CAN STRUCTURAL CHANGE EXPLAIN THE DECREASE IN RETURNS TO TECHNICAL ANALYSIS?

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2000

Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
In partial fulfillment of
the requirements for
the Degree of
MASTER OF SCIENCE
August, 2002

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THE DECREASE IN RETURNS TO

TECHNICAL ANALYSIS?

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ACKNOWLEDGEMENTS

I would like to express my sincere appreciation to my advisor, Dr. B. Wade Brorsen, whose valuable and seemingly endless suggestions and revisions have greatly enhanced the quality of this thesis. He has managed to challenge and at the same time confuse me like no one else ever has. I would also like to thank the other two members of my graduate committee, Dr. Dan Tilley and Dr. Robert Oehrtman. A special thanks goes to Jean and Patsy Neustadt whose financial contributions helped purchase the intraday data used in this study. I would also like to thank Louis Lukac, former principal of Wizard Trading, for suggesting the topic. And finally I would like to express my gratitude to the Department of Agricultural Economics for financial support during my graduate studies.

TABLE OF CONTENTS

LIST OF TABLES AND FIGURES

CHAPTER 1

INTRODUCTION

Problem Statement

The managed futures industry has been a quickly growing segment of the financial world. In recent years however, futures fund returns have decreased and the value of assets invested in managed futures has decreased along with returns. Managed futures funds are typically limited partnerships that speculatively trade futures contracts for a profit. The manager that actively trades the account is called a Commodity Trading Advisor (CTA). Figure 1.1 shows the Barclay Commodity Trading Advisor Index versus time and shows a steady trend of decreasing returns during the past twenty years. The causes of this decrease in fund performance are not fully known. Two possible explanations for the decrease are a decrease in market volatility (therefore profit opportunities) and price distortion caused by the growth of the industry. Certainly there must have been changes in the distribution of futures prices in order for returns to have decreased so dramatically[1]. This naturally leads to the research question, "What structural changes have occurred in futures price movements?"

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[1] Indeed there have been many charges that trading by the funds has distorted prices, including cattle prices in 2002. But the evidence in support of these charges is still inconclusive (Brorsen and Irwin; Holt and Irwin; Commodity Futures Trading Commission).

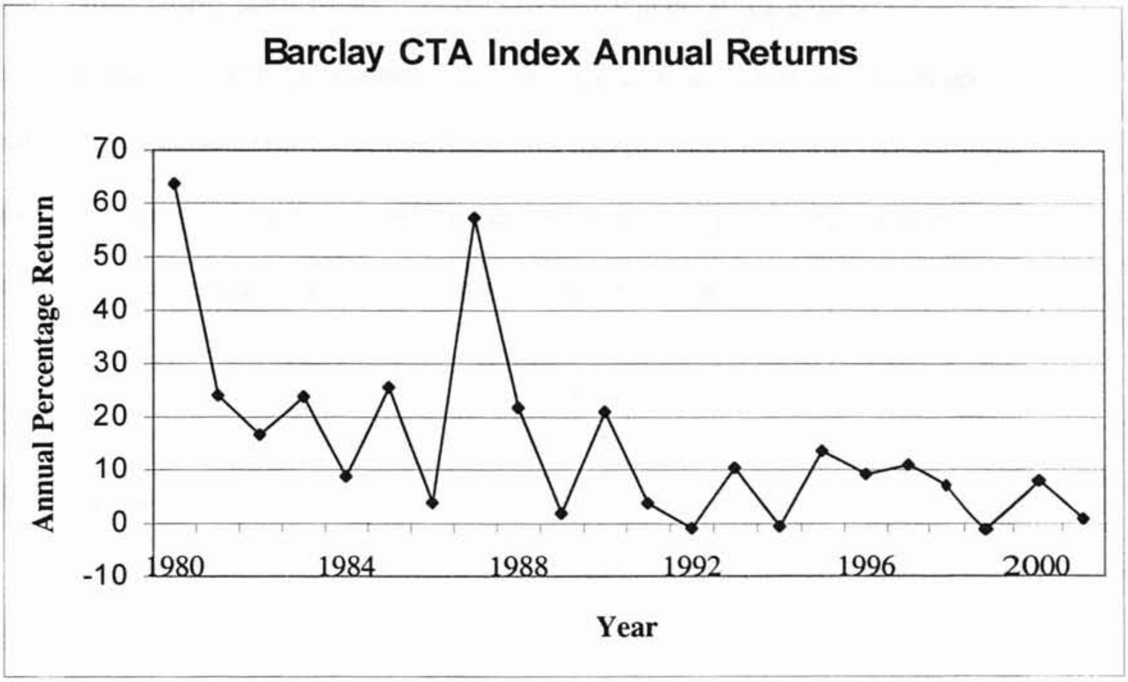

Figure 1.1 Barclay CTA index annual percentage returns by year
Source: The Barclay Group

Knowing the way futures price distributions have changed will help explain why futures fund returns have decreased.

Most financial participants are at least superficially interested in the return characteristics of managed futures funds and Commodity Trading Advisors. Technically traded managed futures funds rely almost exclusively on past prices to generate buy and sell signals. Accordingly the returns to these funds depend on weak-form inefficiency of the markets. Therefore the return attributes of managed futures funds are of high interest not only to investors but also to regulators, investment advisors, and policy makers. Technical analysis has been advocated as a way for farmers to make buying and selling decisions (e.g. Purcell; Franzmann and Sronce).

Many of the farmer advisory services tracked by Irwin et. al. base their recommendations partly on technical analysis. The dramatic decrease in technical profitability indicates that futures markets have become more efficient. Research is needed to determine the ways in which the market has changed, thereby allowing technical traders to adjust trading systems to account for these changes.

Objectives

General Objective:

Explain why returns to managed futures funds have decreased.

Specific Objective:

Determine how the movements of futures prices have changed over time.

Conceptual Framework

Managed futures funds overwhelmingly use technical trading systems to formulate buy and sell decisions (Irwin and Brorsen, Billingsley and Chance). Therefore the ability to generate positive net returns depends on the manner in which prices move. Any development in the futures industry that can change the way prices fluctuate could have changed the returns to technical analysis. If a structural change in price fluctuations has occurred, technical trading systems developed prior to the change may be obsolete, or changes may indicate that the need for technical trading to move the market to equilibrium has decreased.

The most popular forms of technical analysis are trend-following methods (e.g. Billingsley and Chance; Kaufmann; Commodity Futures Trading Commission). While some economists have placed technical analysis in the same category as astrology, there are sound theoretical explanations for the profitability of trend-following systems. Disequilibrium models such as those developed by Beja and Goldman and Grossman and Stiglitz are based on the assumption that prices do not instantaneously fully react to an information shock. Fundamental traders start moving the price toward equilibrium, but are unable to fully move the market due to risk aversion, capital constraints, or position limits. The result is price trends that technical analysts can detect and trade. The trending periods would be reflected in positive autocorrelation. Thus any reduction in the autocorrelation of futures prices will decrease the profitability of trend-following systems. Empirical research, however, has only been able to detect a small amount of autocorrelation beyond what would be expected in an uncorrelated series (Irwin and Uhrig). The theoretical arguments for trend-following systems are based on a delayed movement toward equilibrium after new information enters the marketplace. The increased speed of news dissemination and market transactions and the increased use of trend-following systems likely have decreased the duration of market trends.

A structural change in futures markets could be caused by many developments. Fundamental changes in markets have the possibility of modifying the way and speed in which traders react. A decrease in the cost of information, increase in the speed of financial transactions, decrease in computing cost, and an increase in the relative use of technical analysis, all have the potential to change the way prices fluctuate by increasing the reaction to new information and driving the market to equilibrium faster. These developments will have decreased the cost of using technical analysis and therefore may have decreased its profitability. In addition to these developments directly related to the futures industry, there are many economy wide changes that may have affected futures prices. Freer trade, better economic predictions, and fewer major shocks to the economy all may have lowered price volatility and therefore lowered the need for technical speculators to move the markets to equilibrium. Previous research by Boyd and Brorsen supports this theory as they found a strong relationship between market volatility and technical trading profits.

Developments in the past several years may have allowed markets to react faster to new information. If new information becomes available overnight, the gap in prices between the close and open would be large. If price movements occur overnight then funds will either miss trading opportunities or will have to trade in the overnight markets that have higher liquidity costs. It is expected that advancements in markets such as increased news and transaction speed have caused the variance and kurtosis of close-to-open gaps to increase; however, the expected increase in the variance of gaps may be offset by a decrease in overall market volatility.

These possible changes in prices leads to the first hypothesis of structural change in daily futures prices:

1) There is a decreased demand for technical trading due to market developments and macroeconomic change. These changes will be shown through reduced price volatility, and decreased market reaction time.

Another possible explanation for the reduced technical trading profitability is that large increase in the managed futures industry has distorted prices. Lukac, Brorsen, and Irwin found that different simulated technical trading systems signaled trades on the same day a significant number of days, which may allow for price distortion. In a recent Commodity Futures Trading Commission Report, the market surveillance staff reported:

> Over many years of observing the activity of commodity funds, the Surveillance staff has observed that, although a large number of funds may hold positions in a market, most of them do not trade on any given day. When funds do trade, however, they tend to trade in the same directions. Since many funds use technical, trend-following, trading systems, it is not clear whether fund activity contributes to the magnitude or direction of the of the price change or whether they are reacting to the price change.

Empirical research is inconsistent as to whether an increase in the size of managed futures increases price volatility (e.g. Brorsen and Irwin; Holt and Irwin; Irwin and Brorsen). Increased technical trading should speed price adjustments (i.e. reduce inefficiency), but it would also increase the variance and kurtosis of price movements (Brorsen, Oellermann, and Farris).

The possibility of price distortion leads to the second hypothesis of structural change in daily futures prices:

2) The increase in the size of the managed futures industry has increased price volatility, increased price kurtosis, and decreased autocorrelations, by either increasing market efficiency or price distortion through similarity of trading.

These two hypotheses represent two possible ways that a change in daily futures price behavior may be reflected in reduced technical profitability.

In addition to daily futures prices, intraday prices must also be examined to see if liquidity problems have affected technical trading performance. Intraday futures price data gives insight into the way buy and sell orders are transacted. An increase in the size of the managed futures industry relative to other market participants may be met with liquidity constraints in the market if the funds send similar orders to the market during a similar time. This would lead to large price movements and results in the hypothesis for intraday price changes:

3) Market liquidity has not increased at the same rate as the managed futures industry. Therefore part of the decrease in fund returns is due to increased liquidity costs. This would be reflected in increased intraday price variance and kurtosis.

Intraday prices will be examined for evidence of structural changes consistent with hypothesis three. The results of structural change tests for both daily and intraday prices will allow conclusions about how price movements affect technical profitability.

Originality of Research

This research is unique for many reasons. Most previous studies of returns to managed futures funds focus on the predictability of returns (e.g. Schwager; Brorsen and Townsend), factors that increase returns (e.g. Irwin and Brorsen 1987), and if an increase in the trading volume of managed futures funds decreases returns (e.g. Brorsen and Irwin 1987; Holt and Irwin). Some authors have examined the profitability of technical trading (e.g. Lukac and Brorsen 1990; Brock, Lakonishok, and LeBaron, Osler and Chang), and Boyd and Brorsen used simulated technical trading profits to see which price statistics are correlated with technical returns, but no authors have compared actual trading profits to price statistics. Furthermore, many authors have examined the distribution (e.g. Mandelbrot; Gordon; and Feinstone) and dependence (e.g. Gordon; Mann; Trevino and Martell) of futures price changes. The few studies that have evaluated a possible change in price distributions and dependence are limited in statistical techniques and commodities tested. Using cash prices, Brorsen found that autocorrelations of the Standard and Poor 500 stock index had decreased and the variance of returns had increased over the period 1962 to 1986. Although not backed by formal significance tests, Hudson, Leuthold, and Sarassoro suggest that price changes have become more normal over time. No research has comprehensively studied a change in daily return characteristics. This research will analyze futures prices directly to test the hypothesis that a structural change in price fluctuations has occurred that may have affected the profitability of managed futures and technical analysis. This will be accomplished using bootstrap resampling techniques to test for evidence of a structural change in the dependence and distribution of futures prices.

Summary of Procedures

In order to examine both short and long-term effects, both interday and intraday data are used. Tests of structural change in the movements of futures prices are made using bootstrap procedures. The type of bootstrap procedure for determining the statistical significance of a change varies according to data characteristics.

Procedures for Interday Data Analysis

Interday data will be used to test the hypothesis of a structural change in medium and long-run price movements. Price data including the open, high, low, and close of 17 commodities was gathered from the Bridge/CRB data source. In order to reflect the contracts that CTAs use to trade contract prices are recorded until thirty trading day prior to expiration, then the prices for the next contract month are used. This ensures that the prices are liquid and do not come from the delivery month. The data were segmented into two time periods. The first time period is from January 1, 1975 or the beginning of data, whichever came last, until December 31, 1990. The second time period is from January 1, 1991 until December 31, 2001.

Three main variables of interest were formed. The first is the logarithmic return. Returns will be calculated for lengths of 1, 5 (weekly), 10 (biweekly), and 20 (approximately monthly) days. The daily returns will be used to calculate sample variance, skewness, and kurtosis. The long-run returns will be used to form ratios of short-run variance to long-run variance. The second statistic of interest is the close-to-open price change. The mean, variance, skewness, and kurtosis of close-to-open price changes will be analyzed. The third statistic is breakaway gaps, such as when today's low price is above yesterday's high. Gaps are important because they show times when there was no opportunity to trade at a given price. Gaps will be analyzed by calculating the frequency, mean, variance, skewness, and kurtosis.

Structural change tests for these variables will be done using a variation of the stationary bootstrap developed by Politis and Romano and used by Sullivan, Timmerman, and White and White. This procedure will be adapted for use with two samples. Parametric statistical tests are unacceptable because of the nonnormality and dependence of price changes. Standard bootstrap techniques developed by Efron are invalid due to the dependence of prices. The stationary bootstrap is performed by resampling with replacement random-length blocks of data from the first time period. The length of the block is determined by a random draw from a geometric (.10) distribution. Two pseudo-time series are formed by selecting blocks of data until one bootstrapped series is the same length as in the first time period, and the other series is the same length as the second time period. The statistics of interest are calculated on each of these pseudo-time series and the difference is found. This process is repeated 1,000 times to form a bootstrap empirical distribution of the difference. This distribution is then compared to the actual difference in the statistic from the first time period to the second time period.

In addition to returns and gaps, structural change of autocorrelation of daily returns is also tested. Four statistics were calculated: the sum of the first 5 and first 10 autoregressive coefficients, and the sum of the first 5 and first 10 squared autoregressive coefficients.

Any bootstrap tests for autocorrelation statistics must maintain the dependence between observations. In order to fully maintain the dependence, tests for structural change will be performed using a variation of the technique used for distribution tests. Random length blocks of vectors containing current and lagged prices will be sampled with replacement. The length of the blocks of vectors will vary according to a geometric (.10) random variable. Forming the vector of current and lagged returns will ensure day-to-day serial dependency is maintained thereby allowing the calculation of unbiased sample autocorrelations.

Procedures for Intraday Data Analysis

Due to research cost considerations, only five years will be studied as part of the intraday study. These five years are 1985, 1990, 1995, 1998, and 2000. Data for every transaction were collected for six commodities for each of these years. A continuous time sequence was formed by rolling over contracts on the first day of the expiration month. Then the price series were reduced to the first, high, low, and last for five-minute time periods. These trading periods can then be analyzed similar to short trading days. The variable of interest for intraday data is the five-minute logarithmic return. In addition to the variance, skewness, and kurtosis of the five-minute returns, the sum of the first one, five, and ten autocorrelation coefficients and squared autocorrelations will also be examined. No formal statistical tests will be performed because with the large sample size of the intraday data series even very small differences would be statistically significant (McCloskey and Ziliak). Instead, the sample statistics will be calculated and compared to other time periods to determine if a change has occurred.

Organization of the Thesis

The remainder of this thesis will be organized as follows. Chapter II will review previous studies and research related to this topic. These subjects include returns to managed futures, market efficiency, disequilibrium models, returns to technical analysis, and the distribution and dependence of futures prices. Chapter III will describe the data and methods used to determine if a structural change has occurred in futures price movements. The variables that were analyzed will be expressed and the bootstrap methods used to test for statistical significance will be explained. Chapter IV will present the results of the statistical test and an interpretation of these results. The implications of these finding to technical analysis and managed futures fund returns will also be discussed. This thesis concludes with Chapter V, which will summarize the study and implications and will suggests areas of further study and research.

CHAPTER 2

LITERATURE REVIEW

The problem of decreased returns to managed futures funds is related to many areas of modern finance. This chapter begins by explaining the relationship of managed futures funds to technical analysis and market efficiency. An introduction to the efficient market hypothesis that argues that returns to technical analysis should be zero is followed by disequilibrium models that suggest that if the strict assumptions of the efficient market hypothesis are relaxed then technical analysis can theoretically yield positive returns. These models are followed by a review of empirical evidence that shows returns to technical analysis have been positive. The next literature reviewed shows that futures price changes are not normally distributed and are both linearly and nonlinearly dependent. The last section describes the few studies that have looked at possible structural changes in futures markets.

Managed Futures Funds

The managed futures industry has grown dramatically in the last decade and a half. The number of funds increased from 77 at the end of 1984 (Irwin and Brorsen) to over 3,500 in 1999 (Edwards and Liew). This impressive increase in the number of funds was also accompanied by an increase in dollars under management. In 1999 the total amount invested in hedge funds and managed futures funds was more than $200 million (Edwards and Liew).

The reasons for this remarkable growth can be attributed to many factors. One of the most rational reasons is that returns to managed futures are uncorrelated to the equity market (e.g. Edwards and Liew, Billingsley and Chance). Therefore diversification benefits can be obtained by combining managed futures with more traditional investments. Furthermore, the returns to CTAs were very large until the early part of the 1990s. These two factors allowed investors to greatly increase the risk adjusted return of investment portfolios by investing in managed futures.

The large growth in the size of individual managed futures funds may have been partially responsible for the decline in fund profitability. Chen, Hong, Huang, and Kubik show that equity mutual fund performance declines with increases in fund size. Although statistically insignificant, Brorsen and Townsend found that CTA returns decreased with increases in dollars under management. These two studies, however, dealt with the size of individual funds rather that the size of all funds.

Managed futures funds and CTAs overwhelmingly use technical trading systems for trading decisions. Irwin and Brorsen (1985) found that 83 percent of public futures funds relied on technical analysis for trading decision and an additional 17 percent utilized a combination of technical and fundamental analysis. Of the 18,730 monthly CTA returns studied by Billingsley and Chance, 12,330 or almost 66% used some kind of technical trading system.[2] Over 57% (10777 of 18,730) of the returns utilized a trend-following approach for trading strategy. In fact, technical CTAs have a higher mean return than nontechnical CTAs (Billingsley and Chance); however, this higher return is accompanied by a higher standard deviation of returns. Therefore, the increased return may be due to a higher risk associated with technical CTAs.

Market Efficiency and Technical Analysis

Efficient Market Hypothesis

Fama (1970) defined an efficient market as one "in which prices always 'fully reflect' available information." Fama (1970, 1991) reviewed efficient market literature and summarized previous studies in his articles. Fama (1970) classified market efficiency into three categories: (a) weak-form, trading on historical prices only; (b) semi-strong form, trading based on public information; and (c) strong-form, trading on all information. A vast amount of the early finance literature concluded that markets were weak-form efficient. Although literature has consistently found a small amount of linear dependence in returns, Fama (1970) concluded that markets were weak-form efficient and that risk adjusted returns to trading strategies based on past prices alone were highly unlikely. Furthermore the large number of transactions and the costs of these transactions greatly reduce any positive gross returns. Former semi-strong efficiency tests also concluded that the market was efficient. However, when looking at strong form efficiency, trading all available information including nonpublic

[2] Technical trading systems here include CTAs listing Mechanical, Pattern Recognition, Stochastic, Systematic, Trend-Following, or Technical as the trading strategy.

information, Fama (1970) concluded that the market was strong-form inefficient. Therefore abnormal profits could be realized through either superior analytical ability or nonpublic information. Although much of the literature reviewed by Fama was based on stock returns, one could surmise that if stock markets were efficient then commodity markets should also be efficient. This assumption would arise from the fact that if one market was efficient and the other was inefficient, rational speculators would change from trading the efficient market to trading the inefficient market, thereby equating efficiencies in both markets.

Fama (1991) focuses on different types of literature about efficient markets than in his prior article. His first topic of consideration found that stock prices were efficiently priced relative to news events that affect corporate securities. As a result, stock prices are efficiently priced around dividend disbursements and releases of corporate information. The second area of review was returns to private information. Although mutual funds and pension managers have private information, most studies indicated that these funds actually have negative abnormal profits while very few articles cited found mutual fund managers to have positive abnormal profits. When reviewing studies on the predictability of returns, Fama found research that indicated that prices were autocorrelated, but this autocorrelation was small compared to the returns. Several studies found that returns could be predicted based upon various fundamental variables, but the predictability was low for short time horizons and greater for the two to five year range. The fact that returns can be predicted over a multiyear period is of little concern for commodity funds, since few funds trade in non-nearby contracts, and most futures contracts expire within two years. Once again Fama concluded that although some research indicates slight inefficiencies in markets that these inefficiencies are likely unexploitable.

Disequilibrium Models

Although Fama concluded, based on a search of prior research, that markets are efficient with respect to past prices and public information, many authors have developed mathematical models to show that it is possible for past prices, trends, or volume to convey information about the market. Grossman and Stiglitz concluded that markets have an "equilibrium degree of disequilibrium." The positive cost of information causes some market participants to seek and pay for additional information while other participants are merely noise traders. The participants are driven to pay for additional information if the expected utility of the increased knowledge is higher than the expected utility of being a misinformed noise trader. As the price of information decreases, the efficiency of the price system increases and there is less noise. Under costly information, price will never be fully informative. When significant noise exists, traders are driven to seek additional information either through costly news services or past prices.

Beja and Goldman's disequilbrium model assumed that prices do not fully react instantaneously to an information shock. Therefore they concluded that trend-following strategies could in fact be profitable. This is caused by fundamental traders starting the trending process when new information becomes available but not being fully able to take the market to the new equilibrium due to risk aversion, capital constraints, position limits, or other restrictions. Therefore trendists help take the market to the new equilibrium price faster by utilizing price signals given by the fundamental traders. However, the authors do warn that under certain market conditions a "large" number of trendists will cause a price series to become unstable and oscillate, greatly decreasing or reversing the profitability of trend-following systems.

Market price can reveal additional information about a supply shock (Grundy and McNichols). Price changes reveal the existing private information, so price is partially revealing and traders learn from a sequence of historical prices. Price changes induce market transactions allowing traders to align their risk preferences. Therefore historical prices are useful to market participants, and price changes, in addition to the release of new information, can cause markets to move. Noise in the pricing system allows past prices to convey additional information about past and current price signals thereby helping a speculator to become more profitable (Brown and Jennings). If traders were homogenously informed, technical analysis would have no benefit. However, current prices do not reveal all available information; therefore, investors can use information from historical prices to predict future price movements.

Sanders, Irwin, and Leuthold analyzed market sentiment indices as a proxy for noise trader demand. Their empirical results show that noise traders are mainly positive feedback traders. This indicates that past prices influence current prices because noise trader demand is a function of market sentiment, which is heavily influenced by past returns. As a result short-run positive autocorrelation exists in price sequences; therefore, one should be able to conjecture that a trend-following system could be profitable due to the unique demand of uninformed noise traders.

The review of previous articles shows that several models have been presented to show that past prices or volume can reveal additional information about the direction of future prices. Most of these models are based on private information, asymmetric interpretation of information, costly information, or presence of noise traders. All of these are assumed not to exist in many efficient market models, which may be part of the reason for differing conclusions of the two types of studies. However, all of these assumptions are likely to be present in real life; therefore, these theoretical models probably explain futures trading better than efficient market models. Furthermore, these theoretical models show that technical analysis, especially trend-following, can reveal additional information about a market.

Technical Analysis

Although the weak-form efficiency of markets depends only on past prices, many consider technical analysis to be broader. Murphy (page 1) defines technical analysis to be "the study of market action . . . for the purpose of forecasting future price trends. The term 'market action' includes . . . price, volume, and open interest."

Daily Price Studies. Various authors have studied the returns to technical analysis. Following is a short review of a few of the better known studies completed in the last several years. In the most comprehensive study found, Lukac and Brorsen (1990) simulated technical trading using 23 computer systems over 11 years in 30 diverse commodities. The study found significant gross profits that could indicate a possible violation of the efficient market hypothesis. Transaction and liquidity costs appreciably reduced the gross returns; however, many of the systems still generated statistically significant profits after costs. Therefore the authors concluded that markets are likely to be in disequilibrium due to the profitability of trading systems based on using past prices to determine future price movements. Irwin et al (1997) compared the predictive ability of an autoregressive integrated moving average (ARIMA) model to that of a channel technical system for the soybean futures complex. Not only did the channel technical system generate statistically significant profits, but it also outperformed the ARIMA model in forecasting ability.

Other early simulations (e.g. Irwin; Irwin and Uhrig; Lukac; Lukac, Brorsen , and Irwin) also found simulated trading profits. A number of Masters of Science theses in agricultural economics have considered technical trading systems (Sronce; Dunlap; Pluhar), but these have generally either reported in-sample results or considered too few commodities to have any confidence in the results (e.g. Miyort and McLemore; Franzmann and Sronce). The best evidence of the historical profitability of technical analysis remains the profits from commodity futures funds (Irwin and Brorsen; McCarthy, Schneeweis, and Spurgin).

Intraday Price Studies. Using transaction-to-transaction prices, past researchers found mixed results about the profitability of technical analysis. Trevino and Martell found that filter rules could exploit systematic negative autocorrelation patterns that could be used by floor traders to profit from market inefficiencies. When looking at discrete intraday time periods, Feinstone suggested that using prices alone, would fail to produce consistent profits. However, he did not rule out the possibility of profits when price data were accompanied by additional information readily available to traders. Raj used various technical trading strategies using intraday data for the

Japanese Yen and Deutsche Mark futures contracts and found that the few systems with positive gross profits were reduced to net losses when transaction and liquidity costs were added. Only one trading rule generated significant positive gross profit when analyzed with bootstrap methodology at the 5% level. However these studies used relatively short term trading systems. Brorsen and Townsend showed that CTAs with a short term trading horizon earn a lower return than CTAs with a longer trading horizon. Therefore the results of these studies could be biased due to the increased transaction and liquidity costs associated with short-term trading.

Certainly, many books (e.g. Williams) have been sold promoting day trading of futures markets by amateur speculators. Yet the available information suggests that commodity funds do not day trade. Thus the intraday studies of technical analysis are not of interest here. Such strategies could perhaps be used by a floor trader, but would not be practical for a large pool that traded several markets.

Stock Index Studies. Tests of long-term profitability of technical analysis have often been performed using the Dow Jones Industrial Average. Neftci studied the predictive capacity of a moving average technical trading rule for the period 1795 to 1976. A simulated buy order was placed when the index moved above the 150 day moving average, and a simulated sell order was placed when the price moved below the 150 day moving average. Although the profitability of the trading rule was not tested, evidence of significant predictive power of the trading rule was found. Brock, Lakonishok, and LeBaron, simulated trading using a variety of moving average and trading-range breaks for the DJIA from 1897 to 1986. Significance was tested using bootstrap methodologies and found that these simple technical trading rules have statistically significant predictive power. The results by Brock, Lakonishok, and LeBaron were evaluated by Sullivan, Timmerman, and White to look for possible data snooping bias. The results indicated that the former's results were robust against data snooping. In fact, upon further analysis, even more profitable trading rules were found using the same data. However, these results fail to hold up out-of-sample for the following ten years. Sullivan, Timmerman, and White provide three possibilities for this lack of consistency: (a) the dramatic decrease on October 19, 1987, (b) omitted trading rules which may bias the results, (c) and increasingly efficient markets.

There is also evidence that nonlinear chart patterns commonly used by technical analysts can predict prices. Osler and Chang evaluated the performance of the head and shoulders chart patterns. They found statistically significant profits above transactions costs and risk in two of the six foreign exchange rates that were analyzed. The results were very robust against varying the parameters in the computer algorithm, exit strategy, and size of required head and shoulders formations.

While there is still much to learn about long-run profitability of technical analysis, these studies indicate that during the not-to-distant past, technical analysis had predictive power.

Distribution and Dependence of Futures Prices

There have been numerous hypotheses and empirical studies into the distribution of futures and stock price changes. All of these studies are based upon assumptions that may or may not hold for most financial time series. However, many of the empirical studies have similar findings, which suggest that price changes in a broad range of markets are similar.

Distribution of Daily Returns

The first hypothesis for the distribution of prices was by Bachelier, who argued that price changes should be normally distributed. However, this conclusion was based on the central limit theorem and assumed that price changes were independent and identically distributed with a finite variance. If any of these assumptions do not hold, then price changes would not necessarily be normally distributed.

The first empirical study to challenge Bachelier's hypothesis did not appear for six decades. Houthakker studied daily cotton prices from 1944 to 1958 and found that the distribution of day-to-day changes was slightly, but not significantly skewed, and significantly leptokurtic. Furthermore he found that the variance of prices changed over time. He theorized that this changing variance could cause the leptokurtosis. Mandelbrot found these same departures from normality and proposed the Stable Paretian Hypothesis. In this hypothesis, Mandelbrot proposes a non-Gaussian family of distributions in which the variances are infinite. This implies that the variance of a finite sample variance is a meaningless measure of the population distribution.

Almost all studies into the distribution of futures prices find that price changes are not normal. The changes are usually slightly skewed and high leptokurtic. The two competing theories already explained, prices are distributed from a mixture of distributions (or changing variances) and prices vary according to a stable Paretian distribution, formed the basis of several articles.

Nonconstant Variance Literature. Past studies focusing on nonconstant variance suggests that the leptokurtic and other random effects of variance can be attributed to a changing variance. The observed price variance changes over time because different distributions are applicable at different points in time. Usually literature suggests that the variance then comes from a mixture of normal distributions. Therefore the sample variance is calculated from data points generated by more than one distribution. Changes in the variance of futures prices can be attributed to decreased time to maturity (Black and Tonks; Anderson; Gordon), seasonality (Anderson; Gordon), day of the week (Yang and Brorsen), conditional heteroskedasticity (Akgiray), amount of new information entering a market, or many other factors. Flamouris and Giamouridis use implied distributions of prices based on options prices to show that the market consensus can be more accurately reflected by a mixture of normal distributions than a single lognormal distribution.

Literature has consistently found slowly changing time-varying variances (Taylor 1985; Yang and Brorsen). Even after adjusting for all of the factors that can cause time-varying variances, futures returns are still conditionally nonnormal (Yang and Brorsen). Thus the search for a parameter model of daily futures returns is so far unsuccessful.

Stable Paretian Literature. Mandelbrot first proposed the family of stable Paretian distributions for commodity price chances. Much of the reason that this family of distributions was selected is probably due to the fact that these distributions are leptokurtotic and stable under addition. The logarithm of the characteristic function for Stable Paretian distributions is

(2.1) $$\log(t) = i\delta t - |\delta|^{\alpha}(1 + i\beta(t/|t|)\tan(\pi\alpha/2))$$

where t is any real number and i is $\sqrt{-1}$ (Hall, Irwin, and Brorsen). The characteristic component, α, is limited to the interval $0 \leq \alpha \leq 2$. When $\alpha = 2$ the distribution is Gaussian normal and the variance finitely exists. For all other values of α, moments higher than the mean do not exist.

Many researchers have estimated α. The sampling distribution of this parameter is unknown; therefore, it is impossible to test if the estimated α is significantly different from zero. However, many authors have devised procedures to gauge the effectiveness of the stable distribution at fitting the data. Research shows that a nonnormal stable distribution fits empirical data better than an identically distributed normal distribution (e.g. Mandelbrot; Cornew, Town, and Crowson; Mann). Liu and Brorsen and McCulloch have considered generalized autoregressive conditionally heteroskedastic (GARCH) models with stably distributed residuals. The evidence is mixed, but is not strongly in favor of such models.

Comparison of Paretian and Mixture Hypotheses. The results from past empirical studies have interesting results. Almost all of the studies conclude that price changes are slightly skewed and significantly leptokurtotic. The studies that compare the two different hypotheses disagree as to which one better fits that data. Some studies suggest that the stable Paretian distribution better fits the data (e.g. Mandelbrot; Teichmoeller) and other studies suggest the mixture of normals hypothesis (or time varying variance) better describes past price changes (e.g. Hall, Brorsen, and Irwin; Gordon; Lau, Lau, and Wingender). Due to the discrepancies of past research, there is inconclusive evidence as to which hypothesis better fits the data. But, this set of research has dealt with unconditional distributions that assume independence, so they can easily be rejected as models of futures price returns.

Intraday Price Change Distributions

The distribution of intraday price changes has not been studied as intensively as that of daily changes. Similar conclusions about the departures from normality are found when using transaction-to-transaction changes compared to research with daily price changes; however, the results are not as conclusive. Helms and Martell found that transaction price changes are not normally distributed based on skewness and kurtosis. However, when estimating the parameters of the stable distribution, the estimated alpha was approximately equal to 2, indicating that the data fit the normal distribution better than other stable distributions. Helms and Martell also suggest that the price generating process may not be stable. Brorsen found that transaction-to-transaction price changes exhibited negative relative kurtosis (or platykurtic). However he notes "this finding may be related to no zero price changes being included in the data set and the truncation caused by the minimum price change." Feinstone found that 30 second and three-minute changes of Deutsche Mark futures prices were leptokurtic.

Serial Dependence of Daily Price Changes

Price changes must be serially independent if markets are fully efficient; otherwise, prices do not fully adjust to new information and markets exhibit disequilibrium. There are many measures of serial dependency for time series studies.

Many of the statistics that are commonly used in futures prices are nonparametric due to the nonnormality of price changes. The turning-point approach used by Gordon defines a turning-point to be any observation that lies above (or below) both the prior and subsequent prices. The primary purpose of a turning-point test is to measure the significance of cycles. Of the eight commodities studied by Gordon, only one commodity showed significant nonrandomness by the turning-point test. Only 13% of the wheat, soybean, and live cattle contracts analyzed by Hudson, Leuthold, and Sarassoro showed significant turning points, almost all of which were in the period from 1973 to 1975. However, over 97 percent of the contracts studies by Mann showed significant nonrandomness as measured by the turning point test. The difference-in-sign test compares the number of days a market moves up to the number of days a market moves down and thereby tests the significance of market trends. Three of the eight commodities showed significant serial dependency as measured by the difference-in-sign test. The Phase-Length Test measures the significance of the length between turning points. Hudson, Leuthold, and Sarassoro found significant phase lengths in 14 percent of the contracts studied, but Mann found significant phase-lengths in over 90 percent of the contracts studied. The research as a whole clearly indicates more serial dependence than would be expected if price series followed a random walk.

Other authors have used parametric tests to determine the significance of autocorrelation in market prices. Irwin and Uhrig found significant Ljung-Box statistics in seven of the eight commodities tested over the time period from 1961 to 1980. Taylor (1980, 1982) derived a new test for price trend autocorrelations and reported the results in Taylor (1985). Two separate tests for price trends were calculated for eight different commodities. Only one statistic for one commodity failed to reject the null hypothesis of random price movements.

Past research on futures prices have shown that markets exhibit significant serial correlation and price trends more often than would be expected by random movements. The autocorrelation and the deviation from efficient markets is not large, but it does exist. These tests prove that markets do not always fully react to new information and therefore are sometime characterized by disequilibrium.

Independence of Intraday Price Changes

As Working first argued, transaction prices in an actively traded market will exhibit negative autocorrelation. The negative autocorrelation reflects the actions of scalpers as prices bounce back and forth between the bid and ask prices. The serial dependence of transaction-to-transaction futures prices changes as the contract matures. Trevino and Martell studied corn, soybeans, and wheat futures prices and found that at the beginning of a contract, prices exhibit significantly positive serial correlation. As a contract matures and trading volume increases, the serial correlation decreases and becomes insignificantly different from zero, then becomes significantly negative. Brorsen (1989), analyzing corn futures prices, found significantly negative autocorrelation in corn markets for 66 percent of the months analyzed. However, positive autocorrelation was found during the first months of trading for a contract and the delivery month. The highest scalping returns, and therefore the largest negative serial correlation, was found during months that the amount of fundamental information released between transactions is smallest. The positive autocorrelation may be due to the breaking up of large orders when the market is illiquid during first several months of the contract life. The negative autocorrelation at the end of the contract life is due to market scalping. Scalpers provide liquidity in the market by buying slightly below the market price and selling slightly above the market price. Thus, past research suggests that the autocorrelation of transaction-to-transaction futures prices varies according to the commodity, the time of year, the time to maturity of the contract, and the volume.

Futures price changes between discrete time periods produced different results. This is due in part to the reduced transparency of scalping when data are aggregated. An analysis of 30 second and 3 minute time periods yielded few significantly nonzero autocorrelations in Deutsche Mark futures in July 1977 (Feinstone). Furthermore no pattern was evident between the significant and nonsignificant correlations. Standard and Poor's 500 stock index futures traded in 1983 and 1984 showed significant negative autocorrelation at both one and two lags for one-minute price changes (Goldenberg).

When looking at either daily or intraday prices, futures price changes are not independent and identically distributed and thus are not from a normal distribution. The empirical distribution is usually characterized by significant leptokurtosis and slight (generally insignificant) skewness. Interday prices and intraday discrete time periods usually exhibit positive serial correlation, while transaction-to-transaction price movements usually are negatively autocorrelated. Therefore a more complex distribution must be specified for price movements than that originally proposed by Bachelier.

Structural Change

Many practioners feel that returns to technical analysis have decreased during recent years, but little literature has focused on the possibility of a structural change in the movements of futures markets. Edwards and Liew found that equally weighted and value weighted portfolios of all managed futures and hedge funds in their data sets raised the Sharpe ratio (thereby enhancing risk adjusted returns) in a portfolio of stocks and bonds for the entire data set (1982-1996) and for the first sub-period (1982-1988). However, when looking at the second subperiod (1989-1996) an equally weighted portfolio of public futures funds does not enhance portfolio returns and a value-weighted portfolio does not appreciably increase portfolio returns. Osler and Chang found no evidence of a decrease in the profitability of head and shoulders trading rules in foreign exchange futures markets from 1973 to 1994. Using cash prices, Brorsen (1991) showed that autocorrelations of the Standard and Poor 500 stock index had decreased and the variance of returns had increased over the period 1962 to 1986. Brorsen's theoretical model showed that a decrease in autocorrelation would lead directly to an increase in variance. Although not backed by formal significance tests, Hudson, Leuthold, and Sarassoro suggests that price changes have become more normal over time.

If a structural change has indeed occurred, there are many possible causes. Most notable is the possibility that an increase in the trading volume of futures funds have distorted prices and reduced the profitability of technical trading systems. Lukac, Brorsen, and Irwin simulated trading in 12 commodities over 7 years using 12 computerized trading systems. The results showed that all systems were on the same side of the market a significant number of days. Furthermore, 42% of the pairs of trading systems traded the same day a significant number of days, and the percentage of pairs that trade over a three to five day period is higher but fewer are significant. However this study only analyzed pairs of systems and did not analyze to see if a considerable number of systems (rather than just pairs of systems) traded on the same day or within a close range. The research did not indicate whether or not technical systems influence the market, but rather indicated that the possibility does exist for technical systems to move prices. If in fact a disproportionately large number of systems trade on the same day, prices could be distorted and returns to technical analysis would be reduced. Brorsen and Irwin found using regression analysis that an increase in the volume of futures funds (which they argued was a proxy for volume of technical analysis) was correlated with reduced daily volatility of all but one commodity. Holt and Irwin came to the opposite conclusion, that an increase in the trading volume of futures funds increased volatility. Irwin and Brorsen found that open interest in the 21 largest futures funds was unrelated to returns. The evidence is inconclusive as to whether or not an increase in futures fund activity distorts prices or reduces returns to technical analysis; therefore, it is difficult to formulate hypotheses based on past research. Further, data on how much futures funds trade in each market is not available. Thus, the results of past studies attempting to correlate fund returns with fund volume are suspect because there is no measure of actual fund trading.

Another possible reason for a decline in returns to technical analysis is a structural shift in the commodity markets. Lukac and Brorsen (1989) found little differences between various ways of reoptimizing trading systems using past prices. However, this article did not look at the possibility that various fundamental variables could indeed affect the optimal reoptimization factor. If a structural change in the futures markets has occurred and futures funds have not adjusted their trading systems to accommodate this change, returns to technical analysis would surely have decreased. Irwin and Brorsen found that the inflation rate was positively correlated with returns to futures funds; therefore, they concluded that as uncertainty decreases so does returns to technical analysis. Since the inflation rate has decreased over the past several years, uncertainty in the marketplace should have declined which in turn would have decreased technical trading system returns.[3] In separate studies, Peck and Powers argue that decreased long-run variability is correlated with increased market efficiency (which would lower technical trading returns).

Boyd and Brorsen sought to find the sources of futures market technical trading profitability. Monthly technical returns were simulated using five technical trading systems across seven commodities. Therefore the returns analyzed were theoretical

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[3] Attempts were made to correlate futures fund returns with various macroeconomic variables and with measures of the size of funds. No significant relationship was found. The approach was abandoned and is not reported because the results could be either to no relationship or poor data.

returns based on a computer simulation. An autoregressive conditional heteroscedasticity (ARCH) econometric model was used to estimate the parameters. The independent variables included in the model were coefficient of variation of price, trading volume, inflation, and mean futures price. The estimated coefficient for coefficient of variation of futures prices, a measure of price variation, was statistically positive in 86% of the cases, indicating as futures price volatility increases, technical trading profits also increase. Mean futures price was significantly positive in 15 of the 35 cases, but negatively related in 7 cases (none of which were significant). The estimated coefficient for trading volume was positive more than half of the time, but only significant in two of the 35 cases. Inflation was positive in over half of the cases as well, but only one case was significant. Thus Boyd and Brorsen's results are strongly in favor of hypothesis 1, that a decrease in price volatility could explain the decrease in returns to technical trading.

Conclusion

Although the efficient market hypothesis implies that there should not be any risk- adjusted return to technical analysis, futures funds have consistently earned positive profits. However, these returns are highly variable and may be due to CTAs acquiring additional risk. The efficient market theory is based on costless, symmetric information which all participants view the same. If these assumptions are relaxed, many different theoretical models show that past prices and volume can help predict future price. Therefore one can assume that it is theoretically possible for technical analysis to work in the futures market. Various studies have tested the profitability of technical analysis, although the returns vary over time. Returns to CTAs have diminished in the last several years, which concurs with many people's opinion that technical returns have decreased. The diminishing returns to technical analysis could have been caused by decreased price volatility, more efficient dissemination of information, or too much money devoted to technical trading. Although technical analysis is not highly regarded in much of the financial academic world, it is commonly used in the real world. The positive returns to technical analysis clearly show that markets are not perfectly efficient. But, as the assumptions of the efficient market hypothesis come closer and closer to being true, it is reasonable to expect that trading systems that exploit market efficiencies will become less profitable.

CHAPTER 3

DATA AND METHODS

This chapter contains information about the data and procedures used to accomplish the research objectives. The first section describes the daily and five-minute increment futures price data. The next section describes the boostrap procedures used to test the significance of structural change.

The Data

Daily Data

Daily futures prices from seventeen commodities were used to test hypotheses regarding a structural change in daily price movements. A diverse set of commodities was selected representing four sectors: agricultural, financial, foreign exchange rates, and precious metals. These commodities are listed in Table 3.1 along with the exchange where the commodity is traded. The data were collected from the Bridge/CRB commodity database. The tests of structural change separate the data into two distinct time periods. Time period one begins on January 1, 1975 or the first date on which data were available, and ends on December 31, 1990. Time period two begins on January 1, 1991 and ends on December 31, 2001. The split date was selected to coincide with the drop in technical trading returns as shown in Figure 1.1.

Table 3.1 Commodities Tested for Structural Change in Daily Futures Price Movements

Commodity	Exchange[a]	Ticker Symbol
Coffee	NYBOT	KC
Cocoa	NYBOT	CC
Corn	CBOT	C
Crude Oil	NYMEX	CL
Deutsche Marks	CME	DM
Eurodollars	CME	ED
Feeder Cattle	CME	FC
Gold	COMEX	GC
Heating Oil	NYMEX	HO
Japanese Yen	CME	JY
Live Cattle	CME	LC
Pork Bellies	CME	PB
Soybeans	CBOT	S
Standard and Poor's 500	CME	SP
Sugar	NYBOT	SB
Treasury Bonds	CBOT	US
Wheat	KCBOT	KW

[a]CBOT = Chicago Board of Trade
CME = Chicago Mercantile Exchange
COMEX = Commodity Exchange (officially COMEX division of NYMEX after 1994 merger)
KCBOT = Kansas City Board of Trade
NYBOT = New York Board of Trade
NYMEX = New York Mercantile Exchange

Table 3.2 shows the first date in the data series and the number of observations in the first time period. The number of observations differs substantially across commodities during the first time period because six of the seventeen commodities began trading after 1975.

One problem with studying futures prices is a lack of a continuous series of prices. Futures contracts trade with a fixed delivery date; therefore, contracts expire periodically and more than one contract trades at any given moment, typically up to a

Table 3.2 Initial Observation Date and Number of Observations in First Data Period for Tests of Structural Change in Daily Futures Price Movements

Commodity	Initial Observation Date	Period One Observations[a]	Period Two Observations[b]
Coffee	01/01/75	3997	2747
Cocoa	01/01/75	4006	2748
Corn	01/03/75	4034	2756
Crude Oil	01/31/83	1945	2757
Deutsche Marks	01/02/75	4036	2702
Eurodollars	12/10/81	2289	2787
Feeder Cattle	01/02/75	4035	2777
Gold	01/02/75	4023	2758
Heating Oil	11/15/78	2994	2757
Japanese Yen	01/02/75	3844	2774
Live Cattle	01/02/75	4035	2777
Pork Bellies	01/02/75	4036	2777
Soybeans	01/02/75	4034	2773
Standard and Poor's 500	04/22/82	2198	2776
Sugar	01/02/75	4003	2748
Treasury Bonds	08/24/77	3372	2763
Wheat	01/01/75	4035	2774

[a] Number of trading days between initial observation date and December 31, 1990.
[b] Number of trading days between January 1, 1991 and December 31, 2001.

year and a half into the future. Usually the contract with the shortest time to maturity, or "nearby" contract, is the contract with the greatest volume and open interest. There are also problems with trading in the delivery month. In many markets price movement limits are relaxed during the delivery month allowing for a different distribution during the delivery month than other months. Also short position holders may be forced to deliver the physical commodity during the last portion of the delivery month (Brorsen and Irwin, 1987). Because higher volume leads to lower liquidity costs (Brorsen, 1991), many managed futures funds trade primarily in the nearby contract, except during the delivery month. Outstanding contracts are transferred to the next month forward during the last part of the month prior to the delivery month. In order to analyze the contracts typically traded by managed futures funds, a continuous series of prices was constructed utilizing a contract until thirty trading days prior to the expiration of a contract, then the price series uses the next subsequent contract month. In this way, a continuous series of prices is formed consisting of price movements from several years. The statistics calculated involve changes in prices across days. All of the changes were calculated using data from the same contract month. For example, all daily June contract changes were the change in two June contract values. Thus, no outliers were created at rollover.

Three market related variables were analyzed: daily returns, close-to-open price changes, and daily trading gaps. Percent daily returns are defined as:

$$r_t = 100 * (\ln s_t - \ln s_{t-1}) \tag{3.1}$$

where r_t is the daily return for day t, and s_t is the futures settlement price for day t. Close-to-open price changes are the gaps between the settlement price of a futures contract and the opening price on the following day. Therefore,

$$c_t = \ln o_t - \ln s_{t-1} \tag{3.2}$$

where c_t is the logarithmic close-to-open change, o_t is the opening price on day t, and s_{t-1} is the previous day's settlement price. Logarithmic changes have been used in almost all research involving the distribution of daily prices (e.g. Akgiray and Booth; Hall, Brorsen, and Irwin; Cornew, Town, and Crowson; Anderson; Gordon; Houthakker). Logarithmic changes have the appealing property of restricting price levels to be positive and they account for the likely increased volatility in prices as the price level rises. For example, the Standard & Poor's 500 stock index has risen greatly throughout the last ten years. Volatility has likely risen proportionally. Since logarithmic differences are percentage changes in continuous time, they account for the proportional increase in variance. The final statistic, breakaway trading gaps, is

$$g_t = \begin{cases} \ln h_t - \ln l_{t-1}, & \text{if } h_t \le l_{t-1} \\ \ln l_t - \ln h_{t-1}, & \text{if } l_t \ge h_{t-1} \\ \text{"missing"} & \text{, otherwise} \end{cases} \qquad (3.3)$$

where g_t is the trading gap, h_t is the highest price attained on day t, and l_t is the lowest price attained on day t.

Intraday Data

Transaction data was purchased from Tick Data, Inc. The data sets are large and in order to reduce the cost of the study, five years were selected for study and six commodities were analyzed. The contracts selected are the Standard and Poor's 500, Deutsche Mark, Treasury Bonds, Corn, Cocoa, and New York Heating Oil. The selected five years are 1985[4], 1990, 1995, 1998, and 2000[5]. The exchange related statistics for these commodities are shown in Table 3.3. The five-year increments were selected to be equidistant, and 1998 was selected because of the low CTA returns during that year.

[4] The first year that tick data were available for cocoa was 1987; therefore, this year substitutes for 1985 for cocoa.

[5] Deutsche Mark futures started trading exclusively electronically in August 1999; therefore, no open outcry data are available for year 2000.

Table 3.3 Commodities Tested for Structural Change in Intraday Futures Price Movements

Commodity	Exchange[a]	Ticker Symbol
Cocoa	NYBOT	KC
Corn	CBOT	C
Deutsche Marks	CME	DM
Heating Oil	NYMEX	HO
Standard and Poor's 500	CME	SP
Treasury Bonds	CBOT	US

[a]CBOT = Chicago Board of Trade
CME = Chicago Mercantile Exchange
NYBOT = New York Board of Trade
NYMEX = New York Mercantile Exchange

When using transaction-to-transaction prices, many problems arise. The first is that the length of time between trades varies greatly. Also, first order autocorrelations in the data are usually negative (Thompson and Waller; Brorsen 1989). This negative autocorrelation is caused as prices bounce back and forth between bid and ask prices. Liquidity constraints can allow large orders to move in the short-run. The same problem arises as in daily data: contracts mature throughout the year so there is not a continuous series of prices. The transaction data were converted into five-minute trading periods so that the length of time between observations was constant and so that price changes could reflect more than the bid-ask bounce. The first, high, low, and last trades of each five-minute period were calculated. Any five-minute section that had no trades was treated as a missing observation. The prices used were from the contract nearest to delivery. The contract was changed to the next contract month on the fifteenth day of the month prior to the delivery month.

The main variable of interest for the five-minute trading periods is the five-minute logarithmic return

(3.4) $$d_t = 100*(\ln p_t - \ln p_{t-1})$$

where d_t is the five-minute percentage return for period t, p_t is the last trade during the five minute time interval.

Statistics Tested

A variety of statistics are calculated in an attempt to measure price action. These statistics can be divided into two groups: distribution statistics and autocorrelation statistics.

Statistics Calculated for Daily Price Data

Daily Return Statistics. More statistics are calculated for the daily returns than for any other variable. This is because both short-term and long-term statistics are generated. There are three distributional statistics that are calculated for daily returns: sample variance, skewness, and kurtosis.

The p-day logarithmic return was calculated by summing daily returns:

(3.5) $$r_{t,t-p} = \sum_{j=1}^{p} r_{t-j}$$

where $r_{t,t-p}$ is the long-run return from day t-p to day t. Long-run returns will be calculated for lengths of 5 (weekly), 10 (biweekly), and 20 (approximately monthly) days. The long-run returns are overlapping in order to allow for greater power of bootstrap statistical tests (Harri and Brorsen). The variance of weekly, biweekly, and monthly returns is calculated and analyzed for changes in long-run volatility.

The multi-day returns also allow comparing short-run and long-run effects. In order to compare daily returns to returns of longer time horizons, variance ratios were calculated. The short-to-long run variance ratio is defined as

$$v_{1,p} = \frac{v_1}{v_p} \tag{3.6}$$

where v_p is the variance of p-day logarithmic returns and v_1 is the variance of daily returns. The mean and variance ratios are calculated for values of p equal to 5, 10, and 20. Variance ratios have been used in market efficiency tests (Poterba and Summers; Lo and Mackinlay). With independent and identically distributed normality, the variance of p-day returns is p times that of daily returns. Positive autocorrelation would cause variance ratios to be less than $1/p$. The variance ratios of Lo and MacKinlay also use overlapping data.

Daily Breakaway Gap and Close-to-Open Change Statistics. The same statistics will be calculated for both gaps and close-to-open changes. These statistics are intended to summarize the size and distribution of these variables. Four sample statistics will be calculated for each variable: mean, variance, relative skewness, and relative kurtosis. Bootstrap tests will be used to determine if any of the first four moments of gaps or close-to-open changes have significantly changed.

Autocorrelation Statistics. In addition to distributional measures of returns and gaps, structural change in autocorrelation of daily returns is also tested. Four statistics were calculated: the sum of the first 5 and first 10 autoregressive coefficients, and the sum of the first-5 and first-10 squared autoregressive coefficients. The sum of the squared coefficients is linearly related to the Box-Pierce and Ljung-Box Q.[6] A p-lag autoregressive coefficient ρ_p is defined as

$$(3.7) \qquad \rho_p = \frac{\mathrm{cov}(r_t, r_{t-p})}{\mathrm{var}(r_t)}$$

where $\mathrm{cov}(r_t, r_{t-p})$ is the covariance of r_t and r_{t-p}, and $\mathrm{var}(r_t)$ is the variance of daily returns. If $E(r_t)=0$ then equation (3.7) is algebraically equivalent to

$$(3.8) \qquad \rho_p = \frac{\sum_{t=p+1}^{N}(r_t * r_{t-p})}{(N-1)(Var(r_t))}$$

where N is the sample size.

Statistics Calculated for Intraday Price Data

Five-Minute Return Statistics and Five-Minute Trading-Range Statistics. The same statistics will be calculated for both the five-minute returns and the five-minute trading ranges. The statistics computed will quantify the first four sample moments of the returns distribution in order to see if the shape of the distributions has changed. The measures will be mean, variance, relative skewness, and relative kurtosis.

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[6] Under the null hypothesis of no autocorrelation for the Ljung-Box and Box-Pierce tests, the Q statistics are asymptotically pivotal (Ljung and Box; Box and Pierce). An asymptotically pivotal statistic is one whose distribution does not depend on any unknown parameters. For example, if a statistic converges in distribution to a chi-squared distribution, then the statistic is asymptotically pivotal. Horowitz argues that the bootstrap procedure has greater power with asymptotically pivotal statistics. In practice, however, the asymptotic pivotalness property has proven unimportant (Maausoumi), and therefore no attempt is made here to ensure that test statistics are asymptotically pivotal.

Five-Minute Autocorrelation Statistics. Similar autocorrelation measures are calculated for the intraday prices as were calculated for the daily data. The sum of the first one, five, and ten autocorrelation coefficients and first one, five, and ten squared autocorrelation coefficients are examined for structural change. By treating changes across days as a missing value, any lags across days were not used in the computations.

Tests for Structural Change

Formal tests for structural change in variables were performed using bootstrap procedures. Due to the serial dependence of returns and gaps, both parametric tests and standard bootstrap procedures developed by Efron are not appropriate since they assume independence. The bootstrap procedure used varies according to the unique properties of the data and statistic being tested.

The unique nature of the data and statistics requires the type of bootstrap procedure being used to be carefully selected. Two different bootstrap procedures were used to approximate the sampling distributions of the statistics. Non-autocorrelation statistics must be analyzed with a bootstrap that both accounts for serial dependency and also preserves the stationarity of the time series. This ensures that the variance of the bootstrap distribution is not too great for sample means (and therefore other measures of central moments). The bootstrap procedure used for serial correlation statistics must maintain the long-term dependency in the data. Therefore the data must be resampled in a way that preserves the dependency in the original time series.

The Bootstrap

The bootstrap is a nonparametric sample reuse statistical technique for generating an empirical distribution of a statistic when the exact distribution of that statistic is unknown. The bootstrap is a versatile statistical technique that can be used in many different situations. This section introduces the original one-sample bootstrap and provides some background on a few of the many variations.

One Sample Bootstrap. The original one-sample bootstrap procedure developed by Efron requires that the variable being resampled, $\mathbf{X}=x_1, \ldots, x_n$, be serially independent. The variable is randomly resampled with replacement to form a pseudo-series, $\mathbf{X}^*=x_1^*, \ldots, x_n^*$. The statistic of interest is then calculated on this pseudo-series. This process is replicated many times and the generated statistics from the pseudo-series are used to form an empirical bootstrap distribution of the statistic of interest. Two sided hypothesis tests are performed by rejecting the null hypothesis if the hypothesized value of the statistic is less than the $\alpha/2$ percentile or greater than the $1-\alpha/2$ percentile of the bootstrap distribution.

When serial dependence exists in the data, the pure bootstrap procedure must be altered slightly. In order to maintain some of the serial dependence in the variable, blocks of data are resampled with replacement. Kunsch and Liu and Singh independently developed this procedure, called the block bootstrap, which use fixed length blocks of data. These blocks can be either overlapping or non-overlapping;

however, proofs of consistency requires the block size to increase as the sample size increases (Horowitz).

Two-Sample Boostrap Procedures. The bootstrap has been used to test differences in two means. The data from the two samples are pooled, and two random samples are generated by resampling with replacement (Kowalewski; Dufour and Farhat). The difference in sample means is then calculated and the process is repeated many times. However, this procedure imposes the restriction of no structural change of higher moments (such as kurtosis) between the two samples. We use a similar approach that involves sampling with replacement from the first period only to form two pseudo-series. The first pseudo-time series is equal in length to the first subsample[7] of data and the second series is equal in length to the second subsample of data. The statistic of interest is then calculated on these pseudo-series and the difference of the two is then found. The distribution of the difference of statistics is then compared to the actual difference of the statistic from the first time period to the second time period. This allows us to test the hypothesis of structural change for any moment without imposing the restriction that another moment is not changing simultaneously. For variances, however, ratios are used rather than differences. A more detailed description is given below.

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[7] The length of the first subsample is equal to the number of trading days from January 1, 1975 to December 31, 1990. See Table 3.2 for the length of the first and second subsamples.

Bootstrap Method for Daily Returns, Close-to-Open Changes and Gaps

For all statistics other than autocorrelation statistics, the stationary bootstrap (Politis and Romano) is used to construct confidence intervals for the statistics during the first time period. This type of bootstrap is applicable to weakly dependent stationary time series and was used in financial studies such as White, Sullivan, and Timmerman, and White. The stationary bootstrap is a modification of the block bootstrap. The stationary bootstrap resamples blocks of data[8] also, but the length of the blocks is stochastic. The block length varies according to a geometric random variable. The stochastic block length ensures that the resulting pseudo-times series are stationary (Horowitz).

The optimal average block length for the stationary bootstrap has yet to be established. A fragility test was performed to determine the effect of changing the length of the average block. Three average lengths were chosen and simulated 1000 times to determine the significance of the change in significance levels. The smallest average length tested was 8, which is approximately equal to the fourth root of the number of observations in the bootstrapped dataset. This is the length of static length blocks suggested by Zvingelis. Next a random block length with an average of 10 was performed. This is the length of block informally suggested by Politis and Romano. The last was an ad hoc length of 40. The acceptance or rejection of the hypotheses for all statistics was compared. The average length of the block had little effect on the

[8] In this study the data being resampled are daily returns, close-to-open changes, and breakaway gaps. By resampling these variables instead of futures prices, there is no need to ensure the nonstationarity and continuity of futures prices.

level of significance; as a result, in this study the length of the block varies according to a geometric random variable with an average block length of 10.

The formation of the pseudo-time series involves many steps. Let N_1 be the sample size of the first time period and N_2 be the sample size of the second time period. First the length of the block, l, is determined. This random length varies according to a geometric variable. The probability density function for a geometric random variable is

$$p(y) = (1-p)^{y-1} p\,; \qquad y = 1, 2, 3, \ldots; \qquad 0 \le p \le 1\,. \tag{3.9}$$

The mean of a geometric random variable is the reciprocal of p $(\mu = 1/p)$. Therefore in order to generate a series with an average length of $10, p$ is set to .10. Next the starting observation, s, is chosen by randomly selecting a number according to a discrete uniform distribution

$$p(y) = 1/v\,; \quad y = 1, 2, 3, \ldots, v\,; \quad v = N_1 - l \tag{3.10}$$

where n is the number of observations in the original data series, and l is the block length. The starting block is generated by $x_1^* = [x_S, x_{S+1}, \ldots x_{S+l-1}]$. This process is repeated by selecting a new l and s to generate x_2^*. This process is continued and the vector $\mathbf{X}^*$ is generated by concatenating the $\mathbf{x}_i^*$ vectors until the pseudo series is greater in length than N_1. The generated series is then truncated such that the number of observations in $\mathbf{X}^*$ equals N_1, the number of elements in the first time period. This process is repeated to form another pseudo-series $\mathbf{Y}^*$, which is a 1 x N_2 vector generated from stochastic length blocks of data from the first time period.

Using these generated time series, an empirical bootstrap distribution of the change in each of the statistics from the first time period to the second time period can be created. Once the pseudo-time series sample is generated, the statistics of interest are calculated on **X*** and **Y***. For a test of a change in the mean, the difference in the mean of the elements of **X*** and **Y*** is found:

$$\hat{\Theta}_1 = \frac{1}{N_1}\sum_{i=1}^{N_1} X_i - \frac{1}{N_2}\sum_{i=1}^{N_2} Y_i \tag{3.11}$$

Following Good, a test in the change of the variance is performed by calculating the ratio of the variance of **X*** to the variance of **Y***[9]

$$\hat{\Theta}_2 = \frac{\dfrac{1}{N_1 - 1}\displaystyle\sum_{i=1}^{N_1}(X_i - \overline{X})^2}{\dfrac{1}{N_2 - 1}\displaystyle\sum_{i=1}^{N_2}(Y_i - \overline{Y})^2} \tag{3.12}$$

Equation (3.12) is used for daily, 5-day, 10-day, and 20-day returns. Tests of a change in relative skewness and relative kurtosis use the difference in the sample relative skewness and relative kurtosis in **X*** and **Y***. Dufour and Farhat use the absolute value of the change in skewness and relative kurtosis; but their approach assumes a symmetric distribution, which is not necessarily true for futures prices. The statistics used are thus:

$$\hat{\Theta}_3 = \frac{N_1}{(N_1 - 1)(N_1 - 2)} \frac{\displaystyle\sum_{i=1}^{N_1}(X_i - \overline{X})^3}{s_x^{\ 3}} - \frac{N_2}{(N_2 - 1)(N_2 - 2)} \frac{\displaystyle\sum_{i=1}^{N_2}(Y_i - \overline{Y})^3}{s_y^{\ 3}} \tag{3.13}$$

and

---

[9] If the data were independent and identically normally distributed $\hat{\Theta}_2$ would be have an F-distribution with N_1-1 numerator degrees of freedom and N_2-1 denominator degrees of freedom.

$$\hat{\Theta}_4 = \left[\frac{N_1(N_1+1)}{(N_1-1)(N_1-2)(N_1-3)} \frac{\sum_{i=1}^{N_1}(X_i-\overline{X})^4}{s_x^{\ 4}} - \frac{3(N_1-1)^2}{(N_1-2)(N_1-3)} \right] - \tag{3.14}$$
$$\left[\frac{N_2(N_2+1)}{(N_2-1)(N_2-2)(N_2-3)} \frac{\sum_{i=1}^{N_1}(Y_i-\overline{Y})^4}{s_y^{\ 4}} - \frac{3(N_2-1)}{(N_2-2)(N_2-3)} \right]$$

where s_x and s_y are the sample standard deviations of **X*** and **Y***, respectively.

The process is repeated until 1,000 new pseudo-series have been generated and the $\hat{\Theta}_m$ $(m=1,2,3,4)$ statistics calculated. The actual change in the statistic, Θ_m, is then calculated. Θ_m is the value of Equations (3.11) to (3.14) when the actual data from time period one is the vector **X** and the actual data from time period two is the vector **Y**. The null hypothesis of no change (i.e. $\Theta_m = 0$) is rejected if Θ_m is less than the $\alpha/2$ percentile of $\hat{\Theta}_m$ or greater than the 1-$\alpha/2$ percentiles of $\hat{\Theta}_m$. The levels of α selected for this study are .05 and .10.

Bootstrap Methods for Daily Autocorrelations

Any bootstrap autocorrelation tests must maintain the dependence between observations. The block bootstrap methods maintain dependence asymptotically as the size of the block increases to infinity (Horowitz). However, in finite samples block bootstrap methods alone will produce autocovariance estimates that are biased toward zero. In order to fully maintain the dependence, a new type of bootstrap procedure was developed.

$$\hat{\Theta}_4 = \left[\frac{N_1(N_1+1)}{(N_1-1)(N_1-2)(N_1-3)} \frac{\sum_{i=1}^{N_1}(X_i-\overline{X})^4}{s_x^{\,4}} - \frac{3(N_1-1)^2}{(N_1-2)(N_1-3)} \right] - \tag{3.14}$$
$$\left[\frac{N_2(N_2+1)}{(N_2-1)(N_2-2)(N_2-3)} \frac{\sum_{i=1}^{N_1}(Y_i-\overline{Y})^4}{s_y^{\,4}} - \frac{3(N_2-1)}{(N_2-2)(N_2-3)} \right]$$

where s_x and s_y are the sample standard deviations of $\mathbf{X^*}$ and $\mathbf{Y^*}$, respectively.

The process is repeated until 1,000 new pseudo-series have been generated and the $\hat{\Theta}_m$ $(m = 1, 2, 3, 4)$ statistics calculated. The actual change in the statistic, Θ_m , is then calculated. Θ_m is the value of Equations (3.11) to (3.14) when the actual data from time period one is the vector $\mathbf{X}$ and the actual data from time period two is the vector $\mathbf{Y}$. The null hypothesis of no change (i.e. $\Theta_m = 0$) is rejected if Θ_m is less than the $\alpha/2$ percentile of $\hat{\Theta}_m$ or greater than the $1-\alpha/2$ percentiles of $\hat{\Theta}_m$. The levels of α selected for this study are .05 and .10.

Bootstrap Methods for Daily Autocorrelations

Any bootstrap autocorrelation tests must maintain the dependence between observations. The block bootstrap methods maintain dependence asymptotically as the size of the block increases to infinity (Horowitz). However, in finite samples block bootstrap methods alone will produce autocovariance estimates that are biased toward zero. In order to fully maintain the dependence, a new type of bootstrap procedure was developed.

Let N_2 be the sample size of the second sub-period, and let $p=\{5,10\}$ be the length of autoregressive lag tested. Then form **C** to be a $(N_1 - p)$ x $(p + 1)$ matrix comprised of row vectors $\mathbf{c}_t$ where the jth element of $\mathbf{c}_t$ is the return for day $t - j + 1$ from the first subperiod, such that $\mathbf{c}_t=[r_t, r_{t-1},\ldots,r_{t-j+1},\ldots, r_{t-p}]$ for all $t>p$. Bootstrap confidence intervals were formed by resampling blocks of row vectors (with replacement) from the matrix **C** to form a N_1 x $p+1$ matrix **C*** and a N_2 x $p + 1$ matrix **D***. The number of vectors in a block is a geometric (.10) random variable. Therefore, **C*** and **D*** are similar to the pseudo-time series generated by the stationary bootstrap used for returns and gaps. Equation (3.8) can then be rewritten as

$$\rho_{p,\tau} = \frac{\sum_{i=1}^{T-p}(\tau_{i,1} * \tau_{i,k})}{\operatorname{var}(\tau_{i,1})} \quad \text{for } \tau = \{c,d\} \tag{3.15}$$

where $\operatorname{var}(\tau_{i,1})$ is the variance of the first column vector of **T***, ($\mathbf{T}=\{\mathbf{C},\mathbf{D}\}$).

The statistics of interest are the differences in the autocorrelation coefficients from **C*** and **D*** adjusted by the degrees of freedom. These statistics are then calculated from the simulated ρ_p's (3.15) by the equation

$$\hat{\Theta}_5 = \left(N_1 * \sum_{i=1}^{p} \rho_{i,c}^{w} - N_2 * \sum_{i=1}^{p} \rho_{i,d}^{w} \right) \text{for } w = \{1,2\}, \text{ and } p=\{5,10\} \tag{3.16}$$

where p is the lag and w is the power to which the autoregressive coefficient is raised. This process is repeated 1,000 times to form an empirical bootstrap distribution of the $\hat{\Theta}_5$. Let **D** be a $(N_2 - p)$ x $(p + 1)$ matrix formed in the same manner as **C**, but using data from the second time period. Then Θ_5 is the difference in the autocorrelations from the first time period and the second time period (i.e. using the matrices **C** and **D** in Equations 3.15 and 3.16). The null hypothesis of no change (i.e. $\Theta_5 = 0$) was reject if Θ_5 was less than the $\alpha/2$ percentile of $\hat{\Theta}_5$ or greater than the $1-\alpha/2$ percentiles of $\hat{\Theta}_5$.

Methods for Intraday Data

The number of observations in the intraday study is so large, that tests of statistically significant change are likely to be rejected. Each year contains well over 10,000 observations, meaning that a pooled test contains 50,000 observations. DeGroot says that any test with a sample size of over 20,000 observations will likely reject the null hypothesis when the null hypothesis differs only arithmetically slightly from the true value. McCloskey and McCloskey and Ziliak argue for a distinction to be made between statistical significance and economic significance and that it is a mistake to conduct hypothesis tests within large sample sizes. Even though a hypothesis test may reject the null hypothesis, it is not known whether this difference will make any economically significant change. With the large sample sizes, an economically insignificant change could be statistically significant. Further, with the large sample sizes, bootstrap computations are very costly to conduct; therefore, no hypotheses tests are conducted. The sample statistics are calculated and then compared to determine if any economically significant pattern exists.

Bootstrap Techniques Not Used

Other bootstrap techniques were considered, but were rejected. A parametric boostrap similar to that used by Brock, Lakonishok, and LeBaron was tried, but this procedure downwardly biased the confidence intervals for variance measures. Their approach involves estimating an autoregressive moving average (ARMA) model with the residuals following a generalized autoregressive conditionally heteroskedastic (GARCH) process. The process is then dynamically simulated by using a standard bootstrap to select the residuals. Hall and Jing propose a sampling window procedure whereby only a small portion of the data is analyzed at a time. A randomly chosen window is used as a bootstrap pseudo-series and then another window is selected. The procedure was considered for autocorrelation tests as it fully maintains the serial dependence within the window, but this method greatly decreases the sample size and therefore is inappropriate for parametric autocorrelation measures.

Sufficient Evidence for Structural Change in a Statistic

Since it is unlikely that a statistic will significantly change across all commodities, a rule to determine how many commodities represent enough to conclude a change has occurred is desired. However, a rule such as this is difficult to formulate. This is caused by correlation between the prices of different futures commodities. Furthermore, this dependency is not constant between commodities. If there were no cross-commodity correlations, the Bonferroni inequality could be used to test the significance of a change. Therefore any rule devised using standard statistical methods has been ruled out as inappropriate and an ad hoc rule was formulated. If more than one-half of the commodities show a significant change in one direction for a specific statistic or set of related statistics, then this will indicate that this statistic has significantly changed.

Summary

This study examines futures prices for evidence of a structural change that can describe the recent reduction in returns to managed futures funds. Five-minute and daily prices will be examined for evidence of a structural change in both short-run and long-run price changes. A broad range of statistics will be calculated to examine a change in the distribution of daily returns, close-to-open changes, breakaway gaps, and intraday returns, and the serial dependence of long and short-run futures prices. Bootstrap procedures will be used to test for statistical significance of changes. The type of bootstrap will vary based upon the type of statistic being calculated and whether the data are for intraday prices or daily prices. These procedures will allow testing the hypothesis that a structural change has occurred in futures market prices.

CHAPTER 4

RESULTS AND IMPLICATIONS

This chapter presents the results of the statistical procedures for daily and intraday data and explains the consequences of the findings. The first section presents the results of the bootstrap tests for the daily data. The second section presents the summary statistics calculated for the intraday prices. The final section interprets the results and explains what these results imply about the hypotheses regarding why the profitability of managed futures funds has decreased.

Daily Results

The results of the bootstrap tests of structural change of price statistics calculated from the daily futures prices are shown in Tables 4.1 to 4.12. The first five tables present statistics related to daily returns, the next three tables present breakaway gap statistics. Close-to-open price change statistics are in Tables 4.9 and 4.10, and the last two tables present return autocorrelation statistics.

Table 4.1. Variance of Daily and 5-Day Returns for Futures Prices.

	Variance of Daily Returns		Variance of 5-Day Returns	
Commodity	1975[a]-1990	1991-2001	1975[a]-1990	1991-2001
Coffee	3.38	7.10++	19.5	35.6++
Cocoa	3.57	3.16**	19.0	14.7**
Corn	1.41	1.52	7.5	8.1
Crude Oil	3.83	3.60	22.6	16.2
Deutsche Marks	0.44	0.48	2.2	2.4
Eurodollars	0.02	<0.01**	0.1	0.1**
Feeder Cattle	1.14	0.53**	6.3	2.8**
Gold	2.15	0.60**	10.8	2.9**
Heating Oil	2.99	3.14	18.5	14.3
Japanese Yen	0.43	0.58++	2.2	2.7++
Live Cattle	1.33	0.60**	7.1	3.0**
Pork Bellies	4.52	5.08+	25.6	25.9
Soybeans	2.25	1.48**	11.5	7.3**
Standard and Poor's 500	2.02	1.09	7.8	4.8
Sugar	7.42	3.29**	35.6	15.7**
Treasury Bonds	0.71	0.37**	3.8	1.8**
Wheat	1.28	1.52	6.1	8.5++

[a] 1975 or the first date in the time series.

Notes: Hypothesis tests were performed using the two sample stationary bootstrap with 1,000 repetitions.
Statistically significant increases are denoted by + at .10 level and ++ at .05 level.
Statistically significant decreases are denoted by * at .10 level and ** at .05 level.

Table 4.2. Variance of 10-Day and 20-Day Returns for Futures Prices.

	Variance of 10-Day Returns		Variance of 20-Day Returns	
Commodity	1975[a]-1990	1991-2001	1975[a]-1990	1991-2001
Coffee	43.70	69.74++	99.9	162.4++
Cocoa	37.20	29.33**	77.5	60.9**
Corn	15.79	15.93	35.5	36.9
Crude Oil	45.58	29.93**	105.4	67.2
Deutsche Marks	4.79	4.81	10.2	10.6
Eurodollars	0.24	0.03**	0.5	0.1**
Feeder Cattle	13.54	5.28**	27.0	11.1**
Gold	20.99	6.13**	45.5	12.8**
Heating Oil	36.86	28.44	84.6	67.0
Japanese Yen	4.80	5.51	11.1	12.6
Live Cattle	14.37	5.58**	28.2	11.0**
Pork Bellies	54.76	51.63	116.3	114.5
Soybeans	23.21	13.50**	51.0	29.4**
Standard and Poor's 500	14.52	8.46	25.8	17.9
Sugar	74.30	32.09**	160.2	66.2**
Treasury Bonds	7.96	3.29**	16.9	7.3**
Wheat	12.24	17.66++	26.2	40.9++

[a] 1975 or the first date in the time series.

Notes: Hypothesis tests were performed using the two sample stationary bootstrap with 1,000 repetitions.
Statistically significant increases are denoted by + at .10 level and ++ at .05 level.
Statistically significant decreases are denoted by * at .10 level and ** at .05 level.

Table 4.3. Skewness and Kurtosis of Daily Returns for Futures Prices.

	Skewness of Daily Returns		Kurtosis of Daily Returns	
Commodity	1975[a]-1990	1991-2001	1975[a]-1990	1991-2001
Coffee	-0.28	0.47++	4.05	8.08++
Cocoa	0.05	0.37++	0.64	2.27++
Corn	-0.01	-0.02	1.90	1.86
Crude Oil	-0.14	-2.14**	4.85	36.11++
Deutsche Marks	0.20	0.01	2.44	1.90
Eurodollars	0.62	0.33	10.19	6.55
Feeder Cattle	-0.08	-0.07	0.46	1.04++
Gold	-0.10	0.63++	4.00	18.11++
Heating Oil	-0.06	0.10	2.44	3.37
Japanese Yen	0.32	0.84++	3.13	8.62++
Live Cattle	-0.10	-0.02	0.26	0.75++
Pork Bellies	-0.01	0.01	-0.59	0.02++
Soybeans	-0.11	-0.05	0.96	2.99++
Standard and Poor's 500	-5.52	-0.28	158.43	5.11
Sugar	-0.04	-0.05	1.85	2.46
Treasury Bonds	0.21	-0.36	5.80	2.06**
Wheat	0.32	0.15	5.94	1.32**

[a] 1975 or the first date in the time series.

Notes: Hypothesis tests were performed using the two sample stationary bootstrap with 1,000 repetitions.
Statistically significant increases are denoted by + at .10 level and ++ at .05 level.
Statistically significant decreases are denoted by * at .10 level and ** at .05 level.

Table 4.4. Ratio of Daily Variance to 5-Day and 10-Day Variance for Futures Prices.

	Ratio of Daily Variance to 5-Day Variance		Ratio of Daily Variance to 10-Day Variance	
Commodity	1975[a]-1990	1991-2001	1975[a]-1990	1991-2001
Coffee	0.17	0.19^{+}	0.07	0.10^{++}
Cocoa	0.18	0.21^{++}	0.09	0.10
Corn	0.18	0.18	0.08	0.09
Crude Oil	0.16	0.22^{++}	0.08	0.12^{++}
Deutsche Marks	0.19	0.19	0.09	0.10
Eurodollars	0.17	0.17	0.08	0.08
Feeder Cattle	0.17	0.18	0.08	0.10^{++}
Gold	0.19	0.20	0.10	0.09
Heating Oil	0.16	0.21^{++}	0.08	0.11^{++}
Japanese Yen	0.19	0.20	0.08	0.10^{++}
Live Cattle	0.18	0.19	0.09	0.10^{++}
Pork Bellies	0.17	0.19^{++}	0.08	0.09^{++}
Soybeans	0.19	0.20	0.09	0.11
Standard and Poor's 500	0.25	0.22	0.13	0.12
Sugar	0.20	0.20	0.09	0.10
Treasury Bonds	0.18	0.20	0.09	0.11^{++}
Wheat	0.20	0.17**	0.10	0.08**

[a] 1975 or the first date in the time series.

Notes: Hypothesis tests were performed using the two sample stationary bootstrap with 1,000 repetitions.
Statistically significant increases are denoted by $^{+}$ at .10 level and $^{++}$ at .05 level.
Statistically significant decreases are denoted by * at .10 level and ** at .05 level.

Table 4.5. Ratio of Daily Variance to 20-Day Variance for Futures Prices.

Commodity	Ratio of Daily Variance to 20-Day Variance	
	1975[a]-1990	1991-2001
Coffee	0.033	0.043^{++}
Cocoa	0.046	0.051
Corn	0.039	0.041
Crude Oil	0.036	0.053^{++}
Deutsche Marks	0.043	0.045
Eurodollars	0.039	0.034
Feeder Cattle	0.042	0.048
Gold	0.047	0.046
Heating Oil	0.035	0.046^{+}
Japanese Yen	0.038	0.046^{+}
Live Cattle	0.047	0.055^{++}
Pork Bellies	0.038	0.044
Soybeans	0.044	0.050
Standard and Poor's 500	0.078	0.061
Sugar	0.046	0.049
Treasury Bonds	0.042	0.051^{+}
Wheat	0.048	0.037**

[a] 1975 or the first date in the time series.

Notes: Hypothesis tests were performed using the two sample stationary bootstrap with 1,000 repetitions.
Statistically significant increases are denoted by $^{+}$ at .10 level and $^{++}$ at .05 level.
Statistically significant decreases are denoted by * at .10 level and ** at .05 level.

Table 4.6. Frequency and Mean of Breakaway Gaps in Futures Prices.

	Frequency of Gaps		Mean Breakaway Gaps	
Commodity	1975[a]-1990	1991-2001	1975[a]-1990	1991-2001
Coffee	0.19	0.09**	0.102	0.098
Cocoa	0.20	0.12**	0.057	-0.065*
Corn	0.16	0.10**	0.006	0.027
Crude Oil	0.22	0.06**	-0.051	0.016
Deutsche Marks	0.26	0.15**	0.001	-0.025
Eurodollars	0.17	0.03**	0.008	0.001
Feeder Cattle	0.15	0.09**	0.016	0.006
Gold	0.18	0.07**	-0.018	-0.021
Heating Oil	0.26	0.08**	0.002	0.092
Japanese Yen	0.39	0.09**	0.024	-0.007*
Live Cattle	0.13	0.06**	0.023	0.038
Pork Bellies	0.15	0.11**	-0.060	0.012
Soybeans	0.14	0.07**	0.038	0.021
Standard and Poor's 500	0.07	0.03**	-0.008	0.009
Sugar	0.19	0.09**	-0.011	0.003
Treasury Bonds	0.17	0.07**	0.010	-0.004
Wheat	0.16	0.15	0.006	0.050

[a] 1975 or the first date in the time series.

Notes: Hypothesis tests were performed using the two sample stationary bootstrap with 1,000 repetitions. Statistically significant increases are denoted by $^{+}$ at .10 level and $^{++}$ at .05 level. Statistically significant decreases are denoted by * at .10 level and ** at .05 level.

Table 4.7. Variance and Skewness of Breakaway Gaps in Futures Prices.

	Variance of Breakaway Gaps		Skewness of Breakaway Gaps	
Commodity	1975[a]-1990	1991-2001	1975[a]-1990	1991-2001
Coffee	1.73	3.12^{++}	0.33	3.77^{++}
Cocoa	1.14	0.41**	0.39	0.37
Corn	0.74	0.42	0.86	1.06
Crude Oil	1.65	1.43	0.15	-3.94*
Deutsche Marks	0.18	0.21	-0.07	-0.48
Eurodollars	0.01	$<$0.01**	1.73	0.60
Feeder Cattle	0.36	0.15**	-0.26	1.01^{++}
Gold	1.05	0.19**	-0.09	-3.46**
Heating Oil	1.49	0.81**	-0.17	4.38^{++}
Japanese Yen	0.15	0.10**	0.54	0.73
Live Cattle	0.45	0.11**	-0.30	1.05^{++}
Pork Bellies	2.02	2.06	0.09	-0.16
Soybeans	1.02	0.84	0.15	-0.25
Standard and Poor's 500	0.28	0.34	-0.91	-1.98
Sugar	2.14	0.56**	-0.65	1.09^{++}
Treasury Bonds	0.38	0.14**	1.41	-1.19
Wheat	0.28	0.40	-0.33	2.15

[a] 1975 or the first date in the time series.

Notes: Hypothesis tests were performed using the two sample stationary bootstrap with 1,000 repetitions.
Statistically significant increases are denoted by $^{+}$ at .10 level and $^{++}$ at .05 level.
Statistically significant decreases are denoted by * at .10 level and ** at .05 level.

Table 4.8. Kurtosis of Breakaway Gaps in Futures Prices.

	Kurtosis of Breakaway Gaps	
Commodity	1975[a]-1990	1991-2001
Coffee	7.34	33.27++
Cocoa	2.33	2.40
Corn	11.25	8.79
Crude Oil	25.31	42.95
Deutsche Marks	11.26	5.10
Eurodollars	22.91	11.55
Feeder Cattle	3.65	7.71++
Gold	9.01	30.84++
Heating Oil	6.85	42.02++
Japanese Yen	4.96	5.30
Live Cattle	3.55	9.53++
Pork Bellies	2.21	2.62
Soybeans	6.50	7.84
Standard and Poor's 500	6.56	13.17
Sugar	7.23	6.44
Treasury Bonds	23.34	14.42
Wheat	28.12	13.95

[a] 1975 or the first date in the time series.

Notes: Hypothesis tests were performed using the two sample stationary bootstrap with 1,000 repetitions.
Statistically significant increases are denoted by + at .10 level and ++ at .05 level.
Statistically significant decreases are denoted by * at .10 level and ** at .05 level.

Table 4.9. Mean and Variance of Close-to-Open Changes in Futures Prices.

	Mean Close-to-Open Change		Variance of Close-to-Open Changes	
Commodity	1975[a]-1990	1991-2001	1975[a]-1990	1991-2001
Coffee	-0.075	-0.171**	1.35	1.93++
Cocoa	-0.027	-0.166**	1.37	0.73**
Corn	0.015	-0.039**	0.45	0.28**
Crude Oil	-0.102	-0.012++	1.82	0.68**
Deutsche Marks	-0.023	-0.026	0.23	0.14**
Eurodollars	0.007	0.001**	<0.01	<0.01**
Feeder Cattle	-0.002	0.007	0.31	0.11**
Gold	-0.027	-0.035	1.03	0.15**
Heating Oil	-0.045	<0.001	1.57	0.86**
Japanese Yen	0.001	-0.017	0.26	0.09**
Live Cattle	0.008	-0.002	0.36	0.09**
Pork Bellies	-0.005	0.002	1.17	1.28
Soybeans	0.006	-0.022	0.66	0.32**
Standard and Poor's 500	0.001	-0.007	0.66	0.11*
Sugar	-0.136	-0.142	2.35	0.61**
Treasury Bonds	-0.013	-0.004	0.37	0.06**
Wheat	0.005	-0.037**	0.29	0.43+

[a] 1975 or the first date in the time series.

Notes: Hypothesis tests were performed using the two sample stationary bootstrap with 1,000 repetitions.
Statistically significant increases are denoted by + at .10 level and ++ at .05 level.
Statistically significant decreases are denoted by * at .10 level and ** at .05 level.

Table 4.10. Skewness and Kurtosis of Close-to-Open Changes in Futures Prices.

	Skewness of Close-to-Open Changes		Kurtosis of Close-to-Open Changes	
Commodity	1975[a]-1990	1991-2001	1975[a]-1990	1991-2001
Coffee	0.08	1.99++	8.64	67.33++
Cocoa	0.09	-0.07	2.58	2.74
Corn	0.62	0.85	13.44	17.85
Crude Oil	-0.46	-0.23	11.12	25.41++
Deutsche Marks	0.25	-0.47*	5.83	7.26
Eurodollars	4.45	1.91	89.94	32.56
Feeder Cattle	-0.46	0.16	7.90	12.29
Gold	-0.02	-4.02**	9.36	86.64++
Heating Oil	-0.13	1.79++	6.83	32.02++
Japanese Yen	0.26	-0.14*	3.44	8.21++
Live Cattle	-0.07	0.64++	4.01	7.96++
Pork Bellies	-0.14	-0.29	3.80	6.42++
Soybeans	-0.06	-0.38	9.16	30.39++
Standard and Poor's 500	-10.30	-1.34	410.12	42.18
Sugar	-0.14	-0.25	6.61	7.25
Treasury Bonds	0.45	-0.96**	12.65	16.10
Wheat	0.50	0.88	25.96	12.98

[a] 1975 or the first date in the time series.

Notes: Hypothesis tests were performed using the two sample stationary bootstrap with 1,000 repetitions.
Statistically significant increases are denoted by + at .10 level and ++ at .05 level.
Statistically significant decreases are denoted by * at .10 level and ** at .05 level.

Table 4.11. Sums of First 5 and First 10 Autoregressive Coefficients Times the Number of Observations for Futures Prices.

	Sum of First Five Autoregressive Coefficients		Sum of First 10 Autoregressive Coefficients	
Commodity	1975[a]-1990	1991-2001	1975[a]-1990	1991-2001
Coffee	463.4	-61.6*	780.1	88.3*
Cocoa	14.2	-57.3	53.5	-48.1
Corn	76.3	20.1	395.5	257.1
Crude Oil	199.7	-247.7	526.6	-291.4
Deutsche Marks	54.9	25.5	286.5	47.9
Eurodollars	167.2	288.2	375.2	644.5
Feeder Cattle	459.2	79.4**	284.8	-188.0
Gold	-61.5	204.0	-38.0	111.4
Heating Oil	309.1	-113.2	402.4	-91.8
Japanese Yen	144.9	-61.5	503.1	53.6
Live Cattle	241.0	-19.5	56.0	-375.5*
Pork Bellies	349.4	-9.2**	484.5	257.4
Soybeans	68.9	-256.4	183.3	-94.8
Standard and Poor's 500	-436.4	-344.8	-599.0	-438.5
Sugar	-6.1	76.6	102.9	-136.5
Treasury Bonds	157.1	-260.2**	252.6	-229.3
Wheat	-187.5	174.3+	101.2	397.0

[a] 1975 or the first date in the time series.

Notes: Hypothesis tests were performed using the two sample stationary bootstrap with 1,000 repetitions. Statistically significant increases are denoted by + at .10 level and ++ at .05 level. Statistically significant decreases are denoted by * at .10 level and ** at .05 level.

Table 4.12. Sums of First 5 and First 10 Squared Autoregressive Coefficients Times the Number of Observations for Futures Prices.

	Sum of First Five Squared Autoregressive Coefficients		Sum of First 10 Squared Autoregressive Coefficients	
Commodity	1975[a]-1990	1991-2001	1975[a]-1990	1991-2001
Coffee	26.0	16.4	34.8	21.6
Cocoa	9.5	7.6	15.4	10.9
Corn	10.9	14.3	29.1	25.0
Crude Oil	53.7	36.7	72.9	40.2
Deutsche Marks	4.1	4.8	9.8	13.3
Eurodollars	26.9	47.6	30.6	64.5
Feeder Cattle	17.2	10.2	20.6	28.7
Gold	21.3	26.7	25.6	31.2
Heating Oil	54.0	8.8	59.2	18.2
Japanese Yen	4.3	5.5	15.8	9.6
Live Cattle	7.5	7.1	21.2	22.9
Pork Bellies	14.6	10.3	17.9	22.0
Soybeans	2.7	13.8	8.9	20.9
Standard and Poor's 500	54.7	12.6	61.7	19.1
Sugar	7.6	17.7	12.1	25.0
Treasury Bonds	6.0	15.2	8.0	35.4^{+}
Wheat	14.6	33.3	25.7	37.3

[a] 1975 or the first date in the time series.

Notes: Hypothesis tests were performed using the two sample stationary bootstrap with 1,000 repetitions. Statistically significant increases are denoted by $^{+}$ at .10 level and $^{++}$ at .05 level. Statistically significant decreases are denoted by * at .10 level and ** at .05 level.

Table 4.13. Variance, Skewness, and Kurtosis of 5-Minute Intraday Returns for Futures Prices.

Statistic	Commodity	1985[a]	1990	1995	1998	2000
Variance of 5-Minute Returns						
	Cocoa	0.022	0.074	0.035	0.026	0.070
	Corn	0.011	0.022	0.017	0.029	0.032
	Deutsche Marks	0.006	0.003	0.005	0.003	
	Heating Oil	0.040	0.120	0.030	0.079	0.126
	Standard and Poor's 500	0.005	0.012	0.003	0.019	0.020
	Treasury Bonds	0.005	0.004	0.004	0.003	0.004
Skewness of 5-Minute Returns						
	Cocoa	-0.08	0.04	0.02	0.21	-0.52
	Corn	0.14	-0.06	<0.01	0.43	0.20
	Deutsche Marks	0.34	-0.23	-0.44	-0.04	
	Heating Oil	0.44	-0.81	-0.21	-0.26	-0.84
	Standard and Poor's 500	-0.10	-0.26	-0.12	2.04	-0.42
	Treasury Bonds	-0.06	0.22	0.18	-0.15	0.39
Kurtosis of 5-Minute Returns						
	Cocoa	3.54	4.17	9.60	3.41	7.45
	Corn	3.14	8.09	7.73	12.26	63.26
	Deutsche Marks	7.52	21.41	23.48	4.78	
	Heating Oil	10.30	10.63	1.37	5.43	14.25
	Standard and Poor's 500	2.10	15.80	5.44	91.35	12.66
	Treasury Bonds	3.02	13.28	21.07	7.82	14.23

[a]No data were available for cocoa in 1985; therefore, the first cocoa statistics are for 1987.

Table 4.14. Sum of Autocorrelation Coefficients for Five-Minute Intraday Futures Prices.

Statistic	Commodity	1985[a]	1990	1995	1998	2000
First Autocorrelation Coefficient						
	Cocoa	-0.038	-0.028	-0.064	-0.075	-0.111
	Corn	-0.180	-0.060	-0.079	-0.104	-0.158
	Deutsche Marks	-0.082	0.017	0.028	-0.044	
	Heating Oil	0.015	-0.044	-0.120	-0.094	0.017
	Standard and Poor's 500	0.023	-0.002	0.009	-0.085	-0.041
	Treasury Bonds	-0.160	-0.080	-0.046	-0.061	-0.002
Sum of First Five Autocorrelation Coefficients						
	Cocoa	-0.069	-0.078	-0.134	-0.116	-0.160
	Corn	-0.164	-0.124	-0.092	-0.107	-0.172
	Deutsche Marks	-0.095	-0.110	-0.119	-0.092	
	Heating Oil	-0.191	-0.045	-0.090	-0.132	0.044
	Standard and Poor's 500	-0.037	-0.073	-0.071	-0.094	-0.055
	Treasury Bonds	-0.136	-0.057	-0.086	-0.067	-0.056
Sum of First Ten Autocorrelation Coefficients						
	Cocoa	-0.076	-0.023	-0.113	-0.098	-0.158
	Corn	-0.149	-0.104	-0.179	-0.115	-0.179
	Deutsche Marks	-0.101	-0.076	-0.077	-0.058	
	Heating Oil	-0.011	-0.034	-0.125	-0.206	0.008
	Standard and Poor's 500	0.040	-0.047	-0.027	-0.081	-0.047
	Treasury Bonds	-0.131	-0.052	-0.084	-0.026	-0.065

[a]No data were available for cocoa in 1985; therefore, the first cocoa statistics are for 1987.

Table 4.15. Sum of Autocorrelation Coefficients for Five-Minute Intraday Futures Prices.

Statistic	Commodity	1985[a]	1990	1995	1998	2000
First Squared Autocorrelation Coefficient						
	Cocoa	0.001	0.001	0.004	0.006	0.012
	Corn	0.032	0.004	0.006	0.011	0.025
	Deutsche Marks	0.007	0.000	0.001	0.002	
	Heating Oil	0.000	0.002	0.014	0.009	0.000
	Standard and Poor's 500	0.001	0.000	0.000	0.007	0.002
	Treasury Bonds	0.026	0.006	0.002	0.004	0.000
Sum of First Five Squared Autocorrelation Coefficients						
	Cocoa	0.003	0.004	0.006	0.007	0.013
	Corn	0.032	0.007	0.007	0.011	0.025
	Deutsche Marks	0.007	0.005	0.008	0.004	
	Heating Oil	0.016	0.002	0.015	0.010	0.002
	Standard and Poor's 500	0.003	0.002	0.002	0.008	0.002
	Treasury Bonds	0.027	0.007	0.002	0.004	0.001
Sum of First Ten Squared Autocorrelation Coefficients						
	Cocoa	0.003	0.004	0.007	0.007	0.014
	Corn	0.033	0.007	0.008	0.011	0.026
	Deutsche Marks	0.008	0.005	0.009	0.004	
	Heating Oil	0.047	0.003	0.016	0.012	0.004
	Standard and Poor's 500	0.004	0.003	0.003	0.009	0.003
	Treasury Bonds	0.027	0.007	0.003	0.005	0.001

[a]No data were available for cocoa in 1985; therefore, the first cocoa statistics are for 1987.

Daily Returns

The daily and long-run volatility has significantly decreased in almost half of the commodities. Table 4.1 shows that the variances of both daily and weekly returns have decreased in eight of the 17 commodities while only increasing in three commodities. Longer run volatilities have decreased as well. Table 4.2 shows that the 10-day variance has decreased in nine commodities while increasing in two of the commodities, and the 20-day variance has decreased in eight commodities while increasing in only two. These two tables show that most commodities have decreased in volatility for periods of greater than one day. Thus the results are strongly supportive of hypothesis one, that greater price stability has caused the decrease in returns to technical analysis.

The distribution of returns has also changed in a majority of the commodities. The relative skewness has significantly changed in five commodities, but with no pattern in regard to direction. The relative kurtosis has significantly increased in nine of the commodities while decreasing in only two commodities. The increase in kurtosis means that large price changes occur relatively more often since 1990 than before.

Daily Breakaway Gaps

The results for tests of structural change in statistics related to breakaway gaps are reported in Tables 4.6 through 4.8. The most consistent change of any statistic was the decreased frequency of breakaway gaps. Table 4.6 shows that although the mean breakaway gap significantly changed in only two commodities, the percentage of days with a breakaway gap significantly decreased in 16 of the 17 commodities. The one commodity that did not significantly decrease, wheat, also showed a slight, although insignificant, decrease. The distribution of price gaps changed in more than half of the commodities. Table 4.7 shows that the variance of price gaps increased in nine commodities while decreasing in only one. Tables 4.7 and 4.8 show that the skewness and/or kurtosis of price gaps changed in seven of the 17 commodities. Thus, the results with the breakaway gaps are consistent with the daily returns. There seems to be less overall volatility, but large jumps, presumably due to new information, have increased relative to overall volatility.

Close-to-Open Price Changes

Some of the statistics related to close-to-open price changes have also changed. The mean overnight changes shown in Table 4.9 have decreased in four commodities while increasing in one. Overnight volatility, as measured by the variance of close-to-open changes, has decreased, which is consistent with less frequent gaps and decreased daily variance. In Table 4.9, only two of the commodities showed a significant increase in the close-to-open variance while 14 commodities showed a significant decrease in overnight volatility. Table 4.10 confirms that the distribution of overnight changes has also changed. The skewness significantly changed in six commodities with an equal number of increases and decreases. Eight of the 17 commodities showed a significant increase in the kurtosis of overnight price changes, with no significant decreases. The decreased variance and increased kurtosis indicated that while overnight volatility may have decreased, when new information comes available overnight causing price equilibrium to change during nontrading hours, this information is quickly incorporated into a large price change at the open. Thus, price changes that truly reflect new information may be occurring when markets are closed.

Daily Autocorrelation

The results of the tests for structural change in serial autocorrelation of daily returns are presented in Tables 4.11 and 4.12. Five commodities showed a significant decrease in the sum of the first five and/or sum of the first ten autocorrelation coefficients. In addition one of the commodities, wheat, showed an increase in the sum of the first five autocorrelation coefficients. The only commodity that showed any change in the sum of the first five or first ten squared autocorrelation coefficients was Treasury Bonds which showed a marginally significant increase in autocorrelation. It must be remembered that these four statistics only measure a specific pattern of linear dependence. Any other form of linear or nonlinear dependence is not considered.

The changes in the ratio of daily variance to long-run provide weak support for decreased autocorrelation. Tables 4.4 and 4.5 show that the ratios of daily variance to long-run variance have significantly decreased in eight commodities while increasing in only one commodity. The ratio of short-run to long-run variance would be equal to $1/p$ in an efficient, random walk market with normally distributed price changes (Poterba and Summers; Lo and Mackinlay). If there were positive autocorrelation (i.e. market trends) the variance ratios would be less than $1/p$. During the first time period, the variance ratios were mostly less than $1/p$. During the second time period, the variance ratios were much closer to $1/p$, and almost half of the commodities exhibited a significant increase. However this measure of a change in autocorrelation is not robust to nonnormally distributed price changes, and the increase in the variance ratios could be caused by an increase in kurtosis.

Intraday Results

There was very little discernable pattern in the changes in the summary statistics calculated for intraday prices. Whether looking for a trend in the statistics, or locating the minimum and maximum values for each statistic within a commodity, it was difficult to find any evidence of a consistent change in intraday price movements. This may be partially due to the set of commodities studied. The commodities selected for the intraday price study showed little change in the daily study. Because the tick data were purchased before the completion of the daily price study, it was unknown which commodities showed the most promise of change. From this study, all that can be said is that there is no evidence of a significant structural change in the intraday price movements of the commodities examined.

Implications of Observed Structural Changes

This section will explain the implications of the observed structural changes. The implications will focus on explaining how the changes in futures price movements are consistent with reduced technical trading profitability

The structural changes found in daily futures prices support the first hypothesis of daily returns presented in Chapter 1:

(1) There is a decreased demand for technical trading due to market developments and macroeconomic change. These changes will be shown through reduced price volatility, and decreased market reaction time.

Many of the changes that have occurred, represent a decrease in the volatility of markets. The variance of one, five, ten, and twenty-day returns have all decreased in eight commodities or more. In addition, the overnight volatility as measured by the decreased variance of close-to-open price changes has decreased in fourteen of the commodities. There has also been a widespread decrease in the frequency of breakaway gaps. The percentage of days with a gap has decreased by one half or more in 11 of the 17 commodities. This decreased volatility of futures prices is consistent with Boyd and Brorsen's research which showed that decreased price volatility is correlated with decreased simulated technical trading profits and would imply fewer opportunities for technical traders to profit by bringing the market to equilibrium.

In addition to the decreased market volatility, there is also some evidence of decreased market reaction time. Although the variance of daily futures prices has decreased, there has been an increase in kurtosis of daily returns. This demonstrates that although there is typically less day-to-day movement in the markets, when new information becomes available, it is quickly incorporated by traders and the market moves quickly toward equilibrium resulting in a large price changes. When new information is released overnight, the market now reacts more than before. The decreased overnight reaction is demonstrated through decreased frequency and increased size of breakaway gaps and increased kurtosis of close-to-open price returns.

The evidence of reduced autocorrelations has a major impact on technically traded managed futures funds. Autocorrelation was measured by the sum of the first five and ten autocorrelation coefficients and squared autocorrelation coefficients, and the ratios of daily variance to 5, 10, and 20-day variance. Since a majority of managed futures funds use a trend-following methodology, any change in the nature of the serial dependence of futures prices will likely impact the returns to funds. Almost all of the significant changes in autocorrelations were decreases in the serial dependence of prices. Further, the changes in the variance ratios were quite pronounced and consistent with decreased autocorrelation. Therefore, the decreased serial dependence offers further support for hypothesis one.

The results show little support for either the second daily hypothesis, or the intraday hypothesis. Hypothesis two for daily prices stated:

2) The increase in the size of the managed futures industry has increased price volatility, increased price kurtosis, and decreased autocorrelations, by either increasing market efficiency or price distortion through similarity of trading.

There is no evidence to suggest that there has been an increase in the volatility in price movements. Therefore is it unlikely that the large increase in managed futures funds has lead to a significant increase in efficiency or that funds are distorting futures prices.

There is no evidence for the proposed intraday hypothesis:

3) Market liquidity has not increased at the same rate as the managed futures industry. Therefore part of the decrease in fund returns is due to increased liquidity costs. This would be reflected in increased intraday price variance and kurtosis as well as decreased autocorrelation in intraday prices.

The lack of evidence is because there was also no discernable pattern in the changes of intraday price movements; therefore, no proof of a structural change in intraday futures prices was found.

There are fundamental reasons why two of commodities did not change in the same way as the other commodities. Several statistics for both coffee and wheat tended to change in the opposite direction as the other commodities. These changes were likely due to fundamental changes in these two commodities. The International Coffee Organization (ICO) sought to stabilize the world supply and demand of coffee; thereby stabilizing world coffee prices. The ICO established quotas for coffee exporting member countries from October 1980 until July 1989. The ICO abandoned the quota system on July 4, 1989, which led to increased price volatility of coffee prices (Indahsari). The changes exhibited by coffee prices are consistent with this fundamental change in the coffee markets. Wheat price supports were heavily subsidized by the government throughout much of the first subperiod. Agricultural policy began to change in 1985 and this change was extended in 1990 with the passage of farm bills. These changes allowed agricultural prices to be established more by market factors, instead of being heavily influenced by price supports and government stockpiles. The Federal Agriculture Improvement and Reform (FAIR) Act of 1996, which further reduced price distortion cause by government intervention, extended these changes in agricultural price discovery (United States Department of Agriculture). Wheat prices were more heavily subsidized than other agricultural commodities. Therefore, the increase in price volatility exhibited by wheat prices is consistent with a change in government policy. Thus structural changes in wheat and coffee are due to policy changes rather than changes in the overall economy.

Summary

There is significant evidence of a structural change in daily futures price returns, close-to-open changes, and breakaway gaps. And there is some slight evidence of reduced autocorrelation in daily futures prices. However, there is no evidence of a significant change in intraday price movements. The changes that did occur in the daily price study support the first hypothesis, that there is reduced volatility in the marketplace, and therefore the need for technical trading to bring the market to equilibrium has decreased. This decreased demand is visible in the marketplace by decreased profitability of managed futures funds.

CHAPTER 5

SUMMARY AND CONCLUSIONS

This final chapter begins with a summary of the problem, procedures, results, and conclusions. The final section discusses the limitations of the research and suggests areas of further research.

Summary

Returns to technically traded managed futures funds have decreased dramatically during the last two decades. This research examined both daily and intraday futures prices to determine if there is evidence of a structural change in price movements that is consistent with decreased technical trading profitability. Two daily hypotheses were considered: (a) reduced price volatility and quicker market reaction has decreased the demand for technical analysis, and (b) the increase in the size of the managed futures industry has lead to either increased efficiency or price distortion through the similarity of trading systems. In addition one intraday hypothesis was examined: (c) the growth of the managed futures industry has exceeded the growth of the liquidity in the market; thereby increasing slippage costs which have decreased net technical trading returns.

Bootstrap resampling techniques were used to test for significance of structural changes in daily futures price movements. The data were segmented into two time periods: (1) January 1, 1975 through December 31, 1990, and (2) January 1, 1991 through December 31, 2001. The two-sample stationary bootstrap was used to test hypotheses regarding a change in the distribution of price variables. Two pseudo-samples were drawn from the first time period, the statistic of interest was calculated on each pseudo-sample, and the difference of the statistic in each pseudo-sample was found. Tests of structural change in daily autocorrelation were performed by extending the two sample stationary bootstrap to a two-sample vector stationary bootstrap. Instead of resampling only the variable of interest, the vector stationary bootstrap resamples current and lagged returns. This allows calculating unbiased autocorrelation coefficients by maintaining the serial dependence. These processes were repeated 1,000 times to form an empirical bootstrap distribution of the difference of statistics. The null hypothesis of no structural change was rejected if the actual change in the statistic from the first time period to the second time period was less than the $\alpha/2$ percentile or greater than the $1-\alpha/2$ percentile.

This intraday hypothesis was examined by only calculating the summary statistics. The sample sizes were large enough that most statistical tests would likely lead to a rejection of the null hypothesis even if the arithmetic difference was very small (McCloskey and Ziliak; DeGroot).

The results for the daily research are consistent with the first hypothesis. There is significant evidence that a structural change has occurred in a large number of futures commodities that has resulted in decreased volatility, faster market price reaction, and decreased price autocorrelation. The evidence supports the second hypothesis of either increased efficiency or price distortion by managed futures funds since the variance of prices went down rather than up. The results for the intraday study are inconclusive since no consistent pattern of change could be found. There is little evidence to support the intraday hypothesis, and there is no consistent change in any of the statistics tested.

The results indicate that decreased price volatility, faster market reactions, and decreased price autocorrelations have resulted in a decreased demand for technical analysis. Price volatility as measured by the variance of daily returns, long-run returns, and close-to-open changes and the frequency of price gaps all have decreased in a large number of the commodities. These findings are consistent with Boyd and Brorsen who found that the daily variance of prices is positively correlated with simulated technical trading profitability. The decreased volatility has reduced the need for technical analysts to bring the market to equilibrium. The faster reaction time, as measured by the increased kurtosis of daily returns, close-to-open changes, and breakaway gaps, indicates that there is a much shorter window of opportunity to trade a market move. New information comes into the marketplace and is quickly incorporated by fundamental traders; the market price then jumps quickly towards the new equilibrium with less opportunity for the technical trader to trade the move. The decreased serial dependence as measured by a decrease in the sum of autocorrelation coefficients and an increase in the ratio of daily variance to long-run variance indicates that trend-following technical analysis may be less profitable. Although the evidence for decreased autocorrelation is weaker than the evidence for decreased volatility and faster reaction time, it is arguably more important. Since a large percentage of managed futures funds use trend-following methods, any change in the autocorrelation of futures prices will have a large impact on the profitability of the managed futures industry. The results of tests of structural change in futures prices are therefore consistent with the decreased profitability of technically traded managed futures funds and commodity trading advisors.

Purcell and Koontz, in the most widely used textbook on futures markets for undergraduates in Agricultural Economics, still devote considerable space to technical analysis. While technical analysis is important to learn to be able to understand the logic of market newsletters, its returns are now so small that it seems unreasonable to encourage small traders like agricultural producers to use it as a basis for their decisions.

Many of the changes in futures markets are likely due to technological progress and are likely permanent. These permanent changes have been caused by faster news distribution, decreased cost of information, decreased computing cost, more stable macroeconomic policies, and better forecasts. However, it is possible that if overall uncertainty within a commodity increases, then technical profitability may return, but it is unlikely that profits will ever return to the abnormal levels of the 1980s.

Limitations of Research and Suggestions for Future Research

Any comprehensive study of the futures industry must research a wide variety of both commodities and price statistics. For the daily study, an attempt was made to select a group of commodities that represent different parts of the futures industry. The commodities selected include different liquidities, types of commodities, trading hours, and exchanges. A more comprehensive group of commodities would be useful in future research. In doing so, more generalizations could be reached by comparing characteristics of the commodity to the structural changes that have occurred. This would allow more information about what groups of commodities have changed the most and therefore have become efficient the quickest.

Cost considerations limited the amount of data purchased for the intraday analysis. As was mentioned earlier, the inconclusive results of the intraday study may have been related to the choice of commodities and years of analysis. Any future research in this area should include more commodities and more years of data which would allow better insight into how a wider variety of intraday price movements have changed.

In addition to a wider variety of commodities, a wider range of price statistics could have been analyzed. Most of the statistics tested had theoretical reasons for being used because they were related to technical trading indicators. A wider range of statistics would allow insight into other types of changes. One specific addition would be the addition of nonlinear autocorrelation measures (e.g. Brock, Dechert, and Scheinkman). Only a few linear measures of serial dependence were examined. Nonlinear autocorrelation statistics were considered, but the difficulty in forming significance tests of structural change lead to the abandonment of this approach.

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APPENDIX I

SAS CODE TO READ IN DAILY DATA AND HANDLE ROLLOVERS

```
libname daily   'h:/daily2';

%macro dailyin(com= ,c= );

data set30; /*data set that rolls 30 days prior to expiration*/
        infile "h:\daily30\&c.nb01.txt";
        input contract1 $ date1 MMDDYY10. open1 high1 low1 close1 volume1;
        run;

data set45; /*data set that rolls 45 days prior to expiration*/
        infile "h:\daily45\&c.nb01.txt";
        input contract2 $ date2 MMDDYY10. open2 high2 low2 close2 volume2;
        run;

        *ret=daily log returns;
        *change=close to open changes;
        *break=break-away gaps;

data set1;
        merge set30 set45;
        lclose1=lag(close1);
        lopen1=lag(open1);
        lhigh1=lag(high1);
        llow1=lag(low1);
        lclose2=lag(close2);
        lopen2=lag(open2);
        lhigh2=lag(high2);
        llow2=lag(low2);
        lcontract1=lag(contract1);
        if contract1 eq lcontract1 then ret=100*(log(close1)-log(lclose1));
        else ret=100*(log(close2)-(log(lclose2)));
        if contract1 eq lcontract1 then change=100*(log(open1)-log(lclose1));
        else change=100*(log(open2)-log(lclose2));
        if contract1 eq lcontract1 and high1 le llow1
                then break=100*(log(high1)-log(llow1));
        else if contract1 eq lcontract1 and low1 ge lhigh1
                then break=100*(log(low1)-log(lhigh1));
        else if contract1 ne lcontract1 and high2 le llow2
                then break=100*(log(high2)-log(llow2));
        else if contract1 ne lcontract1 and low2 ge lhigh2
                then break=100*(log(low2)-log(lhigh2));
        else break=.;
        year=year(date1);
        run;

data daily.&com;
        set set1;
```

```
run;

%mend dailyin;

%dailyin(com=corn, c=c- );
%dailyin(com=coffee, c=kc );
%dailyin(com=bellies, c=pb );
%dailyin(com=cocoa, c=cc );
%dailyin(com=crude, c=cl );
%dailyin(com=dm, c=dm );
%dailyin(com=edf, c=ed );
%dailyin(com=feeders, c=fc );
%dailyin(com=gold, c=gc );
%dailyin(com=heating, c=ho );
%dailyin(com=livecattle, c=lc );
%dailyin(com=sap, c=sp );
%dailyin(com=soybeans, c=s- );
%dailyin(com=sugar, c=sb );
%dailyin(com=tbonds, c=us );
%dailyin(com=yen, c=jy );
%dailyin(com=wheat, c=kw );
*/;
run;
quit;
```

APPENDIX II

SAS CODE FOR BOOTSTRAP TESTS WITH DAILY RETURNS

```
libname daily 'h:/daily2';
libname output 'h:/brorsenret4';

data outboot;
        run;

data output.output;
        if _n_ ne 0 then delete;
        run;

%macro data2(com= , n= ,n3= );

        data outboot;
                set outboot;
                if _n_ ne 0 then delete;
                run;

        data set3;
                set daily.&com;
                lret1=lag(ret);lret2=lag2(ret);lret3=lag3(ret);lret4=lag4(ret);
                lret5=lag5(ret);lret6=lag6(ret);lret7=lag7(ret);lret8=lag8(ret);
                lret9=lag9(ret);lret10=lag10(ret);lret11=lag11(ret);lret12=lag12(ret);
                lret13=lag13(ret);lret14=lag14(ret);lret15=lag15(ret);
                lret16=lag16(ret);lret17=lag17(ret);lret18=lag18(ret);
                lret19=lag19(ret);lret20=lag20(ret);
                ret5= sum(of lret1 lret2 lret3 lret4 lret5);
                ret10=sum(of ret5 lret6 lret7 lret8 lret9 lret10);
                ret20=sum(of ret10 lret11 lret12 lret13 lret14 lret15
                        lret16 lret17 lret18 lret19 lret20);
                if _n_ lt 22 then delete;
                if year gt 1990 then delete;
                drop lret1-lret20;
                run;

        ********start boot macro loop;

        %macro boot;
                %do i=1 %to 1000;

dm 'log;clear;';*/;

                proc iml;
                        use set3;
                        read all var{ret} into M1;
                        read all var{ret5} into M2;
                        read all var{ret10} into M3;
```

```
                    read all var{ret20} into M4;
                    close set3;
                    n=nrow(m1);
                    slen=int(rand('exponential')*10)+1;
                    start=int((uniform(0)*(n-slen))+1);
                    l=J(slen,1,.);
                    m=J(slen,1,.);
                    o=J(slen,1,.);
                    p=J(slen,1,.);
                    do i=1 to slen;
                         l[i]=M1[start+i-1];
                         m[i]=M2[start+i-1];
                         o[i]=M3[start+i-1];
                         p[i]=M4[start+i-1];
                         end;
                    d=l||m||o||p;
                    n2=slen;
                    do while(n2<(&n3+&n));
                         len1=int(rand('exponential')*10)+1;
                         strt1=int((uniform(0)*(n-len1))+1);
                         e=J(len1,1,.);
                         f=J(len1,1,.);
                         g=J(len1,1,.);
                         h=J(len1,1,.);
                         do j=1 to len1;
                              e[j]=m1[strt1+j-1];
                              end;
                         do j=1 to len1;
                              f[j]=m2[strt1+j-1];
                              end;
                         do j=1 to len1;
                              g[j]=m3[strt1+j-1];
                              end;
                         do j=1 to len1;
                              h[j]=m4[strt1+j-1];
                              end;
                         k=e||f||g||h;
                         d=d//k;
                         n2=nrow(d);
                         end;
                    create iml1 from d;
                    append from d;
                    quit;

data calc;
     set iml1;
     rename col1=r_sim;rename col2=rd5;
     rename col3=rd10;rename col4=rd20;
     if _n_ gt (&n3+&n) then delete;
     run;

data calc1;
     set calc;
```

```
                read all var{ret20} into M4;
                close set3;
                n=nrow(m1);
                slen=int(rand('exponential')*10)+1;
                start=int((uniform(0)*(n-slen))+1);
                l=J(slen,1,.);
                m=J(slen,1,.);
                o=J(slen,1,.);
                p=J(slen,1,.);
                do i=1 to slen;
                        l[i]=M1[start+i-1];
                        m[i]=M2[start+i-1];
                        o[i]=M3[start+i-1];
                        p[i]=M4[start+i-1];
                        end;
                d=l||m||o||p;
                n2=slen;
                do while(n2<(&n3+&n));
                        len1=int(rand('exponential')*10)+1;
                        strt1=int((uniform(0)*(n-len1))+1);
                        e=J(len1,1,.);
                        f=J(len1,1,.);
                        g=J(len1,1,.);
                        h=J(len1,1,.);
                        do j=1 to len1;
                                e[j]=m1[strt1+j-1];
                                end;
                        do j=1 to len1;
                                f[j]=m2[strt1+j-1];
                                end;
                        do j=1 to len1;
                                g[j]=m3[strt1+j-1];
                                end;
                        do j=1 to len1;
                                h[j]=m4[strt1+j-1];
                                end;
                        k=e||f||g||h;
                        d=d//k;
                        n2=nrow(d);
                        end;
                create iml1 from d;
                append from d;
                quit;

        data calc;
                set iml1;
                rename col1=r_sim;rename col2=rd5;
                rename col3=rd10;rename col4=rd20;
                if _n_ gt (&n3+&n) then delete;
```

```
        if _n_ gt &n then delete;
        run;

    data calc2;
        set calc;
        if _n_ le &n then delete;
        run;

        %macro brorsen1(loop= );

        proc means data=calc&loop noprint;
            var r_sim;
            output out=outmeans&loop
                var=var&loop
                skew=skew&loop
                kurt=kurt&loop;
            run;

        proc means data=calc&loop noprint;
            var rd5 rd10 rd20;
            output out=longout&loop
                var =wvar&loop  bvar&loop  mvar&loop ;
            run;

        data outmeans3&loop;
            merge outmeans&loop longout&loop;
            run;

        data outmeans4&loop;
            set outmeans3&loop;
            dwvar&loop=var&loop/wvar&loop;
            dbvar&loop=var&loop/bvar&loop;
            dmvar&loop=var&loop/mvar&loop;
            run;

    %mend brorsen1;

    %brorsen1(loop=1);
    %brorsen1(loop=2);

data outmeans4;
    merge outmeans41 outmeans42;
    var=var1/var2;
    skew=skew1-skew2;
    kurt=kurt1-kurt2;
    wvar=wvar1/wvar2;
    bvar=bvar1/bvar2;
    mvar=mvar1/mvar2;
    dwvar=dwvar1-dwvar2;
    dbvar=dbvar1-dbvar2;
    dmvar=dmvar1-dmvar2;
```

```
data outboot;
        set outboot outmeans4;
        run;

%end;
%mend boot;
%boot;
*****end boot loop;

proc univariate data=outboot noprint;
        var var skew kurt  wvar bvar mvar
                dwvar dbvar dmvar;
        output out=new2
                pctlpts=.5 2.5 5 95 97.5 99.5
                pctlpre= var_ skew_ kurt_ wvar_
                        bvar_ mvar_ dwvar_ dbvar_ dmvar_
                pctlname=P_5 P2_5 P5 P95 P97_5 P99_5;
        run;

        data set4;
                set daily.&com;
                lret1=lag(ret);lret2=lag2(ret);lret3=lag3(ret);lret4=lag4(ret);
                lret5=lag5(ret);lret6=lag6(ret);lret7=lag7(ret);lret8=lag8(ret);
                lret9=lag9(ret);lret10=lag10(ret);lret11=lag11(ret);lret12=lag12(ret);
                lret13=lag13(ret);lret14=lag14(ret);lret15=lag15(ret);
                lret16=lag16(ret);lret17=lag17(ret);lret18=lag18(ret);
                lret19=lag19(ret);lret20=lag20(ret);
                ret5= sum(of lret1 lret2 lret3 lret4 lret5);
                ret10=sum(of ret5 lret6 lret7 lret8 lret9 lret10);
                ret20=sum(of ret10 lret11 lret12 lret13 lret14 lret15
                        lret16 lret17 lret18 lret19 lret10);
                if _n_ lt 22 then delete;
                drop lret1-lret20;
                if year lt 1991 then delete;
                run;

%macro brorsen2(loop= );

proc means data=set&loop noprint;
        var ret;
        output out=outmeans&loop
                var=var&loop
                skew=skew&loop
                kurt=kurt&loop;
        run;

proc means data=set&loop noprint;
        var ret5 ret10 ret20;
        output out=longout&loop
                var =wvar&loop  bvar&loop  mvar&loop ;
        run;

data outmeans3&loop;
```

```
        merge outmeans&loop longout&loop;
        run;

data outmeans4&loop;
        set outmeans3&loop;
        dwvar&loop=var&loop/wvar&loop;
        dbvar&loop=var&loop/bvar&loop;
        dmvar&loop=var&loop/mvar&loop;
        run;

%mend brorsen2;

%brorsen2(loop=3);
%brorsen2(loop=4);

data new8;
        merge outmeans43 outmeans44;
        var=var3/var4;
        skew=skew3-skew4;
        kurt=kurt3-kurt4;
        wvar=wvar3/wvar4;
        bvar=bvar3/bvar4;
        mvar=mvar3/mvar4;
        dwvar=dwvar3-dwvar4;
        dbvar=dbvar3-dbvar4;
        dmvar=dmvar3-dmvar4;
        run;

data new4;
        merge new2 new8;
        run;

data new5;
        set new4;
        %macro stat(stat=);
        if &stat le &stat._P_5 then &stat.sig = "Ret &stat Different at .5%";
        else if &stat ge &stat._P99_5 then &stat.sig = "Ret &stat Different at 99.5%";
        else if &stat le &stat._P2_5 then &stat.sig = "Ret &stat Different at 2.5%";
        else if &stat le &stat._P5 then &stat.sig = "Ret &stat Different at 5%";
        else if &stat ge &stat._P97_5 then &stat.sig = "Ret &stat Different at 97.5%";
        else if &stat ge &stat._P95 then &stat.sig = "Ret &stat Different at 95%";
        else &stat.sig = "Ret &stat Same";
        %mend stat;

        %stat(stat=var);
        %stat(stat=skew);
        %stat(stat=kurt);
        %stat(stat=wvar);
        %stat(stat=bvar);
        %stat(stat=mvar);
        %stat(stat=dwvar);
        %stat(stat=dbvar);
        %stat(stat=dmvar);
```

```
        run;

data output.ret&com;
        set new5;
        vbl="Ret";
        com="&com";
        run;

data output.output;
        set output.output output.ret&com;
        run;

quit;

%mend data2;

%data2(com=corn, n=4034, n3=2756 );
%data2(com=coffee, n=3997, n3=2747  );
%data2(com=bellies, n=4036, n3=2777 );
%data2(com=cocoa, n=4006, n3=2748 );
%data2(com=crude, n=1945, n3=2757 );
%data2(com=dm, n=4036, n3=2702 );
%data2(com=edf, n=2289, n3=2787 );
%data2(com=feeders, n=4035, n3=2777 );
%data2(com=gold, n=4023, n3=2758 );
%data2(com=heating, n=2994, n3=2757 );
%data2(com=livecattle, n=4035, n3=2777 );
%data2(com=sap, n=2198, n3=2776 );
%data2(com=soybeans, n=4034, n3=2773 );
%data2(com=sugar, n=4003, n3=2748 );
%data2(com=tbonds, n=3372, n3=2763 );
%data2(com=yen, n=4034, n3=2774 );
%data2(com=wheat, n=4035, n3=2774 );*/;
```

APPENDIX III

SAS CODE FOR BOOTSTRAP TESTS INVOLVING AUTOCORRELATION

```
libname daily 'h:/daily2';
libname output 'h:/brorsenret4';

data outboot;
        run;

data output.output;
        if _n_ ne 0 then delete;
        run;

%macro data2(com= , n= ,n3= );

        data outboot;
                set outboot;
                if _n_ ne 0 then delete;
                run;

        data set3;
                set daily.&com;
                lret1=lag(ret);   lret2=lag2(ret);  lret3=lag3(ret);  lret4=lag4(ret);
                lret5=lag5(ret);  lret6=lag6(ret);  lret7=lag7(ret);  lret8=lag8(ret);
                lret9=lag9(ret);  lret10=lag10(ret);lret11=lag11(ret);lret12=lag12(ret);
                lret13=lag13(ret);lret14=lag14(ret);lret15=lag15(ret);lret16=lag16(ret);
                lret17=lag17(ret);lret18=lag18(ret);lret19=lag19(ret);lret20=lag20(ret);
                ret5= sum(of lret1 lret2 lret3 lret4 lret5);
                ret10=sum(of ret5 lret6 lret7 lret8 lret9 lret10);
                ret20=sum(of ret10 lret11 lret12 lret13 lret14 lret15
                        lret16 lret17 lret18 lret19 lret20);
                if _n_ lt 22 then delete;
                if year gt 1990 then delete;
                drop lret1-lret20;
                run;

        ********start boot macro loop;

        %macro boot;
                %do i=1 %to 1000;

dm 'log;clear;';*/;

                proc iml;
                        use set3;
                        read all var{ret} into M1;
                        read all var{ret5} into M2;
                        read all var{ret10} into M3;
                        read all var{ret20} into M4;
```

```
        close set3;
        n=nrow(m1);
        slen=int(rand('exponential')*10)+1;
        start=int((uniform(0)*(n-slen))+1);
        l=J(slen,1,.);
        m=J(slen,1,.);
        o=J(slen,1,.);
        p=J(slen,1,.);
        do i=1 to slen;
            l[i]=M1[start+i-1];
            m[i]=M2[start+i-1];
            o[i]=M3[start+i-1];
            p[i]=M4[start+i-1];
            end;
        d=l||m||o||p;
        n2=slen;
        do while(n2<(&n3+&n));
            len1=int(rand('exponential')*10)+1;
            strt1=int((uniform(0)*(n-len1))+1);
            e=J(len1,1,.);
            f=J(len1,1,.);
            g=J(len1,1,.);
            h=J(len1,1,.);
            do j=1 to len1;
                e[j]=m1[strt1+j-1];
                end;
            do j=1 to len1;
                f[j]=m2[strt1+j-1];
                end;
            do j=1 to len1;
                g[j]=m3[strt1+j-1];
                end;
            do j=1 to len1;
                h[j]=m4[strt1+j-1];
                end;
            k=e||f||g||h;
            d=d//k;
            n2=nrow(d);
            end;
        create iml1 from d;
        append from d;
        quit;

data calc;
    set iml1;
    rename col1=r_sim;
    rename col2=rd5;rename col3=rd10;rename col4=rd20;
    if _n_ gt (&n3+&n) then delete;
    run;

data calc1;
    set calc;
    if _n_ gt &n then delete;
```

```
		run;

	data calc2;
		set calc;
		if _n_ le &n then delete;
		run;

		%macro brorsen1(loop= );

		proc means data=calc&loop noprint;
			var r_sim;
			output out=outmeans&loop
				var=var&loop
				skew=skew&loop
				kurt=kurt&loop;
			run;

		proc means data=calc&loop noprint;
			var rd5 rd10 rd20;
			output out=longout&loop
				var =wvar&loop  bvar&loop  mvar&loop ;
			run;

		data outmeans3&loop;
			merge outmeans&loop longout&loop;
			run;

		data outmeans4&loop;
			set outmeans3&loop;
			dwvar&loop=var&loop/wvar&loop;
			dbvar&loop=var&loop/bvar&loop;
			dmvar&loop=var&loop/mvar&loop;
			run;

	%mend brorsen1;

	%brorsen1(loop=1);
	%brorsen1(loop=2);

data outmeans4;
	merge outmeans41 outmeans42;
	var=var1/var2;
	skew=skew1-skew2;
	kurt=kurt1-kurt2;
	wvar=wvar1/wvar2;
	bvar=bvar1/bvar2;
	mvar=mvar1/mvar2;
	dwvar=dwvar1-dwvar2;
	dbvar=dbvar1-dbvar2;
	dmvar=dmvar1-dmvar2;
	run;

data outboot;
```

```
          set outboot outmeans4;
          run;

%end;
%mend boot;
%boot;
*****end boot loop;

proc univariate data=outboot noprint;
          var var skew kurt  wvar bvar mvar
                    dwvar dbvar dmvar;
          output out=new2
                    pctlpts=.5 2.5 5 95 97.5 99.5
                    pctlpre= var_ skew_ kurt_ wvar_
                              bvar_ mvar_ dwvar_ dbvar_ dmvar_
                    pctlname=P_5 P2_5 P5 P95 P97_5 P99_5;
          run;

          data set4;
                    set daily.&com;
                    lret1=lag(ret); lret2=lag2(ret); lret3=lag3(ret); lret4=lag4(ret);
                    lret5=lag5(ret); lret6=lag6(ret); lret7=lag7(ret); lret8=lag8(ret);
                    lret9=lag9(ret); lret10=lag10(ret); lret11=lag11(ret); lret12=lag12(ret);
                    lret13=lag13(ret); lret14=lag14(ret); lret15=lag15(ret); lret16=lag16(ret);
                    lret17=lag17(ret); lret18=lag18(ret); lret19=lag19(ret); lret20=lag20(ret);
                    ret5= sum(of lret1 lret2 lret3 lret4 lret5);
                    ret10=sum(of ret5 lret6 lret7 lret8 lret9 lret10);
                    ret20=sum(of ret10 lret11 lret12 lret13 lret14 lret15
                              lret16 lret17 lret18 lret19 lret10);
                    if _n_ lt 22 then delete;
                    drop lret1-lret20;
                    if year lt 1991 then delete;
                    run;

%macro brorsen2(loop= );

proc means data=set&loop noprint;
          var ret;
          output out=outmeans&loop
                    var=var&loop
                    skew=skew&loop
                    kurt=kurt&loop;
          run;

proc means data=set&loop noprint;
          var ret5 ret10 ret20;
          output out=longout&loop
                    var =wvar&loop  bvar&loop  mvar&loop ;
          run;

data outmeans3&loop;
          merge outmeans&loop longout&loop;
          run;
```

```
data outmeans4&loop;
        set outmeans3&loop;
        dwvar&loop=var&loop/wvar&loop;
        dbvar&loop=var&loop/bvar&loop;
        dmvar&loop=var&loop/mvar&loop;
        run;

%mend brorsen2;

%brorsen2(loop=3);
%brorsen2(loop=4);

data new8;
        merge outmeans43 outmeans44;
        var=var3/var4;
        skew=skew3-skew4;
        kurt=kurt3-kurt4;
        wvar=wvar3/wvar4;
        bvar=bvar3/bvar4;
        mvar=mvar3/mvar4;
        dwvar=dwvar3-dwvar4;
        dbvar=dbvar3-dbvar4;
        dmvar=dmvar3-dmvar4;
        run;

data new4;
        merge new2 new8;
        run;

data new5;
        set new4;
        %macro stat(stat=);
        if &stat le &stat._P_5 then &stat.sig = "Ret &stat Different at .5%";
                else if &stat ge &stat._P99_5 then &stat.sig = "Ret &stat Different at 99.5%";
                else if &stat le &stat._P2_5 then &stat.sig = "Ret &stat Different at 2.5%";
                else if &stat le &stat._P5 then &stat.sig = "Ret &stat Different at 5%";
                else if &stat ge &stat._P97_5 then &stat.sig = "Ret &stat Different at 97.5%";
                else if &stat ge &stat._P95 then &stat.sig = "Ret &stat Different at 95%";
                else &stat.sig = "Ret &stat Same";
        %mend stat;

        %stat(stat=var);
        %stat(stat=skew);
        %stat(stat=kurt);
        %stat(stat=wvar);
        %stat(stat=bvar);
        %stat(stat=mvar);
        %stat(stat=dwvar);
        %stat(stat=dbvar);
        %stat(stat=dmvar);
        run;
```

```
data output.ret&com;
        set new5;
        vbl="Ret";
        com="&com";
        run;

data output.output;
        set output.output output.ret&com;
        run;

quit;

%mend data2;

%data2(com=corn, n=4034, n3=2756 );
%data2(com=coffee, n=3997, n3=2747  );
%data2(com=bellies, n=4036, n3=2777 );
%data2(com=cocoa, n=4006, n3=2748 );
%data2(com=crude, n=1945, n3=2757 );
%data2(com=dm, n=4036, n3=2702 );
%data2(com=edf, n=2289, n3=2787 );
%data2(com=feeders, n=4035, n3=2777 );
%data2(com=gold, n=4023, n3=2758 );
%data2(com=heating, n=2994, n3=2757 );
%data2(com=livecattle, n=4035, n3=2777 );
%data2(com=sap, n=2198, n3=2776 );
%data2(com=soybeans, n=4034, n3=2773 );
%data2(com=sugar, n=4003, n3=2748 );
%data2(com=tbonds, n=3372, n3=2763 );
%data2(com=yen, n=4034, n3=2774 );
%data2(com=wheat, n=4035, n3=2774 );*/;

run;;

%macro output(stat= ,vbl= );
        data print;
                set output.output;
                if vbl ne "Ret" then delete;
                run;

        proc print data=print;
                title "&stat Ret len=10";
                var com &stat._p_5 &stat._p2_5 &stat._p5 &stat._p95 &stat._p97_5
                        &stat._P99_5 &stat &stat.sig;
                run;
%mend output;

%output(stat=var, vbl=Ret);
%output(stat=skew, vbl=Ret);%output(stat=kurt, vbl=Ret);
%output(stat=wvar, vbl=Ret);%output(stat=bvar, vbl=Ret);
%output(stat=mvar, vbl=Ret);%output(stat=dwvar, vbl=Ret);
%output(stat=dbvar, vbl=Ret);%output(stat=dmvar, vbl=Ret);
quit;
```

VITA 2

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Experience: Raised on a farm near Fredonia, Kansas; employed as a farm laborer part time; employed by The Scoular Company during 1998 summer; employed by Botkin LLC during 1999 summer; employed b Oklahoma State University, Department of Agricultural Economics as graduate research assistant, June 2000 to present.