THE EFFICIENCY OF THE U.S. COTTON FUTURES MARKET (1986-2006): NORMAL BACKWARDATION, CO-INTEGRATION, AND ASSET-PRICING

A Thesis

by

MARISSA JOYCE CHAVEZ

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

MASTER OF SCIENCE

August 2007

Major Subject: Agricultural Economics

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Approved by:

Chair of Committee,	Victoria Salin
Committee Members	John Robinson
	David Bessler
	Detlef Hallermann
Head of Department	John Nichols

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ABSTRACT

The Efficiency of the U.S. Cotton Futures Market (1986-2006): Normal Backwardation, Co-Integration, and Asset Pricing. (August 2007)

Marissa Joyce Chavez, B.S., Texas A&M University

Chair of Advisory Committee: Dr. Victoria Salin

The efficiency of commodity futures markets is a widely debated topic in academia. The cotton futures market is no exception. The existence of trends in the futures market is characterized as a price bias, which is a testable trait. When analyzed, it allows a better understanding of market behavior and allows implementation of more effective income enhancing and/or risk reducing strategies. Three different approaches will be used to test the efficiency of the U.S. cotton futures market: pricing patterns, co-integration, and asset-pricing.

In the first approach, pricing patterns, statistical methodology was applied to a dataset of daily futures prices. Returns did not show a consistent trend, supporting arguments of efficiency. Further research into seasonally-differentiated contracts has yielded strong evidence of declining prices. This result differs from previously published work in the most comprehensive study of futures prices, while updating and extending information on pricing patterns in the cotton futures market.

Co-integration, the second approach, is a popular method for testing the efficiency of various commodity future and cash markets. Evidence indicates that the cotton futures and cash markets are co-integrated over the last ten years. Results lead to

the conclusion that price is discovered in the cotton futures market, reinforcing the notion of an efficient cotton futures market that serves as an indicator for future cotton cash prices.

The cotton futures market was also analyzed to explain price movements with an equilibrium asset-pricing framework, in the third approach. In particular, the cotton futures market was analyzed to determine if behavior displayed by the market could be explained by risks specific to the cotton futures contract. Cotton futures do not show significant risk premiums over other financial assets, again supporting the efficient market hypothesis.

The three approaches implemented in this thesis are generally supportive of long-run efficiency in the U.S. cotton futures market. An updated analysis of the cotton futures market will allow market participants the most recent information on pricing patterns and the overall long-run behavior of the market. More effective trading and operating strategies can be implemented that will best meet needs of market participants.

DEDICATION

This thesis is dedicated to my family members and friends who showed me love and support throughout my graduate school career; in particular, to my mom for always believing in me and supporting me. A special thanks also goes to my sisters and roommates, Cynthia and Theresa, and to my brother Rene, for "putting up with me" through the whole process. I would also like to thank my grandma and my aunt for always being there for me, along with everyone at their end. Another special thanks goes to Guillermo for always being able to make me smile. My graduate school experience would not have been the same without you. Without the encouragement from these special individuals, this thesis would not have been possible.

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A special thanks goes to Caroline Gleaton for her assistance and for providing me with the data for my research, and to Ellen DeVries for all of her assistance. I would also like to thank and acknowledge Dr. Fisher, whom I worked for as a teaching assistant my first semester as a graduate student. It was during one of his classes that I got the inspiration for my thesis topic. There are many other individuals whom I would like to acknowledge for their support and friendship; among them are Rafael, Alex, Meri, Lisa, and Hart.

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CHAPTER I

INTRODUCTION

Market Efficiency and Thesis Objectives

Eugene Fama's introduction in 1970 of the efficient market hypothesis has generated much discussion about the efficiency of various financial markets. According to the efficient market hypothesis, prices of assets will reflect all available, relevant information at a given point in time. Madura, in his 2006 work, describes the three forms of market efficiency: weak, semi-strong, and strong. If a market displays weak form market efficiency, then that market's prices fully reflect all trade related information; therefore there are no abnormal returns to be made using a trading strategy based on historical pricing patterns. In the semi-strong form of market efficiency, a security's price will reflect all publicly available information and abnormal returns could be made using private information that was not immediately transferred to in market prices. Strong form market efficiency states that a security's price will reflect all information, both public and private. Various tests have been developed by financial analysts to determine the efficiency level of different types of financial markets (Madura 2006).

The concern over a market's efficiency level is relevant to all market participants. In the futures market, hedgers want to minimize their risk. Speculators, in contrast, are intent on making profits. For the purpose of this thesis, cotton producers, cotton production cooperatives, and cotton merchandising firms will be considered as

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This thesis follows the style of the *American Journal of Agricultural Economics*.

the market hedgers interested in minimizing their risk while large investment funds, who have the ability to influence the market and may have access to the most current market information, will be considered the market speculators, intent on making profits. Both hedgers and speculators need an efficient market that reflects current supply and demand conditions. Further, hedgers need this efficiency to influence both the futures and cash markets in order for hedging to be feasible. However, hedgers and speculators are not the only interested parties when discussing the efficiency of a particular commodity's market. Governments, both domestic and foreign, must also monitor commodity markets and consider their efficiency when developing domestic and foreign policies that deal with the commodity in question.

Building on the importance of agricultural futures markets, and in particular cotton, we will analyze the efficiency of the last twenty years of the U.S. cotton futures market. The objective of this thesis is to determine if the U.S. cotton futures market is functioning efficiently according to Madura's definitions of efficiency. Three different approaches will be employed to study efficiency in the U.S. cotton futures market, using an extensive dataset with cotton futures settlement prices from 1986 through 2006. The first test is an extension of Kolb's 1992 study, which used price differences and statistical tests to examine price patterns. More recently, futures market efficiency has been examined with time series econometric techniques which identify co-integration between the cotton futures settlement prices and cotton spot/cash prices. The co-integration procedures are applied to daily data for five cash markets over 20 years. Finally, an equilibrium asset pricing framework, following procedures adopted by

Bessembinder and Chan's 1992 study of risk premia and forecastable returns in futures markets was used for the third test of efficiency.

Futures Background

Futures markets were originally developed to meet the needs of farmers and merchants. They provided some protection from price fluctuations and market uncertainties. Modern day agricultural futures markets in the U.S. were developed in the early nineteenth century and were tied to the growing trade of grains and the commercial development in the Midwestern frontier. The growing grain trade and development of the frontier eventually led to the development of the Chicago Board of Trade in 1848 and the New York Cotton Exchange in 1870, which would eventually become the New York Board of Trade (Duncan 1992).

Today, futures markets play an important role as a mechanism for price discovery. The information from futures markets is instantly relayed worldwide, assisting many participants in commodity production and trade to finalize contract terms, facilitate efficient exchanges, and make business plans. Because of the importance of futures markets in assisting commerce, they are regulated to prevent market manipulation that would advantage one group of participants over another.

A futures contract, as defined by Hull (2005), is a standardized agreement to buy or sell an asset at a certain time in the future for a certain price and is traded on organized exchanges. This differs from a forward contract, which is a customized agreement to buy or sell an asset at a pre-determined time in the future for a pre-determined price and is traded over-the-counter. The major players in futures markets are hedgers and speculators. Hedgers use futures markets to reduce their exposure to unexpected movements in prices while speculators use the markets to capitalize on expected future price movements. There are two positions that a market player can take: long or short. A long position entails buying of the futures asset while a short position entails selling futures contracts. While all futures contracts specify a delivery date for the underlying asset, less than 2% are actually held until delivery. Most contracts are closed out prior to their expiration date (i.e. that those with long positions will sell their contracts, while those with short positions will buy back their contracts).

Cotton Market Background

According to the most recent Cotton Outlook Report published by the U.S. Department of Agriculture's Economic Research Service in 2007, "cotton is the single most important textile fiber in the world accounting for about 40 percent of all fibers produced." Cotton is known as a universal fiber and is grown in 17 states in the U.S., with the farm value of U.S. cotton exceeding $4.68 billion. The U.S. exports between 6 and 9 million bales of cotton annually, making the U.S. the leading supplier of cotton in the international market (National Cotton Council; Meyer 2007). Cotton contributes over $120 billion in annual retail value to the U.S. economy (National Cotton Council 2007). Because of its importance to economies, it was even used as a currency in the development of world trade. Today, cotton continues to be a vital crop for several regional U.S. economies and economies around the world.

The U.S. cotton industry has faced several challenges in recent years. One of the most notable changes has been the shift from being a largely domestic market to an export-oriented market. Other issues that have arisen in the cotton industry that deal with political policies and include the phase out of Step II and the termination of the Multi-fiber Arrangement (Meyer et al.). In the Step II program, payments were made to domestic users and exporters based on market deviations from the U.S. loan rate. The Multi-fiber Arrangement allowed for country-by-country negotiations of import limitations, allowing for the restriction of imports from developing countries by industrialized countries. A new challenge being faced by the cotton industry deals with the development of ethanol-related demand for corn acreage. As agricultural producers consider the future for ethanol demand, there is potential for shifts in acreage from cotton to those crops used in the production of ethanol (Robinson 2007).

Many studies focusing on the efficiency and forecastability of specific agricultural commodities have been conducted over the years. Tomek summarized these studies in 1997 with the overall consensus that futures markets display weak-form efficiency, meaning that the current price reflects all information that can be found in past prices. Tomek also stated that for results to be good indicators of a market's efficiency, researchers must note any structural changes within the markets, outliers and non-stationary price series, and have an adequate sample size. I have taken all of these into consideration during the process of this thesis.

Most efficiency tests are conducted to investigate the weak-form of efficiency, including Kolb's study (the focus of chapter III) as well as a study by Brorsen, Bailey, and Richardson (1984). Brorsen et al. studied on the cotton futures and cash market between 1976 through 1982. They were interested in determining price discovery and efficiency between the two markets and found evidence of inefficiency for this particular time frame in the cotton market. They did determine, however, that the spot price was discovered in the futures market.

Once the efficiency of a market is determined, the next question usually entails the performance of profitable income enhancing strategies. Wood, Shafer, and Anderson completed a study in 1989 on the opportunities for profitable hedging margins for Texas cotton producers during the 1980 through 1986 period. They concluded that daily profit margins occurred frequently for the cotton producers in the Texas high plains area, with more profitable hedging margins in the pre-planting season than the growing season.

Thesis Organization and Chapter Summary

Few studies exist that focus purely on the efficiency of the cotton cash and futures market. Those that have been completed use data from only a few years, which limits conclusions that can be drawn regarding long-term market performance. The remainder of this thesis will focus on determining if the cotton futures and cash markets are functioning efficiently by performing tests on normal backwardation, co-integration, and asset pricing.

Following a discussion of the data used in this research, the subsequent chapters will discuss the tests used for detecting pricing patterns and forecastability of the U.S. cotton futures market using economic indicators. Chapter III discusses the Kolb section of the research, Chapter IV considers the subject of co-integration between the cotton cash and futures markets, while Chapter V focuses on the economic indicators portion of the research. Within Chapters III, IV and V, a review of past studies will be discussed along with economic interpretations. Following will be the procedures that were followed and the results obtained from those procedures. Each chapter will close with a brief summary. A more in-depth summary of the thesis as a whole will follow Chapter V. This chapter will also include conclusions about the cotton futures and cash markets and the implications that they hold for all market players.

CHAPTER II

DATA DESCRIPTION

To effectively test the efficiency of the cotton market, data on cotton futures and cotton cash prices are essential. For certain models, the prices of the futures contracts are compared with other data, including cash prices of cotton and other economic variables. An extensive dataset, totaling over 60,500 observations, was used in this statistical study to test the efficiency of the U.S. cotton futures market. They can be classified into three different data types: cotton futures settlement[1] prices, cotton cash prices, and economic indicator data. Each data type will be described below with accompanying statistical tables and graphs.

Cotton Futures Data

Data consisted of daily settlement prices for the Cotton No. 2 futures contract, traded at the New York Board of Trade (NYBOT 2006). There are five different cotton futures contracts, representing its delivery month: March, May, July, October and December. An individual Cotton No. 2 futures contract is 50,000 pounds net weight with physical delivery, and is quoted in cents and hundredths of a cent per pound. Delivery points include Galveston, Texas; Houston, Texas; New Orleans, Louisiana; Memphis, Tennessee; and Greenville/Spartanburg, South Carolina. The Cotton No. 2

[1] Hull defines a futures settlement price as the price that is used in calculating daily gains and losses, and margin requirements. It is not necessarily the price that is quoted when trading stops, but rather an average of the prices at which the contract traded just before trading for that day stopped.

futures contract requires the underlying asset to be of strict low middling grade with a staple length of 1 and 2/32nd inches (New York Board of Trade).

Each contract beginning with the 1997 contract is roughly two years, or 24 months in length. For example, the December 2002 contract begins trading on December 14, 2000 and settles on December 9, 2002. Prior to 1997, each contract traded for approximately 18 months. The last trading day is seventeen business days from the end of the delivery month. The first notice day is five business days before the end of the spot contract month, while the last notice day is twelve business days from the end of the spot month. There is a 3 cent daily price limit on the trading cotton futures contracts. The daily settlement price cannot move above or below the previous day's settlement price by 3 cents. The exception is if a contract settles at or above $1.10 per pound, then all contract months will employ a 4 cent price limit (New York Board of Trade). Trading closes in the event of limit moves in order to prevent wide swings in prices that could disrupt the market. We chose the December cotton futures contracts to sample the number of times cotton futures prices reached the limit and to determine if this would be a problem in our data analysis. Table 1 displays the number of times that the daily price limit was reached in each December contract from 1987 through 2006. December futures only reached the daily price limit 26 times out of 8,476 possible times in the last twenty years; therefore, daily price limits should not pose a problem for cotton futures price data analysis.

Table 1. Results of the Market Limit Tests for the December Cotton Futures Contracts Using Daily Settlement Prices, Entire Contract

Contract	Limit Up	Limit Down	Total Daily Obs.
1987	0	0	362
1988	0	1	365
1989	0	0	363
1990	0	0	363
1991	0	0	360
1992	0	0	366
1993	0	0	362
1994	0	0	363
1995	4	3	362
1996	2	0	357
1997	0	0	487
1998	0	0	486
1999	0	0	485
2000	1	0	491
2001	0	0	486
2002	2	2	484
2003	1	2	484
2004	3	1	480
2005	2	1	484
2006	0	1	486
Total	15	11	8476

Source: NYBOT futures price settlement data

Twenty years of daily settlement prices (1986-2006) for each of the five monthly cotton contracts were analyzed, resulting in twenty individual contracts for each contract month. The first contract in the dataset was the 1987 contract which has price data beginning in 1986. The last contract in the dataset is the 2006 contract which has price data beginning in 2004. A total of 100 individual cotton futures contracts were used in this study. The total number of price observations for the full dataset totaled over 42,000 (all data were gathered from the New York Board of Trade at www.nybot.com). The

Nearby futures series, also gathered from the New York Board of Trade, can be defined as the cotton futures contract that has the closest settlement date out of all cotton futures contracts that are being traded at any one time (Robinson). The Nearby data represents the rolling over of a long position in a risky asset which may require a risk premium. Using an asset's Nearby data is done often in the literature and can be found in procedures adopted by Bessembinder and Chan, which will be examined in detail in chapter V.

Tables 2 through 7 show the average settlement prices of each of the twenty contracts for each of the five different cotton futures contracts (March, May, July, October, and December) and for the Nearby series. Included in each of the five tables are the standard deviation for the average contract price and the coefficient of variation for each individual contract. The coefficient of variation is included to give readers an idea of the risk/return tradeoff of cotton prices. As a general rule of thumb, the lower the ratio, the better the risk/return tradeoff. Cotton futures prices peaked in 1996 at over 78 cents per pound for the March, May, October and December contracts. The July contract peaked in 1995 with the average settlement prices of 1996 a close second. As for the Nearby futures series, prices peaked in 1995 with an average of 93.88 cents/lb. Average nearby futures prices for 1996 was 78.16 cents/lb. Figures 1 through 6 show the daily prices of the twenty contracts for each of the five different cotton futures contracts and for the Nearby series.

Table 2. Summary Statistics for the Entire March Cotton Futures Contract, Daily Price Settlement Range from 1986-2006

Contract	Mean (¢/lb)	Std. Deviation (¢/lb)	Coeff. of Variation (%)
1987	45.92	8.1748	17.80
1988	63.50	8.9727	14.13
1989	59.41	4.5570	7.67
1990	66.69	7.1236	10.68
1991	71.32	5.4604	7.66
1992	66.06	5.9126	8.95
1993	61.53	3.9099	6.35
1994	62.26	5.3470	8.59
1995	74.33	9.8913	13.31
1996	79.21	5.7367	7.24
1997	76.95	2.7749	3.61
1998	75.45	3.9831	5.28
1999	72.06	5.1361	7.13
2000	62.67	8.1276	12.97
2001	61.23	3.5858	5.86
2002	52.75	12.1590	23.05
2003	47.15	4.2444	9.00
2004	60.92	8.0924	13.28
2005	59.29	9.5975	16.19
2006	55.94	4.8713	8.71

Source: NYBOT daily cotton futures settlement prices

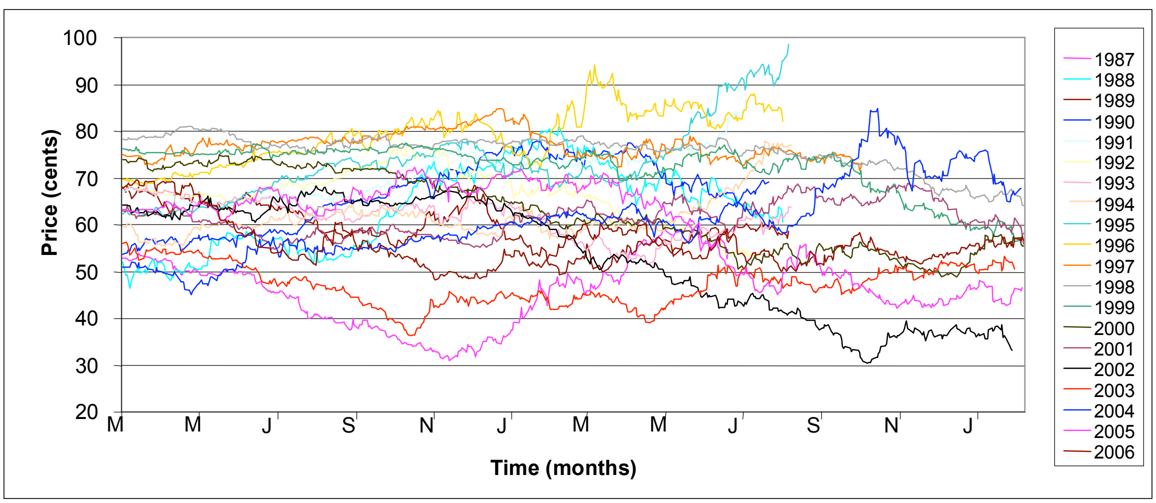

Figure 1. March Contracts: Cotton Futures Settlement Prices, 1986-2006
(Source: NYBOT cotton futures price data)

Table 3. Summary Statistics for the Entire May Cotton Futures Contract, Daily Price Settlement Range from 1986-2006

Contract	Mean (¢/lb)	Std. Deviation (¢/lb)	Coeff. of Variation (%)
1987	47.29	8.6502	18.29
1988	65.32	7.7785	11.91
1989	59.28	4.1745	7.04
1990	69.25	6.1834	8.93
1991	73.85	6.8892	9.33
1992	65.81	6.0710	9.23
1993	61.48	3.3836	5.50
1994	65.35	7.0961	10.86
1995	79.55	12.7419	16.02
1996	81.31	4.7005	5.78
1997	77.22	2.9568	3.83
1998	74.98	4.5561	6.08
1999	71.05	6.1613	8.67
2000	62.12	7.3806	11.88
2001	60.55	5.5896	9.23
2002	51.27	12.3707	24.13
2003	49.66	4.7508	9.57
2004	63.02	7.2535	11.51
2005	59.24	9.6738	16.33
2006	55.27	3.2260	5.84

Source: NYBOT daily cotton futures settlement prices

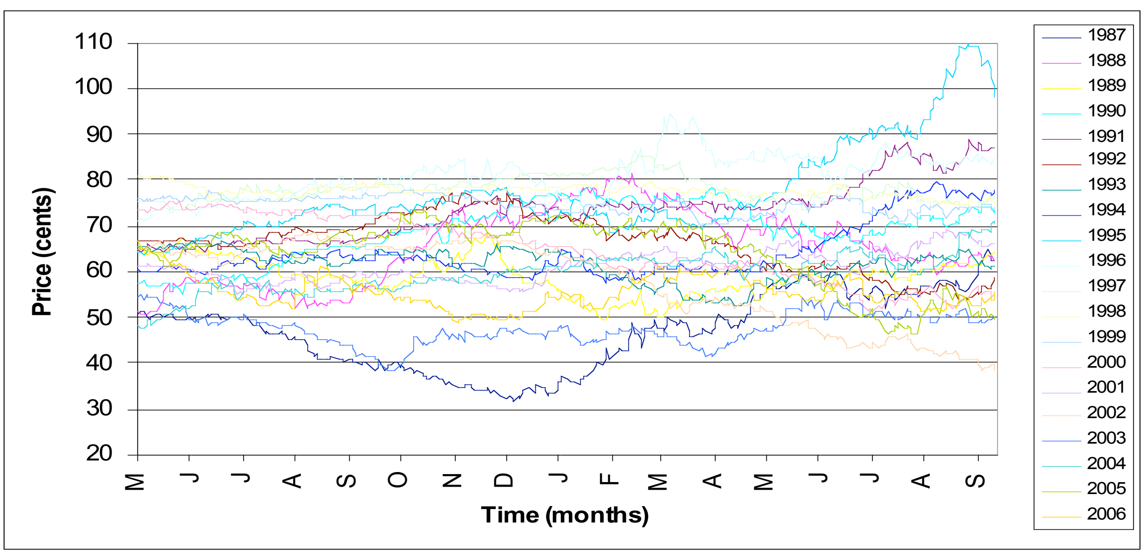

Figure 2. May Contracts: Cotton Futures Settlement Prices, 1986-2006
(Source: NYBOT cotton futures price data)

Table 4. Summary Statistics for the Entire July Cotton Futures Contract, Daily Price Settlement Range from 1986-2006

Contract	Mean (¢/lb)	Std. Deviation (¢/lb)	Coeff. of Variation (%)
1987	50.30	11.7897	23.44
1988	67.11	6.5570	9.77
1989	59.98	4.6294	7.72
1990	71.54	6.2565	8.74
1991	75.34	6.9854	9.27
1992	65.82	5.9116	8.98
1993	61.27	3.2169	5.25
1994	67.76	7.8129	11.53
1995	83.73	13.5094	16.13
1996	82.03	4.2923	5.23
1997	77.36	2.8897	3.74
1998	75.09	4.4024	5.86
1999	69.72	7.4354	10.66
2000	61.43	6.3504	10.34
2001	59.70	7.6944	12.89
2002	50.16	11.9428	23.81
2003	50.87	4.8477	9.53
2004	64.00	7.0117	10.96
2005	58.71	9.7610	16.63
2006	55.40	2.9174	5.27

Source: NYBOT daily cotton futures settlement prices

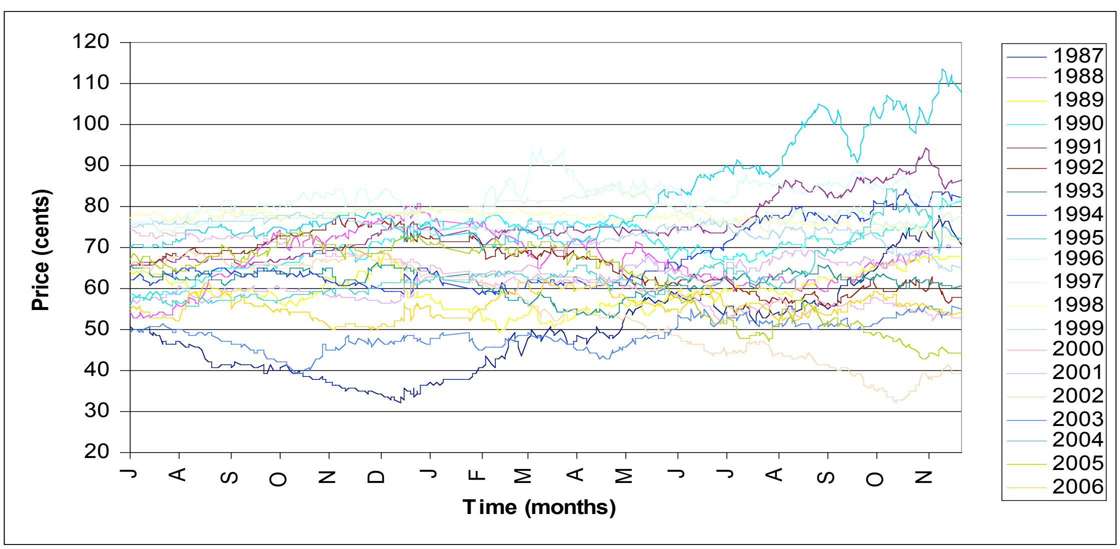

Figure 3. July Contracts: Cotton Futures Settlement Prices, 1986-2006
(Source: NYBOT cotton futures price data)

Table 5. Summary Statistics for the Entire October Cotton Futures Contract, Daily Price Settlement Range from 1986-2006

Contract	Mean (¢/lb)	Std. Deviation (¢/lb)	Coeff. of Variation (%)
1987	50.30	11.7897	23.44
1988	67.11	6.5570	9.77
1989	59.98	4.6294	7.72
1990	69.89	3.6596	5.24
1991	69.81	4.4291	6.34
1992	63.01	3.6654	5.82
1993	60.16	2.9434	4.89
1994	67.53	5.9972	8.88
1995	77.74	6.8935	8.87
1996	78.10	3.2393	4.15
1997	76.49	2.1691	2.84
1998	74.46	2.8169	3.78
1999	65.93	8.4646	12.84
2000	60.90	4.3438	7.13
2001	56.51	9.8334	17.40
2002	47.69	8.6552	18.15
2003	53.38	5.5265	10.35
2004	61.06	6.0891	9.97
2005	56.18	7.5048	13.36
2006	55.79	2.9380	5.27

Source: NYBOT daily cotton futures settlement prices

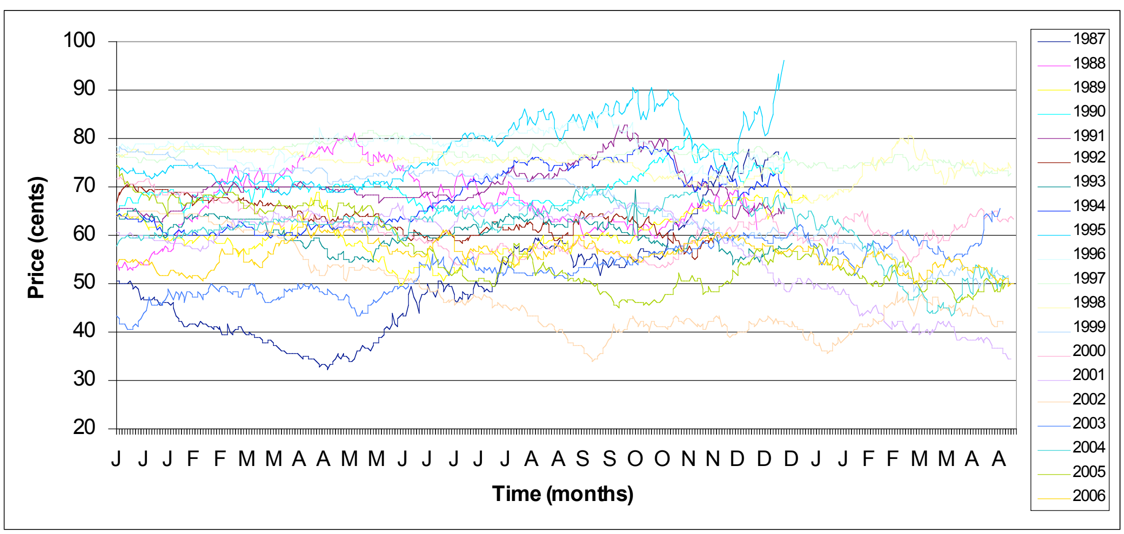

Figure 4. October Contracts: Cotton Futures Settlement Prices, 1986-2006
(Source: NYBOT cotton futures price data)

Table 6. Summary Statistics for the Entire December Cotton Futures Contract, Daily Price Settlement Range from 1986-2006

Contract	Mean (¢/lb)	Std. Deviation (¢/lb)	Coeff. of Variation (%)
1987	58.40	12.7910	21.90
1988	60.40	5.3859	08.92
1989	63.86	7.7367	12.12
1990	68.62	3.5961	5.24
1991	67.26	3.7847	5.63
1992	61.81	4.4410	7.18
1993	59.65	2.3816	3.99
1994	68.06	5.3851	7.91
1995	76.26	6.1884	8.11
1996	76.27	2.9466	3.86
1997	75.81	2.1669	2.86
1998	73.38	3.0622	4.17
1999	63.93	8.2320	12.88
2000	60.63	3.3848	5.58
2001	54.83	11.1133	20.27
2002	47.14	6.7798	14.38
2003	56.46	7.2912	12.91
2004	60.20	7.5969	12.62
2005	55.69	6.5774	11.81
2006	56.50	3.3546	5.94

Source: NYBOT daily cotton futures settlement prices

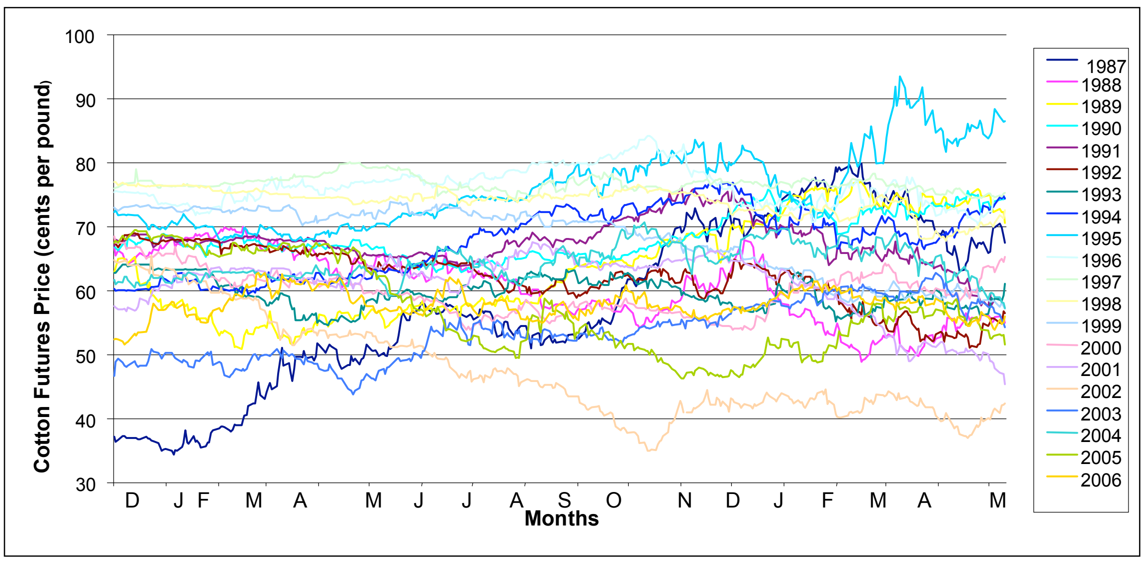

Figure 5. December Contracts: Cotton Futures Settlement Prices, 1986-2006
(Source: NYBOT cotton futures price data)

Table 7. Summary Statistics for the Nearby Cotton Futures Price Series, Daily Price Quotes from 1986-2006

Year	Mean (¢/lb)	Std. Deviation (¢/lb)	Coeff. of Variation (%)
1986	44.93	7.9251	17.64
1987	67.61	7.8149	11.56
1988	59.92	4.8509	8.10
1989	67.74	5.8144	8.58
1990	74.20	4.8457	6.53
1991	73.84	11.3050	15.31
1992	57.99	3.4141	5.89
1993	59.78	2.9253	4.89
1994	75.26	5.5404	7.36
1995	93.88	12.2002	13.00
1996	78.16	5.3321	6.82
1997	72.44	2.1736	3.00
1998	69.01	5.3561	7.76
1999	54.92	4.7735	8.69
2000	60.19	3.8983	6.48
2001	42.96	8.9956	20.94
2002	41.33	4.9655	12.01
2003	59.69	8.4190	14.10
2004	55.45	10.1139	18.24
2005	50.37	3.2980	6.55
2006	52.17	2.7254	5.22

Source: NYBOT daily nearby cotton futures prices

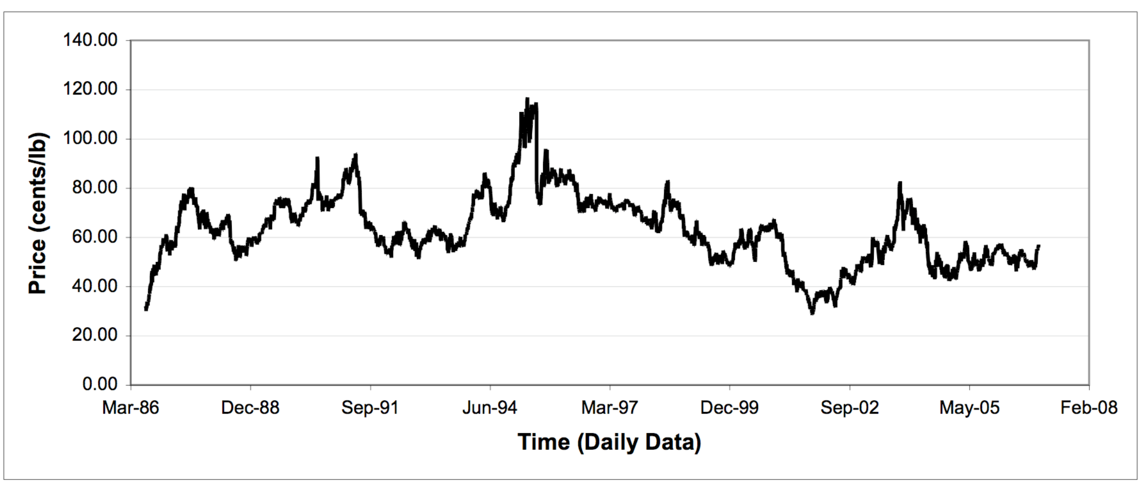

Figure 6. Nearby Cotton Futures Daily Price Quotes, 1986-2006
(Source: NYBOT daily nearby cotton futures prices)

Cotton Cash Price Data

Daily cotton cash price quotes, sometimes referred to as spot prices, from 1987 through 2006, were collected from the United States Department of Agriculture's (USDA) Agricultural Marketing Service and included the Dallas, Lubbock, Memphis, and Adjusted World Price (AWP) series. The Dallas, Lubbock, and Memphis price series represents the spot price of cotton in those particular production regions. The Dallas cotton cash price series represents the raw cotton cash price of cotton for East Texas, while the Lubbock cotton cash price series represents the raw cotton cash price of cotton for West Texas (Robinson).

The Adjusted World Price is a figure that is calculated weekly by the USDA and is based on the A-Index of world prices (Robinson). Price data from the A-Index was also collected from Cotton Outlook (2006). Cotton Outlook is published by Cotlook Limited, which is an independent company that has published cotton news for the last 80 years. The A-Index is the price that is used to represent the value for raw cotton in the international market (Cotlook). It is used in the calculations of the Adjusted World Price and when calculating the Loan Deficiency Payment. The A-Index represents cotton with base quality of cotton of Middling 1-3/32 inches delivered to Northern Europe. The Adjusted World Price and the A-Index price series were included in our dataset because they represent cotton prices at the national and international levels.

Tables 8 through 12 show the basic price statistics for each of the cash series. Included in each of the five tables are the average of the price series for the last twenty years, the standard deviation for the average contract price and the coefficient of variation for each individual contract. A chart that graphs the individual price/rate series accompanies each table and are labeled as figures 7 through 11. Similar price patterns can be seen in figures 7 through 11. Cotton cash prices peaked in 1995 for the Dallas, Lubbock, and Memphis price series, which coincides with the peak of the Nearby series. For example, the Dallas cash prices for cotton in 1995 averaged 93.88 cents/lb, with average cash prices in 1996 (75.95 cents/lb) coming in second highest. Both the Adjusted World Price and the A-Index peaked in 1995 as well, with average prices reaching 97.74 (cents/lb) for the A-Index and 80.43 (cents/lb).

Table 8. Summary Statistics for the Dallas Cotton Cash Price Series, Daily Price Quotes from 1986-2006

Year	Mean (¢/lb)	Std. Deviation (¢/lb)	Coeff. of Variation (%)
1986	39.02	10.6461	27.28
1987	62.26	6.7011	10.76
1988	55.08	3.7858	6.87
1989	61.80	4.7358	7.66
1990	68.34	4.2577	6.23
1991	67.05	8.8666	13.22
1992	53.11	3.6432	6.86
1993	55.19	1.9337	3.50
1994	73.39	4.7046	6.41
1995	91.73	9.1760	10.00
1996	75.95	4.5721	6.02
1997	68.84	2.1077	3.06
1998	64.75	5.0826	7.85
1999	50.16	3.5832	7.14
2000	55.92	4.0935	7.32
2001	39.61	8.3085	20.98
2002	36.06	4.7098	13.06
2003	55.81	7.6957	13.79
2004	51.72	9.0751	17.55
2005	45.91	2.7087	5.90
2006	47.64	1.4110	2.96

Source: Dallas cash price quotes reported by USDA Agricultural Marketing Service

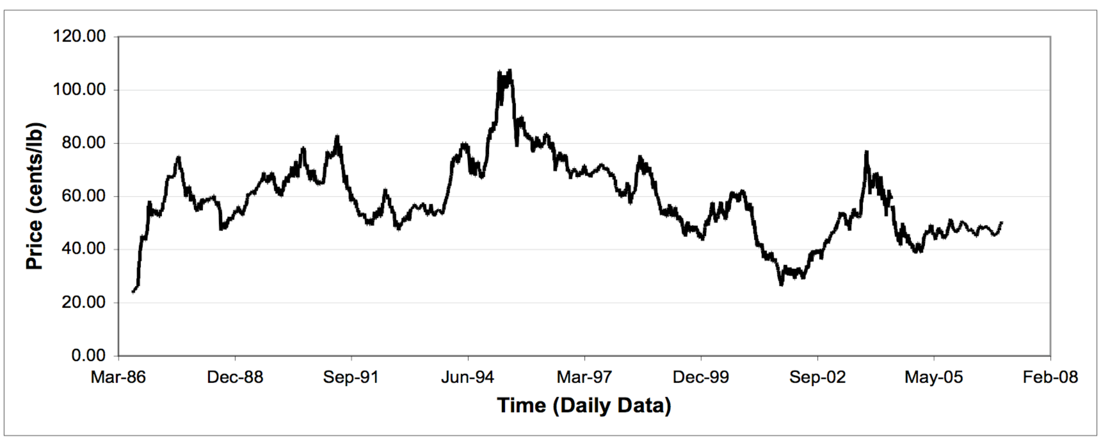

Figure 7. Dallas Cash Cotton Prices, Daily Quotes 1986-2006
(Source: Dallas cash price quotes reported by USDA Agricultural Marketing Service)

Table 9. Summary Statistics for the Lubbock Cotton Cash Price Series, Daily Price Quotes from 1986-2006

Year	Mean (¢/lb)	Std. Deviation (¢/lb)	Coeff. of Variation (%)
1986	38.55	9.9205	25.74
1987	62.72	6.7595	10.78
1988	54.95	3.5649	6.49
1989	61.69	4.8562	7.87
1990	68.19	3.9565	5.80
1991	66.95	8.3985	12.55
1992	52.90	3.6883	6.97
1993	54.96	1.9553	3.56
1994	73.02	4.8482	6.64
1995	91.63	9.2701	10.12
1996	75.45	4.8078	6.37
1997	68.82	2.1124	3.07
1998	64.83	5.0410	7.78
1999	49.84	3.7860	7.60
2000	55.54	3.8370	6.91
2001	39.45	8.4554	21.43
2002	35.65	4.4692	12.54
2003	55.64	7.5209	13.52
2004	51.62	9.1899	17.80
2005	45.84	2.7153	5.92
2006	47.74	1.5660	3.28

Source: Lubbock cash price quotes reported by USDA Agricultural Marketing Service

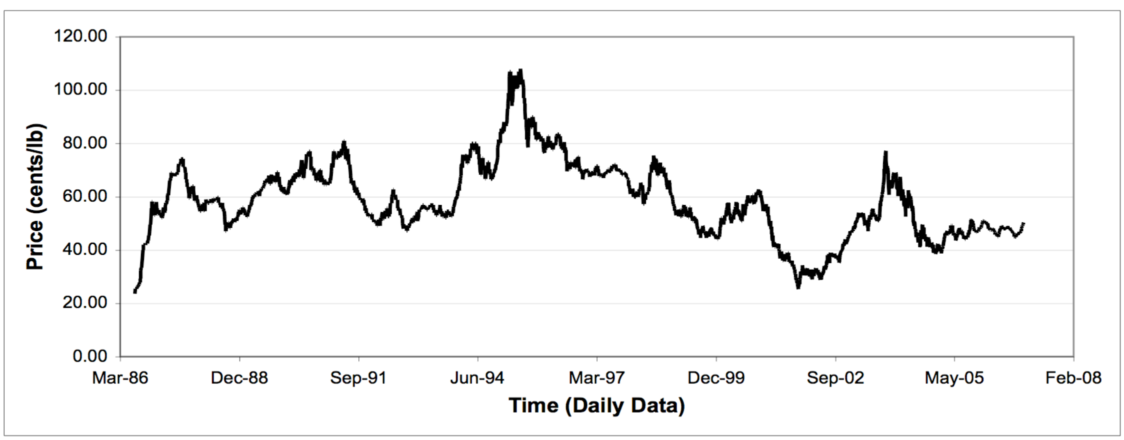

Figure 8. Lubbock Cash Cotton Prices, Daily Quotes 1986-2006
(Source: Lubbock cash price quotes reported by USDA Agricultural Marketing Service)

Table 10. Summary Statistics for the Memphis Cotton Cash Price Series, Daily Price Quotes from 1986-2006

Year	Mean (¢/lb)	Std. Deviation (¢/lb)	Coeff. of Variation (%)
1986	39.28	8.7155	22.19
1987	62.95	7.6270	12.12
1988	56.99	4.4214	7.76
1989	62.67	5.5039	8.78
1990	71.04	6.3772	8.98
1991	70.98	11.5883	16.33
1992	53.63	4.2068	7.84
1993	56.57	2.3315	4.12
1994	73.00	4.9143	6.73
1995	92.67	10.4458	11.27
1996	79.70	5.8411	7.33
1997	70.13	2.3780	3.39
1998	67.95	4.7957	7.06
1999	54.29	4.6486	8.56
2000	58.21	3.5358	6.07
2001	40.21	9.0460	22.50
2002	37.61	5.8721	15.61
2003	56.90	7.5149	13.21
2004	52.68	9.3680	17.78
2005	48.09	3.0775	6.40
2006	49.30	2.2129	4.49

Source: Memphis cash price quotes reported by USDA Agricultural Marketing Service

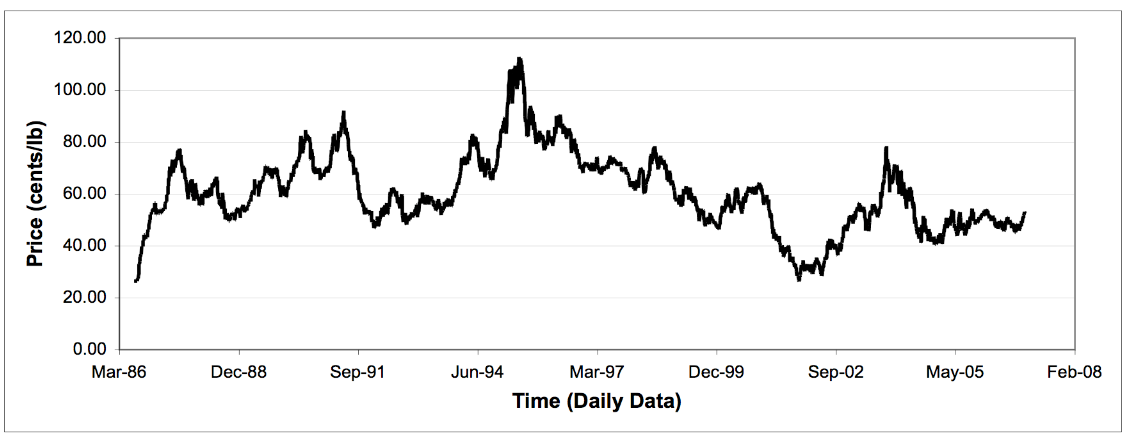

Figure 9. Memphis Cash Cotton Prices, Daily Quotes 1986-2006
(Source: Memphis cash price quotes reported by USDA Agricultural Marketing Service)

Table 11. Summary Statistics for the Adjusted World Price Cotton Cash Price Series, Daily Price Quotes from 1986-2006

Year	Mean (¢/lb)	Std. Deviation (¢/lb)	Coeff. of Variation (%)
1986	33.84	8.0747	23.86
1987	62.34	8.1315	13.04
1988	51.20	5.9335	11.59
1989	60.83	7.1013	11.67
1990	64.82	2.3929	3.69
1991	59.68	8.2109	13.76
1992	43.41	3.5381	8.15
1993	44.11	2.5162	5.70
1994	65.11	5.6057	8.61
1995	80.43	8.4999	10.57
1996	65.82	4.0832	6.20
1997	65.18	1.7527	2.69
1998	51.81	4.8243	9.31
1999	38.97	4.8398	12.42
2000	44.99	5.1274	11.40
2001	34.59	8.6215	24.92
2002	32.96	4.4315	13.44
2003	50.61	6.1464	12.15
2004	47.37	10.2645	21.67
2005	40.28	2.4547	6.09
2006	43.26	1.4690	3.40

Source: Adjusted World Price cash price quotes reported by USDA Agricultural Marketing Service

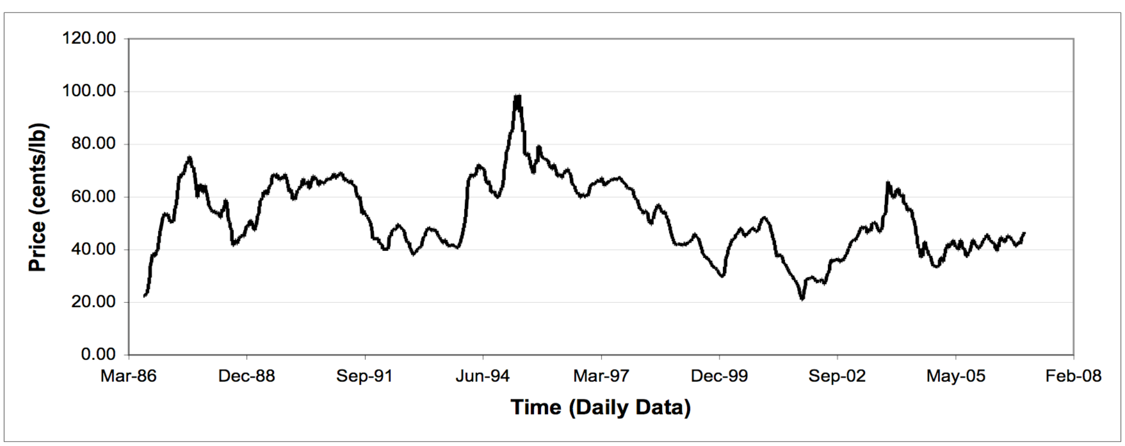

Figure 10. Adjusted World Price Cotton Cash Prices, Daily Quotes 1986-2006 (Source: Adjusted World Price cash price quotes reported by USDA Agricultural Marketing Service)

Table 12. Summary Statistics for the A-Index Cotton Cash Price Series, Daily Price Quotes from 1986-2006

Year	Mean (¢/lb)	Std. Deviation (¢/lb)	Coeff. of Variation (%)
1986	48.74	7.9866	16.39
1987	74.84	7.7938	10.41
1988	63.54	5.0427	7.94
1989	76.09	7.4362	9.77
1990	82.66	4.7441	5.74
1991	76.70	8.5576	11.16
1992	57.98	4.0345	6.96
1993	58.08	2.5574	4.40
1994	79.85	5.6280	7.05
1995	97.74	10.9938	11.25
1996	80.41	3.9103	4.86
1997	79.27	1.9705	2.49
1998	65.30	4.7979	7.35
1999	53.11	5.0899	9.58
2000	59.11	4.6443	7.86
2001	47.98	8.1866	17.06
2002	46.13	4.6012	9.97
2003	63.38	6.7878	10.71
2004	61.71	9.8088	15.90
2005	55.19	2.2896	4.15
2006	58.55	2.0235	3.46

Source: A-Index price quotes reported by Cotlook

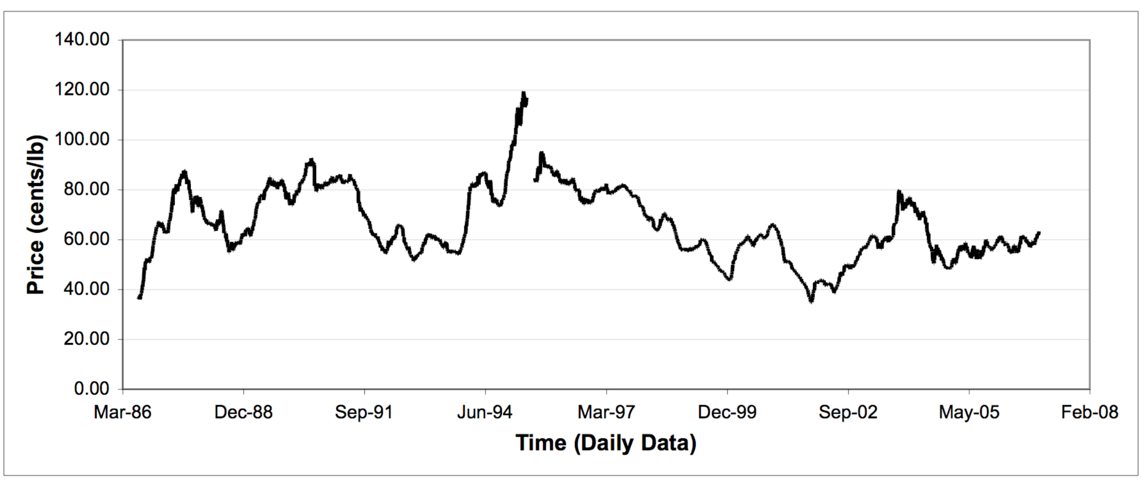

Figure 11. A-Index Cotton Cash Prices, Daily Quotes 1986-2006
(Source: A-Index price quotes reported by Cotlook)

Economic Indicator Data

Additional data on economic indicators gathered from DataStream (2006) included the Dow Jones Industrials Dividend Yield, the U.S. Treasury Constant Maturities 3-Month Middle Rate, the U.S. Corporate Bond Moody's BAA Middle Rate (junk bond), the U.S. Corporate Bond Moody's AAA Middle Rate (investment grade bond), and the U.S. Treasury Benchmark Bond 10 Years. Data for these five variables was gathered in monthly increments and begins in July 1989 and ends in December 2006. The daily 3-Month Treasury rate, also referred to as the 3-month T-bill, was gathered from the Thomson Banker One database (2007), the same publisher of the DataStream database. The T-bill is included in our dataset because it is the rate that most closely resembles the risk-free rate of interest and can be used to represent the time value of money (Madura).

Average rates for the t-bill peaked in 1989 at 8.10% while rates for 1995 averaged around 5.50% (table 13). Figure 12 shows the daily rate for the 3-month t-bill. Table (14) displays the basic statistics for calculated excess returns[2] on the dividend yield, treasury rate, and the junk bond premium, which was calculated using the junk bond and the investment grade bond.

[2] Excess returns were calculated using SAS. First each series (Dow Jones Industrials Dividend Yield, , the U.S. Corporate Bond Moody's BAA Middle Rate (junk bond), the U.S. Corporate Bond Moody's AAA Middle Rate (investment grade bond), and the U.S. Treasury Benchmark Bond 10 Years) were divided by 100. The monthly average of the the U.S. Treasury Constant Maturities 3-Month Middle Rate was then subtracted from each newly calculated series.

Table 13. Summary Statistics for the Three-Month Treasury Bill Rate Series, Daily Rate Quotes from 1986-2006

Year	Mean (%)	Std. Deviation (%)	Coefficient of Variation (%)
1986	5.35	0.1830	3.42
1987	5.78	0.3674	6.36
1988	6.67	0.8026	12.03
1989	8.10	0.4204	5.19
1990	7.50	0.3264	4.35
1991	5.38	0.5753	10.70
1992	3.46	0.4159	12.03
1993	3.00	0.0779	2.59
1994	4.37	1.0585	24.22
1995	5.50	0.2147	3.91
1996	5.02	0.1017	2.03
1997	5.06	0.1000	1.98
1998	4.77	0.3528	7.39
1999	4.64	0.2791	6.02
2000	5.82	0.2603	4.47
2001	3.42	1.0694	31.30
2002	1.61	0.1834	11.39
2003	1.02	0.1151	11.29
2004	1.39	0.4496	32.43
2005	3.21	0.5188	16.16
2006	4.84	0.2364	4.88

Source: Three-Month Treasury Bill rate quotes from Thomson One Banker Database

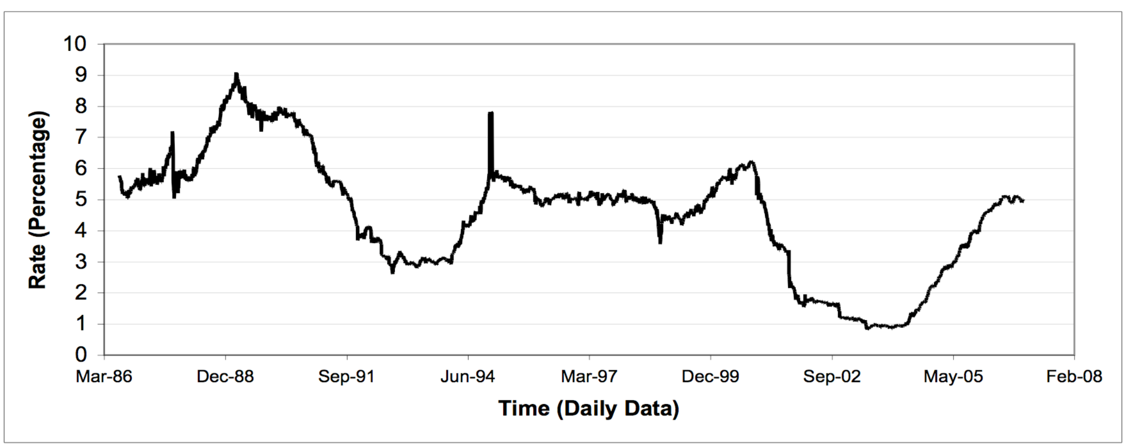

Figure 12. Three-Month Treasury Bill Rate Daily Quotes, 1986-2006
(Source: Three-Month Treasury Bill rate quotes from Thomson One Banker Database)

Table 14. Excess Returns of Factors in the Equilibrium Asset Pricing Model

	Obs.	Mean	Std Dev	Minimum	Maximum
Dividend yield	210	-0.01937	0.01736	-0.0477	0.0132
Junk bond premium	210	-0.03478	0.019248	-0.0729	0.0029
U.S. government bond	210	0.015922	0.012167	-0.00785	0.03807

Source: DataStream Data

Chapter Summary

This chapter is intended to describe general sources and trends of the comprehensive dataset, which will be used in this thesis. My data were gathered from the best available sources and updated to identify long-run trends. My dataset, with over 60,500 observations is the largest to be used for analytical studies in recent literature that focuses on the U.S. cotton futures market. While measurement error remains a possibility, the number of limit moves is not a concern affecting the validity of this dataset, as noted in Table 1. In subsequent data analysis, care has been taken to use futures observations that are too close to expiration, as will be discussed in subsequent chapters. By omitting observations after the last notice day of each futures contract, we can avoid unusual price volatility that occurs with the closing of a futures contract.

CHAPTER III

NORMAL BACKWARDATION AND PRICING PATTERNS IN THE U.S. COTTON FUTURES MARKET

The updated data described in chapter II will be employed in statistical tests of pricing patterns. Pricing patterns are often associated with market efficiency and represent a deviation from the efficient market hypothesis.

Literature Review and Economic Theory

John Maynard Keynes originated the theory that futures prices are less than the expected future spot price leading to the expectation that the futures prices rise over time to equal the expected future spot price at the expiration of the contract. This theory was described by Keynes as normal backwardation (Kolb). The opposite behavior is known as a contango. With the existence of normal backwardation in a market, futures prices will equal spot prices at the maturity of a contract, assuming a risk-neutral economy. Keynes explains the normal backwardation pattern by considering the risk preferences of speculators and hedgers. He hypothesized that "speculators are net long and that hedgers pay speculators for bearing risk," which in turn leads to a pattern of rising futures prices. According to Kolb (1992),

> In order for normal backwardation to prevail, short traders must be more highly risk averse than long traders in the aggregate. In this framework, the highly risk-averse short traders use futures to hedge unwanted risk…………As a speculator, the long trader enters the market and provides risk-bearing services only if he

> expects a profit. The excess of the expected future spot price over the current futures price is the speculator's expected profit and his reward for bearing risk.

The speculator's reward for bearing risk is also referred to as a risk premium. Many tests to find evidence of the existence of normal backwardation have been conducted in various futures markets. These studies have used slightly different methodologies, or have tested for other factors that may lead to different conclusions about normal backwardation. In addition, each study has used a different set of data that represents different time periods. This has lead to varying and often completely different results, resulting in disagreement among academic scholars on the normal backwardation hypothesis as it applies to different futures markets. A thorough review of past studies is required to gain a better understanding of the different methodologies used and the results of these tests to draw educated conclusions.

Many of the studies of agricultural commodities testing for market returns, risk premiums, and/or normal backwardation have tended to focus on major export crops like soybeans, wheat, and corn. Most studies find no evidence of normal backwardation. If normal backwardation is deemed to be present in a market, the efficient market hypothesis for that market with normal backwardation is called into question.

The efficient market hypothesis (EMH) is the leading theory to describe the price patterns of securities traded in competitive markets. The price relationship predicted under the EMH is that the futures price is a linear function of the past price, and price increments are purely random (equation 1). Citing Fama, Zulauf and Irwin (1998) write:

$$P_{t+1} = \alpha + \beta P_t + \varepsilon_t . \tag{1}$$

When there is no drift in this price process, and it takes the characteristic of a pure random walk (β= 1), then

$$E(P_{t+1} - P_t) = 0 , \tag{2}$$

which is to say that expected price differences equal 0 (equation 2). Under these conditions, there is no predictability in pricing that can lead to trading strategies that offer profitable opportunities without risk.

Departures from the theory may be described by either a positive price bias (normal backwardation) or a negative price bias (contango). The size of the parameter α in equation (1) is an indicator of either price pattern. When $\alpha > 0$, prices tend to increase over the life of the contract. Keynes referred to this price pattern as "normal" backwardation, rather than a bias or inefficiency, because he reasoned that it represents compensation to speculators for their willingness to bear risk. Other authors have used the term "risk premium" to describe the price patterns that deviate from the EMH (Bessembinder and Chan).

In empirical research that tests the theory of normal backwardation in various futures markets, sequences of prices and statistical tests on the prices over time have been used to identify the presence of either contango or normal backwardation. Kolb authored the most comprehensive study of the time series patterns of commodity futures prices. Kolb conducted a test of normal backwardation for 29 different commodities over the 1960 through 1991 period. His main finding was that “normal backwardation is not normal.” He found that some commodities exhibited weak evidence of normal backwardation and that those commodities that did not follow normal backwardation exhibited behavior similar to a contango. His results for the cotton market in particular were that the cotton futures market “partially conforms to the normal backwardation hypothesis.” In his background research, he referenced studies conducted by Carter, Rausser and Schmitz (1983) and Raynauld and Tessier (1967), among others. Carter et al. found evidence of normal backwardation in wheat, corn, and soybeans; however, results from the study conducted by Raynauld and Tessier, on corn, wheat, and oats, are inconsistent with the normal backwardation hypothesis. They did, however, find evidence of a risk premium.

Methods

Kolb outlines two assumptions about the normal backwardation hypothesis, which we assume in our update and extension of his approach. First, the futures price must equal the cash price at expiration. This is also known as the “no-arbitrage” principle of futures markets. Secondly, since the expected future spot price at expiration is an unknown value, and given the first assumption, a proxy can be used for the cash price at expiration. This proxy is the futures price at expiration.

According to Kolb, there are three core “testable implications” of the normal backwardation hypothesis:

1.) Futures returns should be positive

2.) Futures prices prior to expiration should be below the terminal futures price and,

3.) Futures prices should be lower the longer the time remaining until maturity.

Three tests devised by Kolb were replicated here to test for the existence of normal backwardation in the U.S. cotton futures market. Each of the tests corresponds to one of the three testable implications of the normal backwardation hypothesis, respectively. $F_{i,t}$ is used to represent the futures price for an individual cotton futures contract. The subscript i is the total number of days within a contract, while t represents the days remaining until expiration of that contract.

Prior to applying these three core tests of normal backwardation to my own cotton futures price dataset, I revised the entire dataset to reduce the impact of extraordinary price fluctuations that are associated with the expiration of a futures contract. Prices may tend to fluctuate after the last notice day of a futures contract because market players are closing their futures position while other larger players may be increasing their speculative practices (Robinson). To correct for these deviations, daily price data starting with the final notice day was deleted from the overall dataset. Definition of the final notice day can be found in chapter II. Any price that was recorded after this date was then removed from our analysis. This approach is common in industry practice and in academic research.

Kolb's three testable implications were then applied to my newly revised dataset in three different ways. First, the tests were applied to each individual futures contract in its entirety. I have identified this as the "whole contract" or "entire contract." Second, I divided each individual futures contract by looking only at its final calendar year. Recall that a cotton futures contract has an estimated 24 months. Price data not in the final calendar year of each contract was removed. I then applied Kolb's tests to these new dataset and identify it as "final calendar year." Finally, I further divided the contracts into specific seasons before applying Kolb's tests. Results from this analysis are identified with "seasonality" and are discussed later in the chapter.

Positive Futures Returns

Under normal backwardation, the expected daily simple and logarithmic returns should be greater than zero, "implying that futures prices should rise over time." To test this assumption, the average daily return for each individual contract in each of the five delivery months was calculated, in both logarithmic form and in simple returns (equation 3):

$$E[\ln (F_{i,t} / F_{i,t+1})] > 0 \quad \text{and} \quad E[(F_{i,t} / F_{i,t+1}) - 1] > 0. \qquad (3)$$

First, the average of the logarithmic and daily returns was calculated across all twenty years within each of the five different contracts. Next, the average of the logarithmic and daily returns was computed combining each yearly average of the five different contracts, resulting in a single average for the entire cotton futures market for the period of 1986 through the present. The aggregated daily and logarithmic returns, for each of the five contracts and for the market as a whole, were then tested to determine if their mean was greater than zero.

Futures Prices Prior to Expiration Are Below Terminal Futures Price

Daily differentials, which are defined as the relative difference between the futures price and the subsequently observed futures price at expiration, for each individual contract were calculated to test if the expected value of the futures price prior to expiration does indeed lie below the terminal futures price (equation 4).

$$E[\, F_{i,t} - F_{i,0} \,] < 0 \,. \tag{4}$$

Following Kolb's methodology, percentage differences were calculated instead of arithmetic differences. The differential is a measure of the percentage by which the futures price at a given time falls below the terminal futures price on that contract (equation 5).

$$D_{i,t} = \left(F_{i,t} \,/\, F_{i,o}\right) - 1 \,. \tag{5}$$

Under the normal backwardation hypothesis, the expected value of the calculated differential should be negative for any day before expiration (equation 6).

$$E\left(D_{i,t}\right) < 0 \quad \text{for} \quad t > 0. \tag{6}$$

The normal backwardation condition implies that differentials should be smaller when there is more time remaining until expiration.

First, the average of the differentials was calculated across all twenty years within each of the five different contracts. Next, the average of the differentials was computed combining each yearly average of the five different contracts, resulting in a single average for the entire cotton futures market for the period of 1986 through the present. The aggregated differential averages, for each of the five contracts and for the market as a whole, were then tested to determine if their mean was greater than zero.

Futures Prices Are Lower the Longer the Time Remaining Until Maturity

In addition to the statistical tests on aggregated returns, Kolb used a linear regression model to examine price patterns, in which he regressed the differentials over time. If it is the case that prices rise during the life of the contract, then the percentage by which the current price falls below the price at expiration should decrease with the life of the contract. The dependent variable in the regression model, the futures price differential, is defined in equation 5.

Time is measured in number of days remaining before expiration; thus, early in the contract life, t is large. For most of the contracts in our dataset, $t = 1, 2, \ldots, 375$ (approximately) although it should be noted that beginning in 1997, contract duration increased to more than two calendar years. Differentials were not calculated for the movement to the contract expiration day ($t = 0$).

The normal backwardation hypothesis implies that the differentials, calculated in equation 5 should be inversely related to the time remaining until the contract matures. The regression specification to test for the hypothesized pricing pattern is:

$$D_{i,t} = \alpha + \beta_i \, t + \varepsilon_t \quad \text{for} \quad t > 0. \tag{7}$$

The coefficient on *t* is expected to be negative under normal backwardation.

$$\beta_i < 0 . \tag{8}$$

As is typical for time-series regression models for very high frequency data, the residuals ε_t are likely to be correlated across time. When autocorrelation is present, tests of statistical inference on the coefficients are not reliable using OLS methods. Kolb corrected for this problem in his very large dataset by randomly selecting observations and estimating the parameters of equation 7 from a sub-sample of the data that did not show evidence of autocorrelation. While this method was considered, it was not sufficient to remove autocorrelation problems in certain subsets of data examined. Therefore, the procedures to correct for autocorrelation in the regression based test were different from those used by Kolb. A generalized least squares estimator, the Yule-Walker method, was used to correct for this autocorrelation, using the AUTOREG procedure in SAS version 9.1.3 (2006). This procedure used an initial ordinary least squares regression to estimate covariances across the observations. Subsequently, the covariance matrix is adjusted to account for the effect. The Yule Walker method was implemented using one lag, ten lags, and thirty lags of the differentials. Results using one lag are displayed in this chapter. Results using ten and thirty lags are shown in Appendix C.

Results

After updating the tests of normal backwardation formulated by Kolb, the results show little to no evidence of normal backwardation in the cotton futures market during 1987-2006. This result differs significantly from Kolb's findings that cotton partially conforms to the idea of normal backwardation. I find very weak to no evidence of the existence of normal backwardation in the cotton market.

My first testable implication is that futures returns should be positive, if normal backwardation exists (equation 3). Equation 3 specifies that both the daily simple and logarithmic returns should be greater than zero. When looking at the whole futures contract, logarithmic returns were greater than zero for the May and July contracts and less than zero for the March, October, and December contracts (table 15). When all the contracts were combined, the average logarithmic return was also less than zero. However, all the mean logarithmic returns for each of the five contract months, and the combined contracts, had t-tests that were not statistically significant from zero, meaning that the normal backwardation hypothesis can neither be accepted nor rejected.

When looking at the final calendar year for each contract, logarithmic returns were greater than zero for the July and October contracts (table 16). Logarithmic returns were negative for the March, May, and December contracts, as well as the market as a whole. Again, all mean logarithmic returns were not statistically significant from zero, meaning that the normal backwardation hypothesis can be neither accepted nor rejected.

The tests for the mean daily simple returns yielded results greater than zero for the March, May, July, and combined contracts, when looking at the whole futures contract (table 15). Results for the mean daily simple returns were less than zero for the October and December contracts. Results of the final calendar year for the mean daily simple returns were positive for March, May July, October, and the combined contracts, but negative for the December contracts (table 16). Like the t-tests for the logarithmic returns, the t-tests for all of the daily simple returns (both whole contracts and final calendar year) were not statistically significant from zero. This implies that one can neither accept nor reject the normal backwardation hypothesis for this particular test.

Table 15. Test 1 Results: Logarithmic and Daily Simple Returns on Cotton Futures, 1986-2006 (Whole Futures Contracts)

(0.000%)	Mar	May	Jul	Oct	Dec	Combined
Logarithmic						
Returns	-0.00003	0.00007	0.00001	-0.00008	-0.00011	-0.00003
(t-test)	-0.0027	0.0059	0.0007	-0.0070	-0.0097	-0.0025
Daily Simple						
Returns	0.00004	0.00014	0.00009	-0.00001	-0.00004	0.00004
(t-test)	0.0036	0.0121	0.0070	-0.0008	-0.0037	0.0037

Source: NYBOT cotton futures price data

Table 16. Test 1 Results: Logarithmic and Daily Simple Returns on Cotton Futures, 1986-2006 (Final Calendar Years of Futures Contracts)

(0.000%)	Mar	May	Jul	Oct	Dec	Combined
Logarithmic						
Returns	-0.00002	-0.000002	0.00006	0.000014	-0.00019	-0.00003
(t-test)	-0.0016	-0.0001	0.0044	0.0011	-0.0148	0.0131
Daily Simple						
Returns	0.00007	0.00009	0.00015	0.00010	-0.00010	0.00006
(t-test)	0.0055	0.0069	0.0114	0.0080	-0.0081	0.0132

Source: NYBOT cotton futures price data

The second testable implication is that futures prices prior to expiration should be below the terminal futures price and is displayed as equation 4. The expected value of the calculated differential should be negative for any day prior to expiration, as stated in equation 4. When the tests for negative differentials were applied to the whole futures contracts, our tests yielded positive average differentials for each of the five contract delivery months and for the combined contracts (table 17). However, the t-tests for the mean differentials for each contract and the combined contracts were not statistically significant from zero; therefore, the normal backwardation hypothesis for the differentials test can neither be accepted nor rejected. When applied to the final calendar years of the futures contract (table 18), the sign of the differentials test also yielded positive differentials for all five contract months and the overall market. Again, the t-tests for each delivery month and the combined contracts were not statistically significant from zero.

Table 17. Test 2 Results: Differentials of Cotton Futures Prices Relative to Expiration Prices, 1986-2006 (Whole Futures Contracts)

(0.000%)	Mar	May	Jul	Oct	Dec	Combined
Differentials	0.0366	0.0247	0.0606	0.0531	0.0723	0.0495
(t-test)	0.3389	0.2336	0.5490	0.5497	0.7150	0.4739

Source: NYBOT cotton futures price data

Table 18. Test 2 Results: Differentials of Cotton Futures Prices Relative to Expiration Prices, 1986-2006 (Final Calendar Years of Futures Contracts)

(0.000%)	Mar	May	Jul	Oct	Dec	Combined
Differentials	0.00575	0.00575	0.01449	0.03339	0.05119	0.02212
(t-test)	0.0686	0.0704	0.1690	0.4453	0.6368	0.0813

Source: NYBOT cotton futures price data

The third testable implication, as indicated by Kolb, is that futures prices should be lower the longer the time remaining until maturity. This can be restated as equation 7 and is tested econometrically. The expected beta coefficient should be less than zero. First-order autocorrelation of the residuals is strongly evident in the large datasets that result from combining the available data on cotton futures prices, 1986-2006. The test statistic, ρ, was larger than 0.99 in the preliminary OLS regressions.

Kolb followed a random sub-sampling procedure when conducting his regressions to correct for the autocorrelation of the errors. In order to retain the full information from the seasonal sub-samples while obtaining reliable estimates from the regression-based test for normal backwardation, two other forms of autocorrelation corrections were applied for the regressions. The first is the Yule-Walker procedure; the second is the unconditional least squares procedure. The estimates given by the unconditional least squares procedure closely identical to those of the Yule Walker procedure; therefore, we reported only the Yule Walker estimates. The Durbin-Watson (DW) statistic is included as a measure of autocorrelation. If the DW statistic approximates 2, then it is regarded that the model is not autocorrelated (Griffiths et al). The R^2 is included as a goodness of fit measure and should approximate 1.

Subsequent to the correction for autocorrelated errors, the results of the tests on the 20-year datasets, for the whole futures contracts, reveal positive betas. This suggests the presence of contango, that is, prices are decreasing as the time to expiration nears (table 19). The t-statistic for this test reveals that our betas are significantly different from zero at a 0.05 percentage level. This result was found for all five of the delivery month contracts and when combined as a whole market. This is a reversal of Kolb's findings on cotton for the 1960 through 1991 period.

Table 19. Test 3 Results: Regression for Rising Cotton Futures Prices, 1986-2006, Yule Walker Method of Autocorrelation Correction (Whole Futures Contracts)

	Mar	May	Jul	Oct	Dec	Combined
			(before correction)			
OLS Method						
Intercept	-0.0415	-0.0551	-0.015	-0.0254	-0.0057	-0.0287
Beta	0.00044	0.00046	0.00044	0.00042	0.0004	0.0004
Std Error	0.00002	0.00002	0.00002	0.00002	0.00002	0.00001
t-statistic	21.8300	23.6000	22.1300	21.4700	22.1000	49.7400
DW	0.0068	0.0073	0.006	0.0059	0.0056	0.0067
Total R^2	0.0546	0.0627	0.0549	0.052	0.0545	0.0557
n	8,264	8,333	8,435	8,411	8,476	41,919
			(after correction)			
Yule Walker						
Intercept	-0.0034	-0.0055	0.0138	-0.0151	-0.0092	0.0146
Beta	0.00024	0.00019	0.00024	0.0003	0.0003	0.0002
Std Error	0.00001	0.00001	0.00001	0.00001	0.00001	0.000004
t-statistic	23.130	19.260	24.980	31.700	37.910	52.6000
DW	2.0066	1.955	1.8903	1.9353	1.9103	1.9875
Total R^2	0.9939	0.9937	0.9946	0.9945	0.9947	0.994
n	8,264	8,333	8,435	8,411	8,476	41,919

Source: NYBOT cotton futures price data

When the regression model was applied to the final year of the futures contracts, the results also reveal positive betas, indicating a contango (table 20). The significance levels of the betas decreased dramatically from the levels shown in table 19. Each coefficient is still largely significant at the 0.01 level. This result was found for all five of the delivery month contracts and when combined as a whole market.

Table 20. Test 3 Results: Regression for Rising Cotton Futures Prices, 1986-2006, Yule Walker Method of Autocorrelation Correction (Final Calendar Years of Futures Contracts)

	Mar	May	Jul	Oct	Dec	Combined
			(before correction)			
OLS Method						
Intercept	-0.0172	-0.0013	0.0128	-0.0087	0.0137	0.00012
Beta	0.00021	0.00006	0.000013	0.00043	0.00033	0.0002
Std Error	0.00004	0.00004	0.00005	0.00004	0.00003	0.00002
t-statistic	5.58	1.43	0.28	10.51	9.52	11.25
DW	0.0151	0.0121	0.0099	0.0163	0.0202	0.0149
Total R^2	0.0069	0.0005	0.0000	0.0252	0.0197	0.0057
n	4,451	4,462	4,463	4,267	4,510	22,153
			(after correction)			
Yule Walker						
Intercept	-0.0216	-0.0331	-0.0282	-0.0029	0.0059	0.0015
Beta	0.00018	0.00023	0.00002	0.00028	0.00035	0.00018
Std Error	0.00002	0.00002	0.00002	0.00002	0.00002	0.00001
t-statistic	9.02	11.11	10.01	12.14	16.07	18.27
DW	1.894	1.9067	1.8184	1.9084	1.9642	1.9729
Total R^2	0.9851	0.9881	0.9903	0.9843	0.9803	0.9852
n	4,451	4,462	4,463	4,267	4,510	22,153

Source: NYBOT cotton futures price data

Extension of Kolb Tests to Relevant Subsets

While it is useful to examine a very long period of price behavior, there have been many changes in the general economy and in the cotton futures markets themselves that could be obscured in a specification that examines the relationships between price differentials and time, on average for pooled contract data. Therefore, I have tested for the existence of shorter-term pricing patterns. First, all contracts expiring in a particular year were tested separately, both as a whole futures contract, then by looking at only the final year of the futures contract. In addition, seasonal sub-samples within a contract year were examined, similar to those used by Wood, Shafer, and Anderson (1989).

Among the 20 years of contracts tested, both as a whole and in its final year, 9 of the contract years show signs of normal backwardation with 8 of these years showing evidence of significance (table 21). Eleven years of contracts exhibited a contango pattern, and each of those years was statistically significant. Contango was the predominant pricing pattern in the late 1990s and 2000s, while normal backwardation was predominant in the late 1980s and early 1990s. These regressions were from data pooled across contracts (the March, May, July, October, and December contracts).

Table 21. Contango or Normal Backwardation Patterns in Cotton Futures Prices, by Contract Years, from Regression of Price Differentials on Time to Expiration Using Yule Walker Method of Regression, Data from 1986-2006

	Price Pattern (sign of β)		t-value (significance)	
Contract Year	**Whole Contracts**	**Final Year of Contracts**	**Whole Contracts**	**Final Year of Contracts**
1987	-	-	Significant	Significant
1988	-	+	Significant	Significant
1989	-	-	Significant	Significant
1990	-	-	Significant	Significant
1991	-	-	Significant	Significant
1992	+	+	Significant	Significant
1993	+	-	Significant	Not Significant
1994	-	-	Significant	Significant
1995	-	-	Significant	Significant
1996	-	+	Not Significant	Significant
1997	+	+	Significant	Significant
1998	+	+	Significant	Significant
1999	+	+	Significant	Significant
2000	+	-	Significant	Significant
2001	+	+	Significant	Significant
2002	+	+	Significant	Significant
2003	-	-	Significant	Significant
2004	+	+	Significant	Significant
2005	+	+	Significant	Significant
2006	+	+	Significant	Significant

Note: "-" indicates backwardation and "+" indicates contango

Source: NYBOT cotton futures price data

The dynamics of normal backwardation and contango may only occur in sub-seasonal segments of the futures price pattern. This suggests replicating the Kolb tests for different segments of a futures price history. For example, figure 13 depicts the last twelve months of the December 2005 contract, while figure 14 depicts the final eleven months of the last five December cotton futures contracts.

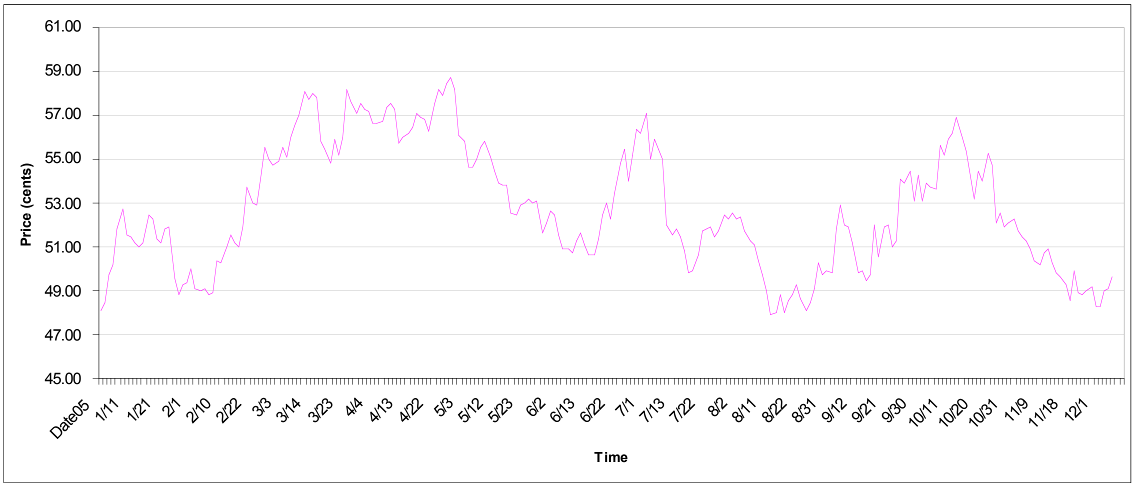

Figure 13. December 2005 Cotton Futures Contract, Whole Contract
(Source: NYBOT cotton futures price data)

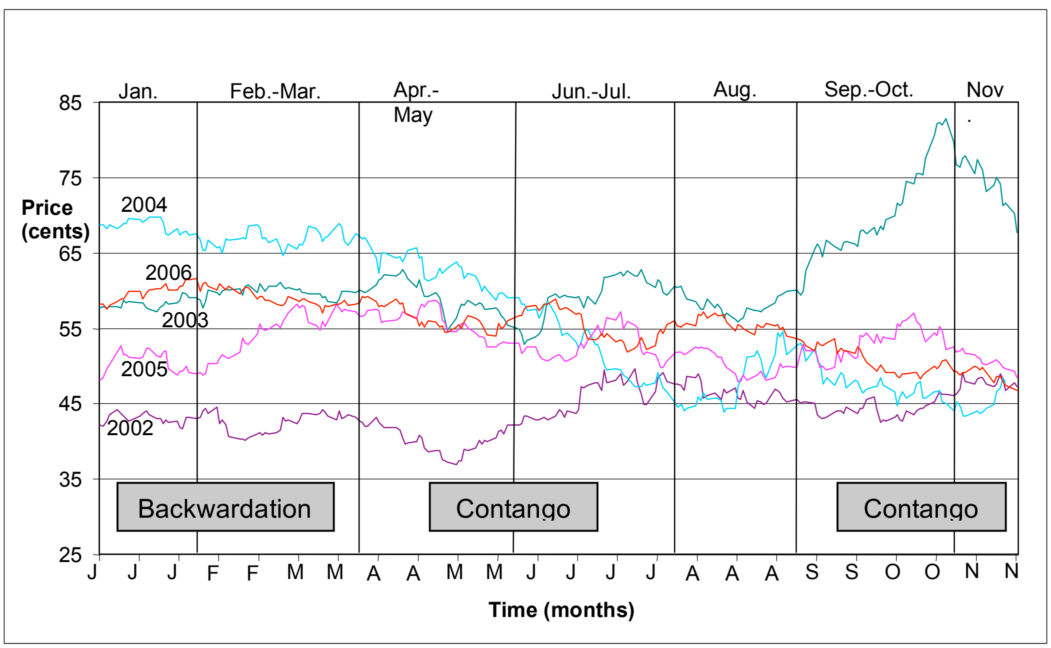

Figure 14. Last Five December Cotton Futures Contracts, Final Year of Contracts
(Source: NYBOT cotton futures price data)

By observing the different price patterns, one can see a general upward price trend from January 2005 thru May 2005, with prices peaking in May. During the planting season, there is uncertainty about the future harvest which can be reflected in rising futures prices being below cash prices. Following Kolb and Keynes' hypothesis, one would expect to find evidence of normal backwardation in this time period. There is a downward trend in prices in June and July with another downward price trend evident beginning in October and ending in December. This leads me to believe that there would be promising evidence of a contango during this timeframe. The October through December period can be referred to as the harvest season and can be characterized by having less uncertainty about the future harvest.

I seasonally-differentiated the December futures contract (final calendar years) into three different seasons: Pre-Planting, Growing, and Harvest/Storage. I then applied Kolb's three tests to our seasonally-differentiated data. During the last twenty years, the pre-planting season of the December contract (final calendar years) showed insignificant evidence of backwardation, or rising futures prices. The growing and harvest storage seasons displayed significant evidence of contangos, or or declining futures prices as the contract approaches maturity (table 22).

To further extend Kolb's study, we took the most recent December cotton futures contracts and sub-divided them by various monthly groupings (final calendar years). The last five December contracts were chosen in an effort to narrow our dataset to more closely resemble the present day market. Figure 14 demonstrates these monthly groupings. After analyzing this new sub-divided dataset, I find that there is significant evidence of backwardation during the months of January, February, and March, while there is insignificant evidence of backwardation in August over the last five years. The months of April, May, June, July, September, October, and November show evidence of significant contangos (table 23).

Table 22. Regression Results for Rising Cotton Futures Prices, December Contracts, 1986-2006, by Season, Yule-Walker Method of Autocorrelation Correction (Final Calendar Years of Contracts)

	Pre-Planting Season (Jan.-Apr.)	Growing Season (May-Jul.)	Harvest/Storage Season (Aug.-Nov.)
	(before correction)		
OLS Method			
Intercept	0.000569	0.00384	0.0067
Beta	-0.00004	0.0005	0.00035
Std Error	0.000074	0.00012	0.00009
t-statistic	-0.54	3.83	4.02
DW	0.043	0.0592	0.0594
Total R^2	0.0002	0.0115	0.01
n	1644	1269	1597
	(after correction)		
Yule Walker			
Intercept	-0.0018	-0.00472	0.00653
Beta	-0.00005	0.00062	0.00041
Std Error	0.0000415	0.00008	0.00006
t-statistic	-1.14	8.07	7.16
DW	1.9564	1.9157	1.9302
Total R^2	0.9574	0.9423	0.9421
n	1644	1269	1597

Source: NYBOT cotton futures price data

Table 23. Regression Results for Rising Cotton Futures Prices, Last Five December Contracts, 2002-2006, by Monthly Groupings, Yule-Walker Method of Autocorrelation Correction (Final Calendar Years of Contracts)

	Jan.	Feb.-Mar.	Apr.-May	Jun.-Jul.	Aug.	Sep.-Oct.	Nov.	Combined
				(before correction)				
OLS Method								
Intercept	0.018	0.018	-0.101	-0.016	-0.054	0.036	-0.17	-0.127
Beta	-0.000	-0.001	0.002	0.001	0.0004	-0.001	0.003	0.0003
Std Error	0.001	0.0002	0.0004	0.0005	0.001	0.0004	0.001	0.0002
t-statistic	-0.350	-2.640	6.060	1.370	0.420	-1.500	2.540	2.1500
DW	0.175	0.156	0.056	0.095	0.192	0.136	0.226	0.116
Total R^2	0.001	0.034	0.150	0.009	0.002	0.011	0.064	0.004
n	105	210	220	215	115	220	100	1,185
				(after correction)				
Yule Walker								
Intercept	0.064	0.053	-0.101	-0.165	-0.013	-0.064	-0.11	-0.041
Beta	-0.001	-0.001	0.002	0.003	-0.001	0.0010	0.002	0.0010
Std Error	0.0004	0.0003	0.0002	0.0004	0.001	0.0004	0.001	0.0001
t-statistic	-2.330	-5.560	8.380	7.620	-0.160	2.5400	2.420	5.7100
DW	1.628	1.916	1.759	1.740	1.929	2.083	2.293	2.016
Total R^2	0.848	0.871	0.957	0.924	0.876	0.899	0.849	0.907
n	105	210	220	215	115	220	100	1185

Source: NYBOT cotton futures price data

Chapter Summary

The existence of pricing patterns in futures markets are often associated with the efficient market hypothesis. Under the efficient market hypothesis, futures price should be a linear function of past price and any price changes should be purely random. Normal backwardation and contangos are departures from this theory. Under normal backwardation, or a positive price bias, futures prices are less than the expected future cash price leading to the expectation that futures prices rise over time to equal the expected future cash price at the expiration of the contract. The opposite behavior, a negative price bias, is referred to as a contango. After applying and extending Kolb's methodology to the U.S. cotton futures market, little evidence suggests the existence of any pricing pattern in the long run. However, there is evidence to suggest that pricing patterns do exist in the short run and within particular cotton crop seasons. Contangos, or falling prices, have occurred in most recent years. Within a crop year, futures prices have risen during pre-planting season and fallen during harvest season.

CHAPTER IV

CO-INTEGRATION BETWEEN THE COTTON CASH MARKET AND THE COTTON FUTURES MARKET

Many recent studies of futures markets have taken advantage of the econometric developments in the field of time series analysis. The statistical and econometric techniques can be applied to the issue of market efficiency in providing a view of the long-run relationships between cash price series and futures prices. In an efficient market, a futures price is expected not to diverge from the cash price over the long-run. Moreover, cash prices are expected to be discovered in the futures market. In this chapter, these principles will be examined with a futures price series and five cash prices for cotton.

Literature Review and Economic Theory

Granger first introduced the concept of co-integration and error correction models in 1981 (Granger 1981). Engle and Granger extended this concept with their 1987 study that develops estimation procedures and tests to complement the existing knowledge of co-integration. Co-integration, as defined by Granger, is the link between non-stationary processes and long-run steady state equilibrium (Griffiths 1993). Engle and Granger (1987) stated that if two time series vectors display evidence of stationarity only after differencing the data, and if a linear combination of the two series does not need to be differenced to be stationary, then those time series vectors are defined as co-integrated of order (1,1). Put differently, when analyzing an individual time series variable, it may display wandering, or non-stationary behavior. However, if that wandering variable is paired with another wandering time series variable, they may appear to be moving in tandem. There are several different forces, as indicated by economic theory, which may be keeping the series together. They include, but are not limited to, interest rates, income and expenditures, and prices of the same commodity in different markets (Engle and Granger). A detailed mathematical representation for testing for co-integration and for building error correction models for forecasting co-integrated series can be found in Engle and Granger's 1987 study.

Co-integration has become widely used in recent literature to test for price discovery and efficiency of various markets. A popular area for implementing co-integration tests is between the cash and futures markets of commodities. There have been some inconsistencies among the recent studies using co-integration tests within commodity futures and cash markets, which paves the way for further research. Zapata and Fortenbery (1996) stated that the failure to account for certain economic factors which may possibly link cash and futures commodity markets may account for some variances in the results of different co-integration tests. They studied the U.S. corn and soybean cash and nearby futures markets, where they implemented the Johansen method to test if the "observed non-stationarity in the cash/futures relationship could be explained by the omission of a common stochastic element (643)." Zapata and

Fortenberry concluded that interest rates provide valuable information for cost of storage, an important factor to consider when dealing with commodities.

Yang, Bessler, and Leatham (2001) used the co-integration approach to test for the efficiency and price discovery performances of corn, oat, soybeans, wheat, cotton, and pork bellies, along with several non-storable commodities. They incorporated Zapata and Fortenberry's interest rate concept to account for costs of asset storage by using the 3-Month Treasury bill rate as a proxy for interest rates. Their results from implementing the Johansen approach of co-integration indicated "that asset storability does not affect the existence of a long-run relationship between cash and futures prices (296)." They conclude that price discovery performances are better for storable commodities than for non-storable commodities.

Wang and Ke (2005) also used co-integration to test for the efficiency of the Chinese wheat and soybean futures markets. Their objectives included examining the markets for a long-run equilibrium relationship and testing the efficiency of the futures market to be used as a predictor for cash prices. They also examined the performance of the futures prices in forecasting cash prices over different time horizons. Their results suggest evidence of efficiency in the Chinese soybean market but evidence of inefficiency for the Chinese wheat market, which they attribute to market manipulation by the government and large traders.

Methods

Three different data types were used for the co-integration tests: daily cash prices, daily nearby futures prices, and daily interest rate data. The cash series included the A-Index, Memphis cash prices, Dallas cash prices, Lubbock cash prices, and the Adjusted World Price (AWP) data. Each of the cash price data series was grouped separately with the Nearby futures prices and interest rate series, for a total of five different data groups (example: Memphis, Nearby and Interest rate). The Engle and Granger two-step approach of testing for co-integration was used for data covering 1997 through 2006.

Before two different data series can be tested for co-integration, they must first be tested for stationarity. The natural logarithm of each cash series and the Nearby series were calculated before the stationarity tests were conducted. Griffiths et al. define a data series as stationary when it's mean, variance, and correlations do not change over time.

The Dickey Fuller test was used to test each of our data series for non-stationarity. The Dickey Fuller test, as summarized by Bessler (2006) "regresses changes in x_t (where x_t represents a data series) on a constant plus the levels of x_t lagged one period (equation 9)."

$$\Delta x_t = \alpha_0 + \alpha_1 x_{t-1} \tag{9}$$

where

$$\Delta x_t = x_t - x_{t-1}\,. \tag{10}$$

I used ordinary least squares to estimate α_0 and α_1. Under the Dickey Fuller test, the null hypothesis for non-stationarity is that α_1 is zero. If the Dickey Fuller statistic is greater than -2.9, then we fail to reject non-stationarity; if it is less than -2.9 then we reject non-stationarity. Once it was determined that the two data series that were to be used in the co-integrating regression were non-stationary, a regression was run with the cash series as the dependent variable and the nearby futures series and the interest rate series as the independent variables (equation 11). This is called the co-integrating regression.

$$\ln Cash_t = \beta_0 + \beta_1 \ln Nearby_t + \beta_2 Interest_t + \varepsilon_t . \tag{11}$$

The residuals from the regression (equation 11) are identified as ε_t in equation 11 and are rewritten according to the Engle and Granger style as:

$$z = \ln Cash - \beta_0 - \beta_1 \ln Nearby - \beta_2 Interest , \tag{12}$$

where z represents the residual, and $\beta_0, \beta_1, \text{and } \beta_2$ are the parameters that were estimated in equation 11. The parameter z represents a linear combination of the two series (cash and futures). May combinations are possible; as long as the combination is stationary, conditions for co-integration are satisfied. After all residuals were calculated, a Dickey Fuller test was performed on the residuals to determine if they were stationary.

After the Dickey Fuller test on the residuals was performed to ensure stationarity of the residuals, the error correction model was estimated according to equations 13 and 14 to determine whether price is discovered in the cash market or the futures market:

$$\Delta \ln Cash_t = \delta_0 + \delta_1\, \Delta \ln Cash_{t-1} + \delta_2\, \Delta \ln Nearby_{t-1} + \delta_3\, z_{t-1} \tag{13}$$

and

$$\Delta \ln Nearby = \gamma_0 + \gamma_1\, \Delta \ln Cash_{t-1} + \gamma_2\, \Delta \ln Nearby_{t-1} + \gamma_3\, z_{t-1}\,. \tag{14}$$

Of course, economic theory and logic of the markets suggest that cash price is expected to be discovered in futures markets. In this procedure, both forms of error correction models are tested in order to have a complete analysis of all possibilities. Once the error correction model was estimated, the parameter estimates associated with the residuals of the co-integrating regression were tested: δ_3 (where the cash series is the dependent variable) and γ_3 (where the futures series is the dependent variable), to determine if they were statistically different from zero. The null hypothesis is $\delta_3 = 0$, where lags of cash and futures errors help to determine the cash price. That is, cash prices are discovered in futures markets. If δ_3 is statistically different from zero, then it indicates that price is not discovered in the cotton cash market. The second hypothesis is on the discovery of prices in futures markets. The null hypothesis is $\gamma_3 = 0$. Economics suggest that this null will hold, meaning that γ_3 will not be statistically different from zero, indicating that price is discovered in the cotton futures market.

Results

Table 24 displays the results for the Dickey Fuller test for each of the seven logged data series used in the co-integration tests: A-Index, Dallas, Lubbock, Memphis, Adjusted World Price, 3-Month Treasury, and the Nearby series. For each data series tested, the Dickey Fuller statistic was greater than -2.9, leading us to fail to reject non-stationarity for each logged series. Since all logged data series were non-stationary, the first requirement of co-integration was met. Next, the co-integrating regressions were estimated using a cash series, the Nearby series and the interest rate series.

The first co-integrating regression that was run used the logged A-Index price series as the dependent variable, the logged Nearby series as an independent variable, and the original interest rate series as a second independent variable. Parameter results from this co-integrating regression can be found in table 25. The residuals for this regression were then tested for stationarity using the Dickey-Fuller test. The result from this test can be found in table 26 and shows evidence consistent with stationarity. The Dickey-Fuller statistic was less than the critical value of -2.9, leading us to fail to reject the null hypothesis of non-stationarity; therefore, confirming co-integration between the A-Index and the Nearby series.

Table 24. Results from the Dickey Fuller Test for Non-Stationarity Using the Price Series to be Used in the Co-integrating Regressions, 1997-2006

Price Series	No. of Differences	Dickey Fuller Statistic
ln A-Index	0	-1.7139
ln Dallas	0	-1.9701
ln Lubbock	0	-1.9509
ln Memphis	0	-2.1793
ln AWP	0	-1.6937
3-Month Treasury	0	-0.6868
Nearby Futures	0	-2.4344

Source: NYBOT, Cotlook, Thomson, and Agricultural Marketing Service data

Table 25. Parameter Estimates from Co-integrating Regression, 1997-2006

Dependent Variable	β_0 Intercept	β_1 Nearby	β_2 Interest
ln A-Index	0.786	0.828	-0.011
(t-test)	(28.146)	(114.430)	(-12.330)
ln Dallas	-0.293	1.051	0.002
(t-test)	(-20.067)	(277.642)	(4.194)
ln Lubbock	-0.337	1.061	0.002
(t-test)	(-23.274)	(282.643)	(4.521)
ln Memphis	-0.307	1.06	0.005
(t-test)	(-22.899)	(305.240)	(12.787)
ln AWP	-0.579	1.105	-0.018
(t-test)	(-15.626)	(114.930)	(-15.349)

Source: NYBOT, Cotlook, Thomson, and Agricultural Marketing Service data

Table 26. Results from the Dickey Fuller Test for Non-Stationarity Using the Residuals from the Co-integrating Regressions, 1997-2006

Residuals	No. of Differences	Dickey Fuller Statistic
ln A-Index	0	-5.9656
ln Dallas	0	-9.54821
ln Lubbock	0	-9.65519
ln Memphis	0	-7.61894
ln AWP	0	-6.17211

Source: NYBOT, Cotlook, Thomson, and Agricultural Marketing Service data

The second, third and fourth co-integrating regressions used the logged Dallas, logged Lubbock, and logged Memphis cotton cash price series as the dependent variables, respectively. Independent variables for each the second, third, and fourth co-integrating regressions were the logged nearby series and the original interest rate series. Parameter estimates from these co-integrating regressions can also be found in table 25. The residuals from each regression were then tested for stationarity using the Dickey-Fuller test. Results from these stationarity tests can be found in table 26 and display evidence consistent with stationarity. The Dickey-Fuller statistic was less than the critical value of -2.9, leading us to fail to reject the null hypothesis of non-stationarity; therefore, confirming co-integration between the Dallas and the Nearby series, the Lubbock and Nearby series, and the Memphis and the Nearby series.

The final co-integrating regression used the logged Adjusted World Price as the dependent variable, the logged Nearby series as an independent variable, and the original interest rate series as another independent variable. Table 25 displays the parameter estimates for this final co-integrating regression. Again the residuals from this regression were tested for stationarity using the Dickey-Fuller test. Results from this stationarity test are found in table 26 and show evidence of stationarity. The Dickey-Fuller statistic was less than the critical value of -2.9, leading us to fail to reject the null hypothesis of non-stationarity; therefore confirming co-integration between the Adjusted World Series price and the Nearby series.

After confirming the existence of co-integration between the cotton futures market and the cotton cash markets, the error correction model was built to determine in which market price was discovered. Parameter estimates from the model can be found in tables 27 and 28. The parameter estimates of the most interest are those associated with the residuals of the co-integrating regression, δ_3 and γ_3 . All of the calculated t-statistics resulting from the error correction model that had the futures series as the dependent variable were not statistically different from zero. This is evidence that cotton price discovery occurs in the futures market. Results also found that all the calculated t-statistics, resulting from the error correction model that had the cotton cash price series as the dependent variable, were statistically different from zero. This is also consistent with expectations of theory.

Table 27. Parameter Estimates from the Cash Price Error Correction Models, 1997-2006

$$\Delta \ln Cash_t = \delta_0 + \delta_1 \Delta \ln Cash_{t-1} + \delta_2 \Delta \ln Nearby_{t-1} + \delta_3 z_{t-1}$$

Dependent Variable	δ_0 Intercept	δ_1 Cash Series	δ_2 Nearby Series	δ_3 Residuals
ln A-Index	4.061	0.535	-0.548	1.016
(t-test)	(1,218.134)	(3.103)	(-3.153)	(21.075)
ln Dallas	3.92	0.615	-0.624	1.044
(t-test)	(885.918)	(1.741)	(-1.824)	(8.420)
ln Lubbock	3.917	0.661	-0.667	1.047
(t-test)	(876.537)	(1.835)	(-1.917)	(8.294)
ln Memphis	3.956	0.256	-0.288	1.014
(t-test)	(876.044)	(0.537)	(-0.613)	(7.411)
ln AWP	3.779	0.693	-0.659	1.020
(t-test)	(855.918)	(3.092)	(-3.133)	(21.162)

Source: NYBOT, Cotlook, Thomson, and Agricultural Marketing Service data

Table 28. Parameter Estimates from the Futures Price Error Correction Models, 1997-2006

$$\Delta \ln Nearby = \gamma_0 + \gamma_1 \, \Delta \ln Cash_{t-1} + \gamma_2 \, \Delta \ln Nearby_{t-1} + \gamma_3 \, z_{t-1}$$

Dependent Variable	Cash Series Used in Regression	γ_0 Intercept	γ_1 Cash Series	γ_2 Nearby Series	γ_3 Residuals
ln Nearby	ln A-Index	4.002	0.645	-0.666	0.019
(t-test)		(957.35)	(2.982)	(-3.054)	(0.318)
ln Nearby	ln Dallas	4.002	0.586	-0.593	0.041
(t-test)		(956.23)	(1.752)	(-1.834)	(0.353)
ln Nearby	ln Lubbock	4.002	0.623	-0.628	0.045
(t-test)		(956.299)	(1.848)	(-1.928)	(0.378)
ln Nearby	ln Memphis	4.0019	0.2454	-0.27295	0.01308
(t-test)		(955.70)	(0.554)	(-0.627)	(0.103)
ln Nearby	ln AWP	4.002	0.623	-0.599	0.018
(t-test)		(957.298)	(2.936)	(-3.007)	(0.389)

Source: NYBOT, Cotlook, Thomson, and Agricultural Marketing Service data

Chapter Summary

Co-integration has become a popular method for testing the efficiency of various commodity future and cash markets. After implementing the Engle and Granger two-step approach, we have found evidence indicating that the cotton futures market and the cotton cash markets are co-integrated over the last ten calendar years (January 1997 through December 2006). The results from the error correction model have led us to conclude that price is discovered in the cotton futures market. This reinforces the notion that the U.S. cotton futures market is functioning efficiently and is serving as an efficient indicator for subsequent cotton cash prices.

CHAPTER V

ASSET-PRICING AND THE U.S. COTTON FUTURES MARKET

While the empirical studies described in the pricing patterns section can identify the presence of deviations from the efficient market hypothesis, those tests do not explain the sources of the pricing patterns. In this chapter, the theoretical basis for the pricing of risky assets is discussed. In an application of an asset pricing framework, the relationship of cotton futures returns to economic state variables is analyzed. The results allow inferences about market efficiency to be drawn. This contributes to market knowledge by allowing for the control of risk that is correlated with other assets in a financial portfolio.

Literature Review and Economic Theory

Equilibrium asset pricing theories were developed to differentiate market-level systematic risk from the specific risks associated with a particular security. Because cotton futures contracts are a type of financial asset, a formal asset-valuation framework is a useful approach to the analysis of market efficiency. The theoretical intuition about the basic principles underlying the prices of assets in general will provide a means by which to check the reasonableness of the results of the futures contracts. In addition, the vast empirical literature in the field of financial asset price modeling will be relied upon in choosing the appropriate model specifications that will be used to provide an up-to-date analysis of the cotton futures market.

Inter-temporal Consumption

Equilibrium asset pricing is based upon the economic theory of inter-temporal consumption. According to Nicholson (1992), the theory of inter-temporal consumption, also referred to as the theory of the demand for future goods, is an expansion of the theory of utility maximization, where the utility function is used as a method for individuals to rank alternative bundles of goods (or assets). An individual can assign a level of utility, or ranking, to their available choices, based on the assumptions of completeness, transitivity, and continuity[3].

To find an individual's utility maximizing point, subject to certain constraints, one must first solve an optimization problem and identify the utility-maximizing choices of goods to be consumed. One common method to achieve this optimization is the Lagrangian multiplier method. This technique also has a significant economic interpretation, which will be discussed after a brief explanation of its mathematical interpretation. Nicholson explains that in the Lagrangian multiplier method, we wish to find the values of $x_1, x_2, \dots, x_n$ that maximize

$$y = f(x_1, x_2, \dots, x_n) \tag{15}$$

[3] Nicholson defines completeness, transitivity, and continuity as the basic axioms of rational behavior, all components of the concept of an individual's preference. Completeness refers to an individual's ability to decide the desirability of any two alternatives. Transitivity assumes that the individual's choices are internally consistent. Continuity is a technical assumption required when analyzing an individual's responses to relatively small changes in income and prices. Using these three axioms, an individual can rank their possible choices and maximize their utility, or overall satisfaction.

subject to the following constraint, where g represents the relationship that must hold among all of the x variables:

$$g = (x_1, x_2, \dots , x_n). \tag{16}$$

An equation can now be written that incorporates the function to be maximized, the corresponding constraints, and a new variable: the Lagrangian multiplier, λ.

$$L = f(x_1, x_2, \dots, x_n) + \lambda\, g(x_1, x_2, \dots, x_n) \tag{17}$$

We can now move on to solve for the first order conditions. One begins by taking the partial derivatives of equation 17 and setting them equal to zero. In other words, one would take the partial derivative of equation L with respect to x_1, set it equal to zero, simultaneously solve all the n+1 first order conditions, and proceed with the same procedure for the multiplier λ.

$$\frac{\partial L}{\partial x_1} = f_1 + \lambda g_1 = 0 \tag{18}$$

$$\frac{\partial L}{\partial x_2} = f_2 + \lambda g_2 = 0 \tag{19}$$

$$\frac{\partial L}{\partial x_n} = f_n + \lambda g_n = 0 \tag{20}$$

$$\frac{\partial L}{\partial \lambda} = g(x_1, x_2, \ldots, x_n) = 0 \tag{21}$$

Once the first order conditions are solved, second order conditions must be calculated to ensure that the values obtained from the first order conditions are truly a maximum point (Nicholson). The second order conditions are obtained from second partial derivatives of each variable, including cross partials.

The economic interpretation of the Lagrangian multiplier deals with the concepts of marginal benefits and marginal costs and can be rewritten to demonstrate this relationship.

$$\lambda = \frac{m\arg inal\ benefit\ of\ x_n}{m\arg inal\ income\ of\ x_n} \tag{22}$$

Keeping in mind that λ indicates a constraint on our original equation 17, the Lagrangian multiplier provides a means of measuring how an overall relaxation of the constraint would affect the value of the objective in equation 15. This provides us with a "shadow price" of the constraint. If we were to relax the constraint, a high λ indicates that y would be greatly affected, while a low λ indicates that not much would be gained by relaxing our constraint. A λ that equals zero indicates that the constraint is not restricting our value of y (Nicholson).

Building from the theory of utility maximization, the theory of the demand for future goods can be obtained as a specific application leading to an understanding of the demand for risky assets. In the case of the demand for future goods, the alternative bundles of goods that an individual has to choose from include, consumption in the present or consumption in the future, subject to the individual's current income. The individual then has the option of investing income not spent on present consumption and earning a rate of return.

This scenario of a two-period consumption choice can be represented graphically, as depicted in figure 15. Present consumption is represented by C_0, while future consumption is represented by C_1. The individual's budget constraint is represented by

$$I = C_0 + P_1C_1, \tag{23}$$

where P_1 represents the present cost of future consumption and I represents current income. P_1 may also be written as

$$P_1 = \frac{\Delta C_0}{\Delta C_1} = \frac{1}{1+r}, \tag{24}$$

where r represents the rate of return[4] between the current and future periods. Substituting equation 24 into equation 23, we now have

[4] Bodie and Merton (2000) describe the four main factors that are used to determine the rates of return in a market economy as productivity of capital goods, the degree of uncertainty regarding the productivity of capital goods, people's time preferences, and their risk aversion. In reference to the variable P_1, Nicholson

$$I = C_0 + \frac{C_1}{1+r}. \quad (25)$$

Utility for this individual is maximized at C_0^*, C_1^*. By rearranging the terms in the budget constraint (equation 23), and by substituting equation 24 for P_1, future consumption can also be found.

$$C_1^* = (I - C_0^*) / P_1 \quad (26)$$

$$C_1^* = (I - C_0^*) (1 + r). \quad (27)$$

Equation 27 means that current savings, $(I - C_0^*)$, or income for future consumption, can be invested at r to yield C_1^* in the next consumption period. If the individual chooses not to spend any income on present consumption ($C_0 = 0$), then C_1 can be given by

$$I / P_1 = I (1 + r), \quad (28)$$

where, according to Nicholson, by investing all income at *r*, the current income will grow in the next period to I(1+r).

One can graphically illustrate the mathematical concepts of utility maximization using figure 15. Figure 15 shows that an individual will choose to maximize their utility

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uses the rate of return as the return an individual receives on consumption that is "put aside" until a later period.

by consuming at point C^*_1 and C^*_0, the point of tangency of the individual's utility function and their budget constraint.

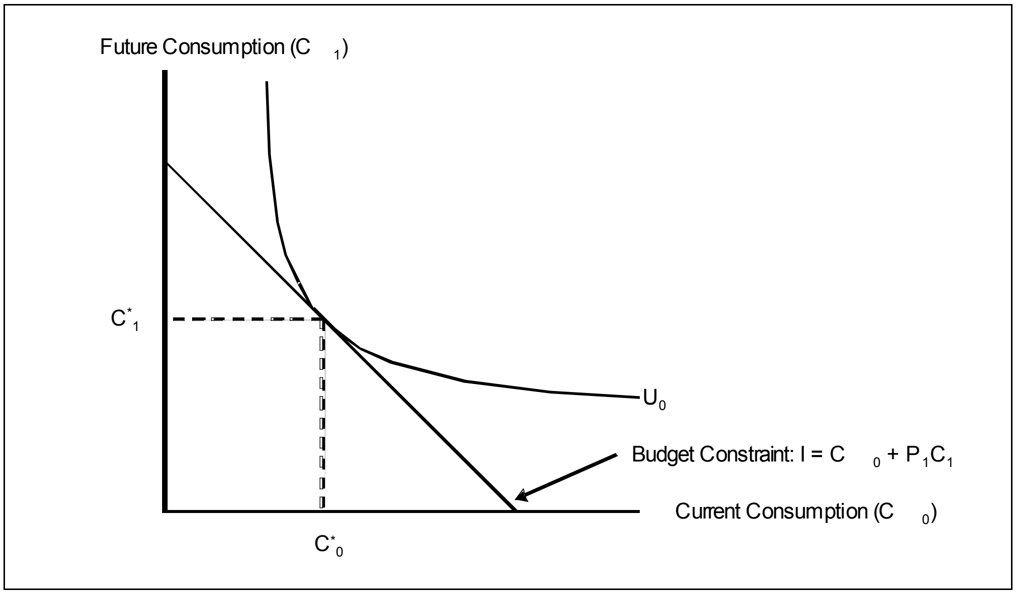

Figure 15. Inter-temporal Utility Maximization
(Source: Nicholson)

There are four key implications from this simple two-period framework:

1. The ratio of marginal utilities over consumption in the two periods determines the choice of investment.
2. The rate of return, r, is a key determining factor for it represents what can be earned on consumption that is withheld until the next period.
3. An individual's "impatience" or time preference is another key determining factor when considering consumption in this period or the next.
4. This simple model does not take into account risk.

Building from the basic economic principles of the two-period consumer utility maximization model, financial economists have developed a variety of economic models to explain the observed prices of assets whose returns are risky and whose payoffs can only be realized after the passage of time. A general framework proposed by Cochrane (2001) is described in the following section. Subsequently, a specific case for shares in publicly traded firms, the well-known Capital Asset Pricing Model (CAPM), is described. The chapter concludes with a factor model applied to the returns on cotton futures contracts.

Models of Equilibrium Asset Pricing

Given the basic theory of consumer behavior, inferences can be made about what the price of an asset must be in order to be consistent with consumer choice. These asset pricing principles are presented in a unified treatment by Cochrane. The basic premise is that the current market price of an asset which conveys the right to a future payoff must be the discounted value of the future payoff. The appropriate discount factor is related to subjective preferences on risk and to the ratio of marginal utilities over future and present consumption.

The theory of consumer behavior highlights the importance of marginal utility in a consumer's allocation of income between (1) consumption today, or (2) investments that will enable consumption at a later date. The principle of marginal utility is similarly fundamental in the pricing of risky assets (Cochrane). The formulation for asset pricing is based on the premise that the price (p) of an asset that has a payoff of x_{t+1} must be determined by the ratio of marginal utilities over consumption in each period. The mathematical representation is :

$$p_t = E_t[\beta \frac{U'(C_{t+1})}{U'(C_t)} x_{t+1}], \tag{29}$$

where E_t denotes expected value at time t, and $U(C_t)$ is a utility function over consumption. Subscripts t and $t+1$ on the consumption variables have been written more generally than in the previous section, but as before they indicate consumption choices made over time. The symbol prime on the utility function denotes the first derivative, or the marginal utility obtained from a change in the amount of the good consumed. The parameter β is the subjective discount factor capturing the time preference, or impatience, of the consumer. Because marginal utilities are unobservable, this formulation of the consumption-based model of asset pricing is not suitable for econometric estimation. To move toward empirical models, Cochrane consolidates the unknown ratio of marginal utilities and the subjective discount factor β into a "stochastic discount factor," defined as m_{t+1}, as shown is equation 30:

$$p_t = E(m_{t+1} x_{t+1}). \tag{30}$$

Then, from this consolidated formulation, a wide variety of asset pricing models can be understood as ways to link m_{t+1} to data. Most of the empirical models in the finance literature have used linear relationships to examine the role that riskiness of an individual asset plays in pricing.

Capital Asset Pricing

There are many equilibrium asset pricing studies in the finance literature, the most well known being the Capital Asset Pricing Model (CAPM) (Sharpe 1964). The CAPM is a leading example of a model that explains the price of a security by its risk. The CAPM, as described by Bodie and Merton (2000), is an equilibrium theory based on the concept of portfolio selection. The model accounts for the fact that the risks associated with an individual asset will tend to cancel out when combined with another asset whose risks move in the opposite direction. According to McDonald (2006), the important risk for investors to consider is the covariance between a stock and the market return because an investor's utility depends on the market return. The CAPM suggests that asset prices will adjust to ensure that the return on an asset precisely compensates investors for the risk of that asset when held with a well diversified portfolio.

There are two basic assumptions underlying the CAPM. The first is that investors hold risky assets in the same relative proportions as the market because investors agree on their expected rates of return, standard deviations, and correlations with the market. The second assumption is that investors will behave in a manner that is optimal for the market. This means that if prices are in equilibrium, the aggregate demand for any individual security is equal to its aggregate supply. This leads to the idea of a market portfolio, in which the portfolio is made up of assets that are in proportion to their observed market values (Bodie and Merton).

Mathematically, the expected return for an asset, denoted as E(r), is written as a function of the rate of return on a risk-free asset, represented by r_f, plus a risk premium.

The rate of return for the market is given by r_m. The difference between the risk-free asset and the risky market portfolio is the risk premium. This basic CAPM formula is:

$$E(r) = r_f + E(r_m - r_f)\,. \tag{31}$$

The parameter that is used to measure the risk of a security is beta (β), which in the CAPM "describes the marginal contribution of that security's return to the standard deviation of the market portfolio's return" and is given by equation 32 (Bodie and Merton). In equation 32, β is used to represent the covariance between the return on a security (in this case, security j) and the return on the market portfolio. With the introduction of beta, the CAPM states that "the risk premium on any asset is equal to its beta times the risk premium on the market portfolio, when in equilibrium" and is given by equation 33 (Bodie and Merton).

$$\beta_j = \frac{\sigma_{jm}}{\sigma^2{}_m} \tag{32}$$

The beta in equation 33 can be estimated in a linear model in which the return on the market is the independent variable while the return on the security is the dependent variable (Bodie and Merton).

$$E(r_j) - r_f = \beta_j[E(r_m) - r_f]\,. \tag{33}$$

Multi-factor Pricing

Refinements of the CAPM that are referred to as the ICAPM (Intertemporal CAPM) include multiple factors that reflect macroeconomic conditions. While the CAPM has been most often used to analyze the price of one stock in relation to a market portfolio, these multi-factor “beta models” use a broader set of explanatory factors than the stock market. The factors that are hypothesized to explain asset prices are related to changes in economic state variables, which are proxies for future consumption. The results of such models indicate which state variables “price risk,” that is, which variables represent the systematic risk that investors must be compensated for bearing. For those states that are identified as pricing risk, a beta coefficient measuring the sensitivity of the particular security being priced (the dependent variable) can be determined, and forecasting performance can be evaluated.

Models used to explain prices of risky assets have often focused on stocks, or equities. Similar frameworks have been used to examine prices of other risky assets, including futures contracts. Bessembinder and Chan (1992) provide a leading example of this conceptual approach to the study of futures prices. They developed and tested equilibrium-type models for pricing futures contracts. Their objective was to determine whether the variables that had recently been found to have predictive power in forecasting equity and bond returns also had an influence on futures market returns. If common shocks across securities markets could be found, the common instruments could improve the pricing of systematic risk. The algebric specification of Bessembinder and Chan is:

$$E(\tilde{r}_{i,t} \mid Z_{t-1}) = \sum_{k=1}^{K} \beta_{ik} E(\tilde{\lambda}_k \mid Z_{t-1}). \tag{34}$$

The expected return (r) on asset i, conditional on state variables Z, is linearly related to the expected factor prices of risk, represented by λ. The factor prices of risk are also conditioned on state variables Z. The coefficients β_{ik} represent the sensitivity of asset i to the k factors whose risk is price by λ. Estimates from this model would permit analysts to decompose movements in securities markets prices into commodity specific risk factors, separately from the systematic risk reflected in the coefficients β_{ik}.

Bessembinder and Chan studied agricultural commodity futures, currency exchange futures, and metals futures, finding that "…futures are subject to different sources of priced risk than are equities" (p.169). The factors in the equilibrium model Bessembinder and Chan found to forecast futures prices included yield on Treasury bills, equity dividend yields, and the junk bond premium. These variables represent market-wide risk and are likely important controls in any model that is designed to provide an updated understanding of the pricing patterns in the cotton futures market. Cotton futures prices had unusual results in Bessembinder and Chan's multi-factor model estimated for the 1975-1989 period. Interestingly, expected excess returns on cotton futures, measured by the intercept coefficient, were positive and statistically significant. Factors that priced risk of cotton futures included the junk bond default premium (positive sign, unexpectedly) and the 10-year Treasury bill (negative sign, as expected).

Methods

The formulation for the empirical work derives from the beta representation of the expected return on assets. The explanatory factors are chosen to represent expected future growth in consumption; thus they proxy, generally, for an investors' preference for future consumption over present consumption. This rationale leaves researchers with wide discretion regarding the specific variables that are used in empirical work. The economic state variables used in this chapter have been found to be predictive of other securities' returns in previous models of this type (Bessembinder and Chan). Significance of these state variables would be an indication of a common shock in preferences for holding risky assets that affected both the cotton futures market and other risky assets.

It is important in this model framework to choose factors that are *not* asset-specific (Cochrane). Any features that are asset-specific will be encompassed within the beta coefficient, which represents the behavior of the asset with respect to the factor. Hence, we do not include any explanatory variables that are known to be important in a conceptual framework that derives from the economic theory of demand, such as the value of competing fibers, or conditions specific to the key export markets for cotton fiber. The explanatory variables selected are the Dow Jones dividend yield, the junk bond premium and the 10-year Treasury as the independent variables. All variables are in excess returns form, obtained by differencing the return on the factor and the risk-free rate (3-month Treasury). The lag of the factors are used in this application, following Bessembinder and Chan.

Because this model was developed for the pricing of only one risky asset (the cotton futures contract), and the data on factors are in the form of excess returns, the means of the factors are defined directly as the factor risk premium (λ) for that factor. The beta coefficients to be estimated represent the sensitivity of the Nearby cotton futures returns to a change in the factor price of risk.

The monthly returns on Nearby cotton futures contracts were calculated using the monthly percentage change in the nearby futures settlement prices. According to Kolb, long traders in the aggregate are less risk-averse than short traders. Hence, the short traders are using the futures market to hedge their unwanted risk. As a result, the short traders entice the long traders to take their complementary risk-bearing position by paying them a risk premium (Kolb).

A regression was then run with Nearby cotton futures returns as the dependent variable and the excess returns of the Dow Jones dividend yield, the junk bond premium and the 10-year Treasury as the independent variables. The first test is to determine if the intercepts are zero. Next the combined power of the betas is examined to determine forecastability (table 29).

Results

On average, factor price risk along with the test security (cotton futures) should account for all predictable excess returns and there should be no significant average return to be reflected in an intercept coefficient. The data using the Nearby cotton futures prices satisfies this condition with a t-statistic of 0.37 (table 29). This finding is not consistent with the results of Bessembinder and Chan, who found that cotton futures were an exception among other futures contracts in that cotton futures exhibited significant positive excess returns during the 1970s-80s. These updated results indicate that cotton futures prices do not include a significant risk premium.

The next question of interest is regarding the explanatory power of the betas. Betas measure the exposure of asset *i* to each factor's risk, and combined, they indicate "forecastability." When all beta coefficients are simultaneously not indistinguishable from zero, then it is said that the factors do not have forecast power. The estimates for each individual beta for the Nearby cotton futures prices (table 29) indicate that no individual beta is statistically different from zero at the 0.05 level. This can therefore be interpreted as cotton futures do not have any common risk prices with those found to forecast returns on equities. These results again differ from the dividend yield and the Treasury bond. The absence of forecastability is supportive of efficient markets.

Table 29. Coefficient Estimates for Factor Model of Cotton Futures Returns, 1987-2006 (Nearby Cotton Futures Prices)

	Estimate	Standard Error	t Statistic	Pr > |t|
Intercept	0.0066	0.0177	0.37	0.7083
Equity Dividend Yield (Dow Jones 30 Industrials)	0.4776	0.9290	0.51	0.6078
Junk Bond Premium (Moody's)	-0.1563	0.6811	0.23	0.8188
U.S. Government Long Bond Premium	-0.1262	0.6349	-0.20	0.8426

All explanatory variables are in excess return format (differenced by the 3-month Treasury bill yield), lagged one month.

Source: DataStream and NYBOT data

While none of the factors are important to pricing risk of cotton futures in a statistical sense, there were some findings from this updated analysis that differ from previous studies. Most importantly, the sign of the coefficient on the Treasury bill variable was positive, contrary to what was expected from the literature.

With regard to each specific coefficient, the estimates indicate that cotton futures returns, are positively related to dividend yield on equities, but are less risky (coefficient size less than 1). When equity excess returns increase by one percent, Nearby cotton futures excess returns increase by only 0.48%, for nearby cotton futures. Nearby cotton futures returns move in opposite direction to the variation in high-yield corporate bond premiums. Cotton futures returns and U.S. government long bond premiums have an estimated negative relationship.

The lack of forecastability of cotton futures from the economy-wide factors is demonstrated graphically. Using the estimated beta coefficients with the observed factors from 1987 to 2006, the predicted values of monthly excess returns on the Nearby cotton futures contracts are illustrated in figure 16. Figure 17 illustrates the actual excess returns on the Nearby cotton futures. Risk premiums for cotton futures have been both positive and negative over the period 1987 to the present, according to the fitted values from the equilibrium pricing model. Excess returns were predicted to be positive during the early 1990s and during the most recent period.

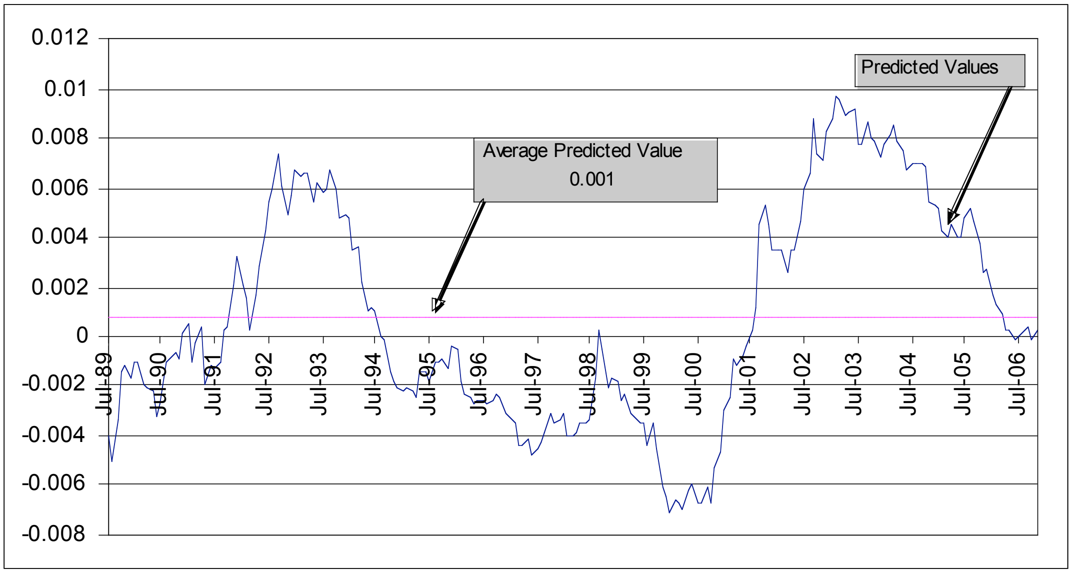

Figure 16. Predicted Excess Returns on Nearby Cotton Futures, by Month, 1987-2006
(Source: DataStream and NYBOT data)

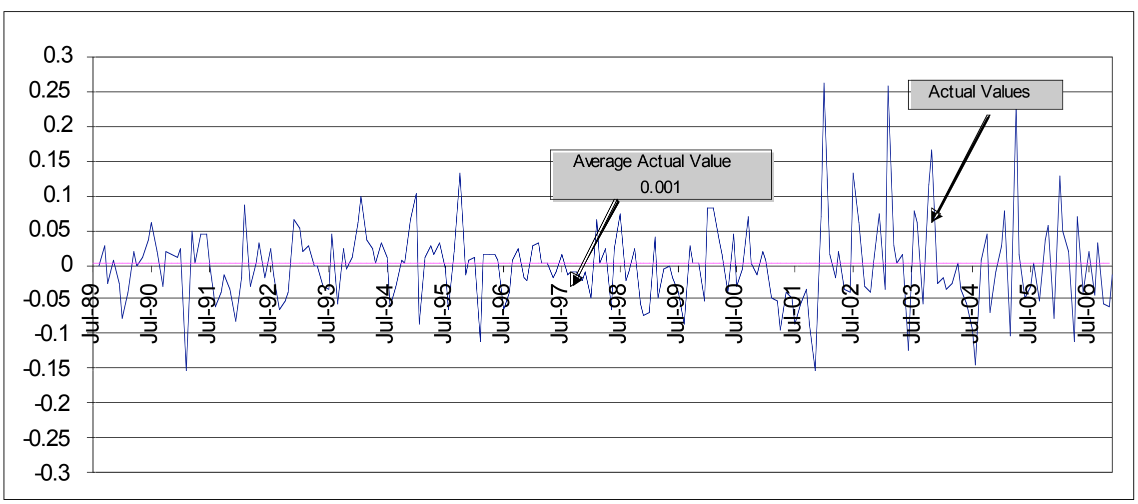

Figure 17. Actual Excess Returns on Nearby Cotton Futures, by Month, 1987-2006
(Source: DataStream and NYBOT data)

Non-diversifiable risk for an investor to hold Nearby cotton futures is, on average, 0.1 percent when calculated from the model parameters

$$E(R^e) = \beta' f \,. \tag{35}$$

The predicted risk measures are shown with horizontal lines on figure 16. The excess return never reaches 1% over the risk-free rate, according to these findings.

The persistence of excess returns to cotton futures is an interesting question raised by examining figures 16 and 17. For the conditions prevailing in the securities market in general, the duration of positive excess returns on cotton futures was more than two years, before a gradual decline in returns. There was a fairly rapid shift in excess returns from the negative to positive ranges around July 2001, which could be a signal of structural changes in the preferences of investors or some industry or asset-specific conditions.

Chapter Summary

The development of an asset-valuation framework is imperative to any financial analysis. Building off of the theory of inter-temporal consumption (or the theory of the demand for future goods), I derive an equilibrium asset-pricing model. While financial asset-pricing models, such as the Capital Asset Pricing Model, are more commonly used to value stocks, Bessembinder and Chan apply the same concepts to the commodity futures markets. Following their approach, I tested the cotton futures market to determine if it follows patterns similar to those of equities. I found that the cotton futures market does not have any apparent risks that distinguish them from other assets included in the regression model that were used to test for economic indicators; there was no risk premium found. Evidence from the model indicates that cotton futures returns are positively related to dividend yield on equities, but are less risky (coefficient size less than 1). Results also found that cotton futures returns move in opposite direction to the variation in high-yield corporate bond premiums. The relatively small difference in expected rates of return to cotton futures and lack of forecastability with the factors in the model provides support for efficiency in the futures market.

CHAPTER VI

THESIS SUMMARY AND CONCLUSIONS

The contribution of this research is to update and extend the information available on the efficiency of the U.S. cotton futures market from 1986 through 2006 with regard to pricing patterns, co-integration, and asset valuation. The most updated cotton price data available were used in this analysis, including 42,000 observations and five cash market prices, along with the Nearby futures market prices. Overall, the cotton futures market, ***in the long-run*** (last twenty years), displays evidence that is most consistent with weak-form market efficiency, meaning that the market's prices fully reflect all trade related information. Therefore, there are no abnormal returns to be made using a trading strategy based on historical pricing patterns. However, as evident by our extension of Kolb's normal backwardation study, pricing patterns are found when the cotton futures prices are sub-divided into crop seasons in the short-run.

Results from the normal backwardation study differed from Kolb's original findings and may be explained in several different ways. First, contracts that expired in the late 1980s often exhibited statistically significant risk premiums consistent with normal backwardation. Later, cotton futures prices from the late 1990s to the present day have demonstrated declining prices, or contango. Within a contract, there are different factors affecting futures markets. Basing one choice of sub-samples on the production seasons for cotton within the December contract data from 1987 through 2006, we find that preplanting and planting periods had no price rises or declines. Later in the year, the cotton futures price had a significant declining trend. The different results may be due to structural changes in the cotton market. For example, Kolb's results were based on price data from a period when the U.S. cotton industry was largely a domestic market. Since the mid 1990s, the U.S. cotton industry has changed into an export market, introducing new and greater forces of uncertainty and price volatility. This could have altered the pre-existing hedger-speculator dynamics that were reflected by Kolb's data. Second, seasonality may be a key factor in analyzing agricultural commodity futures markets, with normal backwardation being present during certain time intervals and contango being present during another time interval within the same contract.

The findings from the co-integration analysis showed some consistencies and inconsistencies when compared with Brorsen, Bailey, and Richardson's original findings regarding the cotton futures and cash market. Both studies confirm that the price of cotton is discovered in the cotton futures market, consistent with the theory of efficient markets. However, where the recent data support market efficiency, Brorsen et al. found market inefficiency. This may be attributed to the timeframe of price data that was used in each study. Where this cotton price data dated from 1997 through 2006, Brorsen et al. used cotton price data ranging from 1976 through 1982. Again the change may be explained by structural changes in the market, as explained previously. As for our asset-pricing model for cotton futures, we also find evidence of efficiency. Our findings indicate that the cotton futures market does not show evidence of risks that are not also found among other common financial market instruments that were used in the model.

Yet another area of market efficiency is found in the relatively small differences in expected rates of return to cotton futures.

The efficiency of the U.S. cotton futures market is a concern to all market participants: producers, merchants, U.S. government, foreign governments, as well as market speculators. This research serves as a foundation with which future studies can benefit. Our findings reinforce the notion that the cotton futures market is functioning efficiently in the long-run. Further research is needed to determine hedging strategies that will most benefit cotton producers and merchants in the short-run, where pricing patterns have been indicated to exist.

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APPENDIX A

SAMPLE SAS CODE FOR THE PRICING PATTERNS ANALYSIS

The following SAS code was used for the entire March cotton futures contract from 1987 through 2006 and for the market as a whole (also referred to as combined). Similar code was used for the May, July, October, and December contracts as well as in the analysis of the final year of the cotton futures contracts. Abbreviations were used throughout the programming for the contract's delivery month. Letters representing the contract delivery months were also used in the programming and are consistent with those used by the New York Board of Trade (H for March, K for May, N for July, V for October and Z for December).

The first section of code, referred to as Sample SAS Code 1, was used to adjust the dataset to account for price variations associated with the last notice day. The price observations following the last notice days were dropped from the dataset. The second section of code, referred to as Sample SAS Code 2, was used to replicate the first and second tests devised by Kolb. The differentials that were used in the third test, along with basic statistics for the dataset, were also calculated in the second section of code. Sample SAS Code 3 displays a section of programming that was used in replicating Kolb's third test: the regression of the differentials over time. Notes detailing the specific functions of code are located throughout the programming and are separated from the code with "/*."

Sample SAS Code 1

```
/*Start of SAS code to adjust dataset to account for price variations related
to the last notice day of the March cotton futures contracts.*/

DATA MARCH87;
SET SASUSER.MARCOTFUTURES;
KEEP CONTRACT87 PRICE87;
IF CONTRACT87 >= '01MAR1987'D - 6 THEN DELETE;
RUN;

DATA MARCH88;
SET SASUSER.MARCOTFUTURES;
KEEP CONTRACT88 PRICE88;
IF CONTRACT88 >= '01MAR1988'D - 7 THEN DELETE;
RUN;

DATA MARCH89;
SET SASUSER.MARCOTFUTURES;
KEEP CONTRACT89 PRICE89;
IF CONTRACT89 >= '01MAR1989'D - 7 THEN DELETE;
RUN;

DATA MARCH90;
SET SASUSER.MARCOTFUTURES;
KEEP CONTRACT90 PRICE90;
IF CONTRACT90 >= '01MAR1990'D - 7 THEN DELETE;
RUN;

DATA MARCH91;
SET SASUSER.MARCOTFUTURES;
KEEP CONTRACT91 PRICE91;
IF CONTRACT91 >= '01MAR1991'D - 7 THEN DELETE;
RUN;

DATA MARCH92;
SET SASUSER.MARCOTFUTURES;
KEEP CONTRACT92 PRICE92;
IF CONTRACT92 >= '01MAR1992'D - 7 THEN DELETE;
RUN;

DATA MARCH93;
SET SASUSER.MARCOTFUTURES;

KEEP CONTRACT93 PRICE93;
IF CONTRACT93 >= '01MAR1993'D - 7 THEN DELETE;
RUN;

DATA MARCH94;
SET SASUSER.MARCOTFUTURES;
KEEP CONTRACT94 PRICE94;
IF CONTRACT94 >= '01MAR1994'D - 7 THEN DELETE;
RUN;

DATA MARCH95;
SET SASUSER.MARCOTFUTURES;
KEEP CONTRACT95 PRICE95;
IF CONTRACT95 >= '01MAR1995'D - 7 THEN DELETE;
RUN;
```

```
DATA MARCH96;
SET SASUSER.MARCOTFUTURES;
KEEP CONTRACT96 PRICE96;
IF CONTRACT96 >= '01MAR1996'D - 7 THEN DELETE;
RUN;

DATA MARCH97;
SET SASUSER.MARCOTFUTURES;
KEEP CONTRACT97 PRICE97;
IF CONTRACT97 >= '01MAR1997'D - 7 THEN DELETE;
RUN;

DATA MARCH98;
SET SASUSER.MARCOTFUTURES;
KEEP CONTRACT98 PRICE98;
IF CONTRACT98 >= '01MAR1998'D - 7 THEN DELETE;
RUN;

DATA MARCH99;
SET SASUSER.MARCOTFUTURES;
KEEP CONTRACT99 PRICE99;
IF CONTRACT99 >= '01MAR1999'D - 7 THEN DELETE;
RUN;

DATA MARCH00;
SET SASUSER.MARCOTFUTURES;
KEEP CONTRACT00 PRICE00;
IF CONTRACT00 >= '01MAR2000'D - 7 THEN DELETE;
RUN;

DATA MARCH01;
SET SASUSER.MARCOTFUTURES;
KEEP CONTRACT01 PRICE01;
IF CONTRACT01 >= '01MAR2001'D - 7 THEN DELETE;
RUN;

DATA MARCH02;
SET SASUSER.MARCOTFUTURES;
KEEP CONTRACT02 PRICE02;
IF CONTRACT02 >= '01MAR2002'D - 7 THEN DELETE;
RUN;

DATA MARCH03;
SET SASUSER.MARCOTFUTURES;
KEEP CONTRACT03 PRICE03;
IF CONTRACT03 >= '01MAR2003'D - 7 THEN DELETE;
RUN;

DATA MARCH04;
SET SASUSER.MARCOTFUTURES;
KEEP CONTRACT04 PRICE04;
IF CONTRACT04 >= '01MAR2004'D - 7 THEN DELETE;
RUN;

DATA MARCH05;
SET SASUSER.MARCOTFUTURES;
KEEP CONTRACT05 PRICE05;
IF CONTRACT05 >= '01MAR2005'D - 7 THEN DELETE;
RUN;
```

```
DATA MARCH06;
SET SASUSER.MARCOTFUTURES;
KEEP CONTRACT06 PRICE06;
IF CONTRACT06 >= '01MAR2006'D - 7 THEN DELETE;
RUN;

DATA SASUSER.NEWMARDATA;
MERGE MARCH87 MARCH88 MARCH89 MARCH90 MARCH91 MARCH92 MARCH93 MARCH94 MARCH95
MARCH96 MARCH97 MARCH98 MARCH99 MARCH00 MARCH01 MARCH02 MARCH03 MARCH04 MARCH05
MARCH06;
RUN;

PROC PRINT DATA=SASUSER.NEWMARDATA;
RUN;

PROC EXPORT DATA=SASUSER.NEWMARDATA
OUTFILE="F:\KOLB\WHOLE CONTRACTS\NEWMARDATA.CSV"
DBMS=CSV REPLACE;
RUN;
```

Sample SAS Code 2

```
/*Start SAS Code for the March contract, analyzing data for normal
backwardation according to Kolb's tests.  Creates datasets from permanent SAS
dataset already imported into SAS.*/

DATA KOLBMAR;
SET SASUSER.NEWMARDATA;

/*Creates the logarithmic form of the original price data.*/

LNPRICE87=LOG(PRICE87);
LNPRICE88=LOG(PRICE88);
LNPRICE89=LOG(PRICE89);
LNPRICE90=LOG(PRICE90);
LNPRICE91=LOG(PRICE91);
LNPRICE92=LOG(PRICE92);
LNPRICE93=LOG(PRICE93);
LNPRICE94=LOG(PRICE94);
LNPRICE95=LOG(PRICE95);
LNPRICE96=LOG(PRICE96);
LNPRICE97=LOG(PRICE97);
LNPRICE98=LOG(PRICE98);
LNPRICE99=LOG(PRICE99);
LNPRICE00=LOG(PRICE00);
LNPRICE01=LOG(PRICE01);
LNPRICE02=LOG(PRICE02);
LNPRICE03=LOG(PRICE03);
LNPRICE04=LOG(PRICE04);
LNPRICE05=LOG(PRICE05);
LNPRICE06=LOG(PRICE06);

/*Creates the lag of the logged dataset.*/

LAGLNPRICE87=LAG(LNPRICE87);
LAGLNPRICE88=LAG(LNPRICE88);
LAGLNPRICE89=LAG(LNPRICE89);
```

```
LAGLNPRICE90=LAG(LNPRICE90);
LAGLNPRICE91=LAG(LNPRICE91);
LAGLNPRICE92=LAG(LNPRICE92);
LAGLNPRICE93=LAG(LNPRICE93);
LAGLNPRICE94=LAG(LNPRICE94);
LAGLNPRICE95=LAG(LNPRICE95);
LAGLNPRICE96=LAG(LNPRICE96);
LAGLNPRICE97=LAG(LNPRICE97);
LAGLNPRICE98=LAG(LNPRICE98);
LAGLNPRICE99=LAG(LNPRICE99);
LAGLNPRICE00=LAG(LNPRICE00);
LAGLNPRICE01=LAG(LNPRICE01);
LAGLNPRICE02=LAG(LNPRICE02);
LAGLNPRICE03=LAG(LNPRICE03);
LAGLNPRICE04=LAG(LNPRICE04);
LAGLNPRICE05=LAG(LNPRICE05);
LAGLNPRICE06=LAG(LNPRICE06);

/*Calculates the daily return of the lagged and logged data.*/

LOGRETURN87=LNPRICE87-LAGLNPRICE87;
LOGRETURN88=LNPRICE88-LAGLNPRICE88;
LOGRETURN89=LNPRICE89-LAGLNPRICE89;
LOGRETURN90=LNPRICE90-LAGLNPRICE90;
LOGRETURN91=LNPRICE91-LAGLNPRICE91;
LOGRETURN92=LNPRICE92-LAGLNPRICE92;
LOGRETURN93=LNPRICE93-LAGLNPRICE93;
LOGRETURN94=LNPRICE94-LAGLNPRICE94;
LOGRETURN95=LNPRICE95-LAGLNPRICE95;
LOGRETURN96=LNPRICE96-LAGLNPRICE96;
LOGRETURN97=LNPRICE97-LAGLNPRICE97;
LOGRETURN98=LNPRICE98-LAGLNPRICE98;
LOGRETURN99=LNPRICE99-LAGLNPRICE99;
LOGRETURN00=LNPRICE00-LAGLNPRICE00;
LOGRETURN01=LNPRICE01-LAGLNPRICE01;
LOGRETURN02=LNPRICE02-LAGLNPRICE02;
LOGRETURN03=LNPRICE03-LAGLNPRICE03;
LOGRETURN04=LNPRICE04-LAGLNPRICE04;
LOGRETURN05=LNPRICE05-LAGLNPRICE05;
LOGRETURN06=LNPRICE06-LAGLNPRICE06;

/*Creates the lag of the original price data.*/

LAGPRICE87=LAG(PRICE87);
LAGPRICE88=LAG(PRICE88);
LAGPRICE89=LAG(PRICE89);
LAGPRICE90=LAG(PRICE90);
LAGPRICE91=LAG(PRICE91);
LAGPRICE92=LAG(PRICE92);
LAGPRICE93=LAG(PRICE93);
LAGPRICE94=LAG(PRICE94);
LAGPRICE95=LAG(PRICE95);
LAGPRICE96=LAG(PRICE96);
LAGPRICE97=LAG(PRICE97);
LAGPRICE98=LAG(PRICE98);
LAGPRICE99=LAG(PRICE99);
LAGPRICE00=LAG(PRICE00);
LAGPRICE01=LAG(PRICE01);
LAGPRICE02=LAG(PRICE02);
LAGPRICE03=LAG(PRICE03);
```

```
LAGPRICE04=LAG(PRICE04);
LAGPRICE05=LAG(PRICE05);
LAGPRICE06=LAG(PRICE06);

/*Calculates the daily return of the original price data using the original
data and the lagged data just created.*/

DAILYRETURN87=(PRICE87-LAGPRICE87)/LAGPRICE87;
DAILYRETURN88=(PRICE88-LAGPRICE88)/LAGPRICE88;
DAILYRETURN89=(PRICE89-LAGPRICE89)/LAGPRICE89;
DAILYRETURN90=(PRICE90-LAGPRICE90)/LAGPRICE90;
DAILYRETURN91=(PRICE91-LAGPRICE91)/LAGPRICE91;
DAILYRETURN92=(PRICE92-LAGPRICE92)/LAGPRICE92;
DAILYRETURN93=(PRICE93-LAGPRICE93)/LAGPRICE93;
DAILYRETURN94=(PRICE94-LAGPRICE94)/LAGPRICE94;
DAILYRETURN95=(PRICE95-LAGPRICE95)/LAGPRICE95;
DAILYRETURN96=(PRICE96-LAGPRICE96)/LAGPRICE96;
DAILYRETURN97=(PRICE97-LAGPRICE97)/LAGPRICE97;
DAILYRETURN98=(PRICE98-LAGPRICE98)/LAGPRICE98;
DAILYRETURN99=(PRICE99-LAGPRICE99)/LAGPRICE99;
DAILYRETURN00=(PRICE00-LAGPRICE00)/LAGPRICE00;
DAILYRETURN01=(PRICE01-LAGPRICE01)/LAGPRICE01;
DAILYRETURN02=(PRICE02-LAGPRICE02)/LAGPRICE02;
DAILYRETURN03=(PRICE03-LAGPRICE03)/LAGPRICE03;
DAILYRETURN04=(PRICE04-LAGPRICE04)/LAGPRICE04;
DAILYRETURN05=(PRICE05-LAGPRICE05)/LAGPRICE05;
DAILYRETURN06=(PRICE06-LAGPRICE06)/LAGPRICE06;

/*Calculates a return for the contract using the first price for each of the
twenty contract years.*

CONTRACTRETURN87=(PRICE87-52.75)/52.75;
CONTRACTRETURN88=(PRICE88-52.00)/52.00;
CONTRACTRETURN89=(PRICE89-67.90)/67.90;
CONTRACTRETURN90=(PRICE90-53.60)/53.60;
CONTRACTRETURN91=(PRICE91-67.25)/67.25;
CONTRACTRETURN92=(PRICE92-68.50)/68.50;
CONTRACTRETURN93=(PRICE93-67.50)/67.50;
CONTRACTRETURN94=(PRICE94-59.60)/59.60;
CONTRACTRETURN95=(PRICE95-62.25)/62.25;
CONTRACTRETURN96=(PRICE96-69.75)/69.75;
CONTRACTRETURN97=(PRICE97-74.90)/74.90;
CONTRACTRETURN98=(PRICE98-78.38)/78.38;
CONTRACTRETURN99=(PRICE99-76.15)/76.15;
CONTRACTRETURN00=(PRICE00-73.95)/73.95;
CONTRACTRETURN01=(PRICE01-63.00)/63.00;
CONTRACTRETURN02=(PRICE02-64.25)/64.25;
CONTRACTRETURN03=(PRICE03-55.90)/55.90;
CONTRACTRETURN04=(PRICE04-51.00)/51.00;
CONTRACTRETURN05=(PRICE05-63.25)/63.25;
CONTRACTRETURN06=(PRICE06-67.75)/67.75;

/*Calculates the differentials using the last price for each contract.  Data
has already been altered to comply with variation resulting for the last notice
day.*

DIFFERENTIAL87=(PRICE87-54.65)/54.65;
DIFFERENTIAL88=(PRICE88-60.40)/60.40;
DIFFERENTIAL89=(PRICE89-58.57)/58.57;
DIFFERENTIAL90=(PRICE90-69.11)/69.11;
```

```
DIFFERENTIAL91=(PRICE91-84.90)/84.90;
DIFFERENTIAL92=(PRICE92-53.17)/53.17;
DIFFERENTIAL93=(PRICE93-63.80)/63.80;
DIFFERENTIAL94=(PRICE94-77.03)/77.03;
DIFFERENTIAL95=(PRICE95-98.48)/98.48;
DIFFERENTIAL96=(PRICE96-82.13)/82.13;
DIFFERENTIAL97=(PRICE97-73.10)/73.10;
DIFFERENTIAL98=(PRICE98-63.90)/63.90;
DIFFERENTIAL99=(PRICE99-60.09)/60.09;
DIFFERENTIAL00=(PRICE00-58.80)/58.80;
DIFFERENTIAL01=(PRICE01-55.76)/55.76;
DIFFERENTIAL02=(PRICE02-33.06)/33.06;
DIFFERENTIAL03=(PRICE03-50.57)/50.57;
DIFFERENTIAL04=(PRICE04-67.69)/67.69;
DIFFERENTIAL05=(PRICE05-46.54)/46.54;
DIFFERENTIAL06=(PRICE06-56.68)/56.68;

/*Gives basic statistics for each of the twenty March contracts.*/

PROC MEANS DATA=KOLBMAR;
VAR PRICE87 LNPRICE87 LOGRETURN87 DAILYRETURN87 CONTRACTRETURN87
DIFFERENTIAL87;
OUTPUT OUT=MARSTATS87 MEAN=MEANPRICE87 MEANLNPRICE87 MEANLOGRETURN87
MEANDAILYRETURN87 MEANCONTRACTRETURN87 MEANDIFFERENTIAL87 STD=STDPRICE87
STDLNPRICE87 STDLOGRETURN87 STDDAILYRETURN87 STDCONTRACTRETURN87
STDDIFFERENTIAL87;
RUN;

PROC MEANS DATA=KOLBMAR;
VAR PRICE88 LNPRICE88 LOGRETURN88 DAILYRETURN88 CONTRACTRETURN88
DIFFERENTIAL88;
OUTPUT OUT=MARSTATS88 MEAN=MEANPRICE88 MEANLNPRICE88 MEANLOGRETURN88
MEANDAILYRETURN88 MEANCONTRACTRETURN88 MEANDIFFERENTIAL88 STD=STDPRICE88
STDLNPRICE88 STDLOGRETURN88 STDDAILYRETURN88 STDCONTRACTRETURN88
STDDIFFERENTIAL88;
RUN;

PROC MEANS DATA=KOLBMAR;
VAR PRICE89 LNPRICE89 LOGRETURN89 DAILYRETURN89 CONTRACTRETURN89
DIFFERENTIAL89;
OUTPUT OUT=MARSTATS89 MEAN=MEANPRICE89 MEANLNPRICE89 MEANLOGRETURN89
MEANDAILYRETURN89 MEANCONTRACTRETURN89 MEANDIFFERENTIAL89 STD=STDPRICE89
STDLNPRICE89 STDLOGRETURN89 STDDAILYRETURN89 STDCONTRACTRETURN89
STDDIFFERENTIAL89;
RUN;

PROC MEANS DATA=KOLBMAR;
VAR PRICE90 LNPRICE90 LOGRETURN90 DAILYRETURN90 CONTRACTRETURN90
DIFFERENTIAL90;
OUTPUT OUT=MARSTATS90 MEAN=MEANPRICE90 MEANLNPRICE90 MEANLOGRETURN90
MEANDAILYRETURN90 MEANCONTRACTRETURN90 MEANDIFFERENTIAL90 STD=STDPRICE90
STDLNPRICE90 STDLOGRETURN90 STDDAILYRETURN90 STDCONTRACTRETURN90
STDDIFFERENTIAL90;
RUN;

PROC MEANS DATA=KOLBMAR;
VAR PRICE91 LNPRICE91 LOGRETURN91 DAILYRETURN91 CONTRACTRETURN91
DIFFERENTIAL91;
OUTPUT OUT=MARSTATS91 MEAN=MEANPRICE91 MEANLNPRICE91 MEANLOGRETURN91
MEANDAILYRETURN91 MEANCONTRACTRETURN91 MEANDIFFERENTIAL91 STD=STDPRICE91
```

```
STDLNPRICE91 STDLOGRETURN91 STDDAILYRETURN91 STDCONTRACTRETURN91
STDDIFFERENTIAL91;
RUN;

PROC MEANS DATA=KOLBMAR;
VAR PRICE92 LNPRICE92 LOGRETURN92 DAILYRETURN92 CONTRACTRETURN92
DIFFERENTIAL92;
OUTPUT OUT=MARSTATS92 MEAN=MEANPRICE92 MEANLNPRICE92 MEANLOGRETURN92
MEANDAILYRETURN92 MEANCONTRACTRETURN92 MEANDIFFERENTIAL92 STD=STDPRICE92
STDLNPRICE92 STDLOGRETURN92 STDDAILYRETURN92 STDCONTRACTRETURN92
STDDIFFERENTIAL92;
RUN;

PROC MEANS DATA=KOLBMAR;
VAR PRICE93 LNPRICE93 LOGRETURN93 DAILYRETURN93 CONTRACTRETURN93
DIFFERENTIAL93;
OUTPUT OUT=MARSTATS93 MEAN=MEANPRICE93 MEANLNPRICE93 MEANLOGRETURN93
MEANDAILYRETURN93 MEANCONTRACTRETURN93 MEANDIFFERENTIAL93 STD=STDPRICE93
STDLNPRICE93 STDLOGRETURN93 STDDAILYRETURN93 STDCONTRACTRETURN93
STDDIFFERENTIAL93;
RUN;

PROC MEANS DATA=KOLBMAR;
VAR PRICE94 LNPRICE94 LOGRETURN94 DAILYRETURN94 CONTRACTRETURN94
DIFFERENTIAL94;
OUTPUT OUT=MARSTATS94 MEAN=MEANPRICE94 MEANLNPRICE94 MEANLOGRETURN94
MEANDAILYRETURN94 MEANCONTRACTRETURN94 MEANDIFFERENTIAL94 STD=STDPRICE94
STDLNPRICE94 STDLOGRETURN94 STDDAILYRETURN94 STDCONTRACTRETURN94
STDDIFFERENTIAL94;
RUN;

PROC MEANS DATA=KOLBMAR;
VAR PRICE95 LNPRICE95 LOGRETURN95 DAILYRETURN95 CONTRACTRETURN95
DIFFERENTIAL95;
OUTPUT OUT=MARSTATS95 MEAN=MEANPRICE95 MEANLNPRICE95 MEANLOGRETURN95
MEANDAILYRETURN95 MEANCONTRACTRETURN95 MEANDIFFERENTIAL95 STD=STDPRICE95
STDLNPRICE95 STDLOGRETURN95 STDDAILYRETURN95 STDCONTRACTRETURN95
STDDIFFERENTIAL95;
RUN;

PROC MEANS DATA=KOLBMAR;
VAR PRICE96 LNPRICE96 LOGRETURN96 DAILYRETURN96 CONTRACTRETURN96
DIFFERENTIAL96;
OUTPUT OUT=MARSTATS96 MEAN=MEANPRICE96 MEANLNPRICE96 MEANLOGRETURN96
MEANDAILYRETURN96 MEANCONTRACTRETURN96 MEANDIFFERENTIAL96 STD=STDPRICE96
STDLNPRICE96 STDLOGRETURN96 STDDAILYRETURN96 STDCONTRACTRETURN96
STDDIFFERENTIAL96;
RUN;

PROC MEANS DATA=KOLBMAR;
VAR PRICE97 LNPRICE97 LOGRETURN97 DAILYRETURN97 CONTRACTRETURN97
DIFFERENTIAL97;
OUTPUT OUT=MARSTATS97 MEAN=MEANPRICE97 MEANLNPRICE97 MEANLOGRETURN97
MEANDAILYRETURN97 MEANCONTRACTRETURN97 MEANDIFFERENTIAL97 STD=STDPRICE97
STDLNPRICE97 STDLOGRETURN97 STDDAILYRETURN97 STDCONTRACTRETURN97
STDDIFFERENTIAL97;
RUN;

PROC MEANS DATA=KOLBMAR;
```

```
VAR PRICE98 LNPRICE98 LOGRETURN98 DAILYRETURN98 CONTRACTRETURN98
DIFFERENTIAL98;
OUTPUT OUT=MARSTATS98 MEAN=MEANPRICE98 MEANLNPRICE98 MEANLOGRETURN98
MEANDAILYRETURN98 MEANCONTRACTRETURN98 MEANDIFFERENTIAL98 STD=STDPRICE98
STDLNPRICE98 STDLOGRETURN98 STDDAILYRETURN98 STDCONTRACTRETURN98
STDDIFFERENTIAL98;
RUN;

PROC MEANS DATA=KOLBMAR;
VAR PRICE99 LNPRICE99 LOGRETURN99 DAILYRETURN99 CONTRACTRETURN99
DIFFERENTIAL99;
OUTPUT OUT=MARSTATS99 MEAN=MEANPRICE99 MEANLNPRICE99 MEANLOGRETURN99
MEANDAILYRETURN99 MEANCONTRACTRETURN99 MEANDIFFERENTIAL99 STD=STDPRICE99
STDLNPRICE99 STDLOGRETURN99 STDDAILYRETURN99 STDCONTRACTRETURN99
STDDIFFERENTIAL99;
RUN;

PROC MEANS DATA=KOLBMAR;
VAR PRICE00 LNPRICE00 LOGRETURN00 DAILYRETURN00 CONTRACTRETURN00
DIFFERENTIAL00;
OUTPUT OUT=MARSTATS00 MEAN=MEANPRICE00 MEANLNPRICE00 MEANLOGRETURN00
MEANDAILYRETURN00 MEANCONTRACTRETURN00 MEANDIFFERENTIAL00 STD=STDPRICE00
STDLNPRICE00 STDLOGRETURN00 STDDAILYRETURN00 STDCONTRACTRETURN00
STDDIFFERENTIAL00;
RUN;

PROC MEANS DATA=KOLBMAR;
VAR PRICE01 LNPRICE01 LOGRETURN01 DAILYRETURN01 CONTRACTRETURN01
DIFFERENTIAL01;
OUTPUT OUT=MARSTATS01 MEAN=MEANPRICE01 MEANLNPRICE01 MEANLOGRETURN01
MEANDAILYRETURN01 MEANCONTRACTRETURN01 MEANDIFFERENTIAL01 STD=STDPRICE01
STDLNPRICE01 STDLOGRETURN01 STDDAILYRETURN01 STDCONTRACTRETURN01
STDDIFFERENTIAL01;
RUN;

PROC MEANS DATA=KOLBMAR;
VAR PRICE02 LNPRICE02 LOGRETURN02 DAILYRETURN02 CONTRACTRETURN02
DIFFERENTIAL02;
OUTPUT OUT=MARSTATS02 MEAN=MEANPRICE02 MEANLNPRICE02 MEANLOGRETURN02
MEANDAILYRETURN02 MEANCONTRACTRETURN02 MEANDIFFERENTIAL02 STD=STDPRICE02
STDLNPRICE02 STDLOGRETURN02 STDDAILYRETURN02 STDCONTRACTRETURN02
STDDIFFERENTIAL02;
RUN;

PROC MEANS DATA=KOLBMAR;
VAR PRICE03 LNPRICE03 LOGRETURN03 DAILYRETURN03 CONTRACTRETURN03
DIFFERENTIAL03;
OUTPUT OUT=MARSTATS03 MEAN=MEANPRICE03 MEANLNPRICE03 MEANLOGRETURN03
MEANDAILYRETURN03 MEANCONTRACTRETURN03 MEANDIFFERENTIAL03 STD=STDPRICE03
STDLNPRICE03 STDLOGRETURN03 STDDAILYRETURN03 STDCONTRACTRETURN03
STDDIFFERENTIAL03;
RUN;

PROC MEANS DATA=KOLBMAR;
VAR PRICE04 LNPRICE04 LOGRETURN04 DAILYRETURN04 CONTRACTRETURN04
DIFFERENTIAL04;
OUTPUT OUT=MARSTATS04 MEAN=MEANPRICE04 MEANLNPRICE04 MEANLOGRETURN04
MEANDAILYRETURN04 MEANCONTRACTRETURN04 MEANDIFFERENTIAL04 STD=STDPRICE04
STDLNPRICE04 STDLOGRETURN04 STDDAILYRETURN04 STDCONTRACTRETURN04
STDDIFFERENTIAL04;
```

```
RUN;

PROC MEANS DATA=KOLBMAR;
VAR PRICE05 LNPRICE05 LOGRETURN05 DAILYRETURN05 CONTRACTRETURN05
DIFFERENTIAL05;
OUTPUT OUT=MARSTATS05 MEAN=MEANPRICE05 MEANLNPRICE05 MEANLOGRETURN05
MEANDAILYRETURN05 MEANCONTRACTRETURN05 MEANDIFFERENTIAL05 STD=STDPRICE05
STDLNPRICE05 STDLOGRETURN05 STDDAILYRETURN05 STDCONTRACTRETURN05
STDDIFFERENTIAL05;
RUN;

PROC MEANS DATA=KOLBMAR;
VAR PRICE06 LNPRICE06 LOGRETURN06 DAILYRETURN06 CONTRACTRETURN06
DIFFERENTIAL06;
OUTPUT OUT=MARSTATS06 MEAN=MEANPRICE06 MEANLNPRICE06 MEANLOGRETURN06
MEANDAILYRETURN06 MEANCONTRACTRETURN06 MEANDIFFERENTIAL06 STD=STDPRICE06
STDLNPRICE06 STDLOGRETURN06 STDDAILYRETURN06 STDCONTRACTRETURN06
STDDIFFERENTIAL06;
RUN;

/*Creates new dataset by merging the results from the individual March
contracts.*/

DATA TOTALMARSTATS;
MERGE MARSTATS87 MARSTATS88 MARSTATS89 MARSTATS90 MARSTATS91 MARSTATS92
MARSTATS93 MARSTATS94 MARSTATS95 MARSTATS96
      MARSTATS97 MARSTATS98 MARSTATS99 MARSTATS00 MARSTATS01 MARSTATS02
MARSTATS03 MARSTATS04 MARSTATS05 MARSTATS06;

PROC PRINT DATA=TOTALMARSTATS;
RUN;

DATA MARCONTRACT;
SET TOTALMARSTATS;

/*Calculates the basic statistics for all twenty March contracts combined.*/

HTOTALCONTRACTMEANPRICE=(MEANPRICE87+MEANPRICE88+MEANPRICE89+MEANPRICE90+MEANPR
ICE91+MEANPRICE92+MEANPRICE93+MEANPRICE94+MEANPRICE95+MEANPRICE96+MEANPRICE97+M
EANPRICE98+MEANPRICE99+MEANPRICE00+MEANPRICE01+MEANPRICE02+MEANPRICE03+MEANPRIC
E04+MEANPRICE05+MEANPRICE06)/20;

HTOTALCONTRACTMEANLNPRICE=(MEANLNPRICE87+MEANLNPRICE88+MEANLNPRICE89+MEANLNPRIC
E90+MEANLNPRICE91+MEANLNPRICE92+MEANLNPRICE93+MEANLNPRICE94+MEANLNPRICE95+MEANL
NPRICE96+MEANLNPRICE97+MEANLNPRICE98+MEANLNPRICE99+MEANLNPRICE00+MEANLNPRICE01+
MEANLNPRICE02+MEANLNPRICE03+MEANLNPRICE04+MEANLNPRICE05+MEANLNPRICE06)/20;
HTOTALCONTRACTMEANLOGRETURN=(MEANLOGRETURN87+MEANLOGRETURN88+MEANLOGRETURN89+ME
ANLOGRETURN90+MEANLOGRETURN91+MEANLOGRETURN92+MEANLOGRETURN93+MEANLOGRETURN94+M
EANLOGRETURN95+MEANLOGRETURN96+MEANLOGRETURN97+MEANLOGRETURN98+MEANLOGRETURN99+
MEANLOGRETURN00+MEANLOGRETURN01+MEANLOGRETURN02+MEANLOGRETURN03+MEANLOGRETURN04
+MEANLOGRETURN05+MEANLOGRETURN06)/20;

HTOTALCONTRACTMEANDAILYRETURN=(MEANDAILYRETURN87+MEANDAILYRETURN88+MEANDAILYRET
URN89+MEANDAILYRETURN90+MEANDAILYRETURN91+MEANDAILYRETURN92+MEANDAILYRETURN93+M
EANDAILYRETURN94+MEANDAILYRETURN95+MEANDAILYRETURN96+MEANDAILYRETURN97+MEANDAIL
YRETURN98+MEANDAILYRETURN99+MEANDAILYRETURN00+MEANDAILYRETURN01+MEANDAILYRETURN
02+MEANDAILYRETURN03+MEANDAILYRETURN04+MEANDAILYRETURN05+MEANDAILYRETURN06)/20;
HTOTALCONTRACTMEANCONTRACTRETURN=(MEANCONTRACTRETURN87+MEANCONTRACTRETURN88+MEA
NCONTRACTRETURN89+MEANCONTRACTRETURN90+MEANCONTRACTRETURN91+MEANCONTRACTRETURN9
2+MEANCONTRACTRETURN93+MEANCONTRACTRETURN94+MEANCONTRACTRETURN95+MEANCONTRACTRE
```

```
TURN96+MEANCONTRACTRETURN97+MEANCONTRACTRETURN98+MEANCONTRACTRETURN99+MEANCONTR
ACTRETURN00+MEANCONTRACTRETURN01+MEANCONTRACTRETURN02+MEANCONTRACTRETURN03+MEAN
CONTRACTRETURN04+MEANCONTRACTRETURN05+MEANCONTRACTRETURN06)/20;

HTOTALCONTRACTMEANDIFFERENTIAL=(MEANDIFFERENTIAL87+MEANDIFFERENTIAL88+MEANDIFFE
RENTIAL89+MEANDIFFERENTIAL90+MEANDIFFERENTIAL91+MEANDIFFERENTIAL92+MEANDIFFEREN
TIAL93+MEANDIFFERENTIAL94+MEANDIFFERENTIAL95+MEANDIFFERENTIAL96+MEANDIFFERENTIA
L97+MEANDIFFERENTIAL98+MEANDIFFERENTIAL99+MEANDIFFERENTIAL00+MEANDIFFERENTIAL01
+MEANDIFFERENTIAL02+MEANDIFFERENTIAL03+MEANDIFFERENTIAL04+MEANDIFFERENTIAL05+ME
ANDIFFERENTIAL06)/20;



HTOTALCONTRACTSTDPRICE=(STDPRICE87+STDPRICE88+STDPRICE89+STDPRICE90+STDPRICE91+
STDPRICE92+STDPRICE93+STDPRICE94+STDPRICE95+STDPRICE96+STDPRICE97+STDPRICE98+ST
DPRICE99+STDPRICE00+STDPRICE01+STDPRICE02+STDPRICE03+STDPRICE04+STDPRICE05+STDP
RICE06)/20;

HTOTALCONTRACTSTDLNPRICE=(STDLNPRICE87+STDLNPRICE88+STDLNPRICE89+STDLNPRICE90+S
TDLNPRICE91+STDLNPRICE92+STDLNPRICE93+STDLNPRICE94+STDLNPRICE95+STDLNPRICE96+ST
DLNPRICE97+STDLNPRICE98+STDLNPRICE99+STDLNPRICE00+STDLNPRICE01+STDLNPRICE02+STD
LNPRICE03+STDLNPRICE04+STDLNPRICE05+STDLNPRICE06)/20;
HTOTALCONTRACTSTDLOGRETURN=(STDLOGRETURN87+STDLOGRETURN88+STDLOGRETURN89+STDLOG
RETURN90+STDLOGRETURN91+STDLOGRETURN92+STDLOGRETURN93+STDLOGRETURN94+STDLOGRETU
RN95+STDLOGRETURN96+STDLOGRETURN97+STDLOGRETURN98+STDLOGRETURN99+STDLOGRETURN00
+STDLOGRETURN01+STDLOGRETURN02+STDLOGRETURN03+STDLOGRETURN04+STDLOGRETURN05+STD
LOGRETURN06)/20;

HTOTALCONTRACTSTDDAILYRETURN=(STDDAILYRETURN87+STDDAILYRETURN88+STDDAILYRETURN8
9+STDDAILYRETURN90+STDDAILYRETURN91+STDDAILYRETURN92+STDDAILYRETURN93+STDDAILYR
ETURN94+STDDAILYRETURN95+STDDAILYRETURN96+STDDAILYRETURN97+STDDAILYRETURN98+STD
DAILYRETURN99+STDDAILYRETURN00+STDDAILYRETURN01+STDDAILYRETURN02+STDDAILYRETURN
03+STDDAILYRETURN04+STDDAILYRETURN05+STDDAILYRETURN06)/20;
HTOTALCONTRACTSTDCONTRACTRETURN=(STDCONTRACTRETURN87+STDCONTRACTRETURN88+STDCON
TRACTRETURN89+STDCONTRACTRETURN90+STDCONTRACTRETURN91+STDCONTRACTRETURN92+STDCO
NTRACTRETURN93+STDCONTRACTRETURN94+STDCONTRACTRETURN95+STDCONTRACTRETURN96+STDC
ONTRACTRETURN97+STDCONTRACTRETURN98+STDCONTRACTRETURN99+STDCONTRACTRETURN00+STD
CONTRACTRETURN01+STDCONTRACTRETURN02+STDCONTRACTRETURN03+STDCONTRACTRETURN04+ST
DCONTRACTRETURN05+STDCONTRACTRETURN06)/20;

HTOTALCONTRACTSTDDIFFERENTIAL=(STDDIFFERENTIAL87+STDDIFFERENTIAL88+STDDIFFERENT
IAL89+STDDIFFERENTIAL90+STDDIFFERENTIAL91+STDDIFFERENTIAL92+STDDIFFERENTIAL93+S
TDDIFFERENTIAL94+STDDIFFERENTIAL95+STDDIFFERENTIAL96+STDDIFFERENTIAL97+STDDIFFE
RENTIAL98+STDDIFFERENTIAL99+STDDIFFERENTIAL00+STDDIFFERENTIAL01+STDDIFFERENTIAL
02+STDDIFFERENTIAL03+STDDIFFERENTIAL04+STDDIFFERENTIAL05+STDDIFFERENTIAL06)/20;

HINDIVIDUALCONTRACTTTESTPRICE=(HTOTALCONTRACTMEANPRICE-
0)/HTOTALCONTRACTSTDPRICE;
HINDIVIDUALCONTRACTTTESTLNPRICE=(HTOTALCONTRACTMEANLNPRICE-
0)/HTOTALCONTRACTSTDLNPRICE;
HINDIVIDUALCONTRACTTTESTLOGRET=(HTOTALCONTRACTMEANLOGRETURN-
0)/HTOTALCONTRACTSTDLOGRETURN;
HINDIVIDUALCONTRACTTTESTDAILYRET=(HTOTALCONTRACTMEANDAILYRETURN-
0)/HTOTALCONTRACTSTDDAILYRETURN;
HINDIVIDUALCONTRACTTTESTCONTRET=(HTOTALCONTRACTMEANCONTRACTRETURN-
0)/HTOTALCONTRACTSTDCONTRACTRETURN;
HINDIVIDUALCONTRACTTTESTDIFF=(HTOTALCONTRACTMEANDIFFERENTIAL-
0)/HTOTALCONTRACTSTDDIFFERENTIAL;

RUN;
```

```
PROC PRINT DATA=MARCONTRACT;
VAR HINDIVIDUALCONTRACTTTESTPRICE HINDIVIDUALCONTRACTTTESTLNPRICE
HINDIVIDUALCONTRACTTTESTLOGRET HINDIVIDUALCONTRACTTTESTDAILYRET
HINDIVIDUALCONTRACTTTESTCONTRET HINDIVIDUALCONTRACTTTESTDIFF;
RUN;


/*Begin SAS code for the cotton futures market as a whole by combining datasets
of individual contract delivery months.*/

DATA COMBINEDCONTRACTS;
MERGE MARCONTRACT MAYCONTRACT JULCONTRACT OCTCONTRACT DECCONTRACT;

KEEP HTOTALCONTRACTMEANPRICE HTOTALCONTRACTMEANLNPRICE
HTOTALCONTRACTMEANLOGRETURN HTOTALCONTRACTMEANDAILYRETURN
HTOTALCONTRACTMEANCONTRACTRETURN HTOTALCONTRACTMEANDIFFERENTIAL
HTOTALCONTRACTSTDPRICE HTOTALCONTRACTSTDLNPRICE HTOTALCONTRACTSTDLOGRETURN
HTOTALCONTRACTSTDDAILYRETURN HTOTALCONTRACTSTDCONTRACTRETURN
HTOTALCONTRACTSTDDIFFERENTIAL

KTOTALCONTRACTMEANPRICE KTOTALCONTRACTMEANLNPRICE KTOTALCONTRACTMEANLOGRETURN
KTOTALCONTRACTMEANDAILYRETURN KTOTALCONTRACTMEANCONTRACTRETURN
KTOTALCONTRACTMEANDIFFERENTIAL
KTOTALCONTRACTSTDPRICE KTOTALCONTRACTSTDLNPRICE KTOTALCONTRACTSTDLOGRETURN
KTOTALCONTRACTSTDDAILYRETURN KTOTALCONTRACTSTDCONTRACTRETURN
KTOTALCONTRACTSTDDIFFERENTIAL

NTOTALCONTRACTMEANPRICE NTOTALCONTRACTMEANLNPRICE NTOTALCONTRACTMEANLOGRETURN
NTOTALCONTRACTMEANDAILYRETURN NTOTALCONTRACTMEANCONTRACTRETURN
NTOTALCONTRACTMEANDIFFERENTIAL
NTOTALCONTRACTSTDPRICE NTOTALCONTRACTSTDLNPRICE NTOTALCONTRACTSTDLOGRETURN
NTOTALCONTRACTSTDDAILYRETURN NTOTALCONTRACTSTDCONTRACTRETURN
NTOTALCONTRACTSTDDIFFERENTIAL

VTOTALCONTRACTMEANPRICE VTOTALCONTRACTMEANLNPRICE VTOTALCONTRACTMEANLOGRETURN
VTOTALCONTRACTMEANDAILYRETURN VTOTALCONTRACTMEANCONTRACTRETURN
VTOTALCONTRACTMEANDIFFERENTIAL
VTOTALCONTRACTSTDPRICE VTOTALCONTRACTSTDLNPRICE VTOTALCONTRACTSTDLOGRETURN
VTOTALCONTRACTSTDDAILYRETURN VTOTALCONTRACTSTDCONTRACTRETURN
VTOTALCONTRACTSTDDIFFERENTIAL

ZTOTALCONTRACTMEANPRICE ZTOTALCONTRACTMEANLNPRICE ZTOTALCONTRACTMEANLOGRETURN
ZTOTALCONTRACTMEANDAILYRETURN ZTOTALCONTRACTMEANCONTRACTRETURN
ZTOTALCONTRACTMEANDIFFERENTIAL
ZTOTALCONTRACTSTDPRICE ZTOTALCONTRACTSTDLNPRICE ZTOTALCONTRACTSTDLOGRETURN
ZTOTALCONTRACTSTDDAILYRETURN ZTOTALCONTRACTSTDCONTRACTRETURN
ZTOTALCONTRACTSTDDIFFERENTIAL;


KEEP HINDIVIDUALCONTRACTTTESTPRICE HINDIVIDUALCONTRACTTTESTLNPRICE
HINDIVIDUALCONTRACTTTESTLOGRET HINDIVIDUALCONTRACTTTESTDAILYRET
HINDIVIDUALCONTRACTTTESTCONTRET HINDIVIDUALCONTRACTTTESTDIFF
KINDIVIDUALCONTRACTTTESTPRICE KINDIVIDUALCONTRACTTTESTLNPRICE
KINDIVIDUALCONTRACTTTESTLOGRET KINDIVIDUALCONTRACTTTESTDAILYRET
KINDIVIDUALCONTRACTTTESTCONTRET KINDIVIDUALCONTRACTTTESTDIFF
NINDIVIDUALCONTRACTTTESTPRICE NINDIVIDUALCONTRACTTTESTLNPRICE
NINDIVIDUALCONTRACTTTESTLOGRET NINDIVIDUALCONTRACTTTESTDAILYRET
NINDIVIDUALCONTRACTTTESTCONTRET NINDIVIDUALCONTRACTTTESTDIFF
```

```
VINDIVIDUALCONTRACTTTESTPRICE VINDIVIDUALCONTRACTTTESTLNPRICE
VINDIVIDUALCONTRACTTTESTLOGRET VINDIVIDUALCONTRACTTTESTDAILYRET
VINDIVIDUALCONTRACTTTESTCONTRET VINDIVIDUALCONTRACTTTESTDIFF
ZINDIVIDUALCONTRACTTTESTPRICE ZINDIVIDUALCONTRACTTTESTLNPRICE
ZINDIVIDUALCONTRACTTTESTLOGRET ZINDIVIDUALCONTRACTTTESTDAILYRET
ZINDIVIDUALCONTRACTTTESTCONTRET ZINDIVIDUALCONTRACTTTESTDIFF;

RUN;

DATA COMBINEDCONTRACTS;
SET COMBINEDCONTRACTS;

/*Calculates basic statistics for the cotton futures market as a whole.*/

TOTALMEANPRICE=MEAN(HTOTALCONTRACTMEANPRICE,KTOTALCONTRACTMEANPRICE,NTOTALCONTR
ACTMEANPRICE,VTOTALCONTRACTMEANPRICE,ZTOTALCONTRACTMEANPRICE);
TOTALMEANLNPRICE=(HTOTALCONTRACTMEANLNPRICE+KTOTALCONTRACTMEANLNPRICE+NTOTALCON
TRACTMEANLNPRICE+VTOTALCONTRACTMEANLNPRICE+ZTOTALCONTRACTMEANLNPRICE)/5;

TOTALMEANLOGRETURN=(HTOTALCONTRACTMEANLOGRETURN+KTOTALCONTRACTMEANLOGRETURN+NTO
TALCONTRACTMEANLOGRETURN+VTOTALCONTRACTMEANLOGRETURN+ZTOTALCONTRACTMEANLOGRETUR
N)/5;

TOTALMEANCONTRACTRETURN=(HTOTALCONTRACTMEANCONTRACTRETURN+KTOTALCONTRACTMEANCON
TRACTRETURN+NTOTALCONTRACTMEANCONTRACTRETURN+VTOTALCONTRACTMEANCONTRACTRETURN+Z
TOTALCONTRACTMEANCONTRACTRETURN)/5;

TOTALMEANDAILYRETURN=(HTOTALCONTRACTMEANDAILYRETURN+KTOTALCONTRACTMEANDAILYRETU
RN+NTOTALCONTRACTMEANDAILYRETURN+VTOTALCONTRACTMEANDAILYRETURN+ZTOTALCONTRACTME
ANDAILYRETURN)/5;

TOTALMEANDIFFERENTIAL=(HTOTALCONTRACTMEANDIFFERENTIAL+KTOTALCONTRACTMEANDIFFERE
NTIAL+NTOTALCONTRACTMEANDIFFERENTIAL+VTOTALCONTRACTMEANDIFFERENTIAL+ZTOTALCONTR
ACTMEANDIFFERENTIAL)/5;

TOTALSTDPRICE=(HTOTALCONTRACTSTDPRICE+KTOTALCONTRACTSTDPRICE+NTOTALCONTRACTSTDP
RICE+VTOTALCONTRACTSTDPRICE+ZTOTALCONTRACTSTDPRICE)/5;

TOTALSTDLNPRICE=(HTOTALCONTRACTSTDLNPRICE+KTOTALCONTRACTSTDLNPRICE+NTOTALCONTRA
CTSTDLNPRICE+VTOTALCONTRACTSTDLNPRICE+ZTOTALCONTRACTSTDLNPRICE)/5;

TOTALSTDLOGRETURN=(HTOTALCONTRACTSTDLOGRETURN+KTOTALCONTRACTSTDLOGRETURN+NTOTAL
CONTRACTSTDLOGRETURN+VTOTALCONTRACTSTDLOGRETURN+ZTOTALCONTRACTSTDLOGRETURN)/5;

TOTALSTDCONTRACTRETURN=(HTOTALCONTRACTSTDCONTRACTRETURN+KTOTALCONTRACTSTDCONTRA
CTRETURN+NTOTALCONTRACTSTDCONTRACTRETURN+VTOTALCONTRACTSTDCONTRACTRETURN+ZTOTAL
CONTRACTSTDCONTRACTRETURN)/5;

TOTALSTDDAILYRETURN=(HTOTALCONTRACTSTDDAILYRETURN+KTOTALCONTRACTSTDDAILYRETURN+
NTOTALCONTRACTSTDDAILYRETURN+VTOTALCONTRACTSTDDAILYRETURN+ZTOTALCONTRACTSTDDAIL
YRETURN)/5;

TOTALSTDDIFFERENTIAL=(HTOTALCONTRACTSTDDIFFERENTIAL+KTOTALCONTRACTSTDDIFFERENTI
AL+NTOTALCONTRACTSTDDIFFERENTIAL+VTOTALCONTRACTSTDDIFFERENTIAL+ZTOTALCONTRACTST
DDIFFERENTIAL)/5;

RUN;

PROC EXPORT DATA=COMBINEDCONTRACTS
OUTFILE="F:\THESIS\COMBINEDCONTRACTS.CSV"
```

```
DBMS=CSV REPLACE;
RUN;

PROC PRINT DATA=WORK.COMBINEDCONTRACTS;
VAR TOTALMEANPRICE;
RUN;

/*Calculates the final t-tests for the cotton futures market as a whole.*/

DATA FINALTTESTS;
SET COMBINEDCONTRACTS;

KEEP TOTALMEANPRICE TOTALMEANLNPRICE TOTALMEANLOGRETURN TOTALMEANCONTRACTRETURN
TOTALMEANDAILYRETURN TOTALMEANDIFFERENTIAL TOTALSTDPRICE TOTALSTDLNPRICE
TOTALSTDLOGRETURN TOTALSTDCONTRACTRETURN TOTALSTDDAILYRETURN
TOTALSTDDIFFERENTIAL;

DATA FINALTTESTS;
SET COMBINEDCONTRACTS;

TTESTPRICE=(TOTALMEANPRICE-0)/TOTALSTDPRICE;
TTESTLNPRICE=(TOTALMEANLNPRICE-0)/TOTALSTDLNPRICE;
TTESTLOGRETURN=(TOTALMEANLOGRETURN-0)/TOTALSTDLOGRETURN;
TTESTCONTRACTRETURN=(TOTALMEANCONTRACTRETURN-0)/TOTALSTDCONTRACTRETURN;
TTESTDAILYRETURN=(TOTALMEANDAILYRETURN-0)/TOTALSTDDAILYRETURN;
TTESTDIFFERENTIAL=(TOTALMEANDIFFERENTIAL-0)/TOTALSTDDIFFERENTIAL;

RUN;

PROC PRINT DATA=FINALTTESTS;
VAR TTESTPRICE TTESTLNPRICE TTESTLOGRETURN TTESTCONTRACTRETURN TTESTDAILYRETURN
TTESTDIFFERENTIAL;
RUN;

/*Changes name of outfile to reflect proper data; Combined data includes means
and stdevs; Combinedcontracts is just individual t-tests.*/

PROC EXPORT DATA=FINALTTESTS
OUTFILE="F:\THESIS\FINALTTESTS.CSV"
DBMS=CSV REPLACE;
RUN;

/*To calculate m, need to extract the differentials for each year of each
contract delivery month.*/

PROC EXPORT DATA=KOLBMAR
OUTFILE="F:\THESIS\KOLBMAR.CSV"
DBMS=CSV REPLACE;
RUN;
```

Sample SAS Code 3

```
PROC IMPORT OUT= WORK.DURATION
            DATAFILE= "F:\KOLB\WHOLE CONTRACTS\DURATION.XLS"
            DBMS=EXCEL2000 REPLACE;
          GETNAMES=YES;
RUN;
```

```
/*March Regression Data Prep and Regression for March Contract*/

DATA MARDURATION;
SET DURATION;

* calculates days remaining in contract;

TIMETOEXP87 = 327-KDUR;
TIMETOEXP88 = 357-KDUR;
TIMETOEXP89 = 360-KDUR;
TIMETOEXP90 = 348-KDUR;
TIMETOEXP91 = 338-KDUR;
TIMETOEXP92 = 348-KDUR;
TIMETOEXP93 = 361-KDUR;
TIMETOEXP94 = 361-KDUR;
TIMETOEXP95 = 360-KDUR;
TIMETOEXP96 = 357-KDUR;
TIMETOEXP97 = 401-KDUR;
TIMETOEXP98 = 484-KDUR;
TIMETOEXP99 = 485-KDUR;
TIMETOEXP00 = 486-KDUR;
TIMETOEXP01 = 484-KDUR;
TIMETOEXP02 = 478-KDUR;
TIMETOEXP03 = 480-KDUR;
TIMETOEXP04 = 482-KDUR;
TIMETOEXP05 = 483-KDUR;
TIMETOEXP06 = 484-KDUR;

RUN;

DATA MARREGRESSIONDATA;
SET KOLBMAR;
SET MARDURATION;

KEEP DIFFERENTIAL87 DIFFERENTIAL88 DIFFERENTIAL89 DIFFERENTIAL90 DIFFERENTIAL91
DIFFERENTIAL92 DIFFERENTIAL93 DIFFERENTIAL94 DIFFERENTIAL95 DIFFERENTIAL96
DIFFERENTIAL97 DIFFERENTIAL98 DIFFERENTIAL99 DIFFERENTIAL00 DIFFERENTIAL01
DIFFERENTIAL02 DIFFERENTIAL03 DIFFERENTIAL04 DIFFERENTIAL05 DIFFERENTIAL06;

KEEP TIMETOEXP87 TIMETOEXP88 TIMETOEXP89 TIMETOEXP90 TIMETOEXP91 TIMETOEXP92
TIMETOEXP93 TIMETOEXP94 TIMETOEXP95 TIMETOEXP96 TIMETOEXP97 TIMETOEXP98
TIMETOEXP99 TIMETOEXP00 TIMETOEXP01 TIMETOEXP02 TIMETOEXP03 TIMETOEXP04
TIMETOEXP05 TIMETOEXP06;

RUN;

/* rename variables so they can be concatenated */

DATA ALLMAR87;
SET MARREGRESSIONDATA;
DIFF = DIFFERENTIAL87;
TTEXP = TIMETOEXP87;
KEEP DIFF TTEXP;
IF TTEXP <= 0 THEN DELETE;

DATA ALLMAR88;
SET MARREGRESSIONDATA;
DIFF = DIFFERENTIAL88;
TTEXP = TIMETOEXP88;
KEEP DIFF TTEXP;
```

```
IF TTEXP <= 0 THEN DELETE;

DATA ALLMAR89;
SET MARREGRESSIONDATA;
DIFF = DIFFERENTIAL89;
TTEXP = TIMETOEXP89;
KEEP DIFF TTEXP;
IF TTEXP <= 0 THEN DELETE;

DATA ALLMAR90;
SET MARREGRESSIONDATA;
DIFF = DIFFERENTIAL90;
TTEXP = TIMETOEXP90;
KEEP DIFF TTEXP;
IF TTEXP <= 0 THEN DELETE;

DATA ALLMAR91;
SET MARREGRESSIONDATA;
DIFF = DIFFERENTIAL91;
TTEXP = TIMETOEXP91;
KEEP DIFF TTEXP;
IF TTEXP <= 0 THEN DELETE;

DATA ALLMAR92;
SET MARREGRESSIONDATA;
DIFF = DIFFERENTIAL92;
TTEXP = TIMETOEXP92;
KEEP DIFF TTEXP;
IF TTEXP <= 0 THEN DELETE;

DATA ALLMAR93;
SET MARREGRESSIONDATA;
DIFF = DIFFERENTIAL93;
TTEXP = TIMETOEXP93;
KEEP DIFF TTEXP;
IF TTEXP <= 0 THEN DELETE;

DATA ALLMAR94;
SET MARREGRESSIONDATA;
DIFF = DIFFERENTIAL94;
TTEXP = TIMETOEXP94;
KEEP DIFF TTEXP;
IF TTEXP <= 0 THEN DELETE;

DATA ALLMAR95;
SET MARREGRESSIONDATA;
DIFF = DIFFERENTIAL95;
TTEXP = TIMETOEXP95;
KEEP DIFF TTEXP;
IF TTEXP <= 0 THEN DELETE;

DATA ALLMAR96;
SET MARREGRESSIONDATA;
DIFF = DIFFERENTIAL96;
TTEXP = TIMETOEXP96;
KEEP DIFF TTEXP;
IF TTEXP <= 0 THEN DELETE;

DATA ALLMAR97;
SET MARREGRESSIONDATA;
```

```
DIFF = DIFFERENTIAL97;
TTEXP = TIMETOEXP97;
KEEP DIFF TTEXP;
IF TTEXP <= 0 THEN DELETE;

DATA ALLMAR98;
SET MARREGRESSIONDATA;
DIFF = DIFFERENTIAL98;
TTEXP = TIMETOEXP98;
KEEP DIFF TTEXP;
IF TTEXP <= 0 THEN DELETE;

DATA ALLMAR99;
SET MARREGRESSIONDATA;
DIFF = DIFFERENTIAL99;
TTEXP = TIMETOEXP99;
KEEP DIFF TTEXP;
IF TTEXP <= 0 THEN DELETE;

DATA ALLMAR00;
SET MARREGRESSIONDATA;
DIFF = DIFFERENTIAL00;
TTEXP = TIMETOEXP00;
KEEP DIFF TTEXP;
IF TTEXP <= 0 THEN DELETE;

DATA ALLMAR01;
SET MARREGRESSIONDATA;
DIFF = DIFFERENTIAL01;
TTEXP = TIMETOEXP01;
KEEP DIFF TTEXP;
IF TTEXP <= 0 THEN DELETE;

DATA ALLMAR02;
SET MARREGRESSIONDATA;
DIFF = DIFFERENTIAL02;
TTEXP = TIMETOEXP02;
KEEP DIFF TTEXP;
IF TTEXP <= 0 THEN DELETE;

DATA ALLMAR03;
SET MARREGRESSIONDATA;
DIFF = DIFFERENTIAL03;
TTEXP = TIMETOEXP03;
KEEP DIFF TTEXP;
IF TTEXP <= 0 THEN DELETE;

DATA ALLMAR04;
SET MARREGRESSIONDATA;
DIFF = DIFFERENTIAL04;
TTEXP = TIMETOEXP04;
KEEP DIFF TTEXP;
IF TTEXP <= 0 THEN DELETE;

DATA ALLMAR05;
SET MARREGRESSIONDATA;
DIFF = DIFFERENTIAL05;
TTEXP = TIMETOEXP05;
KEEP DIFF TTEXP;
IF TTEXP <= 0 THEN DELETE;
```

```
DATA ALLMAR06;
SET MARREGRESSIONDATA;
DIFF = DIFFERENTIAL06;
TTEXP = TIMETOEXP06;
KEEP DIFF TTEXP;
IF TTEXP <= 0 THEN DELETE;

RUN;

/*NEED TO STACK ALL INDIVIDUAL YEARS INTO A SINGLE DATASET WITH TWO VARIABLES:
DIFF AND TTEXP*/

DATA FINALMARREGRESSIONDATA;
SET ALLMAR87 ALLMAR88 ALLMAR89 ALLMAR90 ALLMAR91 ALLMAR92 ALLMAR93 ALLMAR94
    ALLMAR95 ALLMAR96 ALLMAR97 ALLMAR98 ALLMAR99 ALLMAR00 ALLMAR01 ALLMAR02
    ALLMAR03 ALLMAR04 ALLMAR05 ALLMAR06;

RUN;

PROC AUTOREG DATA = FINALMARREGRESSIONDATA;
MARWHOLECONTRACT: MODEL DIFF = TTEXP / NLAG=1 DWPROB;
MARWHOLECONTRACT: MODEL DIFF = TTEXP / NLAG=1 METHOD=ULS;
RUN;

/*****************COMBINED CONTRACTS REGRESSION DATA AND RESULTS*************/

DATA COMBINEDREGRESSIONSWHOLE;
SET FINALMARREGRESSIONDATA FINALMAYREGRESSIONDATA FINALJULREGRESSIONDATA
    FINALOCTREGRESSIONDATA FINALDECREGRESSIONDATA;
RUN;

PROC AUTOREG DATA = COMBINEDREGRESSIONSWHOLE;
COMBINEDWHOLECONTRACT: MODEL DIFF = TTEXP / NLAG=1 DWPROB;
COMBINEDWHOLECONTRACT: MODEL DIFF = TTEXP / NLAG=1 METHOD=ULS;

RUN;
```

APPENDIX B

SAS CODE FOR ASSET-PRICING MODEL

The SAS program was used in the development of the asset-pricing model for cotton futures. The variables included in the dataset for the asset-pricing model were: the Dow Jones Industrials Dividend Yield, the U.S. Treasury Constant Maturities 3-Month Middle Rate, the U.S. Corporate Bond Moody's BAA Middle Rate (junk bond), the U.S. Corporate Bond Moody's AAA Middle Rate (investment grade bond), and the U.S. Treasury Benchmark Bond 10 Years (a more detailed description of the data can be found in chapter II). Abbreviations were used to represent variables in the dataset: diviyld for the Dow Jones, t3mon for the 3-Month Middle Rate, baa for the junk bond, aaa for the investment grade bond, and tre10yr for the 10 year bond.

In the following SAS code, excess returns for each variable in the dataset were calculated first. Second, a dataset was created for the lag of each of the excess returns, followed by the calculation of risk premiums. Basic statistics for the calculated risk premiums were also estimated. Finally a regression model was built and run with cotton futures returns as the dependent variable.

SAS Code For Asset-Pricing Model

```
PROC IMPORT OUT= SASUSER.DATASTREAM
            DATAFILE= "F:\THESIS\DATASTREAM\ECONOMIC INDICATORS REGRESSION
DATA.XLS"
            DBMS=EXCEL2000 REPLACE;
          GETNAMES=YES;
RUN;

DATA SASUSER.DATASTREAM;
SET SASUSER.DATASTREAM;

DIVIYLD=DIVIYLD/100;
```

```
LONGBOND=LONGBOND/100;
T3MON=T3MON/100;
T3MONCON=T3MONCON/100;
BAA=BAA/100;
AAA=AAA/100;
TRE10YR=TRE10YR/100;

DYER=DIVIYLD-T3MONCON;
LAGDYER=LAG(DYER);

JUNKPREMIUM=BAA-AAA;
BAAER=JUNKPREMIUM-T3MONCON;
LAGJUNKPREMIUM=LAG(BAAER);

GOVER=TRE10YR-T3MONCON;
LAGGOVER=LAG(GOVER);

RUN;

PROC MEANS DATA=SASUSER.DATASTREAM;
VAR DIVIYLD   LONGBOND    T3MON   T3MONCON BAA  AAA    TRE10YR;
OUTPUT OUT=MEANS MEAN=ECONOMIC DATA;
RUN;

PROC MEANS DATA=SASUSER.DATASTREAM;
VAR DYER BAAER GOVER;
RUN;

PROC REG DATA = SASUSER.DATASTREAM;
MODEL NEARBYRTN = LAGDYER LAGJUNKPREMIUM LAGGOVER / DW P;

RUN;

PROC REG DATA = SASUSER.DATASTREAM;
MODEL CTZRTN = LAGDYER LAGJUNKPREMIUM LAGGOVER / DW P;

RUN;
```

APPENDIX C

AUTOCORRELATION CHECK FOR DATA USED IN THE PRICING PATTERNS ANALYSIS

When analyzing time series data, it is important to account for autocorrelation. Autocorrelation was considered when conducting this analysis for pricing patterns in the cotton futures data of daily settlement prices. The Yule Walker method was implemented to correct for autocorrelation using 1 lag, 10 lags, and 30 lags of the differentials. Results using 1 lag of the data can be found in chapter II but are also shown in table A-1, while results using 10 and 30 lags of the differentials are found in table A-1. While there was a significant drop in autocorrelation using 1 lag, there was little change in the estimated coefficients and test statistics when the lags were increased to 10 and 30. The Durbin Watson statistic approximates 2, indicating little evidence of autocorrelation, when 1, 10, and 30 lags are used.

Table A-1. Test 3 Results: Regression for Rising Cotton Futures Prices, 1986-2006, Yule Walker Method of Autocorrelation Correction (Whole Futures Contracts

	Mar	May	Jul	Oct	Dec	Combined
			(before correction)			
OLS Method						
Intercept	-0.0415	-0.0551	-0.015	-0.0254	-0.0058	-0.0287
Beta	0.00044	0.00047	0.00044	0.00042	0.00042	0.00044
Std Error	0.00002	0.00002	0.00002	0.00002	0.00002	0.00001
t-statistic	21.830	23.600	22.130	21.470	22.100	49.740
DW	0.0068	0.0073	0.0060	0.0059	0.0056	0.0067
Total R^2	0.0546	0.0627	0.0549	0.0520	0.0545	0.0557
n	8,264	8,333	8,435	8,411	8,476	41,919
			(after correction)			
Yule Walker With 1 lag						
Intercept	-0.0034	-0.0055	0.0138	-0.0151	-0.0092	0.0146
Beta	0.00024	0.00019	0.00024	0.0003	0.0003	0.0002
Std Error	0.00001	0.00001	0.00001	0.00001	0.00001	0.000004
t-statistic	23.130	19.260	24.980	31.700	37.910	52.6000
DW	2.0066	1.955	1.8903	1.9353	1.9103	1.9875
Total R2	0.9939	0.9937	0.9946	0.9945	0.9947	0.9940
n	8,264	8,333	8,435	8,411	8,476	41,919
Yule Walker With 10 Lags						
Intercept	-0.0035	-0.0056	0.0148	-0.0153	-0.0090	0.0146
Beta	0.00020	0.00020	0.00020	0.00030	0.00030	0.00020
Std Error	0.00001	0.00001	0.00001	0.00001	0.00001	0.000004
t-statistic	23.2200	19.2400	25.0100	31.7500	38.0300	52.5900
DW	1.9992	1.9731	1.9484	1.938	1.8805	2.0031
Total R^2	0.9939	0.9937	0.9947	0.9945	0.9948	0.994
n	8,264	8,333	8,435	8,411	8,476	41,919
Yule Walker With 30 Lags						
Intercept	0.0033	-0.0057	0.0151	-0.0134	-0.0075	0.0147
Beta	0.0002	0.0002	0.0002	0.0003	0.0003	0.0002
Std Error	0.00001	0.00001	0.00001	0.00001	0.00001	0.00001
t-statistic	23.300	19.230	25.110	31.750	38.090	52.710
DW	1.9984	1.9729	1.9489	1.9372	1.8782	2.0030
Total R^2	0.9939	0.9937	0.9947	0.9945	0.9948	0.9940
n	8,264	8,333	8,435	8,411	8,476	41,919

Source: NYBOT cotton futures price data

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