MEASURING BASIS VOLATILITY IN HARD RED WINTER WHEAT MARKETS

A Thesis

by

CASEY JOE PARISH

Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

| | |
|---|---|
| Chair of Committee, | David P. Anderson |
| Committee Members, | James M. Welch |
| | Clark B. Neely |
| Head of Department, | Mark L. Waller |

December 2019

Major Subject: Agricultural Economics

# ABSTRACT

Wheat market volatility research has lessened in recent years, especially since the beginning of the ethanol boom in the late 2000s. Moreover, when digging deeper in preparation for this thesis, basis volatility research, specifically for hard red winter wheat, was virtually nonexistent in the recent literature. In this paper, basis is evaluated over a twenty-five-year period and is separated into five separate periods for evaluation. This analysis is focused toward measuring volatility for basis, and for the sake of completeness, futures and cash prices, as well, using different measures. Furthermore, market types were assessed to determine if they provided different perspectives on their own, while also analyzing them in conjunction with each other. Recent research following the latest price spike from 2008 – 2009 concentrated on whether volatility of the current period differs from that of previous periods. When comparing the volatility between the five periods using different measures, particularly the first and last period of the data, the results depended on the measure being used. When using measures that take the mean into account, differences in basis volatility between the current period and the first period of this analysis are minimal. However, when the mean price is not taken into account, we found that the basis volatility of the present period is even higher than during the price spike of 2008 – 2009. Lastly, results of this analysis support the conclusion that cash price provides greater pressure on basis in terms of volatility than does futures price.

ACKNOWLEDGEMENTS

I would like to acknowledge several faculty members of Texas A&M University, specifically Dr. David Anderson, Dr. James Welch, and Dr. Clark Neely who served as the members of my thesis committee and who have guided me throughout this process. I believe further acknowledgement should be given to Dr. Anderson as he has served as a great mentor who has given advice, knowledge, and especially patience. This serves as a testament of the great man he is and as someone who will always have my respect.

Next, I would like to thank the team at Attebury Grain, LLC, including George Gurganus, Matt Gruhlkey, and Dale Lock for their contributions in the form of advice and experience in the field and for always being there in times of need over the past years. In particular, George Gurganus has been a great first boss and is someone who has my respect and has taught me that even through deep loyalty it is important to take into consideration what is best for me when dealing with tough decisions.

There are three mentors that I would like to thank for their continuous support and life advice throughout my time at Texas A&M University. They have given me advice about my career, tough life choices, and have helped me to determine where I want to go in life and who I want to become. Dr. John Park, someone whom I see a lot of in myself and someone who has taught me that it is okay to be yourself even when I thought that might not have been enough, I want to say thank you. Leon Perry, someone who I believe has one of the greatest extents of fairness and consideration for people that I have ever seen in a man and from whom I believe has helped me develop these same qualities through our long and multiple conversations, I want to say thank you. Dr. Craig Rotter, someone who has helped me through many tough times of self-doubt and life questions, and is someone who has taught me my most cherished lesson that life is precious and that it should not be wasted or taken for granted, I want to say thank you.

Next, I would like to thank my parents, family, friends, and classmates for their support and motivation over the course of the past two years. Specifically, I would like to give further acknowledgment to my parents Janice and Tracy Parish, as without them I would not be where I am at today.

## CONTRIBUTORS AND FUNDING SOURCES


### Contributors

Committee members who provided leadership for this thesis include Dr. David P. Anderson, Committee Chair of the Department of Agricultural Economics, Dr. James M. Welch of the Department of Agricultural Economics, and Dr. Clark B. Neely of the Department of Soil and Crop Science. Assistance of data collection was provided by Caroline S. Gleaton and Emmy W. Kiphen. Editing was provided by Corey Parish throughout the compilation of this thesis.

### Funding Sources

No funding was received for the work done in the compilation of this thesis.

# NOMENCLATURE

| | |
|---|---|
| HRS | Hard Red Spring |
| HRW | Hard Red Winter |
| SRW | Soft Red Winter |
| HW | Hard White |
| SW | Soft White |
| KCBT | Kansas City Board of Trade |
| CME | Chicago Mercantile Exchange |
| USDA | United States Department of Agriculture |
| GARCH | Generalized Autoregressive Conditional Heteroskedasticity |
| OLS | Ordinary Least Squares |
| JT | Jorckheere-Terpstra |
| SUR | Seemingly Unrelated Regression |
| GLS | Generalized Least Squares |

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Page

# CHAPTER I

# INTRODUCTION

Wheat is just as important as when it was discovered and spread across the world. From its beginnings in Europe, to its introduction to the western hemisphere, and its role in the Green Revolution in Mexico, wheat has benefited the world. The production and consumption of wheat products in the United States and the rest of the world has a significance to human nutrition shared by only a handful of other food staples.

Wheat is used in many different products due to the attributes of different varieties grown today. The major varieties of wheat grown in the United States, with some being grown mainly in the Great Plains, include hard red spring (HRS) wheat, hard red winter (HRW) wheat, soft red winter (SRW) wheat, durum wheat, hard white (HW) wheat, and soft white (SW) wheat. Unlike most other commodities, wheat is included in the diet of most people around the world. Examples include bread, pasta, flat breads, and many other baked goods depending on the culture represented. While corn and soybeans are major staple crops grown today and are used in many items that you see at the grocery store, some products require a unique quality only obtained from wheat. Wheat's quality allows us to enjoy goods such as bread and pasta. However, to make these products, flour is necessary. Flour is the largest product produced from wheat. Flour serves as a main ingredient because of the functions that it provides in baking such as its ability to provide texture and strength derived from its gluten content. Wheat is used to make many baked goods including biscuits, cakes, pastries, and crackers. Grown in almost every area in the United States, wheat provides an advantage compared to other crops due to winter and spring wheat types being grown and harvested at different times of the year. Winter and spring production reduce the impacts of a single annual planting and harvest cycle, thus reducing the impact of production seasonality.

Wheat is the third largest field crop in area planted in the U.S. behind corn and soybeans. HRW wheat, the focal point of this research, represents the largest portion of the wheat produced in the United States. HRW wheat is produced mostly in the Great Plains from Texas to Montana. For example, Kansas produced 19.2 percent of the U.S. wheat crop in 2017 and 95 percent of Kansas wheat was HRW wheat (Wheat Sector, Agriculture.ks.gov; Which wheat is for what?, kswheat.com). Additionally, in 2017, the wheat industry in Kansas directly contributed 3,215 jobs and, as a result, approximately $1.44 billion to the economy (Wheat Sector, Agriculture.ks.gov).

The major wheat varieties have different end uses and are grown in different regions of the U.S. The various commodity exchanges offer wheat contracts based on the wheat in the region where the exchange developed. Founded in 1856, the Kansas City Board of Trade (KCBT) was the largest trading market for HRW wheat futures and options. The KCBT was acquired by the CME Group in 2013 and all trading operations transferred to Chicago. Similarly, the Minneapolis Board of Trade trades HRS wheat and the Chicago Board of Trade trades SRW wheat.

Commodity price volatility has been an area of much concern and research over the last 15 years. Wheat markets have not been immune to volatility. Hypotheses about the causes of volatility include the introduction of electronic trading around the turn of the century, the Great Recession, government policies around the world, and the emergence of commodity-specific index funds. Previous research on volatility has mainly focused on other commodities, such as corn, while wheat has been mostly overlooked. The reasoning behind this could be that corn is more extensively grown and is used in ethanol production in the United States, so it receives more attention from researchers.

This thesis is structured as follows: Chapter 2 provides detailed history of wheat and literature review on determinants of volatility. Chapter 3 addresses methods of analysis and data. Chapter 4 includes analysis and results. This thesis ends with some conclusions in Chapter 5.

# CHAPTER II

# LITERATURE REVIEW

Wheat has served as a pillar of American agriculture. Built upon the eagerness of Americans to move west and settle the plains during the 1800's, the family was not the only thing that they brought with them. Although the Great Plains is a center of American agriculture, it was not always that way. Settling in the Great Plains, Americans faced many challenges that had not been faced in eastern homesteads. With a vastly different climate of cold and dry winters and dry summers, the settlers found that the familiar types of wheat were less than desirable. Geographic features such as the soil and hardness of the ground also proved to be a challenge to the mechanical equipment accustomed to do the job. What wheat the settlers managed to grow was mostly used as food. Subsistence wheat use limited the spread of wheat types early in the settlement of the Great Plains.

The major types of wheat grown in the United States are differentiated by kernel texture (hard or soft), seed coat color (red or white), and growth habits (spring or winter) (Wishart 2005). The Great Plains, which was settled in the 19th and early 20th century, can be divided into two regions, each having wheat types with different growth habits; the northern Great Plains and the southern Great Plains. The northern Great Plains, growing mostly HRS wheat and durum wheat, includes the states of Montana, North Dakota, Minnesota, Wyoming, and South Dakota. The southern Great Plains, growing mostly HRW wheat and some HW wheat and SRW wheat, represents the central and southern part of the United States including Texas, Oklahoma, Kansas, Colorado, Nebraska, and parts of Wyoming and South Dakota.

Hard Red Spring wheat is categorized as a spring-type wheat because of its growth habit. Planted early in the spring when the temperature begins to rise and moisture is present to a greater degree than in the fall and harvested in the late summer months of August and September, this type of wheat is better suited to the northern states. Winter wheats are not favorably grown in the northern states due to their inability to survive the colder winters. HRS wheat is a shorter season crop compared to HRW wheat and does not lay dormant over the winter. While HRS wheat was grown in North Dakota as early as around 1812 and spread across the northern plains as it was settled, Red Fife, a type of HRS wheat, was the cultivar that changed northern Great Plains agriculture in the middle of the century (Paulsen, Shroyer 2008). Compared to other cultivars in terms of its hard kernel texture and resistance to rust diseases that plagued farmers at that time, Red Fife quickly began to spread and served a large role in the development of later cultivars, as well as the region that had been compromised by Red Fife for over forty years (Paulsen, Shroyer 2008). Olmstead and Rhode agree, stating that Red Fife "…became the basis for the spread of the wheat frontier into Wisconsin, Minnesota, [and] the Dakotas…" (Pg. 8). The settlement of these western states and an increase in overall productivity per person were mainly the culmination of different mechanical improvements allowing farmers to farm these less-than-favorable regions. From the time of the Civil War until the turn of the century yields increased at a very slow rate, and it wasn't until the 1940s that yields began to increase rapidly (Dalrymple

1988). A variety named Bluestem was widely planted during the back half of the 19$^{th}$century and "by 1914 slightly more than half the crop of hard red spring consisted of Bluestem" (Pradesh 1953). Other cultivars such as Marquis, introduced in 1912 and founded from the Red Fife cultivar, ultimately replaced most of the Red Fife by 1919 and grew to 67% of the HRS wheat area (Paulsen, Shroyer 2008). While HRS wheat and its different varieties over time were favored by farmers in terms of a wheat crop that could survive the conditions of the northern Great Plains, initially detested HRS wheat for its milling difficulty. Noted for its hardness, it was difficult for millers to grind the grain and separate the bran, causing the grain to be discounted by millers and disliked by consumers. However, milling technology overcame those drawbacks and HRS wheat is produced in large quantities and has many admired qualities, particularly its strong gluten content and highest protein content of the hard-red wheats. Used today for baked goods such as "…artisan breads rolls, croissants, bagels, and pizza crust…", HRS wheat has many high quality uses along with "… often [being] blended with domestic wheat supplies to improve the strength of a flour blend." (kswheat.com) (Which wheat is for what?  http://kswheat.com/news/2014/12/02/which-wheat-for-what)

Durum wheat, while like HRS wheat grown in a similar location today, was not introduced into the northern Great Plains, particularly North Dakota, until the end of the 19th century and did not begin to be heavily produced until the early years of the next century. Introduced to the United States around the same time that Red Fife HRS wheat was introduced into North Dakota, durum wheat exhibits the same growing qualities as HRS wheat but was not able to be grown profitably in the humid conditions of the eastern United States (Paulsen & Shroyer 2008). The first popular durum wheat cultivar was Kubanka variety from Russia due to its high drought resistance (Dalrymple 1988). While originally intended for the southern plains, it was needed to a larger extent in the northern Great Plains with M.A. Carleton, the originator of the Kubanka variety stating, "… the need appeared more urgent in the northern plain states, making it desirable to secure a spring wheat able to resist more extreme conditions" (Paulsen & Shroyer 2008). Due to durum wheat's ability to overcome these extreme conditions at the time, it was also able to out-yield spring wheat. In the early 1900s, a stem rust epidemic plagued the HRS wheat crop and led to the rapid adoption of durum wheat in the region. Kubanka, "practically [represented] all the durum wheat in the country by 1914" and remained the premier cultivar for nearly 30 years (Paulsen & Shroyer 2008). Like HRS wheat, durum wheat was a less-than-favorable wheat to the millers in the northern Grain Plains at its inception. Furthermore, it is the hardest wheat type out of all wheat grown in the United States. After slowly being accepted by millers once newer milling technology was developed in the United States, durum wheat was found to have a great quality: high gluten content. With this high gluten content, durum wheat is used for most pasta but is sometimes used for Mediterranean bread types (kswheat.com)

Hard White wheat, while grown in a smaller scale than the types of wheat previously mentioned, is grown in the western section of the southern Great Plains. While discarded by most HRW wheat breeders in the past, HW wheat has a higher flour extraction rate and a better taste than the red wheats (Paulsen, Shroyer 2008). Known to the plains at an earlier time than its official recognition as a separate class by the USDA in 1990, this softer white wheat with a white tint was introduced by the early settlers of the region. Today, HW wheat is grown in the western part of the southern Great Plains, particularly western Kansas, western Nebraska, and eastern Colorado. HW wheat's main disadvantage is pre-harvest sprouting in moist and humid conditions in the eastern part of the region. A quality of HW wheat is the "naturally milder and sweeter flavor" in relation to other wheats and is the reason it is used to make whole white wheat flour (kswheat.com). Other uses for this type of wheat are pan breads, Asian-style noodles, and flat breads(kswheat.com). While mostly grown only as a specialty crop in the past centuries, HW wheat could possibly become a greater market if cultivars are found to solve pre-harvest sprout and demand for the products of this wheat type expands. (Paulsen, Shroyer 2008).

Hard Red Winter wheat, while like HRS wheat and durum wheat in their hard kernel texture, exhibits a different growth habit, categorizing it as a winter-type wheat. HRW wheat is planted in the fall, lays dormant throughout the winter, and is then harvested in the early summer months of May and June. While HRW wheat is the primary wheat type in Kansas, it is also grown from Texas to Montana because of its ability to withstand the extreme conditions of winter and summer to a greater degree than spring wheat. When first introduced into the United States, the HRW wheat cultivars available did not exhibit the ability to survive the extreme climates such as harsh winters in the north and hot summers in the south. This is the reason that up until the 1870's in Kansas and the 1900's in Nebraska that HRS wheat was the leading wheat type in terms of production (Paulsen & Shroyer 2008). While SRW wheat was a popular wheat type among farmers and millers due to farmers' past experience with the cultivar and its ease of milling, its inability to survive the extreme conditions of winter and lack of overall hardiness led it to fall behind HRS wheat in acres planted (Quisenberry & Reitz 1974).

A HRW wheat variety named Turkey was introduced into Kansas around 1873 and jumpstarted HRW wheat production in Kansas and Nebraska. Like many early cultivars of the different wheat types grown, Turkey-type HRW wheat came from eastern Europe. It was introduced by the Mennonite settlers from Crimea and Ukraine looking for a new home who settled in the Central Plains states of Nebraska and Kansas (Paulsen & Shroyer 2008). While the wheat they brought was well suited to the environment they moved to, they were also well-adapted to how the cultivar grew, as well. However, one disadvantage that led to slow-spread production and communication of the qualities of Turkey-type HRW wheat across the plains was that the Mennonite settlers brought very little seed (Quisenberry & Reitz, 1974). It is stated by Quisenberry & Reitz that "The first settlers brought small amounts, ranging from a few pounds to as much as a bushel or two per family…" which contributed to "…only small plots [being] seeded, and no doubt most of each crop was needed for food and feed, rather than for seed increase." Millers were also attributed to the slow growth in production and recognition of Turkey-type HRW wheat, as well. Much like the hard kernel texture of HRS wheat and durum wheat in the northern Great Plains, the southern Grain Plains Turkey-type HRW wheat presented some of the same problems with milling.

Turkey-type HRW wheat spread throughout the southern Great Plains region through research and the importation of HRW wheat seed into the United States. The importation of HRW wheat from Russia later in the century allowed Turkey-type HRW wheat for the first time to be sold to the public (Quisenberry & Reitz 1974). This allowed more Turkey-type HRW wheat to be grown by farmers beyond the Mennonite settlers. The recognition of Turkey-type wheat's qualities by many researchers of the last part of the 19th century, however, was slow for some, but even slower for the farmers growing the cultivar. This is because farmers of this pre-research era, which lasted from when wheat was first grown up until the 1890s, still believed that the SRW wheat that they were accustomed to was better than the HRW wheat varieties. This pre-research era was a time where "finding good cultural practices, pest and disease controls, and well adapted varieties was mostly a matter of trial and error" (Quisenberry & Reitz 1974). Skepticism by farmers and some researchers is a large reason the qualities of Turkey-type HRW wheat was slow to spread. This was until the wheat industry moved into the research era with the passage of the Hatch Act of 1887 which allowed for experiment stations to be created. While these experiment stations played a large part in the spread of information through research detailing the qualities of Turkey-type HRW wheat, in the beginning it took time for them to be created and operational, especially in the Great Plains. Until this time, researchers of this era of the late 19th century performed experiments and published research about the Turkey-type HRW wheat's qualities.

Among the researchers that contributed to the spread of Turkey-type HRW wheat are M.A. Carleton and C.C. Georgeson. Carleton's research on the "…growth; resistance to rust, cold, and drought; and grain quality … of nearly 1000 cultivars from around the world in Maryland in 1895 and in Kansas in 1896 and 1897" greatly attributed to Turkey-type HRW wheat's reputation (Paulsen & Shroyer 2008). Interestingly, Carleton did not test for yielding ability. C.C. Georgeson, became the first to publish research on the cultivar's yielding ability after administering experiments at the Kansas State Agricultural College from the years 1890 to 1898. Georgeson stated the "…cultivar labeled Turkey… [was] a 'heavy yielder' and '…perhaps the hardiest wheat of any we have tested'" (Paulsen & Shroyer 2008). The Nebraska Agricultural Experiment Station also conducted experiments on different winter wheats in 1890 and found that "of the varieties tested before 1902, Turkey proved to be the best for yield, winterhardiness, and quality" (Quisenberry & Reitz 1974).

Quisenberry & Reitz also stated that the first reliable acreage report of Turkey-type varieties was not until the 1919 crop and "… was estimated to be growing on 83 percent of the wheat acreage in Nebraska, 82 percent in Kansas, 67 percent in Colorado, 69 percent in Oklahoma, and 34 percent in Texas." While these percentages are made up of many different varieties that have the same qualities of the Turkey variety, the sole cultivar named Turkey remained the leading wheat variety until 1944 when it was replaced by Tenmarq (Quisenberry & Reitz). Among these Turkey-type HRW wheat varieties that were grouped with and grown alongside Turkey in the Great Plains because of their similar qualities, and as a result were labeled Turkey-type, were Kharkoff and Crimean, two varieties from Russia and Siberia, respectively, that were introduced by M.A. Carleton to the United States from 1898-1900. Noteworthy for its greater winterhardiness than Turkey, the use of Kharkoff as stated by Paulsen & Shroyer was the main reason farmers in Montana were able to grow winter wheat. The Crimean variety, on the other hand, is most noteworthy for being the parent cultivar of Tenmarq, which replaced Turkey in later decades. Turkey HRW wheat has played a very important role and has added great value as a parent to many different crosses of varieties created through its qualities in winterhardiness, yield, and many others.

HRW wheat mostly noted for its hard texture and ability to survive the extreme winters in the north and hot summers in the south, also exhibits a strong gluten and high protein content. This allows it to be used in products such as rolls and yeast bread but is also seen being used in cereal, flat breads, Asian style noodles, and general-purpose flour (kswheat.com).

Even though HRW wheat had a slow start in the Great Plains, it has come far from where its once was. Through trials of extreme climates, HRW wheat has attested to be a major wheat type in the Great Plains. Starting from the plots of Mennonite settlers of Kansas to being the largest wheat type grown in the Great Plains, HRW wheat is a large part of the reason we enjoy the wheat products produced today. HRW wheat being traded on the KCBT commodity exchange also exemplifies its importance as a wheat type, as this is the wheat type the exchange is built upon. Through the volume of HRW wheat traded in this exchange coupled with its importance as a wheat type in the Great Plains, is part of the reason my research is based upon HRW wheat. Volatility is present in many commodity exchanges such as those in Chicago and Minneapolis. The KCBT is not exempt from this and is why it is the exchange of choice in this thesis.

**Price Volatility**

Discussion on the determinants of volatility on agricultural commodities has been a highly researched subject for the last half-century. Different determinants have been linked to volatility and provide a foundation as to the cause of the movements in futures and cash prices, leading to a deeper understanding of changing commodity prices. Historically, commodity price volatility research has mainly focused on the causes of volatility and on the historical presence of volatility in the marketplace. Included in this area are the past periods of volatility such as rising price changes that have taken place in the $21^{st}$ century and previous decades of the $20^{th}$ century with attention attributed to comparing the two for selected time periods.

Historical price volatility has been linked to different commodities in time and can be viewed through actions taken by contributors to this area of research such as (Gilbert and Morgan, 2010; Crain and Lee, 1996; Bourdon, 2011; Cashin and McDermott, 2002; Sumner, 2009; etc.) However, it is hard to enter into the sphere of volatility of commodity markets in recent years without considering the recent increase in commodity prices in 2006 – 2008 and the following decline in prices. Recent volatility has emphasis on price research for many different commodities in the agricultural arena. Figure 1 shows these periods of recent price spikes in North of the Canadian wheat weekly cash price for the 2004 – 2019 period.

Gilbert and Morgan (2010) using a standard deviation measurement in "the changes in logarithmic prices" and a GARCH model looked to measure volatility using "… monthly price averages at an annualized rate." The goal of their research was to investigate whether the price increase and decrease of the period of late 2006 – mid 2008 was anything out of the ordinary from previous times of price volatility. They argue that even though there has been a rise in food prices and price volatility over the late 2006 – mid 2008 period, recent price volatility for most of the commodities studied has been lower than that of past decades. The years examined in their research to test this hypothesis were split into two periods: 1970 – 1989 and 1990 – 2009. For the standard deviation calculation, they find that volatility in prices for agricultural commodities seemed to be larger for fresh fruit compared to the grains and meats when looking at 1990 – 2009 compared to 1970 – 1989, rice being the one exception. Using a GARCH model to test the same question, similar results were found. With the exception of rice, their analysis determined that price volatility of agricultural commodities "...was generally lower over the past two decades than in the nineteen seventies and eighties…" and that while volatility has been high when looking at late 2006 – mid 2008, it is not out of the ordinary when compared to past price spikes.

Bourdon (2011) also recognizing the price changes found in the 2006 – 2009 period, historically analyses whether the volatility in prices in the 2006 – 2009 period was an increase relative to past periods such as the 1970s and 1990s. The commodities analyzed in their research were crop, livestock, and processed product agricultural commodities including "… beef, butter, maize, rice, soybean oil, sugar, wheat and whole milk power…" In overview, the authors find that except for wheat and rice, commodity price volatility has been higher than that of the 1990's, but lower than the 1970's. Their analysis consists of three calculation to measure volatility: the standard deviation of first differences using logarithmic prices, the coefficient of variation using price levels, and the corrected coefficient of variation using price levels. In addition, the author uses a moving average for the analysis as it "…permits a homogenous analysis whatever the observation frequency (monthly or annual)." A monthly moving average was used in the analysis as "…price volatility is greater for monthly data compared to annual price changes…" Bourdon (2011) finds that for all commodities except for whole milk powder, wheat, and butter, the volatility was lower in 2007 at the 5% level when compared to previous periods. For wheat a statistical significance was found for larger volatility in 2007 compared to the 1970s. For 2008, it was found for the majority of commodities that volatility was higher when compared to the past periods. For 2009, the analysis presents results showing that for the data analyzed for 2009, volatility seems to be in the decline similar to previous periods of past decades, with the exception of soybean oil and dairy products.

Sumner (2009) using a graphical analysis compares the large jump in commodity prices in 2006 - 2008 to the price jumps of the 1970s and periods before for corn and wheat. The long history of price jumps, as stated by the Sumner (2009),include a "… handful of extreme price jumps in commodity prices [having occurred] in the late 1890s (for corn) around World War I, around the New Deal and the 1934 drought, and around World War II and the 1970s…" These time of price jumps can be seen by periods of downturns soon after. Sumner (2009) finds that the price spikes of 2006 – 2008, which are significant, are barely noticeable against the long history. For corn, when comparing the price spikes of the 1970's and 2006 – 2008, the rise of prices for the 1970s was much more gradual compared to the latter period.

Cashin and McDermott (2002) also investigates the long run behavior of commodity prices such as Sumner (2009), however, Cashin and McDermott (2002) implement an empirical analysis and a larger data set of 140 years using annual data of "… the nominal industrial commodity-price index." This long run price behavior analysis includes in particular the change in the growth of trend, the variability of prices, and the duration of cycles involving price booms and sumps when they occur. They select exchange rate sub periods to test the aspects in the analysis and they include: Gold Standard period (1862 – 1913), Bretton Woods system (1946 – 1971), and the flexible exchange rate period that followed the Bretton Woods system (1972 – 1999). For the trend growth test, Cashin and McDermott (2002) find that trend is very volatile in the commodity prices used. Over the sub periods that were tested the authors found an inability to differentiate whether the differences in trend growth over the periods are statistically significant. However, when testing for the volatility in prices using, the authors found increased variance in prices over the time tested, presenting 1899 and the 1970s in particular. Cashin and McDermott (2002) state "the first increase was due to price movements with bigger amplitudes. The second increase was due to a rise in the frequency of large price movements…" Overall, Cashin and McDermott (2002) find support for a downward trend in commodity prices and an increase in volatility over the 140 period. However, an interesting result is found through their analysis as with the long run trends that are found over the 140-year period, they are overshadowed by large variability in prices.

Overall, each of these researchers listed above (Gilbert and Morgan 2010), (Bourdon 2011), (Sumner 2009), and (Cashin and McDermott 2002), bring attention to the long history of price levels and price volatility with different sample sizes. There has always been price volatility throughout the past but with different aspects and causes affecting each time period.

## Determinants of Volatility

When discussing the determinants of futures market volatility, it is important to mention that researchers have linked different causes of futures price volatility on different commodity markets. The following discussion is organized by past research and literature on the different determinants of futures price volatility in different commodity markets, by topic. A summary of this past research on the determinants mentioned below can be found in table 1.

### Time-to-Maturity

In 1965 Samuelson introduced the theoretical basis for time to maturity as a potential determinant of futures market volatility. Time to maturity states that as a contract approaches maturity or as the time to maturity decreases, the volatility of the futures contract should rise in effect as more information comes into the marketplace. In present research, this determinant of volatility has come to be known as the Samuelson hypothesis or the "time-to-maturity" effect. The Samuelson hypothesis has been studied and has resulted in many different opinions on whether it is supported as a significant determinant of volatility, depending on the data analyzed. Rutledge (1976) and Miller (1979) both using daily futures market price changes, expressed in logarithms, found mixed results for support for the time to maturity effect on the different commodities tested. Rutledge (1976) using a goodness of fit test for a three-way contingency table found that for silver and cocoa, evidence to support the Samuelson hypothesis was present, but for soybeans and Kansas City wheat no support was found for time to maturity as a contributor to volatility. Miller (1979) however, using a classical normal test of the simple correlation coefficients between dispersion and time to maturity found that for live beef contracts on the Chicago Mercantile Exchange an inverse relationship was present, finding support for the Samuelson hypothesis.

Anderson and Danthine (1983) found evidence against the Samuelson hypothesis by not rejecting the hypothesis in a total sense, but providing research revolving around resolution of uncertainty in the market and how it effects volatility. The authors suggested that as uncertainty is resolved in the market, volatility tends to increase, and the opposite is true in unresolved uncertainty. Uncertainties can be caused by demand and supply factors in production and those factors allow a certain flow of information into the marketplace. This State Variable hypothesis has been known as a special case of the Samuelson Hypothesis.

Anderson (1985) and Milonas (1986), using daily data, measured the variance of the changes in logarithms of prices using non-parametric and parametric tests to test the Samuelson hypothesis. Anderson (1985), while testing for the state variables and the Samuelson hypothesis on 9 futures prices from 1966 – 1980, found support for the time to maturity effect. However, Anderson (1985), also found seasonality in grain markets to be an important and even greater factor in volatility. Milonas (1986) who tested the Samuelson hypothesis on 11 different commodities in agricultural, metal, and financial markets, finds support for the Samuelson hypothesis in 10 out of the 11 futures markets and states that time to maturity is a significant determinant of volatility. However, Milonas (1986) also states that the correlation among information that affects volatility and the Samuelson hypothesis play a factor in its integrity. Castelino and Francis (1982), using data from 1960 – 1971, a similar period as Anderson (1982), tested the Samuelson hypothesis on basis volatility for wheat, soybeans, soybean oil, and soybean meal. The data selected was spot and futures prices from the Chicago Board of Trade. Castelino and Francis (1982) found that different factors affecting basis and the volatility around it such as storability, existing supplies, and sustainability of the physical commodity, affect each commodity differently. Volatility for each commodity is different in its reaction to new information in the marketplace. Overall, unlike the support Anderson (1985) and Milonas (1986) found for the Samuelson Hypothesis in their study of futures prices, Castelino and Francis (1982) discovered that as time to maturity decreases, basis volatility also decreases for each commodity tested.

Streeter and Tomek (1992) and Khoury and Yourougou (1993) tested the Samuelson hypothesis using regression models in their analyses. Streeter and Tomek (1992) tested soybean futures using daily data over the years 1976 – 1986 for the months of March and November and found evidence to support the Samuelson hypothesis by introducing "information flow" effects and "market structure" effects to explain the volatility in the marketplace. They found that information flow effects correspond to factors that affect the amount of information entering the marketplace. Through their analysis, Streeter and Tomek (1992) found support for the Samuelson hypothesis.

Khoury and Yourougou, while also using a regression model using daily data for the years 1980 – 1988, found support for the hypothesis in testing canola, rye, feed barley, feed wheat, flaxseed, and oats at the Canadian Winnipeg Commodity Exchange. Finding support for the time-to-maturity hypothesis in all agricultural commodities, including feed wheat, the conclusion was that the volatilities of the U.S and Canadian markets are comparable.

Hennessy and Wahl (1996), using a contingent claims methodology, created a model to estimate the demand and production inflexibilities that arise from decision making and found no support to back up the Samuelson hypothesis. They focused mainly on the soybean, corn, Chicago wheat, Minneapolis wheat, and Kansas City wheat futures price contracts using data from 1985 – 1994 and 24 contracts over that period. Hudson and Coble (1999) focused just on cotton price futures contracts from 1982 – 1997, used a regression and a GARCH model, and found no support for the time to maturity effect when other factors were considered. The regression equation used in the analysis by Hudson and Coble (1999) is provided: $VOL_i$ = f(TTM, P, Policy, SEA, W, SUD), where "…$VOL_i$ is the volatility for month i … , TTM is the number of months to contract maturity or 'time to maturity', P is the average futures price for month i, Policy is a vector of policy variables, SEA is the vector of seasonal variables, W represents weather effects, and SUD is a variation of the stock-to-use ratio used to represent potential supply/demand effects on volatility.  The Hennessy and Wahl (1996) and Hudson and Colble (1999) analyses added to the growing support for the conclusion that the time to maturity effect is accounted for by other factors. In other words, time to maturity is a proxy for other factors that impact volatility closer to maturity.

In more recent research, Kalev and Duong (2008) took a different approach by using intraday data from 1996 – 2003 to calculate the realized range of prices. They analyzed the effect of the Samuelson hypothesis on volatility using descriptive statistics, the JT test, OLS regression, and Seemingly Unrelated Regression (SUR). Each of the tests indicates that agricultural futures show stronger support for the Samuelson hypothesis than do the energy, financial, and metal commodities.

Karali and Thurman (2010), using a Generalized Least Squares (GLS) estimator, updated the research done in the past for multiple commodities such as corn, soybeans, wheat, and oats on the Chicago Board of trade using intraday and close-to-close prices for the years 1987 – 2007and found support for the Samuelson hypothesis.

Seasonality

The determinant of seasonality in agricultural commodity futures is a subject that has seen intense research. Yield expectations every growing season contribute to volatility due to weather conditions. Demand uncertainty can have a large effect on prices. In terms of grains, seasonal volatility of futures market prices seems to be similar every year. As stated earlier this could be because of weather conditions linked to yield expectations. However, this also could be because crops are planted and harvested around the same time every year along with demand schedules for these commodities built around seasonal harvest periods. As stated by Anderson (1985) "starting from a period of relatively low-price volatility, volatility rises through the spring, reaching a peak in July or June (for Kansas City wheat) after which volatility falls." Volatility and the level of prices seem to follow the same seasonal pattern.

Anderson (1985) used non-parametric and parametric tests on daily data for the years 1966 – 1980 tested for time to maturity and found that seasonality has a much larger effect on futures market volatility than the Samuelson hypothesis. Anderson (1985) also found that the variance of futures price changes is not constant and that the changes of variances follow a particular pattern. Evidence indicated that seasonality is present in agricultural futures contracts as harvest patterns are incredibly similar year after year for a certain crop. What makes this study important is that the literature before this research did not include seasonality as a determinant of volatility. For many years, the time to maturity effect was the main concern for the research of the determinants of futures market volatility while seasonality was overpassed.

Looking at this newly recognized determinant of volatility, seasonality was tested (using seasonal dummy variables) by Kenyon, et al. (1987) to try to observe what "economic variables generate large fluctuations in volatility from year to year." Economic factors presented in this paper include level of production, which can show great levels of uncertainty especially in the agricultural industry "…and the level of futures prices relative to the loan rate." Moving through the year, futures price volatilities do not remain constant, especially in times of supply uncertainty. These can include weather and crop shifts and in times of harvest for example, weather can play a major role in the price of commodities as yield fluctuations relay back to the marketplace in the form of USDA reports. Kenyon, et al. (1987) looked specifically at 1974 – 1983 daily closing prices for wheat, corn, soybeans, and two animal futures and found using an OLS model that the seasonal effect is highly significant in corn and soybeans, rejecting that the seasonal effect is zero at the 1% level. For wheat however, they found that the hypothesis of zero seasonality cannot be rejected at the 10% level. In addition, Kenyon, et al. (1987) work indicated though it is not statistically significant, wheat price volatility is lowest at the beginning of the year and the highest around June.

Hennessy and Wahl (1996), continuing the same methods of testing seasonality as Kenyon, et al. (1987) using seasonal dummy variables, found again that seasonality is present in agricultural commodities tested which include soybeans, corn, Minneapolis wheat, Chicago wheat, and even Kansas City wheat for the years 1985 – 1994. While also following the research included in the Kenyon, et al. (1987) study, Streeter and Tomek (1992), used regression analysis to find that seasonality is again affected by information flows and identifies seasonality as a factor in volatility when looking into the soybean market. The data used in their research included daily data on March and November soybean contracts from 1976 – 1986.While previous studies have used seasonal dummies, this research used harmonic variables to analyze the effect seasonality has on volatility. Streeter and Tomek (1992) research was to not only to test information flow effects such as the Samuelson hypothesis and seasonality, but economic and market structure effect as well.

Khoury and Yourougou (1993), while studying the Winnipeg Commodity Exchange of Canada using daily data from 1980 – 1988, found that for canola, rye, feed wheat, and barley the “case that average variances are equal” is rejected. These go along with the results of Kenyon, et al. (1987) in that agricultural commodities have the highest variance in the summer and is reduced in the fall in winter. Khoury and Yourougou (1993) also mentions that feed wheat variances are much higher in July and September for the Canadian market versus the higher volatility in June and August in the U.S markets.

When examining past seasonality research on different commodity markets for the U.S (authors) and Canada, that seasonality seems to affect agricultural futures markets in a similar way each year. Volatility rises in the growing season, peaking during harvest time when new information on yield expectations is introduced and then levels out as planting information is received.

Yang and Brorson (1993) using a GARCH model to test market volatility effects found that many of the agricultural commodities tested exhibited seasonality, which includes Kansas City wheat. The GARCH model used in this study was chosen as it provides for a better representation of the effects by “adjusting for heteroskedasticity and autocorrelation”. The data used in their research include daily data of 11 different futures commodity prices over the 1979 – 1988 period. Hudson and Coble (1999) also used a GARCH model and an OLS regression and found seasonality for cotton when studying the 1982 – 1997 period. Hudson and Coble (1999) suggests that the move to GARCH models in research is caused by the batches of information introduced into the marketplace that can create autocorrelated error terms. With the continuation of GARCH models, Goodwin and Schnepf (2000) found strong seasonality effects with the corn and wheat futures and like Streeter and Tomek (1992), found that price variance is at its highest during the summer months. The data used in Goodwin and Schnepf (2000) research included weekly average closing prices over the period of 1986 – 1997.

In more recent research in the area of seasonality, Karali and Thurman (2010) focused on U.S markets of corn, oats, soybean, and wheat futures for the 1986 – 2007 period using daily data and identified seasonality as a cause of volatility in those markets. The authors state alongside Goodwin and Schnepf (2000), Kenyon, et al. (1986), and Anderson (1985) and also found evidence to support that volatility peaks in the summertime.

Khan (2014), focusing on cotton futures for the 2001 – 2010 period, used weekly returns and a GARCH model to test for seasonality as a significant determinant of volatility and found that seasonality does not have a statistically significant impact on cotton price volatility.

<u>Level of Inventory</u>

While the theory of storage was originally purposed by Working (1933) in the early part of the 20th century, Carpantier and Dufays (2012) present a well described explanation of the theory. They state that “one implication of the theory states that the variance of the commodity price increases in time of low inventories and decreases when the inventories are abundantly furnished.” Furthermore, the theory of storage explains that as the inventories of a commodity are low, spot price tends to be higher than the futures price, and when inventories are high the spot price tends to be lower than futures price. These two conditions in the marketplace are described as backwardation and contango, respectively. Carpantier and Dufays (2012) also include in their description that “theory explains the difference between spot and futures commodity prices in terms of storage costs, foregone interest and ‘convenience yield’.” Convenience yield can be described when dealing with commodities for example, as the benefit to the holder of the commodity in the form of a return for holding said commodity in a time of market volatility. Overall, inventories in markets such as those dealing with agricultural commodities are ever changing, as are the markets they trade in. Moreover, the theory of storage is displayed as an explanation to this market volatility and its contents within as a determinant to it.

Kenyon, et al. (1986) using regression analysis to study corn, soybean, wheat, live cattle, and live hog futures contracts using daily closing prices from 1974 – 1983, presented research to determine economic variables that cause variability in prices year to year. Of these economic variables, the quantity effect (inventory effect) is presented in the research and is measured through stocks-to-use ratios. The authors, while supporting the inventory effect and the theory behind it, eliminated it for the grains out of their research. The reasoning behind this was when considering the loan rate effect variable alongside it in the analysis, the inventory effect became insignificant for the grains. However, the authors state that “for the grains, volatility appears lower (higher) when production and ending stocks are relatively large (small) compared to use…” which conforms to the inventory effect theory.

Streeter and Tomek (1992) also used regression analysis to research soybean futures contracts for 11 years for the months of March and November using daily data. Stating that volatility was usually studied in focus of information flows variables, economic variables, and market structure variables, the authors develop a more comprehensive model to measure the variance in futures prices. Of the economic variables studied are the current supply conditions which are then broken down into annual total supply which includes annual production plus carry in, monthly disappearance, and mill stocks at the beginning of the month to “reflect the current economic situation.” The authors find that annual total supply is significant in their research, however, mill stocks present a negative sign which means that “large inventories are associated with large volatility.” Moreover, the authors found a relationship between lower volatility and the higher disappearance. Overall, the authors found a positive relationship between stocks and volatility in the commodities analyzed.

Hennessey and Wahl (1996) focused on monthly data on a total of 24 contracts spread over 5 commodities from 1985-1994, meaning that multiple contracts were used per commodity. The authors also use a contingent claims methodology as “[this] approach is based on a specification of the nature of uncertainty and a law governing how that uncertainty affects the value of a function.” The authors present results for the inventory effect (stock effect) and conclude that with the vast quantity of negative stock coefficients in their analysis, the effect on volatility was found to be negative. In addition, while all of these contracts have a negative coefficient, three are all that are statistically significant at the 5% level.

Karali and Thurman (2010) using generalized least squares (GLS) methodology focuses on intraday and close to close daily data from the Chicago Board of Trade for corn, soybeans, wheat, and oats for the years 1986-2007. Their purpose of using GLS in their research is "to account for contemporaneous correlation among overlapping contracts" as at any point in time during the year, multiple contracts are trading at the same time. Karali and Thruman (2010) find support for the inventory effect while studying seasonality, as the seasonal pattern of low inventories during the period before harvest is paired with higher volatility. The authors provide this as "indirect confirmation" of the inventory effect in their research.

Karali and Dorfman (2010) using daily closing prices for corn, soybeans, and oats uses a smoothed Bayesian estimator in their analysis. This allows for the analysis to use different delivery horizons for the commodities and form of volatility studied. The authors find for corn across all delivery horizons, a negative inventory effect is present and as inventories increase price volatility increases. For soybeans and oats, the same evidence of a negative inventory was found, and the authors summarize that support for the theory of storage was found in their research.

Goodwin and Schnepf (2000) study weekly average closing prices for 1986-1997 and analyze volatility for both the December corn and September wheat contracts using a GARCH model. This model was used because as stated by the authors "conditional variance terms often exhibit autocorrelation." Using stock to use ratios, corn presents support for the inventory effect as the use (demand) for corn stocks is greater than the given level of stocks in the analysis. For wheat, the same effects were found in the analysis as the use (demand) for wheat stocks appear to be greater than the stocks. Both of these results provide support for the inventory effects as the demand for the stocks is greater than the supply, putting positive pressure on volatility of prices.

Carpantier and Dufays (2012) looked at the inventory effect specifically for 16 different commodities using weekly data from 1994 – 2011 and a GJR-GARCH model in the analysis of volatility. The authors use a proxy of the sign of past returns through the GJR-GARCH model to capture the past shocks and test for the inventory effect. The authors find that out of all of the agricultural commodities studied, sugar has the largest significance for the inventory effect. For the other agricultural commodities, the inventory effect was found "with alternative specifications, but not in the benchmark case." The metal commodities in their analysis were also seen to have a "strong inventory effect."

Karali and Power (2013) used a spline GARCH model and a Seemingly Unrelated Regression (SUR) to test daily data on "lower frequency macroeconomic determinants" for 11 different futures markets. Of these contracts that are used to test the inventory effect include grains (corn, soybeans, wheat), livestock (live cattle, lean hogs), and energy (crude oil, natural gas, heating oil). The authors also separate the analysis into two time periods and find that for the first time period of 1990 – 2005, corn, wheat, lean hogs, and crude oil, volatility is lower for large inventories, but also find that for crude oil and lean hogs, volatility decreases as inventory levels decrease, suggesting empirical support. For the period of 2006 – 2009, "corn, wheat, and live cattle volatility decreases as inventories increase, and for natural gas volatility increases as inventories decrease".

Khan (2014) tested volatility on cotton using weekly returns on cotton futures from 2001 – 2010 and utilized a GARCH model to analyze many different determinants of volatility including the inventory effect. The author uses the GARCH model in his analysis as it "accounts for heteroscedasticity and volatility clustering… and allows for simultaneous examination of both the mean and the variance of the time series." He finds that through the use of stocks to use ratios in the GARCH model, that the cotton futures analyzed display the inventory effect.

**Price Volatility Measures**

Price volatility can have a number of causes, as detailed above. Various methods of measuring price volatility have been used in the past. This section details various methods for measuring price movements.

All commodities exhibit price variability including wheat. Spot and futures markets both exhibit price variability. The "spot" market is where wheat, in this case, is traded between a buyer and seller. Spot sales deal with buying or selling a commodity, at a "spot" price set for immediate delivery. Taking the wheat spot market for example, reflects current supply and demand because wheat is a storable commodity. This storability in wheat, while having the ability to go on for an extended period, is not indefinite. The futures market, while also exhibiting variability in prices, is different than the spot market because it deals with prices in the future based on today's knowledge. A futures contract, also presented as a "futures", is an agreement to buy or sell a commodity in the future for a predetermined price. This definition sounds a lot like a forward contract; however, futures contracts are traded at specified quantities and certain qualities, while also being traded on exchanges. In the agricultural industry for example, producers use futures contracts to avoid the risk associated with the spot market in the future. When using a spot contract for an agricultural commodity, immediate delivery of the commodity is expected. The producer takes a risk as he/she must wait until the crop is ready to be marketed before it can be priced. This puts the producer at risk to whatever the spot price happens to be at that time. Futures contracts, on the other hand, allow producers to price their crop at an earlier date than when it must be delivered. This lessens the price risk as they are able to watch the market and execute the agreement when desired.

However, these spot and futures contracts are subject to variability themselves as represented through prices in the marketplace. Figure 2 represents the KCBT weekly futures prices. Figure 3 represents the weekly cash (spot) prices for the North of Canadian area. Figure 4 represents a combination of figure 2 and figure 3. These figures are representative of the 1994 to 2019 period.

Substantial price variability is present in both markets. This change in the variability in prices around the mean is a representation of volatility. Bahattin Buyuksahin (2011) presents a well described definition of volatility stating:

> "The concept of volatility may itself at times be confused simply with rising prices; however, volatility can equally result in prices that are significantly lower than historical average levels. Volatility is the term

used in finance for the day-to-day, week-to-week, month-to-month or year-to-year variation in asset or commodity prices. It measures how much a price changes either about its constant long-term level, or about a long-term trend. That is to say, volatility measures variability, or dispersion about a central tendency. In this respect, it is important to note that volatility does not measure the direction of price changes; rather it measures dispersion of prices about the mean."

When looking at the different ways to measure volatility and the models that are used, we can separate them into two factions: historical volatility and implied volatility. Historical volatility uses data on past prices and looks to measure the variability of those prices through their movements. This type of historical volatility uses various models and measures. Implied volatility looks to measure the variability in prices using option-based prices to determine how volatile a commodity or other form of assets is in the future. It can then be implied that historical volatility is a backward-looking measurement of volatility and implied volatility is a forward-looking measurement (Buyuksahin, 2011).

Types of calculations and models used to measure historical volatility in some forms are simpler while others are more complicated. Probably the simplest and most straightforward way to calculate volatility is through the estimation of the range of prices in the data set. This calculation is estimated by taking the highs and lows of the period that has been selected, such as a single day, and calculating the difference. This is also called open-to-close (intraday) prices as it considers the price period on a day to day basis and does not roll over to the next trading day, such as close-to-close prices. In this calculation, as the range of the highs and lows of the trading period specified becomes larger, greater volatility is present. Conversely, as the range of these same highs and lows becomes smaller, less volatility is present.

Another simple calculation that is used to measure volatility is the standard deviation. This calculation as described by Buyuksahin involves “the return calculated as the natural log of daily price changes” and “the mean during the look back period” (Buyuksahin, 2011). Buyuksahin also presents this calculation by involving these aspects just mentioned (price and lookback period), which allows for various ways of measuring volatility. For example, the various price periods that can be chosen are the close-to-close prices or open-to-close (intraday) prices recorded in the marketplace. The lookback period in the standard deviation formula puts into perspective what data in the specified time period will go into the mean. This includes, for example, historical average, moving average, and exponentially weighted average, all of which consider different parts of the price data. The historical average accounts for all historical data in the data set while the moving average discards some older observations (Buyuksahin 2011). The exponentially weighted average uses more recent prices from the data set. This standard deviation formula, while simple compared to other calculations and models, still provides various ways to determine volatility in the data set of interest.

The next two forms used to measure volatility are realized volatility and absolute return volatility. Realized volatility is an estimation of volatility and is calculated through the realized variance. This calculation is mostly used to estimate volatility through intra-day prices but can also be used for "lower data frequencies" such as weekly, monthly, or annual data (Breaking Down Finance). Breaking Down Finance also provides the simplest calculation of estimating realized volatility. The formula that they use to estimate this measure of volatility is presented below:

$$RVol_t = \sqrt{RV_t}$$

This estimation starts with calculating the log returns of the prices for the asset being calculated. This formula by Breaking Down Finance is presented below:

$$r_t = log(P_t) - log(P_{t-1})$$

Using this calculation of log returns, we can move on to the next step of calculating realized volatility by obtaining the realized variance calculation. This equation is calculated by taking the sum over the past N squared return, which gives us the daily realized variance. The formula to this part of the equation by Breaking Down Finance is presented below:

$$RV_t = \sum_{i=1}^{N} r_t^2$$

Realized volatility at this point is a square root calculation of daily realized variance which can be seen in the first formula presented. To transform this calculation of daily realized volatility to estimate the volatility, say for annual data, the formula by Breaking Down Finance is presented below:

$$RV^{ann} = 260 \cdot RV^{day}$$

First, we would multiply the daily realized variance by the number of trading days in the year. This would give us the annual realized variance for our chosen asset. To find the annual realized volatility, like with the daily realized volatility, we would take the square root of the annual realized variance. This same method can be done for weekly and monthly data as well, as we would just substitute the number of trading days of those time ranges into the formula.

Zheng, et al. (2014) also estimates realized volatility using intra-day data using the following formula:

$$\sigma_{\mathrm{RV}}(t) = \frac{V(t)}{\sigma_V},$$

The authors find the sum of squares returns using intra-day data by subtracting the natural log price of the current period by the natural log of the previous period, which in this case could be the closing price of the day and the opening price, since we are working with intra-day data. This calculation by Zheng, et al. (2014) is presented below:

$$r_{t+i\Delta} = \ln p_{t+i\Delta} - \ln p_{t+(i-1)\Delta}$$

Next, the authors calculated the realized volatility that is non-normalized by squaring the previous sum of squares calculation. This calculation by Zheng, et al. (2014) can be found below:

$$V(t) = n\langle r^2_{(t+i\Delta)} \rangle$$

Finally, to normalize the realized volatility formula so that the units are on a common scale, the author used the first formula posted above. The purpose of this publication was to "study the clustering and memory effects in two commonly used nonparametric methods of calculating volatility, absolute return volatility and realized volatility" (Zheng, et al., 2014).

Absolute return volatility differs from realized return volatility as it is usually calculated using daily closing prices. However, the estimation of absolute return volatility is similar to realized volatility in that it is a measure to estimate volatility and how prices deviate from the mean. Zheng, et al. (2014) explore the estimation of volatility through the measurement of absolute return volatility. The beginning of this estimation requires the calculation of daily log returns for the daily closing prices. This is calculated by taking the log of the current price period and subtracting it from the log of the price of the previous period. For example, this could be the closing price of the current day subtracted by the closing price of the previous day. Below is the formula by Zheng, et al. (2014) to equate this estimation:

$$R_t = \ln p_t - \ln p_{t-1}.$$

The next step to estimate absolute return volatility, by Zheng, et al. (2014), is to use the daily log returns result and input this into the formula below:

$$\sigma_{\mathrm{AV}}(t) = \left| \frac{R_t - \langle R_t \rangle}{\sigma_R} \right|,$$

where $R_t$ represents the daily log returns, $\langle R_t \rangle$ represents the daily average log returns, and $\sigma_R$ represents the standard deviation of the return series.


**Figure 1. North of the Canadian Wheat Weekly Cash Price: 2004 – 2019**


**Figure 2. KCBT Weekly Futures Prices: 01/07/1994 – 03/01/2019**

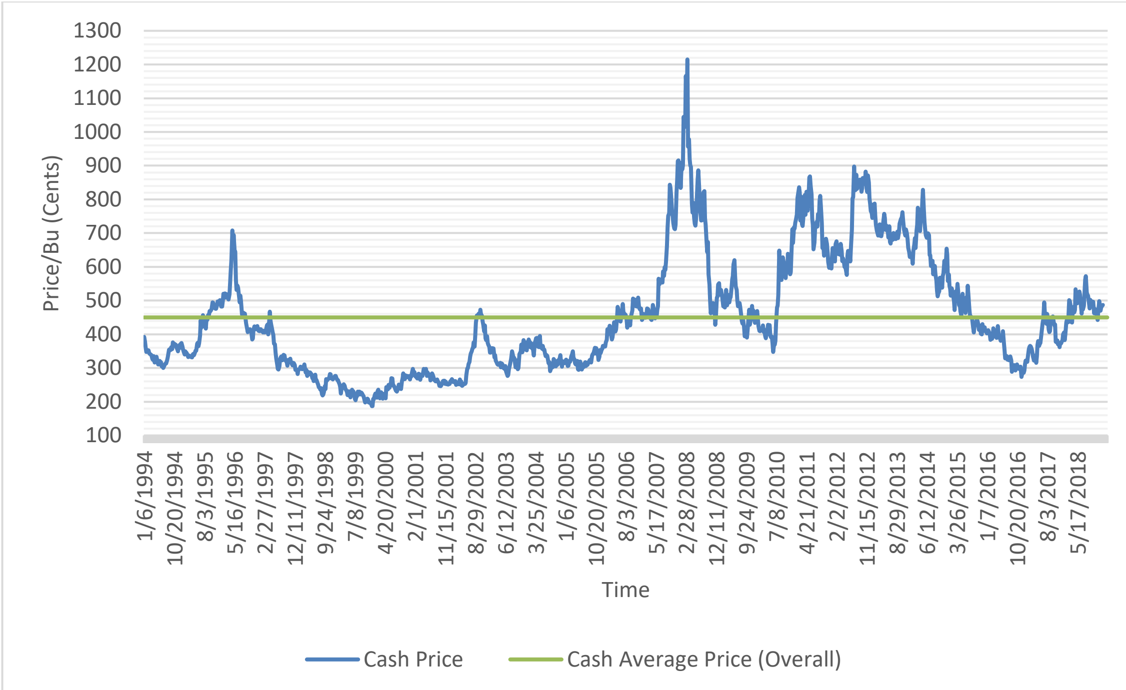


**Figure 3. Weekly Cash Prices: 01/07/1994 – 03/01/2019**

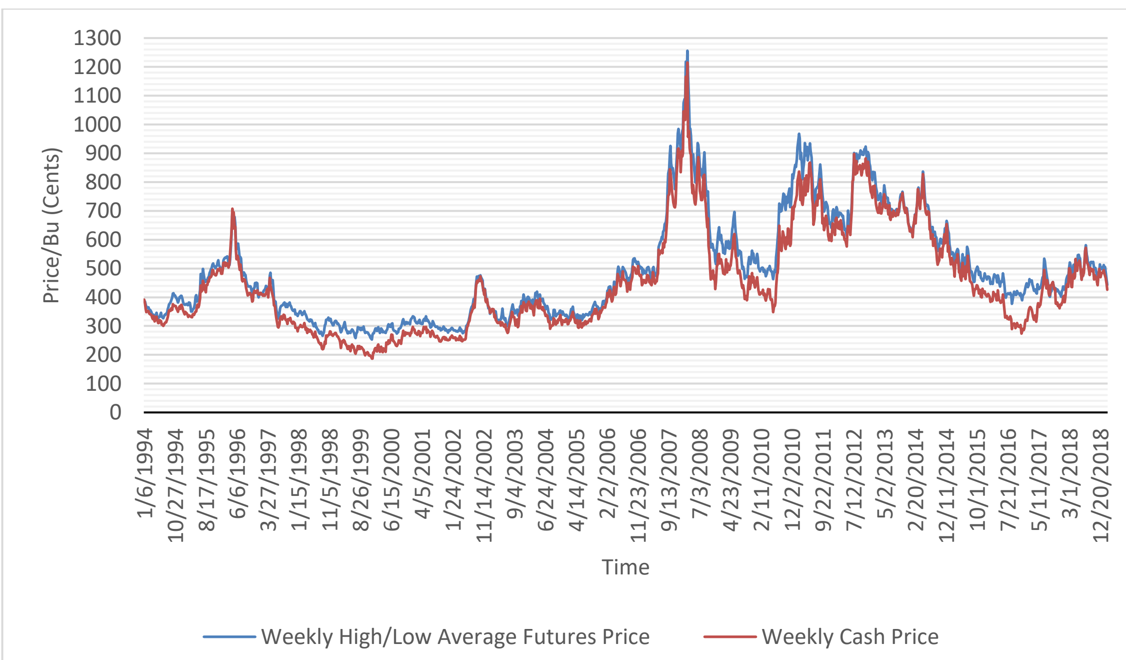


**Figure 4. Weekly High-Low Average Futures Prices and Weekly Cash Prices: 01/07/1994 – 03/01/2019**

**Table 1. Determinants of Commodity Price Volatility - Literature Review Summary**

| Author(s) | Data Frequency | Data Range | Commodities | Method | Time to Maturity Effect | Seasonality Effect | Level of Inventory Effect |
|---|---|---|---|---|---|---|---|
| Rutlege (1976) | Daily | 1969 – 1971 | Silver, Cocoa, Wheat, Soybean Oil | Goodness of Fit Test | Mixed Results[2] | Not Stated | Not Stated |
| Miller (1979) | Daily | 1964 - 1971; 1965 - 1972 | Live Cattle | Classical normal test | YES | Not Stated | Not Stated |
| Anderson and Danthine (1983) | N/A | N/A | N/A | N/A | NO | Not Stated | Not Stated |
| Anderson (1985) | Daily | 1966 - 1980 | Chicago Wheat, Kansas City Wheat, Corn, Oats, Soybeans, Soybean Oil, Live Cattle, Silver, Cocoa | Non parametric and Parametric tests | YES | YES | Not Stated |
| Milonas (1986) | Daily | 1972 – 1983[1] | 11 Futures: Agricultural, Financial, Metals | Non parametric and Parametric tests | Mixed Results[3] | Not Stated | Not Stated |
| Kenyon, et al. (1987) | Daily | 1974 - 1983 | Corn, Soybeans, Wheat, Live Cattle, Live Hog | Regression analysis | Not Stated | Mixed Results[4] | Not Stated[7] |
| Castelino and Francis (1982) | N/A | 1960 - 1971 | Wheat, Soybeans, Soybean Oil, Soybean Meal | Difference in Means Test | NO | Not Stated | Not Stated |
| Streeter and Tomek (1992) | Daily | 1976 - 1986 | Soybean | Regression analysis | YES | YES | NO |
| Khoury and Yourougou (1993) | Daily | 1980 - 1988 | Canola, Rye, Feed Barley, Feed Wheat, Flaxseed, Oats | Regression analysis | YES | Mixed Results[5] | Not Stated |
| Yang and Brorson (1993) | Daily | 1979 - 1988 | 11 Futures: Agricultural, Metals, Financials | GARCH Model | Not Stated | Mixed Results[6] | Not Stated |

**Table 1. Continued**

| Author(s) | Data Frequency | Data Range | Commodities | Method | Time to Maturity Effect | Seasonality Effect | Level of Inventory Effect |
|---|---|---|---|---|---|---|---|
| Hennessy and Wahl (1996) | Monthly | 1985 – 1994 | Soybean, Corn, Chicago Wheat, Minneapolis Wheat, Kansas City Wheat | Contingent Claims Methodology | NO | Mixed Results[11] | Mixed Results[12] |
| Hudson and Coble (1999) | Monthly | 1982 – 1997 | Cotton | GARCH Model & Regression | NO | YES | Not Stated |
| Goodwin and Schnepf (2000) | Weekly | 1986 – 1997 | Corn, Wheat | GARCH Model | Not Stated | YES | YES |
| Kalev and Duong (2008) | Daily | 1996 – 2003 | 14 Futures: Agricultural, Energy, Financial, Metal | Non parametric tests[8]and Regression Analysis[9] | Mixed Results[10] | Not Stated | Not Stated |
| Karali and Thurman (2010) | Daily | 1986 – 2007 | Corn, Soybeans, Wheat, Oats | GLS Methodology | YES | YES | YES |
| Karali and Dorfman (2010) | Daily | 1987 – 2004[1] | Corn, Soybeans, Oats | Smoothed Bayesian Estimator | Not Stated | Not Stated | YES[13] |
| Carpantier and Dufays (2012) | Weekly | 1994 – 2011 | 16 Futures: Agricultural, Metals, Precious Metals, Tree Crops | GJR-GARCH Model | Not Stated | Not Stated | Mixed Results[14] |
| Karali and Power (2013) | Daily | 1990 – 2009 | 11 Futures: Grain, Livestock, Energy, Precious Metals, Industrial Metals | Spine GARCH Model & SUR Regression | Not Stated | Not Stated | Mixed Results[15] |
| Khan (2014) | Weekly | 2001 – 2010 | Cotton | GARCH Model | Not Stated | NO | YES |

**Table 1. Continued**

(Notes below refer to superscripts presented in the table above and provide further information)

1. Varied time period per commodity (type)
2. YES - Silver and Cocoa; NO - Kansas City Wheat and Soybeans
3. YES - 10 out of 11 commodities (every commodity but corn)
4. YES - Corn and Soybeans (Seasonal effects being zero is rejected at the 1% significance level); NO -Wheat, Live Cattle, and Live Hogs (Seasonal effects being zero cannot be rejected at 10% significance level)
5. YES - Canola, Rye, Feed Wheat, and Feed Barley; NO – Flaxseed and Oats
6. The author states that some ag commodities such as wheat, corn, and soybeans are found to have a seasonality effect
7. The authors eliminate the inventory effect for grains out of their research
8. Descriptive Statistics and JT Test
9. OLS Regression and SUR
10. Stronger for agricultural commodities versus other commodity types tested
11. YES – Positive coefficients for Corn, Soybeans, and some Minneapolis Wheat contracts; NO – Low t-statistic for the winter wheat contracts (Chicago Wheat and Kansas City Wheat) and a negative coefficient for the May Kansas City Wheat contract
12. Inventory Coefficients are negative for all commodity contracts tested, however, only three are significant at the 5% significance level
13. Results vary across delivery horizons, but overall an inventory effect is found for the commodities tested
14. Look in article for further explanation
15. Look in article for further explanation

# CHAPTER III

# DATA

The futures price data used in this research was obtained from the Chicago Mercantile Exchange (CME) and is the Kansas City Board of Trade (KCBT) futures prices. KCBT prices were used because this thesis focuses on Hard Red Winter wheat. The futures data includes open, high, low, and close prices from the KCBT. Cash prices utilized in this research were obtained from the Texas Agrilife Extension service basis project and are comprised of North of the Canadian cash prices.

The data frequency chosen for this research includes daily and weekly wheat prices for the KCBT and weekly cash wheat prices for the North of the Canadian River region. Weekly average futures prices were not calculated by the author from the daily futures prices, but instead were collected separately as the data were easily accessible. The weekly futures prices were computed from a series of daily prices throughout the week, while the weekly cash price is a single price collected from elevators in the region during the week and is presented as the weekly price. Weekly futures price was chosen over daily or intra-day futures price, due to the cash prices reported weekly.

Microsoft Excel and Simetar, an add-in of Microsoft Excel developed by Dr. James Richardson of Texas A&M University, were used for data analysis. As stated before, we used KCBT weekly futures prices and North of the Canadian weekly cash prices to calculate basis, so it could be analyzed. An augmented Dickey-Fuller test was used through Simetar to evaluate futures, cash, and basis calculations for stationarity.

The data used in this analysis includes weekly cash and futures prices ranging from January 7, 1994 – March 1, 2019. The 1994 to 2019 time period was split into five periods: January 7, 1994 – June 13, 1997; June 20, 1997 – May 31, 2002; June 7, 2002 – July 20, 2007; July 27, 2007 – May 13, 2011; and May 20, 2011 – March 1, 2019. The data set was separated into these time periods through ad hoc means, specifically by visual observation of the data.

Statistically, the mean was calculated for the data set selected to be evaluated. This made it possible to compare to the other periods evaluated to find the best representation. Also, high-low (range) calculations and periods with similar volatility were evaluated so as to not hide volatility that would stand out if measures were to be calculated on a larger scale or if periods were widened.

# CHAPTER IV

# METHODOLOGY

Descriptive statistics including the mean, standard deviation, and range calculations are calculated using Microsoft Excel. The mean, standard deviation, and data range calculations outlined above are computed for each of the five periods for cash, futures, and basis. However, the price range average, calculated due to the futures data including a daily high and low, is only computed for futures price for each of the five periods. Wheat basis data is calculated through the method of subtracting the futures price of a particular week from the cash price of the same week. Included in this research is the calculation of a weekly average futures price. The process of calculating this average consists of taking the high and the low weekly prices and averaging the two.

A table outlining the mean, standard deviation, and data range statistics for the overall data set is displayed as table 2. It contains the previously mentioned statistics for the high-low average futures price, cash price, and basis.

## Mean

The mean is calculated for the futures price, cash price, and basis and is calculated for the entire data set and each of the five periods analyzed. For the futures data, the mean is calculated for open, close, high, low, and high-low average prices for each period. For cash prices, the mean is calculated for each period using the weekly cash price. Similarly, the same process was used for basis by using weekly basis figures calculated from the cash price and each of the types of futures price in each period.

**Standard Deviation**

The standard deviation calculation used in this analysis is calculated for the futures price, cash price, and calculated basis data. The standard deviation is calculated for the entire data set and each of the five periods. However, the calculation of standard deviation is different from the mean calculation. The process of calculating standard deviation in Microsoft Excel consists of taking the data of the particular period and using the (=stdev) formulation. For the futures data, standard deviation is calculated for open, high, low, close, and high-low average prices, the same as the mean calculation. For cash prices and basis, the standard deviation is calculated using the same data that was used to calculate the mean for each period.

**Price Range Average**

The price range average was the first range measure calculated in this thesis and was used for futures price data for each of the five periods. This metric was found by finding the range of each week of the period in question using the weekly high and low futures price data points. These ranges were then averaged together to find the price range average for each period.

**Price Range Average as a Percentage of the Mean**

The price range average as a percentage of the mean futures price was another measure used in this analysis. This was calculated by taking the price range and dividing it by the mean futures price (e.g. open price) for each period. This calculation was repeated for the other four periods and each of the types of futures price such as open, high, low, close, and high-low average. The result was then converted into a percentage.

**Data Range**

The second range metric, referred to as the data range, is calculated for cash price, futures price, and basis for each period. The range is the high price for the period minus the low price for the period.

**Data Range as a Percentage of the Mean**

The data range as a percent of the mean futures price is calculated by first finding the futures price range over the entire period under evaluation, then dividing this by the mean open price for that same period. This calculation was repeated for the other four periods. Similarly, this process was conducted for high, low, and close prices, as well as the high-low average. Each of these calculations were converted into percentages. This calculation was also done for cash and basis data for each of the five periods, as well. The difference of the high and low cash and basis prices of each period was calculated and divided by the mean of the period under evaluation just like the futures data range.

**Realized Volatility**

The next metric used in this analysis is the realized volatility calculation. This calculation was conducted for open, high, low, close, high-low average futures prices and cash prices. The formula used for each of these sections begins with finding the difference between the logarithms of the price in period t and period t-1, then squaring this difference, naturally omitting the first data point in the series because there is no value for period t-1. These squared values were summed together for the first of the five established periods, then the square root was taken to arrive at the realized volatility of the type of price being evaluated. This procedure was repeated for the other four time periods. It should be noted that the realized volatility using the basis data was not calculated.

# CHAPTER V

# ANALYSIS AND RESULTS

In this research, we analyzed volatility of basis (price) over a time period of twenty-five-years using both cash and futures data. The goal of this thesis was to uncover basis volatility trends over time and discover whether cash prices or futures prices were driving the volatility of basis in the different periods analyzed. Using the data and methodology from the previous section, the following analysis was completed.

## Stationarity and Data Break Tests

The analysis began with the determination of stationarity of futures prices, cash prices, and basis using Augmented Dickey-Fuller tests in the Simetar Add-In of Microsoft Excel. These calculations showed that the futures and cash prices exhibited non-stationarity. The cash and futures prices were differenced to correct for non-stationarity.

Basis, however, was of greater focus in this analysis with respect to stationarity and the number of differences this data exhibited through an Augmented Dickey-Fuller Test. Basis proved to be stationary.

The regression model estimated in this analysis used the basis data calculated. Basis was calculated by taking the cash prices minus high-low average futures prices for the entire period.

The regression model estimated used dummy variables to determine if the periods representative in this analysis are statistically different from each other.

Knowing whether the period is statistically different from the others allows us to compare the periods in the analysis. Furthermore, 6 lags were also tested in this model to determine whether lags in the basis yielded any degree of statistical significance. The variables that were tested in this first set of regressions include: Time, D1, D2, D3, D4, and Basis T-1, Basis T-2, Basis T-3, Basis T-4, Basis T-5, and Basis T-6. Each of the (D) variables represents a different time period in the analysis. The regression results are contained in table 3 and can be summarized as follows: the statistically significant variables are Basis T-1, Basis T-2, Basis T-3, Basis T-4, Basis T-5, and D2 with respective p-values under the .05 threshold and an adjusted R-squared metric of 82.7%. The p-values of these variables indicate that for the dependent variable of variation, the lagged variables going back five lagged periods and the dummy variable D2 have a significant effect in explaining the variability in the data set. Specifically, the statistically significant lagged variables provide certainty in saying that the current price is affected by past prices.

The next set of measures completed in this analysis included descriptive statistics such as mean, standard deviation, and range for open, close, high, low, and high-low average futures prices, cash prices, and basis, when applicable. Tables 4, 5, and 6 display the descriptive statistics for futures prices, cash prices, and basis, respectively.

**Mean**

Beginning with the mean calculation, this measure was used for the open, close, high, and low futures prices, as well as the high-low averages of futures prices, for each of the five periods mentioned earlier. The five mean calculations using different futures types exhibited similar trends during and across each period, specifically decreasing in period two, increasing in period three, peaking in period four, and decreasing once again in period five. For example, the mean futures close price was 436.01 in period one, decreased to 305.25 in period two, increased to 398.23 in period three, peaked at 707.41 in period four, and decreased in period five to 593.35, a level above the first three periods. A graphical representation of the mean for each period can be found in figures 5-10 for open prices, figures 11-16 for close prices, and figures 23-28 for high-low average prices. Cash prices followed the same pattern as mentioned above. Specifically, the mean started at 413.89 during period one, fell to 260.08 in period two, rose to 376.02 in period three, peaked at 620.04 in period four, and fell to 552.41 in period five. A graphical representation of the mean for each period for cash prices can be found in figures 29-34. Finally, three means of basis were calculated using the cash price and the open futures price, close futures price, and high-low average futures price. These metrics follow a different pattern than the one found in futures and cash price. For example, the mean of basis calculated using the close futures price began at -22.12 in period one, fell to -45.17 in period two, increased to -22.21 in period three, declined to -87.37 in period four, and ended at -40.94. In addition to basis following a different pattern than its components, the fact that periods one and three, as well as two and five, are similar to one another. A graphical representation of the mean for each period for basis calculated using cash prices and high-low futures prices can be found in figures 35-40. The means mentioned above for futures price, cash price, and basis can be summarized in tables 4, 5, and 6, respectively.

## Standard Deviation

Continuing this analysis with standard deviation, this measure was calculated for the same prices as the mean calculation including open, close, high, and low futures prices, as well as the high-low averages of futures prices for each of the five periods under evaluation. The five standard deviation calculations using different futures types exhibited similar trends to the futures and cash mean calculations across each period. Specifically, the standard deviation decreased in period two from period one, increased in period three, peaked in period four, and decreased once again in period five. For example, the standard deviation using close prices was 78.56, 27.84, 68.95, 181.86, and 147.89 for the respective five periods. A graphical representation of the standard deviation to the first degree for each period can be found in figures 6-10 for open prices, figures 12-16 for close prices, and figures 24-28 for high-low average prices. The standard deviation calculation using cash price followed a similar trend as the futures price calculation and experienced very little differences. The standard deviation using cash prices was 80.48, 32.64, 67.18, 181.96, and 157.92 over the five periods. A graphical representation of the standard deviation to the first degree for each period for cash price can be found in figures 30-34. Interestingly, the standard deviation for basis followed a different pattern than the calculations using different futures figures and cash price. For example, the set of standard deviations for basis using close futures price fell from 13.91 to 13.31 and 9.94 in periods two and three, respectively, then rose during periods four and five to 26.34 and 29.90, respectively. Rather than reaching its highest point in period four in past measures, the standard deviation for basis continued to rise even in period five. A graphical representation of the standard deviation to the first degree for each period for basis calculated using cash prices and high-low futures prices can be found in figures 36-40. The standard deviations for futures price, cash price, and basis can be summarized in tables 4, 5, and 6, respectively.

**Price Range Average**

The next calculation that was measured for each of the five periods was the price range average. This calculation allows for the understanding of how much on average the prices ranged over a given week for the period being evaluated. Additionally, this calculation was only able to be calculated for futures data as the futures data allows for high and low prices, unlike cash price and basis. The results for this measure include a decrease to period two from period one, specifically from7.66 to 4.43, an increase in period three to 8.57, a further increase and peak in period four of 23.00, and a decrease in period five to a level greater than the first three periods of 13.38. The price range results can be found in table 4 and a graphical representation can be found in figures 17-22.

**Price Range Average as a Percentage of the Mean**

The price range average was then converted to a percentage by dividing it by the average open, high, low, close, and high-low average price as described in the methodology. This calculation is presented as the price range average of the mean prices mentioned above. The results are similar in pattern to the price range average and the results can be found in table 4.

**Data Range**

A second measure was used which provides another means of calculating range, this time by finding the range of the entire period using high and low futures price, cash price, and basis data once calculated. This range calculation is described in the tables provided as the data range. The results of this measure for the futures data followed the same pattern as the price range average, however, the magnitude of the numerical results differed from the price range average in each period. The price range average calculation used weekly high and low prices while the data range calculation used the high and low price of the entire period under evaluation. The data range calculation for futures price are as follows: 384.40 for period one, 133.10 for period two, 320.00 for period three, 824.90 for period four, and 574.50 for period five. The data range for cash price followed the same pattern as the futures price data range. For cash prices, the results are as follows for each period: 408.00 for period one, 152.00 for period two, 289.00 for period three, 867.00 for period four, and 624.00 for period five. Basis, which can be calculated using open or close futures prices or high-low average futures price, followed a mixed pattern than the futures price and cash price results. The data range for the basis using open futures price in its calculation followed a pattern of a decrease in period one to period two, a slight increase in period three, an increase and peak in period four, and a decrease in period five which is higher than the first three periods. For example, period one began with a data range of 85.44, then it changed to 65.78, 68.37, 214.58, and 154.88 in periods two, three, four, and five, respectively. The data range for the basis using close futures prices followed a slightly different pattern. Unlike the basis using open futures prices, this trend consists of a decrease for two consecutive periods, then an increase in the final two consecutive periods. Also noteworthy is the difference in the peak values in period four. Specifically, the data range for basis using open futures price reaches a level of 214.58, whereas the range using close futures price is only 150.75. The results for the two data range calculations can be found in table 6.

**Data Range as a Percentage of the Mean**

Like the price range average, the data range was also expressed as a percentage. Beginning with the futures price dataset, this metric was calculated for open, high, low, and close price, as well as the high-low average. Each of these prices experienced a trend of decrease in period two, an increase in period three, a peak in period four, and a decrease in period five. Two notable characteristics include the results in period four being above 100% of the mean and the results in period five falling to levels close to the mean. For example, the results of the close price data range expressed as a percentage of the mean is 88.16%, 43.60%, 80.36%, 116.61% and 96.82% for each respective period. This percentage with respect to cash price follows the same trend, yet these figures are greater than their futures price counterparts, and the percentage in period five is greater than 100% of the mean as opposed to falling in the mid-90% range. The cash price calculations are as follows for period one through five, respectively: 98.58%, 58.44%, 76.86%, 139.83%, and 112.96%. When looking at basis, the pattern and magnitude in the form of a percentage is different from the futures and cash price calculations. The basis data range expressed as a percentage of the mean is found using the basis data which was calculated from the open, close, and high-low average futures prices. For example, the results for the close (basis) price data range expressed as a percentage of the mean are 342.32%, 143.44%, 283.43%, 172.54%, and 371.01% for each respective period. Each of these figures experienced a trend of sharp decrease in period two, an increase in period three, a decrease in period four, and a sharp increase in period five. The same pattern could be seen when using the open and high-low average means to compare the data range and can be seen in table 6. There are three characteristics to take away from these results: the pattern of the basis data range as a percent of the mean is different than what was seen in the futures and cash price results, the peak of period four was not experienced with the basis data and that the fifth period is considerably higher than the fourth period, and that the percentages in all periods is greater than 100% of the basis mean.

**Realized Volatility**

The next calculation to assess volatility was the realized volatility measurement. This measure was performed for the open, high, low, and close price, as well as the high-low average of futures price for each of the five periods. Each of these five futures prices exhibited an identical trend. For example, realized volatility using close futures prices experienced a decrease from 0.19 in period one to 0.17 in period two, an increase to 0.22 in period three, an increase to 0.28 in period four, and an increase to 0.29 in period five. The results for realized volatility for the remaining futures prices can be found in table 4. The results of the calculation of realized volatility or cash prices exhibited a different pattern than what was found for futures prices. For cash prices, realized volatility increased steadily over the five periods. The results for cash prices across each time period is as follows: 0.20 in period one, 0.25 in period two, 0.28 in period three, 0.37 in period four, and 0.38 in period five. As mentioned in the methodology, the process used to calculate realized volatility included logarithms. However, because basis is calculated by subtracting futures price from cash price, and as a result can be negative, this metric is not always achievable due to this potential negativity. Even though this calculation was not able to be completed for basis, we can still determine whether futures or cash prices have more of an effect on basis volatility since they are its only two components. To reiterate, as well as add to, the above discussion, futures price realized volatility initially falls, then rises, whereas cash price realized volatility rises over each of the five periods. Furthermore, cash price realized volatility increases at a greater rate than that of futures price.

**Summary of Calculation Trend Patterns**

In summary, five patterns were exhibited across the metrics analyzed for futures price, cash price, and basis. The first pattern of a decrease from period one to period two, an increase in periods three and four, and a decrease in period five was the most prominent in this analysis and was present in all of the calculations completed for futures price except realized volatility. Similarly, this pattern was present in all of the cash price calculations except for realized volatility, as well. Finally, this pattern was found to be mixed in the calculation of the basis data range, specifically for the calculations which used open futures price and the high-low average. The second trend of a decrease from period one to period two, followed by alternating increases and decreases throughout the periods, was present in two calculations: all three means and data ranges of mean price shown as a percentage for basis. Trend three of two consecutive decreases followed by two consecutive increases across the five periods was present in the three standard deviation calculations for basis and the basis data range that used close futures price. Trends four and five were unique to the realized volatility metric. Specifically, trend four was expressed by a decrease from period one to period two while the three remaining periods had a subsequent increase. Trend four was only present for the five futures realized volatility metrics. The final trend, which can be described as a steady increase across the total timeframe, was only present in the realized volatility calculation for cash price.

**Explaining Basis Volatility Through Each Calculation**

Throughout this analysis, volatility of futures prices, cash prices, and basis has been measured through many different metrics over a twenty-five-year period. While futures and cash volatility contribute to the discussion of volatility, basis volatility has served as the primary focus of this analysis, and as such, will be discussed in greater detail below with regard to the metrics presented above.

The mean metric calculation presented above for basis, while important in knowing the average price level of a period in question, does not say much in terms of volatility. The mean is useful because it serves as a point of reference when discussing other measures. For example, the standard deviation can be used to gain a better understanding of variability, but unless there is a mean to be used as a reference, it is virtually useless when comparing variables with different standard deviations and means. The mean may not give a lot of information about price volatility, but it can help gain a better understanding of price movement and around what price the period under question has been. As stated previously in the analysis, basis was calculated using open, close, and high-low average futures prices. The mean of basis being measured using all three futures types follows a similar pattern of increasing and decreasing from one period to the next, also stated earlier in the analysis. However, the comparison of average basis across the five periods has been left out until this point. Looking at table 6, it can be seen that the three mean calculations for basis exhibit almost identical price levels for periods one and three and periods two and five. For example, the mean calculation for basis using close futures prices is -22.12 for period one and -22.21 for period three. Furthermore, the means for period two and five were -45.17 and -40.94, respectively. The one period with a mean that is not similar to the other four periods is period four with a basis mean of -87.37. What this means is that even though these periods are years apart in some cases, the average basis that represents them are similar or almost identical. This is important to keep in mind when assessing the standard deviation and range calculations.

The standard deviation basis results presented earlier in this section present an interesting story of basis volatility. The standard deviation calculation provides a quantitative value of dispersion around the mean. This allows for the understanding of how close or far a selective data set is from the mean based on confidence intervals. In this case, the mean is the basis and the standard deviation represents how close or far basis was from the mean over each time period to a certain confidence interval. The results presented in this thesis are representative of the first confidence interval. This means that the quantitative value for standard deviation presented in the results plus or minus from the mean accounts for about 68% of the data set of the period in question. Throughout period one through five, the results for the standard deviation of the basis calculated using close futures prices are as follows: 13.91 for period one, 13.31 for period two, 9.94 for period three, 26.34 for period four, and 29.90 for period five. As can be seen with these results, the dispersion around the mean at one confidence interval was around the same level for the first three periods with the first two periods being almost identical. The third period standard deviation increased into the fourth period and then increased even further into the fifth period. The results of the other two basis standard deviations calculated using the two other futures types can be found in table 6. It can be seen from the results that the variation in basis in the last period is substantially greater when compared to the first three periods. It is interesting to note that the standard deviation of the last period for basis is slightly greater than the fourth period even though it has a substantially lower mean. A similar comparison can be made for the fifth period and the second period having almost identical means but substantially different standard deviation results. In summary, when looking at the standard deviation calculation, variation of basis throughout the twenty-five-year period has increased when comparing the first three similar periods to the last two similar periods. Additionally, the variation of basis in these first three periods using standard deviation decreased slightly from period one to period two and decreased again form period two to period three, with the first two periods having almost identical basis standard deviation results. Lastly, the last two periods' standard deviation results saw an increase in variation from the fourth period with the lower basis mean to the fifth period with the higher basis mean.

The data range calculation used in this thesis, while similar to the standard deviation calculation in that it provides information on the dispersion of basis from the mean, conveys slightly different information on basis volatility. Using three standard deviations ensures that 99% of the data in the period in question will fall within this distribution of the respective period. The data range calculation in this thesis goes even further as it views the basis data over the entire period in question in order to subtract the lowest basis from the highest basis. This calculation provides the spectrum in which basis traveled over the period in question without leaving out any basis data points. The basis data range calculations for periods one through five using close futures prices are as follows: 75.71 for period one, 64.79 for period two, 62.94 for period three, 150.75 for period four, and 151.88 for period five. As can be seen from the data range calculations, there was a decrease from period one to period two, a slight decrease from period two to period three, a large increase in period four, and a slight increase in period five. Additionally, it can also be seen that the data range calculations for the first three periods are very similar to each other while the last two periods are similar to each other. Moreover, period two and three have data ranges that are almost identical while periods four and five have the same experience. Overall, like the standard deviation calculation, the data range calculation exhibited an increase in variability when comparing the last period to the first period. It is also noteworthy to mention that just like the standard deviation calculation, there was an increase in the data range for basis from the fourth period to the fifth period. Both of these points provide reasoning to suggest that variability has increased over the twenty-five-year period and that variability, while high in the fourth period, increased to a higher rate in the final period. Both the standard deviation calculation and the data range calculation show that while the variability of basis did not increase much in recent years, it still increased, nonetheless.

The next measure testing the volatility of basis was the data range as a percentage of the basis mean. This allows for a deeper understanding of how volatile basis has been over a period in question in terms of the average basis of the same period. In other words, the data ranges of the five periods are fairly static in that they can be compared to one another, yet can also be misinterpreted without a point of reference, as was the case with standard deviation. Comparing the data ranges of periods one and four of 75.71 and 150.75, one might come to the conclusion that period four is more volatile given its higher data range. However, when introducing the data range as a percentage of the mean metric, this conclusion can be contradicted. By including the mean in this calculation, a point of reference is introduced and makes the results more dynamic. For example, this metric for the same periods mentioned above are 342.32% and 172.54%, the opposite of what was described with the data range. The newer conclusion one could reach is that period one is, in fact, more volatile since the range is over three times its mean. The results for this calculation for basis using close futures prices for each of the five periods analyzed are as follows: 342.32% for period one, 143.44% for period two, 283.43% for period three, 172.54% for period four, and 371.01% for period five. The observation can then be made that although the data ranges of the period follow one order, the volatility expressed through the second range calculation can follow another. In essence, from most to least volatile, this new order would be: period five, period one, period three, period four, then period two.

The next and final metric measured to assess volatility in this thesis is realized volatility. However, as stated in the methodology section, realized volatility was not able to be calculated for the majority of basis data as it is in contango. This means that futures prices are higher than cash prices, so the basis becomes negative. The means taken from these basis calculations would also be negative, which would prove to be problematic since logarithms cannot be calculated using negative numbers. Although realized volatility could not be calculated for basis, due to futures and cash prices not encountering this same problem, it can be determined from those realized volatility calculations whether futures or cash prices have a greater effect on basis volatility, if present. For example, when looking at the results in table 4 and 5 for futures and cash realized volatility a few observations can be made. First, it can be seen that for each period throughout the twenty-five-year period realized volatility is larger for cash than it is for each futures type. Also, as mentioned before, the cash price realized volatility is rising at a steady rate while the close futures price realized volatility, for example, decreases for period two and increases thereafter. Moreover, this increase of realized volatility for cash from period one to period five is about 0.18 while realized volatility for close futures price is about 0.10. Given the figures for cash and futures realized volatility, as well as the fact that cash price realized volatility increased by a greater amount from the first to fifth period and increased each period, it is not unreasonable to presume that cash price plays a larger role in basis realized volatility.

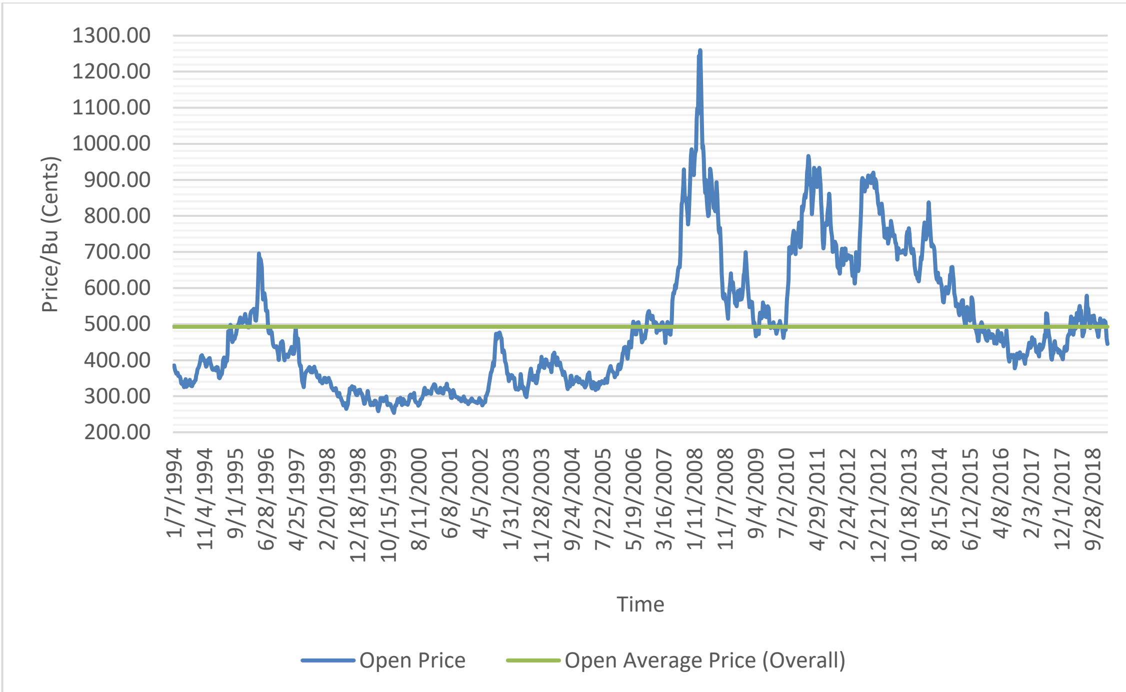


**Figure 5. KCBT Weekly Open Prices: 01/07/1994 – 03/01/2019**

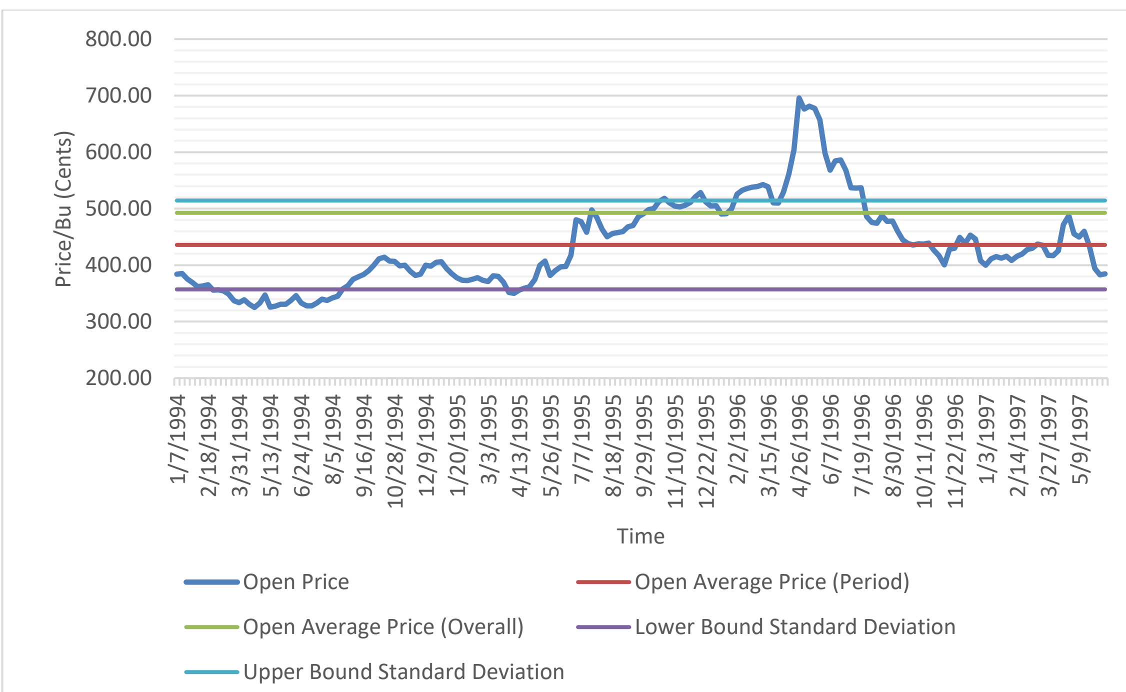


**Figure 6. KCBT Weekly Open Prices: 01/07/1994 – 06/13/1997**

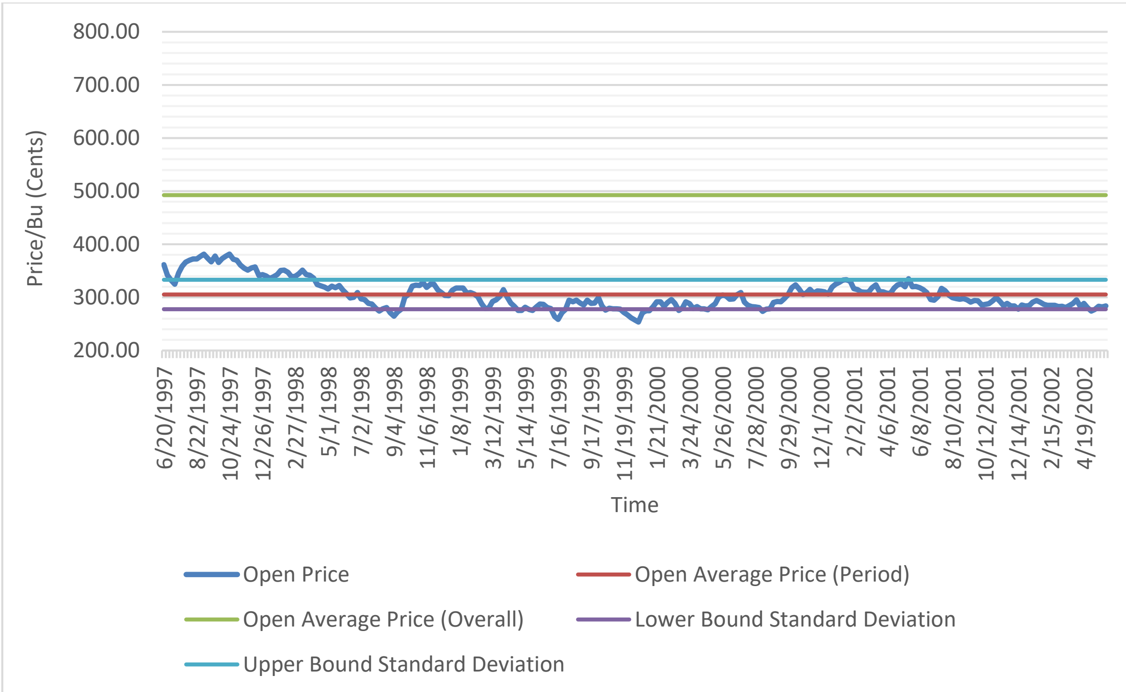


**Figure 7. KCBT Weekly Open Prices: 06/20/1997 – 05/31/2002**

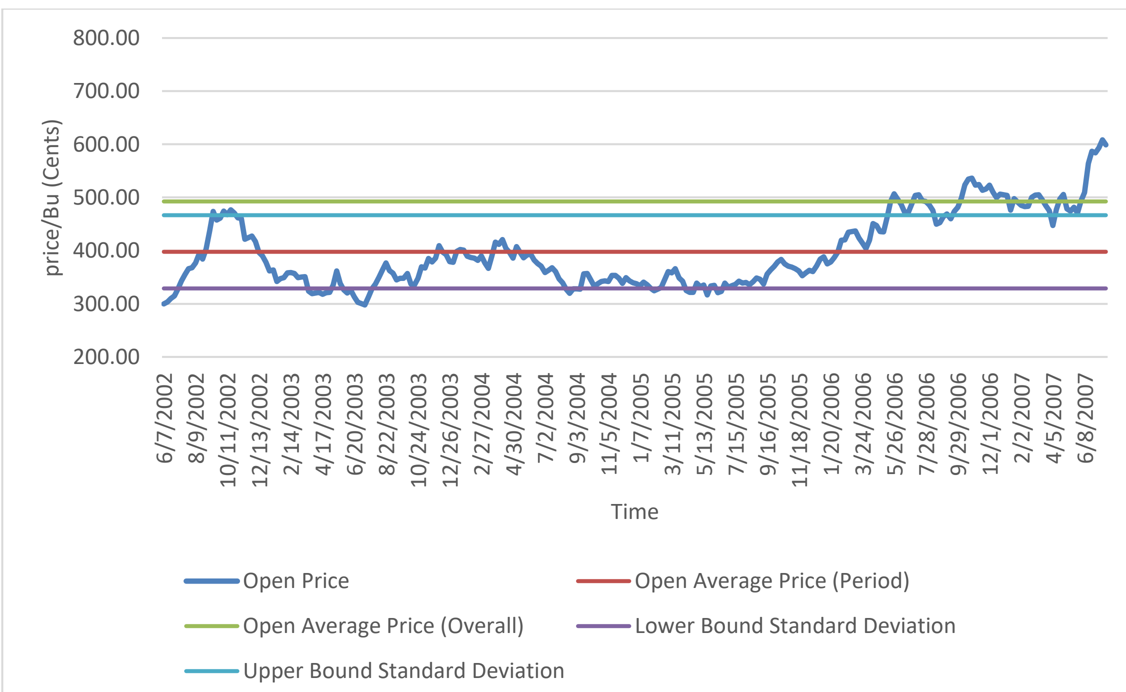


**Figure 8. KCBT Weekly Open Prices: 06/07/2002 – 07/20/2007**

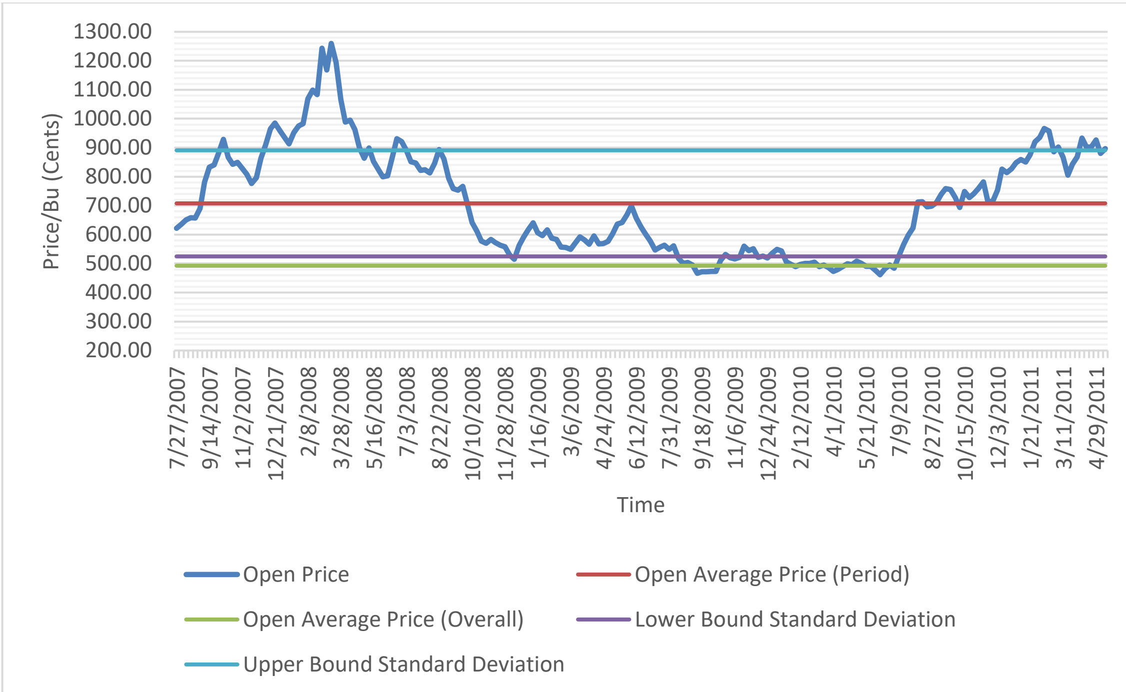


**Figure 9. KCBT Weekly Open Prices: 07/27/2007 – 05/13/2011**

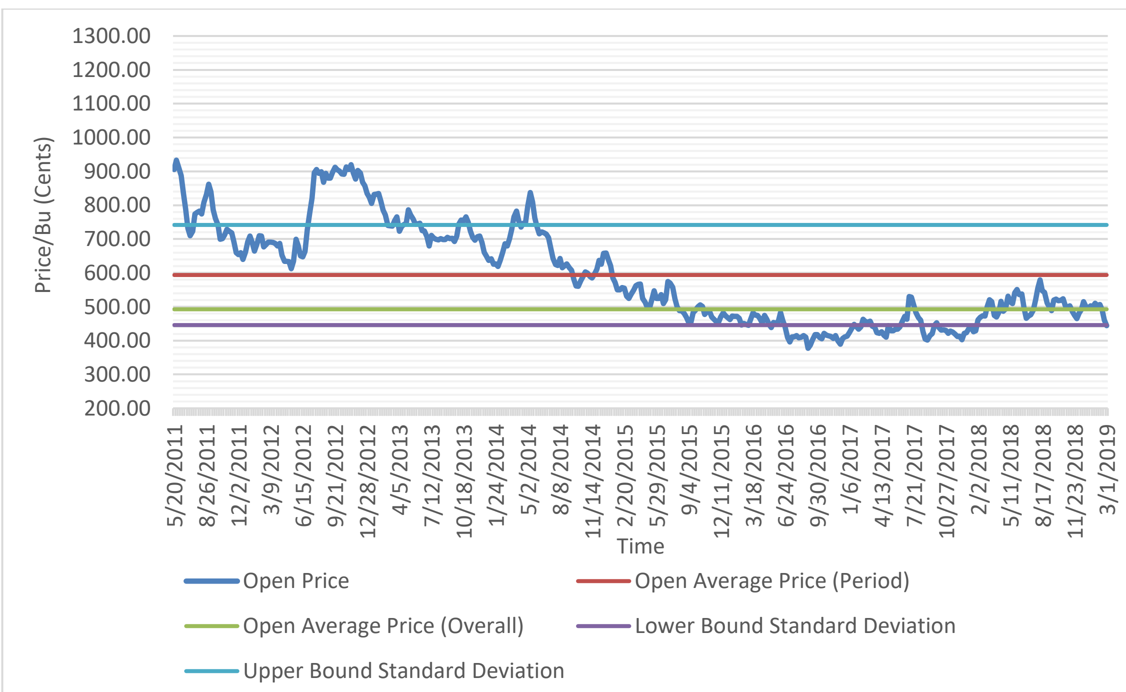


**Figure 10. KCBT Weekly Open Prices: 05/20/2011 – 03/01/2019**

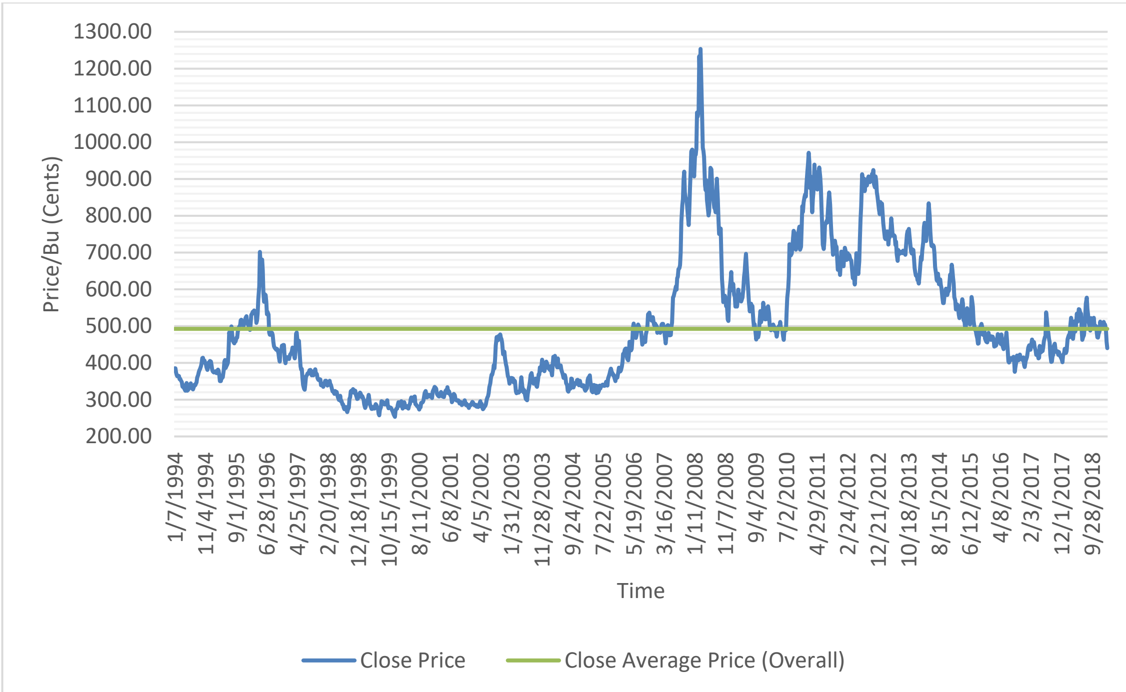


**Figure 11. KCBT Weekly Close Prices: 01/07/1994 – 03/01/2019**

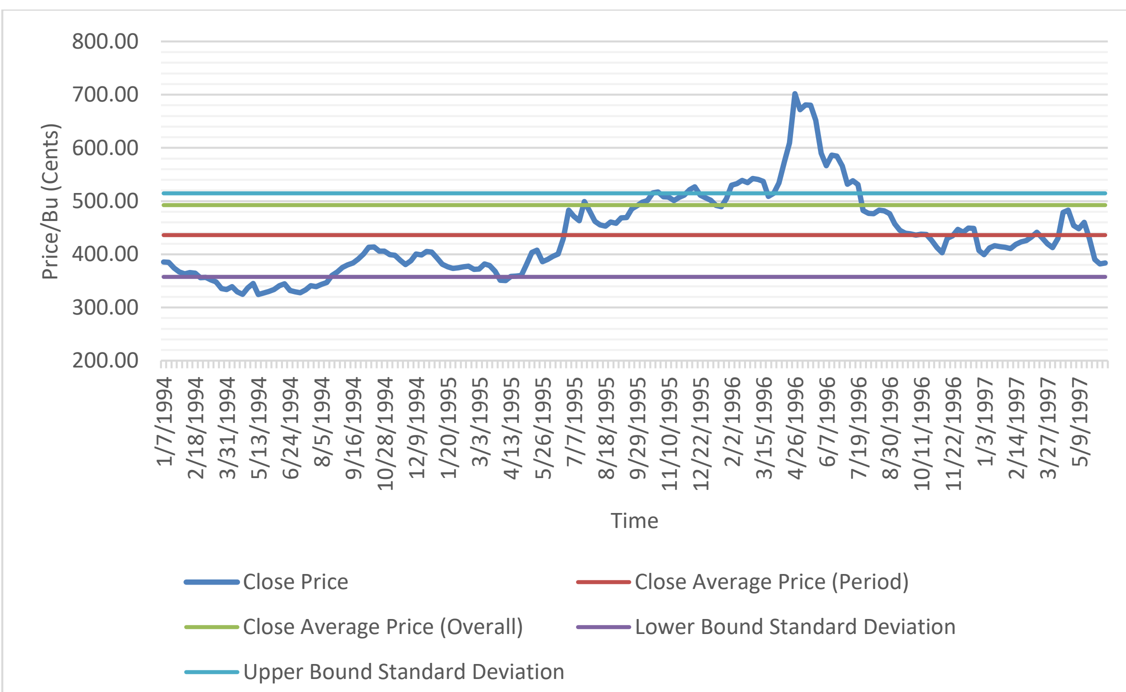


**Figure 12. KCBT Weekly Close Prices: 01/07/1994 – 06/13/1997**

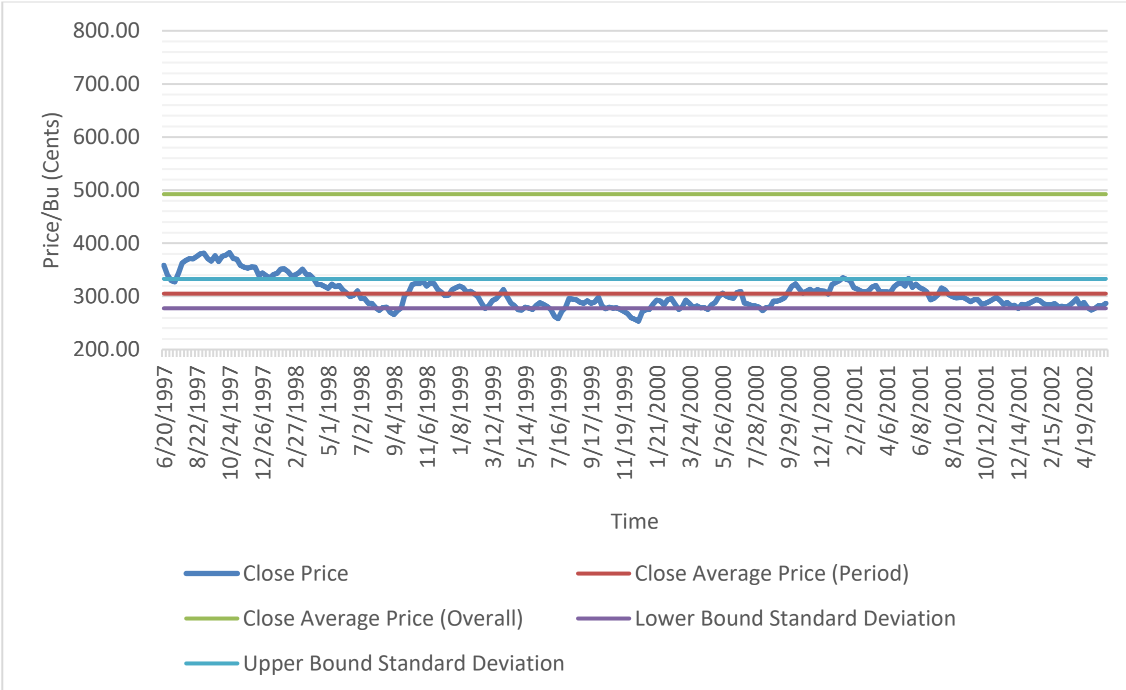


**Figure 13. KCBT Weekly Close Prices: 06/20/1997 – 05/31/2002**

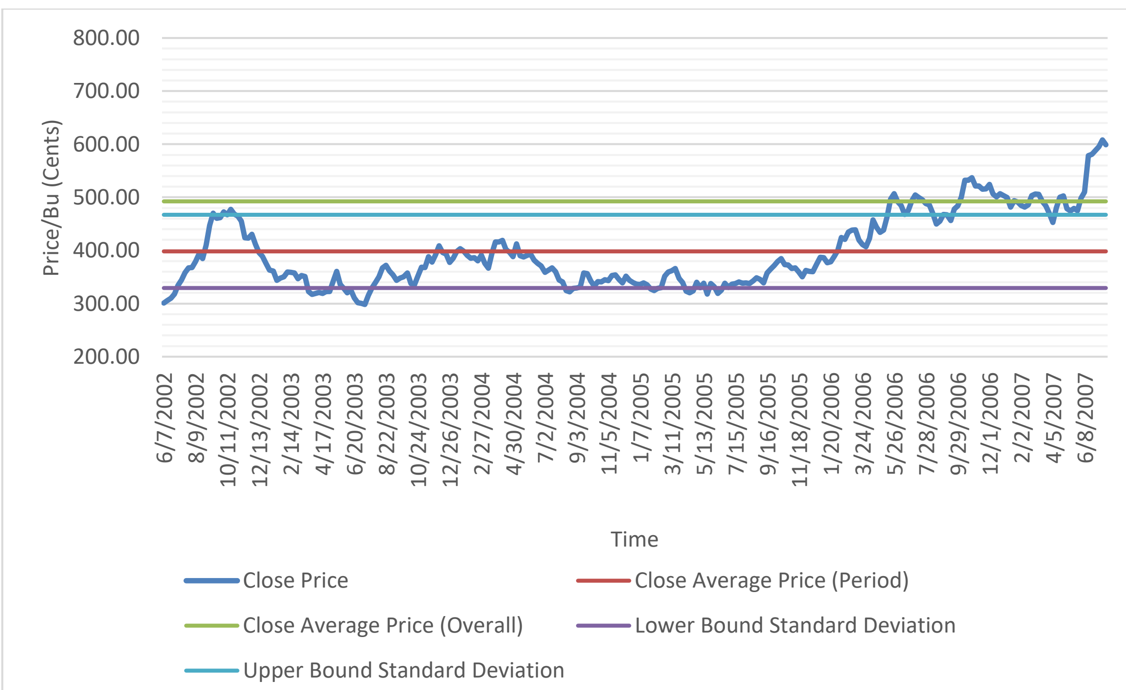


**Figure 14. KCBT Weekly Close Prices: 06/07/2002 – 07/20/2007**

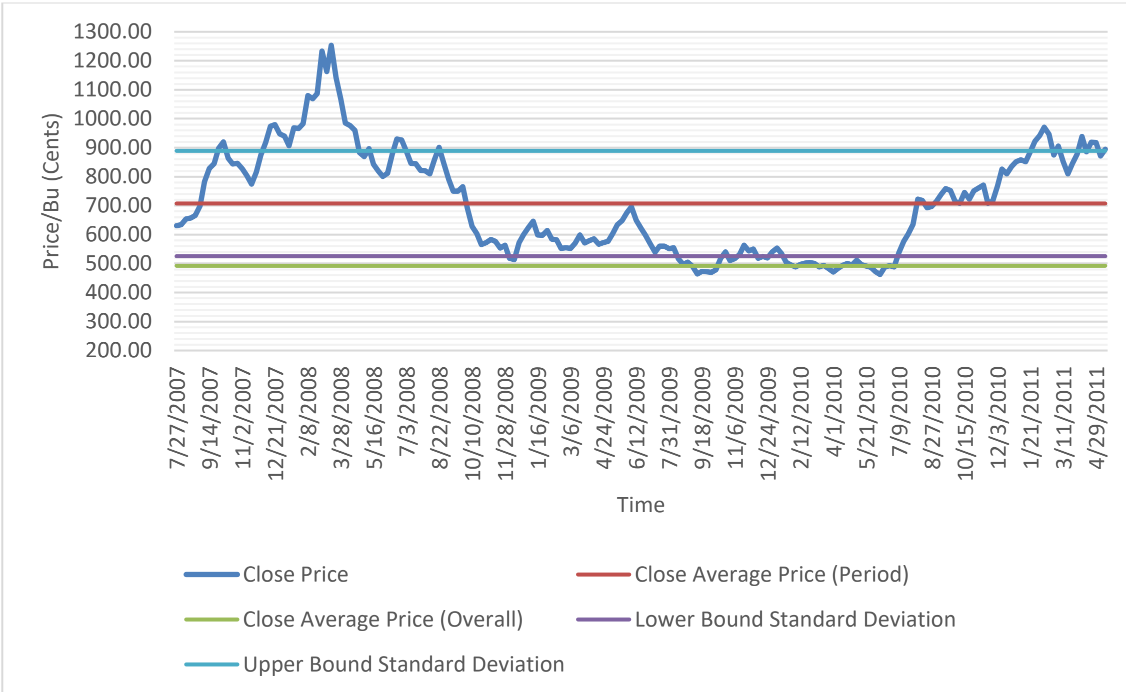


**Figure 15. KCBT Weekly Close Prices: 07/27/2007 – 05/13/2011**

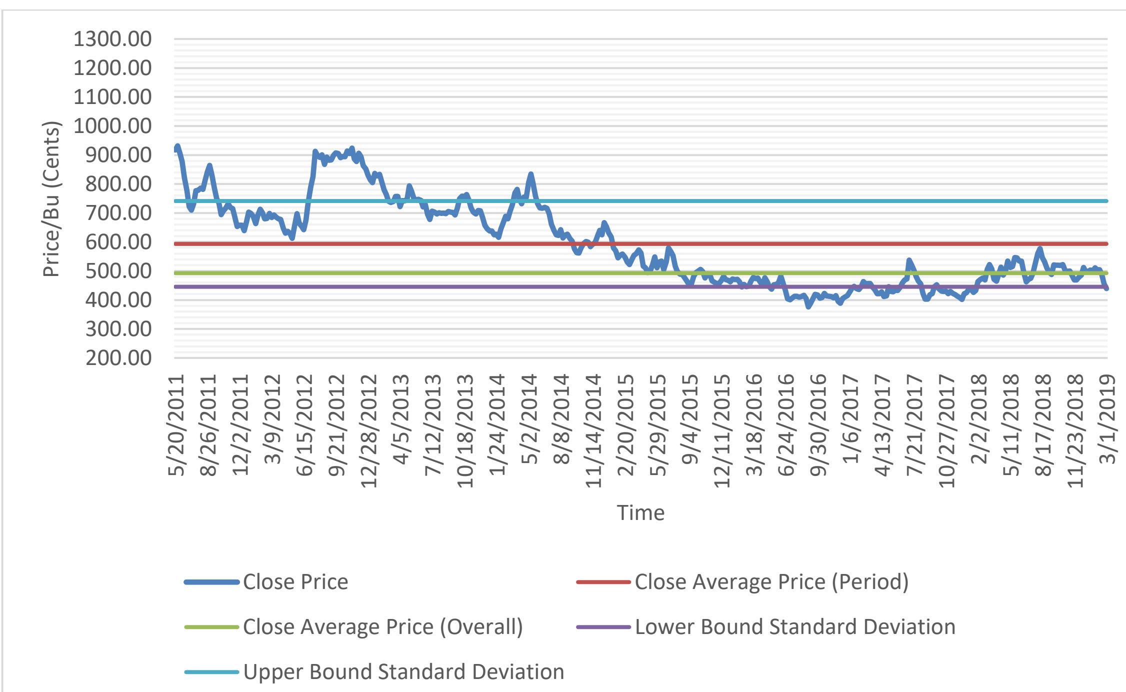


**Figure 16. KCBT Weekly Close Prices: 05/20/2011 – 03/01/2019**

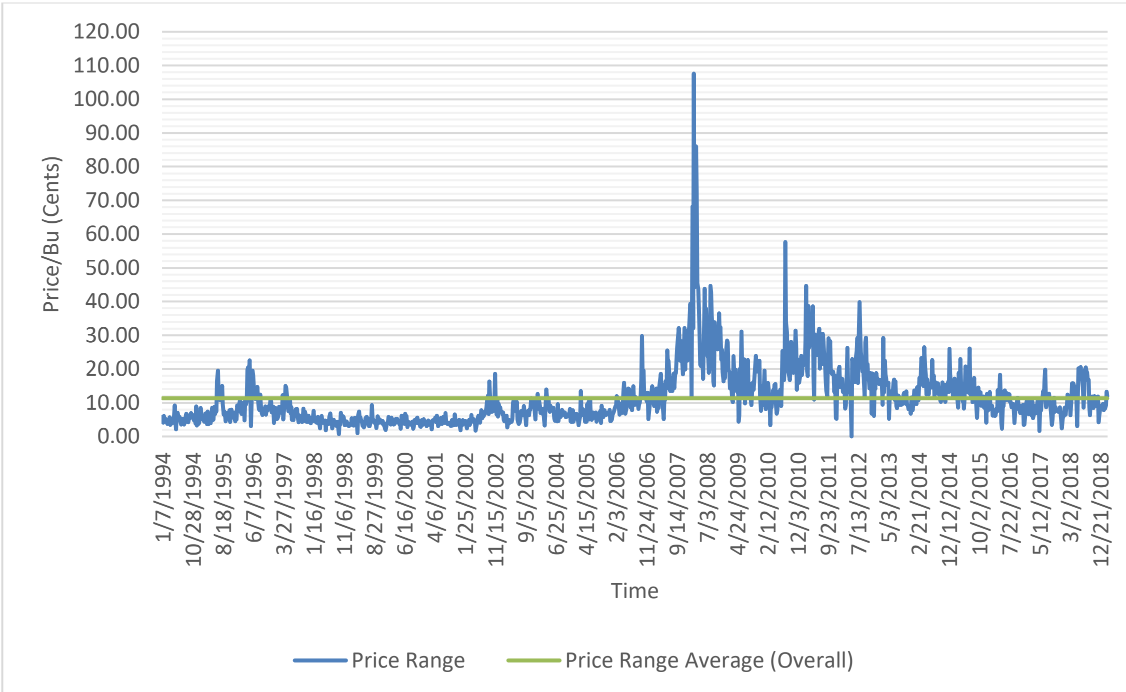


**Figure 17. KCBT Weekly Price Range: 01/07/1994 – 03/01/2019**

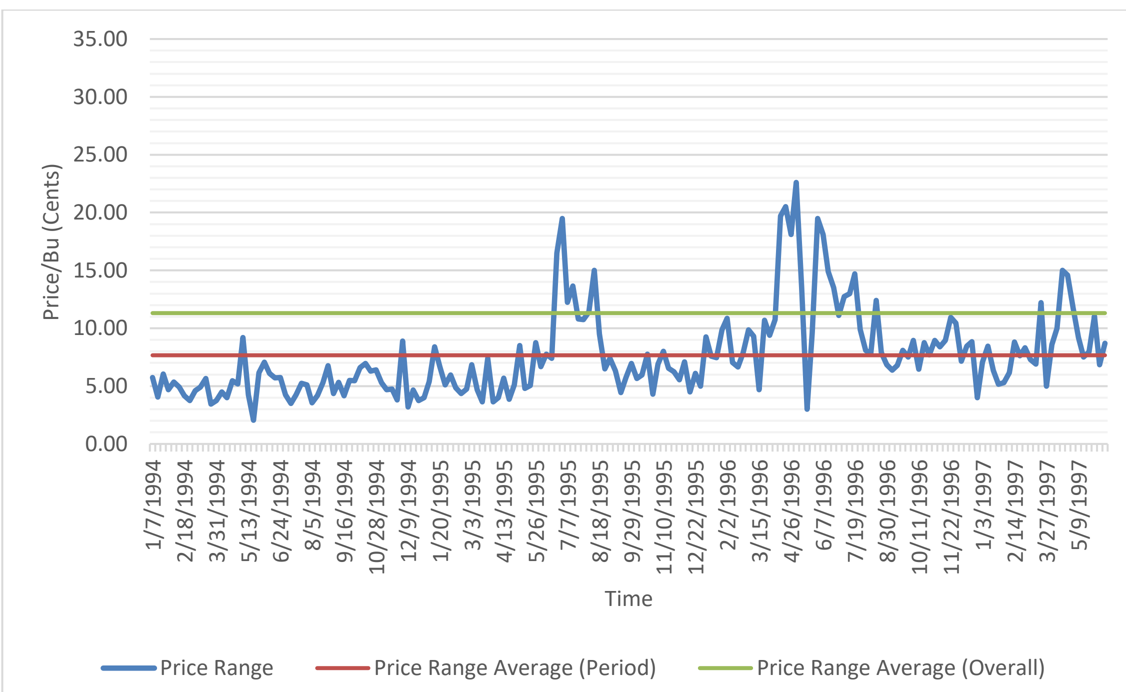


**Figure 18. KCBT Weekly Price Range: 01/07/1994 – 06/13/1997**

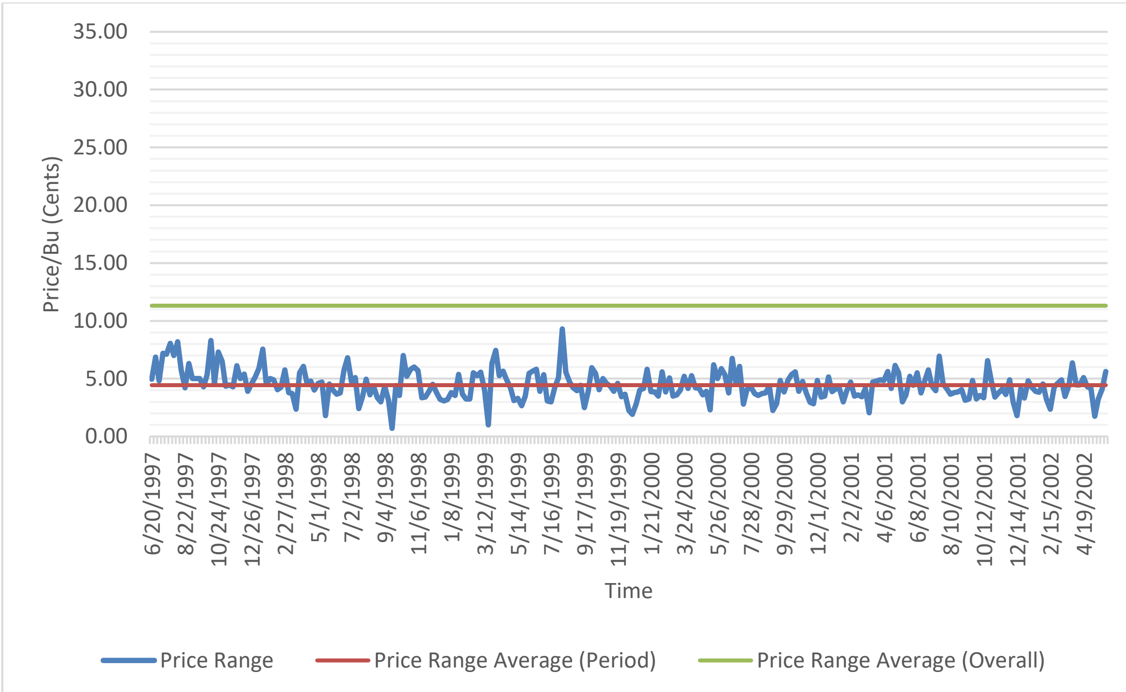


**Figure 19. KCBT Weekly Price Range: 06/20/1997 – 05/31/2002**

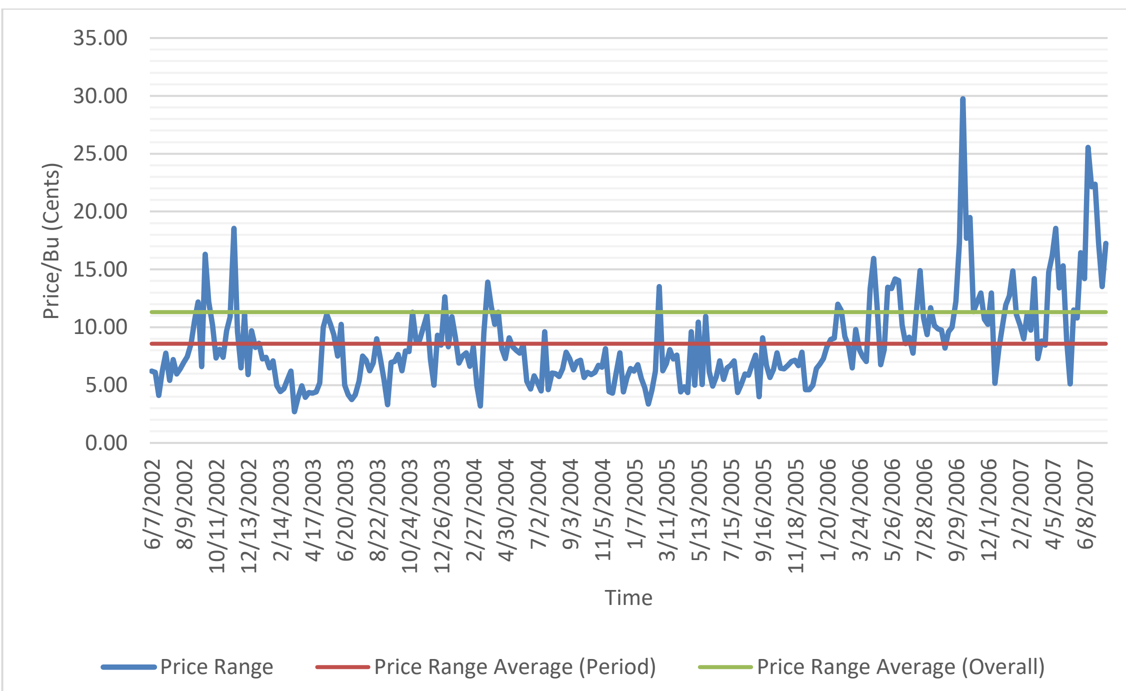


**Figure 20. KCBT Weekly Price Range: 06/07/2002 – 07/20/2007**

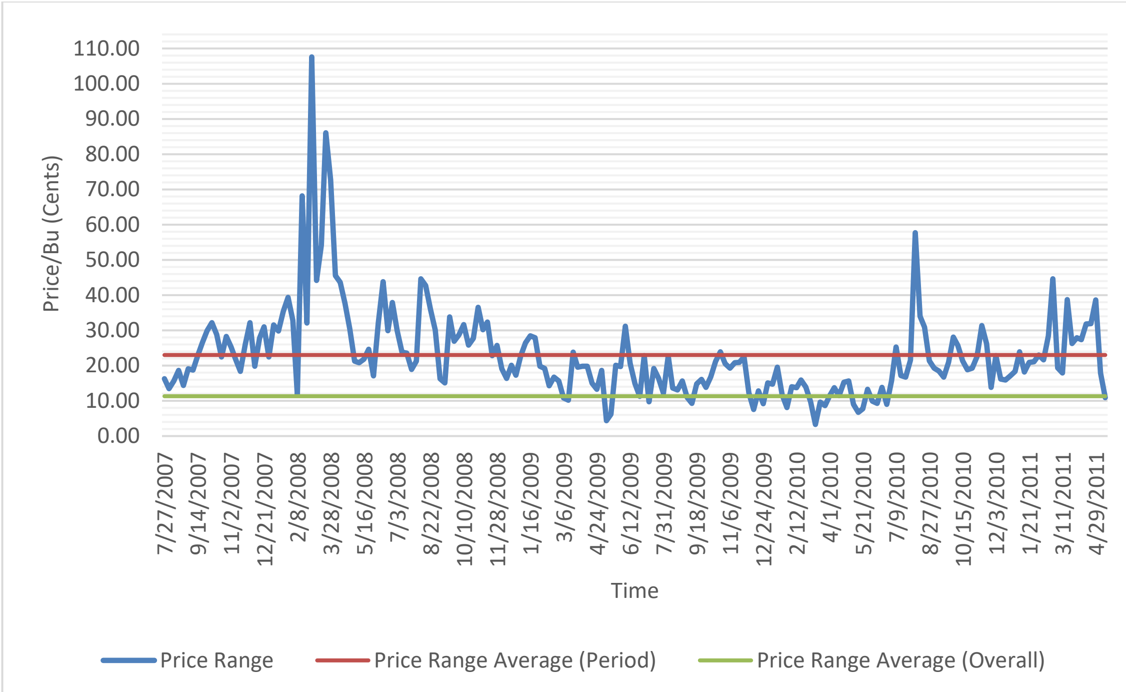


**Figure 21. KCBT Weekly Price Range: 07/27/2007 – 05/13/2011**

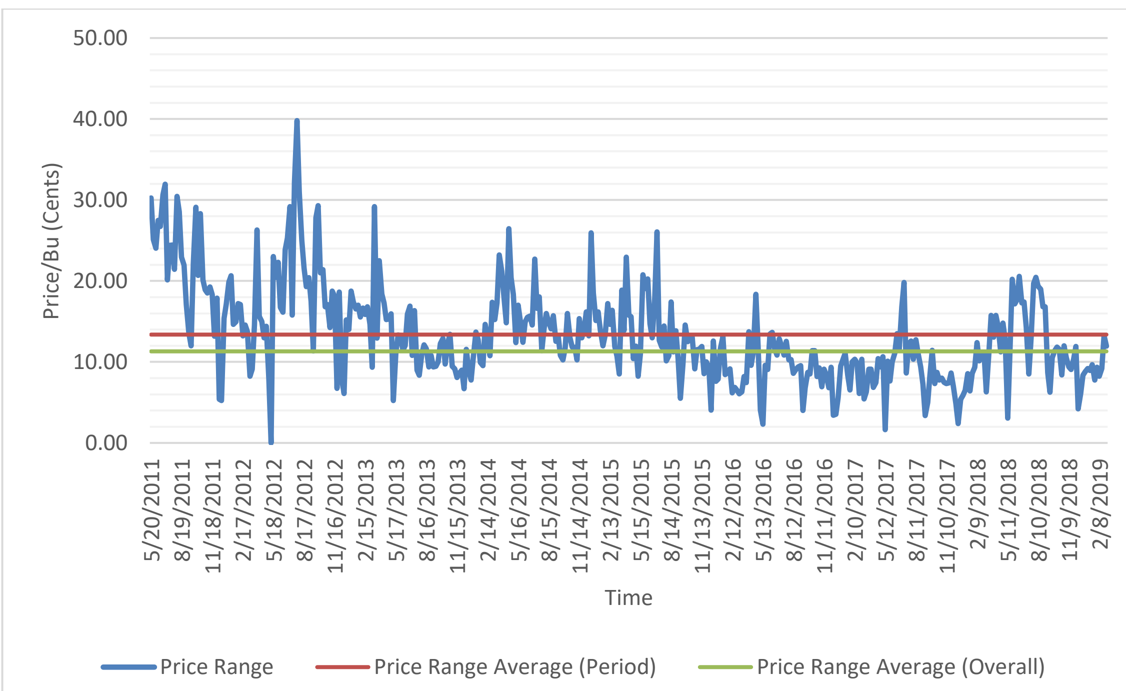


**Figure 22. KCBT Weekly Price Range: 05/20/2011 – 03/01/2019**


**Figure 23. KCBT Weekly High-Low Average Prices: 01/07/1994 – 03/01/2019**

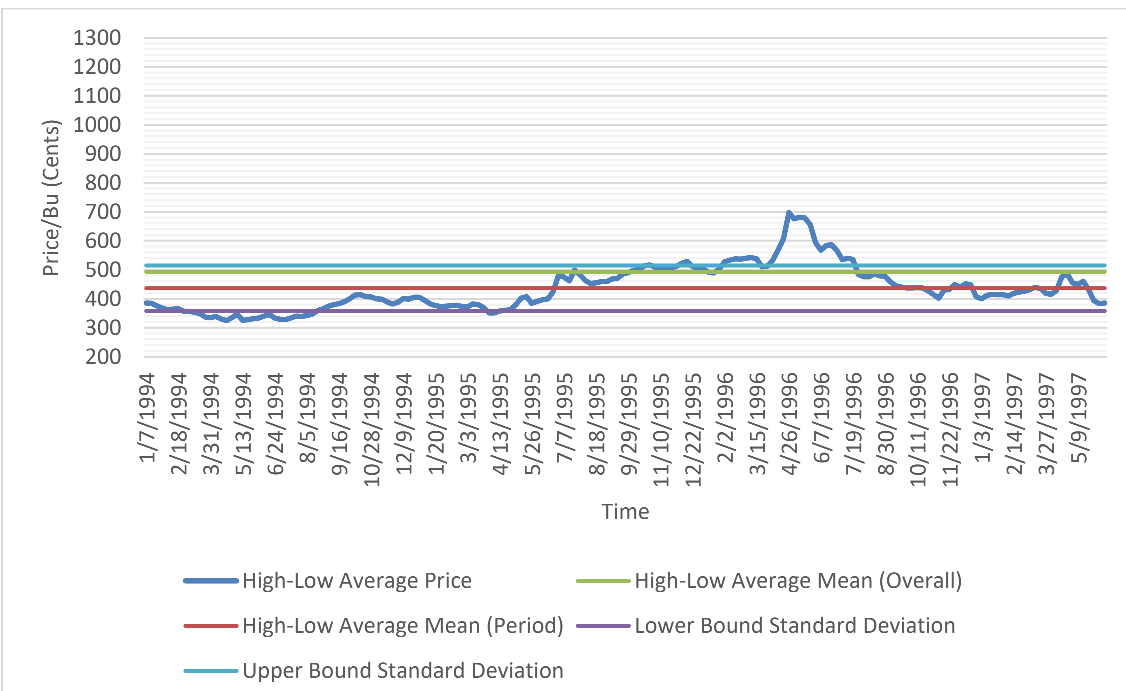


**Figure 24. KCBT Weekly High-Low Average Prices: 01/07/1994 – 06/13/1997**

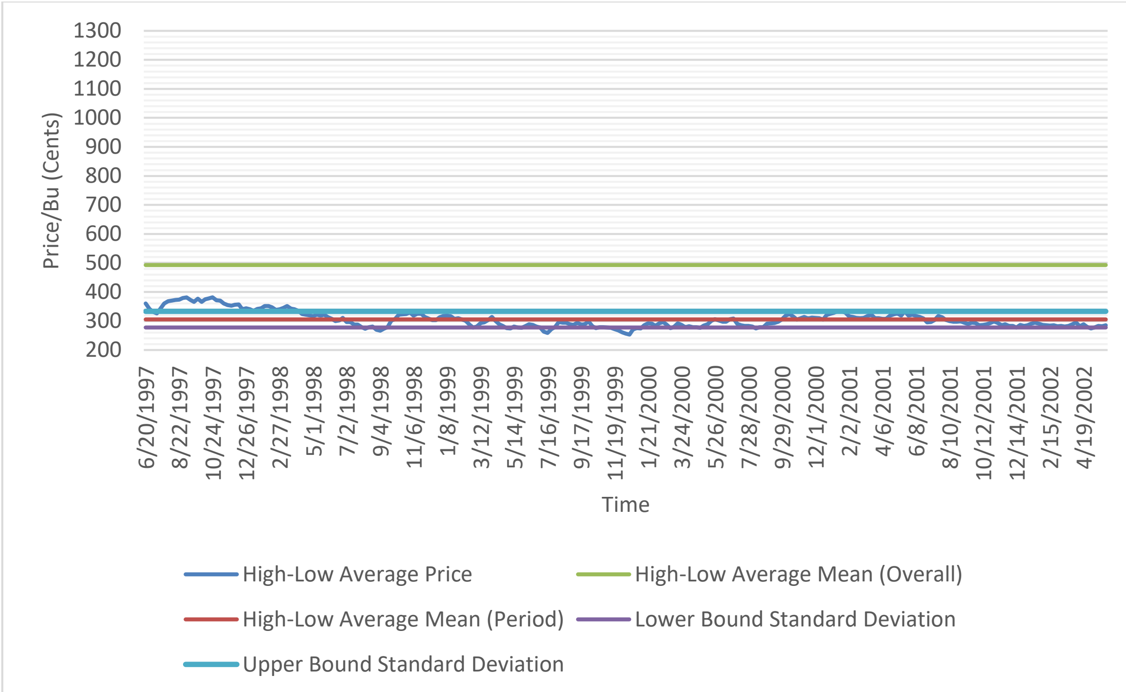


**Figure 25. KCBT Weekly High-Low Average Prices: 06/20/1997 – 05/31/2002**

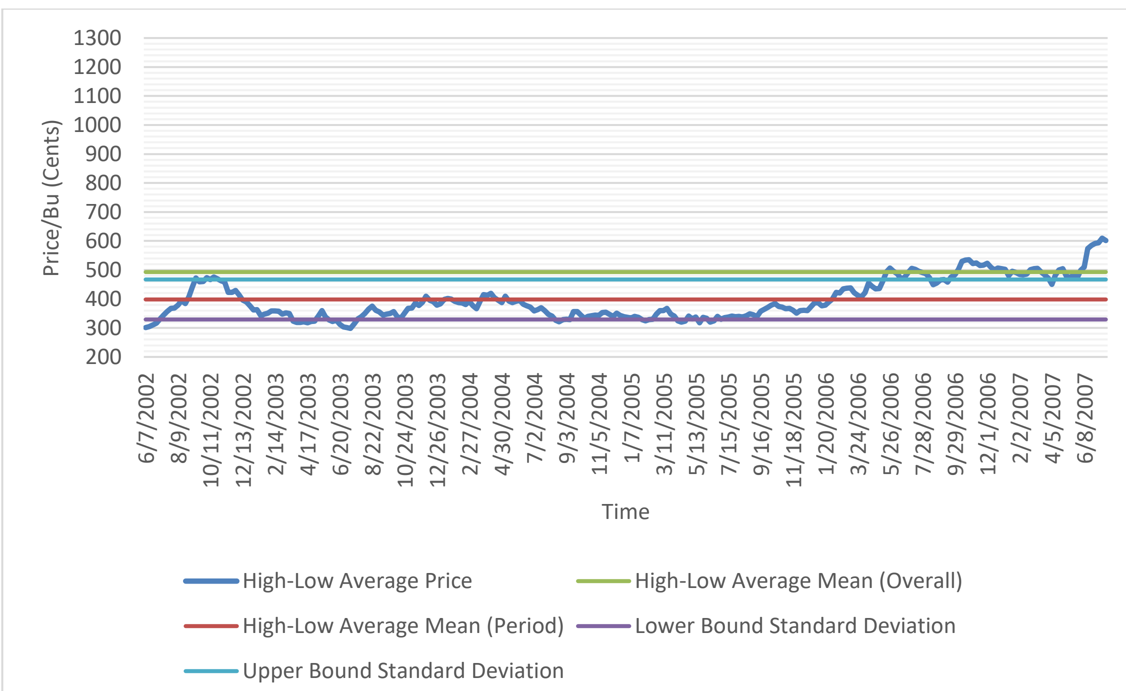


**Figure 26. KCBT Weekly High-Low Average Prices: 06/07/2002 – 07/20/2007**

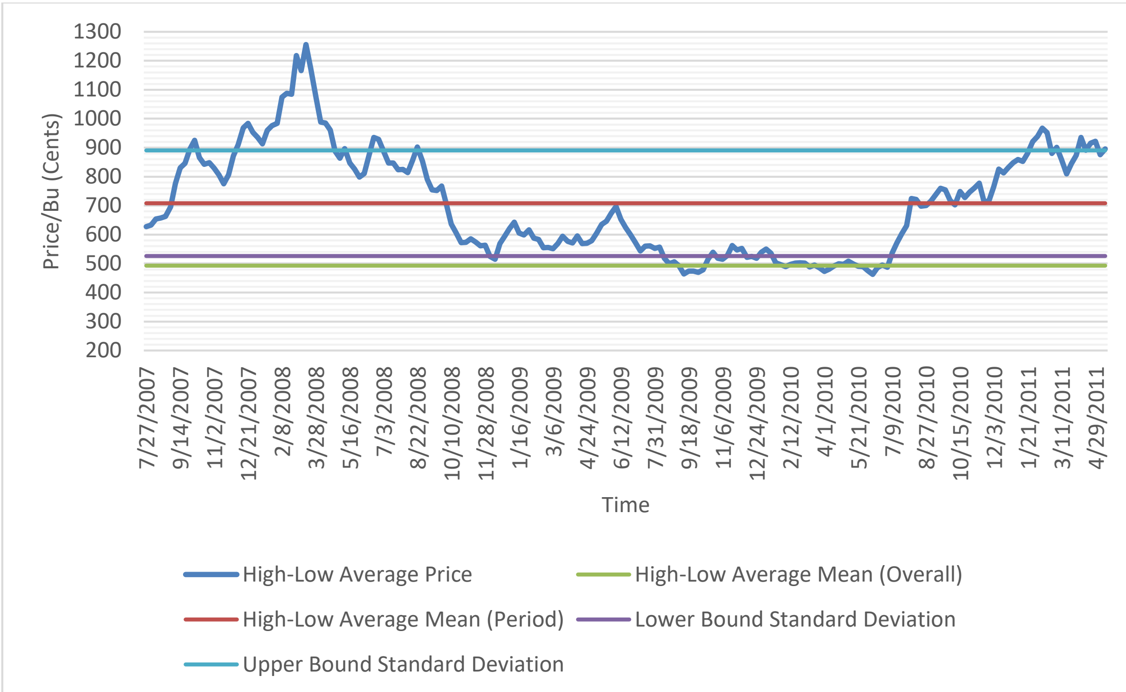


**Figure 27. KCBT Weekly High-Low Average Prices: 07/27/2007 – 05/13/2011**

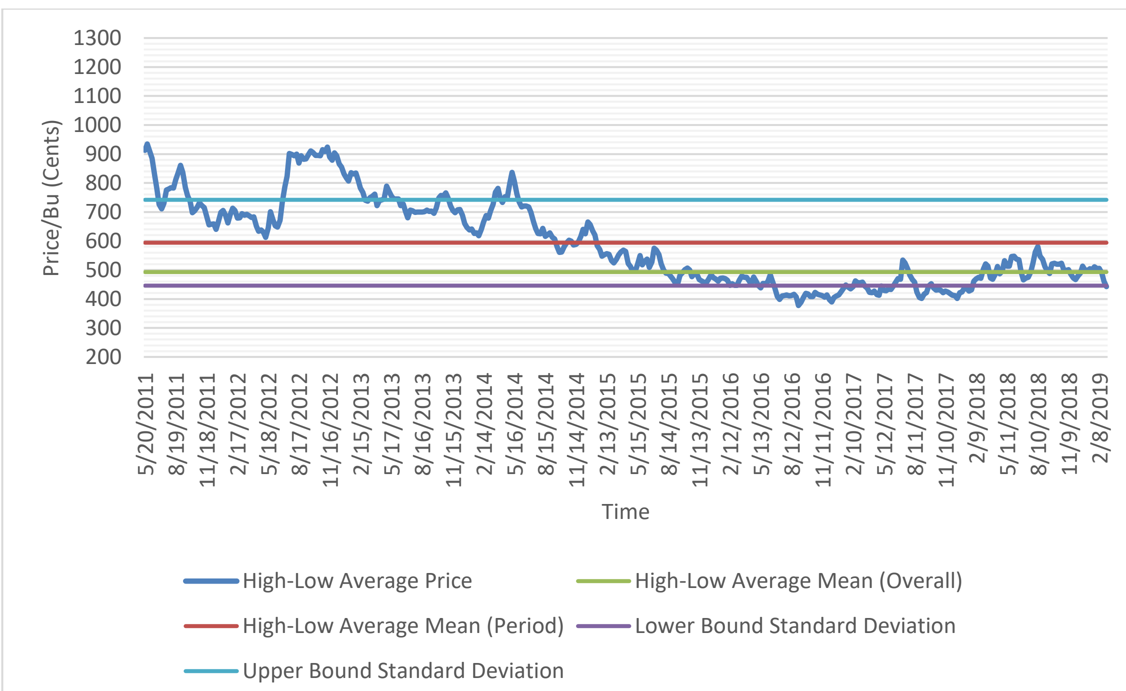


**Figure 28. KCBT Weekly High-Low Average Prices: 05/20/2011 – 03/01/2019**


**Figure 29: Weekly Cash Prices: 01/07/1994 – 03/01/2019**

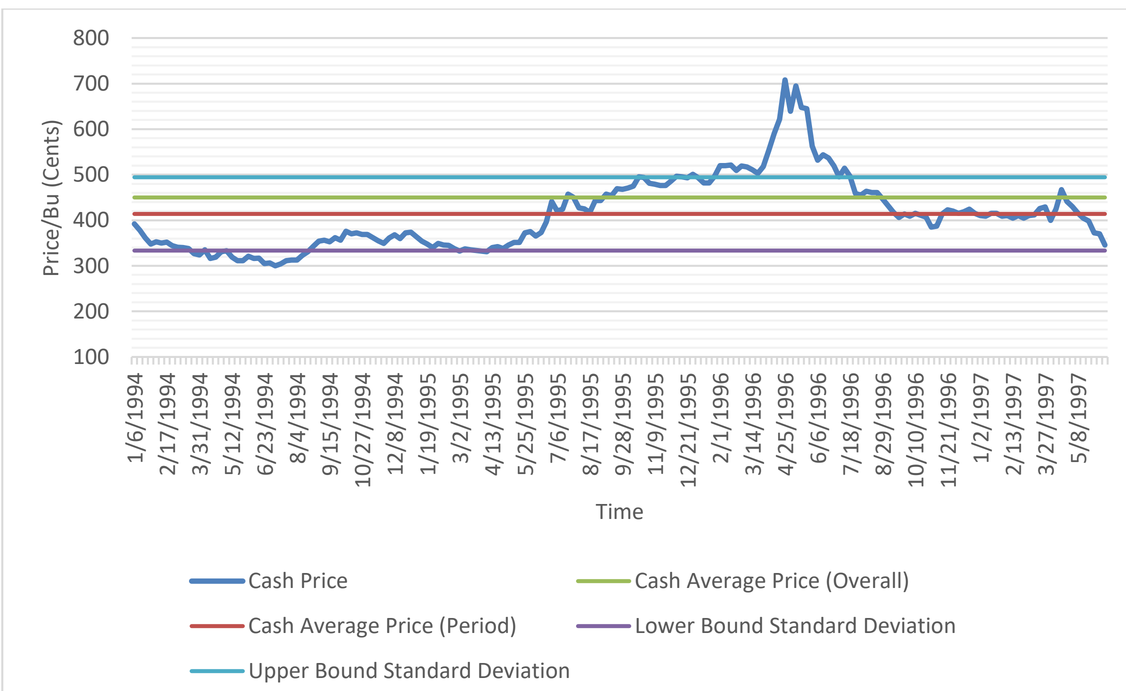


**Figure 30. Weekly Cash Prices: 01/07/1994 – 06/13/1997**

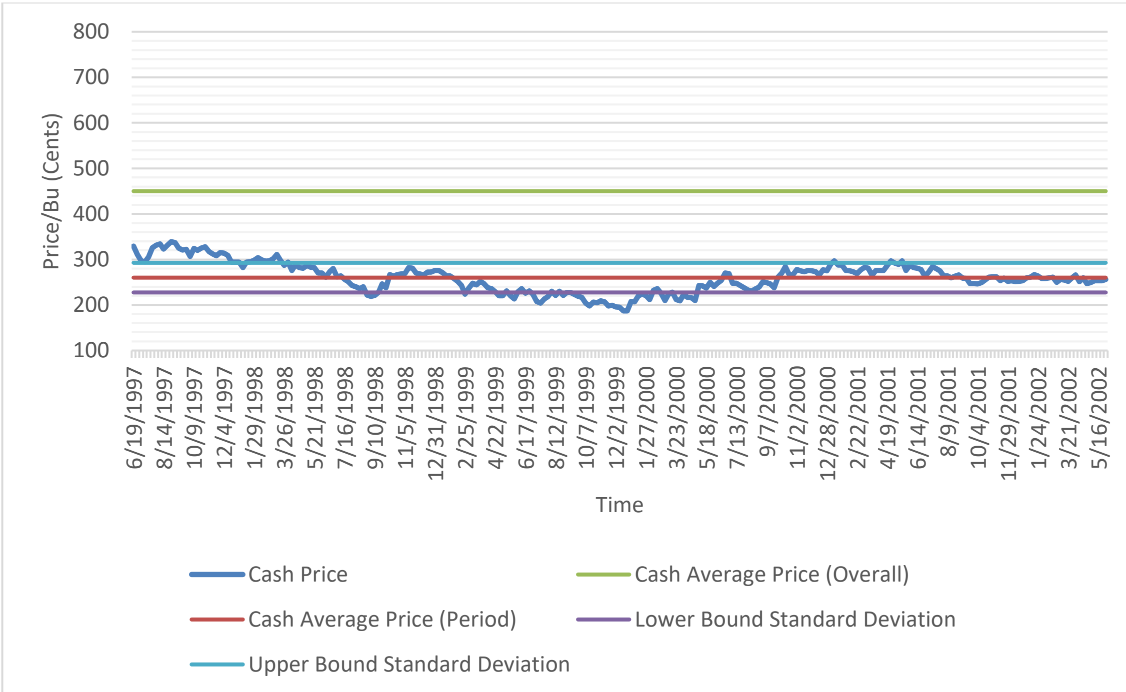


**Figure 31. Weekly Cash Prices: 06/20/1997 – 05/31/2002**

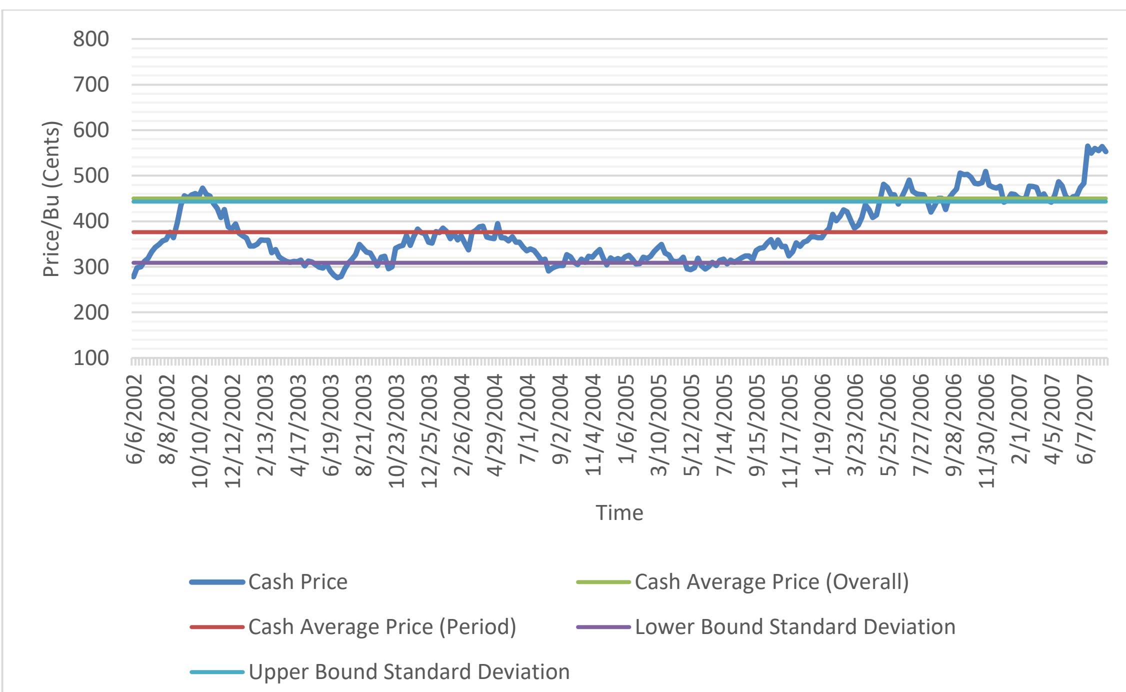


**Figure 32. Weekly Cash Prices: 06/07/2002 – 07/20/2007**

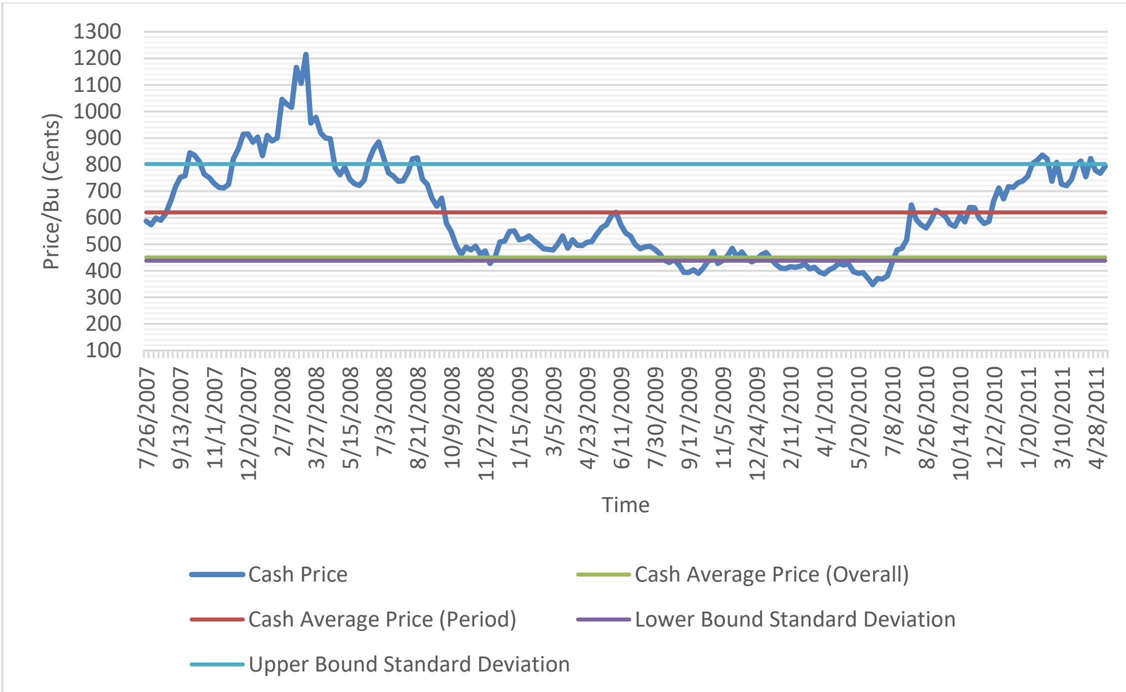


**Figure 33. Weekly Cash Prices: 07/27/2007 – 05/13/2011**

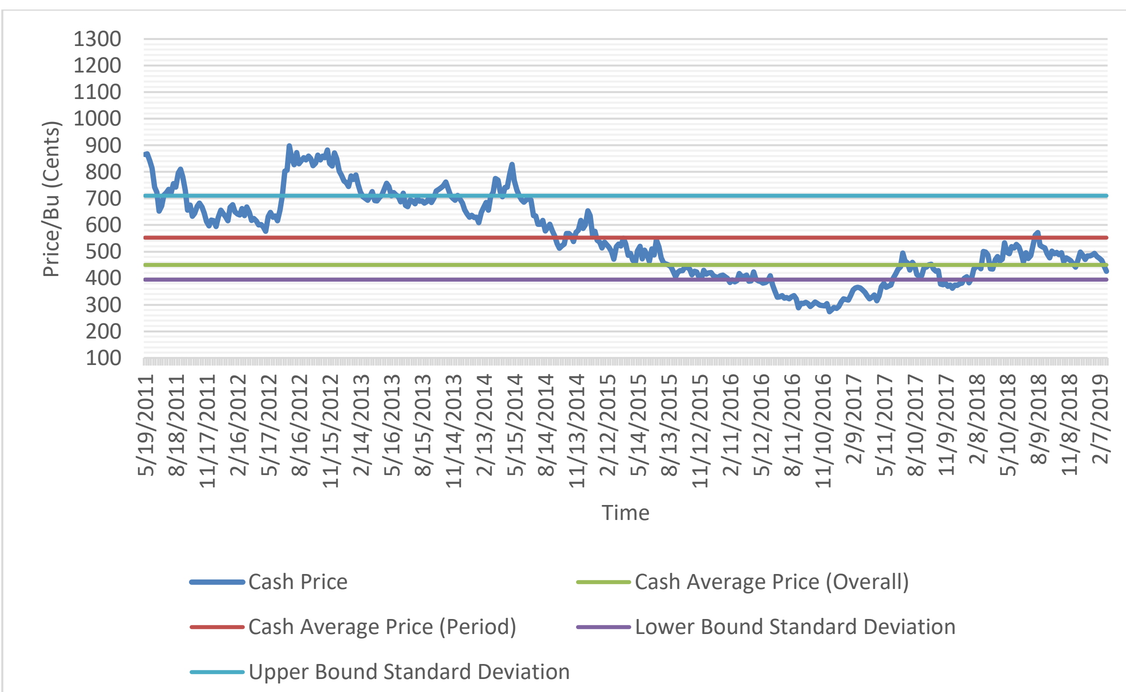


**Figure 34. Weekly Cash Prices: 05/20/2011 – 03/01/2019**

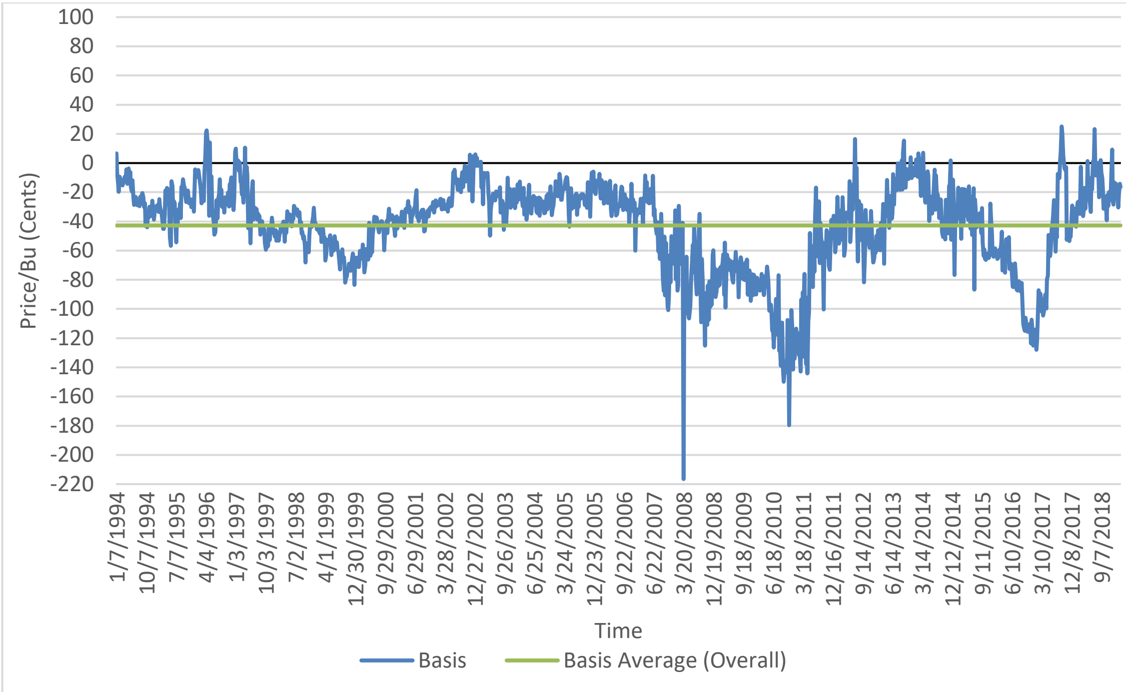


**Figure 35. Weekly Basis: 01/07/1994 – 03/01/2019**

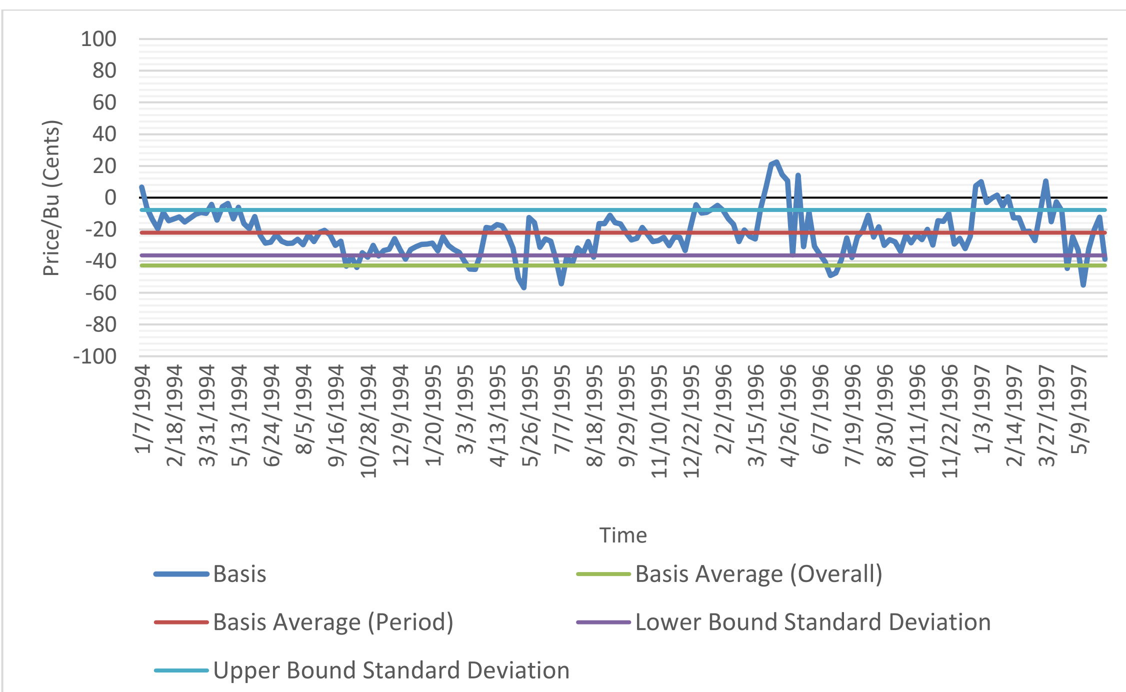


**Figure 36. Weekly Basis: 01/07/1994 – 06/13/1997**

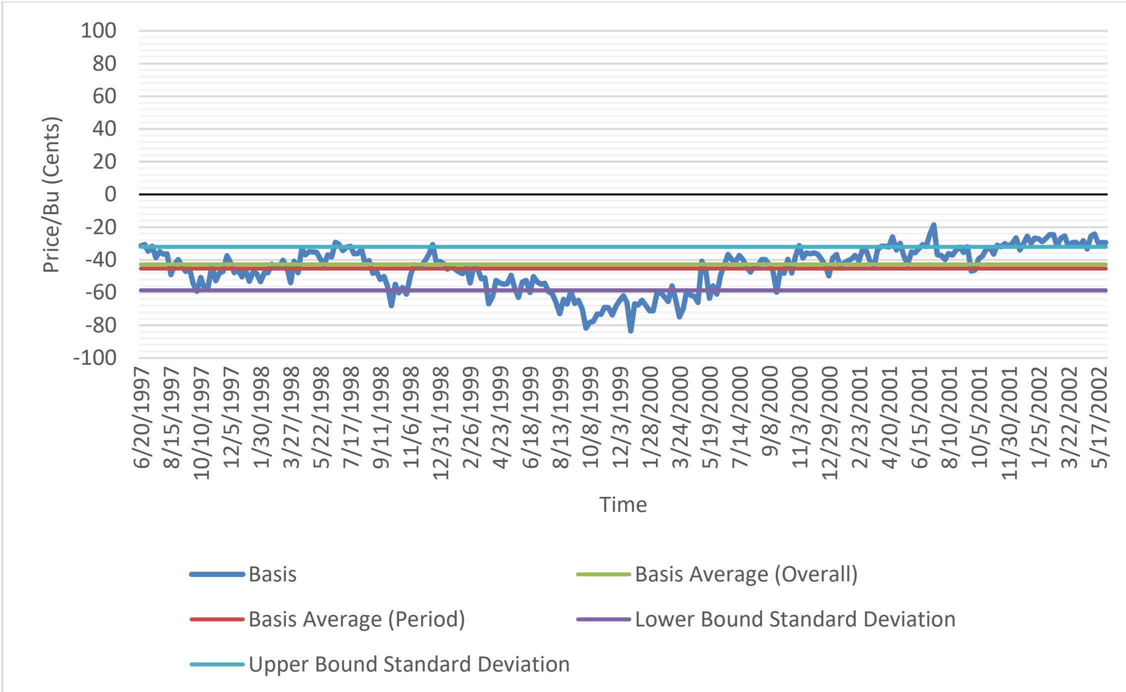


**Figure 37. Weekly Basis: 06/20/1997 – 05/31/2002**

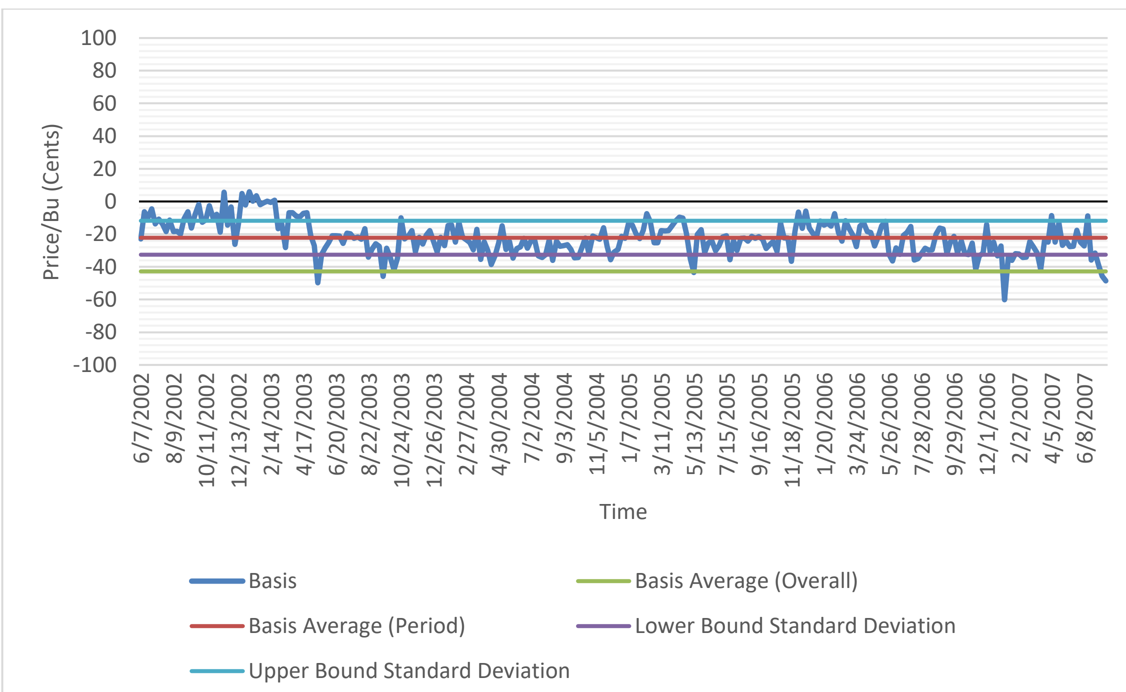


**Figure 38. Weekly Basis: 06/07/2002 – 07/20/2007**

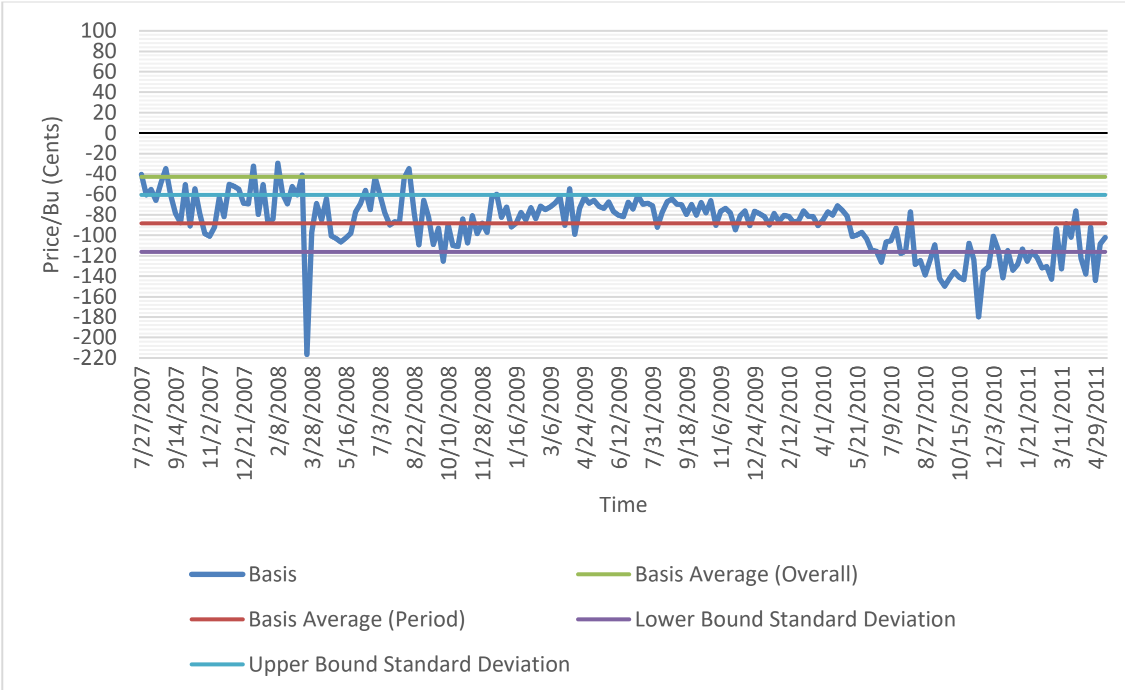


**Figure 39. Weekly Basis: 07/27/2007 – 05/13/2011**

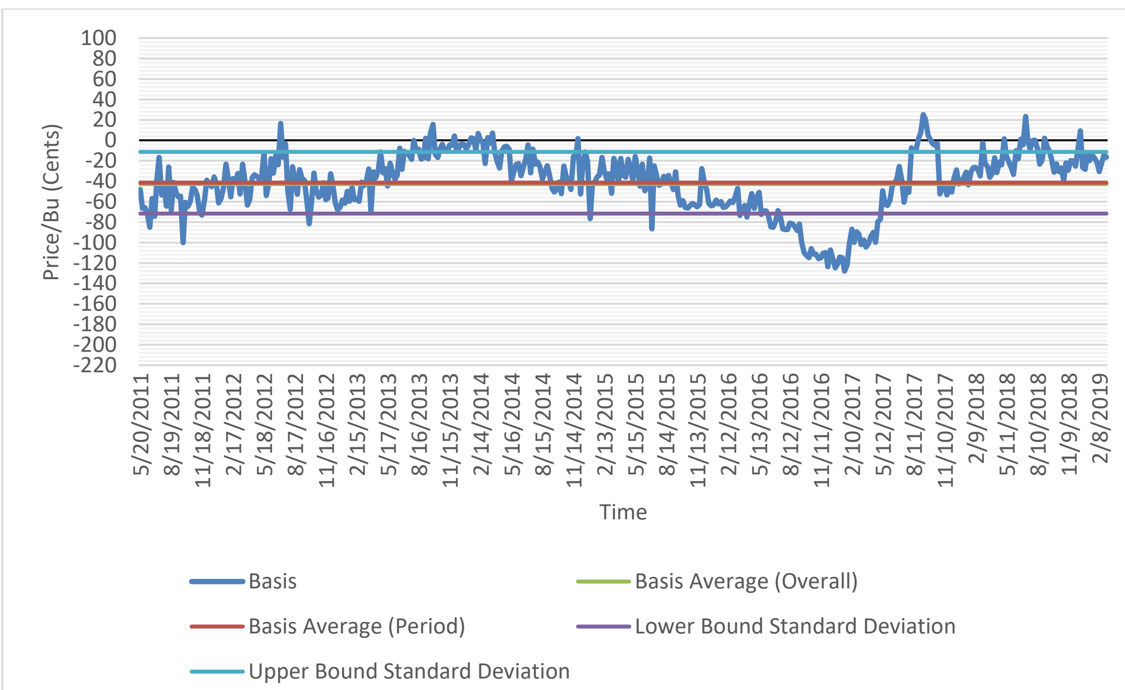


**Figure 40. Weekly Basis: 05/20/2011 – 03/01/2019**

**Table 2. Descriptive Statistics Specs - Overall Data**

| <u>**Statistics Specs: 01/06/94 – 03/01/2019**</u> | | | |
|---|---|---|---|
| | **High-Low Average Futures** | **Cash** | **Basis** |
| **Mean** | 492.76 | 450.00 | -42.75 |
| **Standard Deviation** | 182.14 | 175.45 | 30.73 |
| **Data Range** | 1,002.75 | 1,028.00 | 241.59 |

**Table 3. Basis Regression Analysis Results**

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **F-test** | | 567.172 | **Prob(F)** | | 0.000 | **Unrestricted Model** | | | | | | |
| **MSE1/2** | | 12.818 | **CV Regr** | | -29.92 | **F-test** | | | | 567.12 | | |
| **R2** | | 0.828 | **Durbin-Watson** | | 1.991 | **R2** | | | | 0.828 | | |
| **RBar2** | | 0.827 | **Rho** | | 0.004 | **RBar2** | | | | 0.827 | | |
| **Akaike Info. Criterion** | | 5.109 | **Goldfeld-Quandt** | | 0.000 | **Akaike Info. Criterion** | | | | 5.109 | | |
| **Schwarz Info. Criterion** | | 5.153 | | | | **Schwarz Info. Criterion** | | | | 5.153 | | |
| **95%** | **Intercept** | Time | **Basis T-1** | **Basis T-2** | **Basis T-3** | **Basis T-4** | **Basis T-5** | Basis T-6 | D1: 01/07/94 - 06/13/97 | **D2: 06/07/02 - 07/20/07** | D3: 07/27/07 - 05/13/11 | D4: 05/20/11 - 03/01/19 |
| **Beta** | **-3.759** | -0.003 | **0.395** | **0.230** | **0.086** | **0.063** | **0.139** | -0.020 | 1.500 | **3.246** | -3.537 | 3.572 |
| **S.E.** | 1.665 | 0.004 | 0.028 | 0.030 | 0.030 | 0.030 | 0.030 | 0.028 | 1.579 | 1.633 | 2.445 | 3.450 |
| **t-test** | -2.257 | -0.826 | 14.209 | 7.755 | 2.846 | 2.088 | 4.711 | -0.725 | 0.950 | 1.988 | -1.447 | 1.035 |
| **Prob(t)** | 0.024 | 0.409 | 0.000 | 0.000 | 0.005 | 0.037 | 0.000 | 0.469 | 0.342 | 0.047 | 0.148 | 0.301 |
| **Elasticity at Mean** | | 0.052 | 0.395 | 0.230 | 0.086 | 0.063 | 0.139 | -0.020 | -0.005 | -0.016 | 0.013 | -0.026 |
| **Partial Correlation** | | -0.023 | 0.367 | 0.211 | 0.079 | 0.058 | 0.130 | -0.020 | 0.026 | 0.055 | -0.040 | 0.029 |
| **Semipartial Correlation** | | -0.009 | 0.163 | 0.089 | 0.032 | 0.024 | 0.054 | -0.008 | 0.010 | 0.0228 | -0.016 | 0.011 |

Table 4. Futures Price Volatility Measures (Rolled Over Contracts)

| | Time Periods | | | | |
|---|---|---|---|---|---|
| Method | 01/07/94 - 06/13/97 | 06/20/97 - 05/31/02 | 06/07/02 - 07/20/07 | 07/27/07 - 05/13/11 | 05/20/11 - 03/01/19 |
| **Mean (Open Price)** | 435.73 | 305.42 | 397.79 | 707.92 | 593.81 |
| **Mean (High Price)** | 439.80 | 307.63 | 402.50 | 719.85 | 600.63 |
| **Mean (Low Price)** | 432.14 | 303.20 | 393.92 | 696.85 | 587.25 |
| **Mean (Close Price)** | 436.01 | 305.25 | 398.23 | 707.41 | 593.35 |
| **Mean (High/Low Average Price)** | 435.97 | 305.42 | 398.21 | 708.35 | 593.94 |
| **Standard Deviation (Open Price)** | 78.61 | 27.75 | 68.88 | 183.09 | 147.94 |
| **Standard Deviation (High Price)** | 79.69 | 28.09 | 70.43 | 186.66 | 149.82 |
| **Standard Deviation (Low Price)** | 77.34 | 27.59 | 67.60 | 177.96 | 146.16 |
| **Standard Deviation (Close Price)** | 78.56 | 27.84 | 68.95 | 181.86 | 147.89 |
| **Standard Deviation (High Low Average Price)** | 78.50 | 27.83 | 69.00 | 182.25 | 147.97 |
| **Price Range Average** | 7.66 | 4.43 | 8.57 | 23.00 | 13.38 |
| **Price Range Average of Mean Open Price** | 1.76% | 1.45% | 2.16% | 3.25% | 2.25% |
| **Price Range Average of Mean High Price** | 1.74% | 1.44% | 2.13% | 3.20% | 2.23% |
| **Price Range Average of Mean Low Price** | 1.77% | 1.46% | 2.18% | 3.30% | 2.28% |
| **Price Range Average of Mean Close Price** | 1.76% | 1.45% | 2.15% | 3.25% | 2.25% |
| **Price Range Average of Mean High-Low Average Price** | 1.76% | 1.45% | 2.15% | 3.25% | 2.25% |
| **Data Range** | 384.40 | 133.10 | 320.00 | 824.90 | 574.50 |
| **Data Range of Mean Open Price** | 88.22% | 43.58% | 80.44% | 116.52% | 96.75% |
| **Data Range of Mean High Price** | 87.40% | 43.27% | 79.50% | 114.59% | 95.65% |
| **Data Range of Mean Low Price** | 88.95% | 43.90% | 81.23% | 118.38% | 97.83% |
| **Data Range of Mean Close Price** | 88.16% | 43.60% | 80.36% | 116.61% | 96.82% |
| **Data Range of Mean High-Low Average Price** | 88.17% | 43.58% | 80.36% | 116.45% | 96.73% |

**Table 4. Continued**

| | Time Periods | | | | |
|---|---|---|---|---|---|
| Method | **01/07/94 - 06/13/97** | **06/20/97 - 05/31/02** | **06/07/02 - 07/20/07** | **07/27/07 - 05/13/11** | **05/20/11 - 03/01/19** |
| **Realized Volatility (Open Price)** | 0.20 | 0.17 | 0.22 | 0.27 | 0.29 |
| **Realized Volatility (High Price)** | 0.19 | 0.17 | 0.23 | 0.28 | 0.29 |
| **Realized Volatility (Low Price)** | 0.19 | 0.16 | 0.22 | 0.26 | 0.28 |
| **Realized Volatility (Close Price)** | 0.19 | 0.17 | 0.22 | 0.28 | 0.29 |
| **Realized Volatility (High-Low Average Price)** | 0.19 | 0.17 | 0.22 | 0.27 | 0.28 |

**Table 5. Cash Price Volatility Measures**

| | Time Periods | | | | |
|---|---|---|---|---|---|
| Method | **01/06/94 - 06/12/97** | **06/19/97 - 05/30/02** | **06/06/02 - 07/19/07** | **07/26/07 - 05/12/11** | **05/19/11 - 02/28/19** |
| **Mean** | 413.89 | 260.08 | 376.02 | 620.04 | 552.41 |
| **Standard Deviation** | 80.48 | 32.64 | 67.18 | 181.96 | 157.92 |
| **Price Range Average** | N/A | N/A | N/A | N/A | N/A |
| **Price Range Average of Mean** | N/A | N/A | N/A | N/A | N/A |
| **Data Range** | 408.00 | 152.00 | 289.00 | 867.00 | 624.00 |
| **Data Range of Mean** | 98.58% | 58.44% | 76.86% | 139.83% | 112.96% |
| **Realized Volatility** | 0.20 | 0.25 | 0.28 | 0.37 | 0.38 |

**Table 6. Basis Volatility Measures**

| | Time Periods | | | | |
|---|---|---|---|---|---|
| Method | **01/07/94 - 06/13/97** | **06/20/97 - 05/31/02** | **06/07/02 - 07/20/07** | **07/27/07 - 05/13/11** | **05/20/11 - 03/01/19** |
| **Mean (Open Price)** | -21.84 | -45.34 | -21.77 | -87.88 | -41.40 |
| **Mean (Close Price)** | -22.12 | -45.17 | -22.21 | -87.37 | -40.94 |
| **Mean (High-Low Average Price)** | -22.08 | -45.33 | -22.19 | -88.31 | -41.53 |
| **Standard Deviation (Open Price)** | 14.87 | 13.34 | 10.82 | 29.41 | 30.78 |
| **Standard Deviation (Close Price)** | 13.91 | 13.31 | 9.94 | 26.34 | 29.90 |
| **Standard Deviation (High-Low Average Price)** | 14.32 | 13.27 | 10.39 | 27.83 | 30.16 |
| **Data Range (Open Price)** | 85.44 | 65.78 | 68.37 | 214.58 | 154.88 |
| **Data Range (Close Price)** | 75.71 | 64.79 | 62.94 | 150.75 | 151.88 |
| **Data Range (High-Low Average Price)** | 79.23 | 64.84 | 66.04 | 187.11 | 153.00 |
| **Data Range (Open Price) of Mean Open Price** | 391.14% | 145.08% | 314.13% | 244.16% | 374.13% |
| **Data Range (Close) of Mean Close Price** | 342.32% | 143.44% | 283.43% | 172.54% | 371.01% |
| **Data Range (High-Low Average) of Mean High-Low Average Price** | 358.79% | 143.04% | 297.65% | 211.87% | 368.44% |
| **Realized Volatility (Open Price)** | N/A | N/A | N/A | N/A | N/A |
| **Realized Volatility (Close Price)** | N/A | N/A | N/A | N/A | N/A |
| **Realized Volatility (High-Low Average Price)** | N/A | N/A | N/A | N/A | N/A |

# CHAPTER VI

# CONCLUSION

The focus of this thesis was to research wheat volatility in previous literature and assess basis volatility after having found that the literature on basis volatility was lacking. This analysis concentrated on a twenty-five-year period, specifically from January 1994 to March 2019, and included several metrics in order to shed more light on the subject. Naturally, futures price and cash price volatility were also analyzed since these are the two components of basis.

Over the course of this analysis many of the metrics used to measure volatility for futures prices, cash prices, and basis followed a similar pattern with exceptions. The majority of the metrics measuring futures and cash volatility presented a decrease from period one to period two, an increase in period three, another increase in period four, and a decrease in period five. On the other hand, the majority of metrics measuring basis volatility saw two different patterns not seen for futures and cash. These include a decrease in period two from period one, an increase in period three, a decrease in period four, and an increase in period five for the basis mean and data range as a percentage of the mean calculations. The other pattern seen for the basis volatility metrics includes a decrease from period two from period one, a decrease in period three, an increase in period four, and an increase in period five for the basis standard deviation calculations and one of the data range calculations. The other two data range calculations for basis is included with the pattern mostly found for the futures and cash metrics.

Presenting an interesting story for basis is the fact that the basis metrics follow a different set of patterns when compared to futures and cash prices. Also interesting is that the metrics tasked with measuring basis volatility are split between two different patterns over time as well. The main takeaway from this analysis is that the metrics say little by themselves, but need to be observed holistically as they are all interconnected. Depending on the measure being used, different patterns emerge across futures price, cash price, and basis, so it is difficult to conclude with a concrete statement regarding volatility. For example, the mean and data range as a percentage of the mean calculations follow one trend, the standard deviation follows another, and even the data range calculation is split between two patterns depending on what futures price is used. Furthermore, because basis is a result of futures and cash price, basis volatility is even harder to narrow down and predict; depending on the measure analyzed, different results can be gathered as to whether the current period is similar or different to previous periods, as can be seen by the stark contrast between the standard deviation of periods one and five or the similar data ranges as percentages of the mean in those same periods. Having determined that the results can vary depending on the measure used, the next question to be answered in this thesis was whether futures price or cash price affected basis volatility more. Given the results of realized volatility, and the inability to calculate it for basis, it is our observation that cash price serves as a greater influencer of basis volatility. However, this does not end the analysis of basis volatility or the search for variables that influence it. This analysis was simply a contribution to previous literature and serves as groundwork for future research in this area.

REFERENCES


Anderson, R.W. 1985. "Some Determinants of the Volatility of Futures Prices." *The Journal of Futures Markets*, 5:331-48.

Anderson, R.W., and J. Danthine. 1983. "The Time Pattern of Hedging and the Volatility of Futures Prices." *Oxford University Press.* The Review of Economic Studies 50:249-66.

Balcombe, K. 2011. “The nature and determinants of volatility in agricultural prices: an empirical study”, in A. Prakash eds., *Safeguarding food security in volatile global markets*. Rome: Food and Agriculture Organization of the United Nations.

Ball, C.R. 1930. "The History of American Wheat Improvement." *Agricultural History Society*. Agricultural History 4:48-71.

Benavides, G. 2004. "The Theory of Storage and Price Dynamics of Agricultural Commodity Futures: The Case of Corn and Wheat.” *SSRN Electronic Journal*

Booth, G.G., P. Brockman, and Y. Tse. 1998. "The relationship between US and Canadian wheat futures." *Applied Financial Economics* 8:73-80.

Bourdon, M.H. 2011. “Agricultural Commodity Price Volatility: An Overview.” OECD Food, Agriculture and Fisheries Paper No. 52:1-51

Breaking Down Finance. “Realized Volatility.” Retrieved from: https://breakingdownfinance.com/finance-topics/risk-management/realized-volatility/ (accessed: March 12, 2019).

Buyuksahin, B. 2011. “Volatility: How to measure it.” Retrieved from: http://buyuksahin.blogspot.com/2011/05/volatility-how-to-measure-it.html (accessed: March 7, 2019)

Carpantier, J.-F., and A. Dufays. 2013. “Commodities Inventory Effect.” University of Luxembourg, CREA

Carpantier, J.-F., andA. Dufays. 2012. “Commodities volatility and the theory of storage.” *CORE Discussion Paper* 2012/37

Cashin, P., and C.J. McDermott. 2002. "The Long-Run Behavior of Commodity Prices: Small Trends and Big Variability." *IMF Staff Papers* 49:175-199

Castelino, M.G., and J.C. Francis. 1982. "Basis Speculation in Commodity Futures: The Maturity Effect." *Journal of Futures Markets* 2:195-206.

Choi, J.W., and F.A. Longstaff. 1985. "Pricing Options on Agricultural Futures: An Application of the Constant Elasticity of Variance Option Pricing Model." *The Journal of Futures Markets* 5:247-58.

Crain, S.J., and J.H. Lee. 1996. "Volatility in Wheat Spot and Futures Markets, 1950-1993: Government Farm Programs, Seasonality, and Causality." *The Journal of Finance* 51:325-43.

Dalrymple, D.G. 1998. "Changes in Wheat Varieties and Yields in the United States, 1919-1984." *Agricultural HistorySociety*. Agricultural History 62:20-36.

Dawson, P.J. 2015. "Measuring the Volatility of Wheat Futures Prices on the LIFFE." *Journal of Agricultural Economics* 66:20-35.

Deaton, A., and G. Laroque. 1992. “On the Behaviour of Commodity Prices.” *Review of Economic Studies* 59:1-23.

Debes, J. 2014. “Which Wheat for What?” Retrieved from: http://kswheat.com/news/2014/12/02/which-wheat-for-what (accessed: February 10, 2019).

Du, X., C.L. Yu,and D.J. Hayes. 2011. "Speculation and volatility spillover in the crude oil and agricultural commodity markets: A Bayesian analysis." *Energy Economics* 33:497-503.

Easterling, W.E. 1996. "Adapting North American agriculture to climate change in review." *Agricultural and Forest Meteorology* 80:1-53.

Fama, E.F., and K.R. French. 1987. "Commodity Futures Prices: Some Evidence on Forecast Power, Premiums, and the Theory of Storage." *The Journal of Business* 60:55-73.

Ghoshray, A. 2013. “Dynamic Persistence of Primary Commodity Prices.” *American Journal of Agricultural Economics* 95:153-164

Gilbert, C.L., and C.W. Morgan. 2010. “Has food price volatility risen?” Dept. Economics. No. 2/2010, University of Trento – Italy.

Giles, D.E. 2008. “Some properties of absolute returns as a proxy for volatility.” *Applied Financial Economics Letters* 4:5:347-350

Gilmour, B., and P. Fawcett. 1987. "The Relationship between U.S. and Canadian Wheat Prices." *Canadian Journal of Agricultural Economics* 35:571-89.

Goodwin, B.K., and R. Schnepf. 2000. "Determinants of Endogenous Price Risk in Corn and Wheat Futures Markets." *The Journal of Futures Markets* 20:753-74.

Hennessy, D.A., and T.I. Wahl. 1996. "The Effects of Decision Making on Futures Price Volatility." *American Journal of Agricultural Economics* 78:591-603.

Hudson, D., and K. Coble. 1999. "Harvest Contract Price Volatility for Cotton." *The Journal of Futures Markets* 19:717-33.

Kalev, P.S., and H.N. Duong. 2008. "A Test of the Samuelson Hypothesis using Realized Range." *The Journal of Futures Markets* 28:680-96.

Kansas Department of Agriculture. 2018. “Wheat Sector” Retrieved from: https://agriculture.ks.gov/docs/default-source/ag-growth-summit/january-2018-documents/wheat-sector.pdf?sfvrsn=970380c1_16 (accessed: May, 17, 2019)

Karali, B., and W.N. Thurman. 2010. "Components of Grain Futures Price Volatility." *Journal of Agricultural and Resource Economics* 35:167-82.

Karali, B., J.H. Dorfman, and W.N. Thurman. 2010. “Delivery Horizon and Grain Market Volatility.” *The Journal of Futures Markets* 30:846-873.

Karali, B., and G.J. Power. 2013. “Short- and Long-Run Determinants of Commodity Price Volatility.” *American Journal of Agricultural Economics* 95:724-738.

Karali, B., and G.J. Power. 2009. “What Explains High Commodity Price Volatility? Estimating a Unified Model of Common and Commodity-Specific, High- and Low-Frequency Factors.” Selected paper for presentation at the Agricultural and Applied Economics Association meeting, Milwaukee, Wisconsin, 26-29 July.

Kenton, W. 2019. “Sum of Squares.” Retrieved from: https://www.investopedia.com/terms/s/sum-of-squares.asp (accessed: March 5, 2019)

Kenyon, D., K. Kling, J. Jordan, W. Seale, and N. McCabe. 1987. "Factors Affecting Agricultural Futures Price Variance." *The Journal of Futures Markets* 7:73-91.

Khan, B.F. 2014. “Determinants of Futures Price Volatility of Storable Agricultural Commodities: The Case of Cotton.” MS Thesis, Texas Tech University.

Khoury, N.,and P. Yourougou. 1993. "Determinants of Agricultural Futures Price Volatilities: Evidence from Winnipeg Commodity Exchange." *The Journal of Futures Markets* 13:345-56.

Kislev, M.E. 1984. "Emergence of Wheat Agriculture."*Paléorient* 10:61-70.

Koekebakker, S., and G. Lien. 2004. "Volatility and Price Jumps in Agricultural Futures Prices-Evidence from Wheat Options." *American Journal of Agricultural Economics* 86:1018-31.

McCalla, A.F. 2009. "World Food Prices: Causes and Consequences." *Canadian Journal of Agricultural Economics* 57:23-34.

Miller, K.D. 1979. “The Relation Between Volatility and Maturity in Futures Contracts.”*Commodity Markets and Futures Prices*

Milonas, N.T. 1986. "Price Variability and the Maturity Effect in Futures Markets." *The Journal of Futures Markets* 6:443-60.

Nath, G.C., and T. Lingareddy. 2008. “Impact of Futures Trading on Commodity Prices.” *Economic and Political Weekly* 43:18-23.

Olmstead, A.L., and P.W. Rhode. 2002. "The Red Queen and the Hard Reds: Productivity Growth in American Wheat, 1800-1940." *NBER working paper series*. NBER working paper series: 8863. Nation Bureau of Economic Research, Cambridge, MA.

Olmstead, A.L., and P.W. Rhode. 2010. "Adapting North American wheat production to climatic challenges, 1893 – 2009."Department of Economics. University of California, Davis CA and Department of Economics, University of Michigan, Ann Arbor, MI.

Paulsen, G.M., and J.P. Shroyer. 2008. "The Early History of Wheat Improvement in the Great Plains." *Agronomy Journal* 100:70.

Quisenberry, K. S., and L. P. Reitz. 1974. "Turkey Wheat: The Cornerstone of an Empire." *Agricultural History Society*. Agricultural History 48:98-110.

Rutledge, D.J.S. 1976. "A Note on the Variability of Futures Prices." *The MIT Press*/ The review of economics and statistics 58:118-20.

Salmon, S.C., O.R. Mathew, and R.W. Leukel. 1953. *A Half Century of Wheat Improvement in the United States*. Beltsville, Maryland: U.S. Department of Agriculture. 3-141.

Sekhar, C.S.C. 2003. "Price formation in world wheat markets - implications for policy." *Journal of Policy Modeling* 25:85-106.

Silveira, R.L.F.d., L.d.S. Maciel, F.L. Mattos, and R. Ballini. 2017. "Volatility persistence and inventory effect in grain futures markets: evidence from a recursive model." *Revista de Administração* 52:403-18.

Smith, A. 2005. “Overlapping Time Series: A New Model for Volatility Dynamics in Commodity Futures.” *Journal of Applied Econometrics* 20:405-442.

Streeter, D.H., and W.G. Tomek. 1992. "Variability in Soybean Futures Prices: An Integrated Framework." *The Journal of Futures Markets* 12:705-28.

Sumner, D. 2009. "Recent Commodity Price Movements in Historical Perspective." *American Journal of Agricultural Economics* 91:1250-6.

Vivian, A., and M.E. Wohar. 2012. "Commodity volatility breaks." *Journal of International Financial Markets, Institutions & Money* 22:395-422.

Wang, Y., and Roberts, M.C. 2004. “Forecasting Daily Volatility Using Range-based Data.” Selected paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Denver, Colorado, 1-4 August.

Wishart, D.J., ed. 2005. *ENCYCLOPEDIA OF THE GREAT PLAINS*. University of Nebraska Press.

Yang, J., R.B. Balyeat, and D.J. Leatham. 2005. "Futures Trading Activity and Commodity Cash Price Volatility." *Journal of Business Finance & Accounting* 32:297-323.

Yang, J., J. Zhang, and D.J. Leatham. 2003. "Price and Volatility Transmission in International Wheat Futures Markets." *Annals of Economics and Finance* 4:37-50.

Yang, S., and B.W. Brorsen. 1993. "Nonlinear Dynamics of Daily Futures Prices: Conditional Heteroskedasticity or Chaos?" *The Journal of Futures Markets* 13:175-91.

Yang, J., M.S. Haigh, and D.J. Leatham. 2001. "Agricultural liberalization policy and commodity price volatility: a GARCH application." *Applied Economic Letters* 8:593-598.

Zheng, Z., Z. Qiao, T. Takaishi, H.E. Stanley, and B. Li. 2014. "Realized Volatility and Absolute Return Volatility: A Comparison Indicating Market Risk." Retrieved from: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4108408/ (accessed: March 11, 2019).