High Technology ETF Forecasting: Application of Grey Relational Analysis and Artificial Neural Networks

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Abstract

This study employs the grey relational analysis model and provides robust identification of the S&P 500 stock index as having the greatest influence on exchange-traded funds (ETFs). The subsequent influencing factors are the volatility index (VIX), commodity research bureau (CRB) index, Brent crude oil index, put-call ratio, and trade index (TRIN). Our results show that the back propagation network model outperforms the recurrent neural network model in predicting both high technology and non-high technology ETFs. The low grey relational grade (GRG) variables (i.e., put-call ratio, TRIN and crude oil index) have greater influence than the group of high GRG variables (i.e., S&P 500 stock index, VIX, and CRB index) and the group of all variables in high technology ETFs, while on non-high technology ETFs, the all variables group showed stronger influence.

Keywords: high technology and non-high technology ETFs; grey relational analysis; artificial neural network
JEL classification: E27, F47, G17

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1 - Introduction

Fundamental analysis of market prospects has always complemented technical analysis to capture market swings in both the short run and the long run. Fund managers, investors, and traders are particular in forecasting their investment decisions to guarantee profit and minimize losses. Econometric models that are commonly used to forecast macroeconomic and financial market variables include the autoregressive integrated moving average (ARIMA) and the autoregressive conditional heteroscedasticity (ARCH) models. However, the studies of Lim and McNeils (1998), Rodriguez (2005), and Kadilar et al. (2009) prove that capturing nonlinearities through artificial neural network (ANN) models provide improved forecasting ability. According to White (1990), the power of ANN models relies on its ability to model complicated and nonlinear relationships without a priori knowledge on the nature of the data generating process.

The ANN model has been applied to forecast inflation [(e.g. Nakamura, 2005; Haider and Hanif, 2009)], interest rate [(e.g. Tappinen, 1998)], exchange rate [(e.g. Kadilar et al., 2009; Pradhan and Kumar, 2010)], options [(e.g. Wang, 2009)], stock prices [(e.g. Malliaris and Salchenberger, 1996; Chang and Foo, 2002; Pradhan and Kumar, 2010)], and mutual funds [(e.g. Chiang et al., 1996)]. This paper applies ANN to exchange-traded funds (ETFs)[4], a relatively new investment instrument that is gaining ground in mainstream trading and investment opportunities. Forecasting in ETFs has been studied in literature but not one has used ANN models. For example, Bollapragada et al. (2009) show that the multiple regression technique has better forecasting results with low errors of Standard & Poor’s Depositary Receipts (SPDRs) against single exponential smoothing, Holt’s exponential smoothing and Box-Jenkins (ARIMA) models. De Fusco et al. (2011) discover the pricing deviations of Spiders, Diamonds, and Cubes could be predicted because of its stationarity. Return and volatility predictability can be concluded from Madura and Ngo (2008), who reported ETF inception results in positive and significant valuation effects on dominant component stocks that increase their trading volume. In a similar study, Datar et al. (2008) provide evidence of intraday spillover in the mean, volatility, and depth of US ETF SPDRs to the EINTF EWJ of Japan.

This research uses two types of ANN models namely, back propagation network (BPN) and recurrent neural network (RNN). Avci (2007)

[4] See the study of Deville (2008).

utilizes the BPN to model the Istanbul stock exchange, and reports that the use of the ANN model achieves better results. Zhang and Xiao (2000) reveal that RNN is an effective tool in making one- and multiple-step forecasts with a few data points by using a chaotic computer-generated time series. Chen and Fang (2008) use both models in predicting the performance of the Asian currency unit, and report that ANN models outperform GARCH and random walk models.

In the current study, we utilize grey relational analysis (GRA), which is a very effective method in selecting the best alternatives among multiple alternative options as reported by Feng and Wang (2000), Kung and Wen (2007), and Hamzacebi and Pekkaya (2011). This work examines the relationship between ETFs and six financial market indicators. This technique has been used in business decision-making [(e.g. Kuo et al., 2008)], financial ratios [(e.g. Feng and Wang, 2000; Kung and Wen, 2007), marketing research (Li et al., 2007)], credit risk analysis [(e.g. Lin and Wu, 2011)], and stock investment choices [(e.g. Hamzacebi and Pekkaya, 2011)]. These studies have all found that the proposed GRA is a reliable and reasonable approach in screening variables that affect a dependent variable, and is efficient in selecting the best alternatives among multiple choices. Moreover, this paper investigates the power of GRA in selecting the primary factor out of six considered variables, such as put-call ratio, trading index (TRIN), Brent crude oil index, S&P 500 stock index (S&P), volatility index (VIX), and commodity research bureau (CRB) index.

This research applies ANN to high technology ETFs composed of technology equity ETFs. Non-high technology ETFs composed of utility and financial equity ETFs serve as an ideal comparison group and in identifying differences on the applied model. According to the ETF database website category report (as of December 14, 2010), market capitalization of high technology equity ETFs, including software, hardware, semiconductor, and internet industries, totaled approximately USD 14.4 billion. Utility equity ETFs, which include electrical, gas, nuclear, wind, and water and power utilities, totaled USD 6.45 billion as of November 18, 2010, whereas capitalization of financial equity ETFs, comprising banks, brokers, asset managers, and insurance companies, totaled approximately USD 12.92 billion as of December 17, 2010.[5]

The objective of this research is to apply ANN, which is a relatively more powerful forecasting tool, to predict ETFs. The next objective is to

[5] See http://etfdb.com/etfdb-categories.

examine several differences in forecasting higher volatility technology ETFs and lesser volatility utility ETFs. According to Nobanee (2007), industries related to information technology have higher volatility and predicting these instruments may reveal some degree of disparity to non-high technology firms. The final objective of this paper is to examine the possibility that stock index, volatility index, put–call ratio, TRIN, CRB, and crude oil future index can be utilized to forecast ETFs, and identify the indicators that have the strongest effect through GRA.

By providing a new understanding in forecasting ETFs, the results of the current study will provide economic importance for fund managers, investors, and traders in creating trading strategies to gain profits, and additional avenues and basis of research for academicians and researchers. The findings should contribute to reinforcing the view idea that these trading instruments can be forecasted given related inputs, and thereby convincing potential investors on the viability of ETFs as investment instruments. The findings can also augment current knowledge of academicians and provide another research path.

This study is structured as follows. Section II describes the data and explains the methodology. Section III interprets the results, and Section IV provides the conclusions.

2 - Data and Research Methods

This paper utilizes daily values of 10 high technology ETFs and 10 non-high technology ETFs. The ETF classification and total market capitalization of approximately USD 33.77 billion as of December 2010 are based on the ETF database website. The data period is obtained from the Google Finance website dated July 6, 2005 to March 31, 2011, with 1,438 observations for each ETF. Table 1 shows the summary of ETFs used in this study.

This study uses relevant financial market indicators, such as the S&P 500, VIX, put–call ratio, TRIN, CRB, and Brent crude oil future index as variables that influence high technology and non-high technology ETFs. In linking the relationship of the six financial market factors to several investment instruments, Chen and Huang (2010) and Chen (2011) already establish the existence of bilateral influence between stock index and ETF volatilities. Cremers and Weinbaum (2010) show that the differences from put-call parity provide helpful information in influencing future stock returns.

Table 1: Summary of high technology and non-high technology ETFs data

High technology ETFs	*Ticker*	*Market Cap.* *	*Inception Date*
Technology Select Sector SPDR ETF	XLK	7,221.82	Dec. 22, 1998
Vanguard Information Technology ETF	VGT	1,793.06	Jan. 30, 2004
Semiconductor HOLDRs ETF	SMH	1,397.64	Jun. 5, 2000
iShares Dow Jones US Technology ETF	IYW	1,385.40	May 19, 2000
iShares S&P North America Tech-Software ETF	IGV	610.53	Nov. 26, 2001
iShares S&P Global Technology ETF	IXN	546.36	Nov. 26, 2001
Internet HOLDRs ETFs	HHH	480.12	Sep. 23, 1999
iShares S&P North America Technology ETF	IGM	400.64	Mar. 19, 2001
iShares S&P North America Tech-Multimedia ETF	IGN	228.14	Aug. 27, 2001
SPDR Morgan Stanley Technology ETF	MTK	197.73	Oct. 2, 2000
Non-high technology ETFs	*Ticker*	*Market Cap.*	*Inception Date*
Financial Select Sector SPDR ETF	XLF	6,877.69	Dec. 22, 1998
Utilities Select Sector SPDR ETF	XLU	4,715.46	Dec. 22, 1998
Vanguard Utilities ETF	VPU	747.68	Jan. 30, 2004
Vanguard Financials ETF	VFH	610.10	Jan. 30, 2004
iShares Dow Jones US Utilities ETF	IDU	516.24	Jun. 20, 2000
iShares Dow Jones US Financials ETF	IYF	471.94	May. 26, 2000
Utilities HOLDRs ETF	UTH	331.10	Jun. 23, 2000
Regional Bank HOLDRs ETF	RKH	325.31	Jun. 23, 2000
iShares S&P Global Financials ETF	IXG	236.90	Nov. 26, 2001
iShares Dow Jones US Financials ETF	IYG	207.85	Jun. 21, 2001

* unit: millions.

Wang et al. (2006) state that both put-call ratio and trading index (TRIN) form most of the sentiment indicators, and reveal that sentiments can affect returns as supported by Neal and Wheatly (1998) and Wang (2001). A similar study by Simon and Wiggins (2001) indicate the contrarian indicators of VIX, put–call ratio, and TRIN determine S&P futures returns. Regarding the effect of the CRB price index, Crowder (2006) finds that positive changes in the price index lead to lower equity returns. Tsai (2008) supports this view as indicated in the record of the negative effects of CRB future price index on US share prices. Tansuchat et al. (2010) show volatility spillovers between crude oil and financial markets. Their findings were backed by Soytas and Oran (2011), who claimed that world oil prices were caused changes in the stock market returns in Turkey, particularly on the electricity index returns.

2.1. Grey relational analysis (GRA)

The GRA is a method to quantify the association between two discrete time-series in a grey system with the probability that this relationship can change with time. This process, proposed by Deng (1989), calculates lacking messages on different related factors by examining the random factor series, and thus, determining such correlation requires less data.

Data preprocessing, the initial step in the GRA, is composed of the following three equations.

“The-higher-the-better” expectancy indicates the higher the expected objective, the better.

$$x_i^*(k) = \frac{x_i(k)}{\max x_i(k)} \cdot \tag{1}$$

“The-smaller-the better” expectancy indicates the smaller expected objective, the better.

$$x_i^*(k) = \frac{x_i(k)}{\min x_i(k)} + 2 \cdot \tag{2}$$

“Nominal-the-best” is a particular value that is expected to be obtained between the maximum and minimum objectives.

$$x_i^*(k)\begin{Bmatrix} \dfrac{x_i(k)}{x_{\exp}} \ldots x_i(k) \le x_{\exp} \\ -\dfrac{x_i(k)}{x_{\exp}} + 2 \ldots x_i(k) > x_{\exp} \end{Bmatrix}. \tag{3}$$

where, $x_i(k)$ is the k th coordinate of the i th point is the generating value of the GRA; min $x_i^0(k)$ is the minimum value of $x_i^{(0)}(k)$; and max $x_i^{(0)}(k)$ is the maximum value of $x_i^{(0)}(k)$. The grey relation is determined by the size of the grey level arrangement and the main factors can be found in the levels.

Computing for the grey relational grade (GRG) is the second step in obtaining the grey relational coefficient. The GRG is a measurement method for identifying the relationship of the series, which can be classified into localization and globalization GRGs.

Localization GRG utilizes the particular series $x_0(k)$ as the reference series and the other series $x_i(k)$ as the comparison series. The grey relational coefficients $x_0(k)$ and $x_i(k)$ are calculated as:

$$\gamma(x_0(k), x_i(k)) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{0i}(k) + \zeta\Delta_{\max}} \ , \tag{4}$$

where, $\zeta \in (0,1]$ is called the distinguished coefficient; $\Delta_{0i}(k) = |x_0(k) - x_i(k)|$;

$$\Delta_{\min} = \min_{\forall i} \min_{\forall k} \Delta_{0i}(k) = \min_{\forall i} \min_{\forall k} |x_0(k) - x_i(k)|, \tag{5}$$

$$\Delta_{\max} = \max_{\forall i} \max_{\forall k} \Delta_{0i}(k) = \max_{\forall i} \max_{\forall k} |x_0(k) - x_i(k)|. \tag{6}$$

The distinguished coefficient normally uses 0.5 because of its moderate distinguishing effect, which only affects the grey relational value of the series, but not the rank of the GRG.

By contrast, globalization GRG treats each series $x_i(k)$ as the reference series, and the other series $x_j(k)$ as comparison series. The grey relational coefficients $x_i(k)$ and $x_j(k)$ are computed as:

$$\gamma(x_i(k), x_j(k)) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{ij}(k) + \zeta\Delta_{\max}} \ , \tag{7}$$

where, $\zeta \in (0,1]$ is called the distinguished coefficient;

$\Delta_{ij}(k) = \left| x_i(k) - x_j(k) \right|$; and

$$\Delta_{\min} = \min_{\forall i, \forall j} \min_{\forall k} \Delta_{ij}(k) = \min_{\forall i, \forall j} \min_{\forall k} \left| x_i(k) - x_j(k) \right| , \qquad (8)$$

$$\Delta_{\max} = \max_{\forall i, \forall j} \max_{\forall k} \Delta_{ij}(k) = \max_{\forall i, \forall j} \max_{\forall k} \left| x_i(k) - x_j(k) \right| , \qquad (9)$$

The distinguished coefficient is generally assigned as 0.5 for a moderate distinguishing effect that only affects the grey relational value of the series and not the rank of the GRG.

Calculating the grey relational coefficient leads to the computation of the GRG among x_0 and x_i , or x_i and x_j through the following formula:

$$\gamma(x_0, x_i) = \sum_{k=1}^{n} \beta_k \gamma(x_0(k), x_i(k)), \qquad (10)$$

$$\gamma(x_i, x_j) = \sum_{k=1}^{n} \beta_k \gamma(x_i(k), x_j(k)), \qquad (11)$$

where, β_k is the weighted value and $\sum_{k=1}^{n} \beta_k = 1$. Different weights are assigned to different factors based on their relevance within the system. GRG is calculated by having equal weights and relying on the average value of the grey relational coefficient. Therefore, let

$$\beta_k = \frac{1}{n} \text{, k=1, 2… n.}$$

Arranging the GRG in descending order is the last step in the process. The grey relational order identifies the primary factors of the series that are closely related to the reference series. The highest value mean has the greatest influence, whereas the lowest has the least.

To check whether the findings of GRA are robust, the variables were divided in half depending on their GRGs, namely high and low GRGs. The study applies ANN to identify the group of determinants (all variables, high GRG variables, and low GRG variables) that has the greatest impact on ETFs to verify whether the GRA results are consistent with that of the ANN results.

2.2 Artificial neural network (ANN)

The ANN is a mathematical model based on the processes of biological nervous systems. This model consists of a highly interconnected group of artificial neurons with a flexible structure dependent on external or internal information that enters through the network during the learning process. The strength of an ANN lies in its ability to model nonlinear approximations. According to Vasilescu (2009), this model is also very powerful in modeling extremely complicated function. An ANN has three levels of network structure. The first one is called the processing element (or artificial neural) and is considered the basic unit. The second level forms the "layers" created by the processing element. The third is the "network," which consists of the layers. This paper uses the BPN and RNN types of ANN [(e.g. Chang and Huang, 2003)], which are discussed in the next paragraphs.

2.2.1 Back propagation network (BPN)

The BPN is a supervised learning method of the neural network model that has multilayer perceptron architecture (normally with one input, one hidden, and one output layer) and uses error BPN as learning algorithm. Its architecture is divided in two phases, namely, propagation and weight update. The hidden layer receives information from the input layer. The weighted accumulation, which produces an output using transfer functions, is first computed then transferred to the output layer. The transfer function commonly utilized is the sigmoid function:

$$f(x) = \frac{1}{1+e^{-x}}. \tag{12}$$

The setup of BPN augments the hidden layer to the system, which constitutes the network showing the interaction among input processing elements. The output of processing element j in layer n is the nonlinear function for the output of processing element in layer $n-1$. Multilayer networks require nonlinear activation functions to utilize the hidden layers.

BPN uses the smooth transition function and gradient steepest descent method to minimize the error function. The process for computing the formula of a modified network weights is as follows:

$$A_j^n = f\left(net_j^n\right) = f\left(\sum_i w_{ij} A_i^{n-1} - \theta_j\right), \tag{13}$$

where, f denotes the transfer function; W_{ij} stands for the weight of net_j^n = activity function processing element i in layer $n-1$ and the processing element j in layer n ; θ_j represents the bias of processing element j in layer n , or the so-called threshold value.

BPN minimizes the difference between network and target outputs to measure the speed and the superiority of learning. The learning quality is denoted by the error function E,

$$E = \frac{1}{2}\sum_j (T_j - A_j)^2 , \tag{14}$$

where, T_j denotes the target output of processing element j and A_j represents the network output of processing element j.

The goal of the gradient steepest descent method is to minimize the value of error function E by having the network moderately adjust the weights in the learning process. The proportional relation between the weight value and error function can be written as:

$$\Delta W_{ij} = -\eta \cdot \frac{\partial E}{\partial W_{ij}} , \tag{15}$$

where, η denotes the learning rate that decides the amplitude for the gradient steepest descent method in adjusting the error function. Here, W_{ij} is between the output and the hidden layers, and the equation can be calculated by a chain rule represented as:

$$\frac{\partial E}{\partial W_{ij}} = -\delta_j^n \cdot A_i^{n-1} , \tag{16}$$

where, A_i^{n-1} stands for the output of processing element in lower layer, and is connected by W_{ij} and δ_j^n, which represent the gap of processing element in the upper layer also connected by W_{ij}. Thus, substituting into $\Delta W_{ij} = -\eta \cdot \frac{\partial E}{\partial W_{ij}}$ yields the formula for the BPN algorithm, where each input can be adjusted to serve as training examples for the weight:

$$\Delta W_{ij} = \eta \cdot \delta_j^n \cdot A_i^{n-1} . \tag{17}$$

2.2.2 Recurrent neural network (RNN)

The RNN is a class of neural network that creates an internal state of network that exhibits dynamic temporal behavior. RNN sends time factors directly to loop into the network structure, and uses its internal memory to process a random series of outputs. This process creates a feedback system between neurons that accelerate the learning rate. The output value of a neuron in the hidden or output layer serves as the output of another neuron in the next stage of the process.

The forward propagation of the network multiplies output $x_i(t)$ by the equivalent weight $w_{ji}(t)$ to get the product $net_j(t)$. The network transforms $net_j(t)$ through a nonlinear function f to obtain the output $y_j(t)$ in the feedback-processing layer. We again obtain the product of $y_j(t)$ with the corresponding weight $v_{kj}(t)$ to obtain $net_k(t)$. Transforming $net_j(t)$ through a nonlinear function f obtains $z_k(t)$ in the output layer. This process can be represented as follows:

$$y_j(t) = f(net_j(t)) \ ,$$

$$net_k(t) = \sum v_{kj}(t) y_j(t) \, . \qquad (18)$$

Real-time recurrent learning algorithm (RTLR) is a commonly utilized type of RNN. RTLR demonstrates the weight vector of the neural network connection that requires real-time adjustments. The method of calculation is expressed as follows:

$$e_k(t) = d_k(t) - z_k(t) \ , \qquad (19)$$

where, $d_k(t)$ denotes the output value of neuron k in output layer at time t, the error vector at time t is $e(t)$, and the unit k.

The instantaneous error function $E(t)$ at time t can be expressed as:

$$E(t) = \frac{1}{2}\sum_{k=1}^{K} e_k^2(t) \cdot \qquad (20)$$

(a) The adjustment of specific weight $v_{kj}(t)$ is based on the gradient steepest descent method, which can be calculated as:

$$\Delta v_{kj}(t) = -\eta_1 \frac{\partial E(t)}{\partial v_{kj}(t)} \, , \qquad (21)$$

where, η_1 is the learning rate, denoted by a positive constant.

The partial differential of error function $E(t)$ with reference on weight $v_{kj}(t)$ can be computed by the chain rule:

$$\frac{\partial E(t)}{\partial v_{kj}(t)} = -e_k(t) f'(net_k(t)) y_j(t) \, , \qquad (22)$$

(b) The correction of specific weight $w_{mn}(t)$ through the gradient steepest descent method is as follows:

$$\Delta w_{mn}(t-1) = -\eta_2 \frac{\partial E(t)}{\partial w_{mn}(t-1)} \quad , \tag{23}$$

where, η_2 is the learning rate, denoted by a positive constant.

The partial differential of error function $E(t)$ with reference on weight $w_{mn}(t)$ can also be computed using the following chain rule:

$$\frac{\partial E(t)}{\partial w_{mn}(t-1)} = [\sum_{k=1}^{K} - e_k(t) f'(net_k(t)) v_{kj}(t)] \frac{\partial y_j(t)}{\partial w_{mn}(t-1)}. \tag{24}$$

3 - Empirical Results and Analysis

This section proceeds as follows. First, we interpret the ranks of the six determinants of ETFs through the GRA. Second, we determine the ANN model that can predict ETFs. Third, we test the results of the GRA through the ANN methods.

3.1 Grey relational analysis (GRA)

Tables 2 and 3 of the GRA reveal consistent results in all 20 ETF samples, regardless of whether it is high or non-high technology ETFs. The ranking shows that stock index has the greatest influence, followed by volatility index, CRB index, crude oil index, put-call ratio, and trade index.

The strong relationship between stock index and ETFs was established in the recent works of Chen and Huang (2010) and Chen (2011). According to their studies, a bilateral relationship between the two investment instruments exists. In particular, ETF returns from the ETFs of France, Hong Kong, and Singapore are influenced easily by stock index returns [(e.g. Chen and Huang, 2010)]. For the volatility index, according to French et al. (1987) and Lee (2006), a positive relationship exists between stock market volatility and expected returns. In another study, Crowder (2006) explains that positive innovations in the CRB commodity price result in lower equity returns. We posit that the effects of crude oil on financial markets, as discussed by Tansuchat et al. (2010) and Soytas and Oran (2011), are overpowered by the stronger effects of the closer relationship of determinants such as the stock index, volatility index, and CRB. The last two factors, put-call ratio and TRIN, have the least effect on ETFs based on their GRGs. We found that not all studies agree that sentiment influences returns. Solt and Statman (1988) and Brown and Cliff (2004) report a reversal on causality in which returns actually determine sentiments.

3.2 ANN model for high technology and non-high technology ETFs

A comparison of the forecasting ability of the six independent variables utilizing two ANN models, BPN and RNN, was conducted to predict high and non-high technology ETFs. The lowest values of the mean absolute error (MAE) and the root mean square error (RMSE) were used as bases to identify the best forecasting model or fittest hidden neurons from either BPN or RNN. Following the studies of Andreou et al. (2002) and Chen and Fang (2008) in manipulating training and testing data sets, 10%, 20%, 33%, and 50% were used to examine available forecasting information in the time-series of the predictors.

Table 4 compares the forecasting power of the two ANN models in predicting ETFs. We averaged the values of MAE and RMSE in our four data sets and identified their lowest values. The results show that 60% of the 20 ETFs for both high and non-high technology ETFs are predicted by the BPN model. The better performance of BPN in comparison to RNN is consistent with Moshiri et al. (1999) and Chen and Fang (2008).

According to our findings, the lowest MAE of BPN for high technology ETFs was at 0.0767 of IGN ETF, compared to 0.0916 of IXN ETF for RNN. This result indicates that fund managers and traders have a relatively stronger chance of obtaining accurate forecasting results by using the six independent variables to forecast IGN ETF (using BPN model) and IXN ETF (using RNN model), in contrast with the weaker prediction for SMH ETF (BPN) with an MAE of 0.1833, and IGM ETF with an MAE of 0.1422.

For non-high technology ETFs, BPN also appear to outperform RNN. However, notably, 40% of the non-high technology ETFs predicted by RNN had relatively lower MAEs compared to BPN. For example, the lowest MAE for BPN was 0.1887 from IXG ETF, whereas RNN was 0.1303 from XLU ETF. The highest for BPN was 0.2944 from XLF ETF, whereas RNN was only 0.1447 from UTH ETF. In general, fund managers and traders should be careful in using BPN as the best predictor for these ETFs because, with further exploration and diligence, they can benefit more from RNN with little forecasting error and achieve higher forecasting accuracy.

Table 2: High technology ETFs and GRGs of the six determinants

ETFs	variables	1	2	3	4	5	6
		S&P 500 index	Volatility index	CRB Index	Put-call ratio	Trade Index	crude oil index
1	XLK	239.2186	236.9511	226.4293	220.4866	199.2241	224.4402
	Ranking	1	2	3	5	6	4
2	VGT	239.0981	237.0011	226.3634	220.423	199.1668	224.374
	Ranking	1	2	3	5	6	4
3	IYW	239.0759	237.0189	226.3475	220.4077	199.1532	224.3583
	Ranking	1	2	3	5	6	4
4	SMH	239.1313	237.0516	226.2794	220.3513	199.1343	224.2992
	Ranking	1	2	3	5	6	4
5	IXN	239.2297	236.9669	226.4052	220.4647	199.2083	224.4168
	Ranking	1	2	3	5	6	4
6	IGV	238.955	237.2519	226.1368	220.2116	199.0036	224.1518
	Ranking	1	2	3	5	6	4
7	HHH	238.9097	237.2654	226.055	220.1377	198.953	224.0747
	Ranking	1	2	3	5	6	4
8	IGM	239.0902	237.004	226.3612	220.4209	199.1649	224.3717
	Ranking	1	2	3	5	6	4
9	IGN	239.2293	236.9449	226.3756	220.4413	199.203	224.391
	Ranking	1	2	3	5	6	4
10	MTK	239.0839	237.035	226.3109	220.3748	199.1322	224.3232
	Ranking	1	2	3	5	6	4

Table 3: Non-high technology ETFs and GRGs of the six determinants

ETFs \ variables		1	2	3	4	5	6
		S&P 500 index	Volatility index	CRB Index	Put-call ratio	Trade Index	Crude oil index
1	XLF	238.5952	237.4524	225.8058	219.9177	198.836	223.8448
	Ranking	1	2	3	5	6	4
2	XLU	239.2211	237.0991	226.3526	220.4196	199.1923	224.3688
	Ranking	1	2	3	5	6	4
3	VPU	239.2575	237.0347	226.4108	220.4736	199.2328	224.4254
	Ranking	1	2	3	5	6	4
4	VFH	238.73	237.381	225.9193	220.022	198.9099	223.9543
	Ranking	1	2	3	5	6	4
5	IDU	239.2581	237.0495	226.3947	220.4591	199.2231	224.41
	Ranking	1	2	3	5	6	4
6	IYF	238.7022	237.3967	225.8971	220.0016	198.8957	223.9329
	Ranking	1	2	3	5	6	4
7	UTH	239.2286	237.1547	226.2983	220.3714	199.1647	224.3185
	Ranking	1	2	3	5	6	4
8	RKH	238.7922	237.3293	226.0118	220.1076	198.974	224.0445
	Ranking	1	2	3	5	6	4
9	IXG	238.8198	237.3619	225.9373	220.0401	198.9275	223.9705
	Ranking	1	2	3	5	6	4
10	IYG	238.5908	237.4663	225.8128	219.9238	198.8393	223.8519
	Ranking	1	2	3	5	6	4

Table 4: The comparison of forecasting ability of neural networks for high technology and non-high technology ETFs

High tech	Test	BPN	RNN	Non-high tech	Test	BPN	RNN
XLK	MAE	**0.1222**	0.1268	XLF	MAE	**0.2944**	0.3047
	RMSE	0.3491	0.3545		RMSE	0.5249	0.5404
VGT	MAE	0.1512	**0.1423**	XLU	MAE	0.1415	**0.1303**
	RMSE	0.3876	0.3751		RMSE	0.3736	0.3591
IYW	MAE	0.1613	**0.1422**	VPU	MAE	0.1503	**0.1332**
	RMSE	0.4006	0.3761		RMSE	0.3862	0.3636
SMH	MAE	**0.1833**	0.1857	VFH	MAE	**0.2556**	0.2776
	RMSE	0.4277	0.4299		RMSE	0.4819	0.5124
IXN	MAE	0.1082	**0.0916**	IDU	MAE	0.1408	**0.1356**
	RMSE	0.3284	0.3018		RMSE	0.3722	0.3653
IGV	MAE	**0.1690**	0.1767	IYF	MAE	**0.2557**	0.2766
	RMSE	0.4099	0.4166		RMSE	0.4820	0.5123
HHH	MAE	**0.1017**	0.1140	UTH	MAE	0.1825	**0.1447**
	RMSE	0.3173	0.3364		RMSE	0.4042	0.3766
IGM	MAE	0.1677	**0.1460**	RKH	MAE	**0.2654**	0.2909
	RMSE	0.4083	0.3815		RMSE	0.4958	0.5226
IGN	MAE	**0.0767**	0.0838	IXG	MAE	**0.1887**	0.2015
	RMSE	0.2732	0.2880		RMSE	0.3932	0.4202
MTK	MAE	**0.1317**	0.1420	IYG	MAE	**0.2931**	0.3117
	RMSE	0.3622	0.3765		RMSE	0.5250	0.5470

Table 5 shows the detailed behavior of the data sets of high technology ETFs. We listed the MAEs of each of the four testing data sets, and found that 70% of the data contained the lowest values of MAEs from RNN model. Of the seven ETFs modeled by RNN, four were best predicted at the 10% testing level (XLK, VGT, IYW, and IGV), while the remaining three were from 20% (SMH), 33% (IXN), and 50% (IGM) levels. By using a computer-generated time-series, Zhang and Xiao (2000) discovered the power of RNN on small data, and proved that RNN was effective in making predictions based on few data points. The reversal of findings for the predicting power of high technology ETFs from Table 4 (BPN is 60%, whereas RNN is 40%) to Table 5 (RNN has 70%, whereas BPN has 30%) can be attributed to the lower standard deviations of BPN testing data set values. By contrast, RNN is more dispersed, which is why the latter model can predict a larger number of high technology ETFs with a lower value of MAEs and RMSEs, and consequently, with higher forecasting precision. Fund managers and traders can learn from this experience by not overlooking the fact that a low volume of data can also mean high prediction accuracy, as far as the RNN model is concerned.

The predictive power of BPN in Table 4 for non-high technology ETFs is supported by the detailed description in Table 6. As the table shows, 70% of the non-high technologies ETFs were best modeled by BPN. Of the seven ETFs, six were best predicted on the 10% testing level (XLF, VFH, IYF, RKH, IXG, and IYG), and the remaining at 20% level (UTH). The three ETFs modeled by RNN were best forecasted at the 10% level (XLU, VPU, and IDU), which supports the findings of Zhang and Xiao (2000). Although related evidence on the power of BPN regarding small samples could not be found, this paper establishes that BPN generally has a better forecasting power than ANN, which is consistent with Moshiri et al. (1999) and Chen and Fang (2008). However, the exploration of other ANN models could also yield similar or sometimes even better results.

3.3 Verifying GRA results through the ANN

The GRA provides robust findings in all 20 ETFs samples, whether high or non-high technology ETFs. The GRG shows that the stock, volatility, and CRB indices have relatively higher ranks, thus having more power in influencing ETFs, whereas the lower half, crude oil index, put–call ratio, and trade index have weaker determining ability. This section of the research attempts to verify these results by dividing the six determinants into two groups (i.e., high and low GRG), tests whether the high GRG group has better influence than the low GRG group, and compares these results with previous results from all of the variables combined.

Table 7 shows that high technology ETFs are actually best forecasted by low-GRG variables, with 70% of the samples having the lowest MAEs and RMSEs. The remaining 30% are best modeled by high GRG variables, whereas none is determined by all variables. These counterintuitive results are best explained by the combined pure explanatory power of the sentiment indicators in addition to the crude oil index. The studies of Neal and Wheatley (1998), Simon and Wiggins (2001), and Wang (2001) prove that sentiment can determine returns. As established by Nobanee (2007), the high volatility inherent in high technology firms is further explained Lee et al. (2002), who indicate that sentiment and volatility (i.e., DJIA, S&P 500, and NASDAQ) have a negative relationship in equity markets. For the crude oil index, as supported by Soytas and Oran (2011) and Tansuchat et al. (2010), volatility spillovers occur between crude oil and financial markets. The returns and volatility present in this ETF type cause low-GRG variables (i.e., put–call ratio, TRIN, and crude oil index) to have the best influence on high technology ETFs.

Table 8 illustrates more intuitive findings, and indicates that 60% of non-high technology ETFs can be best forecast when all of the variables are included. A high GRG influenced 10% of the samples, while the remaining 30% were best modeled by low GRG variables, which we again hypothesize as resulting from the combined power of sentiment indicators.

Table 5: Forecasting ability of neural network with high technology ETFs as testing samples

BPN	10%	20%	33%	50%	MAE	10%	20%	33%	50%	RMSE
XLK	**0.1064**	0.1413	0.1226	0.1182	0.1222	**0.3261**	0.3759	0.3505	0.3438	0.3491
VGT	**0.1136**	0.1706	0.1694	0.1511	0.1512	**0.3370**	0.4131	0.4116	0.3888	0.3876
SMH	0.196	**0.1654**	0.1710	0.2004	0.1833	0.4431	**0.4067**	0.4135	0.4476	0.4277
IYW	**0.1238**	0.1800	0.1711	0.1704	0.1613	**0.3518**	0.4243	0.4137	0.4128	0.4006
IGV	0.1084	0.1303	0.0978	**0.0964**	0.1082	**0.3607**	0.4389	0.4344	0.4054	0.4099
IXN	0.1084	0.1303	0.0978	**0.0964**	0.1082	0.3293	0.3610	0.3127	**0.3105**	0.3284
HHH	0.1365	0.0988	0.0867	**0.0848**	0.1017	0.3695	0.314	0.2944	**0.2916**	0.3173
IGM	**0.1282**	0.1762	0.1958	0.1704	0.1677	**0.3580**	0.4197	0.4425	0.4129	0.4083
IGN	**0.0416**	0.0898	0.0706	0.1046	0.0767	**0.2041**	0.2997	0.2657	0.3234	0.2732
MTK	**0.1068**	0.1461	0.1273	0.1465	0.1317	**0.3267**	0.3823	0.3569	0.3828	0.3622
RNN	10%	20%	33%	50%	MAE	10%	20%	33%	50%	RMSE
XLK	**0.0967**	0.1594	0.1402	0.1111	0.1268	**0.3109**	0.3992	0.3744	0.3333	0.3545
VGT	**0.0985**	0.1797	0.1534	0.1374	0.1423	**0.3140**	0.4240	0.3917	0.3707	0.3751
SMH	0.2297	**0.1651**	0.1678	0.1802	0.1857	0.479	**0.4063**	0.4097	0.4245	0.4299
IYW	**0.1081**	0.1612	0.1477	0.1520	0.1422	**0.3287**	0.4014	0.3844	0.3898	0.3761
IGV	**0.1070**	0.1678	0.2121	0.2200	0.1767	**0.3271**	0.4096	0.4606	0.4690	0.4166
IXN	0.0857	0.1168	**0.0811**	0.0835	0.0916	0.2917	0.3418	**0.2848**	0.2890	0.3018
HHH	0.1335	0.1032	**0.0890**	0.1301	0.1140	0.3654	0.3213	**0.2983**	0.3607	0.3364
IGM	0.1356	0.1664	0.1566	**0.1255**	0.1460	0.3682	0.4077	0.3957	**0.3542**	0.3815
IGN	**0.0606**	0.1007	0.0757	0.0982	0.0838	**0.2463**	0.3174	0.2751	0.3133	0.2880
MTK	**0.1255**	0.1489	0.1551	0.1387	0.1420	**0.3542**	0.3857	0.3938	0.3724	0.3765

Note: MAE: mean absolute error, RMSE: root mean square error.

Table 6: Forecasting ability of ANN with non-high technology ETFs as testing samples

BPN	10%	20%	33%	50%	MAE	10%	20%	33%	50%	RMSE
XLF	**0.1147**	0.2096	0.3659	0.4873	0.2944	**0.3387**	0.4574	0.6049	0.6980	0.5249
XLU	**0.1074**	0.1563	0.1138	0.1884	0.1415	**0.3278**	0.3959	0.3373	0.4341	0.3736
VPU	**0.1180**	0.1767	0.1315	0.1749	0.1503	**0.3436**	0.4203	0.3627	0.4182	0.3862
VFH	**0.0812**	0.1527	0.3342	0.4542	0.2556	**0.2849**	0.3908	0.5781	0.6740	0.4819
IDU	**0.1016**	0.1548	0.1135	0.1933	0.1408	**0.3187**	0.3934	0.3368	0.4396	0.3722
IYF	**0.0856**	0.1501	0.3120	0.4752	0.2557	**0.2926**	0.3874	0.5586	0.6896	0.4820
UTH	0.2240	**0.0537**	0.1031	0.3490	0.1825	0.4733	**0.2317**	0.3211	0.5908	0.4042
RKH	**0.0970**	0.1754	0.3345	0.4549	0.2654	**0.3115**	0.4189	0.5784	0.6745	0.4958
IXG	**0.0329**	0.0664	0.2361	0.4193	0.1887	**0.1815**	0.2577	0.4859	0.6475	0.3932
IYG	**0.1540**	0.1662	0.3464	0.5058	0.2931	**0.3924**	0.4077	0.5885	0.7112	0.5250
RNN	10%	20%	33%	50%	MAE	10%	20%	33%	50%	RMSE
XLF	**0.1749**	0.1993	0.3658	0.4790	0.3047	**0.4182**	0.4465	0.6049	0.6920	0.5404
XLU	**0.0955**	0.1406	0.1182	0.1669	0.1303	**0.3091**	0.3750	0.3437	0.4085	0.3591
VPU	**0.1033**	0.1510	0.1194	0.1599	0.1332	**0.3213**	0.3875	0.3456	0.3998	0.3636
VFH	**0.1263**	0.1997	0.3223	0.4622	0.2776	**0.3553**	0.4469	0.5676	0.6799	0.5124
IDU	**0.0981**	0.1480	0.1095	0.1869	0.1356	**0.3132**	0.3847	0.3310	0.4323	0.3653
IYF	**0.1337**	0.2009	0.3043	0.4675	0.2766	**0.3657**	0.4482	0.5516	0.6838	0.5123
UTH	0.1192	0.1516	**0.0985**	0.2097	0.1447	0.3453	0.3893	**0.3138**	0.4580	0.3766
RKH	**0.1167**	0.2015	0.4025	0.4430	0.2909	**0.3416**	0.4489	0.6344	0.6656	0.5226
IXG	**0.0560**	0.0938	0.2529	0.4034	0.2015	**0.2367**	0.3062	0.5029	0.6351	0.4202
IYG	**0.1728**	0.2216	0.3599	0.4926	0.3117	**0.4157**	0.4707	0.6000	0.7019	0.5470

Note: MAE: mean absolute error, RMSE: root mean square error.

Table 7: Testing the High Technology ETFs GRA results for ANN prediction

ETFs	All Variables		High GRG Variables		Low GRG Variables	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
XLK	0.0967	0.3109	0.1051	0.3242	**0.0369**	0.1921
VGT	0.0985	0.3140	0.106988	0.32709	**0.0517**	0.2274
IYW	0.1081	0.3287	0.1174	0.3426	**0.0703**	0.2651
SMH	0.1651	0.4063	**0.1246**	0.3530	0.2613	0.5112
IXN	0.0811	0.2848	0.1043	0.3230	**0.0490**	0.2214
IGV	0.1070	0.3271	0.1323	0.3638	**0.0810**	0.2846
HHH	0.0848	0.2916	**0.0758**	0.2753	0.0913	0.3022
IGM	0.1255	0.3542	0.1179	0.3433	**0.0590**	0.2428
IGN	0.0416	0.2041	**0.0403**	0.2007	0.0891	0.2984
MTK	0.1068	0.3267	0.0933	0.3054	**0.0451**	0.2123

Note: MAE: mean absolute error, RMSE: root mean square error.

Table 8: Testing the Non-high Technology ETFs GRA results for ANN prediction

ETFs	All Variables		High GRG Variables		Low GRG Variables	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
XLF	**0.1147**	0.3387	0.1793	0.4235	0.2424	0.4923
XLU	0.0955	0.3091	0.1037	0.3220	**0.0434**	0.2084
VPU	0.1033	0.3213	0.1128	0.3358	**0.0470**	0.2168
VFH	**0.0812**	0.2849	0.1496	0.3868	0.2150	0.4637
IDU	0.0981	0.3132	0.0981	0.3132	**0.0356**	0.1888
IYF	**0.0856**	0.2926	0.1545	0.3930	0.2224	0.4716
UTH	0.0537	0.2317	**0.0300**	0.1732	0.0543	0.2330
RKH	**0.0970**	0.3115	0.1512	0.3888	0.2059	0.4537
IXG	**0.0329**	0.1815	0.0414	0.2035	0.1127	0.3357
IYG	**0.1540**	0.3924	0.1732	0.4162	0.2417	0.4916

Note: MAE: mean absolute error, RMSE: root mean square error.

4 - Conclusions

Fund managers, investors, and traders frequently attempt to predict securities for wealth accumulation, which is why they constantly search for the best forecasting instruments and related determinants for consideration. This paper has attempted to determine which factors influence the values of both high and non-high technology ETFs by using stock index, volatility index, CRB, put–call ratio, TRIN, and crude oil index.

The current study shows that the BPN model consistently outperformed the RNN model in predicting high and non-high technology ETFs, which implies that fund managers and traders generally obtain more accurate forecasting results by using the BPN model. Listing each of the MAEs from the four testing data sets allowed for 70% of the non-high technology ETFs to be best predicted by BPN. Of the seven ETFs, six were best predicted on the 10% testing level. We found a reversal in high technology ETFs in which 70% of the samples were also best modeled by RNN. Of the seven ETFs, four were best predicted at the 10% testing level. The turnaround of initial findings can be attributed to the lower standard deviations of BPN testing data set values, whereas RNN was more dispersed. Fund managers and traders must be cautioned not to overlook that the low data volume could also mean high prediction accuracy based on both BPN and RNN models, and that with extra effort, investors could benefit from RNN with little forecasting error.

In examining the differences in forecasting the higher volatility high technology ETFs and lesser volatility non-high technology ETFs, this study discovered that the combined low GRG variables of sentiment indicators (put-call ratio and TRIN) and the crude oil index have stronger influence than the group of high GRG variables and all variables in high technology ETFs. By contrast, investors can benefit from forecasting non-high technology ETFs by utilizing all six variables.

The GRA model showed consistent results in all of the 20 ETFs samples, with stock index having the strongest influence, followed by volatility index, CRB index, crude oil index, put-call ratio, and TRIN. The differences in the results of the GRA and ANN, where the low-GRG variables were heavily favored over the high GRG variables, revealed that some variables, when combined together in an ANN framework, can have more powerful influence compared to the individual contributions setting provided by the GRA. Financial market players should be vigilant in searching through the wide variety of determinants and models that could provide the lowest errors and higher forecasting accuracy. This study has proven that with a little exercise in diligence, more accurate forecasting performance can be obtained, and create greater opportunities to attain profits.

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