arise due to non-stationarity of the data , the consensus in the literature has been to transform non-stationary data into stationary data if non-stationarity is detected in the series (Maradiaga, et al., 2013). In other words, the objective is to convert an unpredictable process to one that has a mean returning to a long term average and a variance that does not depend on time (Maradiaga, et al., 2013).

Thus, stationarity of the variables used in this analysis is checked using the Augmented Dickey Fuller (ADF) test. For ADF tests, the null hypothesis is that the series is non-stationary and the alternative hypothesis is that the series is stationary. If p-value is less than .05 the null hypothesis of non-stationarity is rejected at 5% significance level and it is concluded that the data is stationary. The results of the ADF test on the variables appear in the Appendix in Tables A.1 through A.10.

The tests revealed stocks-to-use ratio, price level, speculative index, market concentration in long positions and market concentration in short positions variables are not stationary. To achieve stationarity stocks-to-use ratio, speculative index, market concentration in long positions and market concentration in short positions variables are transformed by taking first differences and price level variable is transformed by detrending.[15] Stationarity of the transformed variables are confirmed by ADF tests. The test results appear in the Appendix in Tables A.11 through A.15.

[15] "Trend in a time series is a slow, gradual change in some property of the series over the whole interval under investigation. Detrending is the statistical or mathematical operation of removing trend from the series"- (Meko, 2013). The price level data was detrended using MATLAB's detrend function which performs a linear fit to the data and then removes the trend from it by subtracting the best-fit line (obtained by least square) from the data (MathWorks, 2014).

4.4 Summary of the Chapter

This chapter provides details of how the variables studied in this thesis are constructed, where the data used to construct the variables are collected from and presents the descriptive statistics associated with the variables studied in a tabular form. This chapter also discusses some analysis that were conducted on the data prior to estimation of the main model. Construction of the variables studied in this thesis closely follows construction methodology of similar variables used in previous published literature. The data used to construct the variables are collected from Commodity Research Bureau database, Commitment of Traders reports published by Commodity Futures Trading Commission, World Agricultural Supply and Demand Estimates reports published by World Agricultural Outlook Board of United States Department of Agriculture and the weekly reports on crop quality published by National Agricultural Statistics Service. The descriptive statistics table shows except for volume and scalping activity variables which have a highly positively skewed distribution the rest of the variables have an approximately symmetric distribution. The stationarity of the variables were checked using the Augmented Dickey Fuller tests. Five of the variables, stocks-to-use ratio, price level, speculative index, market concentration in long positions and market concentration in short positions, were spotted to be non-stationary. Stocks-to-use ratio, speculative index, market concentration in long positions and market concentration in short positions variables were transformed by differencing and price level variable was transformed by detrending to achieve stationarity.

CHAPTER 5

ESTIMATION, RESULTS AND DISCUSSIONS

To make the selection between ARCH and GARCH some analysis is conducted on the data. The presence of ARCH disturbances based on OLS residuals is tested using Q, Lagrange multiplier, Lee and King and Wong and Li test statistics. The null hypothesis in these tests is that there no ARCH effects (i.e. heteroscedasticity) and the alternative hypothesis is that ARCH effects (i.e. heteroscedasticity) is present. The test results appear in Table 5.1. As can be seen in the table, all the tests indicated the presence of strong heteroscedasticity through the 12^{th} lag widow indicating the need for a very high order ARCH model to properly account for the heteroscedasticity. The basic ARCH(p) model (q=0) is a short memory process for it only uses the most recent p squared residuals to estimate the changing variance. The GARCH model (q>0) allows long memory processes since it uses all the past squared residuals to estimate the current variance (SAS Institute Inc. , 2014). Thus, the tests for ARCH disturbances based on OLS residuals suggested the use of the GARCH model (q>0) instead of the ARCH model.

The most widely used GARCH(p, q) specification, a GARCH (1,1) model is employed. Bollerslev (1987) demonstrated that GARCH (1,1) adequately fits most economic time series data (Najand and Yung, 1991). It has since then been repeatedly confirmed that rarely, if at all, any higher order model than GARCH (1,1) is needed to capture the volatility clustering return data usually display (Alexander, 2001; Brooks, 2008; Musunuru, et al., 2013).

Table 5.1: Tests for ARCH Disturbances Based on OLS Residuals

Order	Q	Pr > Q	LM	Pr > LM	LK	Pr > |LK|	WL	Pr > WL
1	23.4386	<.0001	23.3113	<.0001	7.4192	<.0001	28.2521	<.0001
2	67.6635	<.0001	55.9703	<.0001	11.2904	<.0001	59.5044	<.0001
3	81.5967	<.0001	58.1337	<.0001	11.0530	<.0001	68.7603	<.0001
4	101.5656	<.0001	62.2814	<.0001	11.5672	<.0001	91.6525	<.0001
5	119.7296	<.0001	66.6441	<.0001	11.8754	<.0001	124.2434	<.0001
6	141.0300	<.0001	70.8274	<.0001	12.2978	<.0001	157.4400	<.0001
7	147.0048	<.0001	71.0389	<.0001	11.8199	<.0001	177.0536	<.0001
8	156.1337	<.0001	71.2392	<.0001	11.7023	<.0001	191.5755	<.0001
9	183.6678	<.0001	83.4114	<.0001	12.3133	<.0001	214.8137	<.0001
10	191.6909	<.0001	83.4140	<.0001	12.1288	<.0001	227.4569	<.0001
11	218.8110	<.0001	87.9495	<.0001	12.6215	<.0001	250.4014	<.0001
12	230.3358	<.0001	88.6146	<.0001	12.5887	<.0001	275.2507	<.0001

Note: Q, LM, LK and WL stands for Q statistics, Lagrange multiplier, Lee and King, and Wong and Li test statistics, respectively.

5.1 Estimation Results

Table 5.2 presents maximum likelihood estimates of the parameters of the GARCH (1,1) model specified. The mean equation refers to equation (5) and the variance equation refers to equation (6).

The results show that mean of the returns tend to be positively affected by growing conditions but the effect is not statistically significant. Strong and statistically significant ARCH and GARCH effects are identified in the volatility of returns. The volatility of cotton futures prices is not significantly impacted by seasonality, growing conditions, volume traded, speculative index or scalping activity. Only stocks-to-use ratio, price level, market concentration in long positions and market concentration in short positions significantly impact the volatility of cotton futures prices. All four of the statistically significant determinants of volatility of cotton futures prices are identified to have a positive relationship with the volatility of cotton futures prices, i.e., all the four statistically significant determinants cause volatility to increase.

Table 5.2: Parameter Estimates of the GARCH (1,1) Model

Variable	**Estimate**	**Standard Error**
Mean Equation		
Intercept	-0.00121	0.00105
Growing Condition Index	0.00641	0.00481
Variance Equation		
ARCH0	4.1125E-7	0.00004
ARCH1	0.15610***	0.03880
GARCH1	0.78300***	0.04560
Q2	0.00003	0.00003
Q3	0.00007	0.00004
Q4	8.6067E-6	0.00003
Stocks-to-Use Ratio	0.00390**	0.00228
Growing Condition Index	0.00008	0.00006
Discrete Indicator Variable	0.00004	0.00004
Price Level	6.636E-10***	0.00000
Volume	5.0147E-8	1.8454E-6
Speculative Index[16]	0.00009	0.00067
Scalping Activity	1.6757E-6	0.00004
Market Concentration in Long Positions	0.00126**	0.00069
Market Concentration in Short Positions	0.00716***	0.00223

Note: *** indicates significance at 1% level and ** indicates significance at 5% level.

[16] The speculative index is calculated following Peck's (1980) way of classifying all the non-reporting traders as speculators. The model was also estimated with an alternate variation of the index in which all the non-reporting traders were classified as hedgers following Leuthold (1983). Both measures produced almost identical estimations and so are not reported separately.

5.2 Discussions on Findings

Strong presence of ARCH and GARCH effects are indicated by the parameter estimates as the ARCH1 and GARCH1 parameter estimates are identified to be significant at 1% level of significance. The ARCH1 estimate of 0.15610 indicates the extent to which a volatility shock today feeds trough into next period's volatility and the sum of ARCH1 and GARCH1 parameter estimates, .15610+0.78300=0.9391, indicates the rate at which this effect dies over time. An estimate of 0.15610 of the ARCH(1) parameter indicates that volatility of present week depends weakly on the errors squared last week. Sum of the parameter estimates being close to 1 indicates persistence in volatility, i.e. current volatility of weekly returns can be explained by past volatility which tends to persist over time.

Stocks-to-use ratio, price level, market concentration in long positions and market concentration in short positions are identified to be statistically significant determinants of cotton futures price volatility. Parameter estimates of the statistically significant and insignificant explanatory variables alike are numerically low. Najand & Yung (1991), Goodwin & Schnepf (2000) used a GARCH model to study the impact of exogenous variables on futures price volatility and they also found similar numerically low estimates of parameters for the exogenous variables they studied. The hypotheis of negetive relationship between stocks-to-use ratio and volatility of cotton futures prices is rejected at the 10% level of significance. This finding is counterintuitive for it implies higher levels of inventories are associated with higher level of volatility. This goes against what was hypothesized but it is not unusual for cotton futures to display characteristics against the norm. For example, when Yang, et al. (2001) studied the impact of agricultural liberalization policy, i.e. the Federal Agricultural Improvement and Reform act of 1996, on wheat, soybeand, corn and cotton futures price volatitlities using GARCH model, they found the agricultural liberalization policy to increase the price volatility of corn, soybeans and wheat futures but decrease the price volatility of cotton futures. Streeter & Tomek (1992) found a similar positive relationship between inventory levels and volatility of soybean futures prices.

The hypothesis of a positive relationship between price level and volatility of cotton futures prices is accepted at the 1% level of significance; the higher prices go up, the more volatile they become.

Both the market concentration in long positions and market concentration in short positions variables have a positive effect on the volatility of cotton futures prices. Comparing the level of significance, market concentration in short positions are significantly more important than market concentration in long positions. The results agree with Streeter & Tomek (1992) who found these variables to have these same effects on the volatility of soybean futures prices. They inferred:

> "The concentration effect could be the result of manipulative price behavior, but another feasible explanation is that large trades have larger than average transaction effects on prices, particularly in the more thinly traded months."

5.3 Summary of the Chapter

In this chapter the preliminary analysis conducted on the data prior to estimation of the main model, the parameter estimates of the main model and discussions on the findings are presented. To make the selection between ARCH and GARCH (that is whether q should be greater than 0 or not in the model specified and also what the proper order of p should be if an ARCH model is more suitable for the data) the presence of ARCH disturbances based on OLS residuals is tested using Q, Lagrange multiplier, Lee and King and Wong and Li test statistics. The test results indicated the presence of strong heteroscedasticity through the 12^{th} lag widow suggesting the use of the GARCH model ($q>0$) instead of the ARCH model. Thus the GARCH (1,1) model specification is finalized. Parameter estimates of the GARCH (1,1) model is presented next. The estimates reveal the presence of strong ARCH and GARCH effects and significant volatility persistence. Stocks-to-use ratio, price level, market concentration in long positions and market concentration in short positions are identified to be statistically significant determinants of cotton futures price volatility.

CHAPTER 6

CONCLUSION

Given the economic importance of cotton and the heavy reliance of cotton producers and users on the cotton futures market an understanding of the factors affecting the volatility of cotton futures prices makes a very important point of discussion. This thesis aimed at an empirical analysis of the effects of factors hypothesized in the literature to be determinants of volatility of agricultural futures prices on the volatility of cotton futures prices.

A review of the literature review it was revealed that different researchers have adopted different approaches to study the impact of exogenous factors on the volatility of futures prices and have examined the impact of different variables in their studies. Time-to-delivery, seasonality, level of inventory, growing conditions, trading volume, price level, loan rate, speculative activity, scalping activity and market concentration in trading positions have been identified in the literature to be determinants of agricultural futures price volatility.

A GARCH (1,1) model was chosen for analysis in this thesis because it properly accounts for the heteroscedasticity and volatility clustering the time series data in concern display and allows for simultaneous examination of both the mean and the variance of the time series. The variance of the time series is of main concern in this analysis and the GARCH (1,1) model allows the variance to be influenced by exogenous variables whose effects are intended to be studied. Thus, in effect, this model allows examining how the exogenous variables affect the volatility of the time series of interest. Seasonal dummies, stocks-to-use ratio, growing condition index, a discrete indicator variable to indicate time of the year during which the growing condition data were available, volume, price level, speculative index, scalping activity, market concentration in long positions and market concentration in short positions are the exogenous variables included in the variance equation of the GARCH (1,1) model specification.

Parameter estimates of the GARCH (1,1) model reveal presence of strong ARCH and GARCH effects and significant volatility persistence. Stocks-to-use ratio, price level, market concentration in long positions and market concentration in short positions are identified to be statistically significant determinants of cotton futures price volatility.

6.1 Future Work

In the bid to support the domestic cotton farmers as the 2008 global financial crisis substantially curtailed the demand for Chinese cotton and yarn, the Chinese government adopted a policy of buying the domestically produced cotton at above world market prices. The policy continued even after the financial crisis ended and as a result China presently holds more than half of world cotton stocks (Johnson, et al., 2014)

Since the present analysis makes use of market data observed over the period between 2001 and 2010 the effect of China's stockpiling policy on cotton price variability might have not been well captured by the models. Future extensions of this research could include the post-2010 data for analysis so the impact of Chinese stocks on the volatility of cotton prices can be better studied.

Another way this study could be augmented is by studying the impact of the variables in a Markov Regime Switching GARCH model framework. If empirical analysis reveals the presence of two distinct regimes in the volatility of cotton futures prices-a high volatility regime and a low volatility regime-better insight into the effects of the exogenous variables on the volatility of prices can be obtained if their parameters are allowed to change between regimes. Recognizing regime shift as a part of the data generation process would allow for more robust estimation of conditional volatility. (Fong & See, 2002).

BIBLIOGRAPHY

Alexander, C. *Market Models: A Guide to Financial Data Analysis*. New York: John Wiley & Sons, 2001.

Algieri, Bernardina. *Price volatility, speculation and excessive speculation in commodity markets: Sheep or shepherd behaviour?*. No. 166. ZEF Discussion Papers on Development Policy, 2012.

Anderson, Ronald W. "Some determinants of the volatility of futures prices." *Journal of Futures Markets* 5.3 (1985): 331-348.

Ash, Andrew, et al. "Constraints and opportunities in applying seasonal climate forecasts in agriculture." *Australian Journal of Agricultural Research* 58 (2007): 952-965.

Benard, A. and P. Van Elteren. "A Generalization of the Method of m Rankings." *Indagationes Mathematime* 15 (1953): 358-369.

Black, Fischer and Myron Scholes. "The pricing of options and corporate liabilities." *The Journal of Political Economy* (1973): 637-654.

Black, Fischer. "The pricing of commodity contracts." *Journal of Financial Economics* 3 (1976): 167-179.

Bollerslev, T. "A Conditionally Heteroscedastic Time Series Model for Speculative Prices and Rates of Return." *Review of Economics and Statistics* 69 (1987): 542-547.

Bollerslev, Tim. "Generalized autoregressive conditional heteroskedasticity." *Journal of Econometrics* 31.3 (1986): 307-327.

Brooks, C. *Introductory Econometrics for Finance*. New York: Cambridge University Press, 2008.

Brorsen, B. Wade and Scott H. Irwin. "Futures funds and price volatility." *Review of Futures Markets* 6.2 (1987): 118-135 .

Brorsen, B. Wade. "Futures trading, transaction costs, and stock market volatility." *Journal of Futures Markets* 11.2 (1991): 153-163.

—. "Liquidity costs and scalping returns in the corn futures market." *Journal of Futures Markets* 9.3 (1989): 225-236.

Brunner, Allan D. "El Nino and world primary commodity prices: warm water or hot air?" *Review of Economics and Statistics* 84.1 (2002): 176-183.

Bulmer, Michael George. *Principles of statistics*. Courier Dover Publications, 1979.

Büyükşahin, Bahattin and Jeffrey H. Harris. "Do speculators drive crude oil futures prices?" *Energy Journal* 32.2 (2011).

Carpantier, Jean-François and Arnaud Dufays. *Commodities volatility and the theory of storage*. No. 2012037. Université catholique de Louvain, Center for Operations Research and Econometrics (CORE), 2012.

Castelino, Mark G. and Jack Clark Francis. "Basis speculation in commodity futures: The maturity effect." *Journal of Futures Markets* 2.2 (1982): 195-206.

Centre for Excellence in Teaching and Learning in Applied Undergraduate Research Skills . *Why Do We Review Literature?* 2012. 24 10 2014. <http://www.engageinresearch.ac.uk/section_2/why_do_we_review_literature.shtml>.

CFTC. *This Month in Futures Markets*. 2012. 31 March 2014. <http://www.cftc.gov/OCE/web/index.htm>.

Chatrath, Arjun, Bahram Adrangi and Kanwalroop Kathy Dhanda. "Are commodity prices chaotic?" *Agricultural Economics* 27.2 (2002): 123-137.

Choi, Jin W. and Francis A. Longstaff. "Pricing options on agricultural futures: An application of the constant elasticity of variance option pricing model." *Journal of Futures Markets* 5.2 (1985): 247-258.

Cifarelli, Giulio and Giovanna Paladino. "Hedging vs. speculative pressures on commodity futures returns." MPRA Paper 28229. 2011.

Cornell, Bradford. "The relationship between volume and price variability in futures markets." *Journal of Futures Markets* 1.3 (1981): 303-316.

CRB. *Option Implied Volatility and Futures Historical Volatility*. 2014. 23 10 2014. <http://www.crbtrader.com/support/options.asp>.

Dueker, Michael J. "Markov switching in GARCH processes and mean-reverting stock-market volatility." *Journal of Business & Economic Statistics* 15.1 (1997): 26-34.

Engle, Robert F. "Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation." *Econometrica: Journal of the Econometric Society* (1982): 987-1007.

Engle, Robert F., Sergio M. Focardi and Frank J. Fabozzi. "ARCH/GARCH models in applied financial econometrics." *Handbook of Finance* (2008).

Engle, Robert. "GARCH 101: The use of ARCH/GARCH models in applied econometrics." *Journal of Economic Perspectives* (2001): 157-168.

European Commission. *Historical Price Volatility*. Brussels, 2009.

Fagan, Stephen and Ramazan Gencay. "Liquidity-induced dynamics in futures markets." *MPRA Working Paper 6677* (2008).

Fong, Wai Mun and Kim Hock See. "A Markov switching model of the conditional volatility of crude oil futures prices." *Energy Economics* 24.1 (2002): 71-95.

Geman, Hélyette and William O. Smith. "Theory of storage, inventory and volatility in the LME base metals." *Resources Policy* 38.1 (2013): 18-28.

Geyser, Mariette and Michela Cutts. "SAFEX maize price volatility scrutinised." *Agrekon* 46.3 (2007): 291-305.

Glauber, Joseph W. and Richard G. Heifner. "Forecasting futures price variability." NCR-134 Conference on Applied Price Forecasting Proceedings, 1986.

Goodwin, Barry K. and Randy Schnepf. "Determinants of endogenous price risk in corn and wheat futures markets." *Journal of Futures Markets* 20.8 (2000): 753-774.

Grammatikos, Theoharry and Anthony Saunders. "Futures price variability: a test of maturity and volume effects." *Journal of Business* 59.2 (1986): 319-330.

Grauer, Frederick LA. "Equilibrium in commodity futures markets: theory and tests." *Stanford University, 21977* (1977).

Gray, Roger W. "Price effects of a lack of speculation." *Food Research Institute Studies* 7 (1967): 177-194.

Haavelmo, Trygve. "The probability approach in econometrics." *Econometrica: Journal of the Econometric Society* (1944).

Hamilton, J.D. "Models of Non-stationary Time Series." *Time Series Analysis*. Princeton, NJ: Princeton University Press, 1994.

Harvey, Andrew C. "Estimating regression models with multiplicative heteroscedasticity." *Econometrica: Journal of the Econometric Society* (1976): 461-465.

Hennessy, David A. and Thomas I. Wahl. "The effects of decision making on futures price volatility." *American Journal of Agricultural Economics* 78.3 (1996): 591-603.

Investor's Business Daily. *How does the commodity futures market work?* 2014. 23 10 2014. <http://investdaily.custhelp.com/app/answers/detail/a_id/450/~/how-does-the-commodity-futures-market-work%3F>.

Janzen, Joseph P., Aaron D. Smith and Colin A. Carter. "Commodity Price Comovement: The Case of Cotton." *Proceedings of the 2012 NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management*. 2012.

Johnson, James, et al. "The world and United States cotton outlook."*Agricultural Outlook Forum 2014*. No. 168329. United States Department of Agriculture, 2014.

Johnson, Leland L. "The Theory of Hedging and Speculation in Commodity Futures ." *The Review of Economic Studies* 27.3 (1960): 139-151.

Karali, Berna and Walter N. Thurman. "Announcement effects and the theory of storage: an empirical study of lumber futures." *Agricultural Economics* 40.4 (2009): 421-436.

—. "Components of Grain Futures Price Volatility." *Journal of Agricultural and Resource Economics* 35.2 (2010): 167–182.

Kenyon, David, Kenneth Kling, et al. "Factors affecting agricultural futures price variance." *Journal of Futures Markets* 7.1 (1987): 73-91.

Khan, Samir. *GARCH – Tutorial and Excel Spreadsheet*. 2012. 4 November 2014. <http://investexcel.net/garch-excel/>.

Lehecka, G. V. "Hedging and Speculative Pressures: An Investigation of the Relationships among Trading Positions and Prices in Commodity Futures Markets." St. Louis, MO: Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, 2013.

Leuthold, Raymond M. "Commercial use and speculative measures of the livestock commodity futures markets." *Journal of Futures Markets* 3.2 (1983): 113-135.

Maradiaga, David, Aude Pujula and Hector Zapata. "Exploring Time Series Data Properties in SAS®." *SAS Global Forum 2013, Paper 456-2013, Statistics and Data Analysis* (2013).

MathWorks. "Detrending Data." *MATLAB® Data Analysis*. Natick, MA: The MathWorks, Inc., 2014. 21-23.

Meko, Dave. *Detrending*. 2013. 6 November 2014. <http://www.ltrr.arizona.edu/~dmeko/notes_7.pdf>.

Miller, K. D. "The Relation Between Volatility and Maturity in Futures Contracts." *Commodity Murkets and Futures Prices* (1979).

Milonas, Nikolaos T. "Price variability and the maturity effect in futures markets." *Journal of Futures Markets* 6.3 (1986): 443-460.

Musunuru, Naveen, Mark Yu and Arley Larson. "Forecasting Volatility of Returns for Corn using GARCH Models." *The Texas Journal of Agriculture and Natural Resources* 26 (2013): 42-55.

Najand, Mohammad and Kenneth Yung. "A GARCH examination of the relationship between volume and price variability in futures markets." *Journal of Futures Markets* 11.5 (1991): 613-621.

Nathan Associates Inc. "Margins, Speculation and Prices in Grain Futures Markets." U.S. Department of Agriculture. 1967.

National Agricultural Statistics Service. "Usual Planting and Harvesting Dates for U.S. Field Crops, Agricultural Handbook no. 628." 1997.

National Cotton Council of America. *The Importance of Cotton*. 2014. 23 October 2014. <https://www.cotton.org/pubs/cottoncounts/story/importance.cfm>.

Osakwe, Emeka. *Cotton Fact Sheet USA*. 2009. 31 3 2014. <https://www.icac.org/econ_stats/country_facts/e_usa.pdf>.

Peck, A.E. "Measures and Price Effects of Changes in Speculation on the Wheat,Corn, and Soybean Futures Markets." Research on Speculation. 1981.

—. "Reflections of hedging on futures market activity." *Food Research Institute Studies* 17.3 (1980): 327-349.

—. "The Role of Economic Analysis in Futures Market Regulation." *American Journal of Agricultural Economics* 62 (1980b): 1037-1043.

Perales, Guillermo Benavides. "The Theory of Storage and Price Dynamics of Agricultural Commodity Futures: the Case of Corn and Wheat." *Ensayos Revista de Economia* 29.1 (2010): 1-22.

Petzel, Todd E. "A New Look at Some Old Evidence: The Wheat Market Scandal of 1925." *FRI Studies* 8 (1980).

Richter, Martin and Carsten Sørensen. "Stochastic volatility and seasonality in commodity futures and options: The case of soybeans." *Journal of Futures Markets* (2002).

Rutledge, David JS. "A note on the variability of futures prices." *The Review of Economics and Statistics* (1976): 118-120.

—. "Trading volume and price variability: New evidence on the price effects of speculation." *Futures markets: Their establishment and performance* (1979): 137-156.

Samuelson, Paul A. "Proof that properly anticipated prices fluctuate randomly." *Industrial Management Review* 6.2 (1965): 41-49.

Sanders, D. R., S. H. Irwin and R. P. Merrin. "A Speculative Bubble in Commodity Futures Prices? Cross-Sectional Evidence." St. Louis, MO: Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting,and Market Risk Management, 2009.

SAS Institute Inc. . *Heteroscedasticity and GARCH Models*. 2014. 12 October 2014. <http://support.sas.com/documentation/cdl/en/etsug/60372/HTML/default/viewer.htm#etsug_autoreg_sect008.htm>.

Schutter, Olivier de. "Food Commodities Speculation and Food Price Crises." Briefing note by the United Nations Special Rapporteur on the right to food.2010.

Sørensen, Carsten. "Modeling seasonality in agricultural commodity futures." *Journal of Futures Markets* 22.5 (2002): 393-426.

Streeter, Deborah H. and William G. Tomek. "Variability in soybean futures prices: an integrated framework." *Journal of Futures Markets* 12.6 (1992): 705-728.

Tomek, W. G. "Margins on Futures Contracts: Their Economic Roles and Regulation." *Futures Markets: Regulatory Issues* (1985): 143-209.

Tomek, William G. "Speculation and Price Behavior on Commodity Markets: A Survey." *Research on Speculation: Seminar Report*. Chicago Board of Trade. 1981.

Tothova, Monika. "Main Challenges of Price Volatility in in Agricultural Commodity Markets." *Methods to Analyse Agricultural Commodity Price Volatility*. Ed. Isabelle Piot-Lepetit and Robert M'Barek. Springer Science+Business Media, LLC, 2011. 13-29.

Ward, R.W. "Market Liquidity in the FCOJ Futures Market." *American Journal of Agricultural Economics* 56 (1974): 150-154.

Working, Holbrook. "Price effects of futures trading." Stanford University Food Research Institute. 1960.

—. "Price relations between July and September wheat futures at Chicago since 1885." *Wheat Studies* (1933).

Yang, Jian, Michael S. Haigh and David J. Leatham. "Agricultural liberation policy and commodity price volatility: a GARCH application." *Applied Economics Letters* 8 (2001): 593-598.

Yang, Seung-Ryong and B. Wade Brorsen. "Nonlinear dynamics of daily futures prices: conditional heteroskedasticity or chaos?" *Journal of Futures Markets* 13.2 (1993): 175-191.

APPENDIX

Table A.1: ADF Unit Root Tests on Return

Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-433.073	0.0001	-19.72	<.0001		
	1	-506.402	0.0001	-15.88	<.0001		
	2	-579.177	0.0001	-13.43	<.0001		
Single Mean	0	-434.406	0.0001	-19.75	<.0001	195.10	0.0010
	1	-510.517	0.0001	-15.93	<.0001	126.83	0.0010
	2	-589.665	0.0001	-13.49	<.0001	90.98	0.0010
Trend	0	-434.485	0.0001	-19.74	<.0001	194.75	0.0010
	1	-510.826	0.0001	-15.91	<.0001	126.63	0.0010
	2	-590.439	0.0001	-13.48	<.0001	90.86	0.0010

Table A.2: ADF Unit Root Tests on Stocks-to-Use Ratio

Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	0.0068	0.6843	0.03	0.6918		
	1	-0.3124	0.6117	-0.45	0.5202		
	2	-0.2483	0.6262	-0.40	0.5394		
Single Mean	0	-2.0626	0.7709	-1.05	0.7368	0.56	0.9339
	1	-15.5216	0.0341	-2.73	0.0707	3.73	0.1166
	2	-12.6220	0.0703	-2.44	0.1304	2.99	0.3047
Trend	0	-1.7800	0.9752	-0.80	0.9639	0.59	0.9900
	1	-17.9800	0.1016	-2.78	0.2040	4.03	0.3676
	2	-14.4354	0.2015	-2.45	0.3506	3.18	0.5386

Table A.3: ADF Unit Root Tests on Growing Condition Index

Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-29.5885	<.0001	-3.68	0.0003		
	1	-27.2223	0.0001	-3.45	0.0006		
	2	-26.5826	0.0002	-3.34	0.0009		
Single Mean	0	-29.7360	0.0017	-3.70	0.0046	6.89	0.0010
	1	-27.3600	0.0020	-3.46	0.0097	6.05	0.0105
	2	-26.7111	0.0023	-3.35	0.0135	5.68	0.0188
Trend	0	-29.5984	0.0083	-3.66	0.0265	6.83	0.0352
	1	-27.1776	0.0143	-3.41	0.0507	6.00	0.0660
	2	-26.4972	0.0166	-3.30	0.0674	5.63	0.0857

Table A.4: ADF Unit Root Tests on Discrete Indicator Variable

Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-16.8276	0.0041	-3.00	0.0028		
	1	-17.3929	0.0035	-3.02	0.0026		
	2	-18.0000	0.0029	-3.04	0.0024		
Single Mean	0	-39.0094	0.0017	-4.48	0.0003	10.04	0.0010
	1	-42.4445	0.0017	-4.57	0.0002	10.46	0.0010
	2	-46.5623	0.0017	-4.67	0.0002	10.92	0.0010
Trend	0	-39.1241	0.0009	-4.48	0.0018	10.03	0.0010
	1	-42.5599	0.0007	-4.57	0.0013	10.45	0.0010
	2	-46.6783	0.0007	-4.67	0.0009	10.91	0.0010

Table A.5: ADF Unit Root Tests on Volume

Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-94.6347	<.0001	-7.46	<.0001		
	1	-97.6080	<.0001	-7.23	<.0001		
	2	-72.1311	<.0001	-6.07	<.0001		
Single Mean	0	-154.597	0.0001	-9.54	<.0001	45.82	0.0010
	1	-189.935	0.0001	-9.66	<.0001	46.95	0.0010
	2	-161.922	0.0001	-8.27	<.0001	34.45	0.0010
Trend	0	-162.411	0.0001	-9.81	<.0001	48.15	0.0010
	1	-203.351	0.0001	-9.94	<.0001	49.42	0.0010
	2	-177.033	0.0001	-8.51	<.0001	36.25	0.0010

Table A.6: ADF Unit Root Tests on Price Level

Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-0.8609	0.4974	-2.07	0.0369		
	1	-0.8814	0.4937	-1.60	0.1035		
	2	-0.8891	0.4923	-1.75	0.0768		
Single Mean	0	-3.6780	0.5751	-1.98	0.2942	3.37	0.2085
	1	-4.7247	0.4613	-1.92	0.3228	2.57	0.4134
	2	-4.5265	0.4816	-1.98	0.2943	2.86	0.3375
Trend	0	-10.4792	0.4015	-2.27	0.4497	3.26	0.5224
	1	-18.5775	0.0901	-2.98	0.1389	4.77	0.2198
	2	-16.5564	0.1346	-2.80	0.1964	4.39	0.2955

Table A.7: ADF Unit Root Tests on Speculative Index

Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-0.1062	0.6586	-0.20	0.6153		
	1	-0.1824	0.6412	-0.27	0.5870		
	2	-0.1653	0.6451	-0.27	0.5906		
Single Mean	0	-38.1735	0.0017	-4.45	0.0004	9.90	0.0010
	1	-64.2086	0.0017	-5.65	<.0001	15.96	0.0010
	2	-63.7497	0.0017	-5.45	<.0001	14.83	0.0010
Trend	0	-38.7546	0.0010	-4.48	0.0018	10.04	0.0010
	1	-65.2779	0.0007	-5.69	<.0001	16.19	0.0010
	2	-64.9298	0.0007	-5.49	<.0001	15.05	0.0010

Table A.8: ADF Unit Root Tests on Scalping Activity

Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-207.897	0.0001	-11.49	<.0001		
	1	-144.673	0.0001	-8.50	<.0001		
	2	-141.660	0.0001	-7.84	<.0001		
Single Mean	0	-341.129	0.0001	-16.18	<.0001	130.82	0.0010
	1	-337.477	0.0001	-12.94	<.0001	83.78	0.0010
	2	-545.890	0.0001	-13.14	<.0001	86.37	0.0010
Trend	0	-346.399	0.0001	-16.35	<.0001	133.73	0.0010
	1	-348.832	0.0001	-13.15	<.0001	86.52	0.0010
	2	-588.631	0.0001	-13.46	<.0001	90.59	0.0010

Table A.9: ADF Unit Root Tests on Market Concentration in Long Positions

Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-0.7739	0.5138	-0.62	0.4493		
	1	-0.8870	0.4927	-0.66	0.4310		
	2	-0.7515	0.5181	-0.55	0.4772		
Single Mean	0	-13.0379	0.0634	-2.56	0.1016	3.29	0.2288
	1	-15.3270	0.0358	-2.76	0.0657	3.81	0.0991
	2	-16.2722	0.0282	-2.82	0.0564	3.99	0.0876
Trend	0	-18.6468	0.0888	-3.13	0.1013	4.90	0.1919
	1	-22.1427	0.0429	-3.37	0.0574	5.68	0.0830
	2	-22.8989	0.0365	-3.32	0.0646	5.51	0.0921

Table A.10: ADF Unit Root Tests on Market Concentration in Short Positions

Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-1.4414	0.4033	-0.87	0.3405		
	1	-1.9986	0.3308	-0.97	0.2951		
	2	-1.7083	0.3667	-0.90	0.3248		
Single Mean	0	-21.4014	0.0079	-3.30	0.0159	5.44	0.0243
	1	-34.6658	0.0017	-4.16	0.0009	8.68	0.0010
	2	-30.7827	0.0017	-3.85	0.0027	7.43	0.0010
Trend	0	-21.5246	0.0489	-3.30	0.0671	5.46	0.0949
	1	-34.7813	0.0025	-4.16	0.0055	8.67	0.0010
	2	-30.9109	0.0061	-3.85	0.0149	7.43	0.0203

Table A.11: ADF Unit Root Tests on Transformed Stocks-to-Use Ratio

Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-108.625	0.0001	-7.62	<.0001		
	1	-136.947	0.0001	-8.05	<.0001		
	2	-191.018	0.0001	-8.68	<.0001		
Single Mean	0	-108.603	0.0001	-7.61	<.0001	28.97	0.0010
	1	-136.918	0.0001	-8.04	<.0001	32.36	0.0010
	2	-190.977	0.0001	-8.67	<.0001	37.58	0.0010
Trend	0	-108.779	0.0001	-7.61	<.0001	29.06	0.0010
	1	-137.185	0.0001	-8.05	<.0001	32.46	0.0010
	2	-191.404	0.0001	-8.67	<.0001	37.69	0.0010

Table A.12: ADF Unit Root Tests on Transformed Price Level

Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-636.627	0.0001	-30.37	<.0001		
	1	-1109.48	0.0001	-23.48	<.0001		
	2	-16348.4	0.0001	-21.31	<.0001		
Single Mean	0	-636.627	0.0001	-30.34	<.0001	460.15	0.0010
	1	-1109.48	0.0001	-23.45	<.0001	275.03	0.0010
	2	-16347.8	0.0001	-21.29	<.0001	226.58	0.0010
Trend	0	-636.627	0.0001	-30.30	<.0001	459.20	0.0010
	1	-1109.48	0.0001	-23.43	<.0001	274.46	0.0010
	2	-16346.9	0.0001	-21.27	<.0001	226.10	0.0010

Table A.13: ADF Unit Root Tests on Transformed Speculative Index

Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-386.440	0.0001	-17.88	<.0001		
	1	-438.181	0.0001	-14.77	<.0001		
	2	-547.435	0.0001	-13.18	<.0001		
Single Mean	0	-386.443	0.0001	-17.86	<.0001	159.47	0.0010
	1	-438.184	0.0001	-14.75	<.0001	108.79	0.0010
	2	-547.443	0.0001	-13.17	<.0001	86.67	0.0010
Trend	0	-386.443	0.0001	-17.84	<.0001	159.14	0.0010
	1	-438.182	0.0001	-14.74	<.0001	108.56	0.0010
	2	-547.445	0.0001	-13.15	<.0001	86.49	0.0010

Table A.14: ADF Unit Root Tests on Transformed Market Concentration in Long Positions

Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-454.261	0.0001	-20.61	<.0001		
	1	-435.863	0.0001	-14.84	<.0001		
	2	-506.846	0.0001	-12.98	<.0001		
Single Mean	0	-454.261	0.0001	-20.59	<.0001	211.91	0.0010
	1	-435.858	0.0001	-14.83	<.0001	109.91	0.0010
	2	-506.848	0.0001	-12.96	<.0001	84.03	0.0010
Trend	0	-454.284	0.0001	-20.57	<.0001	211.49	0.0010
	1	-435.839	0.0001	-14.81	<.0001	109.68	0.0010
	2	-506.780	0.0001	-12.95	<.0001	83.86	0.0010

Table A.15: ADF Unit Root Tests on Transformed Market Concentration in Short Positions

Type	Lags	Rho	Pr < Rho	Tau	Pr < Tau	F	Pr > F
Zero Mean	0	-384.478	0.0001	-17.88	<.0001		
	1	-457.810	0.0001	-15.12	<.0001		
	2	-477.707	0.0001	-12.62	<.0001		
Single Mean	0	-384.476	0.0001	-17.86	<.0001	159.48	0.0010
	1	-457.811	0.0001	-15.10	<.0001	114.03	0.0010
	2	-477.709	0.0001	-12.61	<.0001	79.46	0.0010
Trend	0	-384.487	0.0001	-17.84	<.0001	159.18	0.0010
	1	-457.827	0.0001	-15.09	<.0001	113.81	0.0010
	2	-477.757	0.0001	-12.59	<.0001	79.30	0.0010