Grey Relational Grades and Neural Networks: Empirical Evidence on Vice Funds

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ABSTRACT

This research examines time-series predictability of Vice Funds Indices through the Grey Relational Analysis (GRA), and also applies three types of Artificial Neural Networks (ANN) model, namely, Back-propagation Perception Network (BPN), Recurrent Neural Network (RNN), and Radial Basis Function Neural Network (RBFNN) to capture nonlinear tendencies of Vice Funds indices. The study finds that among the three ANN models, BPN has the best predicting power. When the data is separated into 10%, 33% and 50% testing data sets to test the proficiency of the available forecasting information in the time-series of the predictors, the predictive power of the BPN model again dominated the findings 60% of the time. Traders, investors and fund manager can rely on BPN predicting power with large or even small data set. Nevertheless, the result also suggests the predicting power of both RNN and RBFNN model with smaller data sets. Overall, it is suggested that traders and fund managers have stronger chance of achieving more accurate forecasting using the BPN model in Vice Funds indices. Findings of this research have policy implications in the creation of forecasting and investing strategies by examining models that minimize errors in predicting Vice Funds indices.

Keywords: Vice Funds Indices, Grey Relational Analysis, Artificial Neural Network

RÉSUMÉ

Cette recherche examine la prévisibilité des séries chronologiques des indices Vice Funds par le biais de l'analyse relationnelle grise (GRA), et applique également trois types de modèle de réseaux de neurones artificiels (ANN), à savoir le réseau de perception à propagation arrière (BPN), le réseau de neurones récurrents (RNN)) et le Radial Basis Function Neural Network (RBFNN) pour capter les tendances non linéaires des indices Vice Funds. L'étude révèle que parmi les trois modèles ANN, BPN a le meilleur pouvoir de prédiction. Lorsque les données sont séparées en 10%, 33% et 50% de jeux de données pour tester la compétence des informations de prévision disponibles dans la série chronologique des prédicteurs, le pouvoir prédictif du modèle BPN de nouveau domine les résultats 60% du temps. Les traders, les investisseurs et le gestionnaire de fonds peuvent compter sur la puissance de prédiction de BPN avec des ensembles de données volumineux ou même petits. Néanmoins, le résultat suggère également la puissance de prédiction des modèles RNN et RBFNN avec des ensembles de données plus petits. Dans l'ensemble, il est suggéré que les traders et les gestionnaires de fonds ont plus de chances d'obtenir des prévisions plus précises en utilisant le modèle BPN dans les indices Vice Funds. Les résultats de cette recherche ont des implications politiques dans la création de stratégies de prévision et d'investissement en examinant des modèles qui minimisent les erreurs de prédiction des indices Vice Funds.
Mots-clés: indices des fonds du vice, analyse relationnelle grise, réseau de neurones artificiels

JEL Classification: G10, G17

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1. INTRODUCTION

Interest continued to grow in Corporate Social Responsibility (CSR) with the expanding investments in CSR funds. Nowadays, both private and institutional investors are increasingly diversifying their portfolios by investing in companies that set industry-wide best practices with regard to sustainability. As responsible investors grow in numbers, money is utilized to initiate a shift toward a more economically-just, ethically-driven and operationally-sustainable businesses. As Porter and Kramer (2007) put it, doing business today with the thinking of saving tomorrow's needs. Thus, Socially Responsible Investing (SRI) has become more appealing to the discerning investors as the number of business and ethical issues being exposed increased over the years.

Despite the rapid success of SRIs, which basically is investing in firms with certain standard in social, environment, ethical, moral or even in religious aspects; investors, traders and portfolio managers still consider investing in what they call "vice" companies during recession or difficult economic times, because they have higher than expected returns (Hong and Kacperzyk, 2009). Investors always have several legal options by which they can benefit at a company's unsavory and unethical habits; and companies that benefit from arms and weapons dealing, and addiction to tobacco and alcohol are examples of this. Investing in firms with much larger scales of operations like the production of tanks, jet fighters, and aircraft carriers are all legal, despite their revenues are coming from the destruction caused by and war.

Most of the non-CSR companies are coming from vice industries such as gaming, alcohol, firearms, tobacco, and the recently legalized (on selected locations), marijuana use. This kind of industry produces, what we consider addictive products, and it's even more sustainable in returns than the other industry. We can find this kind of investment through ETFs (exchange-traded funds) or mutual funds. For example, a sin ETF, simply tracks the ISE SIN index of casinos, alcohol producers, cigarette makers, launched in 2007 in USA and only survived only a year before it closed. An ETF that focused on alcohol and cigarette are also non-existent, even though these products have a huge amount of support from consumers.

One problem that sin ETFs are encountering is the inadequate volume of investor. Sin mutual funds, on the other hand, also succumb to the pressure of the government and the market, and lighten up on their "pro sin" position. They revised their names and are now called the "Barrier Fund" (formerly the Vice Fund) and they trade under the symbol USA Barrier Mutual Investor (ticker: VICEX). Some investors may have moral considerations with investing in such vice industries, but unconstrained investors with no concerns about the morality of such investments, should try considering the Barrier Fund. Investors of Vice Funds are actually experiencing a good number of return. For example, compared with the S&P 500, VICEX has a 10-year annualized return of 10.4%, compared to the S&P's 8.2%. During the 2008 recession, in VICEX gained 17.8%, while on the other hand, the S&P climbed just 12.3%. However, in 2009, when stocks were recovering from the bear market lows, VICEX had a 12.7% gain, but the S&P 500 Index advanced 26.5%. These results can provide investors some ideas on the performance of Vice Funds compared with regular stock investments. Besides VICEX, there is also Fidelity Select Consumer Staples (ticker:

FDFAX) and Rydex Leisure Investments (ticker: RYLIX), these are the 3 known best mutual funds for sin or vice investments.

This paper plans to capture non-linear characteristics of the so-called Vice Funds for a better forecasting accuracy by minimizing errors. Grey relational analysis (GRA) method will be firstly used to determine which among the factors considered, namely, stock index, volatility index, US dollar index, trading index, commodity research bureau (CRB) and crude oil futures index have the greatest influence on 10 Vice Fund indices returns through their relevant ranks. Three types of ANN models will be also utilized to examine the best training data sets of the Thomson Reuters CSR indices returns. The Back-propagation Perceptron Network (BPN), Recurrent Neural Network (RNN), and Radial Basis Function Neural Network (RBFNN), according to the researches made by Huang et al. (2008), Zhang and Xiao (2000), and Shen et al. (2011), respectively, based on their individual studies produced satisfactory performance when it comes to prediction accuracy of ANN models.

The primary motivation of this research is that GRA and ANN models have never been applied to forecast Vice Funds index returns. The first objective of this paper is to apply ANN, a relatively more powerful forecasting tool to predict Vice Funds index returns. Second, is to determine which of the three ANN models are best to forecast returns based on the lowest values of mean absolute error (MAE) and root mean square error (RMSE). The third objective is to determine which of the six determinants have the strongest effect on Vice Funds index returns through their relevant ranks based on their grey relational grades (GRGs). And lastly, to check the robustness of GRA results, this paper divides the six variables in half depending on their relevant ranks based on their grey relational grades (GRGs) between those with high GRGs and low GRGs. And then ANN models will be applied to identify the group of determinants (all variables, high-GRG variable, and low-GRG variables) that has the greatest impact on Vice Funds Indices returns. This will verify whether GRA findings are consistent with that of the ANN results pin-pointing financial variables that affects the Vice Funds index performance.

The fulfillment of these objectives of the paper is a beneficial additional literature in applying GRA and ANN models in examining Vice Funds index returns. Some possible good policy implications from the results of this paper are the following. First, provision of economic value for fund managers, investors, and traders in creating investing strategies to identify factors that greatly affect their returns and volatility. Second, technical analysts of time-series data can consider the findings in this paper as an initial step for extending the methodology of out-of-sample forecasting for Vice funds. Third, academic significance is seen to provide academicians and researchers to have new understanding in forecasting Vice Funds indices. Lastly, future stakeholders like the government and the investing public can also benefit by having better understanding of predicting and knowing factors affecting their returns. The results should contribute in solidifying the fact that these relatively new investment instruments can be forecasted given specific inputs and right modeling, thus, can convince potential investors on the viability of Vice Fund indices as possible portfolio diversification channels.

The paper also contains the following two sections: Section 2 narrates related studies, and Section 3 describes the data and methodology of GRA, BPN, RNN and RBFNN, and Section 4 showed the empirical results and analysis. Lastly, Section 5 showed the conclusion.

2. LITERATURE REVIEW

This paper collected literature that discuss the importance of Vice Funds indices in investing and in performance measures in the business environment, as well as the utilization of methodologies used in this study. This section discusses papers reviewing the performance of vice funds and stocks; and highlights researches that showed the suitability of GRA and ANN models in studying various financial instruments.

Hong and Kacperzcyk (2009) found that social norms affect stock prices and returns, because sin stocks are less held by norm-constrained institutions such as pension funds, and also receive less coverage from analysts than regular stocks. However, the study found that sin stocks have higher expected returns than otherwise comparable stocks, because of the relative high risk (high returns) of them being neglected by norm-constrained investors and facing greater litigation risk heightened by social norms.

Jo et al. (2010) made a direct comparison of vice investing socially-responsible investing, and discovered that vice-oriented investing has historically performed better than socially-responsible investment from 2004 to 2008 period. However, they suggested using a single year of data that in volatile markets the diversification of socially-responsible investment should be prioritized, and thus sin-based investments should be avoided.

In a related study, Areal et al. (2010) studied market timing possibilities by comparing the performance of vice funds to socially-responsible funds. The authors used high and low volatility as proxies for bear and bull markets, respectively. VICEX fund performance is compared to that of 13 religious and 38 socially-responsible funds. Moral stocks are related to investments by religious groups like Catholic doctrine, Islamic principles and Lutheran catechism. On the other hand, socially-responsible funds consider investments in environmental, human rights protection and sustainability initiatives. The study found that vice fund outperforms both the religious and socially-responsible funds during low volatility or markets, but not during high volatility or bear market regimes. Lastly, Herbohn et al. (2014) explores the relationship between sustainability performance and disclosure of non-environmentally-friendly Australian mining and energy firms. The paper found that there is a weak link between the sustainability performance and disclosure, and suggested that extractive companies should do more of CSR activities in order to have more solid reporting.

Chen and Diaz (2012) studied the spillover effects faith and non-faith exchange-traded funds to the stock market, and vice-versa. The authors observed that faith and non-faith ETFs have significant positive and negative relationships with their stock index returns, respectively. They found that non-faith ETFs showed an ability to provide minimal losses during economic downturns and claimed that their results occur because “sin investments can expect positive returns even during an abysmal economy, because vices are insulated from economic slumps and are possible safe havens during recessions. In another set of study, Morales and Krueger (2013) studied the prices of individual vice-oriented firms in the alcohol and tobacco industries, and compared their performance to the Vanguard’s S&P 500-based mutual fund (i.e., VTINX). The paper found that portfolios consisting either of eight alcohol companies or eight tobacco companies are more highly correlated with the S&P 500 than the individual companies.

Regarding the power of GRA in picking financial variables that closely affect the returns of investment instruments, the study of Hamzacebi and Pekkaya (2011) selected the best alternative stocks among different firms and GRA was found to have the greatest optimization technique for stock selection. In another set of related studies, Feng and Wang (2000) and Kung and Wen (2007) utilized the model in looking at financial ratios and other financial indicators that affects financial performance.

This paper is also interested in the predictability of financial markets using neural networks. For example, Chiang et al. (1996), Avci (2007) and Huang et al. (2008) all used the BPN network to forecast financial markets and revealed increased performance when the ANN model is applied. Chaveesuk et al. (1997) and Shen et al. (2011) found that neural networks, including radial basis function network (RBFNN) are more flexible compared to regression models, and are more immune to imperfect data. Also, Zhang and Xiao (2000) proved that recurrent neural network (RNN) is effective and a very powerful tool in making one-step and multi-step predictions based on few data points in using a computer-generated chaotic time-series.

Chen and Fang (2008) predicted the performance of the Asian Currency Unit (ACU) by using the BPN, RNN, Time-Delay Recurrent Neural Network (TDRNN), General Autoregressive Conditional Heteroscedasticity (GARCH), and random walk models. The authors showed that ANN models outperformed GARCH and random walk models, and among the ANN models. Lastly, both studies of Kadilar et al. (2009) and Pradhan and Kumar (2010) used ANN to forecast the Turkish and Indian currencies, respectively against the US dollar. Their paper showed that the method has best forecasting accuracy compared to seasonal ARIMA and ARCH models. The predictability of sustainability indices will be tested by ANN models, which have been vastly applied in the capital markets literature.

The above literature also looked into possible macroeconomic and financial factors that can possibly predict the movements of financial instruments, particularly vice funds and stocks. The literature also discussed combining powerful non-linear tools like GRA and ANN, which motivated this paper that vice funds and indices are a good avenue in contributing to the literature of its predictability based on a number of variables.

3. DATA AND METHODOLOGY

Ten actively-traded Vice Fund indices from the Yahoo! Finance website will be utilized for this research. This study uses daily data starting July 1, 2009 (or right after the National Bureau of Economic Research announced the end of the Subprime Mortgage Crisis of 2008) until December 30, 2016. The data sources of the 6 variables are Google.com/finance for the stock and volatility indices; Forexpros.com for the US dollar index; Jefferies.com for the CRB index; and Theice.com for the Brent crude oil futures index.

3.1. Grey relational analysis (GRA)

GRA necessities only lesser number of data to quantitatively measure the connection among factors, and can measure incomplete message on various relevance factors through examining the random factor series. Deng (1989) suggested the GRA in the Grey system theory; and defined it a process of calculating the association of two discrete series in a Grey system, with the likelihood that this relationship can change with time.

In the GRA process, the first step is the data preprocessing which is composed of the following three equations below:

a) Higher-the-better expectancy denotes that the higher the expected objective, the better.

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

b) Smaller-the-better expectancy means that the smaller expected objective, the better.

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

c) Nominal-the-best expectancy shows that there is a specific value that is expected to achieve between maximum and minimum.

$$(3)\ x_i^*(k) \left\{ \begin{array}{l} \frac{x_i(k)}{x_{\exp}} \ldots x_i(k) \le x_{\exp} \\ -\frac{x_i(k)}{x_{\exp}} + 2 \ldots x_i(k) > x_{\exp} \end{array} \right\}.$$

Where:

$x_i(k)$ is the k th coordinate of the $\boldsymbol{i}$ th point is the generating value of Grey relational analysis;

$\min x_i^0(k)$ is the minimum value of $x_i^{(0)}(k)$;

$\max x_i^{(0)}(k)$ is the maximum value of $x_i^{(0)}(k)$.

The size of the arrangement of grey levels chooses the grey relation and the key factors can be situated in these levels.

The next step in the procedure is to determine the grey relational grade (GRG) through the grey relational coefficient. The GRG is a measurement process that looks at the association of the sequences and can be characterized into localization GRG and globalization GRG.

Localization GRG selects the specific sequence $x_0(k)$, as the reference sequence, and the other sequence $x_i(k)$, as the compared sequence. The grey relational coefficient $x_0(k)$ and $x_i(k)$ is calculated as:

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

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

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

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

The distinguished number is generally set to 0.5 for its controlled distinguishing effect and stability, affecting only the grey relational value of the order, but not the rank of the GRG.

Globalization GRG treats each order $x_i(k)$ as the reference sequence, and the other order $x_j(k)$ as compared sequence. The grey relational coefficient $x_i(k)$ and $x_j(k)$ is designed as:

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

Where: $\zeta \in (0,1]$ is the distinguished coefficient; $\Delta_{ij}(k) = \left| x_i(k) - x_j(k) \right|$; and

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

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

The indicated distinguished coefficient is generally set to 0.5 for a stable and adequate distinguishing effect. It affects only the grey relational value of the sequence, but not the rank of the grey relational grade.

After computing the grey relational coefficient, we can get the GRG among x_0 and x_i, or x_i and x_j based on the formula below:

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

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

Where: β_k represents the weighted value, and $\sum_{k=1}^{n} \beta_k = 1$. Each can be assigned with varying weights based on the significance of the factor within the system. The calculation of GRG is identified by equal weights and according to the average value of the grey relational coefficient. Thus, let $\beta_k = \frac{1}{n}$, k=1,2,…, n.

The last procedure in the GRA process is to organize the grey relational ordinal in a descending order. This constructed sequence offers the priority listing to choose the order that is closely associated to the reference sequence. Highest value specifies that it is the main factor of influence, and the lowest has the least effect.

3.2. Artificial Neural Networks

<u>Back-propagation Perceptron Network (BPN)</u>

The BPN model has a construction called multilayer perceptrons (MLP) and utilizes Error Back Propagation (EBP) as its learning algorithm. The BPN model calculates the input values in the hidden layer. The model involves the diffusion of input directly to the hidden layer from the input layer. This produces an output with transfer functions, which is normally called Sigmoid Function is then moved to the output layer, and is represented with the following equation:

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

The BPN network augments a hidden layer to the system that demonstrates the interaction among input processing elements. The decrease of the error function needs the use of the smooth transition function and Gradient Steepest Descent method. The method of the formula of a modified network weights is set when the yield of processing element j in layer n becomes the non-linear function for the output of processing element in layer $n-1$.

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

Where:

f represents the transfer function;

W_{ij} denotes the weight of net_j^n = activity function processing element i in layer $n-1$, as well as the processing element j in layer n.

θ_j is for the bias of processing element j in layer n, or the threshold value.

The BPN model minimizes the differences between the output of network and target output. The learning quality from this supervised learning is given by the error function E :

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

Where:

T_j represents the target output of processing element j ; and

A_j denotes the network output of processing element j .

Recurrent Neural Network (RNN)

RNN model is a vigorous neural network that creates connections between units form a directed cycle. The RNN model assimilates time factors to go around the network structure. The process feeds back the output number of the neuron in the hidden layer or the output layer to become the output of neuron in the next stage. The learning progression accelerates, because of the mutual feedback progressions between neurons.

The forward propagation of the RNN model multiplies output $x_i(t)$ by an corresponding weight $w_{ji}(t)$, and $net_j(t)$ is the product of that process. Then the network converts $net_j(t)$ through a nonlinear function f to get the output $y_j(t)$ in the feedback processing layer. This procedure of multiplying $y_j(t)$ by an equivalent weight $v_{kj}(t)$ again produces a product $net_k(t)$. The expression $net_j(t)$ is changed through a nonlinear function f and gets the product $z_k(t)$ in the output layer. This relationship can be presented as follows:

$$(15)\ y_j(t) = f(net_j(t)),$$

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

Radial Basis Function Neural Network (RBFNN)

RBFNN model is a mixture learning network that pools both unsupervised and supervised learning instructions. The procedure uses unsupervised learning to classify the cluster center and resolve on the initial value. This network can also model random nonlinear transformations which early linear perceptrons can’t.

The RBFNN model is analogous to the architecture of the BPN, which consists of three layers. The input layer the data is imported from each input node related to all of the hidden nodes of the single hidden layer. The hidden layer is made up of a set of nodes, one for each radial basis function center (Broomhead and Lowe, 1988). The construction of numerous radial basis functions through the use of curve fitting is one of the major features of RBFNN. This aspect of the model leads to the learning and mapping relationships between input and output values. As specified by Bors and Gabbouj (1994) and Bors and Pitas (1996), the Gaussian function is the most commonly utilized in RBFNN and is represented as:

$$(16)\quad \phi_j(X) = \exp\left[-(X-\mu_j)^T \sum\nolimits_j^{-1}(X-\mu_j)\right], \text{ for } j=1,\ldots,L,$$

Where:

X represents the input feature vector,

L denotes the number of hidden units, and

μ_j and $\sum_j$ are the mean and the covariance matrix of the *j*th Gaussian function, respectively.

4. EMPIRICAL RESULTS AND ANALYSIS

This section discusses the findings of this paper from the results of the GRA model, and the ranking of the GRGs to the different results, determines which of the three ANN models are best to forecast returns, identifies which of the six determinants have the strongest effect on Vice Funds index returns.

4.1. Grey Relational Analysis

Table 1 shows the results of the GRA model for the 10 Vice Funds. Based on the GRA rankings, the S&P 500 index dominated the top stop of relational predictors 90% (9 out of 10 Vice Funds index) of the time, while the USD Index is also at the top 2 predictor 90% of the time. Only the INNA.MI index has the rankings of the S&P 500 index and USD index switched. The Volatility Index, Trade Index, CRB Index and Brent Crude Oil Index are the more consistent ranking variable placing 3rd, 4th, 5th, and 6th, respectively, for the ten Vice Funds indices.

The relationship between S&P 500 Stock Index performance and investment instruments have been found in the work of Preston and O'Bannon (1997), and Wang (2011). On one hand, Simon and Wiggins (2001) showed that sentiment indicators such as the Volatility Index, the put–call ratio, and the Trade Index are widely used by technical analysts as contrary market indicators. The results demonstrate that these indicators generally had both statistically and economically significant predictive power for subsequent S&P futures. Sariannidis et al. (2016) have found that an increase in the oil returns, as well as in the oil price volatility, leads to a decrease in the value of the Index employed. It was also found that asymmetry affects positively the stock price of the Eurozone social responsibility companies.

4.2. ANN model for Vice Funds

The three ANN models, namely, BPN, RNN and RBFNN are utilized in this study to compare the predictive efficiency of the six independent variables by having the smallest possible forecast error, that is, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) in determining Vice Funds indices. This paper followed the earlier researches of

Chen and Fang (2008) by manipulating training or testing data sets (i.e., 10%, 33% and 50%) to test the efficiency of the available forecasting information.

Table 1: Vice Funds Indices and GRGs of the six determinants

Currency ETNs and six variables		**1** S&P 500 stock index	**2** Volatility index	**3** US Dollar Index	**4** Trade Index	**5** CRB Index	**6** Brent crude oil index
1	BJK	300.6308	284.5461	289.8785	166.5309	150.3708	125.5525
	Ranking	**1**	**3**	**2**	4	5	6
2	FDFAX	301.5714	272.6208	303.8139	170.9614	154.1699	128.251
	Ranking	**1**	**3**	**2**	4	5	6
3	INAA.MI	280.9571	275.1172	281.1143	144.4655	147.3903	123.7401
	Ranking	**2**	**3**	**1**	5	4	6
4	IYK	310.3167	278.5625	299.7973	169.8683	153.8047	128.5515
	Ranking	**1**	**3**	**2**	4	5	6
5	PBJ	308.9655	279.5752	298.1929	169.2692	153.4117	128.3688
	Ranking	**1**	**3**	**2**	4	5	6
6	PEJ	305.5128	280.8757	294.2764	169.1338	153.5233	128.7386
	Ranking	**1**	**3**	**2**	4	5	6
7	PPA	302.2715	284.9396	291.1839	167.8507	152.4678	128.0078
	Ranking	**1**	**3**	**2**	4	5	6
8	RYLIX	307.881	280.1238	295.8312	169.283	153.5453	128.6181
	Ranking	**1**	**3**	**2**	4	5	6
9	VDC	309.7664	279.5177	298.7966	169.6096	153.6746	128.5609
	Ranking	**1**	**3**	**2**	4	5	6
10	VICEX	308.4168	277.4671	298.4177	170.0984	153.9352	128.5711
	Ranking	**1**	**3**	**2**	4	5	6

Table 2 illustrates the comparison of the forecasting efficiency for the full data set among the three ANN models in determining the Vice Funds index return. The paper finds that the BPN model totally outperformed the RNN and RBFNN models 100% (10 out of 10 Vice Funds index) of the time by having the lowest values of MAE and RMSE. Between RNN and RBFNN models, the latter ANN model has generally the lower forecasting error 80% (8 out of 10 Vice Funds index) of the time. Among the indices PPA has the lowest error from the BPN model with 0.0645 for MAE, and 0.2463 for RMSE, followed by INAA.MI with 0.0738 for MAE, and 0.2559 for RMSE. Contrary to the earlier findings of Ranaweera el at. (1995) that RBFNN model performs better than the BPN model, this paper is not consistent with this claim, and gives more favor to the BPN model. The power of the BPN model has been earlier studied by the works of Chen and Fang (2008), and Adebiyi et al. (2012). From these results, one good trading policy implication is that traders and fund managers have stronger chance of achieving more accurate forecasting results by using the BPN model.

Technical analysts of time-series data can consider these finding as an initial step for an extended methodology of out-of-sample forecasting for Vice funds, and utilizing the BPN model will yield favorable results compared to the other ANN models.

Table 2: The comparison of forecasting ability of neural networks for Vice Funds

ETNs	Test	BPN	RNN	RBFNN
BJK	MAE	**0.0969**	0.1777	0.1815
	RMSE	0.3023	0.4034	0.4025
FDFAX	MAE	**0.0996**	0.1834	0.1469
	RMSE	0.3037	0.3882	0.3680
INAA.MI	MAE	**0.0738**	0.1509	0.1262
	RMSE	0.2559	0.3697	0.3436
IYK	MAE	**0.0985**	0.1846	0.1453
	RMSE	0.3087	0.3965	0.3503
PBJ	MAE	**0.1087**	0.1877	0.1490
	RMSE	0.3171	0.3822	0.3490
PEJ	MAE	**0.0909**	0.1659	0.1305
	RMSE	0.2894	0.3491	0.3285
PPA	MAE	**0.0645**	0.1664	0.1312
	RMSE	0.2463	0.3871	0.3419
RYLIX	MAE	**0.0820**	0.1657	0.0918
	RMSE	0.2683	0.3486	0.2809
VDC	MAE	**0.1029**	0.1800	0.1987
	RMSE	0.3153	0.3958	0.4116
VICEX	MAE	**0.1177**	0.2062	0.1380
	RMSE	0.3384	0.4098	0.3446

Note: MAE: mean absolute error; RMSE: root mean square error

Table 3 illustrates more detailed results for each Vice Funds index's testing data (i.e., 10%, 33% and 50%) using the BPN model. The MAEs of the 33% and 50% testing data set both dominated the 10% data set 100% (10 out of 10 indices) of the time, with each of them having 5 indices. For example, BJK has the lowest MAE of 0.0469 using 50% of data set, compared to 0.0857 and 0.1582 of the 33% and 10% data sets, respectively; also FDFAX has the lowest MAE of 0.0477 using 33% of data set, compared to 0.0740 and 0.1770 of the 50% and 10% data sets, respectively. These results from the MAE are also consistent with the results of the RMSE for the BPN model. These findings are consistent with the earlier study of Moshiri et al. (1999), which proved the forecast power of the BPN in larger data sets, and weak on fewer data sets (i.e., 10% vs. 33% and 50% data sets). Consistent with the earlier findings, this study recommends that technical analysts of traders and fund managers are better off depending on the predicting power of the BPN model using larger data sets (i.e., 33% and 50% of data); and can benefit financial analysts in using out-of-sample forecasting.

Table 3: Forecasting ability of BPN on Vice Funds

Vice Funds on BPN Model	MAE			RMSE		
	10%	33%	50%	10%	33%	50%
BJK	0.1582	0.0857	**0.0469**	0.3977	0.2928	**0.2165**
FDFAX	0.1770	**0.0477**	0.0740	0.4207	**0.2183**	0.2721
INAA.MI	0.1467	0.0443	**0.0304**	0.3830	0.2106	**0.1743**
IYK	0.1508	0.0741	**0.0704**	0.3884	0.2722	**0.2654**
PBJ	0.1828	0.1009	**0.0425**	0.4275	0.3177	**0.2061**
PEJ	0.1588	**0.0370**	0.0768	0.3985	**0.1924**	0.2772
PPA	0.0919	**0.0256**	0.0761	0.3031	**0.1599**	0.2758
RYLIX	0.1660	0.0497	**0.0304**	0.4074	0.2230	**0.1745**
VDC	0.1510	**0.0594**	0.0983	0.3886	**0.2438**	0.3136
VICEX	0.1402	**0.0667**	0.1463	0.3745	**0.2582**	0.3825

Note: MAE: mean absolute error; RMSE: root mean square error

Table 4 shows more detailed results for each Vice Funds index's testing (i.e., 10%, 33% and 50%) using the RNN model. This time, the MAEs of the 33% testing data set has the most number of lowest MAEs and RMSEs 60% (6 out of 10 indices) of the time, followed by the 50% data set with 40% (4 out of 10 indices) accuracy level. For example, IYK has the lowest MAE of 0.0752 using 33% of data set, compared to 0.0814 and 0.3971 of the 50% and 10% data sets, respectively. The 10% data set did not perform compared to the other two larger data sets. According to Zhang and Xiao (2000), the RNN model is good at forecasting using fewer data sets. However, in this study, the RNN model is better off in using larger data sets (i.e., 33% and 50%). Therefore, one policy trading implication of this result is that, chartists of portfolio managers can look at the possibility of relying on the forecasting efficiency of the RNN model on larger data sets, specifically in investing in Vice Funds, contrary to the earlier findings of the literature.

Table 4: Forecasting ability of RNN on Vice Funds

Vice Funds	MAE			RMSE		
RNN Model	10%	33%	50%	10%	33%	50%
BJK	0.3212	0.1381	**0.0738**	0.5668	0.3717	**0.2717**
FDFAX	0.4148	0.0693	**0.0662**	0.6440	0.2633	**0.2573**
INAA.MI	0.2898	0.0824	**0.0805**	0.5383	0.2870	**0.2837**
IYK	0.3971	**0.0752**	0.0814	0.6302	**0.2742**	0.2852
PBJ	0.4490	0.0659	**0.0483**	0.6701	0.2566	**0.2198**
PEJ	0.4165	**0.0352**	0.0460	0.6453	**0.1876**	0.2144
PPA	0.3070	**0.0579**	0.1344	0.5541	**0.2407**	0.3666
RYLIX	0.4128	**0.0266**	0.0578	0.6425	**0.1630**	0.2404
VDC	0.3725	**0.0705**	0.0972	0.6103	**0.2654**	0.3117
VICEX	0.4618	**0.0492**	0.1075	0.6795	**0.2219**	0.3279

Note: MAE: mean absolute error; RMSE: root mean square error

Table 5 illustrates more detailed findings for each Vice Funds index's testing (i.e., 10%, 33% and 50%) using the RBFNN model. For this table, again, the MAEs of the 33% testing data set has 60% (6 out of 10 indices) more number of lowest MAEs and RMSEs, followed by the 50% data set with 40% (4 out of 10 indices) accuracy level. For example, PEJ has the lowest MAE of 0.0376 using 33% of data set, compared to 0.0642 and 0.2895 of the 50% and 10% data sets, respectively. Again, the 10% data set did not perform compared to the other two larger data sets. The predictive power of the RBFNN model on larger data sets is not consistent with the initial findings of Chaveesuk et al. (1999), which showed the flexibility of the model on smaller or imperfect data. However, this paper still recommends the RBFNN model in larger sample of data sets for better forecasting efficiency consistent with the findings of this paper.

4.3. Verifying GRA results through the ANN

The GRA model identified and ranked the best variable that determines Vice Funds indices in Table 2. Following this ranking, the paper separated the top three variables with high GRGs, namely, S&P500 Stock Index, Volatility Index and US Dollar Index; and the bottom three variables with low GRGs, namely Trade Index, CRB Index and Brent Crude Oil Index. Table 6 illustrates the findings of the BPN model in comparing the prediction accuracy of All Variables, High GRG Variables and Low GRG Variables. Among the group of variables, the High GRG group dominated the other two groups 58.33% (7 out of 12 indices) of the time; and has the most number of lower MAEs and RMSEs compared to three Vice Funds Indices of All Variables group, and none from the Low GRG Variables group. For example, FDFAX's MAE of 0.0920 and RMSE of 0.3033 are the lowest from the High GRG Variables compared to the MAE of 0.0996 and RMSE of 0.3156 from All Variables, and lastly, Low GRG Variables with MAE of 0.2077 and RMSE of 0.4557. The ranking made by the GRA model helped in identifying the variables that closely determines Vice Fund Indices. Surprisingly, the BPN model doesn't need the complete set of predictor variables to reach the lowest MAEs and RMSEs. These results of the BPN model having lower prediction error in smaller data sets is not consistent with the earlier study of Moshiri et al. (1999) in studying inflation time-series data. Thus, this study recommends that the BPN model can be also suitable in both smaller and larger data sets as predictors of financial time-series data, and that technical analysts can have more flexibility on the predictive power of the BPN model.

Table 7 shows the results of the prediction accuracy of All Variables, High GRG Variables and Low GRG Variables utilizing the RNN model. This time, the All Variables group, completely dominated the High GRG and Low GRG groups, wherein 100% (10 out of 10 indices) of the time, the MAEs and RMSEs are the lowest when using the complete set of predictor variables. For example, BJK for All Variables has MAE of 0.1777 and RMSE of 0.4034, followed by High GRG Variables with MAE of 0.2228 and RMSE of 0.6771, and lastly, Low GRG Variables has MAE of 0.2247 and RMSE of 0.6840. These findings are not again consistent with the previous work of Zhang and Xiao (2000) in applying the RNN model, which explained the RNN model's more accurate prediction utilizing few data sets. This paper suggests that the RNN model may also be more effective in using larger data sets, thus, technical analyst might want to also consider more data in using the RNN model.

Table 5: Forecasting ability of RBFNN on Vice Funds

Vice Funds RBFNN Model	**MAE**			**RMSE**		
	10%	33%	50%	10%	33%	50%
BJK	0.3370	0.1502	**0.0573**	0.5805	0.3875	**0.2394**
FDFAX	0.2696	0.0918	**0.0793**	0.5193	0.3031	**0.2816**
INAA.MI	0.2215	0.0858	**0.0714**	0.4706	0.2929	**0.2672**
IYK	0.3093	**0.0405**	0.0862	0.5562	**0.2013**	0.2936
PBJ	0.3389	0.0574	**0.0507**	0.5821	0.2396	**0.2252**
PEJ	0.2895	**0.0376**	0.0642	0.5381	**0.1940**	0.2534
PPA	0.2340	**0.0364**	0.1232	0.4837	**0.1909**	0.3510
RYLIX	0.1932	**0.0323**	0.0499	0.4396	**0.1797**	0.2233
VDC	0.4245	**0.0699**	0.1017	0.6515	**0.2643**	0.3190
VICEX	0.2734	**0.0340**	0.1065	0.5229	**0.1845**	0.3264

Note: MAE: mean absolute error; RMSE: root mean square error

Table 6: Testing GRA results for Vice Funds with BPN prediction

BPN	All Variables		High GRG Variables		Low GRG Variables	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
BJK	**0.0969**	**0.3113**	0.2237	0.4730	0.2077	0.4557
FDFAX	0.0996	0.3156	**0.0920**	**0.3033**	0.2061	0.4540
INAA.MI	**0.0738**	**0.2717**	0.1003	0.3167	0.0993	0.3151
IYK	0.0985	0.3138	**0.0825**	**0.2872**	0.2075	0.4555
PBJ	0.1087	0.3297	**0.0783**	**0.2798**	0.2025	0.4500
PEJ	0.0909	0.3015	**0.0723**	**0.2689**	0.1944	0.4409
PPA	0.0645	0.2540	**0.0434**	**0.2083**	0.1519	0.3897
RYLIX	**0.082**	**0.2864**	0.2701	0.5197	0.1814	0.4259
VDC	0.1029	0.3208	**0.088**	**0.2967**	0.2043	0.4520
VICEX	0.1177	0.3431	**0.1004**	**0.3169**	0.2312	0.4808

Note: MAE: mean absolute error; RMSE: root mean square error

Table 7: Testing GRA results for Vice Funds with RNN prediction

RNN	All Variables		High GRG Variables		Low GRG Variables	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
BJK	**0.1777**	**0.4034**	0.2228	0.6771	0.2247	0.6840
FDFAX	**0.1834**	**0.3882**	0.2642	0.8032	0.2641	0.8174
INAA.MI	**0.1509**	**0.3697**	0.2242	0.7134	0.2310	0.7255
IYK	**0.1846**	**0.3965**	0.2540	0.7729	0.2768	0.8029
PBJ	**0.1877**	**0.3822**	0.2598	0.8201	0.2639	0.8198
PEJ	**0.1659**	**0.3491**	0.2438	0.7911	0.2646	0.8215
PPA	**0.1664**	**0.3871**	0.2353	0.7278	0.2468	0.7313
RYLIX	**0.1657**	**0.3486**	0.2467	0.8073	0.2533	0.8179
VDC	**0.1800**	**0.3958**	0.2738	0.7906	0.2866	0.7988
VICEX	**0.2062**	**0.4098**	0.2752	0.8279	0.3031	0.8583

Note: MAE: mean absolute error; RMSE: root mean square error

Table 8 shows the results of the prediction accuracy of All Variables, High GRG Variables and Low GRG Variables utilizing the RBFNN model. This time, the High Variables group, completely dominated the All Variables and Low GRG groups, wherein 100% (10 out of 10 indices) of the time, the MAEs and RMSEs are the lowest when using only the High GRG set of predictor variables. For example, BJK has MAE of 0.1272 and RMSE of 0.3567, while All Variables has MAE of 0.1815 and RMSE of 0.4260, and Low GRG Variables has MAE of 0.1972 and RMSE of 0.4441. This finding relates to the flexibility of the RBFNN model when dealing with imperfect data, as suggested by Chaveesuk et al. (1997) and Shen et al. (2011). Thus, this paper recommends that technical analysts of portfolio management companies may use the RBFNN model when encountering smaller or half the number of predictor data sets.

Table 8: Testing GRA results for Vice Funds with RBFNN prediction

RBFNN	**All Variables**		**High GRG Variables**		**Low GRG Variables**	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
BJK	0.1815	0.4260	**0.1272**	**0.3567**	0.1972	0.4441
FDFAX	0.1469	0.3833	**0.1222**	**0.3496**	0.1768	0.4205
INAA.MI	0.1262	0.3553	**0.1103**	**0.3321**	0.1538	0.3922
IYK	0.1453	0.3812	**0.1189**	**0.3448**	0.132	0.3633
PBJ	0.1490	0.3860	**0.0895**	**0.2998**	0.1845	0.4295
PEJ	0.1305	0.3613	**0.0789**	**0.2809**	0.1391	0.3730
PPA	0.1312	0.3622	**0.0668**	**0.2585**	0.1402	0.3744
RYLIX	0.0918	0.3030	**0.0906**	**0.3010**	0.1651	0.4063
VDC	0.1987	0.4458	**0.1325**	**0.3640**	0.1681	0.4100
VICEX	0.1380	0.3715	**0.1049**	**0.3239**	0.1983	0.4453

Note: MAE: mean absolute error; RMSE: root mean square error

5. CONCLUSIONS AND FUTURE RESEARCH

Socially responsible investing is getting more popular, however, other investors are still considering vice companies and funds, especially during economic downturns, because they produce higher than expected returns (Hong and Kacperzyk, 2009). This research examined time-series predictability of Sin ETFs through the GRA, and also applies three types of ANN models, namely, BPN, RNN, and RBFNN to capture nonlinear tendencies for a better forecasting accuracy. The research aimed to find which ANN model has stronger predictive power compared with the other models, based on the ranking of the GRGs. The paper first applied the GRA model in determining which among the 6 variables of stock and volatility indices, US dollar index, Trade index, CRB index, and Brent crude oil futures index have the strongest influence on Vice Funds based on their relevant ranks. The ANN models were used to predict Vice Fund index returns, based on the lowest values of MAE and RMSE. To check the robustness of GRA results, this paper divided the six variables in half depending on their relevant ranks based on their GRGs between those with high GRGs and low GRGs. This study benefits to financial market players in determining appropriate ANN models in trying to forecast Vice Funds Indices.

The paper found that BPN had the best predicting power compared with RNN and RBFNN, the paper also learned that RNN and RBFNN models also got good performance with predicting accuracy. This paper also separated the data to 10%, 33% and 50% testing data level to test the proficiency of the available forecasting information in the time-series of the predictors. The predicting power of BPN model also showed with Vice Funds indices, 60% of the Vice Funds were best modeled by BPN model, 30% by RNN model and only 10% by RBFNN model. Traders, investors and fund manager can rely on BPN forecasting power with large or even small data sets. The result also suggested the predicting power of RNN and RBFNN model with a smaller set of data. Overall, the best forecasting ability was achieved using the BPN model. The study suggested that traders and fund managers have stronger chance of achieving more accurate forecasting in utilizing the BPN model. The GRAs table showed the dominance of High GRG of the influence toward Vice Funds indices. However, still, traders and fund managers can benefit by combining all six variables to get better forecasting accuracy.

Some possible good policy implications from the findings of this research are the a) creation of investing strategies by examining factors that influence their returns; and b) considering these results as a preliminary procedure to utilize out-of-sample forecasting in the future. The findings also offer academicians and researchers new ideas in minimizing errors in predicting Vice Funds indices. The current GRA and ANN models only utilize data at the end of the trading day, future research may consider using intra-daily data, or broader CSR indices to forecast the direction of the CSR market rather than the purely focusing on individual indices. Future research may also use different ANN architectures and learning algorithms. For example, hybrid intelligent systems, like combining fuzzy logic, expert systems, genetic algorithms, and wavelet networks, (aside from the study's GRA) with ANNs, need to be also explored. ANNs can be performed to forecast time series, while fuzzy logic and expert systems can aid in identifying trading signals. Genetic algorithms can be utilized to pick input variables instead of GRA, as well as the optimal parameters for the system. Wavelet networks have been used in many applications such as time series prediction, and signal classification and compression. These characteristic of the above models are complementary to the other ANNs for a more accurate forecasting, and can be utilized for future research to assist in determining the effect of a particular variable on Vice funds returns, and other time-series data.

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