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TAIWAN 50 ETF FORECASTING AND INVESTMENT ANALYSIS USING BACK PROPAGATION NETWORK

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Abstract. *Neural network is a popular method in forecasting using some input variables and minimizing the sum of square errors between the output values and the target values. In this study for Taiwan 50 ETF price forecasting, we collect nineteen popular indices which are classified into two aspects where the first one is basic analysis variables, and the other is technical analysis variables. We first used the nineteen variables and ETF price to fit a stepwise regression model for selecting the effective variables. Next, using the selected variables to fit the back propagation network model, we derive that the forecasting error in Taiwan 50 ETF price forecasting is better than GARCH(1, 1) model. Finally, an illustration confirms the potential benefits of the BPN model whose transaction strategies make a profitable investment in the transaction of Taiwan 50 ETF.*

Keywords: Taiwan 50 ETF, Back propagation network, Stepwise regression model, Transaction strategies

1. **Introduction.** Exchange traded funds (ETFs) support investors to invest easily and quickly in a transaction where investors can obtain the benefits of portfolio diversification indices without incurring high transaction costs. Taiwan Top 50 Tracker Fund was introduced in June 2003 and used the Taiwan 50 Index as its benchmark asset, which includes the top 50 listed companies by total market capitalisation. ETFs combine the valuation feature of a mutual fund where we can buy or sell at the end of each trading day for its net asset value which trades throughout the trading day at prices that may be more or less than its net asset value. Since ETFs are a kind of convenient tools receiving much attention, many investors pay more attention to the ETF market, and numerous academics have also examined the issues relating to the impacts of ETFs on financial markets. Switzer *et al.* [10], Chu *et al.* [5], dealt with the impact of ETFs on the pricing efficiency of index futures; Chu and Hsieh [4] investigated price discovery among index spot, index futures and ETFs. Massimiliano *et al.* [9] used Taiwan stock market index (TAIEX), TWD/USD exchange rates, various year bonds and golden prices to be the input variables, and used genetic algorithm and neural network to find the best trading price of ETF in a specific trading period. Because ETFs are an efficient portfolio tool in the investment, many researchers have devoted themselves in the field of ETFs. Therefore, most factors that affect the profits in the transaction of ETFs have been considered and induced, including raw materials price, the variation of stocks market, the performance of the chosen corporations, political situation, and the stock markets of the world, whereas some unknown factors are still not derived. Without the information of the unknown factors, ETFs investors are usually difficult to obtain sufficient information to buy or sale their ETFs. In order to derive much more information for investment, Wu

[13] illustrated an empirical example with back-propagation neural network whose input variables are stock market's trading volume, stock trading price and technical analysis index, and the results showed that Moving Average Convergence and Divergence index (MACD) has better trading performance than the other indexes. Ma [8] used technical indexes as input variables into neural network models and simulated stocks trading in the Taiwan stock market, and the empirical results showed that its trading profit is better than 12-day MACD. The above researches showed that neural network is a good tool in analyzing the pricing of ETFs, but how to choose the better input variables is usually decided by the user and derives from the related researches. In order to cope with such problem, in this paper, we plan to survey a large number of the possible input variables, use stepwise regression to choose the better input variable, use the selected variables for fitting neural networks, and then forecast the closing price of Taiwan 50 ETF. Summarily, the goals of this manuscript can be described as follows:

(1) Survey the relative papers and collect all the effected variables with respect to the closing price of Taiwan 50 ETFs.
(2) Using stepwise regression model to select significant variables, then we can use the back-propagation network model to forecast the closing price of Taiwan 50 ETFs.
(3) Compare the forecasting performance among the stepwise regression model, time series model, and back-propagation network model.
(4) Construct the transaction strategies for the Taiwan 50 ETFs.

The organization of this paper is as follows. First, an introduction for this research is shown in Section 1. Next, the input variables for forecasting the closing price of Taiwan 50 ETF are discussed in Section 2. In Section 3, the methods of stepwise regression model and back propagation neural network are introduced. An illustration for the transaction of the Taiwan 50 ETFs is shown in Section 4. Finally, conclusion is drawn in Section 5.

2. **Variable Selections.** The investigation to the stock market index in the literature could be divided into two aspects. The first one is the basic analysis for the factors that affect the macroeconomics with respect to the stock market index. The other one is the technical analysis using the historical trend of the stock market index and then predicts the future fluctuation. In basic analysis, Kimoto *et al.* [6] discussed a buying and selling timing prediction system for stocks on the Tokyo Stock Exchange and analysis of internal representation based on modular neural networks whose inputs are technical and economic indexes, where the prediction system achieved accurate predictions and the simulation on stocks trading with an excellent profit. Yang [14] used economic indexes to back propagation neural network and fitted to increase or decrease the stocks where its forecasting results showed the proposed model had better ability to contribute in rate of returns. Versace *et al.* [12] discussed a solution to the above problem employing a combination of ANNs and GAs that perform relatively well at predicting the closing price of a security by incorporating some of the major stock indices, with the rate of return between 66% and 74%. Lin [7] applied back propagation neural network to predict the opening price of Taiwan 50 ETF and its return rate by considering the Taiwan index futures price between the previous cash market closing time, the daily opening time, several important American stock indices as the inputs of our opening price and return prediction models. Besides, a speculative trading strategy is applied to evaluate the performance of the best return prediction model. The other one is for technical analysis where Tsai *et al.* [11] applied a technical analysis method together with a neural network model to simulate various investment strategies whose results indicated that the use of a neural network model can predict the proper timing for investment, and then most of investors can make better return by using the stop-loss and composite strategies. Wu

[13] applied the predictability of artificial neural network to employ the price, quantity, and tendency technical index as the input items to predict the future rises or drops as the output item and employed the various technical indexes when MACD crossed on that day to serve as the input item, and the output items are the future range and days of rise and drop. The statistics showed that the profitability of the prediction module of crossed MACD and the artificial neural networks are better than the traditional strategy operation. Ma [8] presented a new way to filter the signals of technical indices in stock price forecasting by combining the advantages of fuzzy logic and neural network. The empirical results showed that this neuro-fuzzy trading system has the ability to recognize correction of buying or selling signals. The rate of return by following this neuro-fuzzy trading system was shown to beat that of buy-and-hold strategy and of traditional moving average strategy. Yang [14] studied seventeen technical indices in the application of regression analysis, back propagation network (BPN) and adaptive network-based fuzzy inference system in forecasting tendency of TAIEX in the future whose empirical results show that ANFIS model together with stepwise regression, and BPN model with all input variables possess the best ability of prediction. Clearly, many indices discussed above are important in finance forecasting. In order to derive more information in Taiwan 50 ETF price forecasting, we enlarge the set of input variables from five aspects, which are technical indices, macroeconomical indices, share volume indices, dynamic relationships indices between futures and stock market, and international stock market indices. The chosen input nineteen indices are described as follows.

(1) Technical indices: we collect six indices in order to analyze the trading volume and the closing price of Taiwan 50 ETF with a minimum cost for maintaining the forecasting model. The indices are (i) Moving average (ii) Opening price (iii) Highest-price (iv) Lowest-price (v) Trading volume (vi) Closing price.
(2) Macroeconomic indices: the return rate is the leading indicator which begins to decrease before the economy declines and improve before the economy begins to pull out of a recession. We use economic indices to show the relationship between stock market and macroeconomics. The indices are (i) TWD/USD exchange rates (ii) Brent Crude oil price (iii) Interest rate (iv) The balance of money supply.
(3) Trading volume analysis: there are significant positive return-volume relations across quantiles, showing that a large positive return is usually accompanied by a large trading volume and a large negative return with a small trading volume. Most empirical studies discover the opportune moment of stock investment mainly through the technical analysis from the three key institutional investors. Therefore, the trading volume can be defined as (i) Margin purchasing (ii) Short sell (iii) The three primary professional institutional trading volume.
(4) Linkage between futures and Taiwan 50 ETF: the futures price usually leads the spot price, so, futures price is a good predictor for spot price where TAIFEX used the futures price of Taiwan 50 ETF to forecast the spot price of Taiwan 50 ETF. However, the trading volume of Taiwan 50 ETF futures is little, so we use Taiwan stock index futures for substitute defined as (i) Taiwan Stock Index Futures (ii) Basis.
(5) International stock market: electronics industry has the highest weight of investment in the Taiwan's stock market, so it is easily affected by the Nasdaq Composite Index. In addition, many weighted companies with large revenues issued depositary receipt in the overseas where the linkage between Taiwan and other countries stock market is significant. Therefore, we defined the relative variables as (i) Nasdaq Composite Index (ii) Dow Jones Industrial Average (iii) Nikkei 225 Index (iv) Hang Seng Index.

3. **Reviewed Models.** In order to make a better price analysis in Taiwan 50 ETF, in this study, we collect many input variables to fit a neural network model. However, it is usually overfitting when a model is excessively complex with too many parameters relative to the number of observations. In order to cope with this problem, we try to use this input variable as independent variables and the price of Taiwan 50 ETF as dependent variable, and then fit a multiple linear regression model. We also try to minimize the maintain cost and its efficiency using the stepwise regression model to select the significant variables and derive the regression model by deleting some nonsignificant variables. In the proposed regression model, the independent variables are selected for input variables to train the neural network where the back propagation algorithm is one of the well-known algorithms in neural networks [1]. The back propagation neural network is essentially a network of simple processing elements working together to produce a complex output. These elements are arranged into different layers: input, hidden and output which are shown in Figure 1.

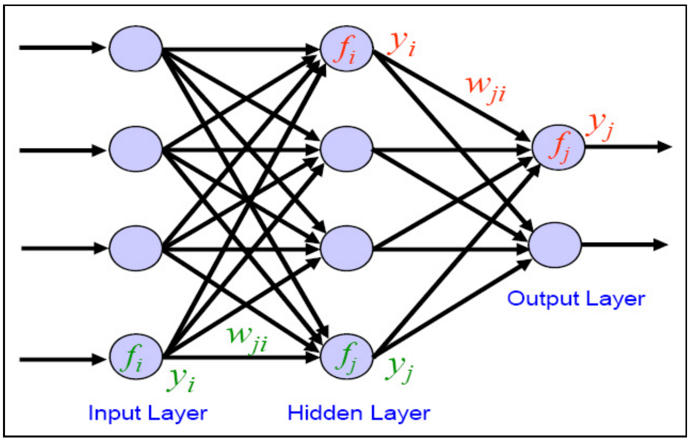

FIGURE 1. A back propagation neural network architecture

The input layer propagates a particular input vector's component to each neuron in the middle layer by a transform function, and hidden layer neurons compute output values which become inputs to the neurons of the output layer. The neurons in the hidden layers are fitted using try-error method and the transformed function is adopted as nonlinear. The output layer nodes compute the network output for the particular input vector. Besides, the neurons in each layer have their own input weights whose sum is assumed to be 1. Since the network weights are supposed to be random values, it is unlikely that reasonable outputs will result before training. The weights are adjusted to reduce the error by propagating the output error backward through the network. In feedforward activation, units of hidden layer 1 compute their activation and output values and pass these on to the next layer, and so on until the output units will have produced the network's actual response to the current input [2]. The activation value net_j of neuron j is computed as Equation (1)

$$net_j = \sum_i w_{ji} y_i + \theta, \tag{1}$$

$$y_j = f(net_j),\ j \geq 1,\ \text{and } f(x) = 1/(1 + e^{-x}), \tag{2}$$

where y_i is the value coming from neuron i in layer $n-1$, w_{ji} is the weight of the connection between neuron j in layer n and neuron i in layer $n-1$, and θ is the threshold of a neuron. Then, the output y_j of neuron j in layer n is computed as Equation (2) where function $f(x)$ is the output continuously increasing function, asymptotically approaching 0 as x decreases, and asymptotically approaching 1 as x increases. By computing the partial derivative of the error because of a single input image pattern with respect to the outputs of the neurons on the n-th layer, the error E due to a single pattern is calculated as follows:

$$E = 0.5 \sum_j (d_j - y_j)^2, \tag{3}$$

where d_j is the target values at the last layer of jth neuron and y_j is the output value at the last layer of jth neuron. Then the adjustment applied to the weight w_{ji} at the last layer is defined as Equation (4). η is a positive learning rate parameter, and gradient of the error surface E is as Equation (5). A simple method of increasing the rate of learning uses the momentum term α between kth and $(k-1)$th training pattern from Equations (6) to (13).

$$\Delta w_{ji} = -\eta(\partial E/\partial \Delta w_{ji}) \tag{4}$$

$$\partial E/\partial \Delta w_{ji} = (\partial E/\partial y_j) \times (\partial y_j/\partial net_j) \times (\partial net_j/\partial w_{ji}) \tag{5}$$

$$\partial E/\partial y_j = -(d_j - y_j) \tag{6}$$

$$(\partial y_j/\partial net_j) = f'(net_j) \tag{7}$$

$$\partial net_j/\partial w_{ji} = y_j \tag{8}$$

$$\partial E/\partial \Delta w_{ji} = -(d_j - y_j) \times f'(net_j) \times y_j \tag{9}$$

$$\delta_j = (d_j - y_j) \times f'(net_j) \tag{10}$$

$$\partial E/\partial \Delta w_{ji} = -\delta_j \times y_j \tag{11}$$

$$\Delta w_{ji} = \eta \times \delta_j \times y_j \tag{12}$$

$$\Delta w_{ji}^k = \eta \times \delta_j \times y_j + \alpha \Delta w_{ji}^{k-1} \tag{13}$$

4. **Experimentation and Result.** In this experiment, the dataset contains many variables such as 5 day Moving average, Opening price, Highest-price, Lowest-price, Trading volume, Closing price, TWD/USD exchange rates, Brent Crude oil price, Interest rate, The balance of money supply, Margin purchasing, Short sell, The three primary professional institutional trading volume, Taiwan Stock Index Futures, Basis, Nasdaq Composite Index, Dow Jones Industrial Average index, Nikkei 225 Index, Hang Seng Index. The above input variables are used for forecasting the next day's price of Taiwan 50 ETF. The 691 data are collected from the beginning of 3 January 2005 to the 26 October 2007. Using the input variables for modelling the multiple linear regression model, according to the results of SPSS software, some variables are deleted under the significant level to be 0.05 and seven input variables are selected for fitting the BPN model. In modelling of BPN, input data processing and output data reprocessing were done as in Equation (14) and Equation (15)

$$V_{new} = (V_{old} - u)/k\sigma \tag{14}$$

$$V_{new} = [(V_{old} - Min)/(Max - Min)] \times (D_{\max} - D_{\min}) + D_{\min} \tag{15}$$

u: mean of the data of the unit, σ: standard deviation of the data of the unit, and $k = 1.96$. $D_{\min}$: minimum of the data of the unit which is suggested as 0.2, $D_{\max}$: maximum of the data of the unit which is suggested as 0.8. In the BPN, it is a common practice to choose better values for number of layers n, learning rate η, and momentum term α so that the established model can be predicted more precisely. However, a large number of possible values for the parameters in BPN model often make a dilemma as: (1) requiring a BPN model to test as many possible values of parameters so that the 'information content' can provide better prediction of value; (2) reducing the testing process for the parameters and to cut down the costs of analysis, model maintenance and calculating time. Therefore, we adopt the some suggestions for the parameters from the references [15] and [1]. Therefore, the hidden layer is set as 2, $\eta = 0.6$, and $\alpha = 0.3$. The chosen parameters are listed as Table 1.

In addition, a couple of data sets with different training data and testing data are tested with the same chosen parameters as shown in Table 1. The forecasting errors with different data set are shown in Table 2. We find that the forecasting result can be the smallest with training data 461 and testing data 230. In order to test the accuracy of the BPN model, we collect 46 Taiwan 50 ETF price data from 27 October 2007 to 3 December 2007, an extrapolation analysis using the BPN model compared to GARCH(1, 1) is shown in Table 3. Clearly, the proposed BPN model has smaller forecasting error than GARCH(1, 1). Furthermore, a sensitivity analysis with different data sets 100, 200, 300, 400, 500, 600, 650 is tested for showing the chosen 691 data with respect to the final collected day. The forecasting errors between BPN model GARCH(1, 1) are shown in Table 4 which show that the decreasing errors with increasing number of collected data in BPN model are more significant than GARCH(1, 1).

Table 1. The chosen values in the BPN model

Parameter	Chosen Value
hidden layer	1
the neurons in the hidden layer	2
input variables in the input layer	7
output variables in the output layer	1
learning rate	0.6
momentum term	0.3
activation function	sigmoid function

Table 2. The forecasting error with different training data/testing data

Training data/Testing data	Training error MSE	Testing error MSE
230/461	0.01086	0.02383
346/345	0.01222	0.02024
461/230	0.01202	0.01565
484/207	0.01237	0.01671
553/138	0.01391	0.01778

Table 3. The extrapolation error between BPN and GARCH(1, 1) model

Error \ Model	BPN Model	GARCH(1, 1) Model
RMS	0.0195	1.453
MAPE	1.11%	1.94%

Table 4. Sensitivity analysis for the collected data between BPN and GARCH models

Error \ Data	100	200	300	400	500	600	650	691
BPN MAPE	4.875	4.245	2.694	2.314	1.605	1.973	1.434	1.110
GARCH MAPE	1.988	1.962	1.960	1.956	1.953	1.949	1.941	1.940

Transaction cost for Taiwan 50 ETF is 2.425‰ which includes 1.425‰ transaction fees and 1‰ securities transaction tax. We use the proposed BPN model to make the transaction strategies for Taiwan 50 ETF. The second-order transfer equation proposed by Chiu [3] is defined as rate of forecasted return which is shown in Equation (16) as below:

$$f(\hat{s}) = (\hat{H}_{t+1} - H_t)/H_t \tag{16}$$

where $\hat{H}_{t+1}$ is the forecasted closing price for the next day, and H_t is the actual closing price of Taiwan 50 ETF in time t. The transaction strategies are decided as follows:

(1) If the rate of forecasted return $f(\hat{s})$ is larger than the transaction cost 1.425‰ then we obtained buy signals. When we obtain the buy signals with two times successively, it is suggested to buy the Taiwan 50 ETF with 1000 shares. However, if the state is in the short sell before the buy signals with two times successively, then it is necessary to cover his short position and then buy the Taiwan 50 ETF 1000 shares.
(2) If the rate of forecasted return is in the range as $-2.425‰ \leq f(\hat{s}) \leq 1.425‰$ then it is suggested to hold the shares.
(3) If the rate of forecasted return $f(\hat{s})$ is smaller than $-2.425‰$ then we obtained the sell signals. When we obtain the sell signals with two times successively, it is suggested to sell the Taiwan 50 ETF. If the previous state is to buy Taiwan 50 ETF before the sell signals with two times successively, then it is necessary to sell the buy position and then short sell the Taiwan 50 ETF.
(4) At the final transaction day, it is necessary to settle stock return.
(5) Based on the above strategies and using the proposed BPN model for the 46 testing days, we can obtain the returns of transactions shown in Table 5. By the transaction

TABLE 5. The testing performance using the transaction strategies

Time	1	2	3	4	5	6	7
Signal	Sell Signal	Sell Signal	Sell Signal	Sell Signal	Hold Signal	Sell Signal	Sell Signal
Trasction	–	Short Sell	Hold	Short Sell	Hold	Hold	Short Sell
Return	0	0	-0.01345	0.04534	0.03986	0.02774	0.04138
Time	8	9	10	11	12	13	14
Signal	Sell Signal	Sell Signal	Hold Signal	Hold Signal	Sell Signal	Sell Signal	Sell Signal
Trasction	Hold	Short Sell	Hold	Hold	Hold	Short Sell	Hold
Return	0.13987	0.09638	0.22929	0.21414	0.15722	0.18641	0.28288
Time	15	16	17	18	19	20	21
Signal	Sell Signal	Sell Signal	Sell Signal	Hold Signal	Buy Signal	Hold Signal	Hold Signal
Trasction	Hold	Short Sell	Hold	Hold	Hold	Hold	Hold
Return	0.25821	0.33025	0.44850	0.46178	0.50156	0.37124	0.48630
Time	22	23	24	25	26	27	28
Signal	Buy Signal	Buy Signal	Buy Signal	Buy Signal	Buy Signal	Buy Signal	Buy Signal
Trasction	Hold	Cover the short sell and Buy	Hold	Buy	Hold	Buy	Hold
Return	0.57341	0.45050	0.45640	0.45885	0.47689	0.48337	0.48437
Time	29	30	31	32	33	34	35
Signal	Buy Signal	Buy Signal	Hold Signal	Hold Signal	Buy Signal	Buy Signal	Buy Signal
Trasction	Buy	Hold	Hold	Hold	Hold	Buy	Hold
Return	0.51339	0.42216	0.44461	0.37405	0.21046	0.19121	0.05162
Time	36	37	38	39	40	41	42
Signal	Buy Signal	Buy Signal	Buy Signal	Buy Signal	Buy Signal	Buy Signal	Buy Signal
Trasction	Buy	Hold	Buy	Hold	Buy	Hold	Buy
Return	0.06788	0.22461	0.12576	0.26964	0.31613	0.37462	0.38128
Time	43	44	45	46			
Signal	Buy Signal	Buy Signal	Buy Signal	Buy Signal			
Trasction	Hold	Buy	Hold	settlement			
Return	0.56725	0.58223	0.65565	0.42114			

cost, the settlement of stock return is 42.114% which supports us that our proposed BPN model is applicable for analyzing the return of transaction.

5. **Conclusion.** In this study, BPN model is used for forecasting the Taiwan 50 ETF price. We use the popular variables in analysis macroeconomics, stock market and select the input variables by using stepwise linear regression model. The price forecasting for Taiwan 50 ETF indicated considerable performance than GARCH$(1,1)$ model in training and testing data sets. The illustrated example confirms the potential benefits of the BPN model in the rate of forecasted return by adopting the transaction strategies. Most importantly, an investor can use the proposed model and strategies to make a reliable investment in the transaction of Taiwan 50 ETF. At the end, this approach will be an applicable tool when an investor would like to avoid any loss in the investment.

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