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Forecasting financial markets using neural networks: an analysis of methods and accuracy

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THESIS

FORECASTING FINANCIAL MARKETS USING NEURAL NETWORKS: AN ANALYSIS OF METHODS AND ACCURACY

by

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September 1998

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FORECASTING FINANCIAL MARKETS USING NEURAL NETWORKS: AN ANALYSIS OF METHODS AND ACCURACY

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Submitted in partial fulfillment
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September 1998

ABSTRACT

This research examines and analyzes the use of neural networks as a forecasting tool. Specifically a neural network's ability to predict future trends of Stock Market Indices is tested. Accuracy is compared against a traditional forecasting method, multiple linear regression analysis. Finally, the probability of the model's forecast being correct is calculated using conditional probabilities. While only briefly discussing neural network theory, this research determines the feasibility and practicality of using neural networks as a forecasting tool for the individual investor. This study builds upon the work done by Edward Gately in his book Neural Networks for Financial Forecasting. This research validates the work of Gately and describes the development of a neural network that achieved a 93.3 percent probability of predicting a market rise, and an 88.07 percent probability of predicting a market drop in the S&P500. It was concluded that neural networks do have the capability to forecast financial markets and, if properly trained, the individual investor could benefit from the use of this forecasting tool.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

I. INTRODUCTION

A. GOALS

This research will examine and analyze the use of neural networks as a forecasting tool. Specifically a neural network's ability to predict future trends of Stock Market Indices will be tested. Accuracy will be compared against a traditional forecasting method, multiple linear regression analysis. Finally, the probability of the model's forecast being correct will be calculated using conditional probabilities. While only briefly discussing neural network theory, this research will determine the feasibility and practicality of using neural networks as a forecasting tool for the individual investor.

The study builds upon the work done by Edward Gately in his book *Neural Networks for Financial Forecasting.* In his book, Gately (1996) describes the general methodology required to build, train, and test a neural network using commercially available software. In this research, one of Gately's S&P500 network models was validated using recent data and provided a benchmark for further improvement. Gately's model was slightly improved upon, a new model was designed, and both models were compared to a multiple regression model. Finally, and potentially most importantly for the investor, model accuracy probabilities were generated. This was done by combining historical market movement probabilities with the model accuracy probability. This conditional probability could prove to be a vital tool for investment decision making.

Until recently, neural network research, as a subset of artificial intelligence, was limited to the realm of universities, research organizations, and large investment firms.

The entrance of the neural network as an investment tool for the individual investor was one of the many things brought about by the explosive growth personal computers. Neural network software is easily available and is profusely advertised in magazines such as *Technical Analysis of Stocks and Commodities*. What isn't advertised as well is the amount of skill and effort required when building an effective model.

This research validates the work of Gately (1996) and describes the development of a neural network that achieved a 93.3 percent probability of predicting a market rise, and an 88.07 percent probability of predicting a market drop in the S&P500. It was concluded that neural networks do have the capability to forecast financial markets and, if properly trained, the individual investor could benefit from using this forecasting tool.

1. Background

Neural network theory grew out of Artificial Intelligence research, or the research in designing machines with cognitive ability. A neural network is a computer program or hardwired machine that is designed to learn in a manner similar to the human brain. Haykin (1994) describes neural networks as an adaptive machine or more specifically:

> A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects: Knowledge is acquired by the network through a learning process and interneuron connection strengths known as synaptic weights are used to store the knowledge.

The basic building block of a brain and the neural network is the neuron. The basic human neuron adapted from Beale and Jackson (1990) is shown below in Figure 1.

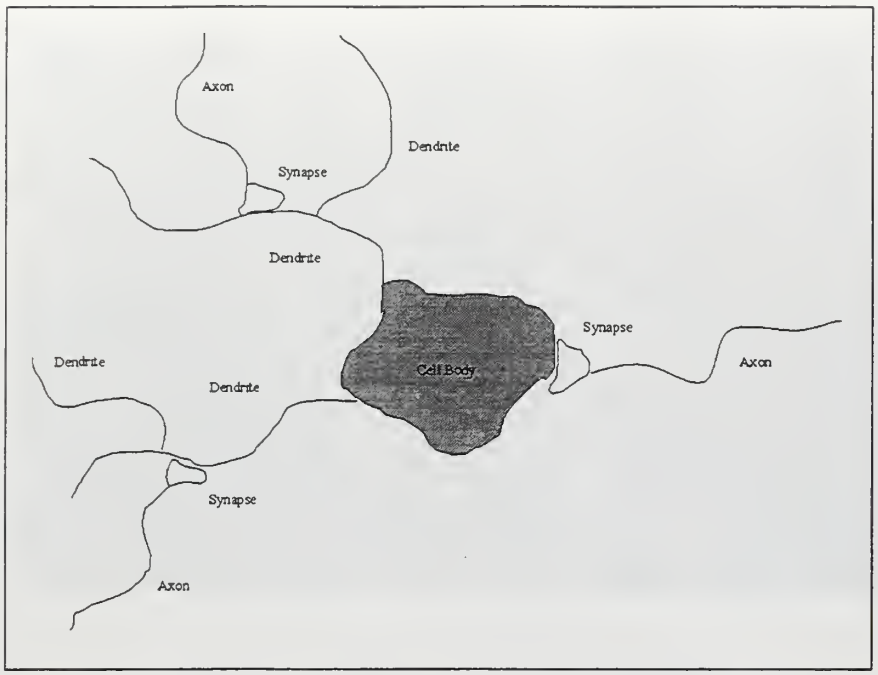


Figure 1. Biological Neuron

As described by Jackson et al. (1990), all inputs to the cell body of the neuron arrive along *dendrites*. Dendrites can also act as outputs interconnecting interneurons. Mathema-tically, the dendrite's function can be approximated as a summation. *Axons,* on the other hand, are found only on output cells. The axon has an electrical potential. If excited past a threshold it will transmit an electrical signal. Axons terminate at *synapses* that connect it to the dendrite of another neuron. When the electrical input to a synapse reaches a threshold, it will pass the signal through to the dendrite to which it is connected. The human brain contains approximately 10^{10} interconnected neurons creating its massively parallel computational capability.

The artificial neuron was developed in an effort to model the human neuron. The artificial neuron depicted below in Figure 2 was adapted from Kartalopoulos (1996) and Haykin (1994). Inputs enter the neuron and are multiplied by their respective synaptic.

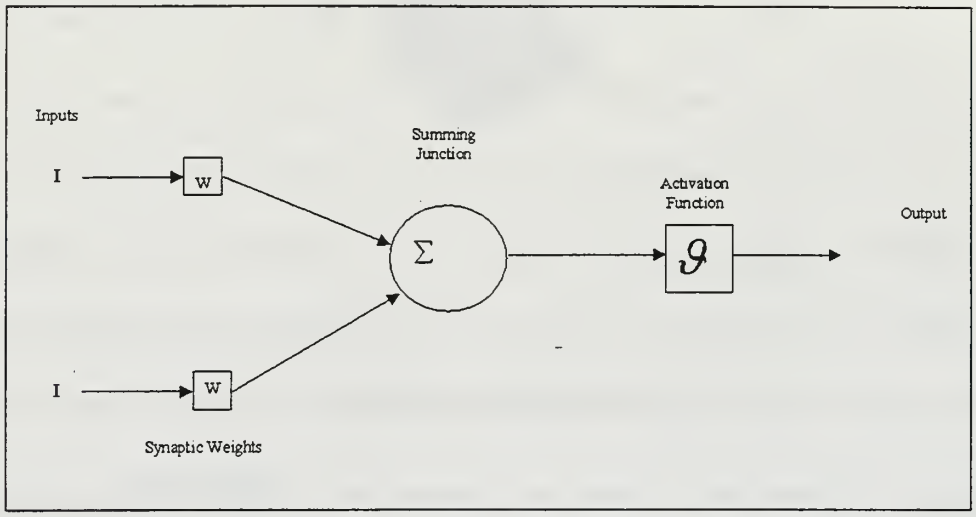


Figure 2. Artificial Neuron Model

weights. They are then summed and processed by an activation function. The activation function dampens or bound's the neuron's output, (Kartalopolous, 1996). Figures 3 and 4 represent two common activation functions which also happened to be used by the network tested during this research. The first is the logistic or sigmoid function f(x) = 1/(1+exp(-X)). The second is the gaussian function f(x) = exp ($-X^2$).

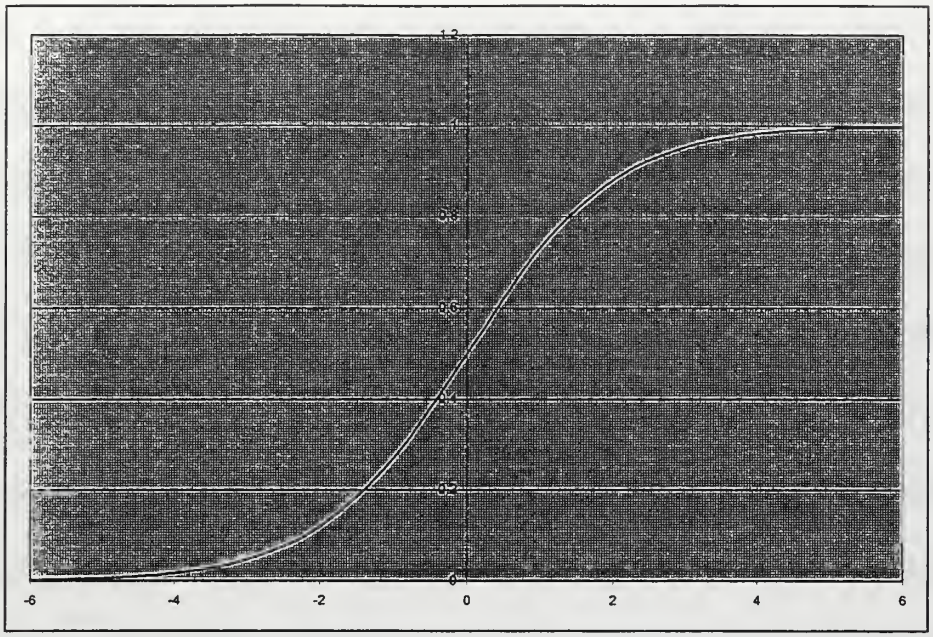


Figure 3. Logistic Activation Function

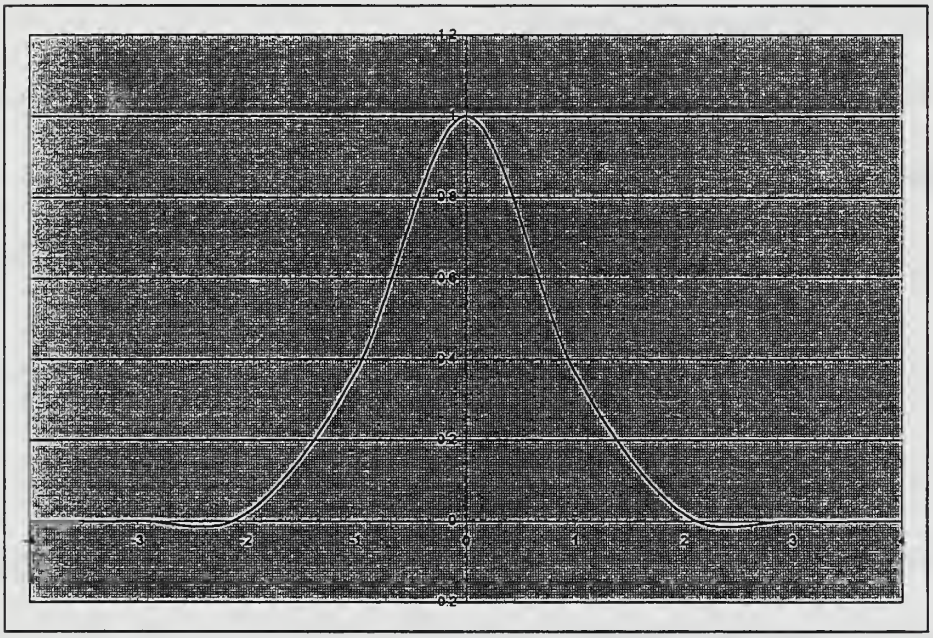


Figure 4. Gaussian Activation Function

The final output of the neuron represents the output of the activation function. Large numbers of interconnected artificial neurons have the ability to learn or store knowledge

in their synaptic weights. The learning ability of an artificial neural network will be discussed later, however this property makes it ideal for trying to identify signals within a noisy data flow. One example of such a data flow would be the closing price of the S&P500.

2. Objectives

The objective of this research was to examine the theory of Backpropagation neural networks and then develop a model that would accurately predict the future closing price of the S&P500 using a commercially available software package. Once this was accomplished, the probability of an accurate forecast would be calculated. Given the accuracy of the forecast, the benefits of the network to the investor would be determined.

3. The Research Question

The following research questions allow the research to meet the objectives proposed:

- What are the similarities between the Backpropagation neural network and the biological systems after which they were designed?
- What is the mathematical theory behind the Backpropagation neural network?
- Can neural networks accurately forecast a stock market index?
- Can multiple regression analysis accurately forecast a stock market index?
- Can neural networks be used as a practical forecasting tool by individual investors?

4. Scope, Limitations and Assumptions

The potential combinations of financial market indices or stocks, and neural network type are virtually limitless. For this reason, the research was limited to one stock market index, one neural network type and one statistical forecast tool. This allowed the research to build upon and validate previous research and place boundaries around the vast topic of time series forecasting.

The single limitation in this research was the availability of data. Gately trained his network on approximately four years of historical data. The Goldman Sachs Technology Indicator Index for Semiconductors was added to the raw data set in 1996, so the availability of data was significantly reduced. This limited the training and testing of the networks to two years of data. However, this did not seem to reduce the effectiveness of the network.

It is assumed that the reader has little or no knowledge of neural networks or statistical time series analysis.

5. Literature Review and Methodology

In his book *Neural Networks for Financial Forecasting,* Edward Gately describes the methodology needed to develop a network to accurately forecast financial markets. As an example, he develops a model that predicts the S&P500 closing value 10 days into the future. This research provides an independent validation of Gately's research and builds on it by comparing the network output to a more traditional statistical tool, multiple regression analysis. Additionally, model accuracy probabilities are examined using Bayes' Theorem.

The methodology used while conducting the research is as follows:

- Conduct a literature search of books, magazines, and the World Wide Web on the topic of neural networks.
- Identify the mathematical theory behind the Backpropagation neural networks.
- Identify a Stock Index to make forecasts upon.
- Determine what to forecast and the future point for the forecast (10 days into the future).
- Determine the inputs to the neural network using economic theory and Ward Systems Group Inc., NeuroShell 2 Professional Optimizer Package.
- Assemble the historical input data and preprocess it using Microsoft Excel.
- Using historical data, train and evaluate two different networks using Ward Systems Group Inc., NeuroShell 2 Professional.
- If needed, reassess the network inputs, retrain and evaluate the networks using Ward Systems Group Inc., NeuroShell 2 Professional.
- Attempt to forecast using multiple linear regression techniques.
- Statistically compare network forecasts vs. regression forecasts.
- Determine the historical averages of the item being forecasted occurring using Microsoft Excel and data taken from the Omega Research, Wall Street Analyst historical data CD-ROM and Dial Data Downloader.
- Determine probabilities for a successful forecast using Bayes' Theorem.

6. Organization of Study

The remaining portion of the thesis is broken up into the following chapters: Literature Review and Theoretical Framework, Methodology, Presentation of Data Collected, Data Analysis, and Conclusions and Recommendations. Within the literature

review, pertinent literature is reviewed and the history and theory of Backpropagation neural networks is discussed. The methodology describes the steps taken to answer the research questions. Presentation of Data Collected compiles pertinent tables and charts collected during the research. Data analysis follows with a statistical and graphical review of the information presented. The thesis closes with the conclusions and recommendations.

II. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

A. LITERATURE REVIEW

The potential use of neural networks as a tool for predicting financial markets has been marketed at increasing levels in recent years. Published research providing a step by step explanation of input data identification through network architecture design and finally output analysis is somewhat sparse, however. Kartalopoulos (1996), Dhar and Stein (1996), and Ward and Sherald (1995) all mention to varying degree that neural networks have the capability to forecast financial markets. Smolensky, Mozer, and Rumelhart (1996, p. 395) provide Weigand's thoughts on time series analysis and prediction. Although extremely technical, it touches on financial market prediction and provides a good overview of time series analysis. He breaks time series analysis into forecasting and modeling. Forecasting is short-term prediction while modeling tries to identify features that accurately predict long term trends. Wiegand states that these can be quite different and that the laws governing a short-term forecast may not substantially relate to the long-term model or the actual characteristics of the system.

More specifically, Weigand claims that the "...complexity of a model useful for forecasting may not be related to the actual complexity of the system." Potentially models can accurately predict markets where they are substantially less complex than the market itself. Lowe (1994) focuses on portfolio optimization and short term equity forecasting. Some believe that efficient market theory causes predictions based upon historical price patterns to be valueless. However, Lowe (1994) postulates that "A system which is apparently random could have significant deterministic components embedded in its data." He states that a neural network's "...ability to create nonlinear

approximations to the underlying generators of data...may be exploited." Lowe (1994) concludes that it would be possible to develop an "...automated trading system based entirely upon quantitative pattern processing techniques capable of consistently outperforming professional traders."

Lederman and Klein (1995, p. 65) provide Jurik's thoughts on trading system development. Although Jurik does not provide specific examples of trading systems, he provides a wealth of advice on data preprocessing techniques. He states, "Strive for simple models having only a few choice input variables." He supports this by explaining that as the number of model inputs increase, the degrees of freedom of the governing equation also increases. While equations with high degrees of freedom have the capability to model the training data effectively, they fail miserably when given test data. This is because models with fewer degrees of freedom do not try to trace the data's random scattering but only follow the general trend. Jurik also states that "When trying to remove unimportant variables, sensitivity analysis of nonstationary or nonlinear models has dubious practical value." This is extremely important because this is one of the standard techniques used in regression analysis. If applied to a neural network model it could seriously fail. Jurik states there are only two ways to correctly remove unimportant variables. The first is to use a genetic algorithm to develop multiple combinations of input variables while only letting the most accurate survive. The second is a manual method of systematically removing one variable at a time and recording network accuracy. This technique is repeated until the accuracy of the model starts decreasing.

While all these authors hint at the capability of neural networks in forecasting financial markets, the researcher found only one text that meticulously tracks the development of the neural network from data gathering and preprocessing to training and application of the net. This text is Edward Gately's *Neural Networks for Financial Forecasting*. This research uses Gately's (1996) techniques for developing a model to predict the closing price of the S&P500. His model is slightly improved upon and compared to more standard regression methods for forecasting. Additionally and potentially most importantly for the investor, model accuracy probabilities were generated. This was done by combining historical market movement probabilities with the model accuracy probability. This conditional probability could prove to be a vital tool for investment decision making.

B. THEORETICAL FRAMEWORK

As described previously, a neural network is a computer program or hardwired machine that is designed to learn in a manner similar to the human brain. Additionally, Figure 2 showed how an artificial neuron processes input data into an output signal. However, the most important feature of a neural network has not been explained: how a neural network learns. This research focuses on the Backpropagation algorithm learning method. The following derivation is taken from the explanation provided by Dhar and Stein (1996). All mathematical formulae refer to Figure 5 below. This figure depicts a single artificial neuron, which learns using the Backpropagation learning algorithm.

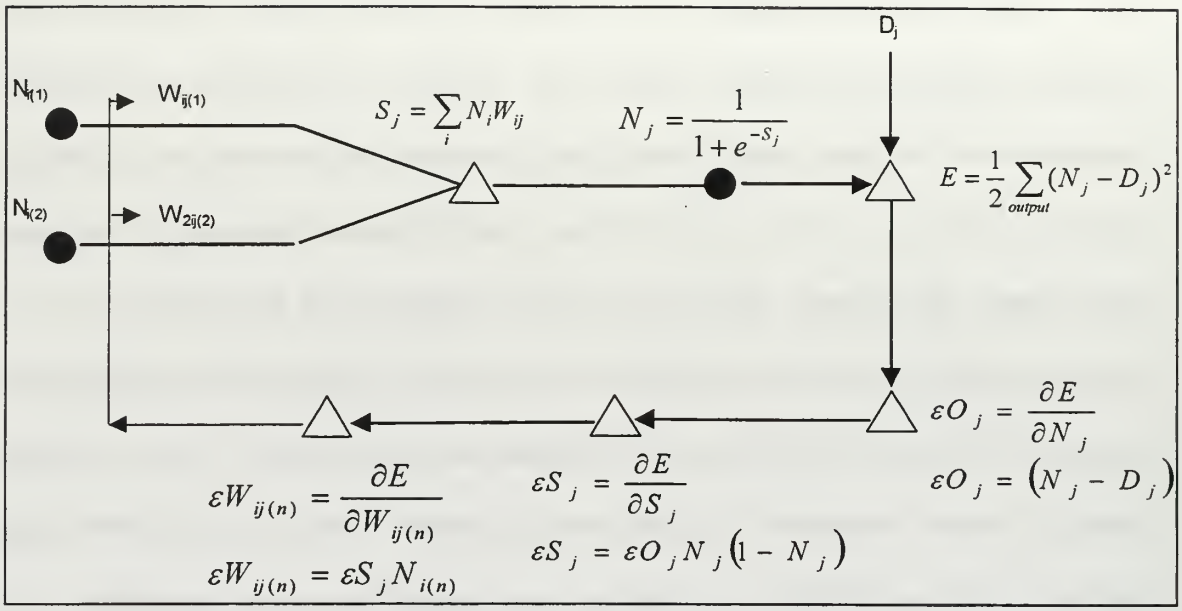


Figure 5. Artificial Neuron Using Backpropagation Learning

The Backpropagation algorithm seeks to minimize the error term between the output of the neural net and the actual desired output value. The error term is calculated by comparing the net output to the desired output and is then fed back through the network causing the synaptic weights to be changed in an effort to minimize error. The process is repeated until the error reaches a minimum value. The network uses Equation 1 to update the weight W_{ij} from a given node N_i to the current node N_j; where t refers to the number of times the network has been updated and λ refers to the learning parameter. The learning parameter, or learning rate, controls the rate the weight is changed as learning takes place. The sensitivity of node N_j to a change in weight W_{ij} is represented by εW_{ij} and will be defined more fully below.

$$W_{ij,(t+1)} = W_{ij,t} + (\lambda)(\varepsilon W_{ij})(N_i) \tag{1}$$

The total input to a node is described in Equation 2 as:

$$S_j = \sum_i N_i W_{ij} \tag{2}$$

where S_j is the sum of all inputs to a node, N_i is the output of the previous node, and W_{ij} is the weight connection between the ith node of the previous layer.

This output is then transformed using the logistic activation function described in chapter I and represented by Equation 3. The total output of node j is represented by N_j.

$$N_j = \frac{1}{1 + e^{-Sj}} \tag{3}$$

The overall error for a single pass of the neural network is represented by Equation 4, where D_j is the desired output of the output node j.

$$E = \frac{1}{2} \sum_{Output} \left(N_j - D_j\right)^2 \tag{4}$$

Now that the error term for the entire network has been calculated, this information is fed back through the network to reduce error. The simplified partial differential equations required to change the connection weights are provided below; the original equation before simplification can be found in Figure 5.

First, the error term for each output node O_j must be calculated. Essentially we are trying to identify how much the error term changes with respect to a change in each output node. This calculation is simplified in Equation 5 below:

$$\varepsilon O_j = \left(N_j - D_j\right) \tag{5}$$

Second, the amount the error term changes as the input is varied to a given output node must be calculated. This is done by determining how much Equation 4 changes when the total input to the node (Equation 2) is changed. This calculation is simplified in Equation 6 below:

$$\varepsilon S_j = \varepsilon O_j N_j (1 - N_j) \tag{6}$$

Next, the weight adjustment needed for W_{ij} is calculated from a layer below the current layer (N_i) to the current node N_j. The calculation is simplified in Equation 7 below:

$$\varepsilon W_{ij} = \varepsilon S_j N_i \tag{7}$$

Finally this operation is continued on nodes in lower layers by allowing nodes in the lower hidden layers to play the role of the output node. All errors from all inputs to the hidden layer must be summed. Additionally, the error in the hidden node is calculated by examining how the error of nodes above the hidden node change with respect to changes in the hidden node. The simplified equation for calculating the weight update is provided in Equation 8 below, where the subscript j represents nodes in the layer above the hidden layer.

$$\varepsilon H_i = \sum_j \varepsilon S_j W_{ij} \tag{8}$$

Dhar et al (1996) states, "In this manner the error of the network is propagated backward recursively through the entire network and all of the weights are adjusted so as to minimize the overall network error."

III. METHODOLOGY

This section discusses the techniques used to develop the neural network and multiple regression financial forecasting models. The combination of these models, with historical and conditional probabilities, will allow the investor to make decisions based on probabilities of success. The presentation first discusses the development of the models, followed by the historical probability calculations and concludes with the conditional probability calculation.

The information to be forecast was first identified. Since this research extended and verified Gately's (1996) work with neural networks, a similar model output was chosen for at least one model for comparison purposes. Two separate model outputs were chosen, the first was the S&P 500 closing value ten days into the future—the output chosen by Gately, and the second was the future S&P500 ten day percent change. As described by Gately, a much more accurate forecast is possible when predicting the percent change versus the actual closing value of a stock or index. For example, if the S&P500 index was valued at 1400 dollars and a model that predicted the closing value had a ten-percent error the potential output inaccuracy would be 140 dollars. If the same index had made a ten-percent price change and the model that predicted the percent change of price had a ten-percent error, the potential output inaccuracy would be one-percent. For a ten-percent price change, from 1272 dollars to 1400 dollars, this inaccuracy would translate into approximately a twelve dollar error.

The first neural network model, named Close Network, was chosen to be a verification of Gately's (1996) work and predicted the S&P500 index ten days into the future. The inputs to the model where developed by first downloading the following raw data from Dial Data using Data Downloader software from Omega Research:

S&P 500 Index	*SPX
Dow Jones Transportation Index	*DWT X
Dow Jones Industrial Index	*DWI X
Dow Jones Utilities Index	*DWU
Commodities Research Bureau	*CRB
AMEX Oil Index	*XOI
Gold and Silver Mining Index	*XAU

The data set encompassed the trading days from March 1, 1991 to August 18, 1998.

The data was charted using stock charting software called Wall Street Analyst Deluxe from Omega research. This established date integrity within each index. The indices were then exported and saved as a text file from Wall Street Analyst. Using Microsoft Excel, each index text file was combined into one spreadsheet. The resulting file was formatted such that each index and its date was in a separate column with each row representing a trading day. An example of a partial data set can be found in Appendix B. Date integrity is extremely important to the neural network. To ensure integrity was maintained, each index's date column was checked for integrity against the S&P500 date using a simple "if then" rule in Excel. If the dates were equal, it placed a

zero in a row. If the dates were not equal, Excel placed a 1 in a row. This function was copied down the entire data set and then summed at the bottom. A sum of zero represented no date integrity discrepancies. A sum of anything greater than zero indicated that a date discrepancy existed. The sum was zero for all indexes with the exception of *CRB. Within *CRB it was found that one trading day was missing. Instead of deleting the index, the trading day was added. The average closing value of the day proceeding and following the missing day was chosen to represent the missing day.

The last column in the spreadsheet was titled "Future (10 day) S&P500 C." This represents the future closing price of the S&P500 Index and was the actual value the network used to compare against its prediction during training. This "future" information was created by simply copying the S&P 500 closing price into the last column of the spreadsheet deleting the first 10 days of data and moving the remaining data up 10 rows. Once this was complete, all date columns were deleted with the exception of the one associated with the S&P 500 data. The file was saved as an Excel 4 worksheet so it could be imported into Neuroshell 2 Professional. The following data was imported into the neural network software package as a pattern file:

Date

S&P500 H

S&P500 L

S&P500 C

Dow Transportation Index C

Dow Utilities Index C

Amex Oil Index C

CRB C Dow Industrial Index V

Gold and Silver Mining C

Future (10 days) S&P500 C

The pattern file was then altered using the software's Market Indicator module to include all the inputs described by Gately (1996). The following technical indicators were added:

MvAvg (30) of Dow Industrial Index V

Lag (10) of CRB C

Lag (10) of Amex Oil Index C

Lag (10) of Dow Transportation Index C

These technical indicators represent a thirty-day moving average of the Dow Industrial Index Volume and a ten-day lag of various other raw data.

Within the Define Inputs module of the Neuroshell2, each column of the data file was identified either as Unused, Input, or Actual Output. The date and raw volume information was excluded by defining it as Unused. The Future (10 days) S&P500 Close was defined as the Actual Output and all others were defined as inputs. The minimum and maximum values for each data column were then automatically calculated for use by the network. Next a test set or "out of sample" data set was extracted from the data set.

Every tenth data set was chosen to represent the test data. There were 1700 training rows and 188 test rows. In the Designing the Network module, the software recommended using a Ward Network. The Ward Network is a backpropagation network with one input layer, three hidden layers and one output layer. Each layer is called a slab. Each slab is made up of one to sixteen individual neurons depending on the location within the network. Each slab also has a different activation function as described below:

Slab 1 (input): Linear [-1,1], 13 Neurons

Slab 2 (hidden): Gaussian, 16 Neurons

Slab 3 (hidden): tanh, 16 Neurons

Slab 4 (hidden): Gaussian comp., 16 Neurons

Slab 5 (output): logistic, 1 Neuron

The learning rate was set to .05 and the momentum was set to .5. Within the Training Criteria module, pattern selection was set to random, calibration interval was set to every 200 patterns and stopping criteria was set to stop training at 40,000 events since min average error within the test set. Within the training module, the network was set to automatically save the weights for the best test set. The network was then trained within the Training module. The trained network was then applied to the 188 sample test patterns.

The network output is a file that contained three columns: Actual (1), Network (1) and Act (1)-Net (1) representing the actual S&P500 closing value, the network prediction and the network error. This file was opened and actual vs. predicted charts

were created within Excel. Additionally, the descriptive statistics for the network error were calculated. The Close Network was able to make predictions with accuracy comparable to Gately's (1996) model.

The second network model, called Percent Network, was designed to predict the future S&P500 ten day percent change taking advantage of the possible reduction in prediction error. The network was provided the same raw data as the Close Network. However, two new columns were created in the raw data file. The first column was defined as the ten-day % change in the S&P500 Closing price. Starting on the 10th day, this was calculated using the following formula (cell 1-cell 11)/cell 1*100. The second column was defined as the future ten-day % change. Essentially, the ten-day % change column was copied into the new column and the values were shifted back ten days. The future ten-day percent change was the actual desired output of the net and was used during training to calculate error.

The file was imported into Neuroshell2 and preprocessed. During preprocessing, the following technical indicators were added to the data file:

MvAvg (30) of Dow Industrial Index V

Lag (10) of CRB C

Lag (10) of Amex Oil Index C

Lag (10) of Dow Transportation Index C

LinRegChange (10,5) of S&P500 C

LinRegChange (10,10) of S&P500 C

The technical indicator LinRegChange (x,n), as described in Neuroshell2 Professional, represents "Predicted change between current value and the value time periods into the future. Prediction is based upon the linear regression line calculated from the last n time periods." The test set extraction, network design and training settings were identical to the Close Network. Essentially, the Percent Network would look at the same raw data, with added indicators, as the Close Network but would predict a percent change versus a closing price. The same out of sample data was used. When the Percent Network (1) was applied to the out of sample data, it performed relatively poorly when compared to the Close Network.

To increase the accuracy of the Percent Network, the net inputs were changed. The LinRegChange (10,5) of S&P500 C was removed and LinRegPredict (10,10) of S&P 500 10 day % Change was added. The technical indicator LinRegPredict (x,n), as described in Neuroshell2 Professional, represents the "Predicted value x time periods into the future. Prediction is based upon the linear regression line calculated from the last n time periods." After training and application to the out of sample data, Percent Network (2) showed only slight improvement in prediction accuracy.

The network inputs were again adjusted to try and increase accuracy. The technical indicator LinRegChange (10,10) of S&P500 C was removed as an input. After training and application to the out of sample data, the Percent Network (3) accuracy decreased.

At this point, the decision was made to augment the moving average of the volume with the raw volume data in the network. The Percent Network (5) performed only slightly better after including raw volume.

A close review of the raw data used in Gately's model and the Close Network showed little if any input from the technology sector. A technology component was added to the net to improve accuracy. This net was called Percent Network (5) and was based on the most accurate network up to that point, Percent Network (2). It included an added indicator, the closing value of GSM the Goldman Sachs Technology Indicator Index for Semiconductors. Unfortunately, GSM has only been in existence since 1996, so the data set was significantly reduced. The full raw data set begins on July 18, 1996 and ends August 12, 1998. Due to the reduced amount of available data, every 5th data set was chosen to represent the test or out of sample data. There were 419 training rows and 104 test rows. Percent Network (5) was trained and applied to the out of sample data. The network showed significant improvement, although the r^2 value was still not as high as the Close Network.

In Percent Network (6), the ten-day lag of GSM C was added as an input to improve prediction capability. The network was trained and applied to the out of sample data set. Although its r^2 value was slightly lower than Percent Network (5), it was chosen as the final Percent Network because it had a lower percent error over 30% and there were predictions within 5%.

The addition of the new GSM C data to the Percent Network had significantly improved its accuracy, and could do the same for the Close Network. Also the networks were using data from significantly different time periods, making comparison between the two questionable. Therefore, the GSM C and Lag of GSM C was added to the Close Network causing the data window to match the Percent Network. All data prior to July 18, 1996 was discarded. In the Extraction Module, every 5th data set was chosen to represent the test or out of sample data. Both models were now training on identical raw data. After training, the network was applied to the out of sample data. The results showed a slight decrease in r^2 value but fully 100 percent of the predictions were within five percent of the actual closing value. This network was chosen to be the final Close Network model.

The actual and predicted values from both the Close and Percent networks were placed into one spreadsheet. The predicted closing value of the S&P500 index was calculated using the predicted % change provided by the Percent Network. This allowed comparison of a single type of data between both networks. The two predicted closing values where compared graphically and statistically. This completed the neural network portion of the research.

A more traditional statistical forecasting tool is regression analysis. This method uses the sum of the least squared errors to fit a curve to a data set. The decision was made to try and predict the S&P500 closing value using the same data used in the Close Network. The dependant variable was designated as the Future (10 days) S&P500 C

column. The following columns were listed as independent variables: S&P500 H, S&P500 L, S&P500 C, Dow Transportation Index C, Dow Utilities Index C, Amex Oil Index C, CRB C, Gold and Silver Mining C, GSM C, MvAvg(30) of Dow Industrial Index V, Lag(10) of CRB C, Lag(10) of Amex Oil Index C, Lag(10) of Dow Transportation Index C, and Lag(10) of GSM C. Using the data analysis tool within Excel, a multiple linear regression analysis was performed on the data set.

When conducting multiple linear regression analysis, the following assumptions must hold for the model to be correct: 1. Normality 2. Homoscedasticity 3. Independence of Errors and 4. Linearity. Normality assumes the value of the Y (the dependant variable) must be normally distributed for each value of X (the independent variable). According to Levine, Berenson, and Stephan (1997), regression analysis is fairly robust against departures from the normality assumption. One method of verifying the normality assumption is to construct and examine a Normal Probability Plot for the dependant variable. The Normal Probability Plot was created in Excel using the regression analysis tool. The points on the plot seemed to deviate from a straight line in a random manner. This indicates normality. If the line had risen more steeply at first and then increased at a decreasing rate it would have indicated a left skewed data set. The opposite is true for a right skewed data set.

Homoscedasticity assumes variation or error around the regression line should be similar for low and high values of the independent variable. This can be verified by examining the residual plots for each independent variable. For each variable, there did

not seem to be major differences in the variability of the residual for different values of the independent variable. Therefore, the Homoscedasticity assumption was valid.

Autocorrelation, or the likelihood that a certain type of error precedes or follows another type of error, violates the independence of errors assumption. If errors are correlated, there will be a pattern of positive errors following positive errors and negative errors following negative errors. The simplest way to rule out Autocorrelation is to plot the residuals over time. The residual vs. time plot showed no pattern and indicated the absence of Autocorrelation. Therefore, the Independence of Errors assumption seemed valid.

The regression line fit plots indicated a probable linear relationship of varying degrees between the dependant variable and each of the independent variables. This was verified because there was no pattern in the residual plots for each independent variable. Therefore, the linearity assumption seemed valid.

All four assumptions of regression analysis were verified so a linear regression model seemed appropriate. When using Multiple Regression, the objective is to utilize only those variables that have a significant relationship with the dependant variable. The first step in determining a significant relationship between the dependant and independent variable was to conduct an F test. The F test was used to determine if there was a significant relationship between the dependant variable and the chosen independent variables. The null hypothesis was that there was no linear relationship between the dependent variable and indeptendent variables; the alternative hypothesis was that at least one regression coefficient was not equal to zero. The null hypothesis is rejected at a

certain level of significance if the estimated value F is greater than the critical value of F. Excel's ANOVA calculation provided the value for F; it was 1416. For a 95% confidence interval, the value of the critical F was obtained from Levin et al's (1997) Critical Values of F table. The critical value for F(14,469) is approximately 1.67. Therefore, F was greater than the critical value of F and the conclusion can be made that at least one of the independent variables was related to the dependant variable.

The next step was to test individual portions of the multiple regression model. If individual variables have no significant effect on the model, they should be removed and a new regression calculated. The t test was used to determine if an individual independent variable had a significant effect on the dependant variable, taking into account the other independent variables. The null hypothesis was that there was no relationship between the independent and dependant variable; the alternative hypothesis was that there was a relationship. The decision rule was to reject the null hypothesis if the estimated t was less than negative t critical or greater than t critical. For a 95% confidence interval, the critical value for t was obtained from Levin et al's (1997) Critical t Table. The critical values for t (.025,14) were –2.1448 and 2.1448. Eight of the 14 independent variables failed the t test and did not have a significant relationship to the dependant variable. The regression was recalculated using only those independent variables that passed the t test.

At this point, all assumptions were reevaluated and found to still be valid. The F test was then repeated on the second regression model. The critical value of F(6,477) is approximately 2.1. The model passed the F test. Therefore, at least one of the

explanatory variables was related to the dependant variable. The t test was then repeated on the second regression model. The critical value of t(.025,6) is 2.4469. In reviewing the t values, it was determined that there is a significant relationship between the dependant variable and all independent variables with the exception of Gold and Silver Mining C. This input was dropped and a third regression was calculated.

Again all regression assumptions were reevaluated and found to be valid. The F test was then repeated on the third regression model. The critical value of F (5,477) is approximately 2.21. The model passed the F test. Therefore, at least one of the explanatory variables is related to the dependant variable. The t test was then repeated on the second regression model. The critical value of t (.025,6) is 2.5706. In reviewing the t values, there was a significant relationship between the dependent variable and all independent variables.

The final test of the validity of the multiple regression model is to verify there is no multicollinearity between the independent variables. According to Levine et al (1997), when two independent variables are highly collinear they can cause the regression coefficients to fluctuate drastically if one or both are included in the model. It is difficult to separate the effect of to two collinear independent variables on the dependant variable. The measure of collinearity is the Variance Inflationary Factor (VIF). For each of the independent variables, the VIF was calculated using excel. If sets of variables are uncorrelated, the VIF will equal 1. For highly intercorrelated variables, the VIF can exceed 10. According to Levine et al (1997), a VIF greater than 10 indicates there is too much correlation between the independent variables. In the third regression model, all

VIF values were less than 10. Therefore, the third regression model was fully optimized and verified and was chosen as the final model to compare to the two neural networks.

With three working forecasting models, the next step was to calculate the probability that each model's prediction will be accurate. The calculation was based upon Bayes' Theorem, or conditional probability. Bayes' Theorem states that a probability depends upon the environment in which it is based. A conditional probability is stated as given X what is the probability of Y or $P\langle Y|X\rangle$. First the researcher had to find something that could easily be identified in the environment. It would be tedious to try and calculate probabilities for individual S&P500 closing values or individual percent changes. However, one could calculate the number of times the market rose or fell; this is potentially enough information for the investor. The market rise or fall corresponds to percent change, which is the output of the Percent Network. Percent changes can also be calculated from the output of the Close Network and the Regression Model.

Therefore, the question used to calculate the probability that each model's prediction is accurate is: given a certain amount of historical daily market rises, when a model predicts a market rise, what is the probability of it actually occurring. Mathematically this would be stated as $P\langle ForecastedRise|HistoricalRise\rangle$. Rather than using the mathematical form of Bayes' Theorem, the conditional probability was calculated in a spreadsheet using a method described by Dr. Katsuaki Terasawa of the Naval Postgraduate School. First, the historical data was calculated within Excel from the raw data during the period from March 3, 1991 to August 18, 1998. An if-then

statement was used to identify a percentage rise. The statement generates a one if the percent change is greater than zero or a zero if the percent change is less than zero. Summing this column provides the total days with a percent increase. This was subtracted from the total number of days in the data set to identify market falls. The number of times the market rose and fell was calculated.

Next, the accuracy of each model was calculated. The output of each model for the out of sample data was used. The if-then technique was used to identify when both the model forecast and the actual data agreed or disagreed as to a market rise or fall. This data could be entered into Bayes' theorem to obtain the conditional probability. However the accuracy of the model was adjusted using the historical environmental data as described by Professor Terasawa. Calculating the probability of accurately predicting a rise or fall in the S&P500 Index became a simple matter of dividing accurate rise or fall predictions by total rise or fall predictions.

IV. PRESENTATION OF DATA COLLECTED

In this section the research data will be presented and important items will be identified. The presentation begins with vital data for each of the forecasting models, follows with the historical probabilities, and concludes by presenting conditional probabilities.

A. CLOSE NETWORK

The following vital data given in Table 1 and Figures 6 and 7 is from the completed training module:

Table 1. Training Module Output Close Network

	Training Set	Test Set
Learning events	559800	N/A
Learning epochs	1446	N/A
Minimum average error	0.0002282	0.0002896
Training Time	02:37 Minutes	

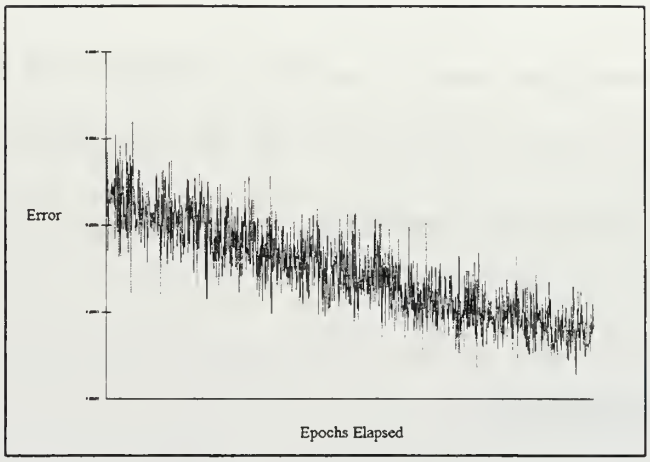


Figure 6. Training Error on Close Network Training Set

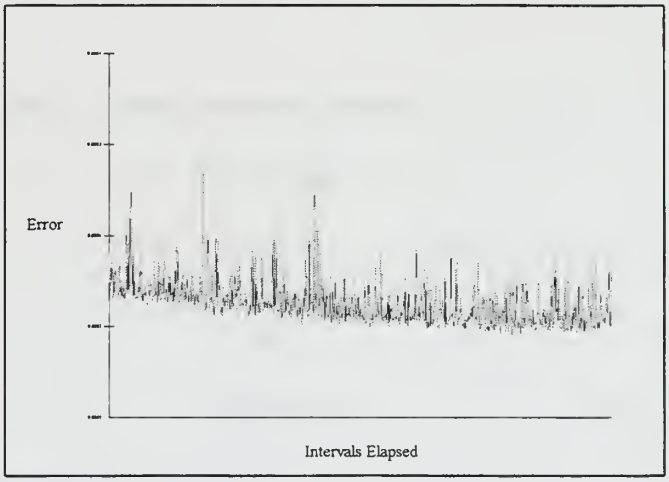


Figure 7. Training Error on Close Network Test Set

The trained network was applied to the 99 out of sample test patterns. The results are shown in Table 2.

Table 2. Close Network Output Statistics

R squared	0.9935
r squared	0.9935
Mean squared error	130.975
Mean absolute error	8.821
Min. absolute error	0.039
Max. absolute error	31.792
Correlation coefficient r	0.9968
Percent within 5%	100
Percent within 5% to 10%	0
Percent within 10% to 20%	0
Percent within 20% to 30%	0
Percent over 30%	0

Figure 8 is a graphical depiction of how the Close Network weighted the contribution of each input to the model.

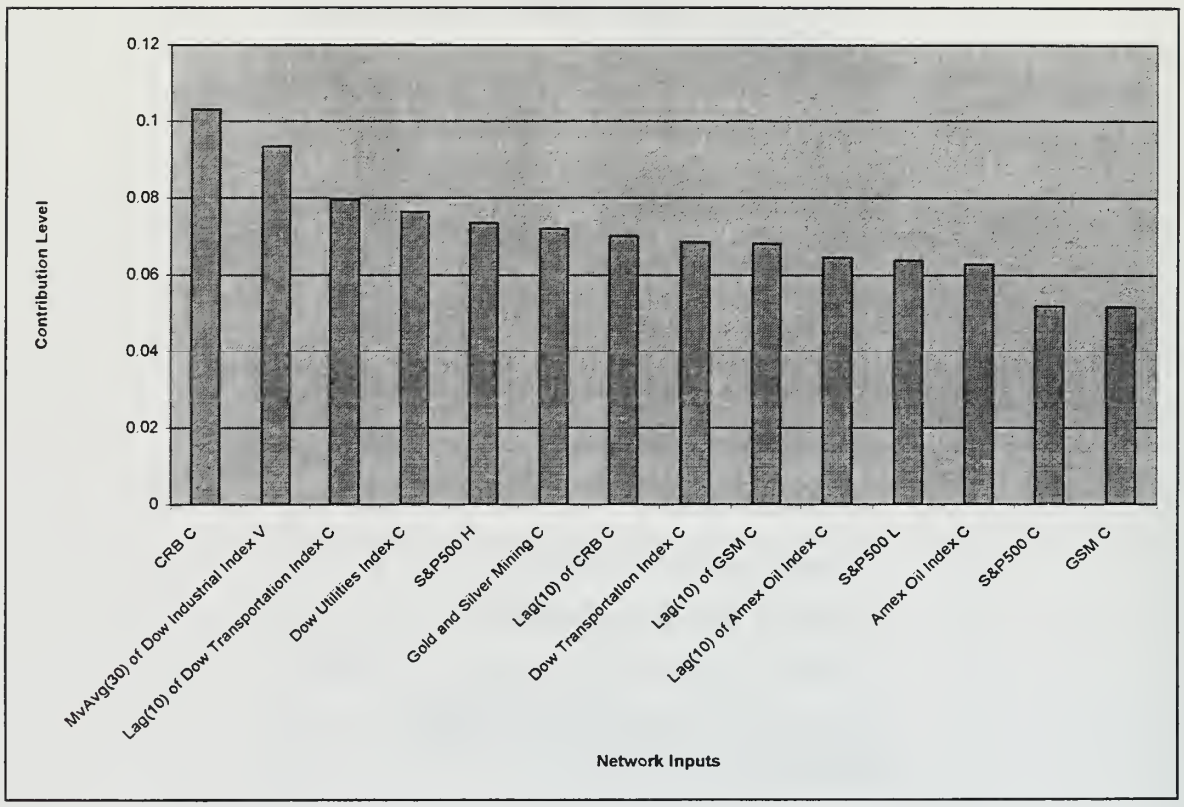


Figure 8. Input Contribution Factors Close Network

Figure 9 is a graphical depiction of the Close Network's forecast versus the actual S&P500 Close.

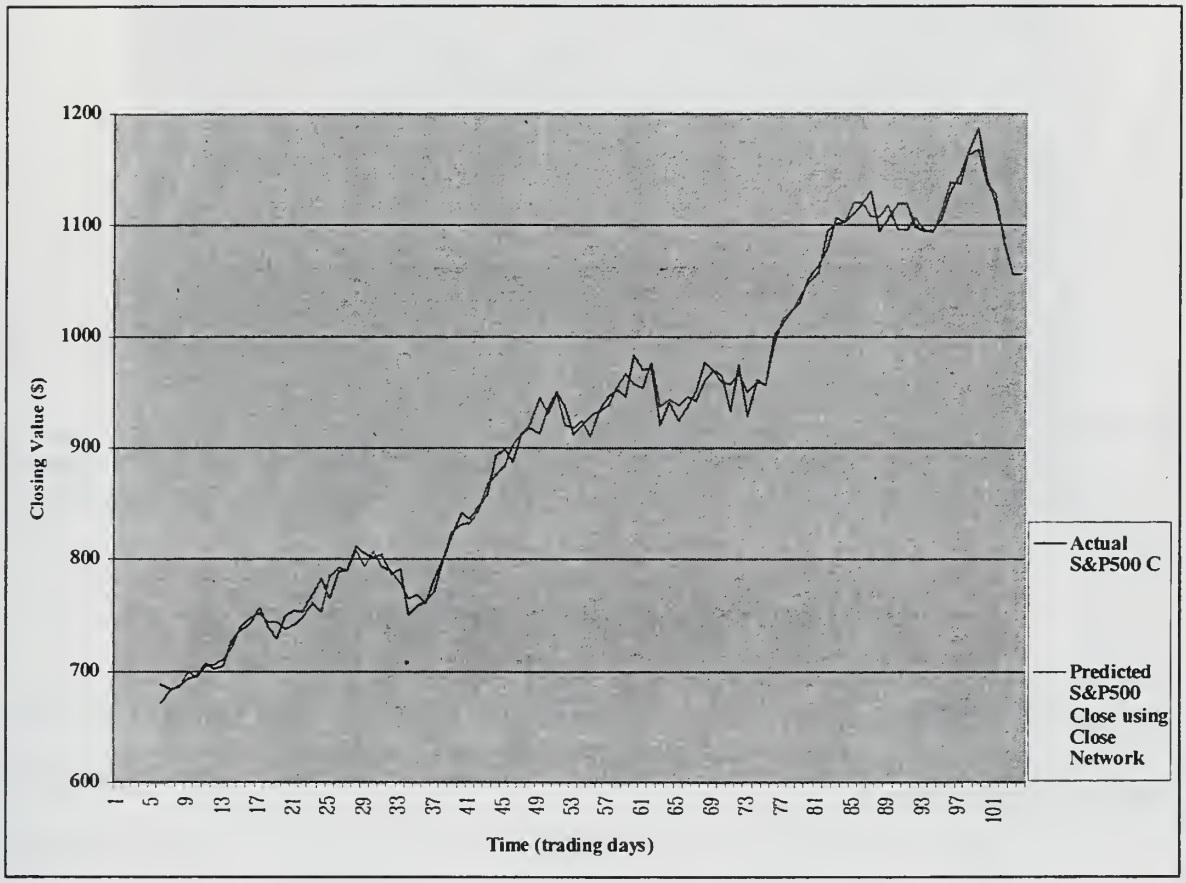


Figure 9. Close Network Actual vs Predicted S&P500 Close

Figure 10 is a graphical depiction of the Close Network's forecast error.

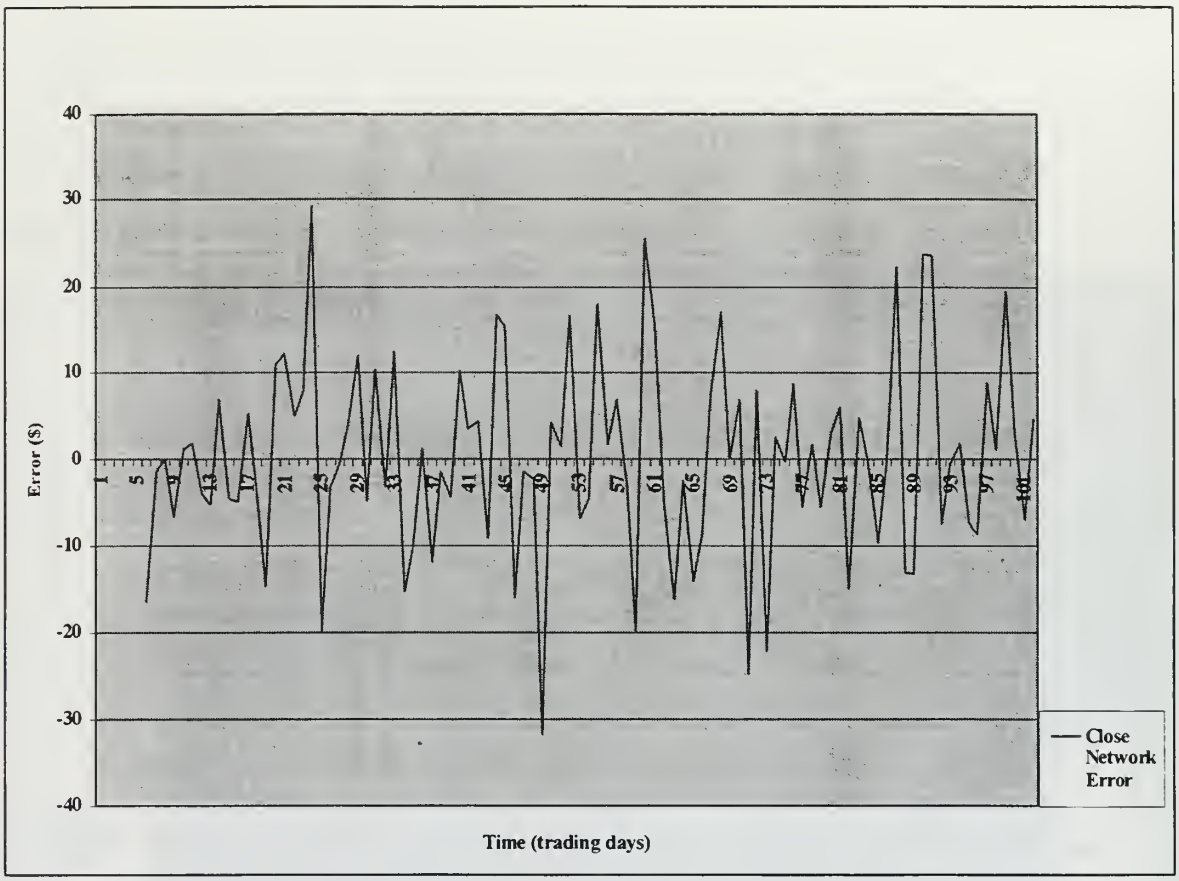


Figure 10. Close Network Error

The Close Network error was input into Excel and the Descriptive Statistics tool was used to generate Table 3.

Table 3. Close Network Descriptive Statistics

Mean	0.175905208
Standard Error	1.167902939
Median	-0.257263184
Standard Deviation	11.50250998
Sample Variance	132.3077358

Table 3 (Continued)

Kurtosis	0.240087928
Skewness	0.050247272
Range	61.15527344
Minimum	-31.79174805
Maximum	29.36352539
Sum	17.06280518
Count	97
Confidence Level(95.0%)	2.318270784

B. PERCENT NETWORK

The following vital data given in Table 4 and Figures 11 and 12 is from the completed training module:

Table 4. Training Module Output Percent Network

	Training Set	Test Set
Learning events	221400	N/A
Learning epochs	572	N/A
Minimum average error	0.0016160	0.0026779
Training Time	01:14 Minutes	

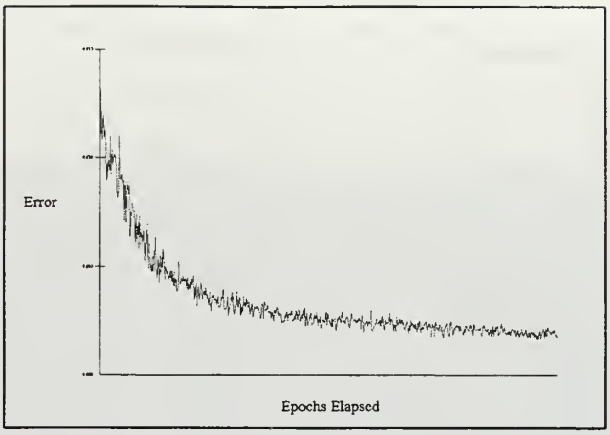


Figure 11. Training Error on Percent Network Training Set

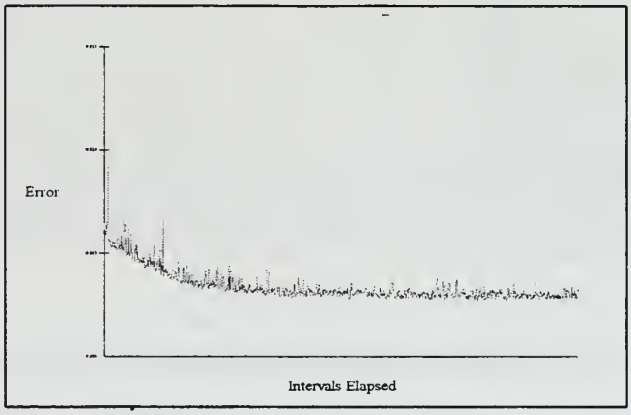


Figure 12. Training Error on Percent Network Test Set

The trained network was applied to the 99 out of sample test patterns. The results are shown in Table 5.

Table 5. Percent Network Output Statistics

R squared	0.7872
r squared	0.7933
Mean squared error	1.449
Mean absolute error	0.919

Table 5 (Continued)

Min. absolute error	0.006
Max. absolute error	4.484
Correlation coefficient r	0.8907
Percent within 5%	10.309
Percent within 5% to 10%	6.186
Percent within 10% to 20%	20.619
Percent within 20% to 30%	11.340
Percent over 30%	51.546

Figure 13 is a graphical depiction of how the Percent Network weighted the contribution of each input to the model.

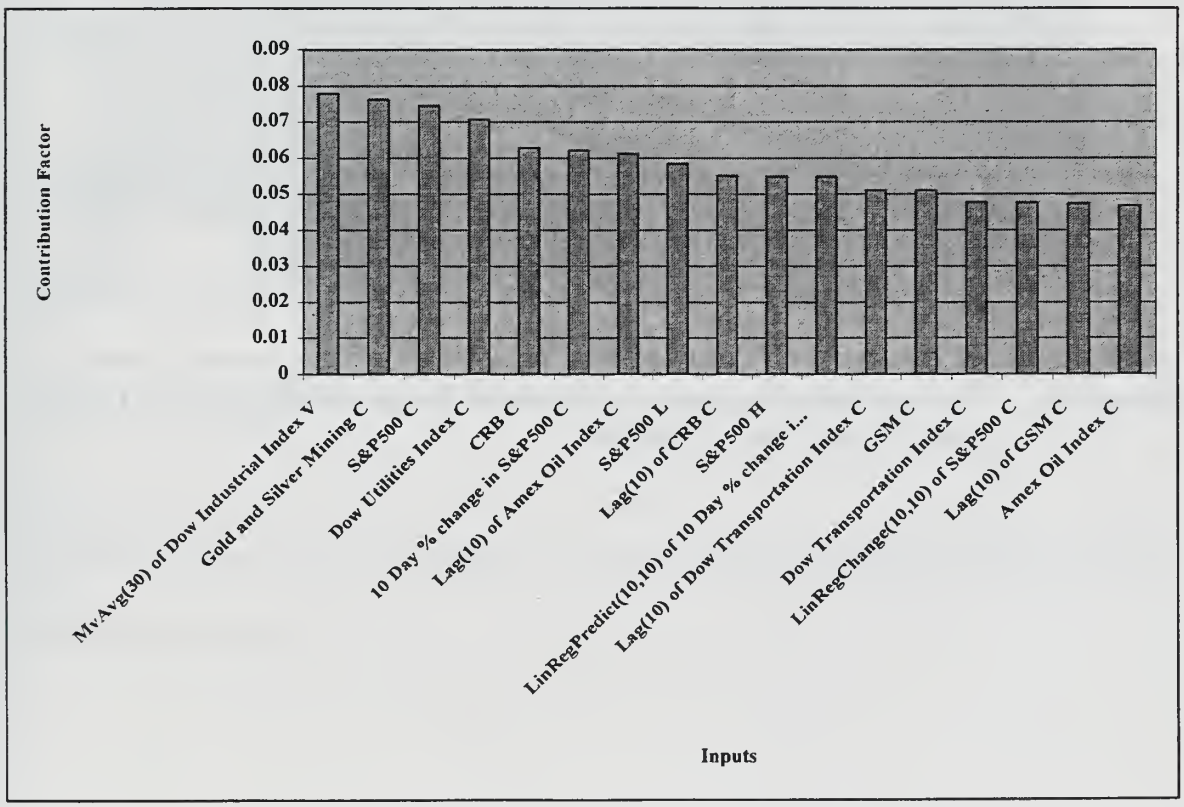


Figure 13. Input Contribution Factors Percent Network

Figure 14 is a graphical depiction of the Percent Network's forecast versus the actual S&P500 Close.

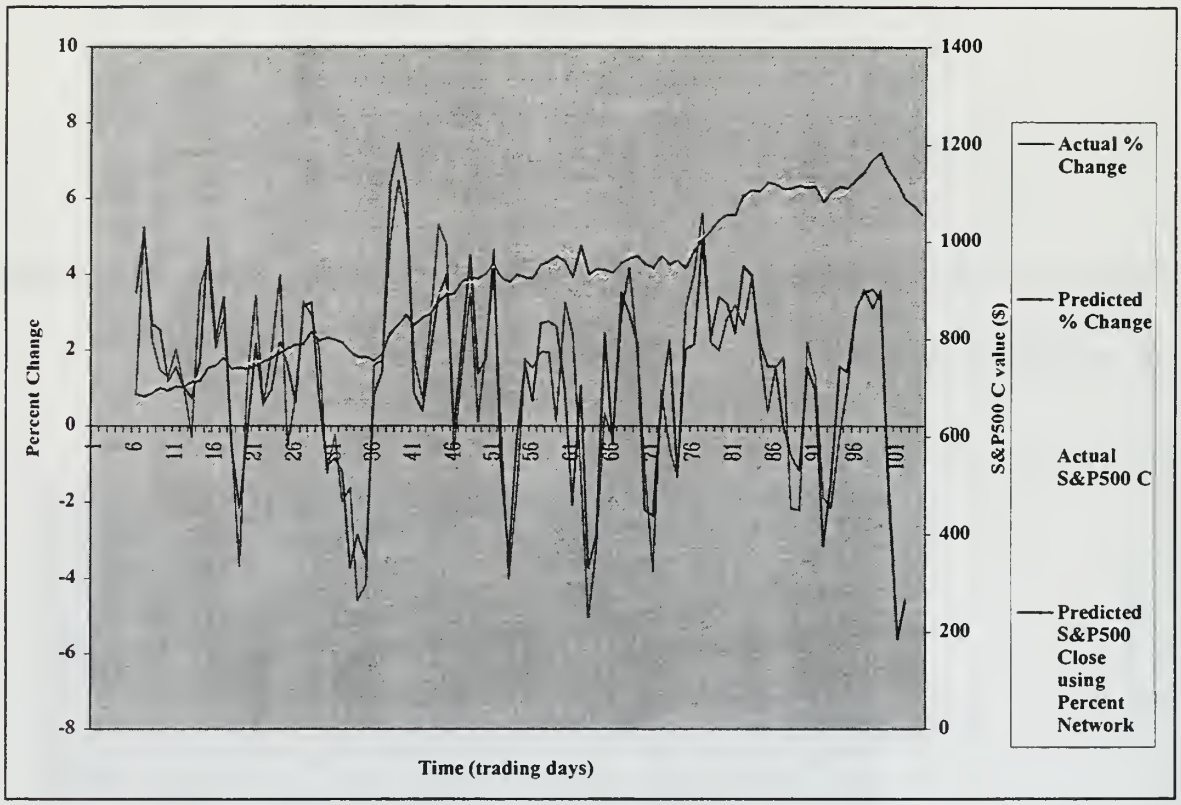


Figure 14. Percent Network Actual vs. Predicted Future 10 Day Percent Change and Closing Price of S&P500

Figure 15 is a graphical depiction of the Percent Network's forecast error.

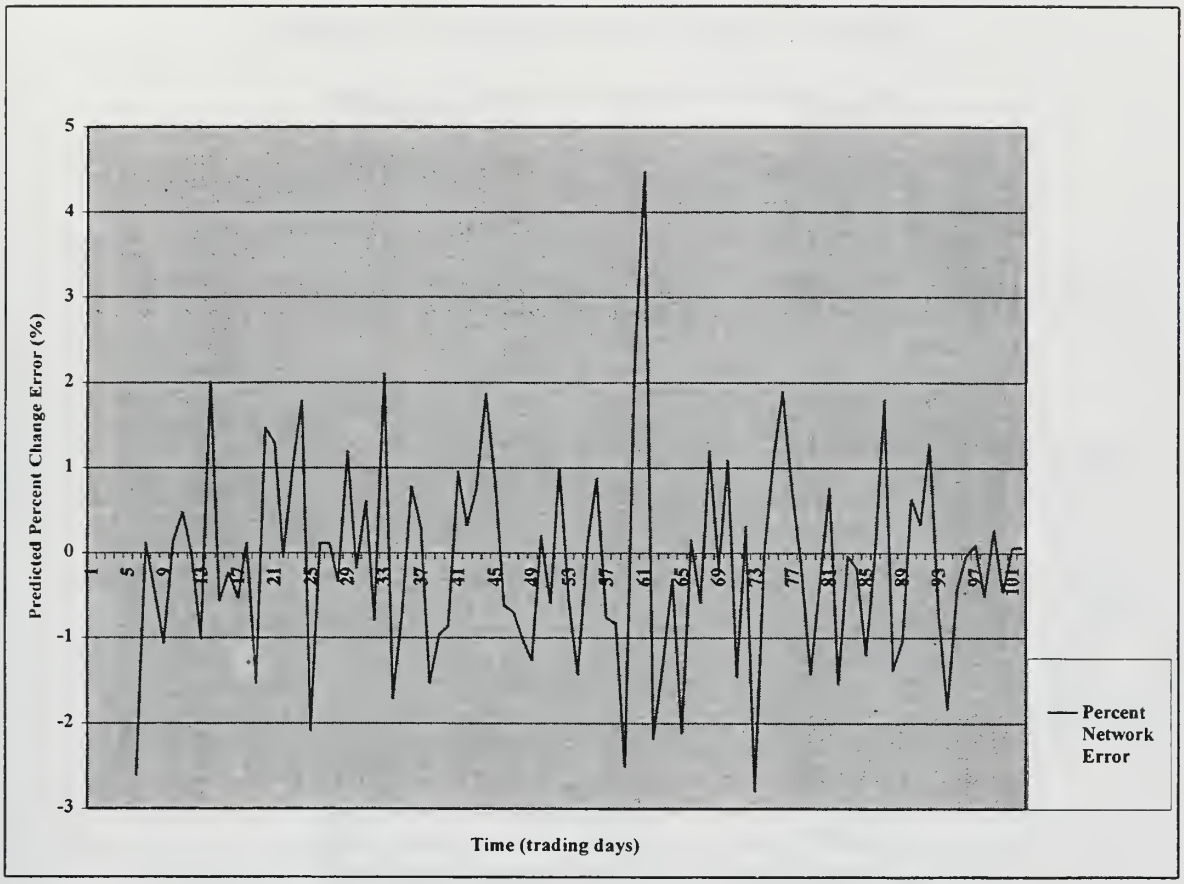


Figure 15. Percent Network Error

The Percent Network error was input into Excel and the Descriptive Statistics tool was used to generate Table 6.

Table 6. Percent Network Descriptive Statistics

Mean	-1.081002006
Standard Error	1.107737379
Median	-0.437339914
Standard Deviation	10.90994792
Sample Variance	119.0269637
Kurtosis	1.792340417
Skewness	0.530272064
Range	68.62393946
Minimum	-26.16139546
Maximum	42.462544
Sum	-104.8571946
Count	97
Confidence Level(95.0%)	2.198842999

Figure 16 is a graphical depiction of the both the Close and Percent Network's forecast versus the actual S&P500 Close.

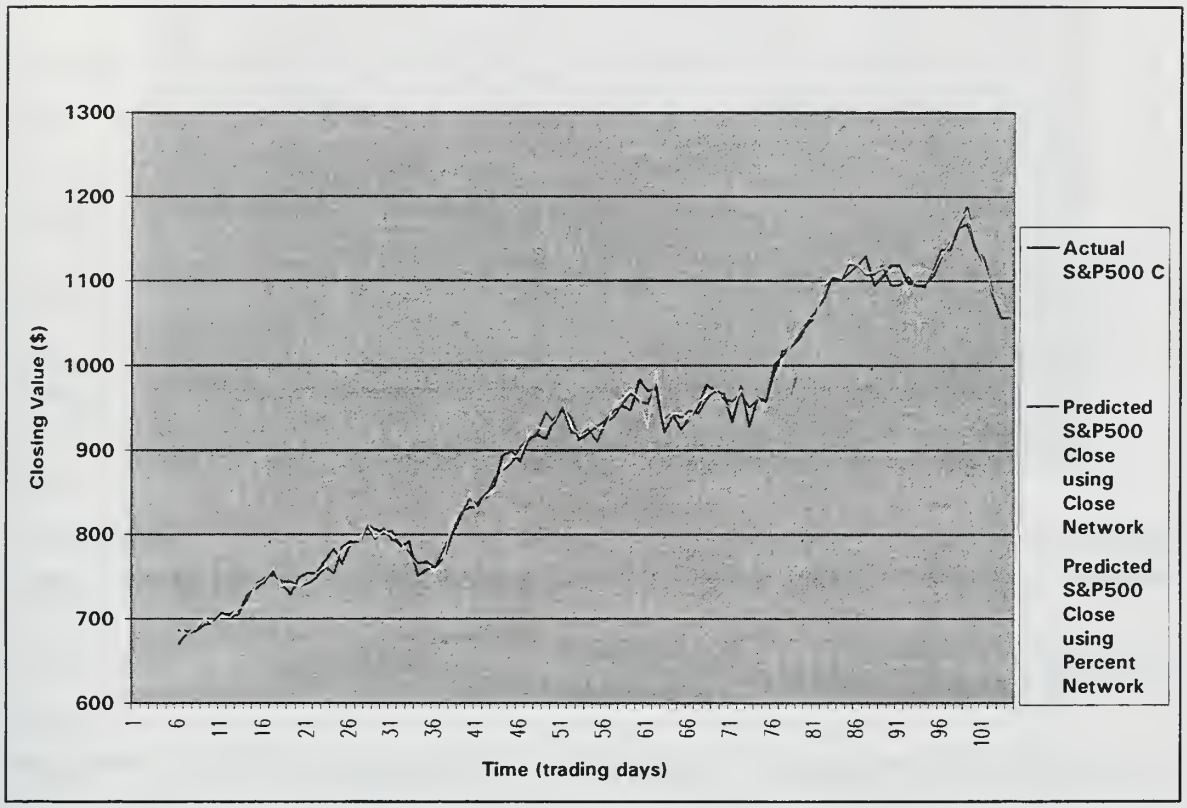


Figure 16. All Network Models Actual vs. Predicted S&P500 C

Figure 17 is a graphical depiction of both the Percent Network and Close Network forecast error.

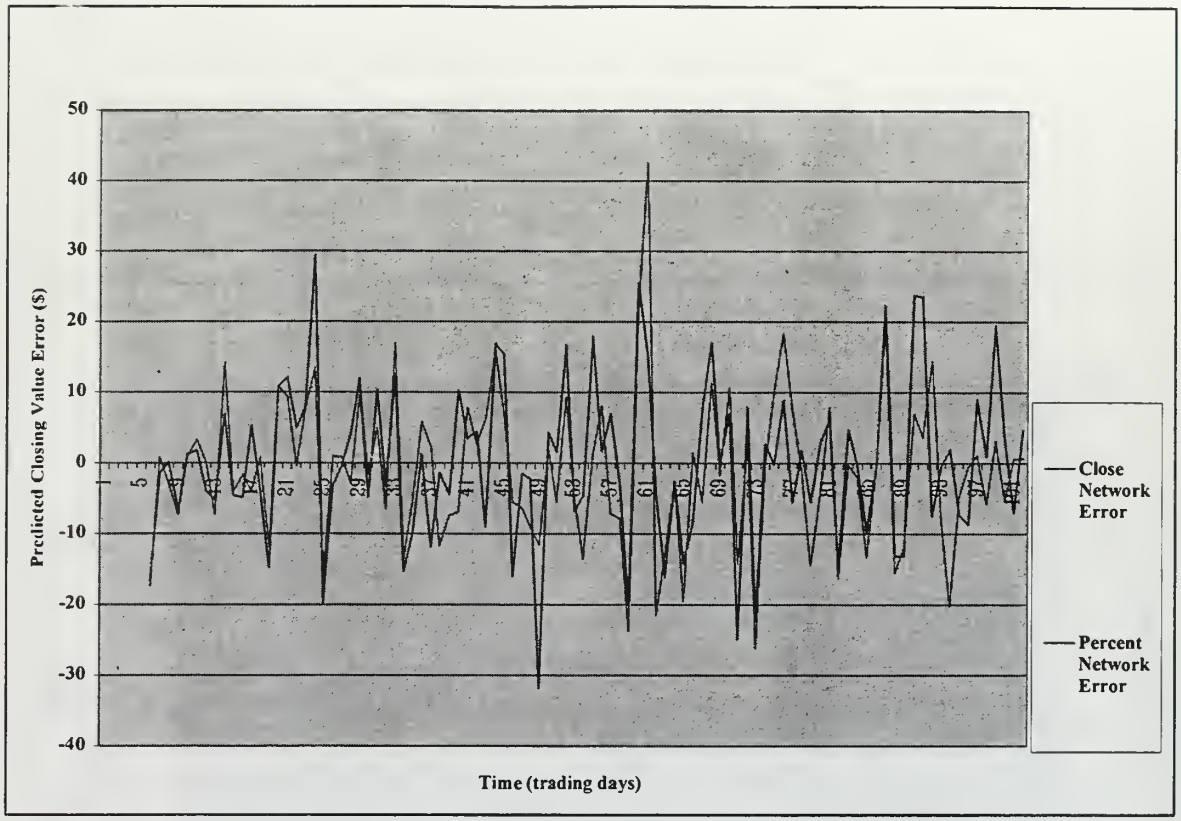


Figure 17. S&P500 Closing Value Prediction Neural Network Model Error Chart

C. MULTIPLE LINEAR REGRESSION MODEL

Multiple linear regression analysis was performed using the Data Analysis tool within Excel. The output of this process for the final model is presented in Table 7.

Table 7. Regression Statistics

Multiple R	0.983432302
R Square	0.967139093
Adjusted R Square	0.96679536
Standard Error	25.81440036
Observations	484

Table 7 (Continued)

ANOVA				
	Df	SS	MS	F
Regression	5	9374786.243	1874957.249	2813.63195
Residual	478	318531.2012	666.3832661	
Total	483	9693317.444		
	Coefficients	Standard Error	t Stat	P-value
Intercept	1523.248565	96.30217982	15.81738407	1.25634E-45
Dow Transportation Index C	0.173215277	0.008063272	21.48200959	3.79263E-72
Dow Utilities Index C	-0.512956407	0.157214185	-3.262787046	0.00118219
Amex Oil Index C	1.455027957	0.117440864	12.38945207	9.13351E-31
CRB C	-5.159128047	0.28529288	-18.08362007	4.48872E-56
Lag(10) of Amex Oil Index C	-0.902950239	0.106686284	-8.463601907	3.19588E-16

Excel was also used to calculate the Variance Inflationary Factor (VIF). The results are given below in Table 8.

Table 8. VIF for Regression Inputs

Dependant Variable	R Square	Variance Inflationary Factor (VIF)
Dow Transportation Index C	0.918384	6.39
Dow Utilities Index C	0.911393	5.90
Amex Oil Index C	0.942674	8.98
CRB C	0.855026	3.72
Lag(10) of Amex Oil Index C	0.936325	8.11

The Normal probability plot, Line Fit Plots, and Residual Plots for the Multiple Regression Model are provided in Appendix A. Figure 18 is a graphical depiction of the Multiple Regression Model's forecast versus the actual S&P500 Close.

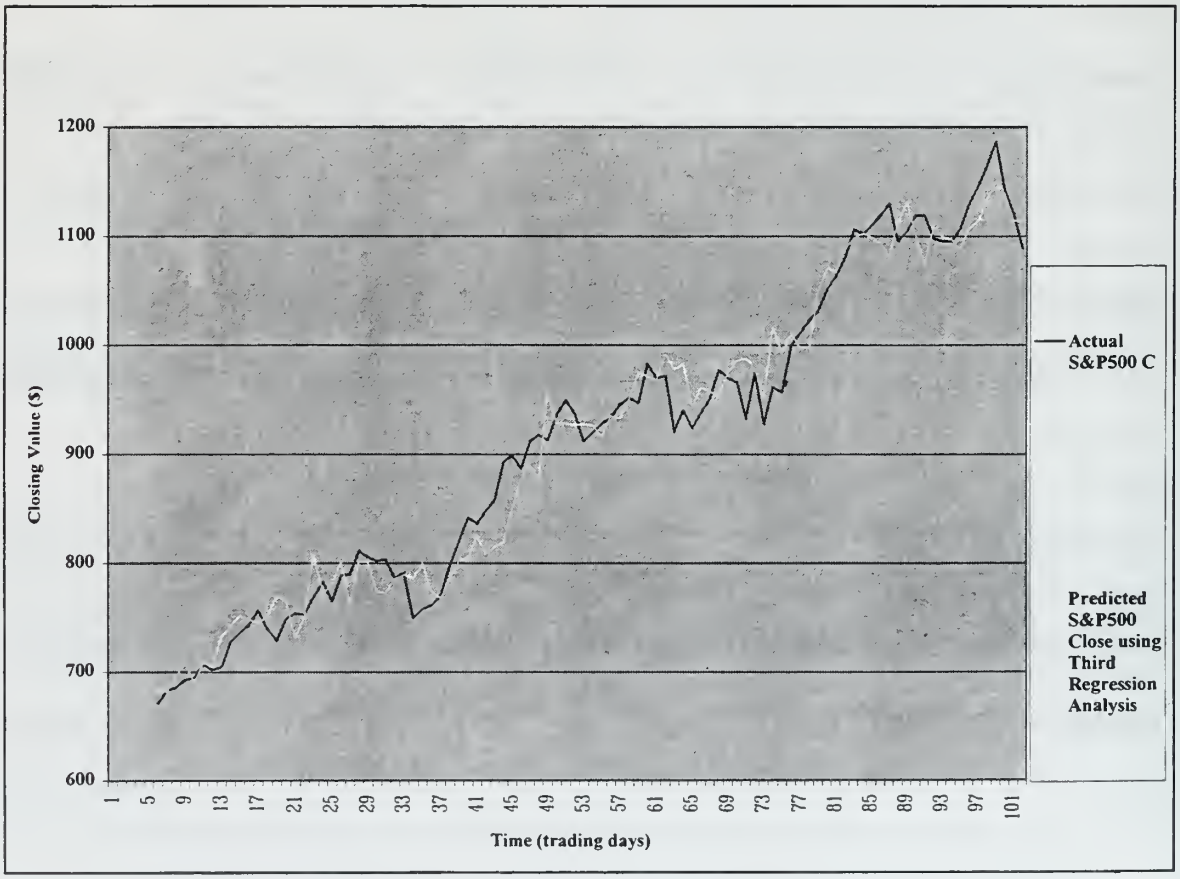


Figure 18. Regression Model Predicted vs. Actual S&P500 Close

Figure 19 is a graphical depiction of the Multiple Regression Model's forecast error.

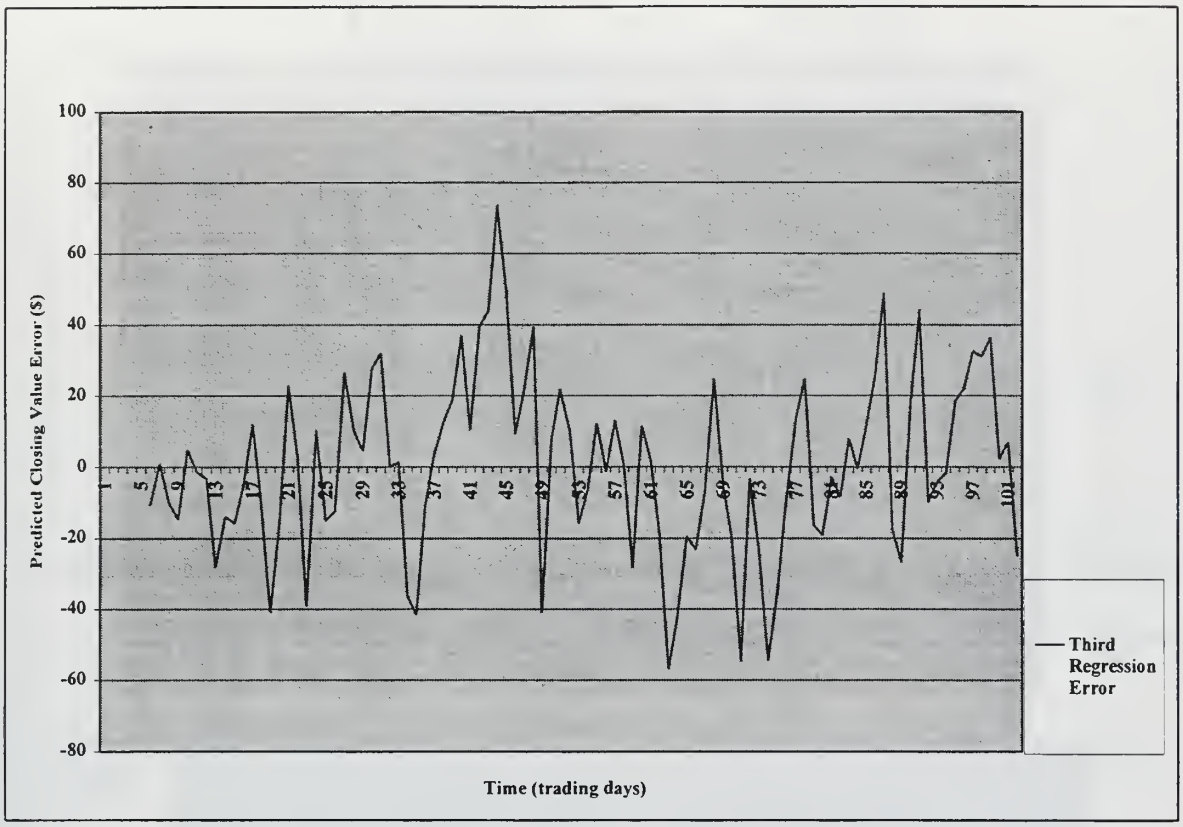


Figure 19. Regression Model Error Chart

The Regression Model error was input into Excel and the Descriptive Statistics tool was used to generate Table 9.

Table 9. Regression Model Descriptive Statistics

Mean	0.291446988
Standard Error	2.533807729
Median	0.001038339
Standard Deviation	24.95511202
Sample Variance	622.7576161

Table 9 (Continued)

Kurtosis	0.138974197
Skewness	0.071861212
Range	130.4937839
Minimum	-56.84815562
Maximum	73.64562832
Sum	28.27035783
Count	97
Confidence Level(95.0%)	5.029572436

Figure 20 is a graphical depiction of all mode forecasts versus the actual S&P500 Close.

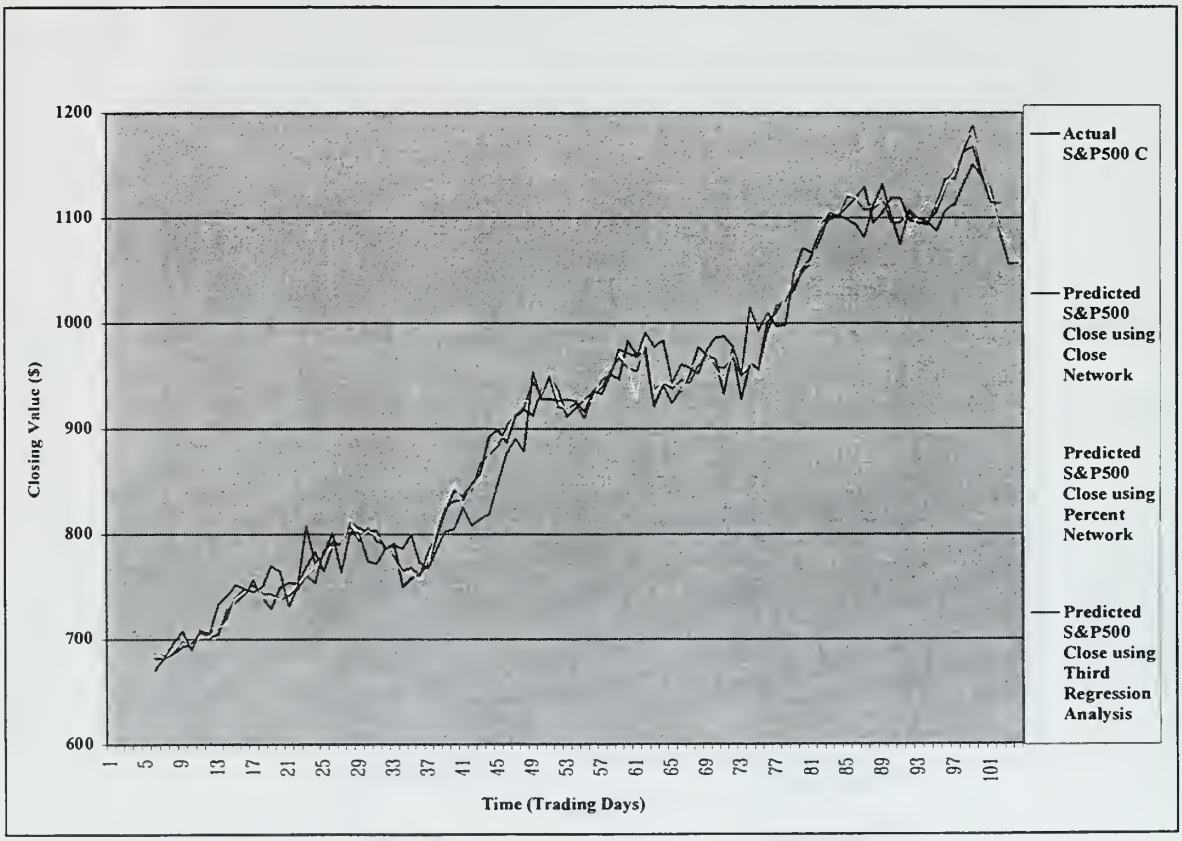


Figure 20. Actual vs. All Model Predictions of S&P500 Close Ten Days Into Future

Figure 21 is a graphical depiction of all models' forecast error.

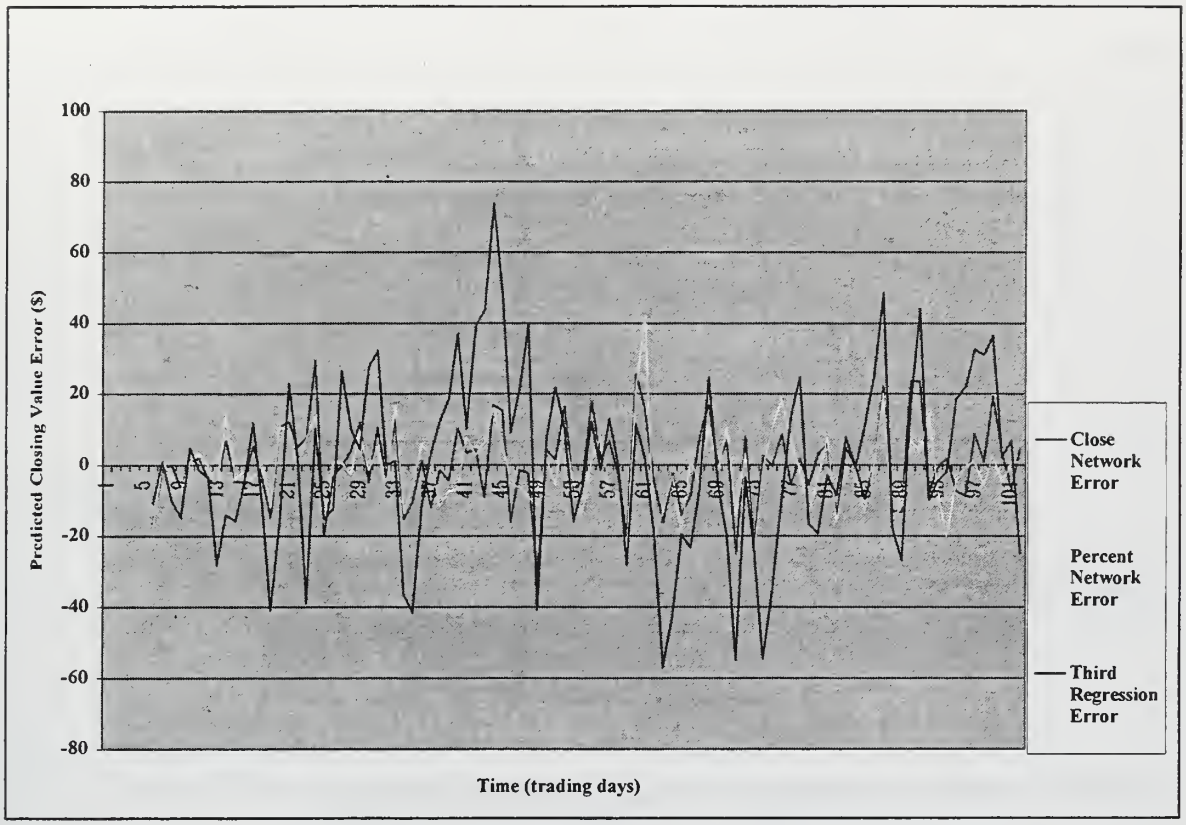


Figure 21. All Model Error Chart

D. CONDITIONAL PROBABILITY

Historical data was calculated for the number of times the market rose and fell during the period from March 3rd, 1991 to August 18th, 1998. The data in Table 10 applies:

Table 10. Historical Market Data

INITIAL KNOWLEDGE	
Total Days the S&P500 Rose	1173
Total Days the S&P500 Fell	696
Total Days	1869

The accuracy of each model was then calculated. The data in Tables 11, 12, and 13 apply:

Table 11. Close Network Accuracy

		Accuracy of Model		
		States of Nature		
		Rise	Fall	Total
Close Network Model	Rise	62	6	68
	Fall	6	23	29
	Total	68	29	97

Table 12. Percent Network Accuracy

		Accuracy of Model		
		States of Nature		
		Rise	Fall	Total
Percent Network Model	Rise	65	3	68
	Fall	5	24	29
	Total	70	27	97

Table 13. Multiple Regression Accuracy

		Accuracy of Model		
		States of Nature		
		Rise	Fall	Total
Multiple Regression Model	Rise	54	14	68
	Fall	15	14	29
	Total	69	28	97

The model accuracy was then adjusted using the environmental data. The data in Tables 14, 15, and 16 apply:

Table 14. Close Network Environmental Adjustment

		Adjustment		
		States of Nature		
		Rise	Fall	Total
Close Network Model	Rise	1069.5	144	1213.5
	Fall	103.5	552	655.5
	Total	1173	696	1869

Table 15. Percent Network Environmental Adjustment

		Adjustment States of Nature		
		Rise	Fall	Total
Percent Network Model	Rise	1089.21	77.3333	1166.54
	Fall	83.7857	618.666	702.452
	Total	1173	696	1869

Table 16. Multiple Regression Environmental Adjustment

		Adjustment States of Nature		
		Rise	Fall	Total
Multiple Regression Model	Rise	918	348	1266
	Fall	255	348	603
	Total	1173	696	1869

Finally the prediction accuracy probability was calculated for each model. The data in Tables 17, 18, and 19 apply.

Table 17. Close Network Accuracy Probability

	Prediction	Probability
Close Network Model	Market Rise	88.1335
	Market Fall	84.21053

Table 18. Percent Network Accuracy Probability

	Prediction	Probability
Percent Network Model	Market Rise	93.37075
	Market Fall	88.0724

Table 19. Multiple Regression Accuracy Probability

	Prediction	Probability
Multiple Regression Model	Market Rise	72.51185
	Market Fall	57.71144

V. DATA ANALYSIS AND INTERPRETATION

Model accuracy can be compared across the three models for the following characteristics:

- Coefficient of Multiple Determination.
- Combined Actual vs. Predicted S&P500 Close Chart.
- Error statistics, specifically the mean and standard deviation.
- All Model Error Chart.
- Conditional Probabilities.

Table 20 compares the ranked Coefficients of Multiple Determination for each model:

Table 20. Coefficients of Multiple Determination

Model	R square
Close Network	.9935
Regression Model	.9671
Percent Network	.7872

The R square value represents the proportion of variation in the dependant variable that is explained by the independent variables. The better the model explains variation in the dependant variable, the higher the R square value. Without further comparison, the Close Network best explains variation in the dependant variable, followed by the Regression Model.

In examining Figure 20, Actual vs. All Model Predictions of S&P500 Close Ten Days into the Future, it is relatively easy to visually verify that the two network models perform better than the regression model. This differs from the model ranking due to R square values. Both network models predict the closing value relatively accurately. However, it is difficult visually to determine which of these is more accurate.

In Table 21, the ranked error statistics are provided for comparison. These statistics are all based on closing price error. The Percent Network error was converted to closing price error, so it could be compared to the other two models.

Table 21. Model Error Statistics

Model	Mean	Standard Deviation
Percent Network	-1.08	10.9
Close Network	.1759	11.50
Regression Model	.2914	24.95

Ideally, the mean error would be zero and the standard deviation would be as small as possible. All of the models' means are relatively close to zero. However, the breakout occurs with standard deviation. Generally it can be said that there is a 95.44 percent probability of the error values falling within two standard deviations of the mean. Therefore, the larger the standard deviation the greater the range of error. Although it has a lower coefficient of determination, the Percent Network is more accurate. This tends to support the theory that predicting a percent change is more accurate than predicting the closing value.

Visually examining Figure 21, All Model Error Chart, clearly shows the Regression Model has the greatest error variation. Differentiation between the two network models is difficult, suggesting that the error statistics should provide the true ranking.

The final ranking test is the conditional accuracy probabilities for each model. Table 22 summarizes and ranks these probabilities for easy comparison.

Table 22. Conditional Probabilities

	Probability of Accurately Predicting	
Model	Market Rise	Market Fall
Percent Network	93.37	88.07
Close Network	88.13	84.21
Regression Model	72.5	57.71

Clearly, the prediction probabilities support the error statistics rankings and verify that the Percent Network is the most accurate predictor of the S&P500 closing price.

VI. CONCLUSIONS AND RECOMMENDATIONS

A. CONCLUSIONS

It is clear from the model accuracy probabilities that neural networks can accurately predict financial markets if given the proper data upon which to train. When compared to regression analysis, neural networks are a better tool for the investor for the following reasons:

- When using multiple linear regression, the governing regression assumptions must be true. The linearity assumption itself may not hold in many cases. Neural networks can model both linear and curvilinear systems.
- When using multiple linear regression analysis, the investor must have a deep understanding of statistics to ensure only the necessary independent variables are used. This is true only to a limited degree with neural networks and can be mitigated by the systematic removal method described by Jurik in *Virtual Trading*.
- For the models studied in this research, neural networks are significantly more accurate than multiple linear regression analysis.

However, the difficulty in identifying good raw data, preprocessing this data, training a network and repeating this process until a good model is developed should not be discounted. The individual investor should be warned that model accuracy is difficult to obtain and can take months or years of investigation.

B. RECOMMENDATIONS

For individual investors to successfully use neural networks to predict financial markets, they must undertake the following:

- As a minimum, read a basic text on neural networks to understand neural network theory and its limitations.
- Understand basic statistical measures and probability.
- Become extremely proficient with a spreadsheet software program so that data can be preprocessed efficiently.
- Study financial market theory so that input data to the neural net is not chosen inappropriately or at random.
- Obtain a neural network software program and test and evaluate many neural networks. Practice by varying inputs and studying the effects on outputs.
- Once a network is developed, do not blindly follow its advice. As Gately (1996) states, try to verify it with other indicators before taking action. In other words use multiple indicators. This could include using multiple networks incorporating different inputs to predict the same output.

Only by meticulously following these recommendations will individual investors improve their potential profits by using neural networks.

Although outside the scope of this research, an important question for any forecasting model is how does the model stand up in an actual trading scenario? Each of these models should be historically tested as if being used for actual trading. Given the same initial capital investment, what is the return for each of these models? What is the maximum drawdown or capital loss for each of these models? If a model has a high return is it due to many steady small gains or is it due to one huge gain surrounded by many losses? These issues revolve around profit and not model accuracy. This raises the question of whether it is important to design a network and train it to maximize profit vs.

forecasting accuracy? These are all critical questions that take the forecasting model from academic research into the actual world of trading.

THIRD REGRESSION SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.983432302
R Square	0.967139093
Adjusted R Square	0.96679536
Standard Error	25.81440036
Observations	484

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	5	9374786.243	1874957.249	2813.63195	0
Residual	478	318531.2012	666.3832661		
Total	483	9693317.444			

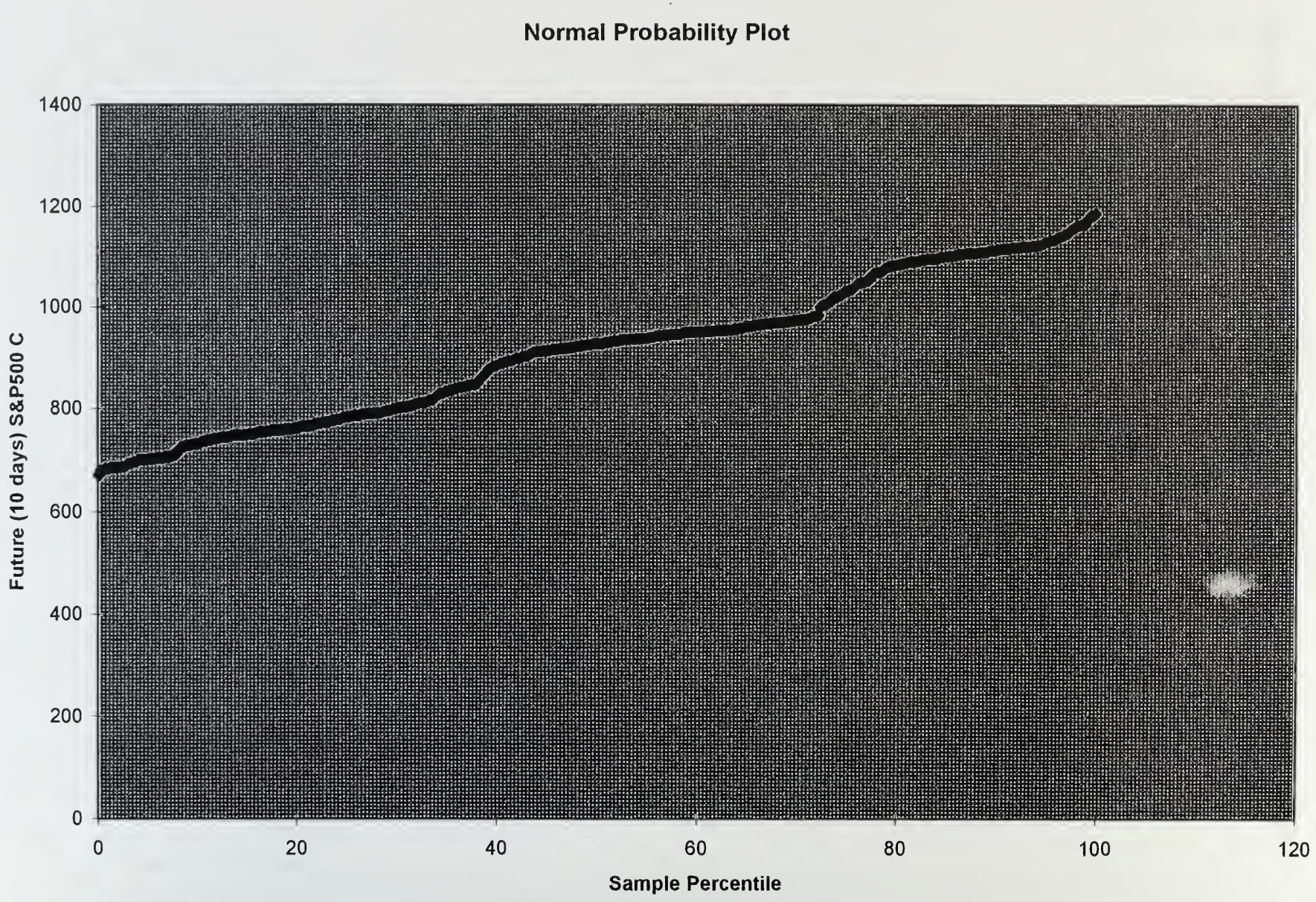
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1523.248565	96.30217982	15.81738407	1.25634E-45	1334.020505	1712.476625	1334.020505	1712.476625
Dow Transportation Index C	0.173215277	0.008063272	21.48200959	3.79263E-72	0.157371428	0.189059127	0.157371428	0.189059127
Dow Utilities Index C	-0.512956407	0.157214185	-3.262787046	0.00118219	-0.821872937	-0.204039877	-0.821872937	-0.204039877
Amex Oil Index C	1.455027957	0.117440864	12.38945207	9.13351E-31	1.224263639	1.685792274	1.224263639	1.685792274
CRB C	-5.159128047	0.28529288	-18.08362007	4.48872E-56	-5.7197116	-4.598544494	-5.7197116	-4.598544494
Lag(10) of Amex Oil Index C	-0.902950239	0.106686284	-8.463601907	3.19588E-16	-1.112582446	-0.693318031	-1.112582446	-0.693318031

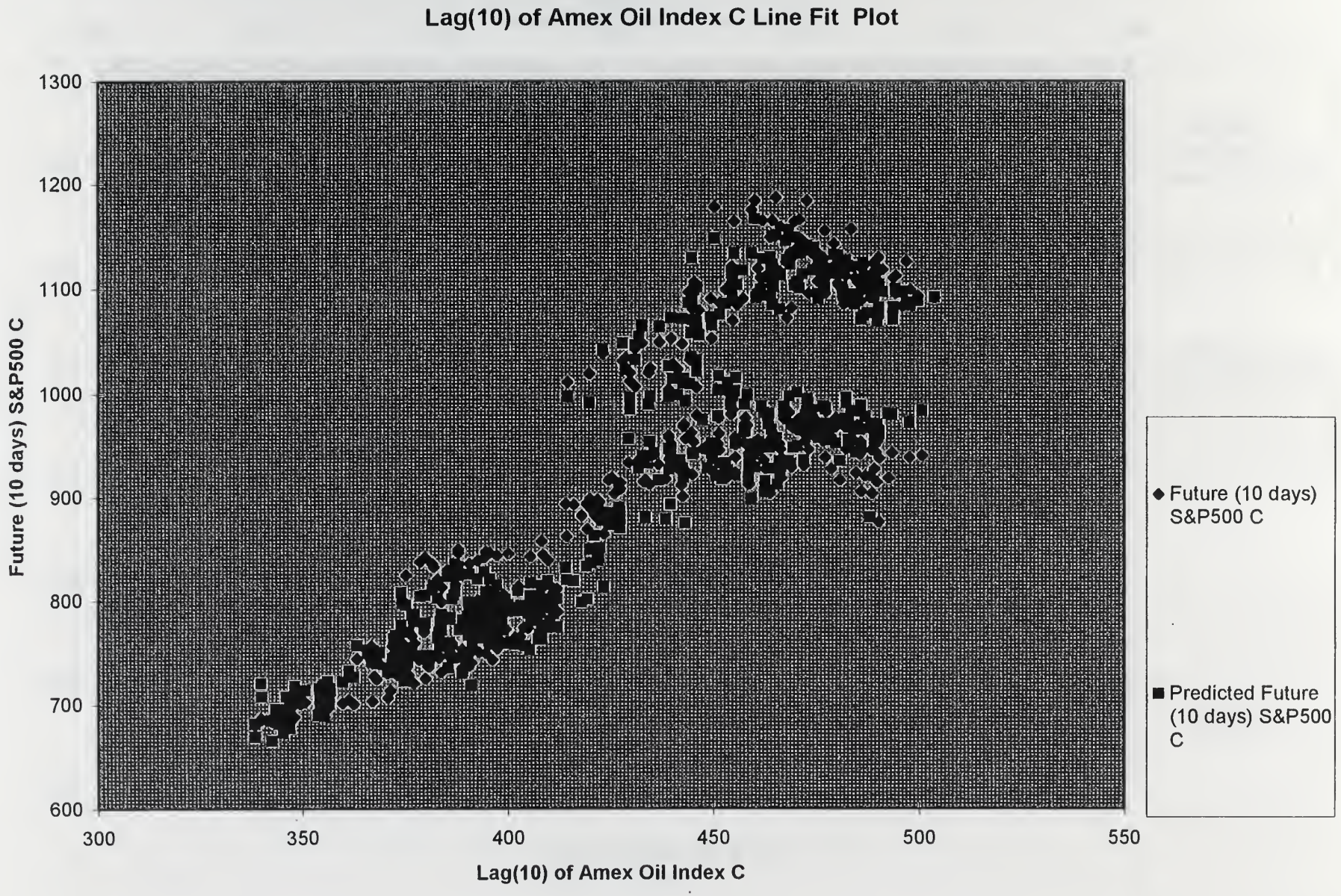
RESIDUAL OUTPUT

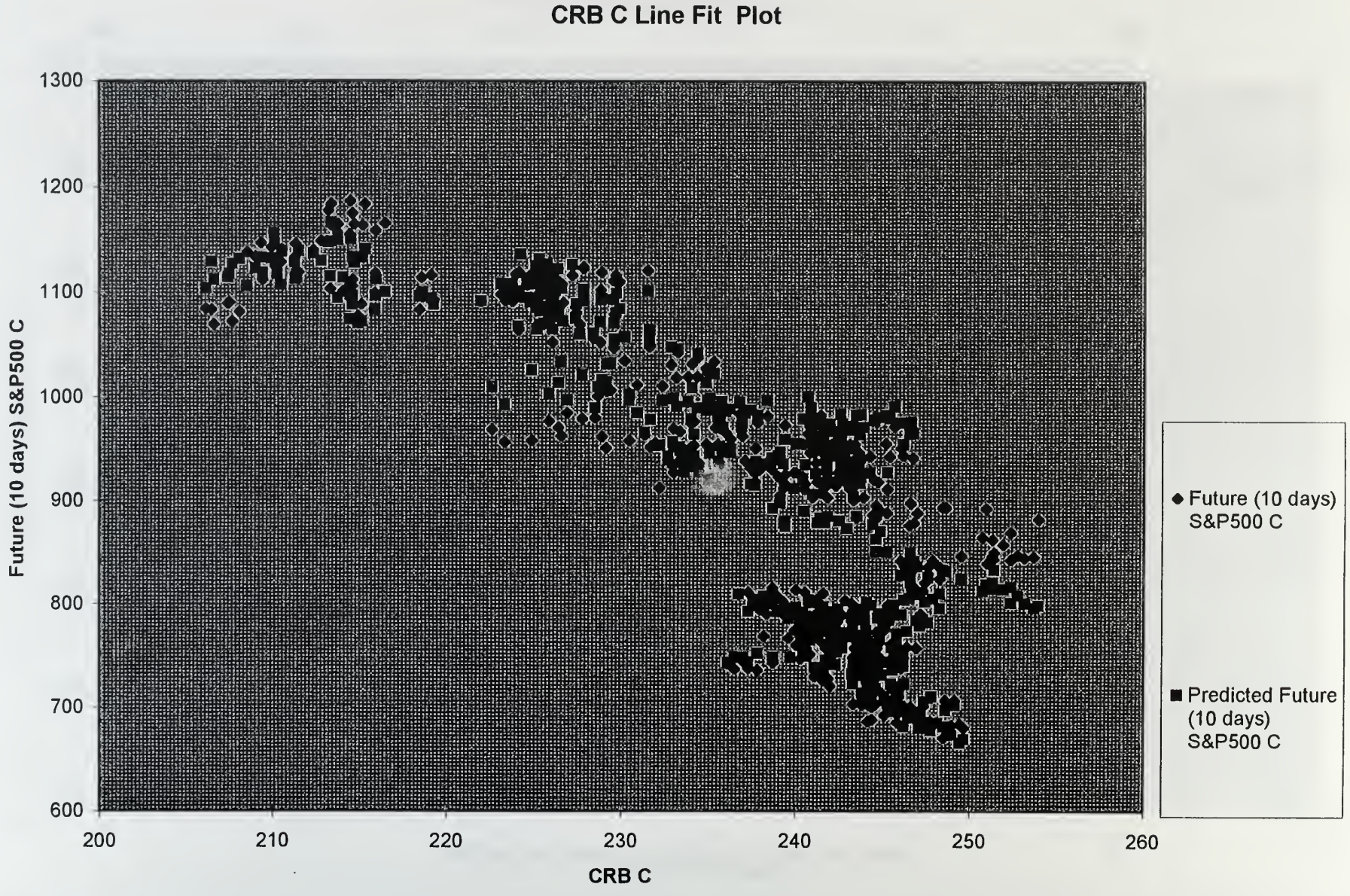
Observation	*Predicted Future (10 days) S&P500 C*	*Residuals*	*Standard Residuals*
1	681.823017	-10.82301703	-0.421449864
2	669.8340231	11.16597689	0.43480477
3	665.77933	18.22066998	0.70951555
4	673.7919767	9.208023315	0.358561772
5	680.5835598	0.416440197	0.016216242
6	682.0541838	0.945816229	0.036830222
7	678.2899603	8.710039653	0.339170216
8	686.0147662	-0.014766183	-0.000574997
9	684.9169039	1.083096139	0.042175922
10	695.8797107	-9.879710731	-0.384717378
11	696.0823088	-10.08230885	-0.392606579
12	708.112211	-22.11221097	-0.861052724
13	721.0778502	-34.07785017	-1.326996462
14	706.9560834	-17.95608336	-0.699212508
15	700.3146103	-6.314610297	-0.245891847
16	707.8388262	-14.83882624	-0.577826061

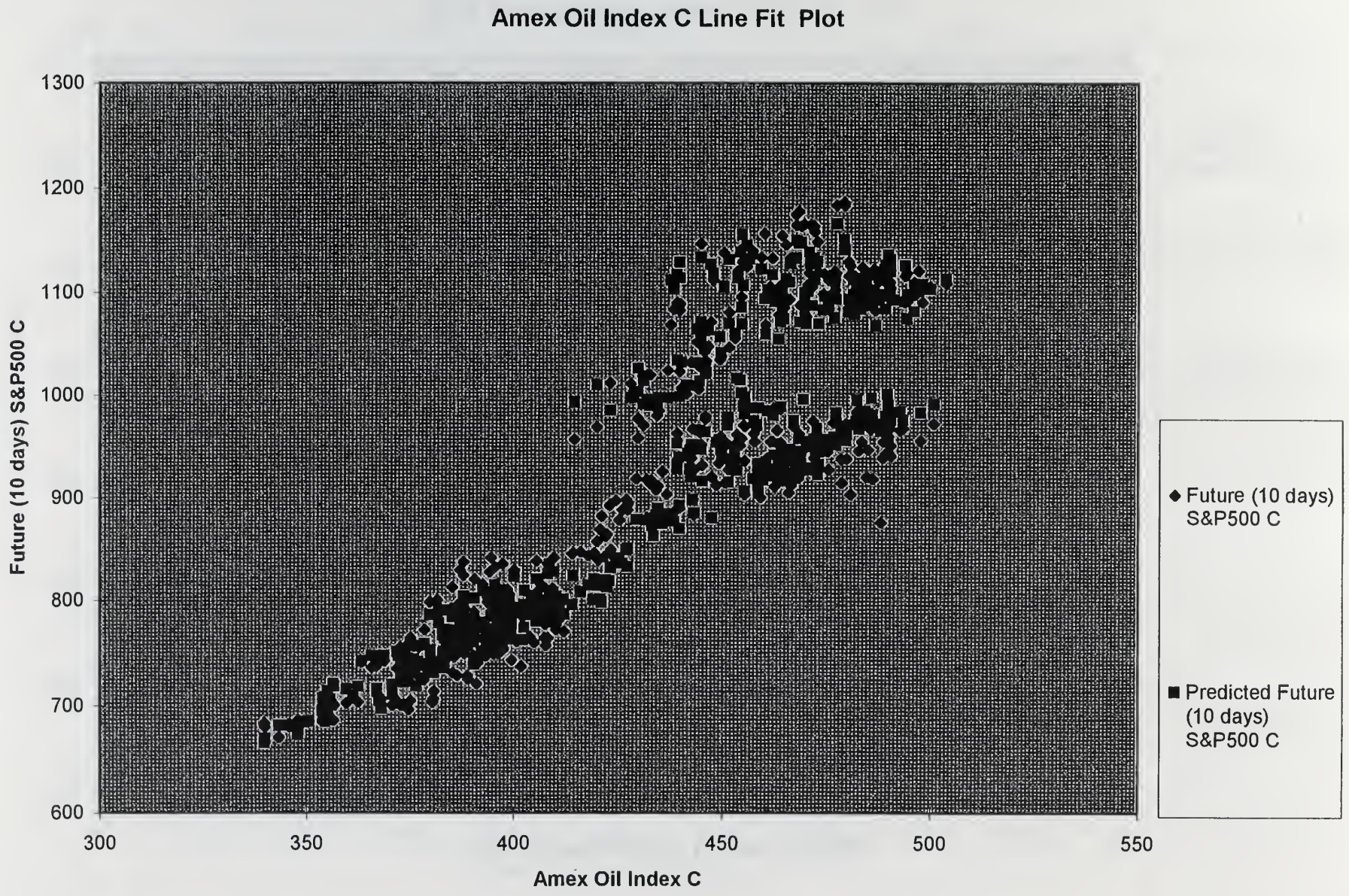
PROBABILITY OUTPUT

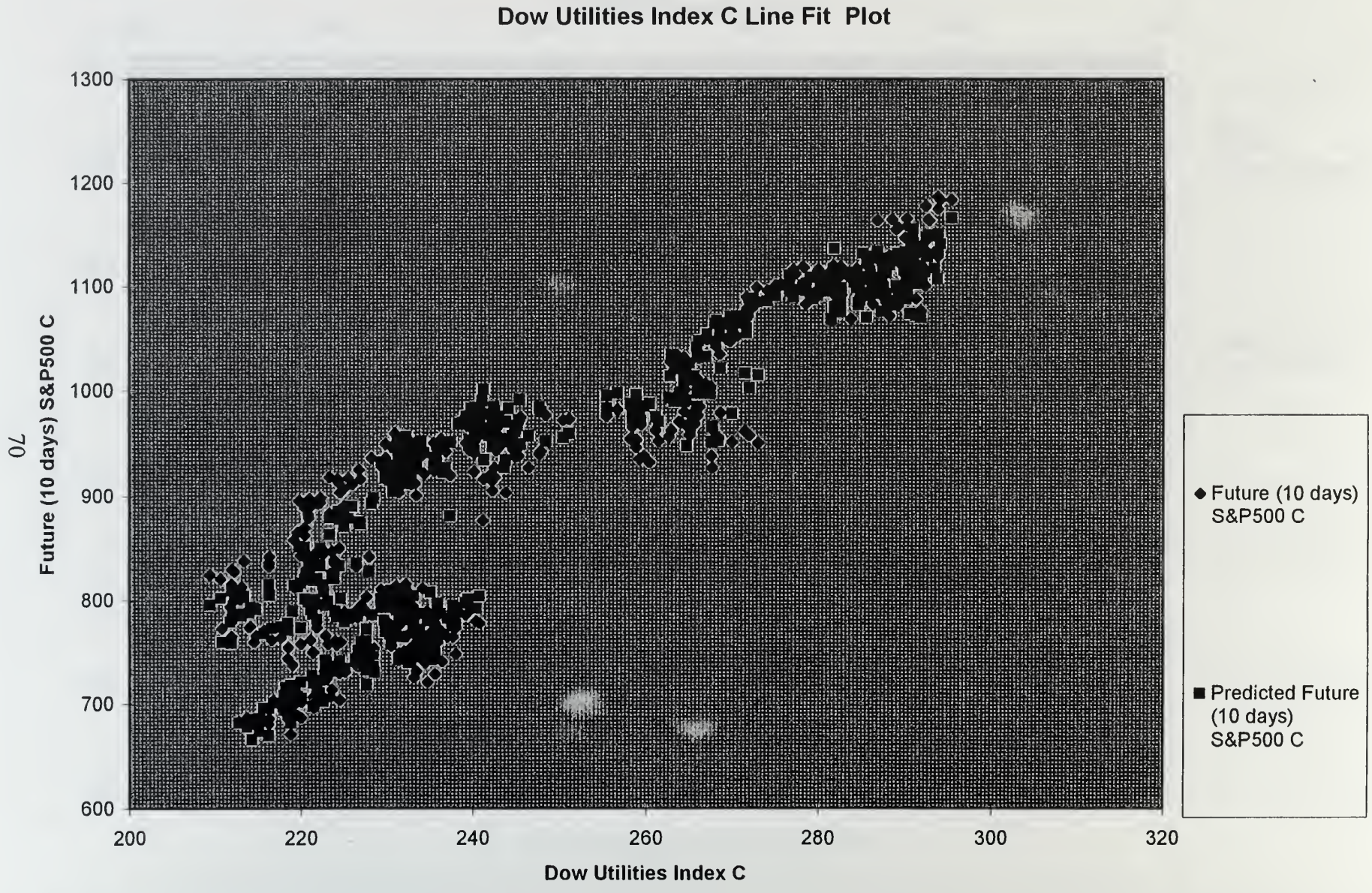
Percentile	*Future (10 days) S&P500 C*
0.103305785	671
0.309917355	681
0.516528926	681
0.723140496	683
0.929752066	683
1.136363636	684
1.342975207	686
1.549586777	686
1.756198347	686
1.962809917	686
2.169421488	686
2.376033058	687
2.582644628	687
2.789256198	689
2.995867769	693
3.202479339	694

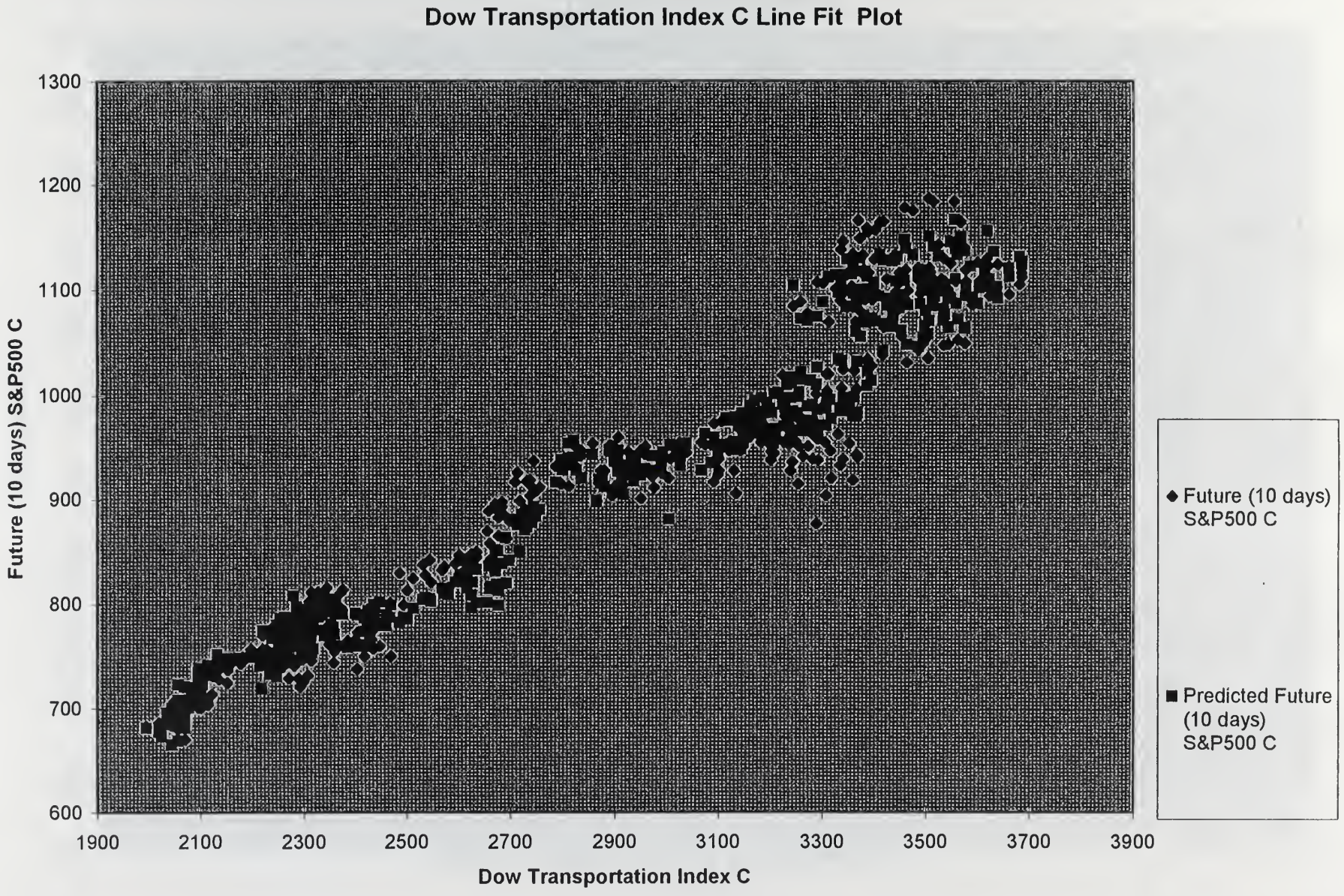

Normal Probability Plot
Future (10 days) S&P500 C
1400
1200
1000
800
600
400
200
0
0
20
40
60
80
100
120
Sample Percentile

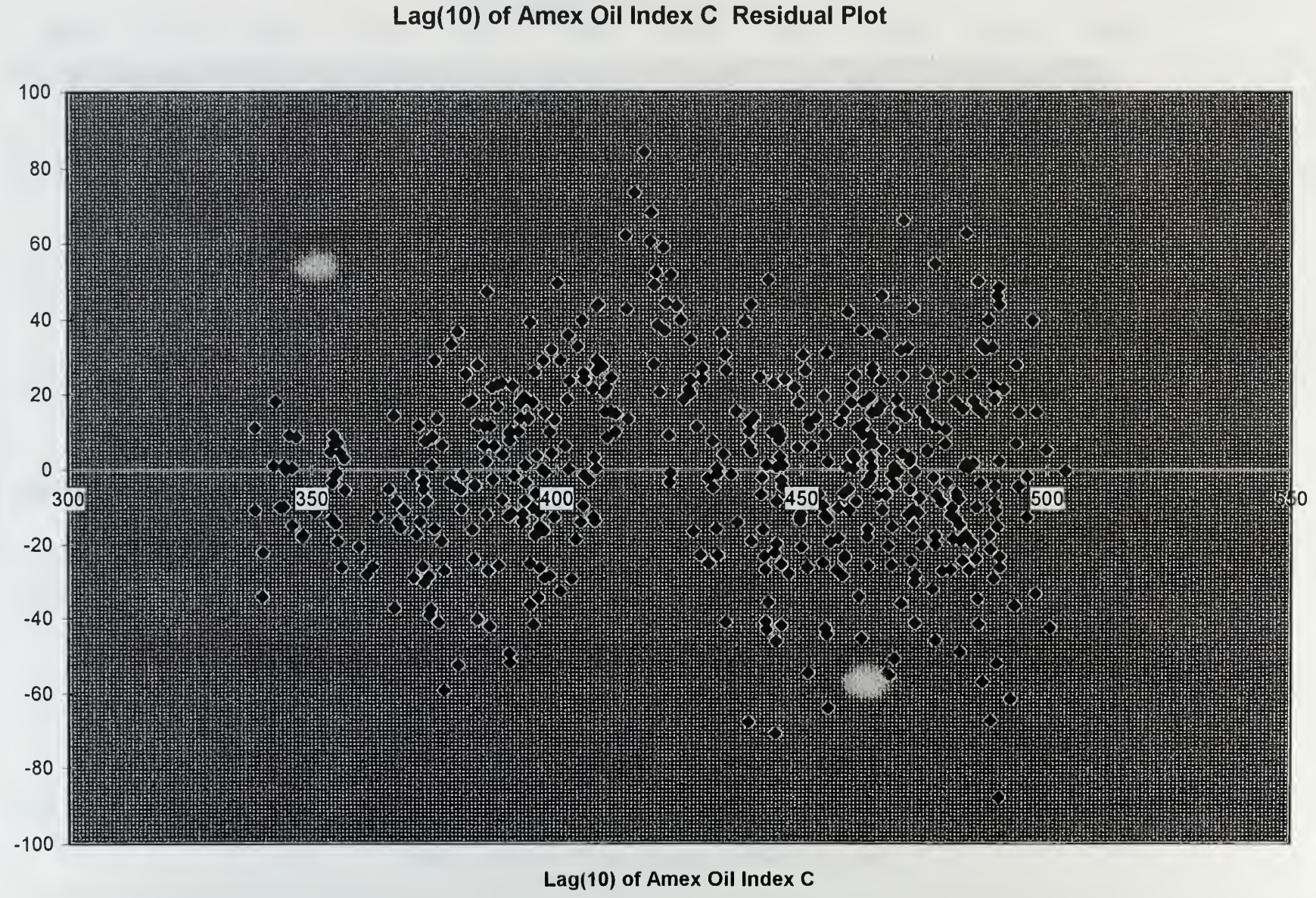

Lag(10) of Amex Oil Index C Line Fit Plot
Future (10 days) S&P500 C
1300
1200
1100
1000
900
800
700
600
300
350
400
450
500
550
Lag(10) of Amex Oil Index C
Future (10 days) S&P500 C
Predicted Future (10 days) S&P500 C

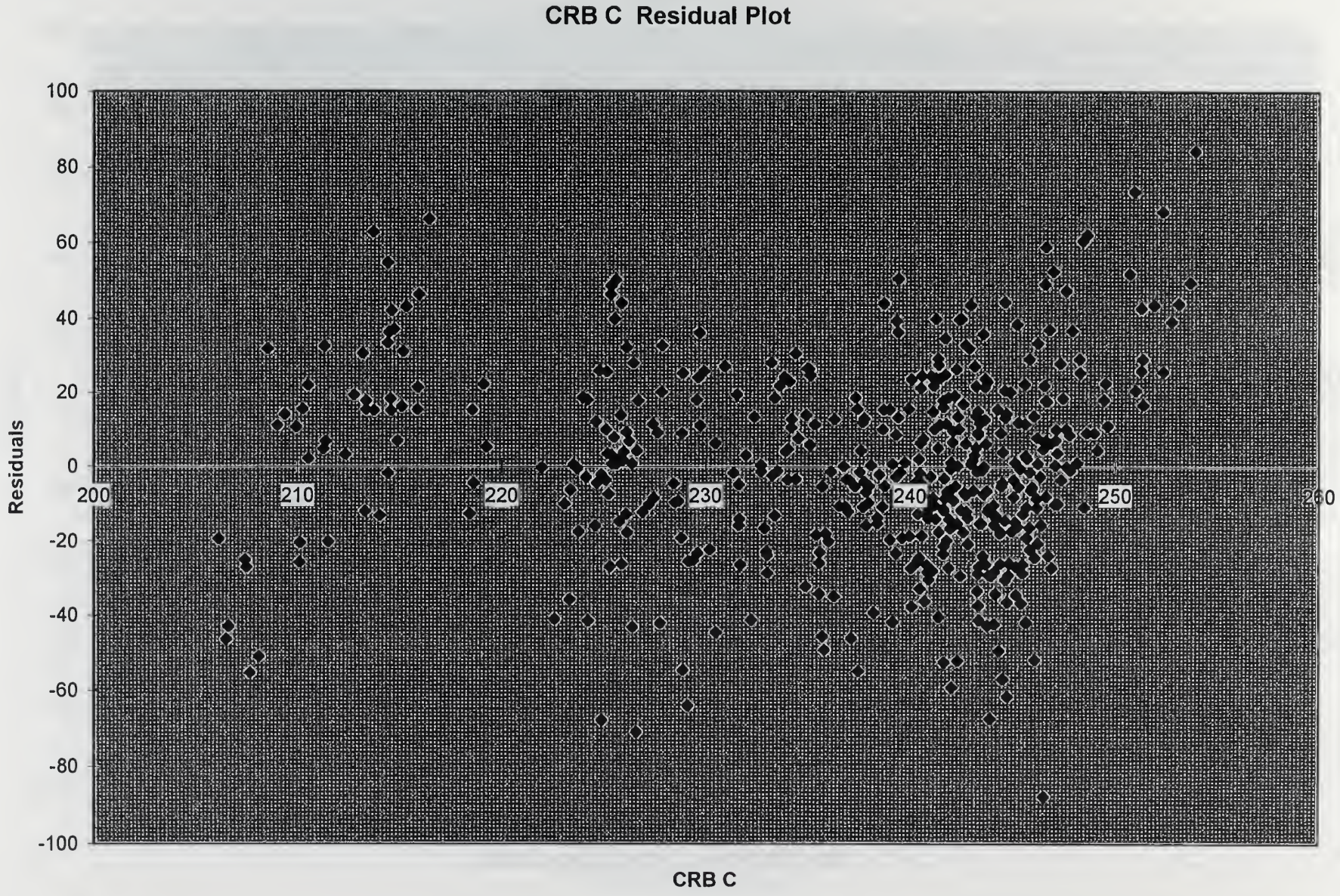

CRB C Line Fit Plot
1300
1200
1100
1000
900
800
700
600
Future (10 days) S&P500 C
200
210
220
230
240
250
260
CRB C
Future (10 days) S&P500 C
Predicted Future (10 days) S&P500 C

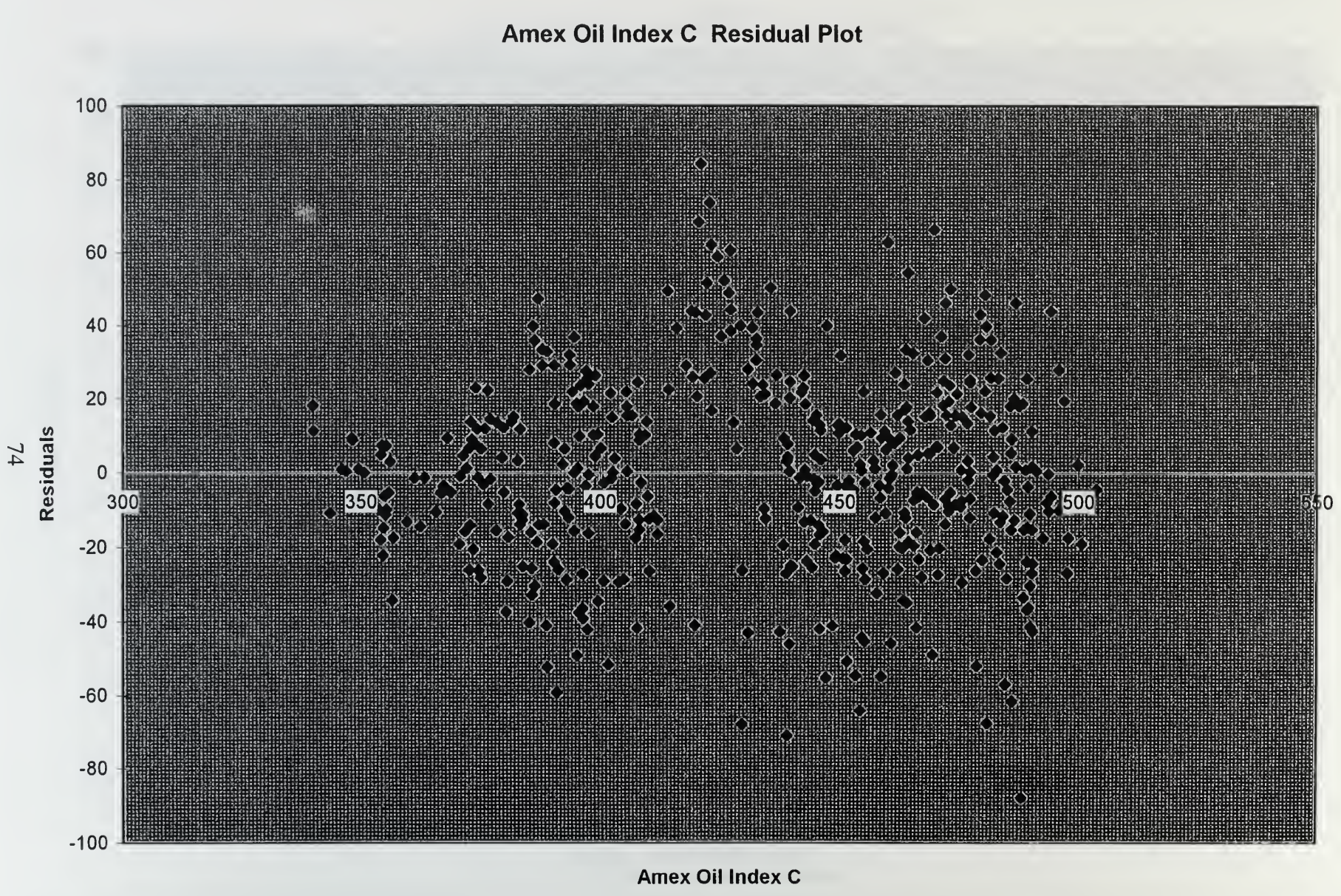

Amex Oil Index C Line Fit Plot
Future (10 days) S&P500 C
1300
1200
1100
1000
900
800
700
600
300
350
400
450
500
550
Amex Oil Index C
Future (10 days) S&P500 C
Predicted Future (10 days) S&P500 C

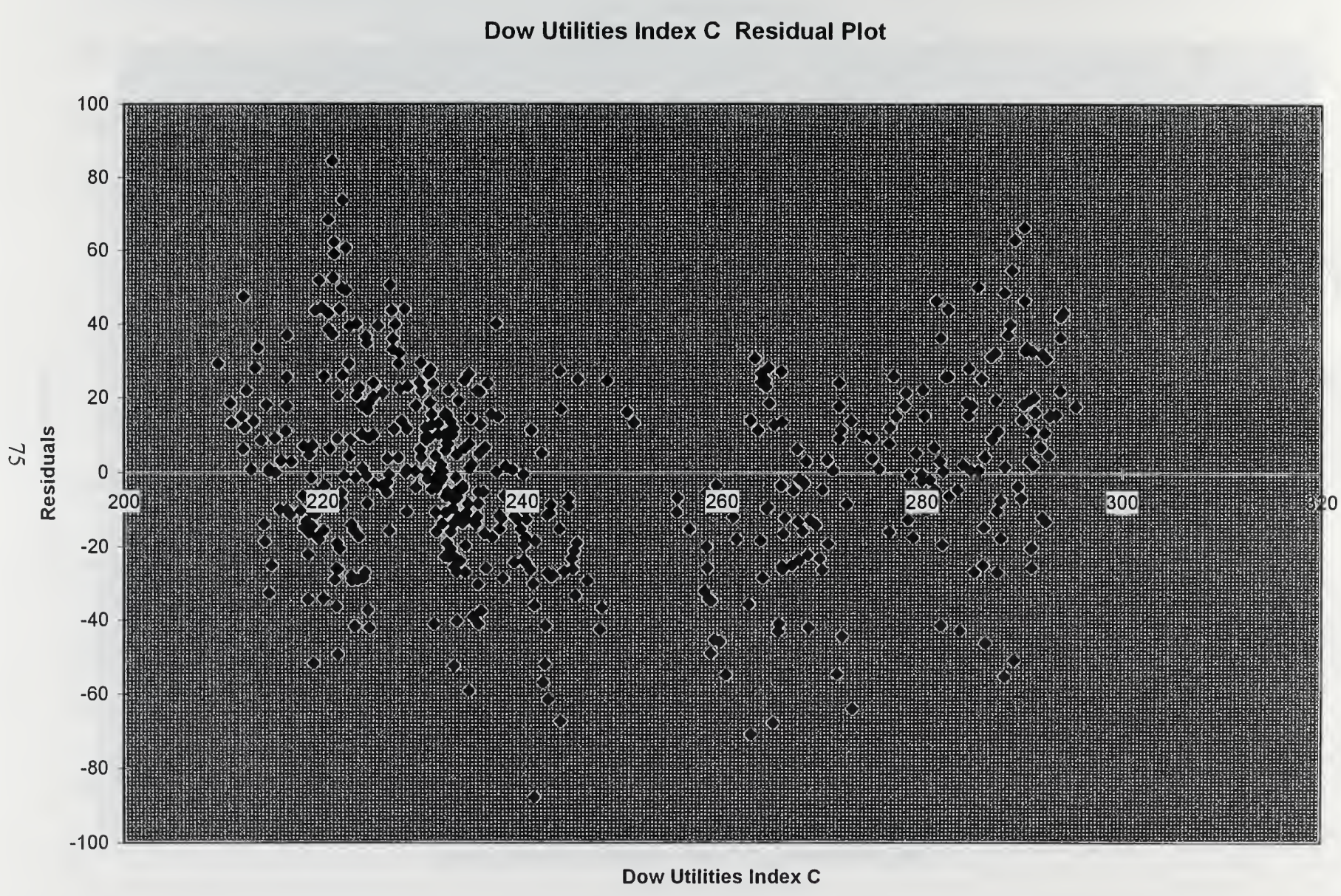

Dow Utilities Index C Line Fit Plot
Future (10 days) S&P500 C
1300
1200
1100
1000
900
800
700
600
200
220
240
260
280
300
320
Dow Utilities Index C
Future (10 days) S&P500 C
Predicted Future (10 days) S&P500 C

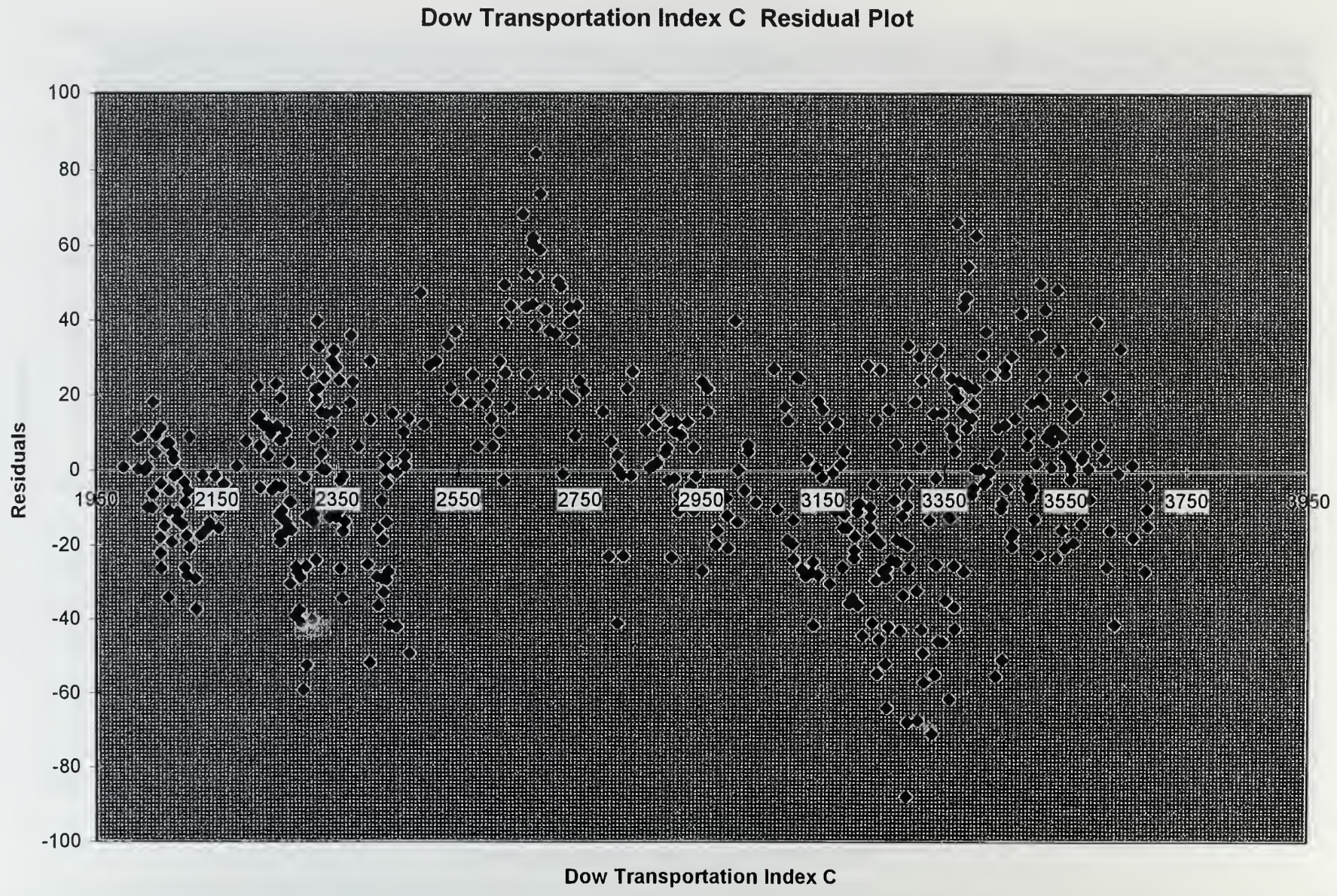

Dow Transportation Index C Line Fit Plot
Future (10 days) S&P500 C
1300
1200
1100
1000
900
800
700
600
1900
2100
2300
2500
2700
2900
3100
3300
3500
3700
3900
Dow Transportation Index C
◆ Future (10 days) S&P500 C
■ Predicted Future (10 days) S&P500 C

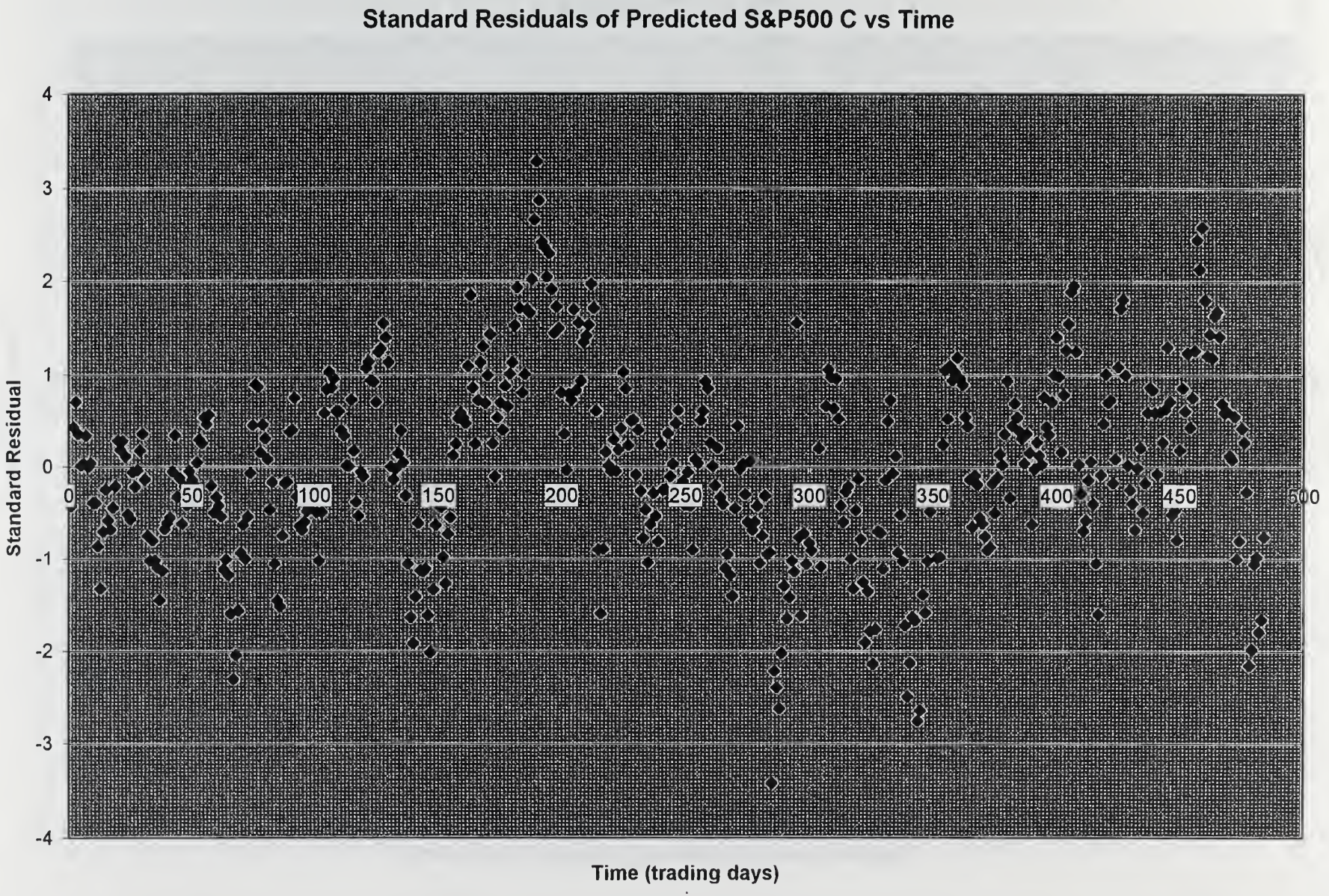

Lag(10) of Amex Oil Index C Residual Plot
100
80
60
40
20
0
-20
-40
-60
-80
-100
Residuals
300
350
400
450
500
550
Lag(10) of Amex Oil Index C


CRB C Residual Plot
100
80
60
40
20
0
-20
-40
-60
-80
-100
Residuals
200
210
220
230
240
250
260
CRB C

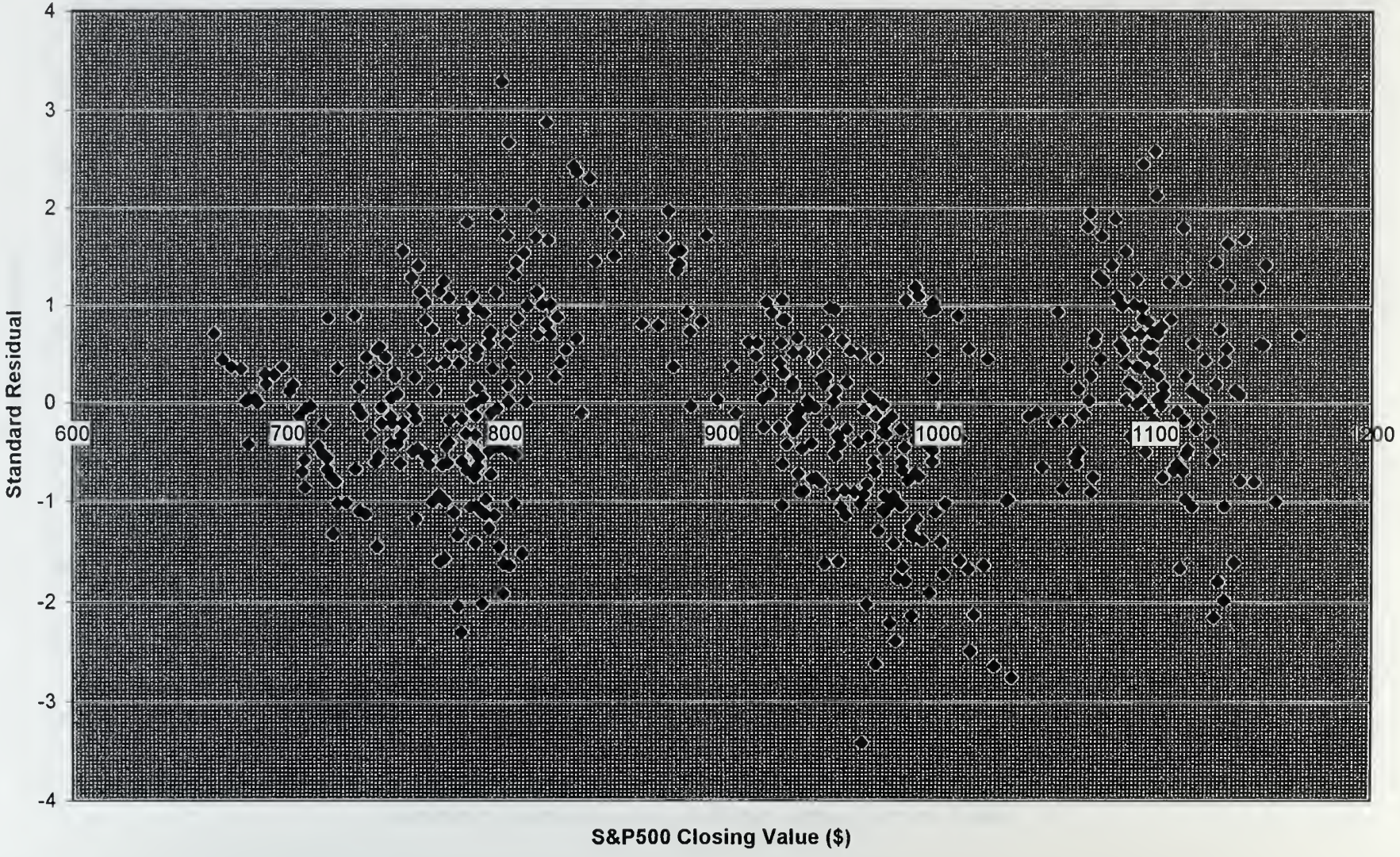

Amex Oil Index C Residual Plot
100
80
60
40
20
0
-20
-40
-60
-80
-100
Residuals
300
350
400
450
500
550
Amex Oil Index C


Dow Utilities Index C Residual Plot
100
80
60
40
20
0
-20
-40
-60
-80
-100
200
220
240
260
280
300
320
Residuals
Dow Utilities Index C


Dow Transportation Index C Residual Plot
100
80
60
40
20
0
-20
-40
-60
-80
-100
Residuals
1950
2150
2350
2550
2750
2950
3150
3350
3550
3750
3950
Dow Transportation Index C


Standard Residuals of Predicted S&P500 C vs Time
Standard Residual
4
3
2
1
0
-1
-2
-3
-4
0
50
100
150
200
250
300
350
400
450
500
Time (trading days)

Predicted S&P500 C Standard Residual Plot



APPENDIX B. PARTIAL LISTING OF RAW AND PREPROCESSED INPUT DATA

Raw Data

Date	S&P500 H	S&P500 L	S&P500 C	Dow Transportation Index C	Dow Utilities Index C	Amex Oil Index C	CRB C	Dow Industrial Index V	Gold and Silver Mining C
3/1/91	370.468	363.729	370.468	1150.739	213.339	252.5	217.94	272472	86.86
3/4/91	371.989	369.07	369.33	1142.449	212.02	250.34	219.69	214533	89.35
3/5/91	377.887	369.33	376.718	1166.26	213.85	253.58	220.82	283650	87.93
3/6/91	379.657	375.02	376.167	1151.62	211.639	253.97	220.809	312750	87.86
3/7/91	377.479	375.58	375.91	1141.57	211.139	254.62	220.91	212886	86.94
3/8/91	378.687	374.427	374.947	1125.179	210.449	254.4	221.839	243278	90.83
3/11/91	375.1	372.52	372.958	1119.36	211.639	251.78	218.99	165280	89.4
3/12/91	374.35	369.55	370.03	1112.479	212.649	251.99	219.949	182985	89.26
3/13/91	374.647	370.03	374.57	1111.419	213.22	253.9	220.77	190201	90.3
3/14/91	378.28	371.76	373.5	1107.37	211.77	251.82	219.88	250042	88.24
3/15/91	374.58	370.208	373.59	1098.729	212.46	251.64	217.929	383815	88.23
3/18/91	374.09	369.458	372.11	1099.79	211.71	248.33	217.52	170371	85.87
3/19/91	372.11	366.54	366.59	1084.8	211.08	249.34	218.72	252888	86.28
3/20/91	368.85	365.8	367.917	1087.449	212.02	250.38	218.639	257186	85.78
3/21/91	371.01	366.51	366.58	1084.8	212.02	250.13	219.86	237244	85.93
3/22/91	368.218	365.58	367.479	1075.459	213.85	250.85	219.779	174325	85.52
3/25/91	371.31	367.458	369.83	1075.28	216.36	250.59	217.809	167894	84.15
3/26/91	376.3	369.37	376.3	1102.79	218.119	251.13	217.279	256327	83.3
3/27/91	378.479	374.729	375.35	1117.949	216.55	248.11	217.339	252850	83.43
3/28/91	376.6	374.397	375.218	1109.489	217.179	246.68	218.47	178992	84.29
4/1/91	375.218	370.27	371.3	1101.55	213.91	244.92	221.619	162162	86.18
4/2/91	379.5	371.3	379.5	1115.479	216.74	248.15	222.199	210661	86.73
4/3/91	381.56	378.489	378.937	1116.179	216.3	246.25	221.49	206521	87.46
4/4/91	381.877	377.05	379.77	1121.649	216.11	244.49	220.72	221632	86.64
4/5/91	381.12	374.147	375.36	1114.949	215.1	242.04	220.449	201704	85.31
4/8/91	378.76	374.687	378.657	1123.239	216.169	244.31	221.509	139629	87.07
4/9/91	379.02	373.11	373.56	1111.6	214.47	243.34	220.85	173841	88.65
4/10/91	374.83	371.208	373.147	1113.889	214.979	244.16	221.139	170128	87.62
4/11/91	379.53	373.147	377.627	1121.12	217.3	249.23	220.66	239427	85.73
4/12/91	381.07	376.887	380.397	1128.879	218.179	253.86	220.71	229422	84.81
4/15/91	382.32	378.78	381.187	1123.239	218.809	256.49	220.58	218905	83.43
4/16/91	387.62	379.637	387.62	1143.51	220.889	258.68	220.57	257896	83.06
4/17/91	391.26	387.3	390.447	1166.26	219.759	259.86	220.16	327501	83.99
4/18/91	390.968	388.127	388.458	1178.07	216.3	258.39	218.039	252516	81.64
4/19/91	388.458	383.897	384.197	1172.07	212.649	256.63	217.72	237757	80.82
4/22/91	384.187	380.157	380.947	1151.62	210.949	254.98	217.789	211280	83.35
4/23/91	383.55	379.667	381.76	1157.09	209.509	257.71	217.949	185519	82.87
4/24/91	383.02	379.989	382.76	1171.02	210.389	258.43	218.139	202077	82.17
4/25/91	382.887	378.427	379.25	1170.129	209.38	255.26	217.72	174769	79.8
4/26/91	380.11	376.77	379.02	1166.08	209.82	255.12	217.74	173306	79.74
4/29/91	380.958	373.657	373.657	1148.8	208.309	253.47	216.149	163819	78.17

Preprocessed Data

Date	S&P500 H	S&P500 L	S&P500 C	Dow Transportation Index C	Dow Utalities Index C	Amex Oil Index C	CRB C	Dow Industrial Index V	Gold and Silver Mining C	GSM C	10 Day % change in S&P500 C	Future 10 Day % change in S&P500 C	Future (1 days) S&P500 C	MvAvg(30) o Dow Industrial Index V	Lag(10) of CRB C	Lag(10) of Amex Oil Index C	Lag(10) of Dow Transportation Index C	LanRegChange (10,10) of S&P500 C	LanRegPredict(10,10) of 10 Day % change in S&P500 C	Lag(10) of GSM C
35264	644	633	644	2031.94	213.32	339.97	244.83	458024	120.16	83.51 *		0.931677019	650 *	*	*	*	*	*	*	*
35265	644	636	639	2018.81	211.43	339.37	243.21	360499	121.36	82.4 *		3.599374022	662 *	*	*	*	*	*	*	*
35268	639	630	634	1983.42	209.61	337.55	240.8	328891	120.47	81.19 *		4.100946373	660 *	*	*	*	*	*	*	*
35269	638	626	627	1982.42	208.77	335.4	241.32	393742	118.87	78.42 *		5.582137161	662 *	*	*	*	*	*	*	*
35270	629	616	627	1965.73	208.36	334.41	241.13	436022	116.81	78.24 *		5.901116427	664 *	*	*	*	*	*	*	*
35271	634	627	631	1967.82	207.24	335.25	241.35	371924	117.21	80.6 *		5.071315373	663 *	*	*	*	*	*	*	*
35272	636	631	636	1982.28	207.31	332.33	240.47	274211	120.82	84.56 *		4.088050314	662 *	*	*	*	*	*	*	*
35275	636	631	631	1967.44	205.42	332.15	240.54	231960	118.44	82.22 *		5.546751189	666 *	*	*	*	*	*	*	*
35276	635	629	635	1985.99	204.86	330.48	240.51	265373	118	84.16 *		3.937007874	660 *	*	*	*	*	*	*	*
35277	641	634	640	2007.96	205.14	333.17	241.99	343022	124.35	84.47 *		3.4375	662 *	*	*	*	-2.909090757 *	*	*	*
35278	651	639	650	2018.81	208.08	333.96	245.42	567080	124.32	86.37	0.931677019	1.846153846	662 *		244.8300018	339.9700012	2031.939941	12 *		83.51000214
35279	662	650	662	2051.34	211.92	336.83	245.13	344713	126.14	90.49	3.599374022	0.453172205	665 *		243.2100067	339.3699951	2018.810059	29.39393997 *		82.40000153
35282	664	659	660	2068.47	212.62	338.38	244.24	226732	129.33	88.4	4.100946372	1.060606061	667 *		240.8000031	337.3499878	1983.420044	39.35755989 *		81.19000244
35283	663	657	662	2052.77	211.71	339.37	244.16	267636	127.68	90.32	5.582137161	0.604229607	666 *		241.3200073	335.3999939	1982.420044	43.03030396 *		78.41999817
35284	665	660	664	2061.62	211.71	337.17	243.9	318433	126.65	94.93	5.901116427	0.13060241	665 *		241.1300049	334.4100037	1965.72998	43.33333588 *		78.23999786
35285	664	661	663	2079.6	211.92	338.38	246	268894	128.75	93.65	5.071315373	1.206636501	671 *		241.3500061	335.25	1967.869995	41.27272797 *		80.59999847
35286	665	660	662	2069.75	211.92	336.68	246.14	224583	127.01	92.8	4.088050314	0.755287009	667 *		240.4700012	332.3299866	1982.280029	38.12121201 *		84.53999756
35289	666	659	666	2068.47	214.57	338.57	249.3	451829	128.13	92.44	5.546751189	-0.3003003	664 *		240.5399933	332.1499939	1967.439941	30.66666603 *		82.22000122
35290	666	659	660	2057.62	213.81	338.16	249.91	373202	126.21	89.92	3.937007874	0.909090909	666 *		240.5099945	330.480011	1985.98999	18.36363602 *		84.16000366
35291	662	658	662	2054.77	214.5	338.46	249.33	278974	123.33	91.1	3.4375	0.453172205	665 *		241.9900055	333.1700134	2007.959961	7.434543498	6.577625275	84.47000122
35292	664	661	662	2048.63	214.29	338.46	248.59	240286	124.34	91.37	1.846153846	-0.755282009	657 *		243.4199982	333.9599915	2018.810059	0.343434562	1.61358881	86.37000275
35293	666	662	663	2052.2	216.18	342.62	249.55	284630	121.66	90.29	0.453172205	-1.954887218	652 *		245.1300049	336.8299866	2051.340088	1.818181872	-2.440194368	90.48999786
35296	667	665	667	2062.9	216.88	345.38	251.97	246174	125.73	90.42	1.060606061	-1.79910045	655 *		244.2400055	338.8300049	2068.469971	2.484848499	-4.965143204	88.40000153
35297	667	665	666	2069.04	216.39	346.02	250.65	245315	127.71	89.71	0.604229607	-1.501501502	656 *		244.1600037	339.3699951	2052.77002	3.090909004	-6.078619003	90.31999969
35298	666	662	663	2077.88	216.6	344.32	249.84	267160	125.8	90.81	0.15060241	-2.406015038	649 *		243.8999939	337.1700134	2061.620117	4	-6.444880962	94.93000031
35299	671	665	671	2071.89	217.58	346.96	249.8	347584	128.17	92.36	1.206636501	-2.235469449	656 *		246	338.3800049	2079.600098	7.393939495	-5.57877636	93.65000153
35300	671	665	667	2061.9	217.16	344.77	250.43	234139	127.12	91.33	0.755282009	-0.449775112	664 *		246.1399994	336.6799927	2069.75	6.969696999	-5.282699223	92.80000305
35303	667	662	664	2057.76	217.93	342.24	250.33	230755	128.19	90.29	-0.3003003	0	664 *		249.3000031	338.5700073	2068.469971	6.969696999	-4.087088108	92.44000244
35304	666	664	666	2071.03	218.84	344.32	249.76	200325	127.79	90.95	0.909090909	0.15015015	667 *		249.9100037	338.1600037	2057.620117	4.303030491	-2.17646718	89.91999817
35305	667	664	665	2071.03	218.91	343.49	248.5	230865	127.77	90.88	0.453172205	0.902255639	671	304433.1875	249.3300018	338.4599915	2054.77002	1.696969748	-0.573755337	91.09999847
35306	665	655	657	2057.34	216.32	340.08	249.66	267972	125.73	91.33	-0.755287009	3.652968037	681	298098.1125	248.5899963	338.4599915	2048.629883	-5.636363506	-0.900318861	91.37000275
35307	658	651	652	2044.78	214.36	339.97	249.46	220799	124.55	90.47	-1.934887218	4.90797546	684	293441.4688	249.5300031	342.6199951	2052.199951	-13.09090805	-3.046645403	90.29000092
35311	655	644	655	2025.66	215.2	348.06	248.98	298231	126.67	90.78	-1.79910045	4.27480916	683	292419.4688	251.9700012	345.3800049	2062.899902	-16	-4.104502678	90.41999817
35312	656	653	656	2020.38	214.64	346.89	247.1	273378	126.46	90.12	-1.501501502	3.81097561	681	288407.3438	250.6499939	346.0199889	2069.040039	-17.57575798	-4.790138245	89.70999908
35313	656	649	649	1995.41	212.83	346.06	246.22	226546	125.41	87.05	-2.406015038	5.238828968	687	281424.8125	249.8399963	344.3200073	2077.879883	-22.42424202	-6.304657936	90.80999756
35314	658	649	656	2019.38	213.81	348.17	247.79	282209	124.94	82.57	-2.235469449	4.725609756	687	278434.3125	249.8000031	346.9599915	2071.889893	-17.51515198	-6.302660942	92.36000061
35317	664	656	664	2031.08	215.27	350.71	247.64	249084	121.26	88.14	-0.449775112	3.313253012	686	277596.7188	250.4299927	344.769989	2061.899902	-9.090909004	-4.495966434	91.33000183
35318	666	662	664	2035.08	214.64	349.46	248.14	328550	121.29	88.49	0	3.313253012	686	280816.4063	250.3300018	342.2399902	2057.76001	-2.303030252	-2.991607189	90.29000092
35319	668	662	667	2035.36	215.69	355.36	247.22	284191	122.39	88.46	0.15015015	2.848575712	686	281443.6875	249.7599945	344.3200073	2071.030029	7.454545498	-0.358119249	90.94999695
35320	673	667	671	2042.5	216.39	353.92	247.09	290233	122.08	88.96	0.902255639	2.255469449	686	279684.0625	248.5	343.4899902	2071.030029	18.60606003	2.683686256	90.87999725
35321	681	671	681	2057.62	218.56	354.64	245.85	363595	124.21	91.01	3.652968037	0.734214391	686	279567.9063	249.6600037	340.0799866	2057.340088	29.15151596	7.049865723	91.33000183
35324	686	681	684	2069.89	220.09	356.64	244.18	331570	125.64	93.38	4.90797546	0.438596491	682	279129.8125	249.4600067	339.9700012	2044.780029	35.09090805	10.71970463	90.47000122
35325	686	680	683	2056.76	219.67	354.15	244.4	381767	122.33	97.97	4.27480916	0.878477306	689	284297.625	248.9799957	348.0599976	2025.660034	38.60606003	12.73426483	90.77999878
35326	684	680	681	2044.78	218	354.98	245.89	342033	121.06	97.47	3.81097561	1.869565416	694	286776.875	247.1000061	346.8900146	2020.380005	38.30302811	13.5659771	90.12000275
35327	684	679	683	2063.9	218.14	354.75	245.14	316410	120.06	99.31	5.238828968	1.464128843	693	286709.4375	246.2200012	346.0599976	1995.410034	31.39393997	13.93215656	82.03000305
35328	687	683	687	2100.71	219.46	356.87	244.42	498233	119.5	99.45	4.725609756	2.037845706	701	294354.0625	247.7899933	348.1700134	2019.380005	27.21212196	12.6452713	82.56999969
35331	687	681	686	2085.59	219.26	355.21	243.84	233108	119.66	98.32	3.313253012	2.478134111	703	294638.2188	247.6399994	350.7099915	2031.079956	24.06060791	10.42423916	88.13999939
35332	691	684	686	2071.89	219.4	355.89	245.31	482130	121.57	102.67	3.313253012	2.186588921	701	295648.2813	248.1399994	349.4599915	2035.079956	18.24242401	7.931633949	88.48999786
35333	688	685	686	2071.6	218.98	354.45	247.12	371853	119.57	103.61	2.848575712	1.603498342	703	295603.3125	247.2200012	355.3599854	2035.359985	11.75757504	4.573848328	88.45999908
35334	690	684	686	2048.77	218.63	334.26	246.49	367715	116.26	103.31	2.235469449	1.311953353	695	298561.3438	247.0899963	353.9200134	2042.5	5.636363506	0.845394552	88.95999908
35335	687	684	686	2067.04	218.14	355.36	246.64	294009	115.74	101.86	0.754214391	2.186588921	704	300352.0938	245.8500061	334.6400146	2057.620117	4.363636494	-2.069911957	91.01000214
35338	690	686	687	2079.02	216.88	356.15	245.63	278362	115.18	100.59	0.438596491	2.474526929	704	300143.1563	244.1799927	356.6400146	2069.889893	5.030303001	-3.647919655	93.37999725
35339	690	684	689	2084.16	218.35	359.78	244.2	347134	116.75	98.77	0.878477306	2.031930334	703	303508.5	244.3999939	354.1499939	2056.76001	5.757575512	-4.597253799	97.97000122
35340	695	689	694	2093.01	218.91	362.58	244.64	546125	120.23	100	1.908957416	1.44092219	704	306868.8438	245.8899994	354.980011	2044.780029	7.151515007	-4.43358326	97.47000122
35341	695	692	693	2079.88	218.84	361.37	245.84	286428	116.9	99.15	1.464128843	2.02020202	707	307511.0938	245.1399994	334.75	2063.899902	7.757575512	-3.094447136	99.30999756
35342	702	693	701	2102.14	221.91	367.08	245.97	399449	117.11	99.64	2.037845706	1.426533524	711	309239.9375	244.4199982	356.8699951	2100.709961	14.18181801	-1.025538802	99.44999695
35345	704	701	703	2085.3	222.19	370.89	247.81	268223	117.22	102.17	2.478134111	0.995732575	710	309709.4063	243.8399963	355.2099915	2085.590088	19.33333206	0.683979213	98.31999969
35346	706	700	701	2076.17	222.68	371.5	249.14	419760	117.66	102.18	2.186588921	0.855920114	707	316009.5625	245.3099976	355.8900146	2071.889893	21.33333397	2.280534744	102.6699982
35347	702	694	697	2049.63	221.49	368.21	248.61	357745	118.16	104.04	1.603498342	1.43472023	707	321256.9063	247.1199951	354.4500122	2071.600098	19.33333206	3.15290904	103.6100006
35348	697	693	695	2058.48	220.16	367.53	247.38	267421	119.38	102.61	1.311953353	1.007194245	702	322475.4375	246.4900055	354.2600098	2048.77002	14.909091	3.45301652	103.3099976
35349	701	695	701	2075.89	221.49	370.71	245.7	236864	117.88	105.13	2.186588921	0	701	321438.5	246.6399994	355.3599854	2067.040039	12.66666603	3.393573807	101.8600006
35352	705	701	704	2058.05	221.56	374.71	245.49	274236	116.39	107.02	2.474526929	-0.994318182	697	323219.7188	245.6300049	356.1499939	2079.02002	10.9090991	3.079185486	100.5899963
35353	708	699	703	2105.28	221.7	373.58	246.24	377247	117.25	107.11	2.031930334	-0.142247511	702	325853.5938	244.1999969	359.7799988	2084.159912	7.878787994	2.393883705	98.76999664
35354	704	699	704	2097.07	221.35	372.82	244.41	346812	117.14	106.94	1.44092219	-0.426156364	701	328301.4063	244.6399994	362.5799866	2093.01001	7.030303001	1.872404218	100
35355	709	705	707	2101.47	222.89	375.24	244.12	343285	115.16	106.04	2.02020202	-0.282885431	705	332192.6875	245.8399963	361.3699951	2079.879883	5.939393997	1.563734559	99.15000153
35356	711	706	711	2116.42	224.57	380.46	243.35	399401	114	105.95	1.426533524	-0.984528833	704	336099.0938	245.9700012	367.0799866	2102.139893	10.66666698	1.125685453	99.63999939
35359	714	708	710	2115.24	223.52	380.69	243.83	419587	116.64	104.01	0.995732575	-0.422535211	707	341782.5313	247.8099976	370.8900146	2085.300049	14.9696997	0.79283762	102.1699982
35360	710	705	707	2123.6	225.66	380.84	244.96	294423	118.6	102.28	0.853920114	0.99009901	714	340644.9688	249.1399994	371.5	2076.169922	15.43434502	0.343300909	102.1800003
35361	707	701	707	2153.35	225.1	378.38	244.11	374775	119.25	104.98	1.43473023	2.545968883	725	343664.4375	248.6100006	368.2099915	2049.629883	12.54545403	0.137952268	104.0400009
35362	708	702	702	2137.81	222.89	373.94	241.9	345826	119.17	103.26	1.007194245	3.703703704	738	345519.1825	247.3800049	367.5299988	2058.47998	4.363636494	-0.671291292	102.6100006
35363	704	701	701	2126.68	223.31	374.56	243.26	259776	118.98	102.03	0	4.279600571	731	342058.5625	245.6999969	370.7099915	2075.889893	-1.212121248	-1.56627059	105.1299973
35366	705	697	697	2105.57	222.75	373.28	243.33	302628	119.1	101.16	-0.994318182	5.021520803	732	341093.8438	245.4900055	374.7099915	2058.050049	-6.969696999	-2.71325967	107.0199966
35367	703	696	702	2097.95	224.5	376.68	241.11	322806	116.18	99.23	-0.142247511	3.983603989	730	339128.4688	246.2400055	373.5799866	2105.280029	-9.818181992	-2.825000477	107.1100006
35368	703	700	701	2096.63	225.19	375.66	241.66	302549	117.73	100.52	-0.426136364	4.279600571	731	337812.3438	244.4100037	372.8200073	2097.070068	-12.42424202	-3.419759274	106.9400024
35369	707	700	705	2133.56	226.73	371.88	237.83	370338	115.6	101.67	-0.282885431	4.397163121	736	339609.9375	244.1199951	375.2399902	2101 469971	-10.48484802	-3.006703834	106.0400009
35370	709	701	704	2137.52	226.45	366.85	257.3	370297	116.38	101.38	-0.984528833	4.829345455	738	333545.4063	243.3500061	380.4599915	2116.419922	-6.181818008	-3.328475237	105.9499969
35373	707	703	707	2154.23	228.48	365.82	236.52	373148	116.71	102.53	-0.422535211	4.243281471	737	340013.4063	243.8300018	380.6900024	2115.23999	-0.060606059	-3.099160194	104.0100021
35374	715	707	714	2147.78	251.41	363.41	256.13	405603	115.88	105.49	0.99009901	3.921568627	742	337462.5	244.9600067	380.8399963	2123.600098	8.242424011	-1.483215928	102.2799988
3375	725	713	735	2161.9	234.07	367.34	257.03	460107	113.44	109.28	2.345968883	2.620689655	744	340404.3125	244.1100006	378.3800049	2153.350098	21.69696999	1.996910573	104.9800034
3376	729	722	738	2179.4	235.68	368.93	238.74	396778	116.88	112.08	3.703703704	2.06043956	743	341373.0625	241.8999939	372.9400024	2137.810059	31.27272797	5.942640305	103.2600021
3377	731	725	731	2183.69	234.77	372.26	259.72	325583	118.63	112.47	4.279600571	2.462580301	749	342425.5313	243.2599945	374.5599976	2126.679932	38.66666412	9.054610252	102.0299988
3380	733	730	732	2198.89	234.77	373.99	240.64	307184	120.91	115.25	5.021520803	3.415300546	757	343486.2813	243.3300018	373.2799988	2105.570068	40.30303192	11.21364594	101.1600037
3381	733	728	730	2221.76	234.21	372.75	240.49	460850	126.07	115.05	3.988603989	3.561643836	756	347176.8125	241.1100006	376.6799927	2097.949951	39.93939209	12.1335783	99.23000336
3382	732	728	731	2216.85	232.88	373.12	242.33	396548	127.3	114.89	4.279600571	3.283173735	755	348857.5625	241.6600037	375.6600037	2096.629883	36.0606041	12.34069729	100.5199966
3383	736	729	736	2228.82	233.16	375.95	243.41	412578	125.19	117.38	4.397163121	2.85326087	757	353062.5625	257.8300018	371.8300049	2133.560059	33.9393939	11.94963741	101.6699982
3384	742	735	738	2221.45	234.91	377.06	244.7	506851	125.07	115.39	4.829343455	2.574525745	757	356642.625	257.3000031	366.8500061	2137.52002	28.48484802	10.51314449	101.3799973
3383	739	734	737	2242.63	233.37	379.96	244.47	312979	122.47	114.3	4.243281471	1.492537313	748	358134.5	236.5200043	365.8699951	2154.22998	20.36363602	8.019536972	102.5299988
3388	742	737	742	2257.06	234.49	383.86	245.51	347465	122.35	116.5	3.921568627	0.404312668	753	355724.6563	236.1300049	363.4100037	2147.780029	16	5.643341813	105.4899979
3389	747	740	744	2273.63	234.63	383.17	246.19	385708	126.56	117.05	2.620689655	0	744	356656.7813	257.0299988	367.3399963	2161.899902	16.66666603	2.941775322	109.2799988
3390	745	741	743	2258.9	234.49	382.91	245.68	362483	120.82	116.47	2.06043956	-0.403768506	740	359825.5	238.7400055	368.9299927	2179.399902	16.48484802	0.731117349	112.0800018
3391	749	743	749	2265.34	235.4	388.2	244.19	328139	119.75	121.67	2.462380301	0 133511348	750	362868	259.7200012	372.2600098	2183.689941	19.75757599	-0.333532797	112.4700012
3394	757	748	757	2289.75	238.12	393.01	243.31	339053	117.88	121.25	3 415300546	-1.188903567	748	365028.5625	240.6399994	373.9899902	2198.889893	25.87878799	0.413188219	115.25
3395	762	753	756	2282.23	236.44	391.31	244.85	309978	119.96	122.05	3.561643836	-1.984126984	741	369452.9375	240.4900055	372.75	2221.76001	27.09090996	0.677389145	115.0500031
3396	757	753	755	2272.71	235.61	386.46	244.65	291974	120.25	124.67	3.283173735	-3.443708609	729	367625	242.3300018	373.1199951	2216.850098	25.27272797	1.020736217	114.8899994
3398	758	755	757	2290.82	235.68	388.88	243.36	322134	120.19	125	2.85326082	-3.698811096	729	360253.3125	243.4100037	375.9500122	2228.820068	24.96969604	1.258088112	117.3799973
3401	757	751	757	2293.89	234.77	391.04	242.02	312236	117.02	127.67	2.574525745	-4.755614267	731	357347.8125	244.6999969	377.0599976	2221.449951	23.45454407	1.893194114	115.3899994
3402	762	748	748	2300.06	253.23	389.04	241.63	383890	115.19	127.16	1.492537313	-2.941176471	726	356157.9063	244.4700012	379.9599915	2242.629883	14.060606	1.452589134	114.3000031
3403	748	738	745	2308.38	233.51	385.4	241.37	449031	118.99	127.66	0.404312668	-1.744966443	732	361311.5	245.5099945	383.8599854	2257.060059	5.030303001	0.247122347	116.5
3404	748	743	744	2515.47	233.86	390.39	243.55	369025	122.13	126.21	0	0.268817204	746	361119.8438	246.1900024	383.1700134	2273.629883	-3.575757504	-1.82779336	117.0500031
3405	744	737	740	2274.16	231.48	385.7	242.06	486585	121.58	125.47	-0.403768506	1.216216216	749	365810.125	245.6799927	382.9100037	2258.899902	-15.030303	-4.287372589	116.4700012

APPENDIX C. SOURCE CODE FOR CLOSE NETWORK

Note - use this code with your calculator or spreadsheet to fire the C:\24XLAN\JASON\SCHOOL\THESIS\SP500M~4\SP1NET~1\SP12NET\SP12NET network
Note - the following are intermediate value cells and arrays:
Note - parens immediately below denote an array where the number of elements is in parens

```
netsum
feature2(9)
feature3(9)
feature4(9)
```

Note - the following are names of inputs and outputs:
Note - inp(1) is S&P500_H
Note - inp(2) is S&P500_L
Note - inp(3) is S&P500_C
Note - inp(4) is Dow_Transportation_Index_C
Note - inp(5) is Dow_Utilities_Index_C
Note - inp(6) is Amex_Oil_Index_C
Note - inp(7) is CRB_C
Note - inp(8) is Gold_and_Silver_Mining_C
Note - inp(9) is GSM_C
Note - outp(1) is Future_(10_days)_S&P500_C
Note - inp(10) is MvAvg(30)_of_Dow_Industrial_Index_V
Note - inp(11) is Lag(10)_of_CRB_C
Note - inp(12) is Lag(10)_of_Amex_Oil_Index_C
Note - inp(13) is Lag(10)_of_Dow_Transportation_Index_C
Note - inp(14) is Lag(10)_of_GSM_C

```
if (inp(1)< 629) then inp(1) =  629
if (inp(1)> 1191) then inp(1) =  1191
inp(1) =  2 * (inp(1) -  629) / 562 -1

if (inp(2)< 616) then inp(2) =  616
if (inp(2)> 1182) then inp(2) =  1182
inp(2) =  2 * (inp(2) -  616) / 566 -1

if (inp(3)< 627) then inp(3) =  627
if (inp(3)> 1187) then inp(3) =  1187
inp(3) =  2 * (inp(3) -  627) / 560 -1

if (inp(4)< 1965.73) then inp(4) =  1965.73
if (inp(4)> 3686.02) then inp(4) =  3686.02
```

```
inp(4) =  2 * (inp(4) -  1965.73) / 1720.29 -1

if (inp(5)< 204.86) then inp(5) =  204.86
if (inp(5)> 295.4) then inp(5) =  295.4
inp(5) =  2 * (inp(5) -  204.86) / 90.53999 -1

if (inp(6)< 330.48) then inp(6) =  330.48
if (inp(6)> 503.75) then inp(6) =  503.75
inp(6) =  2 * (inp(6) -  330.48) / 173.27 -1

if (inp(7)< 202.02) then inp(7) =  202.02
if (inp(7)> 253.96) then inp(7) =  253.96
inp(7) =  2 * (inp(7) -  202.02) / 51.94 -1

if (inp(8)< 60.32) then inp(8) =  60.32
if (inp(8)> 129.33) then inp(8) =  129.33
inp(8) =  2 * (inp(8) -  60.32) / 69.01 -1

if (inp(9)< 78.24) then inp(9) =  78.24
if (inp(9)> 198.23) then inp(9) =  198.23
inp(9) =  2 * (inp(9) -  78.24) / 119.99 -1

if (inp(10)< 277596.7) then inp(10) =  277596.7
if (inp(10)> 713482.1) then inp(10) =  713482.1
inp(10) =  2 * (inp(10) -  277596.7) / 435885.4 -1

if (inp(11)< 206.14) then inp(11) =  206.14
if (inp(11)> 253.96) then inp(11) =  253.96
inp(11) =  2 * (inp(11) -  206.14) / 47.82001 -1

if (inp(12)< 330.48) then inp(12) =  330.48
if (inp(12)> 503.75) then inp(12) =  503.75
inp(12) =  2 * (inp(12) -  330.48) / 173.27 -1

if (inp(13)< 1965.73) then inp(13) =  1965.73
if (inp(13)> 3686.02) then inp(13) =  3686.02
inp(13) =  2 * (inp(13) -  1965.73) / 1720.29 -1

if (inp(14)< 78.24) then inp(14) =  78.24
if (inp(14)> 198.23) then inp(14) =  198.23
inp(14) =  2 * (inp(14) -  78.24) / 119.99 -1

netsum = -.6301715
netsum = netsum + inp(1) *  .4015678
netsum = netsum + inp(2) *  .1923304
netsum = netsum + inp(3) *  .3034808
```

```
netsum = netsum + inp(4) *  .471424
netsum = netsum + inp(5) * -.522025
netsum = netsum + inp(6) * -.3444886
netsum = netsum + inp(7) *  .2156871
netsum = netsum + inp(8) * -.0962563
netsum = netsum + inp(9) *  8.810111E-02
netsum = netsum + inp(10) *  .8480121
netsum = netsum + inp(11) *  1.090916E-02
netsum = netsum + inp(12) * -.1067936
netsum = netsum + inp(13) *  .192736
netsum = netsum + inp(14) *  .2648861
feature2(1) = exp(-netsum * netsum)

netsum =  7.784155E-02
netsum = netsum + inp(1) * -.1590329
netsum = netsum + inp(2) * -6.405292E-02
netsum = netsum + inp(3) *  .1000905
netsum = netsum + inp(4) * -.2733166
netsum = netsum + inp(5) *  .2708781
netsum = netsum + inp(6) * -.2224024
netsum = netsum + inp(7) * -.6161205
netsum = netsum + inp(8) *  .1161777
netsum = netsum + inp(9) *  9.140761E-02
netsum = netsum + inp(10) *  .6487405
netsum = netsum + inp(11) * -6.036293E-02
netsum = netsum + inp(12) *  3.895962E-02
netsum = netsum + inp(13) * -.1787288
netsum = netsum + inp(14) *  .333038
feature2(2) = exp(-netsum * netsum)

netsum = -.2859306
netsum = netsum + inp(1) *  .2471741
netsum = netsum + inp(2) *  .3450775
netsum = netsum + inp(3) *  8.962151E-02
netsum = netsum + inp(4) *  4.607785E-02
netsum = netsum + inp(5) * -6.669939E-02
netsum = netsum + inp(6) * -.1497742
netsum = netsum + inp(7) *  .3083329
netsum = netsum + inp(8) *  8.747423E-02
netsum = netsum + inp(9) * -1.843768E-02
netsum = netsum + inp(10) *  .2710629
netsum = netsum + inp(11) *  .3533338
netsum = netsum + inp(12) * -.1935388
netsum = netsum + inp(13) *  .1157563
netsum = netsum + inp(14) * -.3057612
feature2(3) = exp(-netsum * netsum)
```

```
netsum =  .3307071
netsum = netsum + inp(1) *  7.340278E-02
netsum = netsum + inp(2) *  1.156442E-02
netsum = netsum + inp(3) * -.1988501
netsum = netsum + inp(4) *  .1112011
netsum = netsum + inp(5) *  4.713702E-03
netsum = netsum + inp(6) * -.1553141
netsum = netsum + inp(7) * -.148536
netsum = netsum + inp(8) *  .2287395
netsum = netsum + inp(9) *  .1997013
netsum = netsum + inp(10) * -.4850825
netsum = netsum + inp(11) * -.7133386
netsum = netsum + inp(12) *  .3967151
netsum = netsum + inp(13) * -.6160113
netsum = netsum + inp(14) *  3.598906E-03
feature2(4) = exp(-netsum * netsum)

netsum =  1.679392E-02
netsum = netsum + inp(1) * -5.007538E-03
netsum = netsum + inp(2) * -.237791
netsum = netsum + inp(3) *  8.680119E-02
netsum = netsum + inp(4) *  .229306
netsum = netsum + inp(5) * -.1694554
netsum = netsum + inp(6) *  .1752781
netsum = netsum + inp(7) * -.1325122
netsum = netsum + inp(8) * -3.663547E-02
netsum = netsum + inp(9) * -.1170656
netsum = netsum + inp(10) * -.2149827
netsum = netsum + inp(11) *  .2217486
netsum = netsum + inp(12) *  .1699766
netsum = netsum + inp(13) * -7.920565E-02
netsum = netsum + inp(14) *  .1580922
feature2(5) = exp(-netsum * netsum)

netsum =  4.819342E-02
netsum = netsum + inp(1) * -5.559232E-02
netsum = netsum + inp(2) * -.2133055
netsum = netsum + inp(3) *  .0223891
netsum = netsum + inp(4) *  .1393356
netsum = netsum + inp(5) *  .3481391
netsum = netsum + inp(6) * -.3444548
netsum = netsum + inp(7) *  .1126457
netsum = netsum + inp(8) *  .2515414
netsum = netsum + inp(9) * -.2600302
netsum = netsum + inp(10) *  .1857713
```

```
netsum = netsum + inp(11) *  .1466804
netsum = netsum + inp(12) *  8.555102E-02
netsum = netsum + inp(13) * -6.260171E-02
netsum = netsum + inp(14) * -.1186699
feature2(6) = exp(-netsum * netsum)

netsum =  1.077751E-03
netsum = netsum + inp(1) * -.31528
netsum = netsum + inp(2) * -.3444317
netsum = netsum + inp(3) * -.1208438
netsum = netsum + inp(4) *  .450067
netsum = netsum + inp(5) *  .0752024
netsum = netsum + inp(6) *  8.618691E-02
netsum = netsum + inp(7) *  .1862327
netsum = netsum + inp(8) *  5.465092E-02
netsum = netsum + inp(9) * -.1758856
netsum = netsum + inp(10) * -.1402889
netsum = netsum + inp(11) * -5.002017E-02
netsum = netsum + inp(12) * -8.830319E-02
netsum = netsum + inp(13) *  4.461126E-02
netsum = netsum + inp(14) * -.1783304
feature2(7) = exp(-netsum * netsum)

netsum =  .2010598
netsum = netsum + inp(1) * -.2251198
netsum = netsum + inp(2) * -5.359336E-02
netsum = netsum + inp(3) * -.2414816
netsum = netsum + inp(4) *  .2557169
netsum = netsum + inp(5) *  .3187351
netsum = netsum + inp(6) * -.2540528
netsum = netsum + inp(7) *  .1812858
netsum = netsum + inp(8) * -.2384627
netsum = netsum + inp(9) * -.0457608
netsum = netsum + inp(10) * -.2491588
netsum = netsum + inp(11) * -5.906731E-02
netsum = netsum + inp(12) * -.2001718
netsum = netsum + inp(13) *  .120379
netsum = netsum + inp(14) *  .1183008
feature2(8) = exp(-netsum * netsum)

netsum =  .112657
netsum = netsum + inp(1) * -.1262439
netsum = netsum + inp(2) * -5.584108E-02
netsum = netsum + inp(3) *  5.810664E-02
netsum = netsum + inp(4) *  4.742816E-02
netsum = netsum + inp(5) *  .1374272
```

```
netsum = netsum + inp(6) *  .1569632
netsum = netsum + inp(7) *  .1107642
netsum = netsum + inp(8) *  .1762077
netsum = netsum + inp(9) *  .228175
netsum = netsum + inp(10) *  7.341717E-02
netsum = netsum + inp(11) * -.3403822
netsum = netsum + inp(12) *  .2044954
netsum = netsum + inp(13) *  9.120224E-02
netsum = netsum + inp(14) * -.303437
feature2(9) = exp(-netsum * netsum)

netsum = -.1239542
netsum = netsum + inp(1) *  6.883536E-02
netsum = netsum + inp(2) *  .1504488
netsum = netsum + inp(3) * -.1053862
netsum = netsum + inp(4) * -.1535371
netsum = netsum + inp(5) * -.2344521
netsum = netsum + inp(6) * -.204491
netsum = netsum + inp(7) *  8.043891E-02
netsum = netsum + inp(8) *  7.446315E-02
netsum = netsum + inp(9) * -3.834013E-02
netsum = netsum + inp(10) *  .2165757
netsum = netsum + inp(11) * -.1488486
netsum = netsum + inp(12) *  5.801564E-02
netsum = netsum + inp(13) *  .2320869
netsum = netsum + inp(14) *  .2076355
feature3(1) = tanh(netsum)

netsum =  .3126868
netsum = netsum + inp(1) *  .1616008
netsum = netsum + inp(2) *  3.386919E-02
netsum = netsum + inp(3) * -.1983408
netsum = netsum + inp(4) * -.3485649
netsum = netsum + inp(5) * -.1106689
netsum = netsum + inp(6) * -.1445011
netsum = netsum + inp(7) *  .3310095
netsum = netsum + inp(8) * -.2066913
netsum = netsum + inp(9) * -.2082781
netsum = netsum + inp(10) *  5.758699E-02
netsum = netsum + inp(11) * -6.427113E-02
netsum = netsum + inp(12) *  2.970282E-02
netsum = netsum + inp(13) * -.2802488
netsum = netsum + inp(14) *  .252078
feature3(2) = tanh(netsum)

netsum =  4.668346E-02
```

```
netsum = netsum + inp(1) * -.1714819
netsum = netsum + inp(2) * -6.209589E-02
netsum = netsum + inp(3) * -.1907481
netsum = netsum + inp(4) * -.1376314
netsum = netsum + inp(5) *  .2418897
netsum = netsum + inp(6) * -.2630582
netsum = netsum + inp(7) * -.2526979
netsum = netsum + inp(8) * -.1087746
netsum = netsum + inp(9) *  7.395954E-02
netsum = netsum + inp(10) *  .1435177
netsum = netsum + inp(11) *  .1491603
netsum = netsum + inp(12) *  .1827831
netsum = netsum + inp(13) *  .3284236
netsum = netsum + inp(14) *  .1364697
feature3(3) = tanh(netsum)

netsum =  3.868202E-02
netsum = netsum + inp(1) *  .402357
netsum = netsum + inp(2) *  .2806031
netsum = netsum + inp(3) *  .2690603
netsum = netsum + inp(4) *  6.963006E-02
netsum = netsum + inp(5) *  .1762392
netsum = netsum + inp(6) *  .1347711
netsum = netsum + inp(7) * -.3312288
netsum = netsum + inp(8) *  .4110459
netsum = netsum + inp(9) *  .182495
netsum = netsum + inp(10) *  7.211982E-02
netsum = netsum + inp(11) *  7.574815E-02
netsum = netsum + inp(12) *  .3440028
netsum = netsum + inp(13) *  .4007721
netsum = netsum + inp(14) * -.2247503
feature3(4) = tanh(netsum)

netsum =  1.236538E-02
netsum = netsum + inp(1) *  1.840403E-02
netsum = netsum + inp(2) * -.2597425
netsum = netsum + inp(3) *  .2060692
netsum = netsum + inp(4) *  .1866937
netsum = netsum + inp(5) *  8.070311E-03
netsum = netsum + inp(6) *  6.152835E-02
netsum = netsum + inp(7) * -.183747
netsum = netsum + inp(8) * -.301769
netsum = netsum + inp(9) * -3.505382E-02
netsum = netsum + inp(10) * -4.599997E-02
netsum = netsum + inp(11) *  2.352656E-02
netsum = netsum + inp(12) * -.1942575
```

```
netsum = netsum + inp(13) * -.1482109
netsum = netsum + inp(14) * -8.374985E-02
feature3(5) = tanh(netsum)

netsum = -.2077845
netsum = netsum + inp(1) * -.3183326
netsum = netsum + inp(2) * -.2343775
netsum = netsum + inp(3) *  2.819597E-02
netsum = netsum + inp(4) *  .1284694
netsum = netsum + inp(5) * -.2394804
netsum = netsum + inp(6) * -4.67339E-03
netsum = netsum + inp(7) *  .6174434
netsum = netsum + inp(8) *  .4019511
netsum = netsum + inp(9) *  5.051733E-02
netsum = netsum + inp(10) * -.3909052
netsum = netsum + inp(11) *  7.491957E-02
netsum = netsum + inp(12) *  5.784418E-02
netsum = netsum + inp(13) * -.0298114
netsum = netsum + inp(14) * -.1702783
feature3(6) = tanh(netsum)

netsum =  .1813595
netsum = netsum + inp(1) *  1.982817E-02
netsum = netsum + inp(2) *  .1559182
netsum = netsum + inp(3) *  .0207838
netsum = netsum + inp(4) * -.2390079
netsum = netsum + inp(5) * -8.514214E-02
netsum = netsum + inp(6) * -.2670723
netsum = netsum + inp(7) *  1:109988E-02
netsum = netsum + inp(8) * -7.678013E-02
netsum = netsum + inp(9) *  9.093736E-02
netsum = netsum + inp(10) *  .1590883
netsum = netsum + inp(11) *  .1004014
netsum = netsum + inp(12) *  .2035837
netsum = netsum + inp(13) * -6.611361E-02
netsum = netsum + inp(14) * -.1934318
feature3(7) = tanh(netsum)

netsum =  .2397276
netsum = netsum + inp(1) * -.1992782
netsum = netsum + inp(2) * -.128719
netsum = netsum + inp(3) *  .1892586
netsum = netsum + inp(4) *  9.737152E-02
netsum = netsum + inp(5) * -.1388893
netsum = netsum + inp(6) *  8.414371E-02
netsum = netsum + inp(7) *  .4454928
```

```
netsum = netsum + inp(8) * -.2841288
netsum = netsum + inp(9) *  5.766987E-02
netsum = netsum + inp(10) *  5.085299E-02
netsum = netsum + inp(11) * -.2496866
netsum = netsum + inp(12) *  .3022949
netsum = netsum + inp(13) * -.3111849
netsum = netsum + inp(14) *  .1354086
feature3(8) = tanh(netsum)

netsum = -5.716069E-02
netsum = netsum + inp(1) *  .1918543
netsum = netsum + inp(2) *  .2528775
netsum = netsum + inp(3) * -.1584775
netsum = netsum + inp(4) * -.2948896
netsum = netsum + inp(5) *  .1197234
netsum = netsum + inp(6) *  .3107863
netsum = netsum + inp(7) * -.217381
netsum = netsum + inp(8) *  .1799645
netsum = netsum + inp(9) *  .2089709
netsum = netsum + inp(10) *  .2344017
netsum = netsum + inp(11) *  .142157
netsum = netsum + inp(12) *  .0758443
netsum = netsum + inp(13) * -.2458397
netsum = netsum + inp(14) *  .1971597
feature3(9) = tanh(netsum)

netsum =  .2587757
netsum = netsum + inp(1) *  6.334911E-02
netsum = netsum + inp(2) * -.1395912
netsum = netsum + inp(3) *  .2138192
netsum = netsum + inp(4) * -.1274552
netsum = netsum + inp(5) * -.1393314
netsum = netsum + inp(6) * -.2645777
netsum = netsum + inp(7) *  .2876672
netsum = netsum + inp(8) * -.1303833
netsum = netsum + inp(9) *  .2642182
netsum = netsum + inp(10) *  3.467115E-02
netsum = netsum + inp(11) *  .1072136
netsum = netsum + inp(12) * -.1934204
netsum = netsum + inp(13) * -.1403725
netsum = netsum + inp(14) * -.1843849
feature4(1) = 1 - exp(-netsum * netsum)

netsum =  .2993304
netsum = netsum + inp(1) * -8.428704E-03
netsum = netsum + inp(2) * -.1071872
```

```
netsum = netsum + inp(3) * -8.796584E-02
netsum = netsum + inp(4) *  .1266784
netsum = netsum + inp(5) *  .2506436
netsum = netsum + inp(6) *  4.853629E-02
netsum = netsum + inp(7) * -.4751402
netsum = netsum + inp(8) * -.136122
netsum = netsum + inp(9) * -.3058958
netsum = netsum + inp(10) * -5.209611E-02
netsum = netsum + inp(11) *  .3099503
netsum = netsum + inp(12) * -.1840532
netsum = netsum + inp(13) *  .3218807
netsum = netsum + inp(14) *  .1453303
feature4(2) = 1 - exp(-netsum * netsum)

netsum =  .1933935
netsum = netsum + inp(1) *  .3332409
netsum = netsum + inp(2) *  .2873065
netsum = netsum + inp(3) *  1.045562E-03
netsum = netsum + inp(4) *  .2716179
netsum = netsum + inp(5) *  3.613625E-02
netsum = netsum + inp(6) * -.3512647
netsum = netsum + inp(7) * -.301256
netsum = netsum + inp(8) * -6.802244E-02
netsum = netsum + inp(9) *  5.407644E-02
netsum = netsum + inp(10) *  7.879863E-03
netsum = netsum + inp(11) *  5.932507E-02
netsum = netsum + inp(12) *  3.043652E-02
netsum = netsum + inp(13) * -.1559501
netsum = netsum + inp(14) * -.1701026
feature4(3) = 1 - exp(-netsum * netsum)

netsum =  .1759639
netsum = netsum + inp(1) * -.6680542
netsum = netsum + inp(2) * -.2973823
netsum = netsum + inp(3) * -.3279465
netsum = netsum + inp(4) * -.1164177
netsum = netsum + inp(5) * -.6758547
netsum = netsum + inp(6) * -5.386759E-02
netsum = netsum + inp(7) *  .4030443
netsum = netsum + inp(8) * -.337681
netsum = netsum + inp(9) * -.2303785
netsum = netsum + inp(10) * -.4204697
netsum = netsum + inp(11) *  .2685212
netsum = netsum + inp(12) *  .3571743
netsum = netsum + inp(13) * -.3708806
netsum = netsum + inp(14) * -.4410872
```

```
feature4(4) = 1 - exp(-netsum * netsum)

netsum = -7.085525E-02
netsum = netsum + inp(1) *  .2006301
netsum = netsum + inp(2) *  9.633981E-02
netsum = netsum + inp(3) * -.0126803
netsum = netsum + inp(4) *  .1226519
netsum = netsum + inp(5) * -8.257607E-02
netsum = netsum + inp(6) * -.2301209
netsum = netsum + inp(7) *  .1052367
netsum = netsum + inp(8) *  .230889
netsum = netsum + inp(9) * -.1533706
netsum = netsum + inp(10) * -.1561237
netsum = netsum + inp(11) *  8.230709E-02
netsum = netsum + inp(12) * -.3135089
netsum = netsum + inp(13) * -.2566093
netsum = netsum + inp(14) *  .3265928
feature4(5) = 1 - exp(-netsum * netsum)

netsum =  .2666591
netsum = netsum + inp(1) * -.163848
netsum = netsum + inp(2) * -.633084
netsum = netsum + inp(3) * -.1689773
netsum = netsum + inp(4) * -.5006466
netsum = netsum + inp(5) * -.419012
netsum = netsum + inp(6) *  4.745518E-02
netsum = netsum + inp(7) * -.2422797
netsum = netsum + inp(8) *  .4093167
netsum = netsum + inp(9) * -5.734261E-02
netsum = netsum + inp(10) * -.3980823
netsum = netsum + inp(11) *  1.593639E-02
netsum = netsum + inp(12) * -.2957138
netsum = netsum + inp(13) * -7.563066E-03
netsum = netsum + inp(14) * -8.185922E-03
feature4(6) = 1 - exp(-netsum * netsum)

netsum = -.1909794
netsum = netsum + inp(1) * -.1831633
netsum = netsum + inp(2) * -4.450019E-02
netsum = netsum + inp(3) * -.1683403
netsum = netsum + inp(4) * -.1905011
netsum = netsum + inp(5) *  .1881501
netsum = netsum + inp(6) *  .4262969
netsum = netsum + inp(7) * -.2553455
netsum = netsum + inp(8) *  .1917894
netsum = netsum + inp(9) *  .3827554
```

```
netsum = netsum + inp(10) * -3.722818E-02
netsum = netsum + inp(11) *  .4479087
netsum = netsum + inp(12) *  2.176078E-02
netsum = netsum + inp(13) * -.295205
netsum = netsum + inp(14) *  .1430879
feature4(7) = 1 - exp(-netsum * netsum)

netsum = -.2656472
netsum = netsum + inp(1) * -.2388305
netsum = netsum + inp(2) * -7.188458E-02
netsum = netsum + inp(3) * -.297852
netsum = netsum + inp(4) *  .1506731
netsum = netsum + inp(5) *  .2484149
netsum = netsum + inp(6) *  5.983697E-02
netsum = netsum + inp(7) * -.1939304
netsum = netsum + inp(8) *  6.954922E-02
netsum = netsum + inp(9) * -.2615168
netsum = netsum + inp(10) * -.2277467
netsum = netsum + inp(11) * -.1542342
netsum = netsum + inp(12) * -6.928023E-02
netsum = netsum + inp(13) * -.2817874
netsum = netsum + inp(14) *  .207139
feature4(8) = 1 - exp(-netsum * netsum)

netsum =  .1556563
netsum = netsum + inp(1) * -6.293206E-03
netsum = netsum + inp(2) * -1.832035E-03
netsum = netsum + inp(3) *  .1134438
netsum = netsum + inp(4) *  1.824013E-02
netsum = netsum + inp(5) *  5.927859E-02
netsum = netsum + inp(6) *  .1220353
netsum = netsum + inp(7) *  7.248743E-02
netsum = netsum + inp(8) *  .1827504
netsum = netsum + inp(9) * -2.891132E-02
netsum = netsum + inp(10) * -.1420365
netsum = netsum + inp(11) *  .2402575
netsum = netsum + inp(12) * -.2662137
netsum = netsum + inp(13) * -.2764541
netsum = netsum + inp(14) *  .1470288
feature4(9) = 1 - exp(-netsum * netsum)

netsum = -.2403532
netsum = netsum + feature2(1) *  .8336458
netsum = netsum + feature2(2) *  .7772395
netsum = netsum + feature2(3) * -.3676423
netsum = netsum + feature2(4) * -.8560631
```

```
netsum = netsum + feature2(5) * -3.738723E-03
netsum = netsum + feature2(6) * -.2726331
netsum = netsum + feature2(7) *  .4049881
netsum = netsum + feature2(8) * -9.708894E-02
netsum = netsum + feature2(9) * -.3385944
netsum = netsum +  2.389552E-02
netsum = netsum + feature3(1) * -.2318477
netsum = netsum + feature3(2) * -9.119899E-02
netsum = netsum + feature3(3) * -.3589992
netsum = netsum + feature3(4) *  .4774115
netsum = netsum + feature3(5) *  .1890002
netsum = netsum + feature3(6) * -.6112313
netsum = netsum + feature3(7) * -.1102381
netsum = netsum + feature3(8) *  .4290453
netsum = netsum + feature3(9) * -6.637502E-02
netsum = netsum + -.0645455
netsum = netsum + feature4(1) * -.2677609
netsum = netsum + feature4(2) * -.4827854
netsum = netsum + feature4(3) *  .2690243
netsum = netsum + feature4(4) *  .9494663
netsum = netsum + feature4(5) *  .2479254
netsum = netsum + feature4(6) * -.5345625
netsum = netsum + feature4(7) *  .5549127
netsum = netsum + feature4(8) *  6.048515E-03
netsum = netsum + feature4(9) *  .1529618
outp(1) = 1 / (1 + exp(-netsum))


outp(1) =  538 *  (outp(1) - .1) / .8  +  649
```

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