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FORECASTING TURNING POINTS FOR TRADING COMMODITY FUTURES USING TIME-SERIES AND NEURAL NETWORK MODELS

by

CHRISPIN NTUNGO

A Thesis
submitted to the Faculty of Graduate Studies
in partial fulfilment of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

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University of Manitoba
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ABSTRACT

Forecasting Turning Points for Trading Commodity Futures Using Time-Series and Neural Network Models

Chrispin Ntungo, B.Sc. (Zambia) M.Sc. (Manitoba).

Advised by: Dr. Milton S. Boyd, Ph.D.

This study examines turning point forecasts for commodity futures trading. First, ARIMA turning point forecast implications of various out of sample forecasting steps ahead are examined. The naive and one step ahead ARIMA turning point forecasting models are compared. Data for three commodities traded on the futures exchanges are used. Results suggest that turning point forecasting performance deteriorates as the number of forecasting steps ahead increases. Secondly, neural networks are compared with ARIMA for turning point forecasting ability at ten and twenty-five forecasting steps ahead. Results show that neural networks used here predict a higher percentage of turning points than ARIMA in five out of six cases. However, neural network turning point forecasts are not statistically significant. This result may be attributed to: (i) nondifferenced data, or (ii) nonoptimal software algorithm, or (iii) over fitting of the neural network models.

Thirdly, the ten and twenty-five forecasting steps ahead neural networks and ARIMA models are, respectively, compared for trading performance. Neural networks provide more trades than ARIMA because of the many turning points their forecasts generate. However, returns from neural networks are generally lower than returns from ARIMA because neural network turning point forecasts include small and less important turning points. Overall, all models show positive returns with most models having relatively high Sharpe ratios, thus showing acceptable risk levels. As well, the models have reasonably low and acceptable equity draw downs.

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To become a doctor of philosophy is not a one person's achievement. As such I wish to extend my hearty appreciation to Dr. Milton S. Boyd, who has been my advisor through out my Ph.D. studies, Dr. Daryl Kraft and Dr. Norman Cameron, my other advisory committee members, and Dr. Dana Hoag, my external examiner. I would also like to thank the other faculty members, graduate students and the support staff of the Department of Agricultural Economics. I also owe appreciation to Dr. Nowrouz Kohzadi, Mr. Iebeling Kaastra, and Mr. Giovani DeMatos for insight into neural network application.

My sincere appreciation to the Canadian International Development Agency for financially supporting my graduate studies and this research. As well, I thank my employer, the University of Zambia, for giving me opportunity to pursue graduate studies abroad.

Special thanks to my friends at Mountain Andrews Seventh-day Adventist Church, who have made Winnipeg for me and my family, a home away from home.

Finally, my family, including my wife Grace and my children Myazwe and Mbawemi, deserve all my appreciation for they have been extremely supportive throughout my Ph.D. studies.

Chrispin Ntungo

DEDICATION

To Grace, Myazwe and Mbawemi:

"There is gold, and a multitude of rubies: but the lips of knowledge are a precious jewel."
- *Prov. 20:15*

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CHAPTER 1

INTRODUCTION

Problem Statement

Neural networks are a relatively new class of artificial intelligence computer programs which attempt to learn by copying the brain's problem solving process. Thus, neural networks are named after cells called neurons in the brain.

The application of neural networks to forecasting futures markets is a relatively new area of financial research. In recent years, a number of studies using neural networks to forecast futures markets have been conducted. Kaastra and Boyd (1995) forecast futures trading volume on the Winnipeg Commodity Exchange (WCE) using neural networks. They find that neural networks perform well in forecasting trading volume for four of the six commodities. DeMatos et al (1995, 1996) forecast the Japanese Yen/US dollar futures exchange rate using neural networks. They find that neural networks forecast more accurately than the naive bench mark model.

In another study, Kohzadi et al (1996) compare the forecasting ability of traditional time series models with neural network models. Their results show that feedforward neural networks have the ability to both forecast price level and turning points more accurately than autoregressive integrated moving average (ARIMA) models.

The cited research is not exhaustive. Therefore, there is need for further research in the application of neural networks. One area where neural networks are being applied is in forecasting futures markets and developing trading strategies.

Objectives

The objectives of this study are, therefore (1) to determine the implications of various steps ahead on market direction (turning point) forecasting, and commodity futures trading performance. For example, to determine how quickly turning point forecasting ability declines the further ahead into the future the turning points forecasts are made; and (2) to determine the turning point forecasting performance and trading performance of neural networks relative to ARIMA models.

In brief, the study attempts to find out what happens to the forecasting ability of a model when a model is estimated and used to forecast up to, for example, five or ten or twenty-five steps ahead. The study, as well, examines the implications of such forecasts on commodity trading performance.

Data and Procedure

Data used are nearby weekly futures prices for corn, silver and the Deutsche Mark. First, employing a sliding window model estimation approach turning point forecasting performance is examined in chapter two using ARIMA models for forecasting up to different steps ahead in the future. The percentages of accurate turning point forecasts are compared across forecasting steps into the future and across the three commodities being investigated. Secondly, in chapter three, neural network models are compared with the above ARIMA models for turning point forecasting performance.

Thirdly, in chapter four, commodity futures trading performance over various forecasting steps ahead is examined comparing ARIMA and neural network trading models. The models are used to forecast prices which are used with a trading rule to generate buy and sell signals. Monthly and annual percent returns are calculated and analyzed across forecasting steps ahead, trading systems, and commodities. Finally, in chapter five, a summary of the findings of this research are presented together with some perceived limitations and suggestions for further research.

CHAPTER 2

FORECASTING PERFORMANCE OVER VARIOUS FORECASTING STEPS AHEAD USING ARIMA MODELS

Introduction

Market turning point forecasts are important for trading purposes, yet there are relatively few studies on predicting turning points (market direction). Kohzadi et al (1996) examine turning point forecasting ability of neural networks and ARIMA models. Also, DeMatos et al (1996) examine turning points in the Japanese Yen futures market using neural networks and ARIMA models. These studies show that neural networks out-perform ARIMA at forecasting market turning points. However, the studies have been done on relatively small samples and on one or two commodities.

As well, a number of studies on forecasting accuracy have been conducted with special reference to the accuracy of different forecasting techniques (Mahmoud, 1984). Turning point forecasting ability likely is affected by how far ahead the future forecasts are made. In other words, events further into the future are less similar to the past, the further the event is in the future. Therefore, it is interesting to examine how fast turning point forecasting ability declines when forecasts are made moving from nearer to further ahead forecasting steps. Forecasting further ahead provides a means of testing the robustness of a model. A model need not be re-estimated every so often if it is robust enough to forecast accurately several steps further ahead.

The objective of this chapter, therefore, is to determine market turning point forecasting performance over various out of sample forecasting steps ahead using ARIMA models. Relatively simple models which use only past prices are developed here to test the performance of ARIMA models over various forecasting steps ahead.

The next section describes the data and procedure. Section three discusses the results. Section four is the summary of the results of the study.

Data and Procedure

Weekly data for corn in cents per bushel (1969-1995), silver in dollars per troy ounce (1972-1995), and the Deutsche Mark in US cents per Deutsche Mark (1975-1995) nearby futures prices are obtained from the vendor Technical Tools Data. The first five years of data are used to estimate the model leaving out of sample results for corn (1974-1995), silver (1977-1995) and Deutsche Mark (1980-1995). Contract months are rolled over approximately one month before expiration. Each Tuesday opening and closing prices are used to construct the weekly series. Weekly rather than daily prices are used in order to reduce noise and computation time.

ARIMA Model

A number of studies find that univariate time series, such as autoregressive integrated moving average (ARIMA) models are as accurate as larger econometric models such as vector autoregressive models (Brandt and Bessler, 1984; Dorfman and McIntosh, 1985; and Harris and Leuthold, 1985). ARIMA models may be estimated as autoregressive (AR) models if the moving average (MA) process is invertible. Therefore, AR models are the form of ARIMA estimated in this study because they are simple to estimate, have well developed model selection criteria, and require limited pretesting (DeMatos et al, 1996). The term ARIMA is, however, consistently used through out this study. AR models are identified using the Akaike Information Criteria (AIC) (Akaike, 1981). A standard AR model is presented as:

$$y_t = \alpha + \sum_{i=0}^{p} \beta_i y_{t-i} + e_t \tag{2.1}$$

where y_t is a stationary stochastic process with non-zero mean, α is a constant term, p is the lag length, β is a parameter estimate of the autoregressive process and e_t is a white noise disturbance term. The AIC is used to identify the ARIMA model because it has the desirable feature of weighing the precision of estimate in relation to parsimony in parameterization of a statistical model (Judge, et al., 1988). The AIC measure is given as:

$$AIC = \ln \hat{\sigma}^2 + \frac{2K_1}{N} \tag{2.2}$$

where K_1 is chosen in such a way as to numerically *minimize* the criterion. Effectively, as K_1 increases the variance ($\ln\sigma^2$) decreases and the value of the likelihood function for the AR model increases.

Unit Root Tests

Dickey-Fuller unit root tests are used to test for stationarity of the time series (Davidson and MacKinnon, 1993; Dickey and Fuller, 1981). White (1993) shows that for a time series y_t two forms of the augmented Dickey-Fuller regression equations are:

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \sum_{j=1}^{p} \beta_j \Delta y_{t-j} + \varepsilon_t \tag{2.3}$$

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 t + \sum_{j=1}^{p} \beta_j \Delta y_{t-j} + \varepsilon_t \tag{2.4}$$

where e_t for $t = 1,...,N$ is assumed to be Gaussian white noise.

Equation (2.3) has a constant but no trend. Equation (2.4) has both a constant and trend. Using the AIC helps to ensure that the number of lagged terms p is chosen with the errors uncorrelated. When $\alpha_1 = 0$, a unit root is present in the time series y_t, and therefore the time series y_t is nonstationary. This implies that the standard asymptotic analysis may not be used to obtain distributions of the test statistics.

Unit root tests are first completed on undifferenced data. If a unit root is found then the data is differenced and the second unit root test done. At this point no unit root should be found. The model developed on stationary data is then used for forecasting.

Table 2.1 shows that unit roots are present in undifferenced data. Therefore, the undifferenced data is nonstationary. Table 2.2 shows that there are no unit roots present in differenced data. Therefore, ARIMA models are estimated using first differenced data.

Using the AIC, ARIMA models are identified with two lags for corn, fourteen lags for silver, and twenty lags for the Deutsche Mark. One, three, five, ten and twenty-five steps sliding ARIMA models are estimated on 260 observations. Forecasts are made up to one, three, five, ten, and twenty-five periods ahead for purposes of comparison and determining how robust the models are for forecasting far ahead in the future.

Naive Model

The term "naive" is used here when the current period's price is used as a forecast for the future period's price. The value of naive forecasts is that they are prepared relatively inexpensively and quickly. In this research the naive forecasts are used as a bench mark for evaluating ARIMA time series models. A time series model would be expected to be an improvement upon the naive, since it uses more information in terms of past lags. The naive model used here is expressed as:

$$\hat{X}_{t+1} = X_t \tag{2.5}$$

where X_t is the variable to be forecast, and the subscripts t+1 and t are the period of time involved. This model is also evaluated using all the turning point forecast evaluation measures against which the ARIMA time series models are evaluated.

Turning Point Forecast Evaluation

Turning points (price direction) are important for trading because traders base their buying and selling decisions on them. The ratio of accurate forecasts to the total number of forecasts (RAF) indicates the percentage of correct price direction forecasts that a model captures. The ratio of actual turning point forecasts to the total number of actual turning points (RATPF) is also computed to determine the percentage of actual turning point forecasts.

The following is an example of a turning point forecast. Define A_{t-1} as last period's actual price, A_t as current period's actual price and A_{t+1} as next periods actual price. Also, define P_{t-1} as last period's forecast price, P_t as this period's forecast price and P_{t+1} as next period's forecast price. If $A_{t-1} < A_t > A_{t+1}$ and $P_{t-1} < P_t > P_{t+1}$, then this is a correct actual turning point forecast. If $A_{t-1} < A_t > A_{t+1}$ and $P_{t-1} > P_t < P_{t+1}$, then this is an incorrect actual turning point forecast. RATPF measures the percentage of correct actual turning point forecasts out of the total number of turning points in the time-series. The higher the ratio the better the model.

Merton Test of Turning Point Forecasts

Cumby and Modest (1987) provide a more rigorous statistical method for testing the ability of the model to forecast a significant number of turning points. The method is a version of the Merton test (Merton, 1981). Kohzadi et al (1996) describe the test procedure as follows: Define a forecast variable F_t and actual direction variable A_t such that

$$A_t = 1 \text{ if } \Delta A_t > 0 \text{ and } A_t = 0 \text{ if } \Delta A_t \leq 0 \tag{2.6}$$

$$F_t = 1 \text{ if } \Delta P_t > 0 \text{ and } F_t = 0 \text{ if } \Delta P_t \leq 0 \tag{2.7}$$

where ΔA_t is the amount of change in the actual variable between time t - 1 and t, and ΔP_t is the amount of change in the forecast variable for the same period.

The probability matrix for the forecasted direction of changes in the forecast value conditional upon the direction of changes in the actual value is

$$P_1 = \text{Prob}\,[F_t = 0 \mid A_t = 0] \tag{2.8}$$

$$1 - P_1 = \text{Prob}\,[F_t = 1 \mid A_t = 0] \tag{2.9}$$

$$P_2 = \text{Prob}\,[F_t = 1 \mid A_t = 1] \tag{2.10}$$

$$1 - P_2 = \text{Prob}\,[F_t = 0 \mid A_t = 1] \tag{2.11}$$

In other words, (2.8) and (2.10) is the probability that the forecasted direction has actually occurred and (2.9) and (2.11) is the probability of a wrong forecast. By assuming that the magnitude of changes in F_t and A_t are independent, Merton (1981) showed that a necessary and sufficient condition of market timing ability is that

$$P_1(t) + P_2(t) > 1 \tag{2.12}$$

That is, the forecaster, on average, has to be right in more than half of the time the forecasts are made. Therefore, the null hypothesis to be tested is

$$H_0 : P_1 + P_2 - 1 \leq 0$$

vs $\quad H_1 : P_1 + P_2 - 1 > 0$

Cumby and Modest (1987) show that the above hypothesis can be tested through the regression equation:

$$F_t = \alpha_0 + \alpha_1 A_t + \varepsilon_t \tag{2.13}$$

where F_t is the predicted price direction binary variable defined by (2.7), A_t is the actual price binary variable defined by (2.6), $\alpha_1 = P_1 + P_2 - 1$, and ε_t is the error term.

If α_1 is greater than zero, then the model is correctly forecasting the market direction. If α_1 is greater than zero and significant, then the model is not only correctly forecasting the market direction, but also forecasting with high probability.

Results

Table 2.3 shows various steps ahead turning point forecasting performance of naive and ARIMA models using the Merton test, RAF, and RATPF for corn, silver, and

Deutsche Mark futures price. If the Merton α_1 coefficient is positive and significant then the model is forecasting turning points correctly with high probability.

Results show that only four out of eighteen cases of naive and ARIMA have positive and significant Merton turning point coefficients. Therefore, only four out of eighteen cases of naive and ARIMA have significant numbers of turning point forecasts. The other fourteen cases show either wrong or/and insignificant turning point forecasts.

The naive model fails to capture any statistically significant turning point forecasts, according to the Merton test. However, the ARIMA at one forecasting step ahead has statistically significant turning point forecasts in two out of three cases. Therefore, ARIMA turning point forecasting is more accurate than that of the naive. ARIMA turning point forecasts have wrong signs or become insignificant in eight out of fifteen cases as the number of forecasting steps ahead increases, according to the Merton test. This means that ARIMA loses its ability to forecast turning points as the number of forecasting steps ahead increases. The Deutsche Mark has the highest turning point forecasting performance, followed by corn and silver. The Deutsche Mark has three out of six cases statistically significant turning point forecasts. Corn has one and silver has none.

However, all the models have a fairly similar ratio of accurate forecasts to total number of forecasts (or RAF). According to RAF, price direction forecasting performance has no apparent trend over the various forecasting steps ahead. For corn and silver the RAF is in a range slightly lower than 50 percent. For the Deutsche Mark, however, it is in a range slightly above 50 percent. This implies that ARIMA price direction forecasts are hardly affected by number of forecasting steps ahead.

However, the RATPF shows that the number of correct turning point forecasts declines slightly as the number of forecasting steps ahead increases. This means that ARIMA turning point forecast performance is affected by number of forecasting steps ahead. Therefore, the ARIMA model loses turning point forecasting ability as the number of forecasting steps ahead increases. Also, the naive model has more accurate turning point forecasts than ARIMA for silver and the Deutsche Mark. The ARIMA is slightly better than the naive model for corn. Since by the Merton test ARIMA at one forecasting step ahead has statistically significant turning point forecasts, it is more accurate than the naive model for forecasting market direction.

Summary

The purpose of this chapter is to determine market turning point forecasting performance over various forecasting steps ahead using ARIMA and naive models. Weekly data for Corn (1969-1995), Silver (1972-1995), and the Deutsche Mark (1975-1995) nearby futures prices were used. ARIMA models for forecasting turning points up to one, three, five, ten and twenty-five out of sample forecasting steps ahead are estimated. Results suggest two important points. First, turning points forecasting ability declines as the number of forecasting steps ahead increases. This implies that ARIMA loses its ability to forecast turning points accurately as the number of forecasting steps ahead increases. Secondly, ARIMA shows slightly more accurate market turning point forecasting performance than the naive bench mark model.

Table 2.1 Dickey-Fuller Unit Root Test Results Before Differencing[a]

Null Hypothesis	Test Statistic	Critical Value 10%
CORN 1969-1995		
Constant, no trend		
A(1)=0 T-test	-2.7095	-2.57
A(0)=A(1)=0	3.8457	3.78
Constant, trend		
A(1)=0 T-test	-2.7589	-3.13
A(0)=A(1)=A(2)=0	2.6879	4.03
A(1)=A(2)=0	3.8570	5.34
SILVER 1972-1995		
Constant, no trend		
A(1)=0 T-test	-3.1355	-2.57
A(0)=A(1)=0	4.9280	3.78
Constant, trend		
A(1)=0 T-test	-3.1605	-3.13
A(0)=A(1)=A(2)=0	3.4014	4.03
A(1)=A(2)=0	5.0899	5.34
DEUTSCHE MARK 1975-1995		
Constant, no trend		
A(1)=0 T-test	-0.90097	-2.57
A(0)=A(1)=0	0.99552	3.78
Constant, trend		
A(1)=0 T-test	-1.7466	-3.13
A(0)=A(1)=A(2)=0	1.5007	4.03
A(1)=A(2)=0	1.6606	5.34

[a]Almost all statistics are insignificant for nondifferenced data, which indicates nonstationarity of the time series.

Table 2.2 Dickey-Fuller Unit Root Test Results After Differencing[a]

Null Hypothesis	Test Statistic	Critical Value 10%
CORN 1969-1995		
Constant, no trend		
A(1)=0 T-test	-20.105	-2.57
A(0)=A(1)=0	202.10	3.78
Constant, trend		
A(1)=0 T-test	-20.100	-3.13
A(0)=A(1)=A(2)=0	134.67	4.03
A(1)=A(2)=0	202.01	5.34
SILVER 1972-1995		
Constant, no trend		
A(1)=0 T-test	-8.8879	-2.57
A(0)=A(1)=0	39.498	3.78
Constant, trend		
A(1)=0 T-test	-8.8938	-3.13
A(0)=A(1)=A(2)=0	26.366	4.03
A(1)=A(2)=0	39.550	5.34
DEUTSCHE MARK 1975-1995		
Constant, no trend		
A(1)=0 T-test	-6.9156	-2.57
A(0)=A(1)=0	23.916	3.78
Constant, trend		
A(1)=0 T-test	-6.9264	-3.13
A(0)=A(1)=A(2)=0	16.012	4.03
A(1)=A(2)=0	24.015	5.34

[a]All statistics are significant for differenced data, which indicates stationarity of the differenced time series.

Table 2.3 **Various Steps Ahead Turning Point Forecasting Performance of Naive and ARIMA Models using the Merton Test, RAF, and RATPF for Corn, Silver, and Deutsche Mark Futures Price.**[a]

Model	α_0	α_1	R^2	$r_{P,A}$[b]	RAF[c] (%)	RATPF[d] (%)
Corn (1974-1995)						
NAIVE	0.47* (22.37)	0.04 (1.23)	0.00	0.98	49.77	48.93
ARIMA 1[e]	0.46* (21.82)	0.07* (2.51)	0.01	0.98	52.60	51.88
ARIMA 3	0.58* (28.08)	-0.03 (-1.06)	0.00	0.95	47.58	34.31
ARIMA 5	0.61* (29.15)	-0.05* (-1.66)	0.00	0.94	46.86	20.27
ARIMA 10	0.64* (30.91)	-0.06* (-2.28)	0.00	0.84	45.94	10.14
ARIMA 25	0.62* (29.54)	-0.06* (-1.91)	0.00	0.81	46.40	5.07
Silver (1977-1995)						
NAIVE	0.56* (24.33)	-0.11* (-3.44)	0.01	0.98	44.20	55.19
ARIMA 1	0.52* (22.43)	-0.02 (-0.81)	0.00	0.97	48.56	50.38
ARIMA 3	0.48* (20.77)	-0.00 (-0.21)	0.00	0.93	49.52	48.46
ARIMA 5	0.49* (21.51)	-0.03 (-0.80)	0.00	0.93	48.56	48.08
ARIMA 10	0.48* (20.77)	-0.00 (-0.14)	0.00	0.83	49.63	48.08

(Continued)

Table 2.3

(Continued)

MODEL	α_0	α_1	R^2	$r_{P,A}$	RAF (%)	RATPF (%
ARIMA 25	0.44* (19.44)	0.01 (0.32)	0.00	0.77	50.16	37.69
Deutsche Mark (1980-1990)						
NAIVE	0.48* (19.45)	0.01 (0.37)	0.00	0.99	50.38	52.32
ARIMA 1	0.45* (18.40)	0.06* (1.73)	0.00	0.99	52.90	44.85
ARIMA 3	0.44* (17.96)	0.10* (2.87)	0.01	0.99	54.92	48.20
ARIMA 5	0.47* (19.15)	0.09* (2.62)	0.01	0.99	54.42	49.23
ARIMA 10	0.48* (19.55)	0.01 (0.24)	0.00	0.89	52.53	50.77
ARIMA 25	0.55* (22.40)	0.02 (0.46)	0.00	0.93	50.38	44.33

[a] Results are out of sample; $F_t = \alpha_0 + \alpha_1 A_t + e_t$ is the Merton turning point test equation.
[b] $r_{P,A}$ is the correlation coefficient for predicted and actual price.
[c] RAF stands for ratio of accurate forecasts to total number of forecasts.
[d] RATPF stands for ratio of actual turning point forecasts to total number of actual turning points.
[e] ARIMA forecast made 1 step ahead.
* Significant at 5 percent level; t values in parentheses.

CHAPTER 3

NEURAL NETWORK FORECASTING PERFORMANCE USING COMMODITY FUTURES PRICES

Introduction

Neural networks are a new class of artificial intelligence computer programs attempting to copy the brain's problem solving process. They look for patterns in data, learn these patterns by trial and error, and use the learned information to classify new patterns and make forecasts. Neural networks have been successfully applied in many fields including finance and trading, medical applications and manufacturing. Within finance neural networks have been used for S&P and gold futures prices forecasting (Grudnitski and Osburn, 1993), portfolio trading (Trippi and DeSieno, 1992), stock price prediction (Kimoto et al, 1990; Kamijo and Tanigawa, 1990; Yoon and Swales 1991; White, 1988), corporate bond rating (Dutta and Shekhar, 1988; Surkan and Singleton, 1991), and commodity trading (Collard, 1991).

Much of the attention surrounding neural networks is due to their ability to handle nonlinear data. This ability makes neural networks to be universal approximators capable of approximating any nonlinear function (Cybenko, 1989; Hetcht-Nielsen, 1989; Hornik et al 1989; and White, 1989). Therefore, the data generating process need not be explicitly modeled.

The last few years have seen increased interest in applying neural networks to commodity futures price forecasting. Kohzadi et al (1995) provide an example of price forecasting with neural networks. Their neural network outperforms the ARIMA model and thereby supports the idea that neural networks may be a useful forecasting tool.

In another study, Kaastra and Boyd (1995) forecast monthly futures trading volume using a back-propagation neural network. They find that neural networks are able to forecast up to nine months ahead and outperform the naive model in four of the six commodities. In addition, the neural networks also outperform an ARIMA model, and their performance does not deteriorate with an increase in the forecast horizon. However, besides looking at forecast error, studies need to analyze turning points or market direction. Traders are most interested in market direction because they need to use it for buy and sell signals.

The objective of this chapter, therefore, is to determine market turning point forecasting performance of neural networks. In particular, to compare market turning point forecasting performance of neural networks with ARIMA time series models using commodity futures prices.

The chapter is organized as follows: the next section presents neural network theory. Section three describes neural network development procedure and data. Section four provides an outline of ARIMA model development procedure and turning points forecast evaluation methods. Section five covers discussion of results. Finally, section six is a summary of results.

Neural Network Theory

Neural Network Architecture

Artificial neural networks consist of individual interconnected neurons. These neurons are comparable to neurons in the human brain, and this is why they are called neurons (Medsher, Turban and Trippi, 1993). Each neuron sends (receives) input signals to (from) other neurons. Figure 3.1 depicts a typical neuron where $\mathbf{I}_i$ (i = 1, 2, ..., n) are input neurons, and $\mathbf{W}_i$ (i = 1, 2, ..., n) are connection weights.

Neural network architecture means the number and layout of the neurons, how they are interconnected, and the transfer function. The number of neurons per layer must be selected. For input and output layers the number of neurons depends on the number of inputs and outputs. For any nonlinear problem, the network needs at least one hidden layer. The higher the number of neurons in the hidden layers the more parameters (weights) it will use.

A transfer function in a back-propagation network is required to be a nonlinear, continuously differentiable function. Using a nonlinear transfer function allows the neural network to perform nonlinear statistical modelling. Transfer functions include the sigmoid, hyperbolic tangent functions, sine, tanh, ramping and step transfer functions (Klimasaukas, 1991; DeMatos et al, 1996).

Neural Network Paradigm

Many different neural network paradigms are used for many different problems. For predictive purposes, the feedforward and recurrent back-propagation networks are used (DeMatos, et al 1996; Mendelson, 1993), though the feedforward is most popular for forecasting. A Feedforward back-propagation network consists of an input layer of neurons, some hidden layers and an output layer. Figure 3.2 shows a simple feedforward back-propagation network. The neurons in the first layer are fully connected to the neurons in the second layer. The layers between the input and the output layers are called hidden layers because they are hidden from the view of the network developers and users. A feedforward back-propagation network can have any number of hidden layers.

Operation of the Neural Network

A neural network operates in a relatively straight forward manner. With the layers fully connected, input data are presented to the network at the input layer. The values associated with each individual input neuron feed into the first hidden layer. Each hidden neuron receives these values, multiplied by the appropriate weight W_0-W_n, sums them, runs them through a transfer function and produces an output at the output layer.

Initial values of the weights are randomly selected in training stages of the neural network. Therefore, the first set of input vector may not produce the appropriate output vector. Initially, the objective is to have the network learn that the input vector it is first given contains the factors that will eventually produce the output vector supplied. In its first attempt to do so the network first determines a measure of the error between its generated output and the desired output. The errors are then fed back through the network, layer by layer, and are used to adjust the weights of the connections between the neurons to minimize the total error associated with the output vector. Thereafter, different input values are presented to the network repeatedly during training to try to reduce errors to minimum levels.

The mathematical representation of the above process is straight forward. Define a_i as the activation value of the ith neuron in the input layer, o_i as the output of the input layer and w_i as the weight of the link from the neuron i to the neuron j in the hidden layer. Further, define b_i as the bias value always equal to +1, and considered analogous to the constant term in a regression model. The feed forward phase of the training algorithm is then presented by equations (3.1) to (3.3) below:

$$a_i = f(net_i + b_i) \tag{3.1}$$

$$net_i = \sum_j w_{ij} o_i \tag{3.2}$$

$$f(x) = a_i = \frac{1}{1 + \exp(-x)} \tag{3.3}$$

where $f(x) = f(net_i + b_i)$ is the transfer function, which can be any monotonic linear or nonlinear function.

Transfer functions, also called activation, threshold or squashing functions, are functions which determine the output of processing neurons. In linear transfer functions, output is simply a linear multiple of the inputs. Consequently, they are not useful for nonlinear mapping and classification. In the case of continuous inputs and output models, the sigmoid function is commonly used. Because of its differentiability, it has many desirable properties for training and minimization of the error in the network. The output of a processing unit with a sigmoid function is given by:

$$\frac{df}{dx} = f(x)(1 - f(x)) \tag{3.4}$$

where $f(x)$ can be any monotonic nonlinear function.

McClelland and Rumelhart (1988) show how the back-propagation model is trained on the *steepest gradient descent algorithm* to minimize the mean squared error defined as:

$$E = K^{-1}\sum_k (t_k - o_k)^2 \tag{3.5}$$

where E is the total error, K is the number of output neurons, and o_k is the neuron activation value of the output layer. The changes in weights w_{ij} and biases b_i, which is the backward pass of the training algorithm, are given by:

$$\Delta w_{ij:t} = \eta\, \delta_j a_i + \alpha\, \Delta w_{ij:t-1} \tag{3.6}$$

$$\Delta b_{i:t} = \eta\, \delta_i + \alpha\, \Delta b_{i:t-1} \tag{3.7}$$

where η is the learning rate, α is the momentum, t is the time and δ_i is the change for each neuron. For the output layer

$$\delta_k = (t_k - o_k) f'(o_k) \tag{3.8}$$

and for the hidden layer

$$\delta_j = \sum_k \delta_k w_{kj} f'(o_j) \tag{3.9}$$

Neural Network Design and Forecasting Procedure

An eight-step neural network design procedure provided by Kaastra and Boyd (1996) is used to develop the commodity futures neural network forecasting models.

Input Selection

A separate neural network is designed for each commodity used in this study. The commodities are corn, silver and the Deutsche Mark. Inputs to each neural network are number of lags determined using the Akaike Information Criterion (AIC). Two lags are determined for corn, fourteen lags for silver, and twenty lags for the Deutsche Mark.

Data Collection and Preprocessing

Weekly data on corn in cents per bushel (1969-1995), silver in dollars per troy ounce (1972-1995), and the Deutsche Mark in US cents per Deutsche Mark (1975-1995) nearby futures prices are obtained from the vendor Technical Tools Data. The first five years of data are used to estimate the model leaving out of sample results for corn (1974-1995), silver (1977-1995), and Deutsche Mark (1980-1995).

Contract months are rolled over approximately a month before expiration. Each Tuesday closing price is used to construct the weekly series. Data preprocessing is done by using the automated preprocessing feature provided by the neural network program

Brainmaker Professional version 3.0 (California Scientific Software, 1993). The data are processed automatically using the maximum and minimum values approach. Price levels, rather than differences, are used in this study in order to provide a stronger test for the neural network models. Neural networks are known to be flexible and capable of fitting any data generating processes.

Training and Testing Sets

The neural network model is estimated on 260 observations of weekly data in sample and this is equivalent to five years of data. Neural network training uses 90 percent of the 260 observations and the remaining 10 percent are used for neural network testing.

Neural Network Design

A three layered feedforward back-propagation neural network is developed for each commodity. The corn neural network has two input neurons, one hidden layer with four neurons, and one output layer with one neuron. The silver neural network has fourteen input neurons, one hidden layer with eleven neurons, and one output layer with one neuron. The Deutsche Mark neural network has twenty input neurons, one hidden layer with eighteen neurons and one output layer with one neuron.

Neural Network Evaluation Criteria

Several neural network architectures are constructed and evaluated. The neural networks are evaluated based on the test results after 500 runs. The evaluation criteria involves looking the average error, the root mean square error and the coefficient of determination or R squared.

The neural network is required to produce minimum average and root mean square errors, and maximum R-squared. The architecture that meets this criteria becomes the architecture of the neural network to be trained for forecasting.

Neural Network Training

Training is automated using in built automation features of BrainMaker Professional version 3.0. For all the three neural networks an automated sliding window training technique is employed (Kohzadi, et al. 1996; Kaastra and Boyd, 1995).

Initial weights are chosen at random at the beginning of training. The learning rate is initially set at 3, but is allowed to change automatically depending on the magnitude of errors the neural network encounters and the speed at which the network is learning. Since the errors must decrease in size as the neural network trains, the learning rate is automated to change from 3 down to 0. The learning rate takes any number between 0 and 3. The training tolerance is initially set at 10 percent (DeMatos, et al 1995). Training is automated such that when 95 percent of the training observations have errors equal to training tolerance or below, the training tolerance is cut in half until it reaches 2 percent.

Testing is done while training at every 80 runs. The neural network is programmed to stop training when 90 percent of the test observations have errors less than or equal to 2 percent, or when the neural network reaches 4000 runs. Then the neural network is saved and is ready to be used for forecasting.

Implementation of the Trained Neural Network

Implementing the neural network involves applying it on out of sample data it has not seen before and making a forecast. Forecasting is done up to ten and twenty-five steps ahead ex post. Each neural network is made to read files containing only new observations, but no outputs. Upon reading the observations the neural network makes a forecast of the output corresponding to each observation. The output is saved and later this output is evaluated for turning point forecasting using the procedure outlined in Chapter Two.

ARIMA Model Development and Forecasting Procedure

The procedure for developing the ARIMA model for forecasting turning points up to ten and twenty-five forecasting steps ahead is given in the procedure section of Chapter Two. The different methods for evaluating turning point forecasts are also given in Chapter Two. The next section consists of the results.

Results

Turning Point Forecasting Performance Results

Table 3.1 shows turning point forecasting performance of the 10 and 25 forecasting steps ahead neural network and ARIMA models using the Merton test, RAF, and RATPF for corn, silver, and Deutsche Mark. The Merton test is applied to test for statistically significant turning point forecasts. If the Merton α_1 coefficient is positive and statistically significant then the model is forecasting turning points correctly with high probability.

However, results show no positive and significant Merton α_1 coefficients. Therefore, none of the twelve models have forecasted a statistically significant number of turning points. This means these models are forecasting turning points, but not at a statistically significant level. In other words, the models do not have significant turning point forecasting abilities.

The RAF and RATPF show the percent of correct price direction and turning point forecasts, respectively. The RAF for corn is somewhat the same across neural networks and ARIMA. However, RAF for neural networks is slightly lower for silver and Deutsche Mark. Overall, present results show neural networks to be slightly less accurate than ARIMA at forecasting market direction.

However, the RATPF shows that the neural network has predicted slightly more turning points than ARIMA models for all commodities. For example, the RATPF for the 10 and 25 forecasting steps ahead corn neural network is 51.85 percent and 50.10 percent, respectively. The RATPF for the 10 and 25 forecasting steps ahead ARIMA is 10.14 percent and 5.07 percent, respectively. The same observation may be made for the Deutsche Mark. For silver, however, results are comparable between neural networks and ARIMA models. In general, therefore, there are more turning points predicted by neural networks than by ARIMA models.

Neural Network Performance

Past research suggests that neural networks should perform comparably or better than ARIMA models. However, in reality this may not always be the case for a number of reasons. First, use of nondifferenced data may cause problems for neural networks since nondifferenced data have large ranges, which may cause errors to be larger. Often, neural network developers recommend that neural networks be estimated on a small range data. For example, changes, which have small values and small ranges. However, since this study has used price levels rather than changes for the neural network, some problems may occur.

Secondly, the software error minimization algorithm may fail to reach the global minimum. This results in the neural network not reaching the minimum error on the error function, similar to a nonlinear least squares estimator not reaching a minimum error.

Thirdly, there may be over fitting of the neural network model if the model has a relatively large number of parameters (weights) compared to the number of observations. Neural networks have far more parameters than ARIMA models since they are nonlinear. However, a slightly over fitted model may still perform adequately if it is frequently re-estimated when forecasting. This is because such a model is fitted closely to past data patterns, and does not perform accurately when the data pattern changes. Therefore, it must be re-estimated (or re-fitted) often if it uses a large number of parameters, or its performance will be affected by over fitting.

Fourthly, the neural networks are not compared with ARIMA for forecasting up to one, three, and five steps ahead. Instead neural networks are compared with ARIMA for forecasting up to ten and twenty-five forecasting steps ahead because neural networks would require a large amount of computation time to produce the shorter step ahead forecasts. Neural networks may perform better at short forecasting steps ahead as they have more parameters than ARIMA, though this is a subject for further research.

Summary

Neural networks are a relatively new class of artificial intelligence computer programs that attempt to learn by copying the brain's problem solving process. They look for patterns in data, learn these patterns by trial and error and use the learned information to classify new patterns and make forecasts. The purpose of this chapter is to develop a neural network model to forecast turning points for commodity futures prices. Neural networks for forecasting turning points for corn, silver and Deutsche Mark futures prices are developed. Their turning point forecasting performance up to ten and twenty-five forecasting steps ahead is compared with that of ARIMA time-series models.

Results show that neural networks used here predict a higher percentage of turning points than ARIMA models in five out of six cases. This outcome supports that of Kohzadi et al (1996) who find that neural networks predict turning points more accurately than ARIMA models. However, the Merton test for turning points forecasting ability shows that the turning point forecasts are not significant. This result may be attributed to: (i) nondifferenced data, or (ii) nonoptimal software algorithm, or (iii) over fitting of the neural network models.

Figure 3.1

Typical Neuron

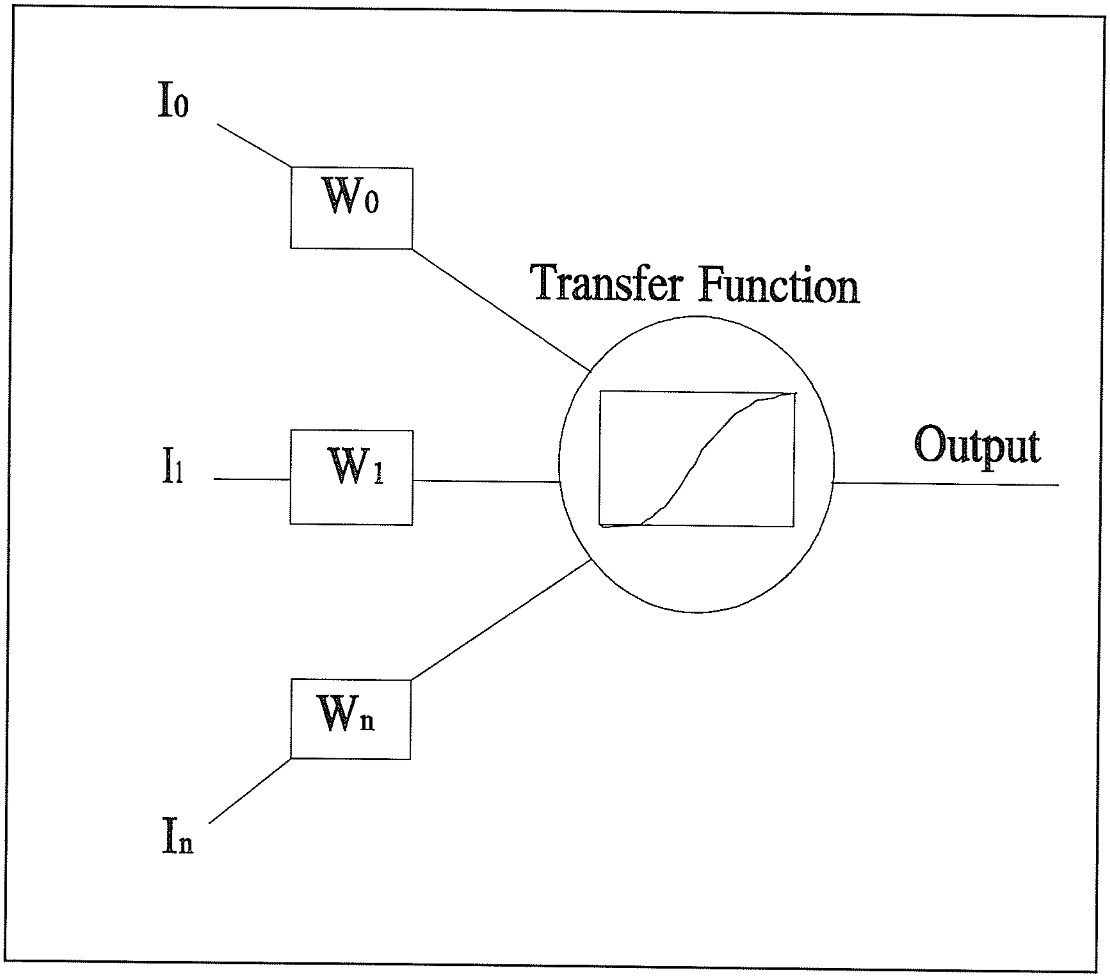

Figure 3.2

Feedforward Back-Propagation Network

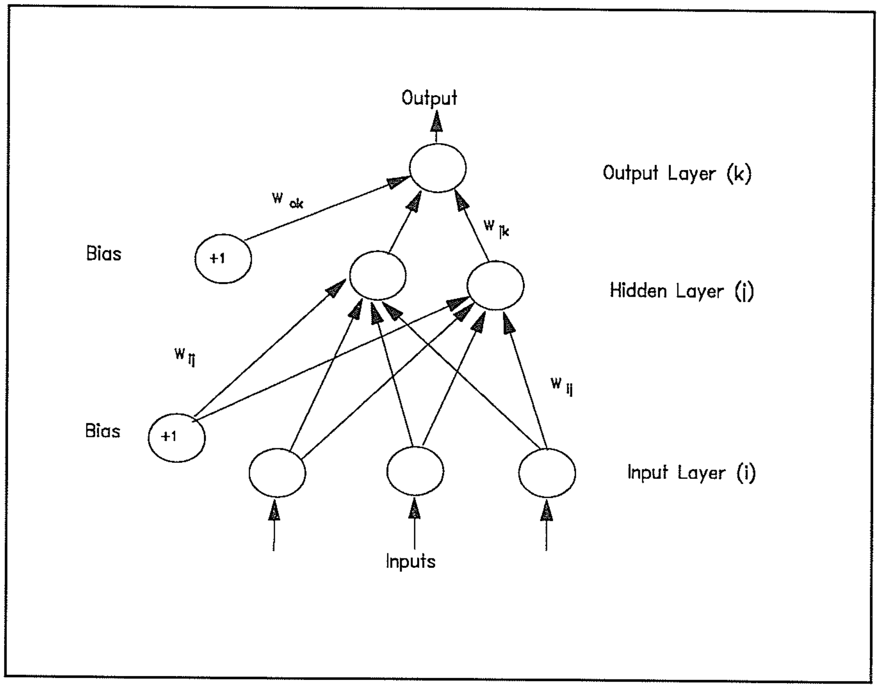

Table 3.1 Turning Point Forecasting Performance of the 10 and 25 Forecasting Steps Ahead Neural Network, and ARIMA Models using the Merton Test, RAF, and RATPF for Corn, Silver, and Deutsche Mark Futures Price Forecasts[a]

MODEL	α_0	α_1	R^2	$r_{P,A}$ [b]	RAF[c] (%)	RATPF[d] (%)
Corn, 1974-1995.						
Neural Network 10[e]	0.46* (21.80)	0.01 (0.36)	0.00	0.24	46.76	51.85
ARIMA 10	0.63* (30.91)	-0.06* (-2.28)	0.00	0.84	45.94	10.14
Neural Network 25[f]	0.459* (21.72)	0.011 (0.36)	0.00	0.27	46.58	50.10
ARIMA 25	0.61* (29.54)	-0.05* (-1.91)	0.00	0.81	46.40	5.07
Silver, 1977-1995.						
Neural Network 10	0.45* (19.73)	-0.03 (-1.16)	0.00	0.64	45.05	40.00
ARIMA 10	0.48* (20.77)	-0.01 (-0.14)	0.00	0.83	49.63	48.08

(Continued)

Table 3.1

(Continued)

Model	α_0	α_1	R^2	$r_{P,A}$	RAF (%)	RATPF (%)
Neural Network 25	0.44* (19.32)	-0.04 (-1.16)	0.00	0.54	44.52	39.04
ARIMA 25	0.44* (19.44)	0.01 (0.32)	0.00	0.77	50.16	37.69
Deutsche Mark, 1980-1995.						
Neural Network 10	0.46* (18.78)	0.01 (0.50)	0.00	0.58	49.87	53.61
ARIMA 10	0.48* (19.55)	0.01 (0.23)	0.00	0.89	52.53	50.77
Neural Network 25	0.47* (19.27)	-0.00 (-0.05)	0.00	0.56	49.12	54.90
ARIMA 25	0.55* (22.40)	0.02 (0.45)	0.00	0.93	50.38	44.33

[a] Out of sample results. $F_t = \alpha_0 + \alpha_1 A_t + e_t$ is the Merton turning point test equation.
[b] $r_{P,A}$ is the correlation coefficient for predicted and actual price.
[c] RAF stands for ratio of accurate forecasts.
[d] RATPF stands for ratio of actual turning point forecasts.
[e] Forecast made 10 steps ahead.
[f] Forecast made 25 steps ahead.
* Significant at 5 percent; t values in parentheses.

CHAPTER 4

COMMODITY FUTURES TRADING PERFORMANCE OVER VARIOUS STEPS AHEAD FORECASTS USING ARIMA AND NEURAL NETWORK MODELS

Introduction

The development of artificial intelligence technology, particularly neural networks, has brought about a new way of forecasting financial markets. Recent research in the use of neural network trading systems has increased. For example, Trippi and DeSieno (1992) attempt to develop, at least in theory, a successful day trading system that combines several trained neural networks to trade equity index futures. They claim that this system outperforms passive investment in the index. Also, research shows that trading performance can be enhanced by integrating neural networks with conventional rule-based expert system techniques (Lee, Trippi, Chu, and Kim, 1990; Trippi, 1990).

The most important aspect of artificial intelligence technology, particularly to commodity futures portfolio managers, is the development of neural network based systems that can directly aid in risk assessment, commodity selection and trading timing decisions. A few such systems have been built to (i) determine the optimal buy and sell timing for an equity index (Kimoto et al, 1990), (ii) drive a trading strategy for a non-financial commodity index (Collard, 1991), and (iii) trade the Japanese yen (DeMatos et al, 1995).

The use of past prices is called technical analysis and this seems to be an integral part of trading decisions of many speculators in futures markets. Brorsen and Irwin (1987) report that 80 percent of commodity investment pools use computerized technical trading systems. Moreover, two highly regarded books by Schwager (1989, 1992) give the trading testimonials of a large number of traders who have used technical analysis to produce significant trading profits over a long period of time.

Lukac and Brorsen (1990) show that twenty-two of the twenty-three technical trading systems simulations conducted in thirty different markets produce significant net returns. Also, Boyd and Brorsen (1991) tests of five technical trading systems on seven commodities yield significant annual net returns. The present research, also, employs technical analysis to develop and apply nonlinear techniques to derive information contained in past prices, and to use this information to make trading decisions.

The objectives of this chapter, therefore, are to (i) determine the implications of different steps ahead forecasts on technical trading performance; and (ii) determine the performance of neural networks relative to ARIMA time series and naive technical trading models. Because neural networks are nonlinear estimators and it is generally believed that financial markets are nonlinear, many believe neural networks should perform better than ARIMA time series models at providing correct and profitable trading signals.

The next section provides the theory. The third section provides the procedure and data. The results are provided and discussed in section four. Finally, section five presents a summary of the chapter.

Theory

Market Efficiency

Fama (1970) defines an efficient market as a market where prices reflect all available past and current information. Jensen (1978) defines a market as efficient with respect to information set Ω_t if it is impossible to make economic profits by trading on the basis of the information set Ω_t. The efficient market hypothesis is defined for three different information sets: First, the weak form of the efficient market hypothesis, in which information set Ω_t is taken to be only the information contained in past price history of the market at time t.

Second, the semi-strong form of the efficient market hypothesis, in which Ω_t is taken to be all available public information and past prices at time t.

Third, the strong form of the efficient market hypothesis, in which Ω_t is taken to be all information both public and private available to anyone at time t.

This study focuses on technical trading profits. Thus, the weak form of the efficient market hypothesis is the most appropriate theory here because it uses past prices as does technical analysis. The weak form hypothesis implies that both past and present prices fully reflect all available information. Therefore, if futures markets are weak form efficient, then technical trading systems should not on average be profitable.

Martingale Model

Samuelson and Mendelbrot assert that if speculative prices in an efficient market fully reflect all available information, then they should follow a Martingale statistical process. The Martingale model is given as:

$$E(P_{t+1}/\Omega_t) = P_t \tag{4.1}$$

The Martingale implies that the expected value of the next period's price, P_{t+1}, given Ω_t is equal to the current price P_t. In other words, the price expected tomorrow given information set Ω_t, is today's price. The Martingale is equivalently defined as the expected return or price change, r_{t+1}, given Ω_t is zero. That is:

$$E(r_{t+1}/\Omega_t) = 0 \tag{4.2}$$

Thus, the model does not permit positive speculative returns over time. From technical analysis perspective, the Martingale model implies that no technical trading system could yield a return above zero.

Random Walk Model

The random walk hypothesis states that today's price P_t, minus yesterday's price, P_{t-1} is equal to r_t, which is a random variable. It is represented as:

$$P_t - P_{t-1} = r_t \tag{4.3}$$

where,

$$f(r_{t+1}/\Omega_t) = f(r_{t+1}) \tag{4.4}$$

which means that the probability distribution of r_{t+1} given information set Ω_t is equal to the probability distribution of r_{t+1}. This means that the conditional marginal probability distribution of r_t are identical, implying that since r_t, or price changes, are independent and uncorrelated, successive price changes are identically, independently distributed (Fama, 1970).

Fama also points out that the random walk is just an extension of the Martingale model because it makes a stronger assumption of complete independence of price changes from one period to the next, whereas the weak form of the Martingale does not. The random walk model is linked to only the weak form of the efficient market hypothesis because the only information it uses is past prices. In contrast, the Martingale model is linked to, and can be used to test, all three levels of the efficient market hypothesis. For the most part, however, the Martingale and random walk models are indistinguishable. This is so because the Martingale's price of dependence is very small (Fama and Blume, 1966). Therefore, for practical purposes, the models are quite similar. Consequently, tests of the weak form efficiency have used the random walk model although many of them have rejected it (Larson, 1963; Stevenson and Bear, 1970; Cargill and Rausser, 1972, 1975; Taylor, 1982). Further, the bulk of these studies conclude that the random walk should not be used as a general description of futures prices (Taylor, 1985).

Taylor argues that "Futures prices are not random with constant returns. Furthermore, it is possible to show that returns are not randomly distributed about fluctuating equilibrium expected returns, determined rationally by interest rates, inflation and risk premia (Taylor 1980, pp. 343-350). Therefore, prices sometimes do not adjust fully and instantaneously when new information becomes available. Thus, futures markets are not perfectly efficient in the manner described by Fama (1976, p. 140)."

Disequilibrium theory and noisy rational expectations theories appear to offer an explanation why technical trading systems may be profitable.

Disequilibrium Theory

Disequilibrium theory argues that markets do not immediately adjust to information shocks because of market frictions, such as cost of acquiring information. With time, however, markets may slowly adjust to new information. Nevertheless, profitable trading systems are possible because of the price trends that exist as a result of the adjustment process caused by information shocks (Beja and Goldman, 1980; Nawrocki, 1984).

Noisy Rational Expectations Theory

If market participants are not heterogeneously informed of new and otherwise difficult information to obtain, then prices tend to be an imperfect aggregator of information. Using a two period noisy rational expectations model, Brown and Jennings (1989) claim that as a result of this imperfect aggregation, the current price is not a sufficient statistic for private information possessed by market participants. Consequently, historical prices add information that is not available with the current price alone. In other words, technical analysis provides additional information to market participants forming an expectation of future prices.

Recent years researchers argue that price generating processes for most assets exhibit nonlinear dynamics. Neftci (1991) argues that if price dynamics are nonlinear, technical analysis may be capturing information contained in higher-order moments of asset prices. Such information would not be captured by traditional linear models. An examination of stock returns generated from some technical trading rules by Brock, Lakonishok, and LeBaron (1992) appears to suggest that the return generating process of stocks is more complicated than that suggested by linear models.

The preceding discussion suggests that the price adjustment process implied by the disequilibrium theory may be nonlinear. Brown and Jennings (1989) claim that past prices are an important factor in futures price determination. Moreover, if the underlying commodity returns generating process is chaotic, then a nonlinear technique such as a neural network, using past prices may be more likely to produce statistically significant returns than a linear model.

Procedure and Data

Neural Network and Time-Series Trade Signal Forecasting Models

Neural network theory, model design, and training procedure are given in Chapter 3. The ARIMA model development procedure is given in Chapter Two. This section discusses the procedure for developing a technical trading system based on neural network and ARIMA futures price turning point forecasts described in Chapters Two and Three.

Trading Model and Assumptions

The trading model is a computer program that simulates the trading of the technical system. The model keeps track of weekly price movements, sell and buy transactions as well as weekly percentage returns. This information is saved for each commodity traded.

The trading model assumes, first, no pyramiding of profits or positions is allowed. Secondly, the nearby futures contract is traded. Thirdly, any draw down in equity is replaced with additional capital.

Trading Strategy and Rule

One major strategy employed by many futures traders is the use of the trend as an aid in making trading decisions. This behaviour is based on the assumption that prices have positive autocorrelation, and that once a trend starts it will continue. Traders want to follow trends so they can take positions early in the trend and maintain that position as long as the trend continues. Traders may, however, change their position when they predict a change in the trend or market direction.

Moving averages are usually considered a simple but effective way to smoothen prices and to measure the market's trend. An alternative to moving averages is the use of longer periods, such as weekly, monthly or annual, prices. This research uses weekly prices in the forecasting model. Accordingly, weekly prices are expected to capture weekly trends in the futures price.

The weekly price trading strategy used here is to buy (sell) on the open if a rising (falling) price trend is forecasted. If no change in the trend from the previous week is predicted the current position is maintained. The trading rule is summarized as:

If $P_{t-1} < P_t > P_{t+1}$ then *Sell (or Go short).*

If $P_{t-1} > P_t < P_{t+1}$ then *Buy (or Go long),* where P_{t-1} is the previous week trading closing futures price, P_t is this week's trading closing futures price and P_{t+1} is next week's trading forecasted closing futures price. These trading rules reflect turning points in the price movement.

The nature of trading of the models is basically the same. The one step ahead forecasting models are re-estimated every step and used immediately to generate trading signals. The three step ahead forecasting models are re-estimated every three steps and used to generate trading signals for the next three steps. The other models are also re-estimated and used in a similar manner.

A priori, the one step ahead forecasting systems are expected to produce the highest number of trades. This is because they are re-estimated every step, and therefore trace out trends quickly. Further steps ahead forecasting models are expected to produce lesser trades because they are not re-estimated so often. Therefore, they may be tracing out trends that have already changed. When this happens they miss out some turning points, and therefore reduce chances of producing a higher number of trading signals.

A stop loss tolerance level is established to allow for exits in case of losses, and entries in case of gains. In this study, if losses on the trade are more than five percent of the entry price, then the trade is exited, and the trader waits for a new signal.

Returns are calculated fron net contract values which are determined by subtracting transaction costs that are made up of two parts. First, a hundred dollar transaction fee per trade, which includes commission costs and skid error or slippage (Mandelbrot, 1963). Skid error is the difference between the actual price received for a buy or sell order on an open or close, and the recorded price for a market opening or closing used in a historical price series published by an exchange. In addition, a transaction cost of one hundred dollars per roll over is also subtracted.

Start-up Equity, Margins, Trading Returns and Draw down

Trading is started with initial investment of $100,000. Margins percentages vary by commodity and are assumed to be 5 percent for corn, 10 percent for silver and 3 percent for the Deutsche Mark. These are consistent with historical average percentage margin levels (Brorsen and Irwin, 1987).

Commodity trading returns are determined as return on investment (ROI). They are calculated by taking the difference between, for example, net contract value of a sell and a buy, and expressed as a percentage of total investment. Twenty-five percent of the initial investment is invested in margins and the 75 percent remainder held back for potential margin calls. This investment strategy is consistent with the capital management practices of large commodity funds (Lukac, Brorsen, and Irwin, 1988). The percent returns are calculated on monthly and annual basis.

Draw down is an important trading analyst statistic because it indicates how close a trader comes to losing all equity. It is the minimum of the percentage change in equity over the entire trading period reported. For example, if a trader started with $100,000 equity whose lowest point of equity at any time over the trading period was $60,000, then the draw down would be $40,000 divided by $100,000 or 40 percent.

Trading Statistics, Significance Tests, Distribution, and Riskiness of Returns

Trading statistics are collected over 1092 weeks for corn, 936 weeks for silver, and 780 weeks for the Deutsche Mark. The statistics include the total number of trades, the number of profitable trades, the number of losing trades, the average profit per profitable trade, the average loss per losing trade, the average profit per trade, and the break-even trades.

A two tailed student t-test is used to test whether statistically significant profits, measured as the mean net return (MNR), are realized. The t-test is sufficiently robust when used with a large sample size as in this study, though it may have lower power when the data is not normally distributed. The null hypothesis is that the mean net return is zero, against the alternate hypothesis that the mean net return is not zero. That is:

$H_0 : \text{MNR} = 0$

$H_1 : \text{MNR} \neq 0$

where MNR is the monthly and/or annual mean net return for a given commodity. The monthly MNR is determined by summing four or five weekly returns, depending on whether the month ends in the fourth or fifth week. The annual MNR is determined by summing twelve monthly returns. The returns are determined beginning from the first week in January and ending with the last week in December of each year. The t-statistic used is expressed as:

$$t = \frac{\bar{X} - X_o}{s/\sqrt{n}} \tag{4.5}$$

where $\bar{X}$ is the mean return, X_0 is the expected mean return, which is assumed from theory to be zero. s is the standard deviation, and n is the sample size.

The shape of the distribution of returns is investigated by the skewness coefficient or the third moment of the normal distribution. The relative skewness coefficient (ξ) formula is:

$$\xi = \frac{\mu_3}{\sqrt{\mu_2^3}} \tag{4.6}$$

where μ_2 is the second moment or variance of returns and μ_3 is the third moment of the returns. If the skewness coefficient is zero, the returns follow a symmetric distribution as in the normal distribution. In other words, profits are symmetric with losses. A skewness coefficient greater than zero implies a right skewness, and one less than zero implies a left skewness.

The kurtosis coefficient (κ) is derived from the fourth moment of the series. It indicates the general concentration around the mean. The relative kurtosis coefficient is expressed as:

$$\kappa = \frac{\mu_4}{\mu_2^2} \tag{4.7}$$

where μ_4 is the fourth moment. Normally distributed returns are consistent with the kurtosis coefficient being equal to zero. A kurtosis coefficient greater than zero implies that returns follow a leptokurtic or high peak distribution. A kurtosis coefficient less than zero means that returns follow a platykurtic or flatter than normal distribution.

One problem associated with using the t statistics to test for the significance of returns is that the t test assumes traders are risk neutral. However, if one assumes that traders are risk averse, and that a market is efficient, then speculators cannot obtain a profit after adjusting for risk. In this study, risk is measured by the Sharpe ratio (Sharpe 1970). The Sharpe ratio is calculated by dividing the mean return value by the standard deviation. Alternatively, the riskiness of the returns may be determined by observing the standard deviation. The larger the standard deviation the riskier the returns. Lastly, the minimum and maximum returns are determined as well.

Results

Trading Results

Table 4.1 shows corn futures trading results over various forecasting steps ahead across the naive, ARIMA, and neural network trading models. As expected, the total number of trades declines with the increase in the forecasting steps. ARIMA 1 step ahead model has the highest number of trades at 532 trades. This is followed by ARIMA 3 at 394 trades, ARIMA 5 at 236 trades, ARIMA 10 at 123 trades and ARIMA 25 at 56 trades. Trading corn with a 1 step ahead forecasting model provides highest number of trades.

Only the 10 and 25 forecasting steps ahead neural networks and ARIMA trading models are compared because shorter steps ahead neural networks require excessive computation time. In general, the neural networks have more trades than ARIMA, likely because of their nonlinear forecasts which would predict more changes. The 10 forecasting steps ahead neural network has 589 trades compared to the parallel ARIMA with 123 trades. The 25 forecasting steps ahead neural network has 588 trades compared to ARIMA which has 26 trades. Table 4.2 shows similar trading results for silver. Again, the total number of trades declines with the increase in the forecasting steps ahead.

The Deutsche Mark results are given in Table 4.3 and overall results are as expected and similar to corn and silver. Tables 4.1 through 4.3 show approximately 50 percent winning trades. This is consistent with most mechanical trading systems as tested by Boyd and Brorsen (1991), and Lukac and Brorsen (1990). It indicates that while there is approximately equal number of winning and losing trades, the winning trades are larger than the losing trades implying the trades are profitable on average.

Monthly and Annual Trading Percent Returns Results

As the number of forecasting steps increases turning point forecast accuracy would be expected to decline. Therefore, mean trading returns are expected to decline as the number of forecasting steps ahead increases. Neural networks returns would be expected to be superior to ARIMA because of neural networks ability to capture nonlinearities in the data if they are estimated properly and have suitable algorithms. Also, trading returns from ARIMA would be expected to be greater than those from the bench mark naive trading model because the naive simply uses this period's price for next period's forecasted price.

Table 4.4 shows monthly and annual percent returns for corn futures naive, ARIMA, and neural network trading models over various forecasting steps ahead. As expected, returns decrease with the increase in the number of forecasting steps ahead. For example, ARIMA 1 has the highest annual mean return at 44.37 percent. This is followed by ARIMA 3 at 36.33 percent, ARIMA 10 at 21.68 percent, ARIMA 5 at 13.73 percent and ARIMA 25 at 1.76 percent. Returns decrease as the number of forecasting steps ahead increases because forecasting models lose turning point forecasting ability the further ahead forecasts are made.

Only the 10 and 25 forecasting steps ahead ARIMA and neural network models could be compared because shorter steps ahead neural networks demand excessive computation time. For corn, returns from neural networks are greater than ARIMA. For example, the annual mean return for the 10 forecasting steps ahead neural network is 30.79 percent compared to the parallel ARIMA with 21.68 percent. The annual mean return for the 25 forecasting steps ahead neural network is 34.05 percent compared to 1.76 percent for ARIMA. Returns from the naive model are about the same as ARIMA for one forecasting step ahead, indicating that ARIMA does not perform any more profitably here.

Similarly, Table 4.5 shows monthly and annual percent returns statistics for silver naive, ARIMA, and neural network trading models over various forecasting steps ahead. The results are very similar to those for corn. All returns from different forecasting steps ahead models are positive, significant and generally decreasing with the increase in the forecasting steps.

Comparing models shows that the 10 forecasting steps ahead ARIMA has higher returns than the parallel neural network. ARIMA has 46.86 percent compared to 36.86 percent for the neural network. The annual mean return for the 25 forecasting steps ahead

ARIMA is 37.68 percent compared to 38.39 percent for the neural network. These returns are comparable. Overall, both neural networks and ARIMA demonstrate abilities to realize significant returns using forecasts made up to 10 and 25 forecasting steps ahead. However, ARIMA generally has higher percent returns than neural networks.

The naive model has a positive and statistically significant annual return of 40.26 percent. However, it is less than the 53.32 percent return for the one forecasting step ahead ARIMA. Therefore, ARIMA performance is slightly higher than that of the naive.

Table 4.6 shows monthly and annual percent returns statistics for Deutsche Mark naive, ARIMA, and neural network trading models over various forecasting steps ahead. Generally, the returns are positive though not significant. This result shows that the Deutsche Mark market may be weak form efficient since the profits are insignificant. With respect to number of forecasting steps, the returns appear to have no apparent trend. This suggests that the Deutsche Mark models are not very different in their forecasting abilities over the various forecasting steps ahead. This implies that any of the Deutsche Mark models may be re-estimated less frequently and the parameters may remain valid over a reasonable number of forecasting steps ahead.

Comparing models shows that returns are generally lower for the neural network than ARIMA models. The annual mean return for the 10 forecasting steps ahead ARIMA is 28.70 percent compared with 19.40 percent for the parallel neural network. Also, the annual mean return for the 25 forecasting steps ahead ARIMA is 23.89 percent compared with 19.42 percent for the parallel neural network. ARIMA performance is better than neural network performance because it has higher annual returns than the neural network.

Annual returns for the naive and ARIMA models are comparable.

Results in general for all three commodities show that mean annual returns are declining as the number of forecasting steps increases. This is because the models forecast fewer turning points as the number of forecasting steps ahead increases. This implies that for trading purposes shorter steps ahead may be preferred to further steps ahead since they result in more trades which lead to higher returns. Also, returns from neural networks are larger than those from ARIMA for corn. However, neural networks have lower returns than the ARIMA for Deutsche Mark and silver.

As well the naive model has provided positive and statistically significant returns for corn and silver, but not Deutsche Mark. It might be expected that the naive model would be profitable only if time series are autocorrelated. However, Table 4.7 shows weekly autocorrelation coefficients for corn, silver, and the Deutsche Mark futures price changes, and only silver autocorrelation coefficient is statistically significant. However, corn is also profitable, but does not show significant autocorrelation. Therefore, corn is profitable probably because of disequilibrium in the market or simply because of a powerful trading rule.

All the models show relatively acceptable return to risk ratio as indicated by the Sharpe ratio, which is the mean divided by standard deviation. Also, the draw down percentages over various forecasting periods are close to 5 percent for corn, about 5 percent for Deutsche Mark, and between 11 and 29 percent for silver. These draw downs should be acceptable by traders since they are reasonably low, and therefore make trading with these models relatively safe. That is, only a small percentage of equity as indicated by draw downs may be at risk. Draw downs from neural networks and ARIMA are comparable.

The positive annual returns and Sharpe ratios in Tables 4.4 through 4.6 are consistent with mechanical trading systems returns and Sharpe ratios found by Boyd and Brorsen (1991). As well, the draw downs found in this study are smaller than the 20 to 30 percent draw downs often found for mechanical trading systems such as those by Lukac and Brorsen (1990).

Most returns are leptokurtic because they have positive kurtosis coefficients. In other words, the returns have high peaks with fat tails, as opposed to a normal distribution which has a bell shape. This means that the mean returns are affected by extreme positive and negative returns concentrated in the tails rather than around the mean as in the normal distribution. These returns are generally skewed to the right as indicated by positive skewness coefficients. This means there are more positive returns concentrated in the right tail. This is why the returns are on average positive. The implication of such distribution of returns is that trading will provide both positive and negative returns, but the positive returns will be higher than negative returns on average.

Correlation of Annual Returns

Traders can diversify across commodities, systems or both in order to reduce risk if there is negative or low correlation of returns. Diversification can be achieved across negatively correlated systems and commodities. Table 4.8 shows correlation coefficients of annual returns for corn, silver, and the Deutsche Mark. It shows that corn and Deutsche

Mark as well as silver and Deutsche Mark are negatively or weakly positively correlated. Therefore, these make strong candidates for diversification.

The corn and silver ARIMA trading models at five steps ahead are negatively correlated. Also, the corn and silver neural network trading models at ten and twenty-five steps ahead are negatively correlated. Therefore, these make strong candidates for diversification as well. However, their correlation is not significant. The corn and Deutsche Mark ARIMA at ten steps ahead is significantly negatively correlated. These make strong candidates for diversification.

Across systems, the 10 and 25 forecasting steps ahead silver neural network and ARIMA systems are relatively uncorrelated. Therefore, they are candidates for diversification. Across both systems and commodities, the 10 forecasting steps ahead silver neural network and the 25 forecasting steps ahead corn ARIMA are negatively correlated. These also make good candidates for diversification. Similarly, the 10 forecasting steps ahead Deutsche Mark neural net and the 25 forecasting steps ahead corn ARIMA are weakly correlated. They also are strong candidates for diversification.

Neural Network Performance

Past research suggests that neural networks should perform comparably or more accurately than ARIMA models. However, in reality this may not always be the case for a number of reasons. First, use of nondifferenced data may cause problems for neural networks since nondifferenced data has large ranges, which may cause errors to be large. Often, neural network developers recommend that neural networks be estimated on a small range data. For example, changes, which have small values and small ranges. However, since this study has used price levels rather than changes for the neural network, some problems may occur.

Secondly, the software error minimization algorithm may fail to reach the global minimum. This results in the neural network not reaching the minimum error on the error function, similar to a nonlinear least squares estimator not reaching a minimum error.

Thirdly, there may be over fitting of the neural network model if the model has a relatively large number of parameters (weights) compared to the number of observations. Neural networks have far more parameters than ARIMA models since they are nonlinear. However, a slightly over fitted model may still perform adequately if it is frequently re-estimated when forecasting. This is because such a model is fitted closely to past data patterns, and so does not perform properly when the data pattern changes. Therefore, it must be re-estimated (or re-fitted) often if it uses a large number of parameters, or its performance will be affected by over fitting.

Fourthly, the neural networks are not compared with ARIMA for forecasting up to one, three, and five steps ahead. Instead neural networks are compared with ARIMA for forecasting up to ten and twenty-five steps ahead because it would require a large amount of computation time to produce the shorter step ahead neural network forecasts. Neural networks may perform better at short forecasting steps ahead as they have more parameters than ARIMA, though this is a subject for further research.

Summary

The objectives of this study are to (1) determine the implications of different steps ahead forecasts on commodity futures trading performance; and (2) determine the trading performance of neural networks, ARIMA, and naive technical trading models. CBT Corn, Comex Silver and IMM Deutsche Mark weekly closing futures forecasts are used with technical trading rules to give buy and sell signals. Trades and percent returns statistics are then determined.

This study shows four important findings. First, the total number of trades declines with the increase in the number of forecasting steps ahead. Secondly, Neural networks provide more trades than naive and ARIMA in the case of corn and the Deutsche Mark. This result may be because of neural networks nonlinear ability to forecast more turning points even at longer forecasting horizons than ARIMA. In case of Silver, however, the neural network generates less trades than ARIMA.

Thirdly, the returns from neural network trades are generally lower than the returns from ARIMA trades. This suggests that ARIMA may be able to capture large and more important turning points than the neural network. The neural network may, however, capture a larger percentage of turning points, but they are small and less important.

Fourthly, all the models have positive returns, and while corn and silver returns are generally statistically significant, Deutsche Mark returns are not. However, the models demonstrate some capabilities to provide information necessary for trading decision making. Positive returns have been realized from these models using past prices, which is the essence of technical analysis, to provide trading signals. Therefore, using technical analysis appears to be profitable in this study. This result supports the findings of Sweeny (1986), Boyd and Brorsen (1991), Taylor (1994) and DeMatos et al (1995) who found positive technical analysis returns. This result contradicts the efficient market hypothesis, which implies that trading should yield zero profits, and supports disequilibrium theory.

The Sharpe ratios for the returns here are comparable to those by Boyd and Brorsen (1991). The draw downs are also relatively smaller than those found by other studies such as Lukac and Brorsen (1990). These draw down levels are acceptable because they imply that the systems developed here could be relatively safe for trading. That is, only a small percentage of equity as indicated by the draw down may be at risk. Finally, the relatively low correlation of returns provide opportunities for diversification across commodities, systems or, both commodities and systems.

Table 4.1 Trading Results of Corn Futures Over Various Forecasting Steps Ahead and Across Naive, ARIMA, and Neural Network Trading Models (1974-1995)[a].

STATISTIC	NAIVE	ARIMA 1[b]	ARIMA 3	ARIMA 5	ARIMA 10	ARIMA 25	NEURAL NET 10[c]	NEURAL NET 25
Total number of trades	514	532	394	236	123	56	589	588
Average profit per trade ($)	58.08	57.61	56.84	44.66	108.07	39.69	35.25	41.35
Total number of profitable trades	263	261	195	105	61	22	293	294
Percent total profitable trades	51.17	49.06	49.49	44.49	49.59	39.29	49.75	50.00
Average profit per profitable trade ($)	283.83	311.57	287.68	331.21	397.42	406.70	269.38	274.29
Total number of losing trades	212	224	177	116	54	29	249	246
Percent total losing trades	41.25	42.11	44.92	46.15	43.90	51.79	42.28	41.84
Average loss per losing trade ($)	(211.29)	(226.21)	(190.42)	(208.94)	(202.78)	(231.90)	(233.59)	(228.98)
Number of break-even trades	39	47	22	15	8	5	47	48
Percent break-even trades	7.59	8.83	5.58	6.36	6.50	8.934	7.98	8.16

Notes: [a] Results are out of sample
[b] 1 step ahead ARIMA trading model.
[c] 10 steps ahead neural network trading model.

Table 4.2 Trading Results of Silver Futures over Various Forecasting Steps Ahead and across Naive, ARIMA, and Neural Network Trading Models (1977-1995)[a].

STATISTIC	NAIVE	ARIMA 1[b]	ARIMA 3	ARIMA 5	ARIMA 10	ARIMA 25	NEURAL NET 10[c]	NEURAL NET 25
Total number of trades	520	465	455	445	447	358	365	357
Average profit per trade ($)	274.39	435.96	408.56	388.27	377.43	336.49	379.67	438.60
Total number of profitable trades	247	233	223	219	212	174	180	175
Percent total profitable trades	47.50	50.11	49.01	49.21	47.43	48.60	49.32	49.02
Average profit per profitable trade ($)	1199.94	1381.12	1314.91	1302.67	1300.54	1190.72	1279.31	1391.89
Total number of losing trades	213	174	176	183	176	143	145	142
Percent losing trades	40.96	37.42	38.68	41.12	39.37	39.94	39.73	39.78
Average loss per losing trade ($)	(721.60)	(684.37)	(609.83)	(614.78)	(607.98)	(606.43)	(632.38)	(612.68)
Number of break-even trades	60	58	56	43	59	41	40	40
Percent break-even trades	11.54	12.47	12.31	9.66	13.20	11.45	10.96	11.20

Notes: [a] Results are out of sample
[b] 1 step ahead ARIMA trading model.
[c] 10 steps ahead neural network trading model.

Table 4.3 Trading Results of Deutsche Mark Futures Over Various Forecasting Steps Ahead and Across Naive, ARIMA, and Neural Network Trading Models (1980-1995)[a].

STATISTIC	NAIVE	ARIMA 1[b]	ARIMA 3	ARIMA 5	ARIMA 10	ARIMA 25	NEURAL NET 10[c]	NEURAL NET 25
Total number of trades	389	371	380	397	397	365	398	409
Average profit per trade ($)	22.62	28.98	78.59	31.86	72.45	86.30	49.87	44.07
Total profitable trades	202	193	211	207	213	196	208	215
Percent total profitable trades	51.93	52.02	55.53	52.14	53.65	53.70	52.26	52.57
Average profit per profitable trade ($)	750.68	783.55	819.55	820.41	898.65	850.77	832.99	832.85
Total number of losing trades	184	175	166	186	181	164	188	192
Percent total losing trades	47.30	47.17	43.68	46.85	45.59	44.93	47.24	46.94
Average loss per losing trade ($)	(776.29)	(802.71)	(861.82)	(845.03)	(898.62)	(824.70)	(816.02)	(838.74)
Number of break-even trades	3	3	3	4	3	5	2	2
Percent Break-even trades	0.77	0.81	0.79	1.01	0.76	1.37	0.50	0.49

Notes: [a] Results are out of sample
[b] 1 step ahead ARIMA trading model.
[c] 10 steps ahead neural network trading model.

Table 4.4 **Monthly and Annual Percent Returns for Corn Futures Naive, ARIMA and Neural Network Trading Models Over Various Forecasting Steps Ahead (1974-1995)[a].**

MODEL	STATISTIC[b,c,d]		MONTHLY	ANNUAL
NAIVE	Mean		4.32*	47.26*
	t-statistic		4.39	5.14
	Sharpe ratio		0.28	1.09
	Kurtosis		3.97	-0.06
	Skewness		1.42	-0.33
	Minimum		-26.40	-54.52
	Maximum		72.24	115.27
	Draw down %	4.87		
ARIMA 1	Mean		4.01*	44.37*
	t-statistic		3.17	2.57
	Sharpe ratio		0.20	0.54
	Kurtosis		1.95	-0.32
	Skewness		1.05	0.16
	Minimum		-40.42	-111.95
	Maximum		75.81	208.90
	Draw down %	4.87		
ARIMA 3	Mean		4.06*	36.33*
	t-statistic		2.78	2.55
	Sharpe ratio		0.20	0.54
	Kurtosis		19.90	8.51
	Skewness		3.01	2.48
	Minimum		-34.60	-35.62
	Maximum		160.00	282.07
	Draw down %	4.37		
ARIMA 5	Mean		2.08	13.73
	t-statistic		1.18	1.06
	Sharpe ratio		0.09	0.22
	Kurtosis		20.51	2.12
	Skewness		3.30	1.45
	Minimum		-38.33	-61.44
	Maximum		156.52	185.47
	Draw down %	4.12		
ARIMA 10	Mean		4.96*	21.68*
	t-statistic		2.52	2.44
	Sharpe ratio		0.29	0.52
	Kurtosis		0.31	3.30
	Skewness		0.50	1.63
	Minimum		-37.96	-23.89
	Maximum		56.52	148.20
	Draw down %	4.13		

(Continued)

Table 4.4
(Continued)

MODEL	STATISTIC[b,c,d]		MONTHLY	ANNUAL
ARIMA 25	Mean		1.08	1.76
	t-statistic		0.32	0.29
	Sharpe ratio		0.05	0.06
	Kurtosis		3.10	1.00
	Skewness		1.48	0.98
	Minimum		-24.18	-40.37
	Maximum		70.61	70.97
	Draw down %	3.95		
NEURAL NET 10	Mean		2.67*	30.79*
	t-statistic		2.07	2.07
	Sharpe ratio		0.13	0.44
	Kurtosis		7.77	0.35
	Skewness		1.46	0.65
	Minimum		-42.53	-77.41
	Maximum		137.56	183.78
	Draw down %	4.87		
NEURAL NET 25	Mean		2.95*	34.05*
	t-statistic		2.30	2.37
	Sharpe ratio		0.14	0.50
	Kurtosis		8.01	-0.24
	Skewness		1.54	0.25
	Minimum		-42.53	-77.77
	Maximum		137.56	180.66
	Draw down %	4.87		

[a] Results are out of sample.
[b] Commodity trading returns are calculated using total investment of $100,000, of which 25 percent is invested in margins and 75 percent held back for potential margin calls.
* Significant at 5 percent
[c] Draw down is the minimum of percentage changes in equity over the entire trading period. For example if a trader started with $100,000 equity whose lowest point of equity at any time over the trading period was $60,000, then the draw down would be $40,000 divided by $100,000 or 40 percent.
[d] Sharpe ratio is calculated by dividing mean return by standard deviation. The higher the Sharpe ratio the lower the risk of returns.

Table 4.5 Monthly and Annual Percent Returns for Silver Futures Naive, ARIMA, and Neural Network Trading Models Over Various Forecasting Steps (1977-1995)[a].

MODEL	STATISTIC[b,c,d]		MONTHLY	ANNUAL
NAIVE	Mean		3.61*	40.26*
	t-statistic		4.82	3.53
	Sharpe ratio		0.33	0.81
	Kurtosis		1.96	0.09
	Skewness		1.09	0.62
	Minimum		-18.17	-29.03
	Maximum		43.72	156.92
	Draw down %	28.21		
ARIMA 1	Mean		5.07*	53.32*
	t-statistic		5.26	4.23
	Sharpe ratio		0.37	0.97
	Kurtosis		2.13	-0.23
	Skewness		1.11	0.30
	Minimum		-26.64	-33.16
	Maximum		60.79	170.65
	Draw down %	20.06		
ARIMA 3	Mean		4.64*	48.37*
	t-statistic		4.95	3.24
	Sharpe ratio		0.35	0.74
	Kurtosis		2.89	-1.13
	Skewness		1.37	0.60
	Minimum		-17.98	-26.93
	Maximum		60.78	161.95
	Draw down %	28.21		
ARIMA 5	Mean		5.22*	53.56*
	t-statistic		6.01	4.76
	Sharpe ratio		0.43	1.09
	Kurtosis		1.51	-0.72
	Skewness		0.89	0.25
	Minimum		-26.72	-19.21
	Maximum		47.53	149.33
	Draw down %	28.21		
ARIMA 10	Mean		4.78*	46.86*
	t-statistic		5.11	3.69
	Sharpe ratio		0.37	0.84
	Kurtosis		1.00	0.68
	Skewness		0.87	0.69
	Minimum		-26.72	-50.13
	Maximum		47.53	179.11
	Draw down %	11.91		

(Continued)

Table 4.5
(Continued)

MODEL	STATISTICS[b,c]		MONTHLY	ANNUAL
ARIMA 25	Mean		4.53*	37.68*
	t-statistic		4.66	3.52
	Sharpe ratio		0.37	0.80
	Kurtosis		0.87	1.13
	Skewness		0.87	0.87
	Minimum		-19.24	-32.90
	Maximum		45.50	159.09
	Draw down %	13.79		
NEURAL NET 10	Mean		4.03*	36.86*
	t-statistic		3.79	2.80
	Sharpe ratio		0.28	0.64
	Kurtosis		5.07	2.50
	Skewness		1.58	1.53
	Minimum		-28.53	-24.70
	Maximum		77.44	200.00
	Draw down %	13.79		
NEURAL NET 25	Mean		4.26*	38.39*
	t-statistic		3.79	2.91
	Sharpe ratio		0.29	0.66
	Kurtosis		4.17	2.15
	Skewness		1.51	1.26
	Minimum		-28.53	-40.50
	Maximum		77.4	198.41
	Draw down %	13.79		

[a] Results are out of sample.
[b] Commodity trading returns are calculated using total investment of $100,000, of which 25 percent is invested in margins and 75 percent held back for potential margin calls.
* Significant at 5 percent.
[c] Draw down is the minimum of percentage changes in equity over the entire trading period. For example if a trader started with $100,000 equity whose lowest point of equity at any time over the trading period was $60,000, then the draw-down would be $40,000 divided by $100,000 or 40 percent.
[d] Sharpe ratio is calculated by dividing mean return by standard deviation. The higher the Sharpe ratio the lower the risk of returns.

Table 4.6 Monthly and Annual Percent Returns for Deutsche Mark Futures Naive, ARIMA and Neural Network Trading Models Over Various Forecasting Steps (1977-1995)[a].

MODEL	STATISTIC[b,c,d]		MONTHLY	ANNUAL
NAIVE	Mean		0.89	10.93
	t-statistic		0.75	0.78
	Sharpe ratio		0.05	0.19
	Kurtosis		1.61	0.14
	Skewness		0.02	0.68
	Minimum		-55.24	-67.15
	Maximum		56.20	136.69
	Draw down %	5.02		
ARIMA 1	Mean		0.64	11.60
	t-statistic		0.48	0.62
	Sharpe ratio		0.04	0.16
	Kurtosis		0.28	1.12
	Skewness		0.04	0.90
	Minimum		-50.83	-96.85
	Maximum		45.59	192.81
	Draw down %	4.55		
ARIMA 3	Mean		1.71	22.43
	t-statistic		1.15	1.71
	Sharpe ratio		0.08	0.42
	Kurtosis		0.60	0.22
	Skewness		-0.35	0.78
	Minimum		-58.74	-45.86
	Maximum		60.41	144.02
	Draw down %	5.02		
ARIMA 5	Mean		0.68	9.52
	t-statistic		0.41	0.58
	Sharpe ratio		0.03	0.14
	Kurtosis		1.85	0.59
	Skewness		0.03	0.62
	Minimum		-62.88	-87.58
	Maximum		91.38	165.65
	Draw down %	5.02		
ARIMA 10	Mean		2.30	28.70
	t-statistic		1.36	1.58
	Sharpe ratio		0.10	0.39
	Kurtosis		1.38	1.24
	Skewness		0.06	0.92
	Minimum		-58.74	-93.23
	Maximum		91.38	204.95
	Draw down %	5.02		

(Continued)

Table 4.6
(Continued)

MODEL	STATISTICS[b,c]		MONTHLY	ANNUAL
ARIMA 25	Mean		2.58	23.89
	t-statistic		1.67	1.42
	Sharpe ratio		0.13	0.35
	Kurtosis		1.60	0.33
	Skewness		0.55	0.79
	Minimum		-39.62	-83.60
	Maximum		84.66	157.03
	Drawdown %	4.87		
NEURAL NET 10	Mean		1.63	19.40
	t-statistic		1.10	1.00
	Sharpe ratio		0.08	0.25
	Kurtosis		1.02	-0.78
	Skewness		0.46	0.03
	Minimum		-44.35	-118.44
	Maximum		78.56	153.02
	Draw down %	5.03		
NEURAL NET 25	Mean		1.56	19.42
	t-statistic		1.03	1.01
	Sharpe ratio		0.07	0.25
	Kurtosis		0.99	-0.55
	Skewness		0.47	0.00
	Minimum		-44.36	-119.98
	Maximum		78.56	159.55
	Draw down %	5.03		

[a] Results are out of sample.

[b] Commodity trading returns are calculated using total investment of $100,000, of which 25 percent is invested in margins and 75 percent held back for potential margin calls.

[c] Drawdown is the minimum of percentage changes in equity over the entire trading period. For example if a trader started with $100,000 equity whose lowest point of equity at any time over the trading period was $60,000, then the drawdown would be $40,000 divided by $100,000 or 40 percent.

[d] Sharpe ratio is calculated by dividing mean return by standard deviation. The higher the Sharpe ratio the lower the risk of returns.

Table 4.7 Weekly Autocorrelation Coefficients for corn, silver and Deutsche Mark Futures Price Changes.

COMMODITY	AUTOCORRELATION COEFFICIENT
Corn	-0.018
(1974-1995)	(-0.612)
Silver	0.133*
(1977-1995)	(4.101)
Deutsche Mark	0.008
(1980-1995)	(0.239)

*Significant at 5 percent; *t*-values in parentheses.

Table 4.8 Correlation Coefficients for Annual Percent Returns for Corn, silver and Deutsche Mark

Corn and Silver Futures Returns Correlation Matrix, 1980-1995.

	CNV[a]	CA1	CA3	CA5	CA10	CA25	CNN10[b]	CNN25	SNV	SA1	SA3	SA5	SA10	SA25	SNN10	SNN25
CNV	1.00															
CA1	**0.57**	1.00														
CA3	0.41	0.32	1.00													
CA5	0.35	0.29	0.92	1.00												
CA10	0.77	0.44	0.78	0.74	1.00											
CA25	0.83	0.41	0.44	0.39	0.70	1.00										
CNN10	0.74	0.39	0.44	0.38	**0.65**	0.96	1.00									
CNN25	0.26	0.59	0.09	0.03	0.20	**0.34**	0.32	1.00								
SNV	**0.11**	0.59	0.13	0.12	0.07	0.14	0.11	0.86	1.00							
SA1	0.18	**0.31**	0.08	0.14	0.13	0.22	0.12	0.61*	**0.73**	1.00						
SA3	0.06	0.41	**0.12**	0.18	0.11	0.14	0.11	0.79*	0.86	0.72	1.00					
SA5	-0.11	0.12	-0.10	**-0.15**	-0.20	0.02	-0.00	0.63*	0.72	0.56	0.76	1.00				
SA10	0.50	0.76	0.02	0.04	**0.23**	0.30	0.20	0.69*	0.59	0.51	0.41	0.22	1.00			
SA25	0.47	0.74*	0.02	0.05	0.24	**0.29**	0.21	0.70*	0.59	0.51	0.42	0.23	0.98	1.00		
SNN10	-0.14	0.24	-0.15	-0.24*	**-0.14**	-0.21	**-0.11**	-0.02	-0.05	-0.09	-0.16	-0.26	**0.01**	0.03	1.00	
SNN25	0.00	-0.00	-0.04	0.03	-0.38	**-0.15**	-0.12	**-0.24**	-0.30	-0.29	-0.20	-0.22	-0.03	**0.00**	0.32	1.00

(Continued)

Notes: [a] CNV is corn naive model; CA1 is a 1 forecasting step ahead corn ARIMA model. [b] CNN10 is a 10 forecasting steps ahead corn neural network model. For the other models S stands for silver and D stands for Deutsche Mark.
* Significant at 5 percent.

Table 4.8 (Continued)

Corn and Deutsche Mark Returns Correlation Matrix, 1980-1995.

	CNV[a]	CA1	CA3	CA5	CA10	CA25	CNN10[b]	CNN25	DNV	DA1	DA3	DA5	DA10	DA25	DNN10	DNN25
CNV	1.00															
CA1	**0.29**	1.00														
CA3	0.65	0.09	1.00													
CA5	0.50	-0.06	0.90	1.00												
CA10	0.87	-0.02	0.81	0.65	1.00											
CA25	0.87	0.29	0.63	0.62	0.69	1.00										
CNN10	0.85	0.38	0.58	0.56	0.62	0.98	1.00									
CNN25	0.18	0.64	0.03	0.04	-0.12	0.32	0.42	1.00								
DNV	**-0.38**	-0.11	-0.28	-0.30	-0.30	-0.41	-0.37	-0.20	1.00							
DA1	-0.37	**-0.09**	-0.37	-0.33	-0.35	-0.40	-0.33	0.19	**0.83**	1.00						
DA3	-0.16	-0.24	**-0.23**	-0.03	-0.10	-0.26	-0.29	-0.18	0.50	0.59	1.00					
DA5	-0.61	-0.06	-0.61*	**-0.57**	-0.62	-0.58	-0.53*	-0.29	0.86	0.63	0.43	1.00				
DA10	-0.53*	-0.06	-0.41	-0.35	**-0.52***	-0.38	-0.34	-0.29	0.82	0.50	0.30	0.94	1.00			
DA25	-0.06	0.12	0.19	0.43	-0.16	**0.09**	0.12	0.47	0.07	0.31	0.38	-0.08	-0.06	1.00		
DNN10	-0.25	-0.46	0.24	0.53	**-0.09**	0.10	**0.07**	-0.04	0.21	0.20	0.19	0.10	**0.31**	0.52	1.00	
DNN25	-0.28	-0.31	-0.19	0.16	-0.37	**0.07**	0.06	**-0.15**	0.24	0.12	0.34	0.39	0.53	**0.40**	0.73	1.00

(Continued)

Notes: [a] CNV is corn naive model; CA1 is a 1 forecasting step ahead corn ARIMA model.
[b] CNN10 is a 10 forecasting steps ahead corn neural network model. For the other models S stands for silver and D stands for Deutsche Mark.
* Significant at 5 percent.

Table 4.8 (Continued)

Deutsche Mark and Silver Returns Correlation Matrix, 1980-1995.

	DNV[a]	DA1	DA3	DA5	DA10	DA25	DNN10	DNN25	SNV	SA1	SA3	SA5	SA10	SA25	SNN10	SNN25
DNV	1.00															
DA1	0.83	1.00														
DA3	0.50	0.59	1.00													
DA5	0.86	0.63	0.43	1.00												
DA10	0.82	0.50	0.30	0.94	1.00											
DA25	0.07	0.32	0.38	-0.08	-0.06	1.00										
DNN10	0.21	0.20	0.19	0.10	**0.31**	0.52	1.00									
DNN25	0.24	0.12	0.34	0.39	0.53	**0.40**	0.73	1.00								
SNV	**-0.22**	0.11	-0.14	-0.21	-0.17	0.38	0.07	-0.14	1.00							
SA1	0.02	**0.37**	0.11	-0.12	-0.03	0.51*	0.61*	0.20	0.73	1.00						
SA3	-0.19	0.23	**-0.03**	-0.25	-0.23	0.52*	0.25	-0.04	0.94	0.87	1.00					
SA5	-0.28	0.11	-0.14	**-0.28**	-0.28	0.49	0.14	-0.13	0.95	0.76	0.96	1.00				
SA10	-0.23	-0.00	-0.27	-0.09	**-0.16**	0.26	-0.36	-0.04	0.47	0.01	0.38	0.43	1.00			
SA25	-0.30	-0.04	-0.30	-0.15	-0.22	**0.19**	-0.37	-0.05	0.47	0.04	0.40	0.43	0.98	1.00		
SNN10	0.75*	0.59	0.08	0.65*	0.65*	0.02	**-0.09**	-0.08	0.20	0.02	0.05	0.05	0.19	0.10	1.00	
SNN25	0.84*	0.63	0.40	0.78*	0.84*	0.33	0.38	**0.57***	-0.12	0.03	-0.12	-0.20	0.06	-0.02	0.72	1.00

Notes: [a] DA1 is a 1 forecasting step ahead Deutsche Mark ARIMA model.
[b] DNN10 is a 10 forecasting steps ahead Deutsche Mark neural network model. For the other models S stands for silver and C stands for Corn.
* Significant at 5 percent.

CHAPTER 5

SUMMARY

The objectives of this study are (1) to determine the implications of various steps ahead on market direction (turning point) forecasting, and commodity futures trading performance; and (2) to determine the turning point forecasting performance and trading performance of neural networks, compared to ARIMA, and naive models.

Weekly data for corn in cents per bushel (1969-1995), silver in dollars per troy ounce (1972-1995), and the Deutsche Mark in US cents per Deutsche Mark (1975-1995) nearby futures prices are obtained from the vendor Technical Tools Data. A nearby futures price series is created with contract months rolled over approximately one month before expiration. Each Tuesday closing price is used to construct the weekly series. Weekly rather than daily prices are used in order to reduce computation time. The first five years of data are used to estimate the model leaving out of sample results for corn (1974-1995), silver (1977-1995) and Deutsche Mark (1980-1995).

One, three, five, ten and twenty-five steps ahead ARIMA and a naive turning point forecasting models are developed for forecasting and trading. Also, ten and twenty-five steps ahead neural network turning point forecasting models are designed for forecasting and trading. The results are compared across forecasting steps, by forecasting models, and by commodity.

Forecasting Performance Over Various Forecasting Steps Ahead Using ARIMA

Chapter two investigates turning point forecasting performance over various forecasting steps ahead using ARIMA and a naive as a bench mark model. Results suggest two important points. First, turning points forecasting ability declines as the number of forecasting steps ahead increases. This implies that ARIMA loses its ability to forecast turning points as the number of forecasting steps ahead increases. Secondly, ARIMA shows slightly more accurate turning point forecasting performance than the naive bench mark model.

Neural Network Forecasting Performance Using Commodity Futures Prices

Chapter three deals with developing a neural network model for forecasting turning points for commodity futures. Neural networks for forecasting turning points for corn, silver and the Deutsche Mark are developed. Their forecasting performance is evaluated against that of ARIMA bench mark models at ten and twenty-five forecasting steps ahead. The contribution of the chapter is an attempt to explain turning points forecasting performance of neural networks relative to ARIMA time-series models.

Results show that neural networks used here predict a higher percentage of turning points than ARIMA models in five out of six cases. This outcome supports that of Kohzadi et al (1996) who find that neural networks predict turning points more accurately than ARIMA models. However, the Merton's test for turning points prediction shows that the turning point forecasts are not statistically significant. This result may be because of using nondifferenced data, or possibly nonoptimal software algorithm, or possibly some over fitting of the neural network models.

Commodity Futures Trading Performance Over Various Steps Ahead Turning Point Forecasts using ARIMA and Neural Network Models

Chapter four examines the implications of different steps ahead forecasts on commodity futures trading performance. The chapter also compares the performance of neural networks against ARIMA time series models at ten and twenty-five trading steps ahead. As well, performance of naive and ARIMA at one forecasting step ahead are compared. A trading rule is constructed to give buy and sell signals.

This chapter provides four important findings. First, the total number of trades declines with the increase in the number of forecasting steps ahead. Secondly, Neural networks provide more trades than naive and ARIMA in the case of corn and Deutsche Mark. This result may be because of neural networks nonlinear ability to forecast more turning points even at longer forecasting horizons than ARIMA. In case of Silver, however, the neural network generates less trades than ARIMA.

Thirdly, the returns from neural network trades are generally lower than the returns from ARIMA trades. This suggests that ARIMA may be able to capture large and more important turning points than the neural network. The neural network may, however, capture a larger percentage of turning points, but they are small and less important.

Fourthly, all the models have positive returns, and while corn and silver returns are generally statistically significant, Deutsche Mark returns are not. However, the models demonstrate some capabilities to provide information necessary for trading decision making. Positive returns have been realized from these models using past prices, which is the essence of technical analysis, to provide trading signals. Therefore, using technical analysis appears to be profitable in this study. This result supports the findings of Sweeny (1986), Boyd and Brorsen (1991), Taylor (1994) and DeMatos et al (1995) who found positive technical analysis returns. This result contradicts the weak form of efficient market hypothesis, which implies that technical trading should yield zero profits, and supports disequilibrium theory.

The Sharpe ratios for the returns here are comparable to those by Boyd and Brorsen (1991). The draw downs are also relatively smaller than those found by other studies such as Lukac and Brorsen (1990). These draw downs are relatively low and they imply that the systems developed here could be relatively safe for trading. That is, only a small percentage of equity as indicated by the draw down may be at risk. Finally, the relatively low correlation of returns provide opportunities for diversification across commodities, or systems, or both.

Limitations of the Study

Neural network models are compared with ARIMA at ten and twenty-five forecasting steps ahead. Comparing these two models at nearer forecasting steps ahead may improve results for the neural network. Neural networks use more parameters than ARIMA models, and therefore need to be re-estimated more often because they are more subject to over fitting. In this study neural networks are not so often re-estimated because they are estimated to forecast up to further ahead forecasting steps.

Suggestions for Further Research

This research is not conclusive, but it has opened up a number of avenues for further research. First, more commodities should be used in order to expand this analysis. Secondly, neural networks and ARIMA should be compared at nearer forecasting steps ahead in order to improve results for the neural network. Thirdly, an alternate neural network software package may be used which may better reach the minimum error on the error function. Fourthly, alternative trading rules to the simple rule used here could be used to further examine trading performance and see if the models can be profitable with different trading rules.

Other areas of research may include a study of a portfolio of returns equally weighted over same years, aggregated across systems, aggregated across commodities, and aggregated across both systems and commodities. Such a study would be important because it would reveal potential opportunities for trading diversification. As well, comparing commodity trading returns with S&P 500 index may provide some insight into performance of commodity trading returns versus stock returns.

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