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Time series and neural network forecast of daily stock prices

Abstract

Time series analysis is somewhat parallel to technical analysis, but it differs from the latter by using different statistical methods and models to analyze historical stock prices and predict the future prices. With the rapid increases in algorithmic or high frequency trading in which trader make trading decisions by analyzing data patterns rather than fundamental factors affecting stock prices, both technical analyses and time series analyses become more relevant. In this study the authors apply the traditional time series decomposition (TSD), Holt/Winters (H/W) models, Box-Jenkins (B/J) methodology, and neural network (NN) to 50 randomly selected stocks from September 1, 1998 to December 31, 2010 with a total of 3105 observations for each company's close stock price. This sample period covers high tech boom and bust, the historical 9/11 event, housing boom and bust, and the recent serious recession and current slow recovery. During this exceptionally uncertain period of global economic and financial crises, it is expected that stock prices are extremely difficult to predict. All three time series approaches fit the data extremely well with R^2 being around 0.995. For the hold-out period or out-of-sample forecasts over 60 trading days, the forecasting errors measured in terms of mean absolute percentage errors (MAPE) are lower for B/J, H/W, and normalized NN model, but forecasting errors are quite large for time series decomposition and non-normalized NN models.

Keywords: forecasting stock prices, time series decomposition, Holt/Winters exponential smoothing, Box-Jenkins ARIMA methodology, neural network model, technical analysis, and fundamental analysis.
JEL Classification: G17.

Introduction

History has shown that over the long period of time stocks have generated higher returns than most other assets such as fixed income securities and real estate (Siegel, 2008). Forecasting stock prices has been an integral part of investing in the stock markets. Practitioners have designed so many techniques and tools to predict stock prices, while academicians have developed all kinds of theories, methods and models to evaluate the basic stock values and prices. With increasing globalization of financial markets and extremely rapid improvement in information technology and quantitative methods, news and rumors can travel quickly around the world and stock prices can drastically change from second to second. Although new information can be interpreted very differently by different market participants, the stock price at a given time reflects the equilibrium price of supply and demand at that particular moment. That equilibrium price may deviate greatly from the intrinsic value of the underlying stock and market participants' expectations and their mood may change quickly from moment to moment. Large institutional investors typically have their own proprietary computer trading techniques guided by their own mathematical and statistical models in buying and selling stocks without human interference. Most investors apply both fundament analysis and technical analysis to make their investment decisions. Since fundamental factors such as earnings, dividends, new products and markets, economic data are not available daily, weekly, or even monthly, short-term price fluctuations are determined by technical analysis, while fundamental analysis is more pertinent to long-term price changes. Over time the institutional trading has accounted for higher and higher trading volume (Hendershott, Jones, and Menkveld, 2011) and high frequency traders trade on the basis of analyzing data patterns in millisecond without considering the fundamental factors. This new development makes technical analysis and time series analysis even more important.

Forecasting is both an art and a science. The company can accurately forecast sales of a basic necessity. However, stock prices are rather difficult to forecast. Proponents of efficient market hypotheses argue that stock prices cannot be predicted since the market prices have already reflected all known and expected fundamentals. However, precisely because the current market price reflect all relevant information, and therefore the current and historical prices are extremely useful for predicting the future prices since some relevant information is entering the stock markets continuously. As we will discuss in more detail in literature review, it is well documented evidence that stock prices demonstrate strong momentum, short-term continuation and long-term reversal, and other identifiable patterns. When the market is in the upward movement, good news tends to reinforce but bad news is discounted. Conversely, when the market suffers downward momentum, market participants will discount the good news and exaggerate the bad news. Many professional analysts, investment advisers, investment news writers, mutual fund managers, and other so-called experts tend to be trend followers. Most individual investors tend to follow the professional advice and trend followers also. Contrarians are the minority. Indeed stock prices may also demonstrate some January, holidays, and year-end effects and other special patterns such as sizes, market to book value ratio, and value versus growth stocks. Even though it is hard to predict stock prices, both professional and individual investors have been exercising their best analyses and judgment to predict stock prices in quite diversified ways.

There are so many possible factors affecting stock prices in a very complicated ways. Haugen (1999) provided a rather concise summary of important factors. First, the risk factors which include market beta from capital asset pricing models, beta derived from arbitrage pricing theory, volatility of total return, nonmarket related variance, standard errors of earnings, debt to equity ratio and trend, times interest earned, and volatilities in earnings, dividend, and cash flow. Second, the liquidity factors: market capitalization, market price per share, trailing 12-month average monthly trading volume to market capitalization, and five year trend in monthly trading volume. Third, ratio and trend factors: earnings-to-price ratio and trend, book-to-price ratio and trend, dividend-to-price ratio and trend, cash flow-to-price ratio and trend, and sales-to-price ratio and trend. Fourth, profitability ratios and trends: profit margin and trend, total asset turnover and trend, return on assets and trend, return on equity and trend, earnings growth, and earnings surprise. Fifth, returns on different industry sectors vary from one sector to another. Finally, technical factors which measure the excess return over S&P 500 in the previous 1 month, 2 months, 3 months, 6 months, 12 months, 24 months, and 60 months. Generally speaking the technical factors are far more complex than what Haugen indicated here (Pring, 1991). In recent years with the sophisticated computer programs and advanced cross-border communications, much more factors such as foreign exchange rates, interest rates, commodity prices, inflation fear, speculations and changes in expectations, changes in investors' sentiment, options, futures, other derivative markets, domestic and foreign economic and political news, and more recently the financial and debt crises have significant impact on global economy and stock markets. Neural network approaches can make important contributions since they can incorporate very large number of variables and observations into their models.

The objective of most neural networks is to determine when to buy or sell stocks on the basis of historical market indicators. The critical task is to find enough relevant indicators to use as input data to train the system properly. The indicators could be technical and fundamental factors as mentioned above and others. Data normalization is common in neural networks since they generally use input data within the range of [0, 1] or [-1, +1]. For some neural networks with large number of inputs some pruning techniques are required to reduce the network size and speed up the recall and training times. Some common network architecture in most financial forecasting is a multilayer feed forward network trained by back-propagation that is back-propagating errors through the system from output layer to input layer during training. Back-propagation is needed since hidden units have no training target value to be used and therefore they must be trained from the errors of previous layers. The output layer has a target value for comparison. When the errors are back-propagated through the nodes, the connection weights are changed. Training will continue until the errors in the weights are small enough to be accepted. When to stop training could be a problem. Overtraining may happen if the system memorizes patterns and becomes unable to generalize. Over-training may also occur due to having too many hidden nodes or training for too many periods. Overtraining can be avoided by training the network on large percentage of patterns and testing the network on the remaining patterns. The network performance on the test set is an important indication of its ability to generalize and handle data it has been trained on. If the test set is unsatisfactory, the network is retrained until the performance is satisfactory.

Given the increasing importance of high frequency trading and their unique focus on analyzing stock data patterns, it is particularly meaningful to apply some statistical forecasting techniques and methods and neural network models to forecast daily stock prices. All market participants are subject to behavioral, emotional, and psychological attributes such as prospect theory, bandwagon effect, mental compartment, fear and greed, and self-attribution. These attributes may form certain predictable patterns reflected by the stock price movements. Literature review will follow this introduction in Section 1. In section 2 we discuss the forecasting techniques and methods. Section 3 shows the empirical findings. Conclusions are in the final section.

1. Brief literature review

One of the most significant contributions of market timing is to stay in the market during the major bull market and to stay out during the major market crashes. For examples, it took 15 years in 1945 to recover the original investment during the peak in October 1929. The real stock return was negative from the end of 1966 to August of 1982, another 15 plus years. The roller coastal rides of US stock market during our sample period make timing especially meaningful. For examples, from January 14, 2000 to September 21, 2001, DJIA fell 29.75% from

11,722.98 to 8,235.81 and again the index plunged 53.78% from October 9, 2007 when DJIA was 14,164.53 to 6,547.05 on March 9, 2009. The S&P 500 index declined 36.49% from 1520.77 on September 1, 2000 to 965.80 on September 21, 2001, and again it plunged 56.78% from 1565.15 on October 9, 2007 to 676.53 on March 9, 2009. For NASDAQ it was far worse with a decline of 71.81% from 5,048.62 on March 10, 2000 to 1,423.19 on September 21, 2001. NASDAQ plunged another 55.63% from 2859.12 on October 31, 2007 to 1,268.64 on March 9, 2009. All these sharp declines occurred within about 1 ½ years. Without such specific dating, during the first decade of this century the market prices all went down: DJIA was down 7.89%, S&P 500 was down 22.99%, and NASDAQ was down 45.50%. Martin Pring (1991, p. 31) showed that investment following the Dow Theory signals to buy and sell would increase from the initial investment of $100 in 1897 to $116,508 in January 1990 compared to $5,682 with a buy and hold strategy. Martin Zweig (1990, p. 121) stated that "I can't overemphasize the importance of staying with the trend of the market, being in gear with the tape, and not fighting the major movements. Fighting the tape is an open invitation to disaster". Professor Siegel (2008) tested DJIA and NASDAQ using 200-day moving average strategy and showed that the returns are higher than the buy-and-hold strategy before adjustment for transaction costs. When transaction costs were taken into account, the extra returns of the timing strategy became negligible, but the risk of timing strategy was lower. In addition, the timing strategy can avoid the major market crashes or prolong market declines and participated in major bull markets or secular market advance.

In recent years the traditional technical analysis and behavioral finance appear to reinforce each other from different perspectives. De Bondt and Thaler (1985, 1987) found that investors tended to overweigh the most recent information and underweight the more fundamental base rate information. The results are stock price short-term continuation and long-term reversal. Based on their two studies, one from January 1926 to December 1982 and the other from 1965 to 1984, they found that prior losers outperformed the prior winners. This momentum pattern makes the forecasts of future stock prices feasible. Kahneman and Turversky (1979) discovered that people in general and investors in particular incline to weigh heavily on memorable, salient, and vivid evidence than truly important information. Odean (1998, 1999) found that investors are prone to overestimate their own abilities and too optimistic about the future conditions. Daniel, Hirshleifer, and Subrahmanyan (1998) pointed out that because of investors' self-attribution bias and representative heuristic, their confidence grows when public information agrees with their private information; but when public information differs from their private information, their confidence declines only slightly. They show that positive autocorrelation results from short-term overreaction and long-term correction. The findings of short-term continuation and long-term reversal are consistent with a study by Balvers, Wu, and Gilliand (2000) of 18 countries from 1969 to 1996. Hong and Stein (1999) found that news-watchers made forecasts based on private observations about future fundamentals, while momentum traders applied simple or univariate functions of past prices to make their forecasts. All these findings lead to the frequent observations of short-term momentum and long-term reversal. Indeed many technical analysts have incorporated this market patterns into their trading strategies to capture some profitable opportunities. In recent years some 75-80% of all daily trading volume has been attributable to high frequency or algorithmic trading. Since algorithmic trading is based on historical data and is programmed by human beings who embed their decisions into their programs, the stock markets become more predictable and algorithmic trading is a friend of technical analyses (Baiynd, 2011).

More recently, Gutierrez and Kelly (2008) found that both winners' and losers' portfolios experienced very short-term return reversal in the first two weeks, and longer term continuation from week 4 to week 52. Menzly and Ozbas (2010) found that returns of both individual stocks and industries demonstrated strong cross-predictability with some lagged returns in supplier and customer industries. They also found that the smaller the number of analysts or institutional ownership, the greater the cross predictability. Based on these empirical findings on short-term to intermediate-term return or price momentum and medium-term to long-term reversal and cross-predictability, stock prices or returns appear to be predictable to some extent and traditional technical analysis indeed has its merits.

Brock, Lakonishok, and Lebaron (BLL) (1992) applied two simple trading rules (the moving averages and trading range break out) to daily Dow Jones Industrial Average from the first trading day of 1897 to the last trading day in 1986, they found that the technical trading strategies could generate returns from buy signals of 0.8 percent higher than the sell signals over the 10-day period. The returns from buy (sell) signals were higher (lower) than the normal returns. They pointed out that the return differentials between buy and sell signals cannot be explained by different risks. Sullivan, Timmermann, and White (1999) considered the on-balance volume indicator in addition to moving average, support and resistance levels, and break-out to DJIA daily data from 1897 to 1996. They found that BLL results are robust to data-snooping and technical trading rules are profitable. Finally, Lo, Mamaysky, and Wang (2000) used heads and shoulders, double tops and bottoms, triangle tops and bottoms, rectangular tops and bottoms and applied the nonparametric kernel regression method to identify the nonlinear patterns of stock price movements. They concluded that some patterns of technical analysis could provide incremental information and practical trading value.

In recent years neural network (NN) has been applied to make various kinds of forecasting. For examples, Mostafa (2004) applied NN to forecast Suez Canal traffic and Mostafa (2010) used NN to forecast the stock market movements in Kuwait, Videnova, Nedialkova, Miitrova, and Popova (2006) applied NN to forecast maritime traffic, Kohzadi, Boyd, Kemlanshahi, and Kaastra (1996) used NN to predict commodity prices, Ruiz-Suarez, Mayora-Ibarra, Torres-Jimenez, and Ruiz-Suarez (1995) applied NN to forecast ozone level, Poh, Yao and Jasic (1998) used NN to predict advertising impact on sales, Aiken and Bsat (1999) applied NN to predict market trends, and Yu, Wang, and Lai (2009) used NN to make financial time series forecasting.

There are a number of studies using NN to predict stock prices or returns. Kimoto, Asakawa, Yoda, and Takeoka (1990) and Ferson and Harvey (1993) applied several macroeconomic variables to capture the predictable variations in stock returns. Kryzanowski, Galler, and Wright (1993) used historical accounting and macroeconomic data to identify some stocks that outperformed the overall market. McNeils (1996) used the Chilean stock market to predict returns on the Brazilian stock market. Yumlu, Gurgen, and Okay (2005) applied NN architectures to model the performance of Istanbul stock exchange over the period of 1990-2002. McGrath (2002) used book-to-market and price-to-earnings ratios to rank stocks with likelihood estimates. Leigh, Hightower, and Modani (2005) applied both the NN and linear regression analyses to model the New York Stock Exchange Composite Index for the period of 1981-1999.

Many researchers have compared NN methods with various forecasting methods and techniques. Hammad, Ali, and Hall (2009) has shown that artificial NN (ANN) models provide fast convergence, high precision, and strong forecasting ability of real stock prices. West, Brockett, and Golden (1997) have concluded that NN offers superior predictive capabilities to traditional statistical methods in forecasting consumer choice in both linear and nonlinear settings. NN can capture nonlinear relationships associated with the use of non-compensatory decision rules. Grudnitski and Osburn (1993) applied NN and used general economic conditions and traders' expectations to predict S&P and gold futures. Tokic (2005) has shown that political events such as war on terror, fiscal policy on changing taxes and spending, monetary policy on changing short-term interest rates, and changes in federal budget deficit can affect stock prices. Nofsinger and Sias (1999) have found strong positive relationship between annual changes in institutional ownership and stock returns across different capitalizations. Dutta, Jha, Laha, and Mohan (2006) applied ANN models to forecast Bombay Stock Exchange's SENSEX weekly closing values. They compared two ANN and used 250 weeks' data from January 1997 to December 2001 to forecast for the period of January 2002-December 2003.

Moshiri and Cameron (2000) compared the back-propagation network (BPN) with six traditional econometric models to forecast inflation. Three of the six models are structural including the well-known Ray Fair's econometric forecasting models. The three time series models including Box-Jenkins autoregressive integrated moving average (ARIMA) models, vector autoregressive (VAR) models, and Bayesian vector autoregressive (BVAR) models. In one-period-ahead forecasts BPN models provide more accurate forecast. In three-period-ahead forecasts BPN is better than VAR and structural models but less accurate than ARIMA and BVAR. In twelve-period-ahead forecasts BPN models match ARIMA and BVAR but are superior to structural and VAR models. Other related methods are data mining (DM) and Bayesian data mining (BDM). Giudici (2001) used BDM for benchmarking and credit scoring in highly dimensional complex data sets. Jeong, Song, Shin, and Cho (2008) applied BDM to a process design. Ying, Kuo, and Seow (2008) applied hierarchical Bayesian (HB) approach to forecast stock prices of 28 companies included in DJIA from the third quarter of 1984 to the first quarter of 1998. They have found that HB can better predict stock prices than the classical models. Finally, Tsai and Wang (2009) applied ANN and decision tree (DT) models and have found that the combination of ANN and DT can more accurately predict stock prices.

The extant literature reviews lead us to believe that some time series forecasting methods such as time series decomposition, Holt/Winters models, NN, and ARIMA methods are likely to help us identify stock price patterns and predict the future stock prices. Realizing that no forecasting method or model is perfect and the stock markets are extremely complex and volatile populated with diversified market participants, it is our intention to find some workable models and methods which may prove to be fruitful for practical applications to the highly inter-connected global stock markets.

2. Data and data sources

We randomly selected daily stock prices of fifty companies from Yahoo Finance from September 1, 1998 through December 31, 2010. This time period was chosen to reflect the very volatile period including high tech boom in the late 1990s, the high tech bust from 2000 and the recession from 2001 to 2002, the historical event of 9/11, the housing boom ended in early 2007 and the great recession and financial crisis beginning in late 2007. For time series decomposition, Holt/Winters, and univariate ARIMA only daily stock prices of 3105 observations are needed to estimate the model and to make 60 trading days' forecasts beyond the sample period, i.e., the hold-out period is from October 7, 2010 to December 31, 2010. To capture the effects of countless relevant factors affecting stock prices, the neural networks are applied in this study.

For NN we need predictor variables in addition to the stock prices of the 50 companies. The predictors are classified into 7 groups: the first group includes 26 world major stock market indexes, group 2 includes 14 commodities and currencies, group 3 includes 213 competitive companies, group 4 consists of 4 major market indexes, group 5 includes CBOE volatility index changes (VIX), group 6 is market sentiment indicator and is represented by Franklin Resources Inc., and group 7 includes daily and monthly dummy variables. Appendix A provides the details of all 7 groups of predictors. These predictors are from the National Bureau of Economic Research (NBER), Yahoo Finance, The Federal Reserve Bank, Market Vane (MV), NYSE, and FXStreet. The Appendix will provide more detailed list of all variables and sources used in this study.

3. Methodology

3.1. Time series decomposition. Time series decomposition (TSD) is a traditional forecasting method that has been widely applied to business and economics. Any time series can be decomposed into four basic components: long-term trend, intermediate term cyclical factor, seasonal factor for a variable with data frequency greater than once a year, and unpredictable irregular component. We follow the widely applied multiplicative model in which variable $Y = T \times C \times S \times I$, where T is the trend component, C is the cyclical component, S is the seasonal component, and I is the irregular component. The forecasting process takes the form of identifying each component except the irregular one, and then multiplying all components together. In general after we take proper moving averages and centered moving averages on the original series, the seasonal and irregular components will be smoothed out. The remaining components are $T \times C$. Then dividing the remaining series into the original series will result in $S \times I$. We take averages of this new series to smooth out irregular component and obtain the seasonal indexes. The trend component is derived from fitting a linear or nonlinear trend on the centered moving average series mentioned previously. Finally, divide the centered moving average series by the trend component to obtain the cyclical component. The trend factor can be extrapolated into future periods, while cyclical and seasonal components are assumed to stay the same. To make any period ahead forecast we simply multiply all three factors together assuming the irregular component stay neutral at 1.

The regression analyses have been widely used due to their ready economic interpretations and policy implications. But this method requires forecasting the future values of explanatory variables before one can forecast the dependent variable(s). In practical applications forecasting the future values of independent variables is just as difficult as forecasting the dependent variable. Since there are so many possible variables affecting daily stock prices, we will use those variables only in NN.

3.2. Holt's exponential smoothing. Holt's exponential smoothing (HES) can not only smooth the original data but incorporate a linear trend into the forecast. The model requires two smoothing constants and three equations to smooth data, update trend, and make forecast for any desirable forecast horizon. The model can be represented by:

$$F_{t+1} = aY_t + (1-a)(F_t + T_t), \tag{1}$$

$$T_{t+1} = b(F_{t+1} - F_t) + (1-b)T_{t,} \tag{2}$$

$$H_{t+n} = F_{t+1} + nT_{t+1}, \tag{3}$$

where F_{t+1} is the smoothed value for period $t + 1$, a is the smoothing constant for the smoothed value (level) with $0 < a < 1$, Y_t is the actual value of the original data in period t, T_{t+1} is the trend estimate in period $t + 1$, b is the smoothing constant for trend estimate with $0 < b < 1$, H_{t+n} is the Holt's forecast value for forecasting horizon of n periods, $n = 1, 2, 3, \ldots$

The smoothed value and trend estimate will stop changing beyond one period after the end of actual data even though n keep increasing. For example, if actual stock price of a company ends on December 31, 2010, F_{t+1} and T_{t+1} will be the smoothed value and trend estimate one day after that. To make 2-day ahead forecast, both stay the same but n is equal to 2 in H_{t+2}. Therefore, Holt's exponential smoothing is more suitable for short-term forecast or if the underlying time series demonstrate a linear trend.

3.3. Winters' exponential smoothing. When a time series demonstrates both trend and seasonality, Winters' exponential smoothing (WES) is more suitable than the HES. WES is an extension of HES by incorporating seasonal adjustment. WES is captured by the following 4 equations:

$$F_t = aY_t / S_{t-p} + (1-a)(F_{t-1} + T_{t-1}), \tag{4}$$

$$S_t = cY_t / F_t + (1-c)S_{t-p}, \tag{5}$$

$$T_t = b(F_t - F_{t-1}) + (1-b)T_{t-1}, \tag{6}$$

$$W_{t+n} = (F_t + nT_t)S_{t+n-p}, \tag{7}$$

where S_t is the seasonality estimate in period t, c is the smoothing constant for seasonality estimate with $0 < c < 1$, p is the number of seasons in a year, e.g., $p = 4$ for quarterly data, W_{t+n} is the Winters' forecast for forecasting horizon of n.

All other symbols in the equations are the same as in HES. When we compare equations (4)-(7) with (1)-(3), it is clear that WES is an extension of HES by adding seasonality adjustment. When the data end, F_t and T_t, will not change. The seasonal index for each season will be fixed. However, the forecast for each season will be adjusted by its respective seasonal index. For daily stock prices, some show seasonality, while others don't. Similar to HES, WES is more appropriate for short-term forecast. The length of time depends on whether the data are quarterly, monthly, or daily. For example, if the data are quarterly, $n = 4$ means one-year ahead forecast.

3.4. Box-Jenkins methodology. Box-Jenkins methodology is statistically very sophisticated and complicated. Most forecasters apply univariate autoregressive integrated moving average (ARIMA) method. The general form of an ARIMA model can be represented by the following equation:

$$Y_t = A_1Y_{t-1} + A_2Y_{t-2} + ... + A_pY_{t-p} + e_t + B_1e_{t-1} + \\ + B_2e_{t-2} + \cdots + B_qe_{t-q}. \tag{8}$$

If a time series is nonstationary, the common method to make it stationary is by taking differences. For most business and economic data, usually it needs only to take first or second differences. If the data demonstrate some seasonality, it requires taking seasonal differences. The general model form of an ARIMA is ARIMA (p, d, q) (P, D, Q) where where p is the order of autoregressive part, q is the order of the moving averages, d is the number of times of taking differences, while P, D, Q refer to the seasonal correspondences of p, d, q. A model is considered to be appropriate when the residuals are random or white noise after a model is fitted. The principal advantages of ARIMA are its ability to analyze and forecast various types of time series whether it's stationary or nonstationary, linear or nonlinear, seasonal or not, and a large number of observations.

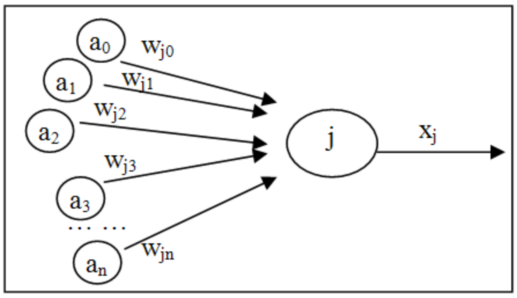
A standard procedure of ARIMA starts with data. By analyzing the data and examine the autocorrelation and partial autocorrelation functions some tentative model can be identified. Then the parameters of the tentative model are estimated and diagnostically checked to see if the model is considered appropriate. A model is considered suitable if the residuals are random or white noise or the Ljung-Box-Pierce Q-statistic is insignificant. This Q-statistic follows the chi-square distribution and is used to test if the autocorrelations of the residuals are random. The Q-statistic is defined as:

$$Q_m = n(n+2)(r_1^2/(n-1) + r_2^2/(n-2) + ... + \\ + r_m^2/(n-m)), \tag{9}$$

which is approximately distributed as a chi-square distribution with m-p-q degrees of freedom, where n is the number of observations in the time series, m is the number of time lags to be tested, r_i is the sample autocorrelation coefficient of the i^{th} residual term.

The Q-statistic is used to test if the residual autocorrelations as a set are significantly different from zero. If they are, the model is considered inappropriate and a new tentative model will be identified and diagnostically tested again. On the other hand, if they are not significantly different from zero, the model is appropriate, and the estimated model can be used for forecasting.

3.5. Neural networks. One of the most significant advantages of neural networks (NN) lies in their ability to handle very large number of observations and variables. In this study we use eight major indicators: aggregate indicators such as global market indices, individual competitors; political indicators such as presidential election date and party, US market indices, market sentiment indicators; institutional investors (Franklin Resources), and calendar anomalies. Data were collected from National Bureau of Economic Research, Yahoo Finance, the Federal Reserve Banks, Market Vane, NYSE, and FXStreet. Altogether there are 213 variables and the detail can be found in the Appendix.



Source: Dayhoff, J. (1990). *Neural Network Architectures*, New York: Van Nostrand Reinhold

Fig. 1. Basic neural network model

The basic neural network model is presented by the following equation:

$$S_j = \sum_{i=0}^{n} a_i w_{ji},$$

where w_{ji} is the weight associated with the connection to processing unit j from processing unit i, a_i is the value output by input unit i. Output of $j = X_j$ $\{0$ if $Sj \leq 0$ and 1 if $Sj > 0$.

A basic NN model's framework is shown in Figure 1 above. Input neurons (1 to n) are connected to an output neuron j and each connection has an assigned weight (w_{jo} to w_{jn}). In this example the output of j becomes 1 (activated) when the sum of the total stimulus (S_j) becomes great than 0. The activation function in this example used a simple unit function (0 or 1), but other functions such as Gaussian, exponential, sigmoid, or hyperbolic functions can be used for complex networks.

Backpropagation is one of the most popular learning algorithms in NN and is derived to minimize the error using the following formula:

$$E = 0.5 \sum_p \left(\sum_k t_{pk} - o_{pk} \right)^2),$$

where p is the pattern i, k is the output unit, t_{pk} is the target value of output unit k for pattern p, o_{pk} is the actual output value of output layer unit k for pattern p.

Genetic algorithm (GA) has the capabilities in pattern recognition, categorization, and association and therefore it has been widely applied in NN. Turban (1992) has shown that a genetic algorithm enables NN to learn and adapt to changes through machine learning for automatically solving complex problems based on a set of repeated instructions. GA enables NN to produce improved solutions by selecting input variables with higher fitness ratings. Alyuda NeuroIntelligence enables us to retain the best network.

First, we used BrainMaker software to create a NN model for four companies (C, GS, JPM, and MS), but BrainMaker had a major limitation of 20 variables, and so it was not adequate for the number of variables in our model. We included independent variables from stepwise regression to BrainMaker due to the limit. However, BrainMaker burst out and unable to learn. BrainMaker failed to perform as shown in Figure 2.

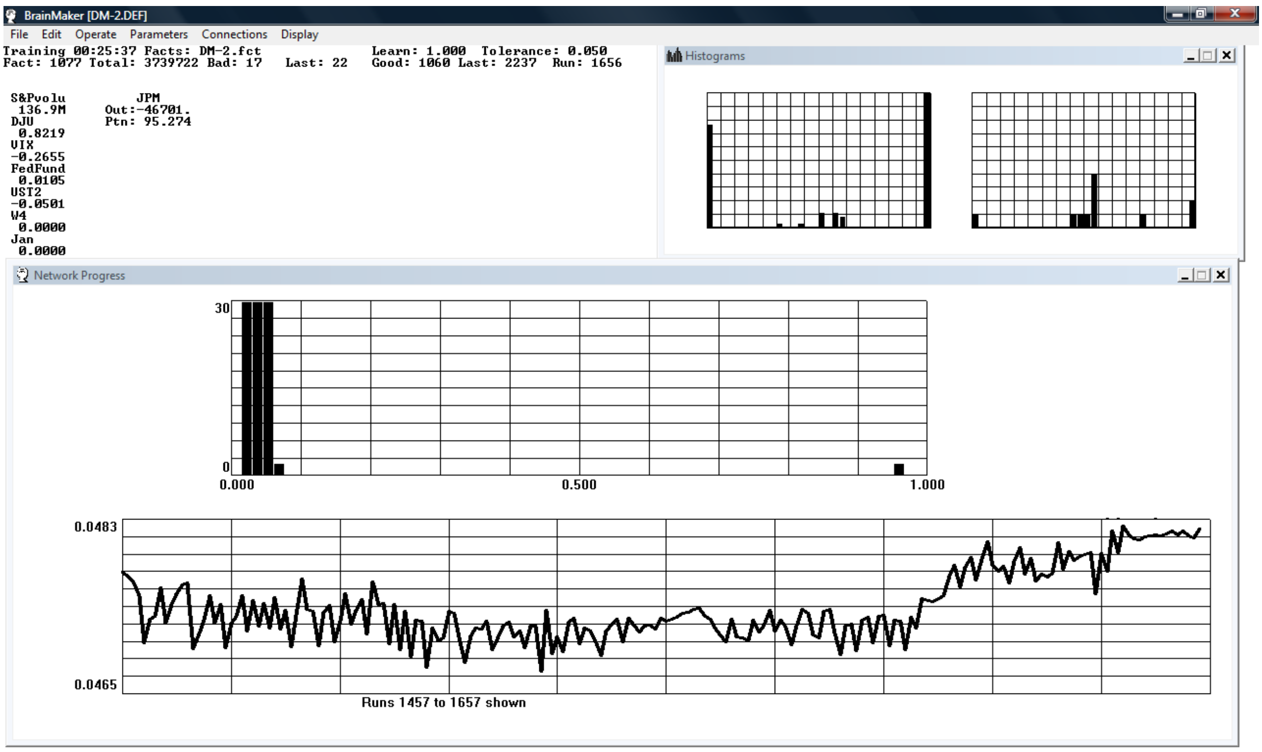


Fig. 2. BrainMaker error distribution

We searched and found Alyuda NeuroIntelligence that allowed us to handle 272 independent variables (Table A1 to A8 in the Appendix) and 50 dependent variables. ANI is used to create the second generation of NN models. We use both the non-normalized and normalized data. We follow the seven-step neural network design process to build up the network. ANI is used to perform data analysis, data preprocessing, network design, training, testing, and query. Logistic function is applied to design the network. The logistic function has a sigmoid curve of $F(x) = 1/ (1+ e^{-x})$ with output range of [-1, 0.1]. Batch backpropagation model with stopping training condition of 501 iterations is used to find the best network during the network training.

We used the same model architecture of 272-41-1 for all normalized data and 272-1-1 for all non-normalized data. The network architecture consisted of 272 input neurons, 41 neurons in the hidden layer, and one output neuron. The number of iterations is intended to escape from local minima and reach a global minimum to achieve the lowest possible errors to train the network. The setup screen of ANI is shown in Figure 3.

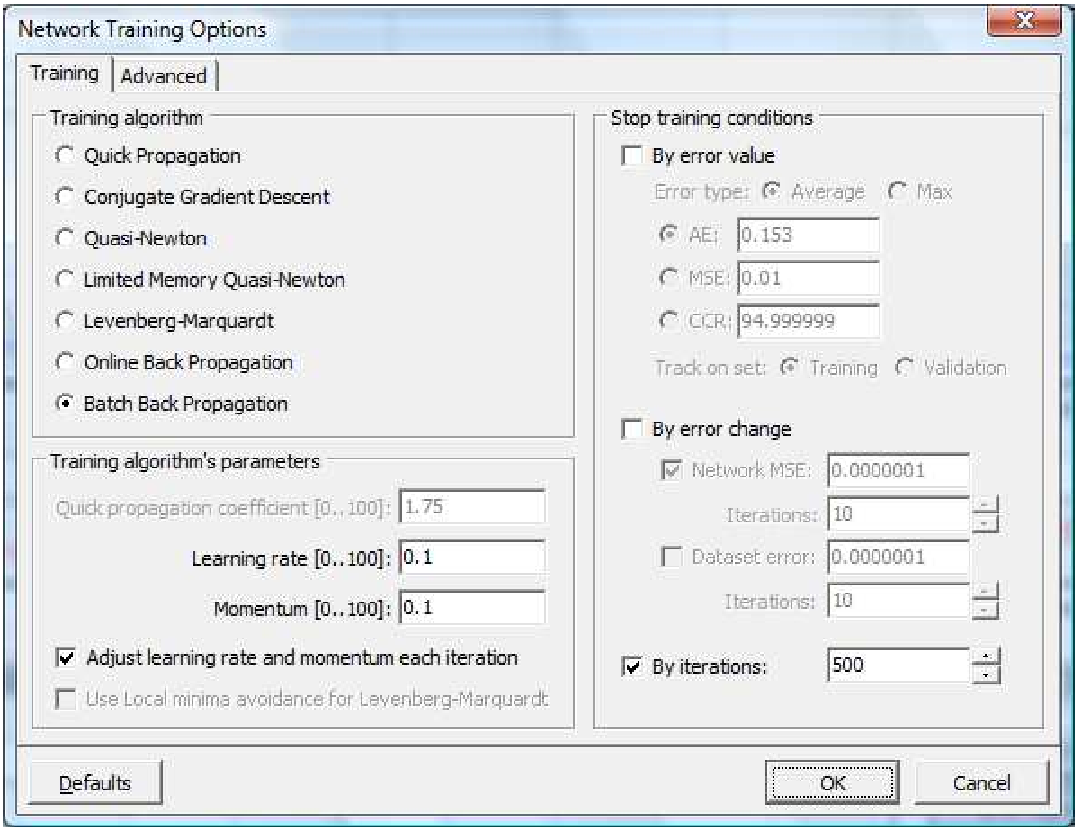


Fig. 3. Alyuda NeuroIntelligence setup screen

3.6. Data – training data set, validation data set, and out-of-sample testing data set. There are three sets of data used in the neural network model: training set, validation set, and testing set. The training set is used to train the NN and adjust network weights. The validation set is used to tune network parameters other than weights, to calculate generalization loss, and retain the best network. The testing set is used to test how well the NN performs on new data after the network is trained. We used training and validation data to train the network and come up with a model. Finally, we used out-of-sample testing data to test the forecasting errors between the actual and predicted values. That is, we have both training (80%) and validation (20%) data from September 1, 1998 to October 6, 2010 and testing data from October 7, 2010 to December 31, 2010.

3.7. Non-normalized data. For non-normalized data, we used an original data directly from the sources without any modifications. The same data are being used for running time series regressions. As the literature in NN suggested, using non-normalized data generated a bigger errors with high standard deviations as shown in Table 5. Therefore, we normalized the data using various techniques and discussed it in the next section. A sample NN run using non-normalized data is shown in Figure 4.

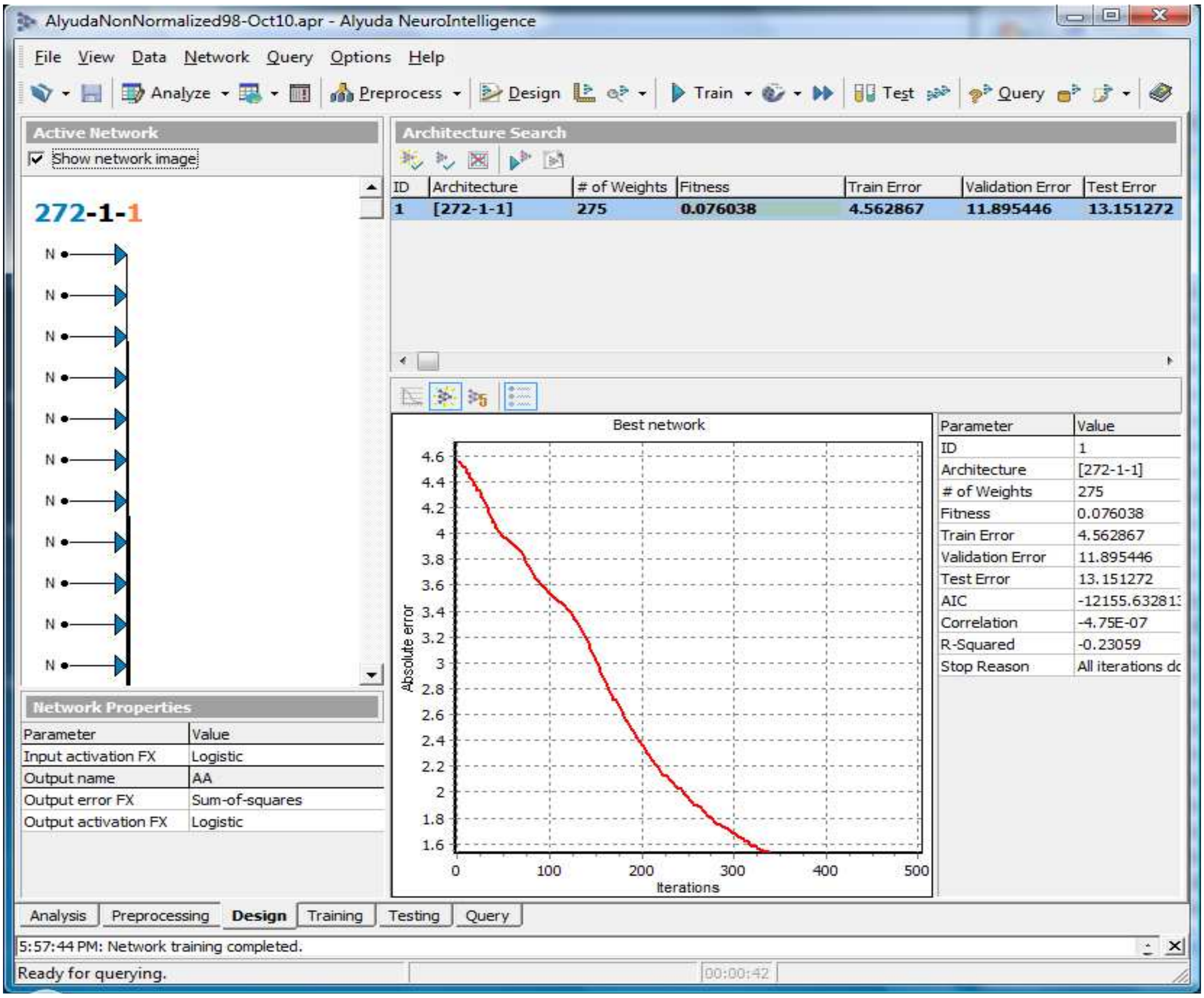


Fig. 4. NN non-normalized network architecture

3.8. Normalized data. We tried various data normalization techniques and compared the performance of the networks. We found that using the stock price difference rather than actual daily stock price worked much better. Then, we looked at the numbers in our data: both positive and negative numbers in daily stock price changes. We thought we would want to have all positive numbers to see how the NN learns. So, we wanted to shift up or normalize the data. First, we searched for the lowest negative numbers. We wanted to add the negative numbers to all numbers to make all numbers positive. Second, we took the absolute value of the lowest negative numbers. If it was not done so, we would have negative numbers, plus negative numbers result in bigger negative numbers. For example -6 + (-6) = -12. Third, we wanted to take into account the rounding error by adding 0.1 to the absolute value of the lowest negative numbers. For example, to normalize the data of company A, we added the absolute value of lowest negative numbers of company A, that is, |-6.7| to 0.1. As a result, we had 6.8. Then we used 6.8 to add all numbers. Let's say we used the lowest numbers: 6.8 + (-6.7) = 0.1. To sum up, the formula we used to normalize the data = (|lowest negative number| +0.1+ all numbers in our data set). After we normalized the data, we had both a lower mean and standard deviation for all NN models.

According to Alyuda NeuroIntelligence manual (2010) "backpropagation algorithm is the most popular algorithm for training of multi-layer perceptrons and is often used by researchers and practitioners. The main drawbacks of backpropagation are: slow convergence, need to tune up the learning rate and momentum parameters, and high probability of getting caught in local minima." Gaussian distribution of network inputs is used to retrain and restore the best network and randomize weights. Retraining and restoring the best network overtraining such as memorizing data instead of generalizing and encoding data relationships can be prevented and thus reduce the network errors. A 10% jitter (random noise) was added to avoid overtraining and local minima. Weights randomization can avoid sigmoid saturation that causes slow training. A sample NN run for normalized network is shown in Figure 5.

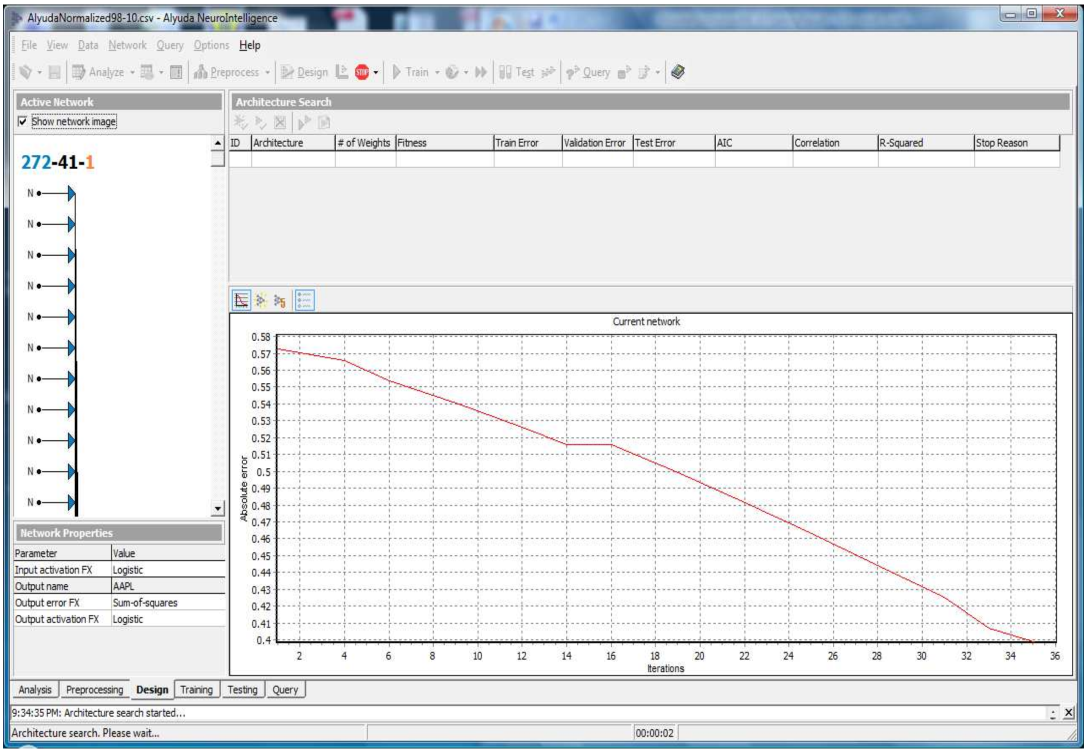


Fig. 5. NN normalized network architecture

The results from normalized and non-normalized data can be better compared with those from the three time series models discussed previously. The findings from normalized data may shed light on the possible improvement from normalization since NN normalizing data has become a common practice.

4. Empirical findings

In this study we apply ForecastX wizard 7.1 by John Galt Solutions to time series decomposition, Holt/Winters, and Box-Jenkins models and for neural networks we use Alyuda NeuroIntelligence. ForecastX^{tm} is a family of diversified forecasting methods which can perform complex forecast models.

Since the sample size is 3105 observations, the R^2 and the adjusted R^2 are basically the same. For time series decomposition the lowest R^2 is 99.46% for JPM and the highest is 99.98% for KMP. The mean absolute percentage error for the whole sample period is 0.01% to 0.00%. The within sample fits for all 50 companies are extremely good. When the whole period is considered, the fitted prices are dominated by the long-term trend factor, T, the seasonal component, S, is basically neutral, and the cyclical factor, C, mostly lies between 0.95 and 1.1. Since we chose Holt's model to forecast trend factor, T, the trend is in turn dominated by level, i.e., F_{t+1} in equation (1). The T_{t+1} factor in equation (2) is generally very small.

For H/W model the lowest R^2 is 98.38% for JPM and only five companies have R^2 below 99%, and the highest R^2 is 99.93% for KMP. The MAPE's for all 50 companies range between 0.00% and 0.03%. Again the whole sample fits of data to the model are exceptionally good for all 50 companies. For Box-Jenkins model, the lowest R^2 is 98.37% for JPM and the highest R^2 is 99.93% for KMP. Only four companies have R^2 below 99%. The MAPE's for all 50 firms are between 0.00% and 0.02%. In the H/W model the fitted values are dominated by trend factor, F_t, in equation (4), and seasonal factor, equation (5) is quite obvious for about half of the 50 stock prices in the sample. When we compare the seasonal factor of H/W model for all 50 stock prices with the B-J model, the results are quite similar. The B-J and H/W models are able to identify seasonality for more companies' stock prices than the TSD model.

In terms of R^2 and MAPE for the whole sample the H/W and B/J performs about the same, while TSD performs somewhat better than both. For such a large sample of 3105 observations, the widely used forecasting error, root-mean-squared error is basically the same as the residual sum of squares. That is, the higher the R^2, the smaller the RMSE. Stock prices vary widely among different companies, and therefore it is easier to compare MAPE across different stock prices than RMSE. That is the reason why we use MAPE instead of RMSE. The neural network model does not have the comparable statistics to compare because from learning to testing and then to forecasting, the processes are different from the three time series models covered in this study.

In the ARIMA (p, d, q) (P, D, Q) model we can detect some clear seasonality of stock prices for many of the 50 companies. ForecastX can identify the best model for a given set of data. The following table summarizes the best models identified for the 50 stocks from B-J models.

Table 1. Summary of the best Box-Jenkins model

Tick symbol	ARIMA (*p*, *d*, *q*) (*P*, *D*, *Q*)
AA	(1, 1, 1) (0, 0, 0)
AAPL	(1, 0, 0) (0, 0, 0)
AMAT	(1, 0, 2) (2, 0, 2)
AMGN	(1, 0, 0) (0, 0, 0)
BAX	(2, 1, 1) (1, 0, 1)
BHP	(0, 1, 1) (0, 0, 0)
BTI	(0, 1, 2) (0, 0, 1)
CBSH	(1, 0, 0) (0, 0, 0)
CERN	(0, 1, 1) (0, 0, 0)
CRH	(1, 1, 2) (1, 0, 1)
CSCO	(0, 1, 1) (0, 0, 0)
CT	(0, 1, 0) (1, 0, 0)
EME	(0, 1, 1) (0, 0, 0)
EXC	(2, 1, 1) (0, 0, 0)
FCX	(0, 1, 0) (1, 0, 0)
GE	(0, 1, 0) (1, 0, 1)
HCP	(1, 0, 0) (0, 0, 0)
HD	(1, 1, 1) (0, 0, 0)
HIBB	(1, 1, 1) (0, 0, 0)
HON	(0, 1, 0) (1, 0, 0)
IBM	(1, 1, 0) (0, 0, 0)
INTC	(1, 0, 0) (1, 0, 0)
JNJ	(0, 1, 0) (1, 0, 1)
JPM	(1, 1, 1) (1, 0, 0)
KMP	(2, 1, 1) (1, 0, 1)
KO	(0, 1, 0) (2, 0, 1)
KYO	(0, 1, 0) (1, 0, 1)
MCD	(0, 1, 0) (1, 0, 1)
MMC	(0, 1, 0) (0, 0, 1)
MS	(2, 1, 1) (1, 0, 1)
MSFT	(1, 1, 2) (1, 0, 0)
MU	(0, 1, 0) (1, 0, 1)
MYL	(0, 1, 0) (0, 0, 1)
NOK	(0, 1, 0) (0, 0, 1)
NTT	(2, 1, 0) (1, 0, 1)
PCAR	(1, 0, 0) (0, 0, 0)
PG	(0, 1, 0) (0, 1, 1)
RF	(0, 1, 1) (0, 0, 0)
RIG	(2, 1, 0) (1, 0, 1)
SCHW	(2, 1, 1) (1, 0, 0)
SLB	(2, 1, 2) (1, 0, 1)
SPG	(1, 0, 0) (0, 0, 0)
SYMC	(1, 1, 1) (1, 0, 1)
T	(0, 1, 0) (1, 0, 1)
USB	(1, 1, 0) (1, 0, 0)
VCO	(0, 1, 0) (1, 0, 1)
VMC	(0, 1, 0) (1, 0, 0)
WHR	(0, 1, 0) (1, 0, 0)
XOM	(1, 0, 0) (2, 0, 0)
YHOO	(2, 1, 1) (1, 0, 1)

Out of the 50 company stock prices the R-squared typically are between 99.5% and 99.95%, while there are three exceptions where R^2 are between 98.5% and 99% from both time series decomposition and Box-Jenkins methodology. Among the 50 company stock prices 16 of them do not demonstrate seasonality, i.e., BHP, CBSH, PCAR, HCP, SPG, AMGN, EME, HD, RF, HIBB, IBM, CERN, CSCO, AAPL, AA, AND EXC), and 34 of them show some seasonality, SLB, GE, PG, JPM, MS, SCHW, JNJ, CT, VMC, KMP, WHR, KO, BTI, FCX, MMC, USB, MYL, BAX, BA, HON, CRH, MCD, VCO, MSFT, NOK, KYO, RIG, YHOO, SYMC, INTC, AMAT, MU, T, XOM, AND NTT. The results are different from those identified by H/W model where only 25 stock prices show some seasonality. The cumulative mean percent errors are from 0.00% to 0.02%, the root-mean-square errors are very small relative to the company stock prices. The mean errors are about zero for all companies and for all four models, which indicate that there is no forecasting bias in any one direction.

From Table 1 it is clear that over the sample period of more than 12 years, most stocks, particularly the emerging technology stocks went up greatly to 2000 and went down extreme fast from 2000 to 2002 and then fluctuated until the current financial crisis beginning in late 2007. As a result the stock prices in our sample did not exhibit strong upward movement. As we pointed out before the first decade of the 21st century is basically a lost decade as far as the stock markets are concerned. Since the stocks in our sample are large or medium capitalization companies and they don't demonstrate large upward or downward movements over the whole sample period. Nine (AAPL, AMAT, AMGN, CBSH, HCP, INTC, PCAR, SPG and XOM) of the 50 stock prices were stationary. All others require only first differencing showing either upward or downward linear trend. Although there were 34 stocks showed some seasonality, except PG the other 33 stocks did not need any seasonal differencing. Most stocks follow the first order autoregressive and/or moving average and none requires more than second order model specifications. This is why H/W and TSD models also fit the data so well since both models capture the general linear trend.

In forecasting the true test of any model is its ability to forecast beyond the sample period. In this study we use the sample observations of daily stock prices from September 1, 1998 to October 6, 2010 to estimate the models and apply the resulting models to forecast the next 60 trading days, i.e., from October 7, 2010 to December 31, 2010. The mean, maximum, minimum, median, and standard deviation of MAPE from B-J model for all companies are as follows.

Table 2. Out-of-sample MAPE (in %) from Box-Jenkins model

Company	Mean	Maximum	Minimum	Standard dev.	Variance	Median
AA	9.51	19.76	1.43	5.19	0.27	7.82
AAPL	7.62	11.15	0.01	2.62	0.07	8.35
AMAT	8.15	17.54	0.04	5.06	0.26	7.15
AMGN	2.81	7.31	0.04	1.94	0.04	2.36
BAX	3.99	7.30	0.15	1.90	0.04	4.36
BHP	7.37	13.96	0.21	4.30	0.18	7.87
BTI	2.30	5.42	0.05	1.41	0.02	2.33
CBSH	2.72	5.68	0.22	1.67	0.034	2.69
CERN	3.81	11.29	0.00	3.63	0.13	2.02
CRH	7.17	1496	0.44	4.53	0.21	7.02
CSCO	9.73	16.86	0.48	4.97	0.25	10.35
CT	15.33	42.66	0.07	10.31	1.06	15.54
EME	7.58	16.27	0.02	5.40	0.29	6.06
EXC	3.93	7.50	0.16	2.21	0.05	4.07
FCX	10.26	22.52	0.36	6.84	0.47	8.78
GE	4.33	8.50	0.37	2.27	0.05	4.62
HCP	4.26	11.49	0.03	3.71	0.14	3.08
HD	4.25	10.61	0.00	3.75	0.14	2.91
HIBB	19.22	37.72	2.67	12.22	1.49	11.76
HON	7.63	15.33	0.09	4.98	0.25	7.70
IBM	4.36	6.68	0.21	1.87	0.03	5.08
INTC	5.69	9.90	0.38	2.96	0.09	6.97
JNJ	0.81	2.38	0.02	0.54	0.00	0.76
JPM	3.41	7.84	0.06	2.53	0.06	3.21
KMP	2.26	3.81	0.75	0.70	0.00	2.26
KO	5.49	9.87	0.15	3.14	0.10	5.68
KYO	2.02	5.20	0.01	1.44	0.02	1.60
MCD	3.34	6.69	0.02	1.50	0.02	3.37
MMC	7.20	13.49	0.25	3.94	0.16	5.86
MS	3.33	8.89	0.04	2.55	0.06	2.66
MSFT	8.05	14.50	0.37	4.04	0.16	8.73
MU	10.81	19.73	2.09	3.92	0.15	11.22
MYL	5.90	12.27	0.21	3.70	0.14	6.53
NOK	4.09	12.59	0.65	2.61	0.07	3.92
NTT	1.88	5.41	0.38	1.01	0.01	1.75
PCAR	8.35	14.52	0.13	4.55	0.21	8.59
PG	4.47	7.13	0.21	1.68	0.03	4.63
RF	18.17	44.06	0.42	12.05	1.45	18.44
RIG	6.16	13.04	0.08	3.56	0.13	6.43
SCHW	9.25	18.65	0.30	5.42	0.29	7.79
SLB	15.25	24.91	0.02	8.17	0.67	16.68
SPG	3.63	10.07	0.10	2.34	0.05	3.65
SYMC	9.74	15.41	0.42	3.88	0.15	10.87
T	1.34	3.29	0.00	0.83	0.01	1.16
USB	9.20	17.57	0.19	5.05	0.26	9.22
VCO	1.34	2.81	0.10	0.76	0.01	1.48
VMC	8.74	20.37	2.37	5.40	0.29	5.90
WHR	6.18	11.58	1.06	2.92	0.09	6.36
XOM	8.32	13.84	0.01	4.25	0.18	9.45
YHOO	14.31	0.62	3.33	0.11	11.07	10.26

From Table 2, 43 out of 50 companies have minimum MAPE less than 10% over the 60 trading days (about 2.9 months), 22 have average MAPE below 5%, 21 with MAPE between 5% and 10%, and only 7 have maximum MAPE greater than 10%. The standard errors of MAPE over the 60 trading days are mostly within 5%. Given the fact that individual daily stock prices are extremely volatile for many stocks during the sample period, this table shows that B-J model can predict fairly accurately the future prices over the extended period of 60 trading days or 2.9 months. For H/W model the similar statistics are shown in Table 3.

Table 3. Out-of-sample MAPE (in %) from H/W model

Company	Mean	Maximum	Minimum	Standard dev.	Variance	Median
AA	9.52	19.79	1.46	5.19	0.27	7.86
AAPL	5.73	8.57	0.10	1.90	0.04	6.31
AMAT	8.06	17.52	0.08	5.06	0.26	7.04
AMGN	2.45	5.99	0.05	1.44	0.02	2.48
BAX	3.84	7.18	0.01	1.90	0.04	4.32
BHP	6.61	12.68	0.09	4.02	0.16	7.10
BTI	1.97	4.91	0.01	1.26	0.02	1.82
CBSH	2.73	5.83	0.16	1.63	0.03	2.62
CERN	3.47	10.54	0.00	3.28	0.11	1.78
CRH	6.99	14.47	0.45	4.27	0.18	6.84
CSCO	9.71	16.95	0.39	4.92	0.24	10.22
CT	15.26	42.23	0.07	10.31	1.06	15.64
EME	7.30	15.70	0.02	5.23	0.27	6.00
EXC	4.24	7.99	0.07	2.31	0.05	4.38
FCX	9.66	21.59	0.64	6.63	0.44	8.13
GE	4.34	8.43	0.46	2.27	0.05	4.63
HCP	4.67	12.43	0.02	4.31	0.19	2.31
HD	4.26	10.61	0.11	3.75	0.14	2.91
HIBB	19.01	37.42	2.67	12.13	1.47	11.54
HON	7.74	15.43	0.07	4.99	0.25	7.82
IBM	3.95	6.11	0.03	1.69	0.03	4.46
INTC	7.50	12.57	0.06	3.82	0.15	9.02
JNJ	0.93	2.19	0.00	0.54	0.00	0.82
JPM	3.38	7.56	0.05	2.53	0.06	3.21
KMP	1.42	3.16	0.15	0.66	0.00	1.49
KO	5.36	9.70	0.22	3.12	0.10	5.54
KYO	1.75	4.83	0.04	1.36	0.02	1.49
MCD	2.71	5.94	0.02	1.47	0.02	2.53
MMC	7.27	13.59	0.10	3.94	0.16	5.97
MS	3.19	8.31	0.08	2.37	0.06	2.74
MSFT	7.85	14.20	0.43	3.96	0.16	8.42
MU	10.79	19.58	1.91	3.94	0.16	11.15
MYL	5.86	12.28	0.10	3.69	0.14	6.28
NOK	4.26	13.32	0.00	2.74	0.08	3.89
NTT	1.60	5.13	0.09	1.01	0.01	1.45
PCAR	8.27	14.34	0.01	4.48	0.20	8.49
PG	4.49	7.06	0.11	1.69	0.03	4.64
RF	17.94	43.78	0.41	12.01	1.44	17.97
RIG	6.16	13.05	0.06	3.56	0.13	0.42
SCHW	9.12	18.50	0.40	5.37	0.29	7.63
SLB	15.04	24.66	0.06	8.16	0.67	14.44
SPG	3.33	10.07	0.13	2.26	0.05	3.05
SYMC	9.73	15.39	0.42	3.88	0.15	10.86
T	1.35	3.54	0.01	0.82	0.01	1.26
USB	9.23	17.52	0.25	5.06	0.26	9.23
VCO	1.27	3.30	0.01	0.79	0.01	1.27
VMC	8.73	20.36	2.43	5.38	0.29	5.93
WHR	6.18	11.54	0.63	2.90	0.08	6.43
XOM	8.13	13.18	0.06	3.99	0.16	9.27
YHOO	10.76	14.69	0.21	3.28	0.11	11.46

The results from H/W model are very close to those from the B-J model. Forty four out of 50 stocks have mean MAPE less than 10%, with 22 less than 5%, 22 between 5% and 10%, and only 6 have mean MAPE greater than 10%. Only 3 have standard deviation of MAPE greater than 10% and 39 have standard deviation less than 5%. The results are marginally better than those from the B-J models. Since it is more difficult to identify the precise autoregressive and moving average orders in B-J modeling, the simple H/W models could be the preferred choice. Although ForecastX can help researchers identify some optimum model specifications, there is no guarantee that they are truly the best specifications. However, based on the excellent fits to the both within and out-of-sample data, ForecastX has shown its accuracy and easiness to use, and so both H/W and B-J methods can be practically applied. From time series decomposition the similar statistics are shown in the following Table 4.

Table 4. Out-of-sample MAPE (in %) from time series decomposition

Company	Mean	Maximum	Minimum	Standard dev.	Variance	Median
AA	2.87	6.95	0.14	1.85	0.03	2.46
AAPL	2.73	7.58	0.26	1.44	0.02	2.46
AMAT	1.73	5.08	0.02	1.58	0.02	1.21
AMGN	14.28	28.27	0.14	8.94	0.80	16.37
BAX	8.35	18.93	0.07	6.29	0.40	7.62
BHP	16.26	30.06	0.23	9.84	0.97	17.45
BTI	6.31	12.76	0.79	3.78	0.14	5.75
CBSH	2.64	5.41	0.02	1.70	0.03	2.67
CERN	20.11	35.43	1.82	9.62	0.92	24.52
CRH	36.12	60.04	5.24	15.64	2.44	36.82
CSCO	16.61	31.46	0.16	12.94	1.68	23.89
CT	18.34	47.14	0.47	11.37	1.29	18.90
EME	3.43	11.56	0.00	2.92	0.09	2.36
EXC	7.24	12.30	0.00	3.71	0.14	7.83
FCX	37.01	60.76	1.66	18.66	3.48	44.95
GE	17.61	29.27	0.22	7.87	0.62	21.21
HCP	11.31	23.56	0.02	7.81	0.61	12.21
HD	4.91	8.90	1.43	2.31	0.05	4.72
HIBB	22.72	42.70	2.68	13.71	1.88	15.96
HON	11.93	23.28	0.37	6.30	0.40	13.30
IBM	11.20	23.40	0.08	7.43	0.55	10.88
INTC	7.71	12.70	0.02	3.74	0.14	9.20
JNJ	9.72	21.69	0.09	6.79	0.46	9.40
JPM	32.64	52.79	3.05	14.66	2.15	32.93
KMP	5.11	11.50	0.21	3.67	0.13	4.90
KO	8.48	15.88	1.91	4.08	0.17	7.92
KYO	41.40	84.52	1.26	25.15	6.33	42.02
MCD	8.93	21.69	0.51	6.66	0.44	8.02
MMC	12.48	23.13	0.15	6.68	0.45	11.50
MS	23.59	39.91	1.75	11.77	1.38	25.30
MSFT	8.73	15.04	1.36	3.92	0.15	9.30
MU	41.69	71.86	4.25	18.22	3.32	39.30
MYL	5.81	12.27	0.02	3.69	0.14	6.18
NOK	40.71	76.55	0.35	26.43	6.99	41.39
NTT	4.78	11.75	0.01	3.74	0.14	3.75
PCAR	12.80	25.28	0.28	7.12	0.51	14.06
PG	4.68	10.96	0.02	3.93	0.15	3.52
RF	52.35	91.15	2.81	27.24	7.42	63.58
RIG	20.04	35.47	0.14	10.44	1.09	20.64
SCHW	9.91	19.39	0.87	5.39	0.29	11.94
SLB	1.95	6.65	0.07	1.66	0.03	1.52
SPG	17.23	34.20	2.78	10.31	1.06	18.37
SYMC	21.19	33.88	0.32	9.87	0.97	23.94
T	16.50	27.29	4.18	7.53	0.57	18.17
USB	13.35	24.70	1.53	8.03	0.64	13.01
VCO	11.90	25.13	0.87	6.40	0.41	10.70
VMC	9.10	21.31	1.28	6.00	0.36	6.87
WHR	15.05	32.46	0.00	9.05	0.82	16.07
XOM	12.15	25.75	0.69	7.48	0.82	16.07
YHOO	6.15	15.89	0.08	4.64	0.21	4.96

We are surprised to discover that TSD beyond sample results are much worse than those from B-J and H/W models while the within sample fits are slightly better. From TSD only 9 stocks have mean MAPE under 5% and another 13 between 5% and 10 % and 4 have mean MAPE over 40% (NOK – 40.71%, KYO – 41.40%, MU – 41.69%, and RF – 52.35%). From B-J models the highest mean MAPE is 19.22% for HIBB, a sporting goods company, and from H/W models HIBB also has the highest MAPE at 19.01%. For practical applications the beyond sample predictability is more relevant and therefore one may opt for H/W or B-J.

To make the comparisons among the five models (B-J, H/W, TSD, normalized NN, and non-normalized NN) the mean MAPEs are summarized in Table 5 as follows.

Table 5. Mean MAPE (in %) for all models

Company	Box-Jenkins	Holt/Winters	Normalized NN	Non-normalized NN	Time series decomposition
AA	9.51	9.52	6.50	80.42	2.87
AAPL	7.62	5.73	18.37	55.38	2.73
AMAT	8.15	8.06	1.44	57.21	1.73
AMGN	2.81	2.45	4.51	2.55	14.28
BAX	3.99	3.84	8.77	4.52	8.35
BHP	7.37	6.61	25.13	46.48	16.26
BTI	2.30	1.97	6.71	24.85	6.31
CBSH	2.72	2.73	4.55	20.20	2.64
CERN	3.81	3.47	12.50	45.39	20.11
CRH	7.17	6.99	11.40	39.32	36.12
CSCO	9.73	9.71	2.33	57.89	16.61
CT	15.33	15.26	1.38	1215.72	18.34
EME	7.58	7.30	9.22	22.04	3.43
EXC	3.93	4.24	3.25	12.04	7.24
FCX	10.26	9.66	26.65	38.53	37.01
GE	4.33	4.34	5.14	43.11	17.61
HCP	4.26	4.67	6.21	26.30	11.31
HD	4.25	4.26	6.06	19.65	4.91
HIBB	19.22	19.01	88.29	39.31	22.72
HON	7.63	7.74	5.13	25.82	11.93
IBM	4.36	3.95	9.26	26.80	11.20
INTC	5.69	7.50	3.05	7.15	7.71
JNJ	0.81	0.93	4.06	7.47	9.72
JPM	3.41	3.38	8.65	10.94	32.64
KMP	2.26	1.42	5.40	39.98	5.11
KO	5.49	5.36	6.39	21.53	8.48
KYO	2.02	1.75	4.61	15.47	41.40
MCD	3.34	2.71	8.77	45.55	8.93
MMC	7.20	7.27	4.46	3.96	12.48
MS	3.33	3.19	4.25	85.88	23.59
MSFT	8.05	7.85	5.55	3.78	8.73
MU	10.81	10.79	1.42	46.54	41.69
MYL	5.90	5.86	8.72	14.50	5.81
NOK	4.09	4.26	2.35	97.76	40.71
NTT	1.88	1.60	2.14	41.67	4.78
PCAR	8.35	8.27	10.93	38.99	12.80
PG	4.47	4.49	5.62	5.80	4.68
RF	18.17	17.94	2.79	178.08	52.35
RIG	6.16	6.16	6.69	19.95	20.04
SCHW	9.25	9.12	2.47	25.15	9.91
SLB	15.25	15.04	12.28	18.27	1.95
SPG	3.63	3.33	8.50	39.39	17.23
SYMC	9.74	9.73	6.24	3.27	21.19
T	1.34	1.35	5.08	14.34	16.50
USB	9.30	9.23	7.79	6.90	13.39

Table 5 (cont.). Mean MAPE (in %) for all models

Company	Box-Jenkins	Holt/Winters	Normalized NN	Non-normalized NN	Time series decomposition
VCO	1.34	1.27	14.77	40.52	11.90
VMC	8.74	8.73	6.85	57.03	9.10
WHR	6.18	6.18	11.19	6.02	15.05
XOM	8.32	8.13	4.51	17.72	12.15
YHOO	10.26	10.76	26.65	38.53	6.15
Average	6.62	6.50	9.30	57.11	15.00
Standard error	4.16	4.17	12.83	169.92	11.93

Table 5 shows that H/W models produce 16 out of 50 lowest MAPEs, normalized NN models generate 11, B-J and TSD have 6 each, and non-normalized NN has 5 lowest MAPEs. However, as we pointed out before the MAPEs from both H/W and B-J are very close and similar for the same stocks. Because NN models take into consideration so many variables, those stocks in which normalized NN models produce the lowest MAPEs are different from the stocks with lowest MAPE from both B-J and H/W. The most conspicuous observation is that the mean MAPEs from non-normalized NN are typically very large with CT having MAPE of 1215.72% and RF of 178.08%. When we take the average and calculate the standard error across all 50 companies from a given model, H/W model has the smallest average, but B-J has smallest standard deviation. However, both models are very close. Normalized NN is just close behind those two and TSD is not too far trailing normalized NN. Clearly we would exclude non-normalized NN models from our consideration. Again this clearly shows why normalizing the original data is the common practice in NN. For HIBB normalized NN also show very high MAPE of 88.29%. B-J and H/W models generate only relatively moderate mean MAPEs. From Table 5 we can conclude that our preferred choices of models are H/W, B-J, and normalized NN, and they all perform very well.

Conclusions

In this study, we applied the traditional TSD, H/W models, B/J methodology, and NN to 50 randomly selected stocks from September 1, 1998 to December 31, 2010 with a total of 3105 observations for each company's close stock price. This sample period covers high tech boom and bust, the historical 9/11 event, housing boom and bust, and the recent serious recession and current slow recovery. During this exceptionally uncertain period of global economic and financial crises, it is expected that stock prices are extremely difficult to predict. All three time series approaches fit the within sample data extremely well with R^2 being around 0.995. For the hold-out period or out-of-sample forecasts over 60 trading days, the forecasting errors measured in terms of mean absolute percentage errors (MAPE) are lower for B/J, H/W, and normalized NN model, but forecasting errors are quite large for TSD and non-normalized NN models.

The stock markets are populated with day traders, high frequency traders, speculators, institutional investors, retail individual investors, momentum chasers, contrarians, influential financial analysts who are biased in favor of buy recommendations, and other diversified market participants with heterogeneous views about current information and future expectations. The rapid advance in information technology has spread news and rumors at near light speed. Even if stock prices are extremely difficult to predict, market participants must make decisions based on their best judgment and the methods and models they applied. The true value of the models and methods we discussed in this study also depends on whether they can perform as well to other sample periods and other types of related studies in the future.

References

1. Aiken, M. & Bsat, M. (1999). "Forecasting Market Trends with Neural Networks", *Information Systems Management*, 16, pp. 42-49.
2. Alyuda NeuroIntelligence (2010). *Alyuda NeuroIntelligence Manual*, available at http://www.alyuda.com/neural-networks-software.htm.
3. Baiyand, A. (2011). *The Trading Book: A Complete Solution to Mastering Technical Systems and Trading Psychology*, New York: McGraw-Hill.
4. Balvers, R., Wu, R. & Gilliand, E. (2000). "Mean Reversion across National Stock Markets and parametric Contrarian Investment Strategies", *Journal of Finance*, 55, pp. 773-806.
5. Box, G. & Jenkins, G. (1976). *Time Series Analysis: Forecasting and Control*, Revised Edition, San Francisco: Holden Day.
6. Brock, W., Lakonishok, J. & LeBaron, B. (1992). "Simple Technical Trading Rules and Stochastic Properties of Stock Returns", *Journal of Finance*, 47, pp. 1731-1764.

7. Daniel, K., Hirshleifer, D. & Subrahmanyam, A. (1998). "Investor Psychology and Security Market Under- and Overreactions", *Journal of Finance*, 53, pp. 1839-1885.
8. DeBondt, W. & Thaler, R. (1985). "Does the Stock *Market* Overreact?" *Journal of Finance*, 40, pp. 793-805.
9. DeBondt, W. & Thaler, R. (1987). "Further Evidence on Investor Overreaction and Stock Market Seasonality", *Journal of Finance*, 42, pp. 557-581.
10. Dutta, G. Jha, P., Laha, A. & Mohan, N. (2006). "Artificial Neural Network Models for Forecasting Stock Price Index in the Bombay Stock Exchange", *Journal of Emerging Market Finance*, 5, pp. 283-295.
11. Ferson, W. & Harvey, C. (1993). "The Risk and Predictability of International Equity Returns", *Review of Financial Studies*, 6, pp. 527-566.
12. Giudici, P. (2001). "Bayesian Data Mining, with Application to Benchmarking and Credit Scoring", *Applied Stochastic Models in Business & Industry*, 17, pp. 69-81.
13. Glickstein, D. & Wubbels, R. (1983). "Dow Theory Is Alive and Well!" *Journal of Portfolio Management*, pp. 28-32.
14. Gordon, W. (1968). *The Stock Market Indicators*, Palisades (N.J.): Investors Press.
15. Grudnitski, G. & Osburn, L. (1993). "Forecasting S&P and Gold Futures Prices: An Application of Neural Network", *Journal of Futures Markets*, 13, pp. 631-643.
16. Gutierrez, R. & Kelly, E. (2008). "The Long-Lasting Momentum in Weekly Returns", *Journal of Finance*, 63, pp. 415-447.
17. Hammad, A., Ali, S. & Hall, E. (2009). "Forecasting the Jordanian Stock Price using Artificial Neural Network", http://www.min.uc.edu/robotics/papers/paper2007/Final%20ANNIE%2007%20Souma%20Alhaj%20Ali%206p.pdf).
18. Hanke, J.E. & Wichern, D.W. (2005). *Business Forecasting*, Upper Saddle River (N. J.): Pearson/Prentice Hall, 8th ed.
19. Haugen, R.A. (1999). *The Inefficient Stock Market What Pays and Why*, Upper Saddle River (N.J): Prentice Hall.
20. Hendershott, T., Jones, C.M., and Menkveld, A.J. (2011). "Does Algorithmic Trading Improve Liquidity?" *Journal of Finance*, 66, pp. 1-33.
21. Hong, H. & Stein, J. (1999). "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets", *Journal of Finance*, 54, pp. 2143-2184.
22. Jegadeesh, N. & Titman (1993). "Returns to Buying Winners and Selling Lossers: Implications for Stock Market Efficiency", *Journal of Finance*, 48, pp. 65-91.
23. Jeong, H., Song, S., Shin, S. & Cho, B. (2008). "Integrating Data Mining to a Process Design Using the Robust Bayesian Approach", *International Journal of Reliability, Quality & Safety Engineering*, 15, pp. 441-464.
24. Kahneman, D. & Tversky, A. (1979). "Prospect Theory: An Analysis of Decision Under Risk: Heuristic and Biases", *Econometrica*, 47, pp. 263-291.
25. Kimoto, T., Asakawa, K., Yoda, M. & Takeoka, M. (1990). "Stock Market Prediction System with Modular Neural Networks", *Proceedings of the IEEE International Conference on Neural Networks*, pp. 1-16.
26. Kohzadi, N., Boyd, M., Kemlanshahi, B. & Kaastra, I. (1996). "A Comparison of Artificial Neural Network and Time Series Models for Forecasting Commodity Prices", *Neurocomputing*, 10, pp. 169-181.
27. Kryzanowski, L., Galler, M. & Wright, D. (1993). "Using Artificial Neural Networks to Pick Stocks", *Financial Analysts Journal*, 49, pp. 21-27.
28. Leigh, W., Hightower, R. & Modani, N. (2005). "Forecasting the New York Stock Exchange Composite Index with Past Price and Interest Rate on Condition of Volume Spike", *Expert Systems with Applications*, 28, pp. 1-8.
29. Lo, A., Mamaysky, H. & Wang, J. (2000). "Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation", *Journal of Finance*, 55, pp. 1705-1765.
30. McGrath, C. (2002). "Terminator Portfolio", *Kiplinger's Personal Finance*, 56, pp. 56-57.
31. McNelis, P. (1996). "A Neural Network Analysis of Brazilian Stock Prices: Tequila Effects vs. Pisco Sour Effects", *Journal of Emerging Markets*, 1, pp. 29-44.
32. Menzly, L. & Ozbas, O. (2010). "Market Segmentation and Cross-predictability of Returns", *Journal of Finance*, 65, pp. 1555-1580.
33. Moshiri, S. & Cameron, N. (2000). "Neural Network versus Econometric Models in Forecasting Inflation", *Journal of Forecasting*, 19, pp. 201-217.
34. Moskowitz, T. & Grinblatt, M. (1999). Do Industries Explain Momentum?" *Journal of Finance*, 54, pp. 1249-1290.
35. Mostafa, M. (2004). "Forecasting the Suez Canal Traffic: A Neural Network Analysis", *Maritime Policy and Management*, 31, pp. 139-156.
36. Mostafa, M. (2010). "Forecasting Stock Exchange Movements using Neural Networks: Empirical evidence from Kuwait", *Expert Systems with Application*, 37, pp. 6302-6309.
37. Nofsinger, J. & Sias, R. (1999). "Herding and Feedback Trading by Institutional and Individual Investors", *Journal of Finance*, 54, pp. 2263-2295.
38. Odean, T. (1998). "Volume, Volatility, Price, and Profits When All Traders Are above Average", *Journal of Finance*, 53, pp.1887-1934.
39. Odean, T. (1999). "Do Investors Trade Too Much?" *American Economic Review*, 89, pp. 1279-1298.
40. Poh, H., Yao, J. & Jasic, T. (1998). "Neural Networks for the Analysis and Forecasting of Advertising Impact", *International Journal of Intelligent Systems in Accounting, Finance and Management*, 7, pp. 253-268.
41. Pring, M. (1991). *Technical Analysis Explained*, 3rd ed, McGraw-Hill.
42. Ruiz-Suarez, J., Mayora-Ibarra, O., Torres -Jimenez, J. & Ruiz-Suarez, L. (1995). "Short-term Ozone Forecasting by Artificial Neural Network", *Advances in Engineering Software*, 23, pp. 143-149.

43. Shefrin, H. (2000). *Beyond Greed and Fear Understanding Behavioral Finance and the Psychology of Investing*, Harvard Business School Press.
44. Siegel, J.J. (2008). *Stocks for the Long Run*, 4th ed, McGraw-Hill.
45. Sullivan, R., Timmermann, A. & White, H. (1999). "Data-Snooping, Technical Trading Rule Perfformance, and the Bootstrap", *Journal of Finance*, 54, pp. 1647-1691.
46. Tokic, D. (2005). "Explaining US Stock Market Returns from 1980 to 2005", *Journal of Asset Management*, 6, pp. 418-432.
47. Tsai, C.-F. & Wang, S.-P. (2009). Stock Price Forecasting by Hybrid Machine Learning Techniques", *Proceedings of International Multi Conference of Engineers and Computer Scientists*, 1.
48. Turban, E. (1992). *Expert Systems and Applied Aartificial Intelligence*, New York: Macmillan Publishing Company.
49. Videnova, I., Nedialkova, D., Dimitrova, M. & Popova, S. (2006). "Neural Networks for Air Pollution Forecasting", *Applied Artificial Intelligence*, 20, pp. 493-506.
50. West, P., Brockett, P. & Golden, L. (1997). "A Comparative Analysis of Neural Networks and Statistical Methods for Predicting Consumer Choice", *Marketing Science*, 16, pp. 370-391.
51. Wilson, J.W., Keating, B. & John Galt Solutions, Inc. (2009). *Business Forecasting with ForecastX^{TM}*, 6th ed, Boston: McGraw-Hill Irwin.
52. Yu, L., Wang, S. & Lai, K. (2009). "A Neural-Network-based Nonlinear Metamodeling Approach to Financial Time Series Forecasting", *Applied Soft Computing*, 9, pp. 563-574.
53. Yumlu, S., Gurgen, F. & Okay, N. (2005). "A Comparison of global, Recurrent and Smoothed-Piecewise Neural Models for Istanbul Stock Exchange (ISE) Prediction", *Pattern Recognition Letters*, 26, pp. 2093-2103.
54. Zweig, M. (1990). *Winning on Wall Street*, New York: Warner Books.

Appendix

Table A1. Macroeconomic indicators (world indexes)

DJI	Dow Jones
IXIC	Nasdaq Composite
FCHI	France
AEX	Netherlands
GDAXI	Germany
N225	Japan
FTSE	United Kingdom
SSMI	Switzerland
ATX	Austria
BFX	Belgium
KFX	Denmark
HEX	Finland
ATG	Greece
XU100	Turkey
AORD	Australia
MERV	Argentina
BVSP	Brazil
MXX	Mexico
IGRA	Peru
BSESN	India
HIS	Hong Kong
KLSE	Malaysia
STI	Singapore
TWII	Taiwan
KSE	Pakistan
PSI	Philippines

Source: YahooFinance.

Table A2. Market indicators

GC	Gold
NG	Natural gas
CL	Light crude oil
HG	Copper
PA	Palladium
PL	Platinum

Table A2 (cont.). Market indicators

SI	Silver
AD	Australian dollar
BR	Brazil real
BP	British pound
CD	Canadian dollar
JY	Japanese yen
MP	Mexican pesso
SF	Swiss franc

Source: Pifin.

Table A3. Microeconomic indicators

Basic materials	Companies
1. Agricultural chemicals	Potash CP Saskatchewan [POT]
2. Aluminum	Alcoa Inc [AA]
3. Chemicals – major diversified	Dow Chemical [DOW]
4. Copper	Freeport Mcmoran [FCX]
5. Gold	Barrick Gold [ABX]
6. Independent oil & gas	Occidental Petroleum [OXY]
7. Industrial metals & minerals	BHP Billiton [BHP]
8. Major integrated oil & gas	Exxon Mobil [XOM]
9. Nonmetallic mineral mining	Harry Winston Diamond [HWD]
10. Oil & gas drilling & exploration	Transocean [RIG]
11. Oil & gas equipment & services	Schlumberger [SLB]
12. Oil & gas pipelines	Kinder Morgan Energy Partners [KMP]
13. Oil & gas refining & marketing	Imperial Oil [IMO]
14. Silver	Coeur D' Alene Mines Copr [CDE]
15. Specialty chemicals	Lubrizol Corp [LZ]
16. Steel & iron	Rio Tinto PLC [RTP]
17. Synthetics	Praxair Inc. [PX]
Conglomerates	
18. Conglomerates	General Electric [GE]
Consumer goods	
19. Appliances	Whirlpool Corp [WHR]
20. Auto manufacturers – major	Honda Motor Co. LTD [HMC]
21. Auto parts	Johnson Controls Inc. [JCI]
22. Beverages – brewers	Formento Economico Mexicano [FMX]
23. Beverages – soft drinks	The Coca-Cola Co. [KO]
24. Beverages – wineries & distillers	Diageo PLC [DEO]
25. Business equipment	Xerox Corp. [XRX]
26. Cigarettes	British American Tobacco PCL [BTI]
27. Cleaning products	Ecolab Inc. [ECL]
28. Confectioners	Cadbury PLC [CBY]
29. Dairy products	Lifeway Foods Inc. [LWAY]
30. Electronic equipment	Sony Corporation [SNE]
31. Farm products	Archer-Daniels-Midland [ADM]
32. Food − major diversified	Hj Heinz Co. [HNZ]
33. Home furnishings & fixtures	Fortune Brands Inc [FO]
34. Housewares & accessories	Newell Rubbermaid Inc [NWL]
35. Meat products	Hormel Foods Corp. [HRL]
36. Office supplies	Ennis Inc. [EBF]
37. Packaging & containers	Owens-Illinois [OI]
38. Paper & paper products	International Paper Co. [IP]
39. Personal products	Procter & Gamble Co. [PG]
40. Photographic equipment & supplies	Eastman Kodak [EK]
41. Processed & packaged goods	Pepsico Inc. [PEP]
42. Recreational goods, other	Fossil Inc. [FOSL]

Table A3 (cont.). Microeconomic indicators

Basic materials	Companies
43. Recreational vehicles	Harley-Davidson Inc. [HOG]
44. Rubber & plastics	Goodyear Tire & Rubber Co. [GT]
45. Sporting goods	Callaway Golf Co. [ELY]
46. Textile – apparel clothing	VF Corp. [VFC]
47. Textile – apparel footwear & accessories	Nike Inc. [NKE]
48. Tobacco products, other	Universal Corp. [UVV]
49. Toys & games	Mattel Inc. [MAT]
50. Trucks & other vehicles	Paccar Inc. [PCAR]
Financial	
51. Accident & health insurance	Aflac Inc. [AFL]
52. Asset management	T. Rowe Price Group Inc. [TROW]
53. Closed-end fund – debt	Alliance Bernstein Income Fund Inc. [ACG]
54. Closed-end fund – equity	DNP Select Income Fund Inc. [DNP]
55. Closed-end fund – foreign	Aberdeen Asia-Pacific Income Fund Inc. [FAX]
56. Credit services	American Express Co. [AXP]
57. Diversified investments	Morgan Stanley [MS]
58. Foreign money center banks	Westpac Banking Corp [WBK]
59. Foreign regional banks	Bancolombia S.A. [CIB]
60. Insurance brokers	Marsh & Mclennan [MMC]
61. Investment brokerage – national	Charles Schwab Corp. [SCHW]
62. Investment brokerage – regional	Jefferies Group Inc. [JEF]
63. Life insurance	AXA [AXA]
64. Money center banks	JPMorgan Chase & Co. [JPM]
65. Mortgage investment	Anally Capital Management [NLY]
66. Property & casualty insurance	Berkshire Hathaway [BRK-A]
67. Property management	Icahn Enterprises, L.P. [IEP]
68. REIT – diversified	Plum Creek Timber Co. Inc. [PCL]
69. REIT – healthcare facilities	HCP Inc. [HCP]
70. REIT – hotel/motel	Host Hotels & Resorts Inc. [HST]
71. REIT – industrial	Public Storage [PSA]
72. REIT – office	Boston Properties Inc. [BXP]
73. REIT – residential	Equity Residential [EQR]
74. REIT – retail	Simon Property Group Inc. [SPG]
75. Real estate development	The St. Joe Company [JOE]
76. Regional – Mid-Atlantic banks	BB & T Corp. [BBT]
77. Regional – Midwest banks	US Bancorp [USB]
78. Regional – Northeast banks	State Street Corp. [STT]
79. Regional – Pacific banks	Bank Of Hawaii Corp. [BOH]
80. Regional – Southeast banks	Regions Financial Corp. [RF]
81. Regional – Southwestbanks	Commerce Bancshares Inc. [CBSH]
82. Savings & loans	People's United Financial Inc. [PBCT]
83. Surety & title insurance	First American Corp. [FAF]
Healthcare	
84. Biotechnology	Amgen Inc. [AMGN]
85. Diagnostic substances	Idexx Laboratories Inc. [IDXX]
86. Drug delivery	Elan Corp. [ELN]
87. Drug manufacturers – major	Johnson & Johnson [JNJ]
88. Drug manufacturers – other	Teva Pharmaceutical Industries LTD [TEVA]
89. Drug related products	Perrigo Co. [PRGO]
90. Drugs – generic	Mylan Inc. [MYL]
91. Health care plans	Unitedhealth Group Inc. [UNH]
92. Home health care	Lincare Holdings Inc. [LNCR]
93. Hospitals	Tenet Healthcare Corp. [THC]
94. Long-term care facilities	Emeritus Corp. [ESC]

Table A3 (cont.). Microeconomic indicators

Basic materials	Companies
95. Medical appliances & equipment	Medtronic Inc. [MDT]
96. Medical instruments & supplies	Baxter International Inc. [BAX]
97. Medical laboratories & research	Quest Diagnostics Inc. [DGX]
98. Medical practitioners	Transcend Services Inc. [TRCR]
99. Specialized health services	Davita Inc. [DVA]
Industrial goods	
100. Aerospace/defense – major diversified	Boeing Co. [BA]
101. Aerospace/defense products & services	Honeywell International Inc. [HON]
102. Cement	CRH PLC [CRH]
103. Diversified machinery	Illinois Tool Works Inc. [ITW]
104. Farm & construction machinery	Caterpillar Inc. [CT]
105. General building materials	Vulcan Materials Co. [VMC]
106. General contractors	Emcor Group Inc. [EME]
107. Heavy construction	McDermott International Inc. [MDR]
108. Industrial electrical equipment	Eaton Corporation [ETN]
109. Industrial equipment & components	Emerson Electric Co. [EMR]
110. Lumber, wood production	Weyerhaeuser Co. [WY]
111. Machine tools & accessories	Stanley Works [SWK]
112. Manufactured housing	Skyline Corp [SKY]
113. Metal fabrication	Precision Castparts Corp. [PCP]
114. Pollution & treatment controls	Donaldson Company Inc. [DCI]
115. Residential construction	NVR Inc. [NVR]
116. Small tools & accessories	The Black & Decker Corp. [BDK]
117. Textile industrial	Mohawk Industries Inc. [MHK]
118. Waste management	Waste Management Inc. [WM]
Services	
119. Advertising agencies	Omnicom Group Inc. [OMC]
120. Air delivery & freight services	Fedex Corp. [FDX]
121. Air services, other	Bristow Group Inc. [BRS]
122. Apparel stores	GAP Inc. [GPS]
123. Auto dealerships	Carmax Inc. [KMX]
124. Auto parts stores	Autozone Inc. [AZO]
125. Auto parts wholesale	Genuine Parts Co. [GPC]
126. Basic materials wholesale	AM Castle & Co. [CAS]
127. Broadcasting – radio	Sirius Xm Radio Inc. [SIRI]
128. Broadcasting – TV	Rogers Communications Inc. [RCI]
129. Business services	Iron Mountain Inc. [IRM]
130. CATV systems	Comcast Corp. [CMCSA]
131. Catalog & mail order houses	Amazon.Com Inc. [AMZN]
132. Computers wholesale	Ingram Micro Inc. [IM]
133. Consumer services	Monro Muffler Brake Inc. [MNRO]
134. Department stores	The TJX Companies Inc. [TJX]
135. Discount, variety stores	Wal-Mart Stores Inc. [WMT]
136. Drug stores	CVS Caremark Corp. [CVS]
137. Drugs wholesale	Mckesson Corp. [MCK]
138. Education & training services	Devry Inc. [DV]
139. Electronics stores	Best Buy Co. Inc. [BBY]
140. Electronics wholesale	Avnet Inc. [AVT]
141. Entertainment – diversified	Walt Disney Co. [DIS]
142. Food wholesale	Sysco Corp. [SYY]
143. Gaming activities	Bally Technologies Inc. [BYI]
144. General entertainment	Carnival Corp. [CCL]
145. Grocery stores	Kroger Co. [KR]
146. Home furnishing stores	Williams-Sonoma Inc. [WSM]
147. Home improvement stores	The Home Depot Inc. [HD]

Table A3 (cont.). Microeconomic indicators

Basic materials	Companies
148. Industrial equipment wholesale	W.W. Grainger Inc. [GWW]
149. Jewelry stores	Tiffany & Co. [TIF]
150. Lodging	Starwood Hotels & Resorts Worldwide Inc. [HOT]
151. Major airlines	AMR Corp. [AMR]
152. Management services	Express Scripts Inc. [ESRX]
153. Marketing services	Valassis Communications Inc. [VCI]
154. Medical equipment wholesale	Henry Schein Inc. [HSIC]
155. Movie production, theaters	Marvel Entertainment Inc. [MVL]
156. Music & video stores	Blockbuster Inc. [BBI]
157. Personal services	H&R Block Inc. [HRB]
158. Publishing – books	The Mcgraw-Hill Co. Inc. [MHP]
159. Publishing – newspapers	Washingotn Post Co. [WPO]
160. Publishing – periodicals	Meredith Corp. [MDP]
161. Railroads	Burlington Northern Santa Fe Corp. [BNI]
162. Regional airlines	Southwest Airlines Co. [LUV]
163. Rental & leasing services	Ryder System Inc. [R]
164. Research services	Parexel Intl Corp. [PRXL]
165. Resorts & casinos	Mgm Mirage [MGM]
166. Restaurants	Mcdonald’s Corp. [MCD]
167. Security & protection services	Geo Group Inc. [GEO]
168. Shipping	Tidewater Inc. [TDW]
169. Specialty eateries	Starbucks Corp. [SBUX]
170. Specialty retail, other	Staples Inc. [SPLS]
171. Sporting activities	Speedway Motorsports Inc. [TRK]
172. Sporting goods stores	Hibbett Sports Inc. [HIBB]
173. Staffing & outsourcing services	Paychex Inc. [PAYX]
174. Technical services	Jacobs Engineering Group Inc. [JEC]
175. Trucking	Jb Hunt Transport Services Inc. [JBHT]
176. Wholesale, other	Vina Concha Y Toro S.A. [VCO]
Technology	
177. Application software	Microsoft Corp. [MSFT]
178. Business software & services	Automatic Data Processing Inc. [ADP]
179. Communication equipment	Nokia Corp. [NOK]
180. Computer based systems	Adaptec Inc. [ADPT]
181. Computer peripherals	Lexmark International Inc. [LXK]
182. Data storage devices	EMC Corp. [EMC]
183. Diversified communication services	Telecom Argentina S A [TEO]
184. Diversified computer systems	International Business Machines Corp. [IBM]
185. Diversified electronics	Kyocera Corp. [KYO]
186. Healthcare information services	Cerner Corp. [CERN]
187. Information & delivery services	Dun & Bradstreet Corp. [DNB]
188. Information technology services	Computer Sciences Corporation [CSC]
189. Internet information providers	Yahoo! Inc. [YHOO]
190. Internet service providers	Easylink Services International Corp. [ESIC]
191. Internet software & services	Cgi Group Inc. [GIB]
192. Long distance carriers	Telefonos De Mexico, S.A.B. De C.V. [TMX]
193. Multimedia & graphics software	Activision Blizzard Inc. [ATVI]
194. Networking & communication devices	Cisco Systems Inc. [CSCO]
195. Personal computers	Apple Inc. [AAPL]
196. Printed circuit boards	Flextronics International Ltd. [FLEX]
197. Processing systems & products	Polycom Inc. [PLCM]
198. Scientific & technical instruments	Thermo Fisher Scientific Inc. [TMO]
199. Security software & services	Symantec Corp. [SYMC]
200. Semiconductor – broad line	Intel Corp. [INTC]
201. Semiconductor – integrated circuits	Qualcomm Inc. [QCOM]

Table A3 (cont.). Microeconomic indicators

Basic materials	Companies
202. Semiconductor – specialized	Xilinx Inc. [XLNX]
203. Semiconductor equipment & materials	Applied Materials Inc. [AMAT]
204. Semiconductor – memory chips	Micron Technology Inc. [MU]
205. Technical & system software	Autodesk Inc. [ADSK]
206. Telecom services – domestic	AT&T Inc. [T]
207. Telecom services – foreign	Nippon Telegraph & Telephone Corp. [NTT]
208. Wireless communications	China Mobile Limited [CHL]
Utilities	
209. Diversified utilities	Exelon Corp. [EXC]
210. Electric utilities	Southern Company [SO]
211. Foreign utilities	Enersis S.A. [ENI]
212. Gas utilities	Transcanada Corp. [TRP]
213. Water utilities	Aqua America Inc. [WTR]

Source: YahooFinance.

Table A4. Market indicators

Market indicators	
GSPC	S&P 500's price changes
DJI	Dow Jones industrial's price changes
DJT	Dow Jones transportation's price changes
DJU	Dow Jones utility's price changes
Market sentiment indicators	
VIX	CBOE volatility index changes
Institutional investor	
BEN	Franklin Resources Inc.

Source: YahooFinance.

Table A5. Calendar anomalies

Mon	Monday
Tue	Tuesday
Wed	Wednesday
Thurs	Thursday
Fri	Friday
Jan	January
Feb	February
Mar	March

Table A5. Calendar anomalies

Apr	April
May	May
Jun	June
Jul	July
Aug	August
Sep	September
Oct	October
Nov	November
Dec	December