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The forecasting of consumer exchange-traded funds (ETFs) via grey relational analysis (GRA) and artificial neural network (ANN)

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Abstract
Our study uses the grey relational analysis (GRA) and artificial neural network (ANN) models for the prediction of consumer exchange-traded funds (ETFs). We apply eight variables, including the put/call ratio, the EUR/USD exchange rate, the volatility index, the Commodity Research Bureau Index (CRB), the short-term trading index, the New York Stock Exchange Composite Index, inflation, and the interest rate. The GRA model results showed that the NYSE, CRB, EUR/USD, and PCR were the four main variables influencing consumer ETFs. The GRA test results of all the ANN models' data showed that the back propagation neural network (BPN) was the best predictive model. Based on the classification of different percentages of training data, the results of GRA revealed that the radial basis function neural network and the time-delay recurrent neural network exhibited consistent results, compared to BPN and the recurrent neural network. The results also pointed out that different percentages of training data were suitable for predicting consumer ETFs' performance based on high and low grey relationship grade variables. Evidence has shown that the ETFs in Brazil and China are more predictable than those in other countries. All ANN models' results indicated that the use of 10% testing data could predict consumer ETFs better, particularly the ETFs of the United States (US) and those excluding the United States (EX-US). The Diebold–Mariano (DM) test results suggest that the best predictability model for consumer ETFs is BPN, which is significantly superior to other models.

Keywords Grey relational analysis · Artificial neural network · Consumer exchange-traded funds

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1 Introduction

The exchange-traded funds (ETFs) database (ETFdb) indicates that, since its introduction in 1993, ETFs have become very popular with investors who are seeking alternatives to mutual funds. Investors may see an advantage in such instruments. ETFs are a set of assets designed to track an index, which offer lower management fees and greater visibility of intraday prices. However, no investment is perfect, and ETFs also have their drawbacks (small dividends, the large spread between the bid, and the ask prices). Identifying the pros and cons of ETFs can help investors to manage the risks and rewards and to decide whether these securities make sense for their portfolios (Palmer 2019).

We consider consumer discretionary and consumer staples ETFs. Discretionary consumption is a sectoral classification of non-essential consumer goods and services monitored by analysts and investors. Consumers tend to spend more on discretionary consumer products during the economic growth stages, usually characterized by higher disposable incomes. Discretionary consumption may be compared to consumer staples, which is a classification of enterprises considered to produce necessities (Scott 2020).

The New York Stock Exchange (NYSE) has started to launch the consumer ETF on December 23, 1998. The first Consumer ETFs are Sector SPDR (XLY) and Sector SPDR Fund (XLP), classified as new ETFs, which have been growing. Since the Consumer ETFs launch, the return rate of the top-ten consumer discretionary ETFs and consumer staple ETFs has increased by approximately 261% and 132%, respectively. Consumer ETFs have become popular to attract investors. By applying the grey relational analysis (GRA) and the artificial neural network (ANN) models, we predict the return volatility of consumer ETFs. Furthermore, we apply four different ANN approaches, namely the back propagation neural network (BPN), the recurrent neural network (RNN), the time-delay recurrent neural network (TDRNN), and the radial basis function neural network (RBFNN). We aim to measure the nonlinear relationship between the discrete time series in a grey system and to examine the possibility of this connection. The ETFs are mainly consumer ETFs from several countries. We also seek to derive the nonlinear trends in order to better forecast consumer ETFs.

We propose a novel methodology for forecasting ETFs, particularly consumer ETFs. The test results of GRAs, which were sorted into different training data, such as 10%, 20%, 33%, and 50%, revealed that RBFNN and TDRNN exhibited more consistent results than BPN and RNN. We apply the root-mean-square error (RMSE), the coefficient of efficiency (CE), and the mean average error (MAE) to compare the forecast ability. The results revealed that the BPN and RNN models consistently have the lowest values for consumer ETFs.

Using the GRA model, we identified the NYSE Composite Index, the Commodity Research Bureau Index (CRB), the EUR/USD Exchange Rate, and the put/call ratio (PCR) as the four key variables influencing the consumer ETFs. Based on the

MSE, RMSE, correlation (r) measurements, and MAE results, we revealed that BPN was the best forecasting model. By applying the ANN models to the consumer ETFs, this work determined that the Global X Brazil Consumer ETF (BRAQ) and Global X China Consumer ETF (CHIQ) were accessible, predicting the consumer ETFs of other countries.

The results revealed that the ANN models using 10% data for test could better predict consumer ETFs, particularly the United States (US) and those excluding the United States (EX-US). However, the findings indicated that using 20% or 33% data for test could better predict the BRAQ and Dow Jones Emerging Markets Consumer Titans Index Fund (ECON). Using 50% data for test can better predict the CHIQ. The Diebold–Mariano test's results revealed that BPN performed the best forecasting accuracy for consumer ETFs and determined that the forecasts are significantly different from other models.

We provide an innovative methodology for determining the best forecasting model to help investors choose the best investments. By reviewing previous research in consumer ETFs, we contribute the analysis to apply the GRA and ANN models to evaluate consumer ETFs and help investors make better decisions when investing in consumer ETFs to enhance investment returns.

We introduce consumer ETFs classified by country, such as the US, excluding the US, emerging markets, Brazil, China, and India. The relevant literature review describes previous studies on forecasting consumer ETFs and appropriate financial instruments. Next, the GRA and four ANN model types, namely BPN, RNN, TDRNN, and RBFNN, are explained. Finally, the empirical findings, as well as the conclusions reached, are discussed.

2 Related literature

Consumer ETFs quickly became famous worldwide and were divided into consumer discretionary ETFs and consumer staple ETFs. Bollapragada et al. (2013) used different techniques, including single exponential smoothing, Holt's exponential smoothing, and various versions of the Box–Jenkins [autoregressive integrated moving average (ARIMA)] models, to forecast ETFs. They found that multiple regression was the most appropriate method. Yang et al. (2010) reported unconvincing predictions using the generalized autoregressive conditional heteroskedasticity (GARCH) models.

The grey relational analysis (GRA) model is formed by estimating the relationship between two discrete time series in a grey system theory (GST). The grey theory stands for insufficient and unclear information compared to white (knowing everything) and black (knowing nothing) dealing with system problems. Also, the incomplete information of grey theory retains considerable room for flexible adjustment. The likelihood of such a relationship may change after a while (Deng 1989). Likewise, Kung and Wen (2007) decided that significant financial variables, such as the ratio of operating revenues to long-term investments and the ratio of operating revenues to total assets, have dealt with venture capitalists' financial transactions. Lin and Wu (2011) reported that the GRA model might analyze the financial data used to construct banks' first financial crisis warning models. Hamzaçebi and Pekkaya (2011) used the GRA. They revealed that financial ratios, such as the price/earnings ratio, the profit margin on sales, and the market/book value, are usually used for stock selection in the production sector. Jiang and He (2012) showed that the GRA model could accurately assess and predict China's financial instruments. The purpose is to examine the power of the GRA model for evaluating the performance and attributes of consumer ETFs. To our best knowledge, there has not been any study on consumer ETFs. We will, therefore, serve as the first consumer ETFs study.

In previous studies, predictions in finance have been focused on artificial neural networks (ANN) models. Bekiros and Georgoutsos (2008) have used recurrent neural networks (RNN) to predict the direction of market changes in the NASDAQ composite index. Sookhanaphibarn et al. (2007) used three neural networks: learning vector quantization, the probabilistic neural network, and the feedforward network with backpropagation learning, for bankruptcy forecasting in Thailand, while Armano et al. (2005) used the feedforward artificial neural network (FANN) to perform local-scale market index predictions. Previous research by Poddig and Rehkugler (1996) provided accurate forecasts for the stock, bond, and currency markets of the United States, Japan, and Germany. Hamzaçebi (2008) suggested an artificial neural network (ANN) structure in the seasonal prediction of time series. The results of previous studies have shown that ANN models could provide accurate forecasts for the financial field. Ho et al. (2002) found that RNN at the optimal weighting factor performs well against the ARIMA model in forecasting time series.

Experimental results suggest that the combined ARIMA and ANN models can improve the predictive accuracy achieved by either of the models used separately. Zhang (2003) and Zou et al. (2007) concluded that the ANN model is the best model, relative to ARIMA, and can be used as an alternative method to model the future price of food grains in China. Singhal and Swarup (2011) revealed that an ANN method is being developed for predicting market clearing prices (MCPs) for one-day energy markets. The neural network structure is a three-layer BPN model and shows that the market's deregulated electricity price depends strongly on the trend in load demand and the clearing price. Their findings showed that the neural network model was reasonably reliable for trend analysis.

ETFs have developed a well-known research topic for finance (Boehmer and Boehmer 2003; Peterson 2003; Alexander and Barbosa 2008; Jarrow 2010; Charupat and Miu 2011; DeFusco et al. 2011). Previous research has shown that ETFs are potential portfolios and one of the investment products that can successfully be scaled up on the capital market. Krause and Tse (2013) defined Granger's daily causal relationship between Canadian and US ETFs using an autoregressive vector model. They noted that US industry ETF returns are higher than those in Canada in a broader marketplace. Chen (2011) found no dissimilarity regarding the impact of volatility and leveraging on ethical and non-ethical ETFs. In contrast, Chen and Diaz (2012) used the exponential generalized autoregressive conditional heteroscedasticity (EGARCH)-in-mean model and revealed the spillover and asymmetric volatility effects of leveraged and inverse leveraged ETFs. Based on the autoregressive fractionally integrated moving average

(ARFIMA)—fractionally integrated generalized autoregressive conditional heteroskedasticity (FIGARCH) model, Chen and Diaz (2013) revealed the existence of long-term memory attributes in the volatilities of non-green ETFs.

Estimating with ANN models has been controversial over the past decade (Zhang et al. 1998; Hamzaçebi et al. 2009). Motivated by examining the human brain, ANN models can simplify practices. ANN models are currently used for various business, industry, and science domains (Widrow et al. 1994). ANN models have been successfully used in training networks to measure the cost curve in the accurate prediction of flour prices (Chakraborty et al. 1992). ANN is much more predictable than linear regression by utilizing 384 subsets of economic and demographic time series from chemical engineering applications (Foster et al. 1992). Enke and Thawornwong (2005) predicted stock market returns and observed that an organizational model's trading approach generated higher risk-adjusted earnings than the buying-and-holding strategy. Chen and Fang (2008) used ANN, GARCH, and random market models for predicting the Asian currency unit. The ANN models performed better than both the GARCH and random models. The research has identified ETFs as being supportive and engaging portfolios for consideration.

Deng (1989), Liu and Lin (2005), and Kayacan et al. (2010) pointed out that the GRA has been one of the best analytical tools. Moreover, this model provides the appropriate tools for observing the ranking of multiple variables and examines the order of particular aspects (Kuo et al. 2008). The GRA model has recently been applied to many applications, including economic decision-making and marketing research (Yamaguchi et al. 2004; Cenglin 2012) and financial performance (Kung and Wen 2007). Furthermore, Hu (2007), Zhao et al. (2012), Cenglin (2012), and Chang et al. (2013) used the GRA to predict and explain the relationship among variables.

Hu (2007) applied efficient methods such as the GRA and RBFNN to measure learning costs across all dual competencies. Li et al. (2012a, b) indicated that the GRA model predicts electricity use more accurately than the limited sample size. Similarly, Chang et al. (2013) examined the relationship between online gaming revenues and Internet users in Taiwan, R.O.C., for predicting the trend in revenue growth. Wang et al. (2012) used a hybrid method by combining the exponential smoothing model, the ARIMA model, and the back propagation network model (BPNN). Their results displayed that the hybrid model could predict and explain the relationship between real stock prices in China and the United States.

Donaldson and Kamstra (1997) utilized the GARCH, EGARCH, and GJR models connected with the ANN and estimated the predictability of return volatility in London, New York, Tokyo, and Toronto. Using ANN models to determine the stock index option price, Tseng et al. (2008) revealed that the Grey-EGARCH volatility was more predictable than other volatility methodologies. Hadavandi et al. (2010) confirmed that fuzzy genetic systems and ANN are the best predictive models to estimate stock prices in the information technology and airline sectors. Ticknor (2013) reported that the ANN standard Bayesian model is robust for forecasting financial market behavior.

3 Data and methodology

This work collected data sources from the ETFdb and Yahoo! Finance website as of May 2014. Consumer ETFs can be sorted by countries like the United States (US), excluding the United States (EX-US), emerging markets, Brazil, China, and India, as shown in Table 1. We will use information from the different inception periods to the most recent data. In this study, several countries compare their highest forecasting levels. The Diebold–Mariano (DM) test is being studied to provide an assessment framework for various consumer ETFs forecast models.

We extracted the macroeconomic and financial variables with the view to influencing consumer ETFs. Table 2 shows the sources of information for the input variables, namely the PCR, the USD/EUR exchange rate, the volatility index (VIX), the CRB index, the short-term TRIN, and the NYSE composite index used in the present study.

This study includes PCR, measured by the market sentiment, and examines the influence for consumer ETFs. The measurement of PCR is a ratio of the number of traded put options to the number of traded call options. Investors may use their money more on put options than on call options with an increase in the PCR. This condition instructs investors to speculate on the market's worsening or the start of hedging their portfolios. Investors need to focus on PCR, as the growth in this ratio reflects a partly bearish market. Simon and Wiggins (2001) indicated the negative relationships between PCR and the Standard and Poor (S&P) Futures Index. The significant results showed that the PCR reflected a bearish market and is a signal for trading, including ETFs (Houlihan and Creamer 2019). Bandopadhyaya and Jones (2011) found that PCR is a better explanatory variable than the VIX for changes in the Standard & Poor's 500 index.

The next variable related to consumer ETFs is the USD/EUR exchange rate. Maya and Chen (2018) revealed that the Euro could strongly affect agricultural ETNs by using ANN. The purpose is to analyze the high correlation between consumer ETFs and exchange rates. Historically, financial analysts have seen a strong linkage between ETFs and the S&P Futures Index. Since the start of 2009, the strong relationship between SPDR S&P 500 (SPY) and the Barclays Aggregate Bond Fund has been significant, reaching 0.94. However, there has been a reverse correlation between the SPDR Gold Trust and SPY.

Another interesting financial variable that is used to determine consumer ETFs is the VIX. Previous research has shown an opposing variable to the S&P futures index (Simon and Wiggins, 2001). The VIX is a widely assessed measure of fear. However, higher volatility is not a new phenomenon. Essentially, the volatility of the S&P 500 index, as measured by 2% index movements on a given trading day, has risen sharply over the past decade, compared to the historical averages. From 1973 to 1982, the S&P 500 index had less than 100 trading days, a 2% movement in both directions.

The CRB index is an index that measures the general track of the commodity sectors, and it distinguishes and determines the directional price movements in the general commodity trade. Acharya et al. (2009) used the CRB index to

Table 1 Summaries of ETFs utilized for the forecasting by ANN. *Source* http://etfdb.com/ETFs/

Country	Consumer ETFs	Code	Inception period	Assets (in million USD)	Average Volume
US	Consumer Discrete Select Sector SPDR	XLY	12/23/1998	$4,924,164	6,443,089
	Consumer Staples Select Sector SPDR Fund	XLP	12/23/1998	$5,992,049	8,102,050
EX-US	SPDR S&P International Consumer Discretionary Sector ETF	IPD	9/10/2008	9674	$19,405
	SPDR S&P International Consumer Staples Sector ETF	IPS	8/26/2008	$42,861	5166
Emerging Market	Dow Jones Emerging Markets Consumer Titans Index Fund	ECON	9/15/2010	$1,235,724	368,252
Brazil	Global X Brazil Consumer ETF	BRAQ	7/9/2010	$14,769	4161
China	Global X China Consumer ETF	CHIQ	12/2/2009	$153,036	70,763
India	EGShares India Consumer Exchange-traded Fund	INCO	8/11/2011	$4824	3374

Table 2 The sources of macroeconomic, financial variables, errors prediction

Variable	Resource	Type I and II errors in predictions
Put and Call ratio (PCR)	www.schwab.com	Put and Call Ratio (PCR) is one of the variables employed to show negative relationships in the Standard and Poor (S&P) Futures Index
Exchange rate USD/EUR (USEUR)	www.investing.com www.investopedia.com	The negative correlation between the US Dollar Index and the impact of total US equity return on consumer behavior
Volatility Index (VIX)	finance.yahoo.com	VIX is an opposing variable for the S&P Futures Index (Simon and Wiggins 2001)
Commodity Research Bureau Index (CRB)	topforeignstocks.com/	The CRB index can also be used as an index for inflation (INF) and its influence on investments. (Acharya et al. 2009)
Trading Index (TRIN index)	www.traderslog.com	Simon and Wiggins (2001) found the TRIN to be negatively related to the S&P Futures Index
New York Stock Exchange Composite Index (NYA)	www.finance.yahoo.com www.investopedia.com	NYA measures the change in overall stock values and reflects the performance of all securities listed on the NYSE
Inflation (INF)	www.statestreetglobalmarkets.com	Hajzler and Fielding (2014) and Georganas et al. (2014) observed a negative correlation between consumer behavior and INF
Interest Rate (ITR)	www.federalreserve.gov	Interest rates negatively affect the spending of consumers (Edelberg 2006; Chisasa and Dlaminier 2013)

represent an Index of Inflation (INF) and examined how it affects investment. Previous research has shown a mutual connection between the CRB index and the Shanghai Index (Göleç et al., 2012). Ho et al. (2010) found a bi-directional relationship between the CRB Index and the Gold Futures Index. We use the CRB index as a financial variable because of the consumer ETFs traded in the commodities sector.

The Arms Index is applied for short-term trading to calculate the intra-day market supply and demand. If the Trading Index (TRIN) value is 1.0, then the ratio from the high volume to the low volume is related to the advancing issues' rate to the declining issues. The market represents a neutral status, where the index equals 1.0. This neutral state indicates that the high volumes are evenly distributed over the ongoing issues, while the low volumes are evenly distributed over the declining issues. Also, the TRIN provides a bullish signal when the index is below 1.0. In the meantime, the average stock has a higher volume than the average downgrade of the stock. Several analysts have determined that the index's long-term balance is below 1.0, which could confirm a bullish bias in the stock market. On the other hand, if the TRIN is above 1.0, seen as a bearish signal, then the average declining stock has a higher volume than the average increasing stock. Simon and Wiggins (2001) found that the TRIN is negatively related to the S&P Futures Index.

We used the NYSE Composite Index to evaluate all listed firms' performance on the NYSE, including real estate investment trusts, American depositary receipts, and tracking stocks. In January 2003, the NYA re-established the NYSE Composite Index by using a new approach that is entirely transparent and rule-based. This approach excludes all fixed funds, ETFs, partial partnerships, and index derivatives. Maya and Chen (2018) found that the NYSE Composite Index strongly influenced agricultural ETFs and ETNs using the GRA model.

The current study uses INF, one of the key financial variables, to examine the relationship of consumer ETFs. An increase in INF will usually affect the consumer's decision to buy goods and services. Many previous studies have pointed out that the INF has an impact on consumer behavior. Arora et al. (2013) and Hajzler and Fielding (2014) observed a negative correlation between INF and consumer behavior, reflecting energy and food prices. Georganas et al. (2014) found that INF influenced consumer perceptions, which caused various goods' prices to increase.

Another variable that influences the purchasing power of the consumer is the interest rate (INT). Juselius (1995) found a link between the purchasing power parity and long-term interest parity. The INT has a significantly strong correlation with the consumers' decisions about household behavior (Edelberg 2006). Chisasa and Dlaminier (2013) reported that higher INTs negatively affect consumer expenses, particularly for durable goods such as automobiles in South Africa. Wang and Hu (2015) also observed a cross-correlation between the INT and commodity markets, such as the rice, corn, soybean, and wheat markets.

3.1 Grey relational analysis

Deng (1989) proposed the GRA and applied it extensively to evaluate financial variables. The GRA theory is created by measuring the relationship between two discrete time series in a grey system. The likelihood of this connection may change over time. The GRA procedure calculates various auxiliary components applied to examine the sets of random factors with missing messages. Therefore, only a small amount of data is needed to control the correlation between the determinants.

Many previous studies have used GRA in their financial application. Kung and Wen (2007) identified the key financial variables affecting the financial success of venture capital companies. Lin and Wu (2011) indicated that financial factors could help develop early financial crisis alert models for banks. Hamzaçebi and Pekkaya (2011) used financial ratios when selecting stocks in the production sector. Jiang and He (2012) accurately predicted China's real-time financial series.

The GRA model provides investors with assistance to assess and recognize venture capital firms' returns and attributes to reduce investment risk. Chang et al. (2013) and Hamzaçebi and Pekkaya (2011) proposed the following formula based on the original study of Deng (1989):

1. Describe the original series:

$$x_i = \left(x_i(1), x_i(2), x_i(3), \ldots, x_i(k)\right) \in X, \tag{1}$$

where criteria: $k = 1, 2, 3, \ldots, n \in N$, *and alternative:* $i = 1, 2, 3, \ldots, m \in X$.

2. Define the reference series: The reference series can exist as maximums or minimums. When the measure desires maximization (minimization), the linked measure's reference series value becomes the maximum (minimum) value of the alternative series.
$x_0 = \left(x_0(1), x_0(2), x_0(3), \ldots x_0(N)\right)$.
3. Normalization data: We conducted the pre-processing stage of the data before calculating the grey relationship grade (GRG), known as the grey relationship generation (Hsia et al. 2004; Kung and Wen 2007). Then the data in the series can be processed for the following three situations (Wu and Chen 1999; Kung and Wen 2007):

    i. A high level of expectancy is favorable. If the situation is "the larger, the better expectation example of the profit," then we can use the following equation:

$$x_i^*(k) = \frac{x_i^{(0)}(k) - \min \cdot x_i^{(0)}(k)}{\max \cdot x_i^{(0)}(k) - \min \cdot x_i^{(0)}(k)}. \tag{2}$$

    ii. A low level of expectancy is favorable. If the situation is "the smaller, the better expectation example of the cost or loss," then we can use the following equation:

$$x_i^*(k) = \frac{\max \cdot x_i^{(0)}(k) - x_i^{(0)}(k)}{\max \cdot x_i^{(0)}(k) - \min \cdot x_i^{(0)}(k)}. \quad (3)$$

iii. A nominal status for the best expectation is favorable. If the expected specific value is between the maximum and the minimum objectives, then we can use the following equation:

$$x_i^*(k) = 1 - \frac{\left|x_i^{(0)}(k) - \mathrm{OB}\right|}{\max \cdot \left\{ \max \left[x_i^{(0)}(k)\right] - \mathrm{OB} \cdot \mathrm{OB}\left[\min \cdot x_i^{(0)}(k)\right] \right\}}, \quad (4)$$

where $x_i^*(k)$ is the value of the grey relation after the normalization, $\min \cdot x_i^{(0)}(k)$: $x_i^{(0)}$ stands for the minimum value of (k) before normalization, $\max \cdot x_i^{(0)}(k)$: $x_i^{(0)}$ denotes the maximum value of (k) before normalization , and OB : $x_i^{(0)}(k)$ is the object value.

4. Calculate the grey relational coefficient: The localization of the GRA reflects the association between the reference sequence $x_i^{(0)}(k)$ and the relative sequence $x_i^*(k)$. Thus, the grey relational coefficient $\varepsilon\,(x_0(k),\ x_i(k))$ is expressed as follows (Lin and Hsu 2001; You et al. 2006; Kung and Wen 2007):

$$\varepsilon(x_0(k), x_i(k)) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{0i}(k) + \zeta\Delta_{\max}}, \quad (5)$$

where $\zeta \in (0, 1)$ is the notable coefficient, $\Delta_{0i}(k) = \left|x_0(k) - x_i(k)\right|$,

$$\Delta_{\min} = \min_{\forall i} \min_{\forall k} \Delta_{0i}(k) = \min_{\forall i} \min_{\forall k} \left|x_0(k) - x_i(k)\right|, \text{ and}$$
$$\Delta_{\max} = \max_{\forall i} \max_{\forall k} \Delta_{0i}(k) = \max_{\forall i} \max_{\forall k} \left|x_0(k) - x_i(k)\right|.$$

5. Calculate the GRG:

The GRG process measures the association between the sequences measured and sorted as a function of localization and GRG globalization (Lin and Hsu 2001; You et al. 2006; Kung and Wen 2007).

When all criteria have the same degree of importance, the GRG can be measured by (6).

For the different degrees of importance of the criteria, the GRG can be calculated by (7).

$$\gamma(x_0, x_i) = \sum_{k=1}^{n} \beta_k \varepsilon\left(x_0(k), x_i(k)\right), \quad (6)$$

$$\gamma(x_i, x_j) = \sum_{k=1}^{n} \beta_k \varepsilon\left(x_i(k), x_j(k)\right), \quad (7)$$

where β_k denotes weight value and $\sum_{k=1}^{n} \beta_k = 1$. Depending on the importance of each determinant in the sample, different weights can be ranked. By using equal weights, GRG derived from the average value of the grey relational coefficient, that is $\beta_k = \frac{1}{n}$, $k = 1, 2, \ldots, n$.

At the last stage, the order of the GRG is sorted in descending order. The grey relational order may be described as the primary factors in the series connected to the reference series. The highest value in the series shows the variable with the most influence; however, the series' lower value shows that the variable has the least effect.

3.2 Artificial neural network for consumer ETFs

The application of ANN in the financial area has increased year by year. Wong et al. (1997) and Wong and Selvi (1998) investigated journal articles published between 1988 and 1996 on how neural networks work across various commercial activities. Kaastra and Boyd (1996) found that neural networks can make predictions with data from economic time series, and Kim and Han (2000) used ANN models to forecast the Korean Stock Price Index. The structure of ANN models has three levels, namely:

(1) the "processing element" (or artificial neurons) defines the basic unit,
(2) the "layers" is formed by the processing elements, and
(3) the "network" is composed of several layers.

The version of Braspenning et al. (1995) discussed as follows:

3.2.1 Back propagation neural network

The BPN has an architecture called multilayer perception (MLP) and uses the EBP as its learning algorithm (Azadeh et al. 2008; Zhang and Wu 2009; Huang and Wang 2008; Wang et al. 2011).

Numerous studies have used the BPN to address the actual issues. Chang and Wang (2006) used it to estimate sales in the printed circuit board industry, while Li et al. (2012a, b) indicated that the BPN could detect fiber optics. Wang et al. (2011) identified the BPN as an efficient algorithm that can be used to predict the Shanghai Composite Index. Guresen et al. (2011) used GARCH, MLP, dynamic ANN, and hybrid neural networks to extract different input variables. They applied the real daily exchange rate values of the NASDAQ Stock Exchange Index.

The BPN involves transmitting directly from the input to the input layer's hidden layer and calculating the weighted accumulation. The BPN generates an output with a transfer function that is fed into the output layer. Note that the transfer function, called the sigmoid function, is typically used as follows:

$$f(x) = \frac{1}{1 + e^{-x}}, \tag{8}$$

where x is called the input layer. Moreover, the network augments related to a hidden layer in the system, revealing the relationship between input processing elements. The reduction of the error function requires the smooth transition function and the gradient steepest descent method. The method used to derive the formula of modified network weights is obtained when the output of processing element j in the layer n becomes the nonlinear function of the output of processing elements in the layer $n-1$, which is expressed as follows:

$$A_j^n = f\left(\mathrm{net}_j^n\right) = f\left(\sum_i w_{ij} A_i^{n-1} - \theta_j\right), \tag{9}$$

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

The BPN decreases the differences between the output of the network and the target output. The learning quality of this supervised learning is stated by the error function E as follows:

$$E = \frac{1}{2} \sum_j (T_j - A_j)^2, \tag{10}$$

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

The procedure modifies the weight in the array, while processing the training example. The sensitivity and error functions of the partial weight-for-adjustment differential and the error function are correlated proportionally, and are extracted as follows:

$$\Delta W_{ij} = -\eta \cdot \frac{\partial E}{\partial W_{ij}}, \tag{11}$$

where η denotes the learning rate, which recognizes the amplitude for the gradient steepest descent method to alter the error function. W_{ij} represents the output and hidden layers and can be calculated as follows:

$$\frac{\partial E}{\partial W_{ij}} = -\delta_j^n \cdot A_i^{n-1}, \tag{12}$$

where A_i^{n-1} is the output of the processing element in the lower layer, which is related by W_{ij}. δ_j^n denotes the gap of the processing element in the upper layer, which is accompanying by W_{ij}. By substituting $\Delta W_{ij} = -\eta \cdot \frac{\partial E}{\partial W_{ij}}$, it derives the following equation:

$$\Delta W_{ij} = \eta \cdot \delta_j^n \cdot A_i^{n-1}. \tag{13}$$

This equation expresses that the input is adjusted and serves as a training sample of weight formation. This equation is critical for the backpropagation algorithm.

3.2.2 Recurrent neural network

The RNN is a dynamic neural network, with links between the units in a directed cycle. The network incorporates the time factors for completing the formation. The procedure feeds the neuron's output value into the hidden layer or output layer to develop the neuron's output in the next step (Elman 1990). The learning process is accelerated due to inter-neuronal feedback mechanisms (Ge et al. 2007; Wang et al. 2013).

The forward propagation of the network multiplies the output $x_i(t)$ by an equivalent weight $w_{ji}(t)$; $\text{net}_j(t)$ is the product of that process. The network converts $\text{net}_j(t)$ through a nonlinear function f to obtain output $y_j(t)$ in the feedback processing layer. This process of multiplying $y_j(t)$ by a corresponding weight $v_{kj}(t)$ again produces a product $\text{net}_k(t)$. Notably, $\text{net}_j(t)$ defines transformed through a nonlinear function f and obtains the product $z_k(t)$ in the output layer. This relationship can be expressed as follows:

$$\begin{aligned} y_j(t) &= f(\text{net}_j(t)), \\ \text{net}_k(t) &= \sum v_{kj}(t) y_j(t). \end{aligned} \tag{14}$$

The real-time recurrent learning (RTLR) algorithm consists of the most commonly used type of RNN (Elman 1990; Ge et al. 2007; Wang et al. 2013). RTLR adjusts the weight vector of the network connection in real time. Assuming that $d_k(t)$ represents the output value of neuron k in the output layer at time t, and $e(t)$ represents the error vector at time t, the unit k can be expressed as follows:

$$e_k(t) = d_k(t) - z_k(t).$$

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

$$E(t) = \frac{1}{2} \sum_{k=1}^{K} e_k^2(t). \tag{15}$$

(a) The gradient steepest descent method serves as the basis of the correction of specific weight $v_{kj}(t)$ and is expressed as follows:

$$\Delta v_{kj}(t) = -\eta_1 \frac{\partial E(t)}{\partial v_{kj}(t)}, \tag{16}$$

where η_1 represents a positive constant and is called the learning rate. The partial differential of the error function $E(t)$ with respect to the weight $v_{kj}(t)$ can be calculated by utilizing the chain rule as follows:

$$\frac{\partial E(t)}{\partial v_{kj}(t)} = -e_k(t) f'(\mathrm{net}_k(t)) y_j(t). \tag{17}$$

(b) The gradient steepest descent method serves as the basis for the correction of specific weight $w_{mn}(t)$ and is expressed as follows:

$$\Delta w_{mn}(t-1) = -\eta_2 \frac{\partial E(t)}{\partial w_{mn}(t-1)}, \tag{18}$$

where η_2 denotes a positive constant called the learning rate. In general, the partial differential of the error function $E(t)$ related to the weight $w_{mn}(t)$ can be measured by utilizing the chain rule as follows:

$$\frac{\partial E(t)}{\partial w_{mn}(t-1)} = \left[\sum_{k=1}^{K} -e_k(t) f'(\mathrm{net}_k(t)) v_{kj}(t) \right] \frac{\partial y_j(t)}{\partial w_{mn}(t-1)}. \tag{19}$$

3.2.3 Radial basis function neural network

The RBFNN is a mix of learning processes, combining mutually unsupervised and supervised learning rules. Unsupervised learning is used to identify the cluster center and to determine the initial value. The RBFNN was recommended by Broomhead and Lowe (1988), in which linear optimization techniques guarantee the learning process for analyzing the adjustable weight layer's special assessment. Shen et al. (2011) used the RBFNN to form data to rapidly and accurately predict Shanghai stock market indexes. Wu and Liu (2012) reported that the RBFNN model was efficient and performed satisfactorily in predicting car fuel consumption. However, the RBFNN may model an arbitrary nonlinear transformation, which is a new linear perception.

The RBFNN model is similar to the architecture of BPN, which consists of three layers. The input layer contains the import information for each input node attached to all hidden nodes in the single hidden layer. The hidden layer consists of an array of nodes, one for each radial base function center (Broomhead and Lowe 1988). The Euclidean standard is generally used for estimating the distance from the middle of the input value. In turn, this process takes into account the optimum number of cluster centers in the second layer. Establishing many radial base functions through curve adjustment is one of the main features of RBFNN, which leads to learning the mapping relationship between the input and output values. As indicated by Bors and Gabbouj (1994) and Bors and Pitas (1996), the Gaussian function is the most widely used in the RBFNN and is expressed as:

$$\varphi_j(X) = \exp\left[-(X-\mu_j)^T \sum_j^{-1} (X-\mu_j) \right], \quad \text{for } j = 1, \ldots, L, \tag{20}$$

where X denotes the input feature vector, L is the number of hidden units, and μ_j and $\sum_j$ stand for the mean and the covariance matrix of the jth Gaussian function, respectively.

The graphical demonstration of the RBFNN model is expressed in the following equation:

$$v_i = \sqrt{\sum_{j=1}^{k} (x_j - c_{ji})^2}, \tag{21}$$

where c denotes the cluster center for each node of the hidden layer, x is the input vector, and v represents the vector that shows the range of length between input nodes and cluster center of each hidden layer.

$$R(\|x-c\|) = \exp\left(-\frac{\|x-c\|^2}{2\sigma^2}\right), \tag{22}$$

where $\left\|x - c_j\right\|$ denotes the Euclidean distance between x and c_j.

3.2.4 Time-delay recurrent neural network (TDRNN)

Based on an extensive neuronal model, the TDRNN model achieves the benefits of adaptive delay and recurrence. It manipulates time information from the input sequences using adaptive delay and recurrent connections (Waibel 1989; Kim 1998; Lin et al. 1992). The internal state units can be assessed as additional inputs at time t under the duplication procedures of hidden units at time $t-1$. The TDRNN uses and adjusts adaptable synaptic weights and flexible time lags for evaluating the interconnection between the input and the hidden units. The delay box comprises interconnections from the input layer to the first hidden layer and the internal state layer to the first hidden layer (Waibel 1989; Kim 1998; Lin et al. 1992). The net inputs are derived from the activation values for the last neuron. They can be summed up through the equivalent time delays, based on each connecting line at the time of unit j on layer h that takes a weighted sum, as follows (Waibel, 1989; Kim, 1998; Lin et al., 1992):

$$\mathrm{net}_{j,h}(t_n) = \sum_{i \in N_{h-1}} \sum_{k=1}^{K_{ji,h-1}} \omega_{jik,h-1} \cdot \alpha_{i,h-1}(t_n - \tau_{jik,h-1}), \tag{23}$$

where $\mathrm{net}_{j,h}(t_n)$ denotes the product of the TDRNN process; $\alpha_{i,h-1}(t_n - \tau_{jik,h-1})$ is the activation level of unit i on layer $h-1$ at time $t_n - \tau_{jik,h-1}$; N_{h-1} represents the set of nodes of layer $h-1$; and $K_{ji,h-1}$ denotes the total number of connections to node j of layer h from node i of layer $h-1$.

Through the selection of a sigmoid function, the output of node j is determined by using a nondiminishing function f of the net input (Kim 1998).

$$\alpha_{j,h}(t_n) = \begin{cases} f_{j,h}(\mathrm{net}_{j,h}(t_n)) & \text{if } h \geq 2 \\ \alpha_{j,0}(t_n) & \text{if } h = 1 \end{cases}, \tag{24}$$

$$f_{j,h}(\text{net}) = \frac{\beta_{j,h}}{1 + e^{-\alpha_{j,h}\,\text{net}}} - \gamma_{j,h}, \tag{25}$$

where $\alpha_{j,0}(t_n)$ denotes the jth channel of the input signal at time t_n; $\alpha_{j,h}$, $\beta_{j,h}$, and $\gamma_{j,h}$ represent real numbers; and $-\gamma_{j,h}$ and $\beta_{j,h} - \gamma_{j,h}$ are the upper and lower limits of the sigmoid function, respectively. The steepness of $f_{j,h}(\text{net})$, for example, $f'_{j,h}(0)$, is $(\alpha_{j,h}\beta_{j,h})/4$ (Kim 1998; Lin et al. 1992).

The internal state vector at a time t_n, $S_{h-1}(t_n)$, is expressed as follows:

$$S_{h-1}(t_n) = A_{h+1}(t_{n-1}), \tag{26}$$

where $A_{h+1}(t_{n-1})$ denotes the activation vector of the second hidden unit at a time t_{n-1}.

An instantaneous error measure stands for the mean square error (MSE) as follows (Kim 1998; Lin et al. 1992):

$$E(t_n) = \frac{1}{2}\sum_{j \in N_{h+2}} (d_j(t_n) - a_{j,h+2}(t_n))^2, \tag{27}$$

where N_{h+2} represents the set of nodes of the output layer, and $d_j(t_n)$ is the preferred target number of output node j at a time t_n.

The weights (w) and time delays (τ) are rearranged by applying an amount that is equivalent to the opposite direction of the error gradient, as follows (Kim 1998; Lin et al. 1992):

$$\Delta w_{jik,h} = -\eta_1 \frac{\partial E(t_n)}{\partial w_{jik,h}}, \tag{28}$$

$$\Delta \tau_{jik,h} = -\eta_1 \frac{\partial E(t_n)}{\partial \tau_{jik,h}}, \tag{29}$$

where η_1 and η_2 stand for the learning rates.

The summary of the learning rules can be expressed as follows:

$$\Delta w_{jik,h-1} = \eta_1 \delta_{j,h}(t_n) a_{i,h-1}(t_n - \tau_{jik,h-1}), \tag{30}$$

$$\Delta \tau_{jik,h-1} = \eta_2 \rho_{j,h}(t_n) w_{jik,h-1} a'_{i,h-1}(t_n - \tau_{jik,h-1}), \tag{31}$$

where

$$\delta_{j,h}(t_n) = \begin{cases} (d_j(t_n) - a_{j,h}(t_n)) f'(\text{net}_{j,h}(t_n)), & \text{if } j \text{ is an output unit} \\ \left(\displaystyle\sum_{p \in N_{h+1}} \sum_{q=1}^{K_{pj,h}} \delta_{p,h+1}(t_n) w_{pjq,h}(t_n)\right) f'(\text{net}_{j,h}(t_n)), & \text{if } j \text{ is an output unit} \end{cases} \tag{32}$$

$$\rho_{j,h}(t_n) = \begin{cases} (d_j(t_n) - a_{j,h}(t_n))f'(\text{net}_{j,h}(t_n)), & \text{if } j \text{ is an output unit} \\ \left(\sum_{p \in N_{h+1}} \sum_{q=1}^{K_{pj,h}} \rho_{p,h+1}(t_n) w_{pjq,h}(t_n) \right) f'(\text{net}_{j,h}(t_n)), & \text{if } j \text{ is an output unit} \end{cases} \tag{33}$$

3.3 Diebold–Mariano (DM) test for ANN models

We use the Diebold–Mariano (DM) test proposed by Diebold and Mariano (1995) to test ANN models for improving predictive accuracy. This comparison includes BPN versus RNN, BPN versus TDRNN, BPN versus RBFNN, RNN versus TDRNN, and RBFNN versus RBFNN for each ETF. The DM test uses it possible to distinguish the significant differences in predictive accuracy between the various models, based on the quantitative analysis diagram (Chen et al, 2014).

Suppose that two predictions $f_1, \ldots, f_n$ and $g_1, \ldots, g_n$ for a time series are linked with $y_1, \ldots, y_n$. Let e_i and r_i be the residuals for the two forecasts, i.e.

The forecast residuals are defined as follows:

$$e_i = y_i - f_i, \quad r_i = y_i - g_i, \tag{34}$$

Forecast residuals are defined as follows:

$$d_i = e_i^2 - r_i^2 \ \text{ or } \ d_i = |e_i| - |r_i|, \tag{35}$$

and let d_i be defined as one of the following.

The time series is called the loss-differential. The key assumption for using the Diebold–Mariano test is that the loss differential time series d_i is stationary (Zaiontz 2020). The first of these formulas is related to the MSE error statistic, and the second is related to the MAE error statistic. Now define Loss-differential mean as:

$$\bar{d} = \frac{1}{n} \sum_{i=1}^{n} d_i \mu = E[d_i], \tag{36}$$

For $n > k \geq 1$, define:

$$r_k = \frac{1}{n} \sum_{i=k+1}^{n} \left(d_i - \bar{d}\right)\left(d_{i-k} - \bar{d}\right), \tag{37}$$

where autocovariance is at lag k.

As described in autocorrelation Function r_k is the autocovariance at lag k.

$$\text{DM} = \frac{\bar{d}}{\sqrt{\left[r_0 + 2\sum_{k=1}^{h-1} r_k\right]/n}}, \tag{38}$$

For $h \geq 1$, we define the Diebold–Mariano (DM) statistic, where the value $h = n^{1/3} + 1$.

The DM test is based on a standard normal distribution. The null hypothesis indicates that an equal predictive capacity exists between the models. The alternative hypothesis regarding the higher predictability of the model has the lowest value of the loss function.

3.4 Empirical results

Table 3 reveals the results of the GRG for consumer ETFs. These studies determined that the NYSE Composite Index, the CRB Index, the EUR/USD Exchange Rate, and the PCR are the four main variables influencing consumer ETFs. However, the short-term TRIN variable has the lowest influence on the classification, followed by INT, INF, and VIX. This study is in line with previous research conducted by Kung and Wen (2007), which used GRA globalization and found a significant relationship between venture capitalists' characteristics and financial performance.

The NYSE Composite Index has a strong impact on the Consumer Discretionary Select Sector SPDR Fund (XLY), the Consumer Staples Select Sector SPDR Fund (XLP), the SPDR S&P International Consumer Discretionary Sector ETF (IPD), the SPDR S&P International Consumer Staples Sector ETF (IPS), and the EGShares India Consumer Exchange-Traded Fund (INCO). The results show that the NYSE Composite Index can measure the performance of equities, tracking equities, and ETFs. A bilateral link between the ETFs and market indices have been observed (Chen 2011; Chen and Diaz 2012; Chen and Malinda 2014).

Table 3 Consumer ETFs and GRGs of eight determinants

Category	ETFs	XI USEUR	X2 CRB	X3 NYA	X4 VIX	X5 PCR	X6 TRIN	X7 INF	X8 ITR
US	XLY	230.520	230.664	230.676	229.889	230.464	195.513	227.862	195.743
	Ranking	3	2	1	5	4	8	6	7
	XLP	230.630	230.737	230.771	229.777	230.393	195.438	227.976	195.656
	Ranking	3	2	1	5	4	8	6	7
EX-US	IPD	176.027	176.237	176.531	174.183	175.562	150.518	171.057	156.864
	Ranking	3	2	1	5	4	8	6	7
	IPS	176.156	176.349	176.521	174.056	175.453	150.432	171.186	156.762
	Ranking	3	2	1	5	4	8	6	7
Emerging Market	ECON	114.188	114.145	114.158	112.886	113.029	92.2163	111.147	101.37
	Ranking	1	3	2	5	4	8	6	7
Brazil	BRAQ	119.997	120.079	119.892	118.666	118.914	96.9119	116.639	106.338
	Ranking	2	1	3	5	4	8	6	7
China	CHIQ	137.790	137.889	137.832	136.845	137.232	117.793	134.621	125.840
	Ranking	3	1	2	5	4	8	6	7
India	INCO	86.6353	86.6424	86.8351	86.1795	86.4375	70.4185	84.7315	77.812
	Ranking	3	2	1	5	4	8	6	7

Further results have shown that the CRB index variable has the most significant influence on BRAQ and CHIQ. The CRB index could be used as an indicator of the INF, taking into account its impact on investments (Acharya et al. 2009). India and China were the two largest countries that have experienced rapid economic growth over the past three decades (Hölscher et al. 2010). Besides, Brazil, India, and China, which are part of the BRIC countries, have reported remarkable economic growth. These findings show that BRAQ, CHIQ, and INCO have good growth opportunities and investment potential. Therefore, investors should pay more attention to the CRB Index when investing in consumer ETFs in Brazil and China. Besides this, the exchange rate variable has a considerable influence on emerging markets, such as ECON. This ETF contains vital consumer goods and services company regulations in developing markets. These corporations obtain most of their income from emerging market sales. Business people from emerging markets mostly use major currencies, such as the EUR, to alleviate currency fluctuation. As such, the exchange rate variable has strongly influenced the emerging market ETFs.

Table 4 reveals the effects of consumer ETFs, using ANN models categorized by all variables, high GRG variables, and low GRG variables. We use MSE, RMSE, MAE, and correlation (r) measurements to measure the ANN model's performance. The results of measuring the MSE of all variables showed that BPN is the best predictive model. Consistent with other MAE measurements, the findings also revealed that BPN performed well. The RMSE measurement shows that BPN is the best prediction model, except for INCO (0.119). As previously reported by Oh and Han (2000), Versace et al. (2004), Chen and Fang (2011), and Trang (2014), the BPN model shows that it has a predictability of financial instruments vis-a-vis RBF, RNN, and TRDNN. The correlation measure (r) indicates that BPN has a high correlation between the variables, except for BRAQ (0.684) with the RNN measure. Zhang and Xiao (2000) and Diaz (2012) also found RNN effectively forecasts for a small sample.

The findings of MSE, RMSE, and MAE measurements revealed that BPN is the best prediction model for high GRG variables. The correlation (r) measurement also shows that BPN is superior to other models that show the connection between variables, except for CHIQ ($r = 0.671$) using TDRNN and ECON ($r = 0.850$) using RNN. The results of the MSE and RMSE measurements showed that BPN performs well for the low GRG variables. The MAE measurement findings also revealed that BPN is the best forecasting model, except for CHIQ (MAE = 0.127) using the RNN model. The correlation measure (r) also shows that BPN is the best predictive model, except for BRAQ (0.366), when using the RNN model. Besides, Zhang and Xiao (2000) and Diaz (2012) found the RNN and RBFNN are relatively significant predictive models when using multiple variables. Tables 4, 5, 6 and 7 present the GRG testing results for consumer ETFs based on the ANN model. The results of the three statistical values (RMSE, CE, and MAE) and the four types of training data for the test (10%, 20%, 33%, and 50%) were consistent with earlier studies conducted by Andreou et al. (2002), Chen and Fang (2011), and Diaz (2012).

The test results of the GRG using the BPN model are presented in Table 5. The RMSE test shows that XLY, XLP, IPS, and BRAQ for all variables performed better, using 10% data for predicting ETFs; for example, XLY (RMSE = 0.342). The use of

Table 4 Testing the GRA results for the neural network for consumer ETFs using ANN

Measurement		MSE				r				RMSE				MAE			
Category	ETFs	BPN	RNN	RBFNN	TDRNN	BPN	RNN	RBFNN	TDRNN	BPN	RNN	RBFNN	TDRNN	BPN	RNN	RBFNN	TDRNN
All variables																	
US	XLY	**0.006**	0.011	0.044	0.036	**0.944**	0.922	0.801	0.821	**0.045**	0.080	0.204	0.165	**0.038**	0.073	0.168	0.141
	XLP	**0.006**	0.011	0.043	0.035	**0.943**	0.925	0.757	0.823	**0.045**	0.069	0.191	0.143	**0.036**	0.058	0.177	0.122
EX-US	IPD	**0.007**	0.010	0.048	0.035	**0.937**	0.922	0.613	0.871	**0.056**	0.069	0.204	0.157	**0.044**	0.055	0.155	0.122
	IPS	**0.004**	0.007	0.046	0.033	**0.960**	0.948	0.843	0.915	**0.055**	0.066	0.213	0.159	**0.043**	0.053	0.157	0.117
Emerging Market	ECON	**0.007**	0.013	0.042	0.038	**0.915**	0.886	0.186	0.830	**0.095**	0.127	0.228	0.212	**0.078**	0.108	0.198	0.183
Brazil	BRAQ	**0.025**	0.027	0.041	0.040	0.680	**0.684**	0.256	0.177	**0.179**	0.187	0.228	0.212	**0.148**	0.154	0.195	0.191
China	CHIQ	**0.013**	0.016	0.031	0.024	**0.793**	0.758	0.640	0.734	**0.135**	0.150	0.210	0.226	**0.100**	0.113	0.174	0.145
India	INCO	**0.015**	0.015	0.035	0.028	**0.822**	0.795	0.707	0.750	0.133	**0.119**	0.232	0.182	**0.113**	0.115	0.168	0.152
High GRG variables																	
US	XLY	**0.013**	0.022	0.034	0.047	**0.857**	0.851	0.506	0.113	**0.119**	0.132	0.168	0.202	**0.099**	0.125	0.149	0.164
	XLP	**0.020**	0.027	0.045	0.050	**0.756**	0.747	0.017	0.042	**0.155**	0.155	0.198	0.191	**0.121**	0.134	0.182	0.174
EX-US	IPD	**0.005**	0.012	0.051	0.038	**0.960**	0.927	0.044	0.929	**0.057**	0.087	0.213	0.177	**0.043**	0.070	0.162	0.135
	IPS	**0.005**	0.009	0.047	0.036	**0.958**	0.952	0.012	0.912	**0.073**	0.089	0.215	0.182	**0.006**	0.072	0.159	0.137
Emerging Market	ECON	**0.012**	0.017	0.022	0.035	0.848	**0.850**	0.769	0.788	**0.124**	0.145	0.165	0.204	**0.102**	0.122	0.136	0.176
Brazil	BRAQ	**0.012**	0.034	0.039	0.039	**0.532**	0.492	0.238	0.295	**0.200**	0.208	0.224	0.224	**0.165**	0.173	0.189	0.189
China	CHIQ	**0.020**	0.023	0.034	0.030	0.665	0.634	0.082	**0.671**	**0.168**	0.182	0.218	0.204	**0.136**	0.148	0.182	0.169
India	INCO	**0.014**	0.015	0.030	0.027	**0.793**	0.789	0.612	0.715	**0.139**	0.140	0.214	0.201	**0.111**	0.116	0.157	0.149
Low GRG variables																	
US	XLY	**0.020**	0.027	0.046	0.043	**0.771**	0.727	0.000	0.615	**0.096**	0.138	0.208	0.187	**0.083**	0.123	0.171	0.153
	XLP	**0.017**	0.026	0.045	0.044	**0.793**	0.725	0.149	0.682	**0.086**	0.120	0.198	0.172	**0.074**	0.097	0.182	0.152
EX-US	IPD	**0.023**	0.027	0.040	0.046	**0.757**	0.735	0.520	0.685	**0.107**	0.124	0.171	0.188	**0.090**	0.103	0.136	0.145
	IPS	**0.013**	0.016	0.046	0.041	**0.856**	0.849	0.551	0.790	**0.090**	0.103	0.212	0.188	**0.071**	0.081	0.157	0.137

Table 4 (continued)

Measurement		MSE				r				RMSE				MAE			
Category	ETFs	BPN	RNN	RBFNN	TDRNN	BPN	RNN	RBFNN	TDRNN	BPN	RNN	RBFNN	TDRNN	BPN	RNN	RBFNN	TDRNN
Emerging Market	ECON	**0.023**	0.027	0.040	0.043	**0.747**	0.722	0.506	0.154	**0.168**	0.181	0.221	0.227	**0.143**	0.156	0.193	0.197
Brazil	BRAQ	**0.037**	0.037	0.039	0.042	0.360	**0.366**	0.235	− 0.294	**0.216**	0.218	0.224	0.231	**0.183**	0.186	0.193	0.197
China	CHIQ	**0.020**	0.022	0.032	0.028	**0.639**	0.627	0.386	0.638	**0.165**	0.170	0.210	0.198	0.132	**0.127**	0.178	0.160
India	INCO	**0.019**	0.020	0.033	0.032	**0.712**	0.705	0.376	0.596	**0.125**	0.132	0.217	0.214	**0.127**	0.131	0.168	0.162

RMSE the root-mean-square error, *MAE* mean absolute error, *MSE* mean square error, r Pearson correlation coefficient

Bold font stands for the minimum value for *MSE*, *RMSE*, and *MAE*; Bold font represents the maximum value for r

Table 5 Testing the GRG results of ETFs for ANN prediction using BPN

Category	ETF	% & AVG	All variables			High GRG variables			Low GRG variables		
			RMSE	CE	MAE	RMSE	CE	MAE	RMSE	CE	MAE
US	XLY	10%	**0.342**	− 94.180	0.348	**0.203**	− 157.40	0.450	0.480	− 178.77	0.479
		20%	0.374	− 11.525	0.354	0.429	− 15.441	0.418	0.459	− 17.869	0.443
		33%	0.364	− 3.737	0.325	0.374	− 4.002	0.345	**0.388**	− 4.387	**0.345**
		50%	0.350	**− 1.959**	**0.306**	0.326	**− 1.571**	**0.282**	0.408	**− 3.025**	0.362
		AVG	0.358	− 27.850	0.333	0.333	− 44.603	0.374	0.434	− 51.014	0.407
	XLP	10%	**0.321**	− 32.495	**0.318**	0.453	− 65.768	0.450	0.437	− 61.236	0.434
		20%	0.364	− 17.175	0.352	0.466	− 28.701	0.459	0.432	− 24.613	0.420
		33%	0.385	− 5.961	0.357	0.430	− 7.680	0.409	**0.322**	− 3.865	**0.280**
		50%	0.372	**− 2.523**	0.321	**0.386**	**− 2.799**	**0.338**	0.403	**− 3.146**	0.355
		AVG	0.360	− 14.538	0.337	0.434	− 26.237	0.414	0.399	− 23.215	0.372
EX-US	IPD	10%	0.294	− 87.702	0.293	0.334	− 113.67	0.333	0.436	− 194.38	0.435
		20%	0.344	− 18.550	0.338	0.368	− 21.445	0.363	0.446	− 31.868	0.438
		33%	0.295	− 1.961	0.252	0.299	− 2.037	0.259	0.351	− 3.195	0.299
		50%	**0.231**	**− 0.221**	**0.179**	**0.227**	**− 0.184**	**0.169**	**0.241**	**− 0.334**	**0.192**
		AVG	0.291	− 27.108	0.265	0.307	− 34.334	0.281	0.368	− 57.444	0.341
	IPS	10%	**0.210**	− 13.178	0.207	**0.235**	− 16.739	0.232	0.346	− 37.226	0.340
		20%	0.224	− 11.953	0.220	0.260	− 16.532	0.256	0.340	− 28.869	0.333
		33%	0.258	**0.906**	0.243	0.281	**0.888**	0.271	0.318	**0.856**	0.300
		50%	0.231	− 1.536	**0.193**	0.248	− 1.905	**0.225**	**0.233**	− 1.567	**0.187**
		AVG	0.231	− 6.440	0.216	0.256	− 8.572	0.246	0.309	− 16.701	0.290
Emerging Market	ECON	10%	0.498	− 44.650	0.349	**0.149**	− 3.064	**0.131**	0.454	− 36.892	0.383
		20%	0.379	− 8.372	0.247	0.379	− 8.372	0.247	0.372	− 8.034	**0.303**
		33%	**0.269**	**− 3.905**	**0.189**	0.215	**− 2.113**	0.192	**0.368**	− 8.155	0.332
		50%	0.327	− 5.149	0.287	0.361	− 6.513	0.339	0.392	**− 7.850**	0.365

Table 5 (continued)

Category	ETF	% & AVG	All variables			High GRG variables			Low GRG variables		
			RMSE	CE	MAE	RMSE	CE	MAE	RMSE	CE	MAE
		AVG	0.368	− 15.519	0.268	0.276	− 5.015	0.227	0.396	− 15.233	0.346
Brazil	BRAQ	10%	**0.273**	− 4.118	**0.249**	**0.209**	− 1.987	**0.174**	**0.232**	− 2.704	**0.219**
		20%	0.368	− 3.900	0.333	0.348	− 3.374	0.306	0.294	− 2.116	0.254
		33%	0.484	− 3.609	0.429	0.363	− 1.593	0.322	0.282	− 0.569	0.250
		50%	0.303	**0.551**	0.264	0.287	**0.392**	0.245	0.282	**− 0.338**	0.247
		AVG	0.357	− 2.769	0.319	0.302	− 1.641	0.262	0.272	− 1.432	0.243
China	CHIQ	10%	0.315	− 41.173	0.222	0.136	− 6.892	0.127	0.250	− 25.673	0.210
		20%	0.228	− 7.165	0.145	**0.092**	**− 0.328**	**0.079**	0.192	− 4.840	**0.142**
		33%	0.193	− 4.717	0.117	0.150	− 2.474	0.134	**0.188**	**− 4.430**	0.143
		50%	**0.111**	**− 0.291**	**0.104**	0.327	− 10.155	0.316	0.276	− 6.942	0.250
		AVG	0.212	− 13.336	0.147	0.176	− 4.962	0.164	0.227	− 10.471	0.186
India	INCO	10%	0.631	− 30.566	0.555	0.346	− 8.481	0.328	0.529	− 21.152	0.495
		20%	0.433	− 4.320	0.286	0.256	− 0.865	0.194	0.400	**3.532**	0.318
		33%	0.368	− 2.338	**0.225**	**0.200**	**0.015**	**0.146**	0.336	− 1.776	**0.242**
		50%	**0.304**	**− 2.200**	0.238	0.211	− 0.540	0.156	**0.301**	− 2.138	0.271
		AVG	0.434	− 9.856	0.326	0.253	− 2.468	0.206	0.391	− 5.383	0.331

RMSE the root-mean-square error, *CE* coefficient of efficiency, *MAE* mean absolute error

Bold font stands for the minimum value for *RMSE* and *MAE*; Bold font is the highest value, close to 1 for *CE*

Table 6 Testing the GRG results of ETFs for ANN prediction Using RNN

Category	ETF	% & AVG	All variables			High GRG variables			Low GRG variables		
			RMSE	CE	MAE	RMSE	CE	MAE	RMSE	CE	MAE
US	XLY	10%	0.369	− 105.06	0.368	0.428	− 142.25	0.428	0.478	− 177.60	0.477
		20%	0.379	− 11.851	0.363	0.418	− 14.631	0.407	0.457	− 17.681	0.439
		33%	**0.363**	− 3.713	**0.329**	0.392	− 4.494	0.367	**0.407**	− 4.916	**0.368**
		50%	0.373	**− 2.359**	**0.329**	**0.345**	**− 1.870**	**0.303**	0.446	**− 3.799**	0.402
		AVG	0.371	− 30.745	0.347	0.396	**− 40.812**	0.376	0.447	− 50.998	0.422
	XLP	10%	**0.329**	− 34.179	0.325	0.413	− 54.628	0.411	**0.144**	− 5.743	**0.133**
		20%	0.380	− 18.762	0.368	0.436	− 25.082	0.430	0.424	− 23.663	0.411
		33%	0.372	− 5.477	0.345	0.435	− 7.864	0.416	0.406	− 6.753	0.375
		50%	0.374	**− 2.561**	**0.325**	**0.391**	**− 2.894**	**0.345**	0.405	**− 3.173**	0.356
		AVG	0.363	− 15.245	0.341	0.419	− 22.617	0.400	0.345	− 9.833	0.319
EX-US	IPD	10%	0.292	− 86.848	0.290	0.287	− 83.497	0.286	0.432	− 190.87	0.431
		20%	0.330	− 16.960	0.323	0.337	− 17.800	0.333	0.444	− 31.661	0.437
		33%	0.274	− 1.563	0.233	0.295	− 1.967	0.259	0.360	− 3.404	0.307
		50%	**0.209**	**− 0.006**	**0.159**	**0.226**	**− 0.174**	**0.175**	**0.271**	**− 0.691**	**0.204**
		AVG	0.276	− 26.344	0.251	0.286	− 25.859	0.263	0.377	**− 56.655**	0.345
	IPS	10%	0.224	− 15.002	0.216	**0.211**	− 13.301	**0.209**	0.355	− 39.280	0.352
		20%	0.212	− 10.658	0.207	0.212	− 10.607	**0.209**	0.348	− 30.280	0.343
		33%	0.252	− 6.970	0.239	0.278	**0.890**	0.271	0.330	**0.842**	0.316
		50%	**0.212**	**− 1.132**	**0.181**	0.253	− 2.025	0.237	**0.270**	− 2.445	**0.226**
		AVG	**0.225**	− 8.441	**0.211**	0.239	− 6.261	0.231	0.326	− 17.791	0.309
Emerging Market	ECON	10%	0.576	− 59.971	0.400	**0.094**	− 0.643	**0.075**	0.601	− 65.446	0.482
		20%	0.456	− 12.575	0.284	0.117	0.101	0.098	0.485	**0.144**	0.355
		33%	0.303	− 5.221	**0.197**	0.150	**0.518**	0.128	0.357	− 7.616	0.336
		50%	**0.285**	**− 3.681**	0.234	0.272	− 3.264	0.250	**0.324**	− 5.035	**0.272**

Table 6 (continued)

Category	ETF	% & AVG	All variables			High GRG variables			Low GRG variables		
			RMSE	CE	MAE	RMSE	CE	MAE	RMSE	CE	MAE
		AVG	0.405	− 20.362	0.279	0.158	− 0.822	**0.138**	0.442	− 19.488	0.361
Brazil	BRAQ	10%	0.362	− 7.979	0.330	**0.198**	− 1.701	**0.168**	0.361	− 7.958	0.321
		20%	0.406	− 4.960	0.359	0.382	− 4.282	0.345	0.347	− 3.360	0.288
		33%	**0.331**	**− 1.161**	**0.286**	0.457	− 3.114	0.407	0.338	− 1.250	0.295
		50%	0.359	− 1.173	0.313	0.306	**− 0.577**	0.261	**0.313**	**− 0.653**	**0.273**
		AVG	0.364	**− 3.818**	0.322	0.336	− 2.418	0.295	0.340	− 3.305	0.294
China	CHIQ	10%	0.477	− 95.961	0.342	0.103	− 3.494	0.091	0.333	− 46.158	0.224
		20%	0.330	**16.217**	0.201	**0.073**	**0.143**	**0.061**	0.344	− 17.674	0.210
		33%	**0.282**	− 11.162	**0.180**	0.092	− 0.294	0.081	**0.290**	− 11.895	**0.170**
		50%	0.352	− 11.920	0.312	0.342	− 11.195	0.330	0.334	**− 10.627**	0.283
		AVG	0.360	− 25.707	0.259	**0.152**	− 3.710	0.141	**0.325**	− 21.589	**0.222**
India	INCO	10%	0.724	− 40.510	0.627	0.288	− 5.546	0.268	0.730	− 41.163	0.652
		20%	0.459	− 4.982	0.342	0.257	− 0.871	0.203	**0.341**	**− 2.306**	0.300
		33%	0.405	− 3.033	0.245	0.170	**0.292**	0.152	0.424	− 3.435	**0.290**
		50%	**0.338**	**− 2.972**	**0.203**	**0.145**	0.270	**0.116**	0.389	− 4.250	0.341
		AVG	0.481	− 12.874	0.354	0.215	− 1.464	0.185	0.471	− 12.789	0.396

RMSE the root-mean-square error, *CE* coefficient of efficiency, *MAE* mean absolute error

Bold font stands for the minimum value for *RMSE* and *MAE*; Bold font is the highest value, close to 1 for *CE*

Table 7 The comparison of forecasting ability of neural network for consumer ETFs (country)

Category	US			EX– US		Emerging Market	Brazil	China	India
	ETF	XLY	XLP	IPD	IPS	ECON	BRAQ	CHIQ	INCO
BPN									
All variables	RMSE	0.358	0.360	0.291	0.231	0.368	0.357	**0.212**	0.434
	CE	− 27.850	− 14.538	− 27.108	− 6.440	− 15.519	**− 2.769**	− 13.336	− 9.856
	MAE	0.333	0.337	0.265	0.216	0.268	0.319	**0.147**	0.326
High GRG variables	RMSE	0.333	0.434	0.307	0.256	0.276	0.302	**0.176**	0.253
	CE	− 44.603	− 26.237	− 34.334	− 8.572	− 5.015	**− 1.641**	− 4.962	− 2.468
	MAE	0.374	0.414	0.281	0.246	0.227	0.262	**0.164**	0.206
Low GRG variables	RMSE	0.434	0.399	0.368	0.309	0.396	0.272	**0.227**	0.391
	CE	− 51.014	− 23.215	− 57.444	− 16.701	− 15.233	**− 1.432**	− 10.471	− 5.383
	MAE	0.407	0.372	0.341	0.290	0.346	0.243	**0.186**	0.331
RNN									
All variables	RMSE	0.371	0.363	0.276	**0.225**	0.405	0.364	0.360	0.481
	CE	− 30.745	− 15.245	− 26.344	− 8.441	− 20.362	**− 3.818**	− 25.707	− 12.874
	MAE	0.347	0.341	0.251	**0.211**	0.279	0.322	0.259	0.354
High GRG variables	RMSE	0.396	0.419	0.286	0.239	0.158	0.336	**0.152**	0.215
	CE	− 40.812	− 22.617	− 25.859	− 6.261	**− 0.822**	− 2.418	− 3.710	− 1.464
	MAE	0.376	0.400	0.263	0.231	**0.138**	0.295	0.141	0.185
Low GRG variables	RMSE	0.447	0.345	0.377	0.326	0.442	0.340	**0.325**	0.471
	CE	− 50.998	− 9.833	− 56.655	− 17.791	− 19.488	**− 3.305**	− 21.589	− 12.789
	MAE	0.422	0.319	0.345	0.309	0.361	0.294	**0.222**	0.396
RBFNN									
All variables	RMSE	0.469	0.470	0.435	0.398	0.340	0.243	**0.194**	0.336
	CE	− 62.328	− 31.867	− 69.655	− 24.059	− 9.347	**− 0.958**	− 6.107	− 4.879
	MAE	0.445	0.449	0.408	0.387	0.321	0.200	**0.179**	0.290

Table 7 (continued)

Category	US			EX– US		Emerging Market	Brazil	China	India
	ETF	XLY	XLP	IPD	IPS	ECON	BRAQ	CHIQ	INCO
High GRG variables	RMSE	0.460	0.463	0.444	0.354	0.327	0.239	**0.179**	0.330
	CE	− 62.766	− 29.751	− 71.299	− 21.306	− 8.354	**− 0.853**	− 5.180	− 4.175
	MAE	0.439	0.444	0.417	0.344	0.306	0.194	**0.164**	0.282
Low GRG variables	RMSE	0.471	0.475	0.382	0.347	0.310	0.241	**0.176**	0.314
	CE	− 58.356	− 31.163	− 67.465	− 21.938	− 7.226	**− 0.883**	− 6.734	− 4.155
	MAE	0.446	0.455	0.350	0.331	0.289	0.199	**0.157**	0.272
TDRNN									
All variables	RMSE	0.469	0.459	0.414	0.382	0.334	0.249	**0.164**	0.344
	CE	− 58.185	− 28.246	− 56.939	− 20.805	− 9.166	**− 0.939**	− 5.197	− 5.121
	MAE	0.446	0.438	0.387	0.370	0.306	0.208	**0.141**	0.287
High GRG variables	RMSE	0.455	0.453	0.416	0.372	0.285	0.267	**0.187**	0.288
	CE	− 57.145	− 28.196	− 59.130	− 19.474	− 6.012	**− 1.273**	− 5.474	− 3.328
	MAE	0.431	0.433	0.391	0.362	0.265	0.227	**0.173**	0.240
Low GRG variables	RMSE	0.484	0.472	0.440	0.403	0.367	0.243	**0.178**	0.342
	CE	− 63.685	− 30.617	− 70.567	− 30.234	− 11.623	**− 1.733**	− 4.799	− 4.316
	MAE	0.461	0.451	0.412	0.390	0.340	0.205	**0.161**	0.302

RMSE the root-mean-square error, *CE* coefficient of efficiency, *MAE* mean absolute error

Bold font stands for the minimum value for *RMSE* and *MAE*; Bold font is the highest value, close to 1 for *CE*

50% data can better predict IPD (RMSE = 0.231), CHIQ (RMSE = 0.111), and INCO (RMSE = 0.304). For emerging markets, the findings for ECON (RMSE = 0.269) show that the use of 33% data leads to the best samples for prediction. The CE test exhibits the best performance for 50% data for all variables, such as XLY, XLP, IPD, BRAQ, CHIQ, and INCO. In contrast, the IPS and ECON test results indicate that 33% of data leads to better predictions. The MAE test results are similar to the results of the CE test. For all variables, 50% of the data can better predict XLY, IPD, IPS, and CHIQ.

The testing results of the high GRG variables, including XLP (RMSE = 0.386; CE = − 2.799; MAE = 0.338) and IPD (RMSE = 0.227; CE = − 0.184; MAE = 0.169), can be better predicted by using 50% data. The ANN tests proposed the use of 20% and 33% data to predict CHIQ and INCO, respectively. Using the BPN model to evaluate low GRG variables, only IPD exhibited consistent results for all the measurement tests (RMSE = 0.241; CE = − 0.334; MAE = 0.192) when using 50% data for prediction. Lee et al. (2008) found that BPN performed better than Chiao's Bayesian model for medium- and long-term forecasts.

Table 6 shows the effects of the RNN model, which was used to anticipate the best samples. For all variables, the RMSE test proposed the use of 50% data for IPD, IPS, ECON, and INCO, and 33% data for XLY, BRAQ, and CHIQ. The CE test results mostly proposed the use of 50% data, except for the use of 33% data for BRAQ (− 1.161) and 20% data for CHIQ (16.217). The high GRG variables results showed consistency for all the tests (RMSE, CE, and MAE), such as using 50% data for XLY, XLP, and IPD predictions and 20% for CHIQ predictions. Moreover, we determined that only IPD and BRAQ for low GRG variables had consistent results for all tests that used 50% data for prediction. Likewise, Tables 10, 11 and 12 in an "Appendix" exhibit the effects of consumer ETFs for the GRG, using the RBFNN and TDRNN models and comparing the forecasting ability using ANN.

As explained above, the NYSE Composite Index, the CRB Index, the EUR/USD Exchange Rate, and the PCR are the top four consumer ETF variables by country. In contrast, the short-term TRIN variable has the least impact on classification, followed by INT, INF, and VIX. Comparing the ANN models' forecast ability for consumer ETFs classified by country, the eight variables divided into two groups, namely high GRG variables and low GRG variables, as shown in Table 7. This work uses three measures, RMSE, MAE, and CE, to examine which group has an improved forecasting capacity.

The GRA's empirical effects constructed with the BPN, RBFNN, and TDRNN models consistently showed that CHIQ has the best forecasting model examined by the RMSE and MAE tests for the groups of all high GRG variables and low variables. Moreover, the CE tests consistently revealed that BRAQ exhibited good predictions. Using the RNN model, we found that the CHIQ for high GRG variables and low GRG variables had an excellent predictive efficiency. Moreover, BRAQ for all variables and low GRG variables and ECON for high GRG variables worked well. At the same time, other findings showed that IPS exhibited better performance for all variable categories, using only the RNN model.

The three ANN models (BPN, RBFNN, and TDRNN) consistently show that BRAQ and CHIQ are the best predictive models based on statistical tests. These findings suggest that consumer ETFs in Brazil and China were more comfortable in predicting reliably. The RNN model's effects indicate that IPS, ECON, BRAQ, and CHIQ have good predictive results. These results differ from previous studies (Zhang and Xiao 2000; Diaz 2012), showing that RNN is the best model, compared to BPN, RBFNN, and TDRNN. However, we found the BPN, RBFNN, and TDRNN models to be more consistent and accurate.

We aim to forecast the accuracy of the consumer ETF return categorized by country. The comparative results of the forecasting ability, using the ANN for consumer ETFs, based on the MSE test for 10%, 20%, 33%, and 50% testing sets, are consistent with the results obtained by Chen and Fang (2011) and Chen and Trang (2013), as shown in Table 8. The results of all variables show that all ANN models consistently proposed the use of 10% data to predict the United States ETFs, XLP, and XLY. This finding indicates that BPN, RNN, RBFNN, and TDRNN can forecast XLP and XLY well at a test level of 10%. Other results of the three ANN models (BPN, RBFNN, and TDRNN) also proposed using 10% data to forecast ETFs that excluded the United States, such as IPD and IPS. In line with previous studies by Zhang and Xiao (2000) and Chen and Trang (2013), ANN models are efficient in providing predictions based on time series data. However, the results of ECON and BRAQ indicated that the forecast utilized 33% data for BPN and RNN. Furthermore, RNN and TDRNN can predict CHIQ using 33% data. Using the 50% testing level, the BPN, RNN, and TDRNN models have good performance in predicting INCO because of the lowest MSE.

From the perspective of high GRG variables, the findings showed that most ANN models proposed using 10% data for prediction, except for 20% data for CHIQ and ECON. Based on the results of BPN, RBFNN, and TDRNN for predicting INCO, we proposed using 33% data excluding the United States (EX-US), while the results of RBFNN indicated the use of 50% data for prediction. The outcomes of the United States' ETFs (such as XLY and XLP) and the IPD for all ANN models indicated the use of 10% and 50% data for forecasting associated with low GRG variables, respectively. ANN models can be useful predictors with different test data samples (Chen and Fang 2008). We revealed that the lowest measure of MSE of all, high GRG, and low GRG variables indicated the use of 10% data for a precise forecast consistent with the results of Hong and Yoon (2011), Gallego et al. (2013), and Monteiro et al. (2012).

The DM test results for ANN models, based on 90% of training data and 10% of testing data to measure whether prediction accuracy is significantly different, are presented in Table 9. For example, BRAQ's training data and testing data are based on the 925 observations from 2010.7.9 to 2014.11.3. We compared several pairs of ANN models, such as BPN versus RNN, BPN versus TDRNN, BPN versus RBFNN, RNN versus TDRNN, RNN versus RBFNN, and TDRNN versus RBFNN, using the DM test. The best predictive model for all variables is BPN, which is superior to other models with the exception of IPD and XLP. However, the DM test results show that no model predicts better for the Dow Jones Emerging markets consumer Titans Index Fund (ECON).

Table 8 The comparison of forecasting ability of neural networks for consumer ETFs use MSE test

Category	ETFs	All variables				High GRG variables				Low GRG variables			
		10%	20%	33%	50%	10%	20%	33%	50%	10%	20%	33%	50%
		MSE	MSE	MSE	MSE	MSE	MSE	MSE	MSE	MSE	MSE	MSE	MSE
BPN													
US	XLY	**0.138**	0.312	0.453	0.455	0.230	0.021	**0.016**	0.395	**0.261**	0.470	0.515	0.619
	XLP	**0.117**	0.275	0.505	0.763	**0.233**	0.450	0.629	0.823	**0.217**	0.388	0.353	0.898
EX– US	IPD	**0.075**	0.166	0.168	0.103	**0.097**	0.191	0.173	0.099	0.165	0.279	0.238	**0.112**
	IPS	**0.044**	0.052	0.119	0.100	**0.055**	0.070	0.141	0.115	0.118	0.119	0.181	**0.101**
Emerging Market	ECON	0.281	0.138	**0.086**	0.200	**0.025**	0.138	0.054	0.244	0.234	**0.133**	0.160	0.287
Brazil	BRAQ	0.074	0.122	**0.006**	0.010	**0.043**	0.109	0.107	0.073	**0.054**	0.077	0.065	0.071
China	CHIQ	0.090	0.045	0.030	**0.011**	0.017	**0.007**	0.018	0.094	0.060	0.032	**0.029**	0.067
India	INCO	0.785	0.328	0.215	**0.158**	0.236	0.115	**0.071**	0.076	0.551	0.280	0.201	**0.155**
RNN													
US	XLY	**0.179**	0.338	0.451	0.517	**0.242**	0.411	0.525	0.441	**0.302**	0.491	0.566	0.738
	XLP	**0.123**	0.299	0.473	0.772	**0.194**	0.395	0.648	0.844	**0.024**	0.373	0.567	0.904
EX-US	IPD	0.099	0.193	0.146	**0.085**	**0.095**	0.202	0.169	0.099	0.216	0.351	0.250	**0.142**
	IPS	**0.050**	0.056	0.118	0.084	**0.045**	0.055	0.144	0.120	**0.126**	0.149	0.207	0.136
Emerging Market	ECON	0.376	0.200	**0.109**	0.152	**0.010**	0.013	0.027	0.139	0.410	0.226	**0.151**	0.196
Brazil	BRAQ	0.130	0.148	**0.089**	0.115	**0.039**	0.131	0.170	0.083	0.130	0.108	0.093	**0.087**
China	CHIQ	0.206	0.096	**0.064**	0.109	0.095	**0.005**	0.007	0.102	0.100	0.104	**0.068**	0.098
India	INCO	1.033	0.369	0.292	**0.196**	0.163	0.116	0.051	**0.036**	1.049	**0.204**	0.321	0.260
RBFNN													
US	XLY	**0.319**	0.562	0.683	0.585	**0.323**	0.557	0.631	0.527	**0.297**	0.527	0.652	0.746
	XLP	**0.289**	0.518	0.727	0.950	**0.275**	0.523	0.709	0.882	**0.292**	0.446	0.729	1.210
EX-US	IPD	**0.199**	0.331	0.315	0.270	0.202	0.333	0.479	**0.187**	0.201	0.262	0.221	**0.147**
	IPS	**0.160**	0.163	0.287	0.287	0.147	0.151	0.264	**0.127**	0.157	**0.146**	0.198	0.156

Table 8 (continued)

Category	ETFs	All variables				High GRG variables				Low GRG variables			
		10%	20%	33%	50%	10%	20%	33%	50%	10%	20%	33%	50%
		MSE	MSE	MSE	MSE	MSE	MSE	MSE	MSE	MSE	MSE	MSE	MSE
Emerging Market	ECON	0.112	**0.086**	0.142	0.301	0.095	**0.082**	0.127	0.301	0.077	**0.071**	0.118	0.288
Brazil	BRAQ	**0.037**	0.070	0.062	0.041	**0.038**	0.065	0.043	0.060	**0.038**	0.066	0.051	0.056
China	CHIQ	0.024	**0.015**	0.027	0.078	0.022	**0.015**	0.019	0.068	0.041	**0.007**	0.016	0.061
India	INCO	0.388	0.196	**0.138**	0.141	0.304	0.215	**0.141**	0.151	0.337	0.198	**0.111**	0.115
TDRNN													
US	XLY	**0.344**	0.571	0.706	0.653	**0.340**	0.554	0.662	0.559	**0.378**	0.608	0.733	0.685
	XLP	**0.249**	0.478	0.712	0.931	**0.273**	0.503	0.755	1.049	**0.248**	**0.469**	0.740	1.012
EX-US	IPD	**0.209**	0.397	0.331	0.228	0.219	0.396	**0.037**	0.233	0.266	0.433	0.362	**0.245**
	IPS	**0.142**	0.167	0.313	0.258	**0.131**	0.158	0.295	0.258	**0.169**	0.200	0.327	0.267
Emerging Market	ECON	0.116	**0.085**	0.126	0.289	0.066	**0.053**	0.103	0.255	0.154	**0.105**	0.161	0.300
Brazil	BRAQ	**0.034**	0.069	0.064	0.059	**0.041**	0.082	0.076	0.059	**0.033**	0.041	0.058	0.061
China	CHIQ	0.024	0.014	**0.011**	0.053	0.019	**0.013**	0.021	0.088	**0.018**	0.018	0.020	0.063
India	INCO	0.419	0.195	0.164	**0.132**	0.285	0.159	**0.094**	0.099	0.364	0.418	0.171	**0.160**

MSE mean square error

Bold font stands for the minimum value for MSE

Table 9 The comparison of Diebold–Mariano (DM) test for ANN models

ETF	Obs	BPN RNN	BPN TDRNN	BPN RBFNN	RNN TDRNN	RNN RBFNN	TDRNN RBFNN	Significantly different
BRAQ	925	5.853 (0.001)***	6.304 (0.001)***	8.914 (0.001)***	5.853 (0.001)***	12.469 (0.001)***	1.204 (0.229)	BPN
CHIQ	925	2.268 (0.023)**	5.314 (0.001)***	7.077 (0.001)***	3.903 (0.001)***	5.626 (0.001)***	2.379 (0.018)**	BPN
ECON	915	3.261 (0.906)	9.897 (0.669)	11.825 (0.651)	7.419 (0.756)	9.430 (0.738)	1.023 (0.980)	–
INCO	696	2.270 (0.023)**	4.452 (0.001)***	6.740 (0.001)***	5.169 (0.001)***	7.320 (0.001)***	4.984 (0.001)***	BPN
IPD	925	1.386 (0.166)	8.479 (0.001)***	9.084 (0.001)***	7.642 (0.001)***	8.133 (0.001)***	1.537 (0.124)	BPN RNN
IPS	925	1.801 (0.072)*	10.904 (0.001)***	12.444 (0.001)***	9.660 (0.001)***	11.463 (0.001)***	1.886 (0.059)*	BPN
XLP	925	1.323 (0.1859)	44.955 (0.001)***	44.955 (0.001)***	3.836 (0.001)***	3.836 (0.001)***	1.387 (0.1653)	BPN RNN
XLY	925	1.695 (0.090)*	7.461 (0.001)***	5.498 (0.001)***	11.986 (0.001)***	5.636 (0.001)***	0.461 (0.6448)	BPN

Obs stands for observation. *p* value is given within parentheses

***$p<0.01$; **$p<0.05$; *$p<0.1$

4 Conclusion

We used the GRA and ANN models for predicting the volatility of consumer ETF returns. The impacts and contributions are summarized. We found that the four main variables affected consumer ETFs according to the GRA, including the NYSE Composite Index, the CRB Index, the USD/EUR Exchange Rate, and the PCR. The criteria test (MSE, RMSE, r, and MAE) revealed that BPN exhibited an outstanding performance concerning consumer ETFs forecasting. The GRA test results, classified into different data samples (10%, 20%, 33%, and 50%), showed that RBFNN and TDRNN performed better than BPN and RNN. This finding is in line with Kim (1998), who proposed that TDRNN obtained the best temporal signal recognition, prediction, and identification results.

We present a comparison of the forecasting ability of the ANN models. The results suggest that the BPN and RNN models consistently have the lowest values and predict consumer ETFs better (Oh and Han 2000; Versace et al. 2004; Chen and Fang 2008; Diaz 2012; Trang 2014). The ANN models examined and compared the forecasting ability of consumer ETFs, classified by country. The results showed that BRAQ and CHIQ were more predictive than other ETFs.

Most ANN models indicated that 10% of the testing data were suitable for prediction, particularly for the ETFs of the United States (US) and those excluding the ETFs of the United States (EX-US). The ANN models were useful in providing predictions that were based on a few time-series data consistent with the findings of Zhang and Xiao (2000) and Chen and Trang (2013). The ANN models' results indicated better predicting performance for evaluating consumer ETFs, with 20% or 30% training data for BRAQ and ECON, and 50% training data for CHIQ. The Diebold–Mariano test results showed that the best prediction model was BPN for consumer ETFs, which outperforms other models except for IPD and XLP.

Finally, we contribute to the research of different learning schemes that influence the efficiency of neural network models (Donaldson and Kamstra 1997; Pradhan and Kumar 2008; Hadavandi et al. 2010; Ticknor 2013; Bekiros and Georgoutsos 2008; Sookhanaphibarn et al. 2007; Ho et al. 2002; Zhang 2003; Singhal and Swarup 2011; Hamzaçebi 2008). From the viewpoint of different input data, we assess the highest-ranking financial variables that influence consumer ETFs among ANN models, and it examines the various input data testing methods. The findings will enable policymakers to make the best decisions to confirm the financial market behavior, identify what additional components are essential or sufficient for influencing investor behavior in the capital market, and formulate appropriate policies.

For fund managers and investors, particularly those interested in consumer ETFs, we imply that ANN models with few data provide accurate predictions and establish appropriate portfolio investment strategies, especially for the consumer ETFs of the international finance market. It suggests that practitioners, investors, and academics can mainly observe stock indices and get involved in theory building. For academics and practitioners, this research bridges the gap and ensures a strong correlation between theory and practice. We aimed at improving neural network models for the best prediction performance. To improve capital gains, investors need to look at equity and benchmarks when investing in ETFs. The application of grey relational analysis (GRA) and the artificial neural network (ANN) positively influence the stock market indices.

The future study can apply ANNs for testing the hypothesis to classify consumer ETFs that will fail as excellent performance ETFs (Type I error) and categorize consumer ETFs that will perform poorly as one that will accept (Type II error). If other approaches are more sensitive to exogenous variables connected with macroeconomic factors and financial ratios, they may obtain different findings related to the various preceding variables.

Appendix

Table 10 presents the impact of consumer ETFs on GRG, using the RBFNN template. We found that high GRG and low GRG variables tested by RMSE, CE, and MAE had similar results by specifying all variables. All tests for XLY, XLP, and IPD suggested using 50% training data to define all variables. For the specification of high and low GRG variables, the CHIQ results proposed using 20% training data, and the INCO results suggested using 20% and 33% training data for forecasting.

Table 11 summarizes the TDRNN model results based on the GRG prediction results. According to RBFNN results for XLY, XLP, and IPD, all measurement tests (RMSE, CE, and MAE) show consistency and strongly suggest that consumer ETFs can be better predicted by using 50% training data. Most measurement tests for INCO propose the use of 50% training data for prediction. Other consumer ETFs,

Table 10 Testing the GRG results of ETFs for ANN prediction using RBFNN

Category	ETF	% & AVG	All variables			High GRG variables			Low GRG variables		
			RMSE	CE	MAE	RMSE	CE	MAE	RMSE	CE	**MAE**
US	XLY	10%	0.531	− 218.817	0.529	0.534	− 221.667	0.532	0.512	− 203.613	0.508
		20%	0.502	− 21.543	0.491	0.500	− 21.372	0.487	0.486	− 20.142	0.475
		33%	0.447	− 6.148	0.415	0.430	− 5.599	0.406	0.437	− 5.821	0.402
		50%	**0.397**	**− 2.805**	**0.343**	**0.377**	**− 2.426**	**0.329**	**0.448**	**− 3.850**	**0.400**
		AVG	0.469	− 62.328	0.445	0.460	− 62.766	0.439	0.471	− 58.356	0.446
	XLP	10%	0.504	− 81.801	0.501	0.492	− 77.830	0.488	0.507	− 82.572	0.504
		20%	0.500	− 33.253	0.492	0.502	− 33.529	0.495	0.464	− 28.437	0.455
		33%	0.462	− 9.028	0.439	0.457	− 5.570	0.434	0.463	− 9.059	0.439
		50%	**0.415**	**− 3.386**	**0.365**	**0.400**	**− 2.075**	**0.357**	**0.468**	**− 4.585**	**0.423**
		AVG	0.470	− 31.867	0.449	0.463	− 29.751	0.444	0.475	− 31.163	0.455
EX− US	IPD	10%	0.478	− 233.948	0.477	0.482	− 238.323	0.481	0.481	− 236.398	0.479
		20%	0.485	− 37.910	0.478	0.487	− 38.228	0.481	0.432	− 29.821	0.424
		33%	0.404	− 4.548	0.368	0.497	− 7.424	0.459	0.338	− 2.887	0.286
		50%	**0.374**	**− 2.214**	**0.311**	**0.311**	**− 1.223**	**0.249**	**0.276**	**− 0.755**	**0.211**
		AVG	0.435	− 69.655	0.408	0.444	− 71.299	0.417	0.382	− 67.465	0.350
	IPS	10%	0.403	− 50.987	0.399	0.387	− 46.930	0.382	0.400	− 50.105	0.389
		20%	0.397	− 39.761	0.393	0.383	− 36.876	0.375	0.376	− 35.536	0.371
		33%	0.401	**0.772**	0.392	0.384	**0.791**	0.376	0.323	**0.843**	0.320
		50%	**0.392**	− 6.262	**0.364**	**0.260**	− 2.208	**0.244**	**0.289**	− 2.953	**0.245**
		AVG	0.398	− 24.059	0.387	0.354	− 21.306	0.344	0.347	− 21.938	0.331
Emerging Market	ECON	10%	0.314	− 17.108	0.305	**0.289**	− 14.373	0.277	**0.260**	− 11.469	0.249
		20%	**0.300**	**− 4.868**	**0.276**	0.291	**− 4.534**	**0.265**	0.271	**− 3.813**	**0.244**
		33%	0.347	− 7.138	0.325	0.328	− 6.247	0.305	0.316	− 5.754	0.293
		50%	0.401	− 8.275	0.379	0.401	− 8.262	0.379	0.392	− 7.870	0.370

Table 10 (continued)

Category	ETF	% & AVG	All variables			High GRG variables			Low GRG variables		
			RMSE	CE	MAE	RMSE	CE	MAE	RMSE	CE	**MAE**
		AVG	0.340	− 9.347	0.321	0.327	− 8.354	0.306	0.310	− 7.226	0.289
Brazil	BRAQ	10%	**0.192**	− 1.533	**0.148**	**0.195**	− 1.611	**0.156**	**0.194**	− 1.593	**0.159**
		20%	0.278	− 1.803	0.226	0.269	− 1.619	0.215	0.271	− 1.652	0.219
		33%	0.276	− 0.499	0.236	0.230	**− 0.046**	0.186	0.249	− 0.225	0.209
		50%	0.225	**0.003**	0.189	0.260	− 0.136	0.220	0.251	**− 0.061**	0.210
		AVG	0.243	**− 0.958**	0.200	0.239	**− 0.853**	0.194	0.241	**− 0.883**	0.199
China	CHIQ	10%	0.163	− 10.346	0.156	0.156	− 9.367	0.148	0.214	− 18.468	0.186
		20%	**0.133**	**− 1.772**	**0.114**	**0.132**	**− 1.755**	**0.115**	**0.089**	**− 0.247**	**0.079**
		33%	0.181	− 4.049	0.163	0.152	− 2.522	0.133	0.139	− 1.964	0.117
		50%	0.298	− 8.261	0.282	0.278	− 7.075	0.260	0.264	− 6.258	0.245
		AVG	**0.194**	− 6.107	**0.179**	**0.179**	− 5.180	**0.164**	**0.176**	− 6.734	**0.157**
India	INCO	10%	0.443	− 14.580	0.428	0.393	− 11.217	0.375	0.414	− 12.560	0.399
		20%	0.334	− 2.172	0.281	0.351	− 2.492	0.289	0.336	− 2.209	0.281
		33%	**0.278**	**− 0.904**	**0.212**	**0.281**	**− 0.941**	**0.214**	**0.249**	**− 0.529**	**0.199**
		50%	0.287	− 1.859	0.241	0.297	− 2.051	0.250	0.259	− 1.323	0.207
		AVG	0.336	− 4.879	0.290	0.330	− 4.175	0.282	0.314	− 4.155	0.272

RMSE the root-mean-square error, *CE* coefficient of efficiency, *MAE* mean absolute error

Bold font stands for the minimum value for *RMSE* and *MAE*; Bold font is the highest value, close to 1 for *CE*

Table 11 Testing the GRG results of ETFs for ANN Prediction Using TDRNN

Category	ETF	% & AVG	All variables			High GRG variables			Low GRG variables		
			RMSE	CE	MAE	RMSE	CE	MAE	RMSE	CE	MAE
US	XLY	10%	0.510	− 202.388	0.509	0.507	− 199.937	0.506	0.535	− 222.515	0.533
		20%	0.493	− 20.718	0.482	0.486	− 20.087	0.475	0.508	− 22.105	0.497
		33%	0.455	− 6.386	0.425	0.440	− 5.921	0.410	0.463	− 6.664	0.433
		50%	**0.419**	**− 3.248**	**0.368**	**0.388**	**− 2.635**	**0.335**	**0.430**	**− 3.457**	**0.380**
		AVG	0.469	**− 58.185**	0.446	0.455	− 57.145	0.431	0.484	− 63.685	0.461
	XLP	10%	0.467	− 70.181	0.464	0.467	− 70.190	0.465	0.490	− 77.082	0.486
		20%	0.476	− 30.012	0.468	0.480	− 30.558	0.473	0.492	− 32.219	0.484
		33%	0.464	− 9.122	0.442	0.456	− 8.739	0.433	0.469	− 9.327	0.446
		50%	**0.428**	**− 3.671**	**0.379**	**0.411**	**− 3.295**	**0.361**	**0.436**	**− 3.841**	**0.388**
		AVG	0.459	− 28.246	0.438	0.453	− 28.196	0.433	0.472	− 30.617	0.451
EX-US	IPD	10%	0.426	− 185.291	0.425	0.436	− 194.144	0.435	0.480	− 235.744	0.479
		20%	0.472	− 35.918	0.466	0.472	− 35.918	0.466	0.493	− 39.245	0.486
		33%	0.414	− 4.834	0.378	0.409	− 4.687	0.375	0.432	− 5.362	0.395
		50%	**0.344**	**− 1.715**	**0.279**	**0.347**	**− 1.773**	**0.289**	**0.356**	**− 1.916**	**0.287**
		AVG	0.414	− 56.939	0.387	0.416	**− 59.130**	0.391	0.440	**− 70.567**	0.412
	IPS	10%	0.377	− 44.471	0.373	0.362	− 41.053	0.359	0.411	− 53.053	0.406
		20%	**0.368**	− 33.993	0.363	**0.358**	− 32.092	0.353	0.403	− 41.010	0.398
		33%	0.410	**0.761**	0.401	0.398	**0.775**	0.390	0.419	− 21.118	0.409
		50%	0.371	− 5.518	**0.344**	0.371	− 5.527	**0.347**	**0.378**	**− 5.756**	**0.348**
		AVG	0.382	− 20.805	0.370	0.372	− 19.474	0.362	0.403	− 30.234	0.390
Emerging Market	ECON	10%	0.319	− 17.774	0.296	0.242	− 9.761	0.231	0.368	− 23.986	0.340
		20%	**0.298**	**− 4.789**	**0.258**	**0.234**	**− 2.571**	**0.211**	**0.329**	**− 6.094**	**0.292**
		33%	0.327	− 6.220	0.300	0.295	− 4.876	0.271	0.369	− 8.189	0.349
		50%	0.393	− 7.883	0.370	0.369	− 6.840	0.347	0.400	− 8.224	0.379

Table 11 (continued)

Category	ETF	% & AVG	All variables			High GRG variables			Low GRG variables		
			RMSE	CE	MAE	RMSE	CE	MAE	RMSE	CE	MAE
		AVG	0.334	− 9.166	0.306	0.285	− 6.012	0.265	0.367	− 11.623	0.340
Brazil	BRAQ	10%	**0.184**	− 1.318	**0.151**	**0.202**	− 1.802	**0.165**	**0.182**	− 1.276	**0.148**
		20%	0.277	− 1.782	0.227	0.303	− 2.324	0.255	0.263	− 1.501	0.222
		33%	0.280	− 0.540	0.238	0.306	− 0.844	0.268	0.266	− 3.996	0.230
		50%	0.257	**− 0.114**	0.214	0.258	**− 0.122**	0.220	0.262	**− 0.160**	0.222
		AVG	0.249	− 0.939	0.208	0.267	− 1.273	0.227	0.243	− 1.733	0.205
China	CHIQ	10%	0.163	− 12.757	0.142	0.146	− 8.041	0.137	**0.143**	− 7.671	0.130
		20%	0.128	− 1.591	0.103	**0.124**	**− 1.409**	**0.107**	0.144	**− 2.279**	**0.126**
		33%	**0.118**	**− 1.146**	**0.096**	0.160	− 2.940	0.143	0.157	− 2.783	0.137
		50%	0.246	− 5.293	0.224	0.317	− 9.506	0.305	0.267	− 6.463	0.250
		AVG	**0.164**	− 5.197	**0.141**	**0.187**	− 5.474	**0.173**	**0.178**	− 4.799	**0.161**
India	INCO	10%	0.461	− 15.381	0.435	0.380	− 10.436	0.363	0.430	− 13.646	0.419
		20%	0.334	− 2.164	0.278	0.301	− 1.572	0.243	0.331	− 2.105	0.286
		33%	0.303	**− 1.268**	**0.205**	**0.230**	**− 0.304**	**0.163**	**0.303**	**0.714**	**0.233**
		50%	**0.277**	− 1.671	0.229	0.240	− 1.000	0.190	0.305	− 2.228	0.272
		AVG	0.344	− 5.121	0.287	0.288	− 3.328	0.240	0.342	− 4.316	0.302

RMSE the root-mean-square error, *CE* coefficient of efficiency, *MAE* mean absolute error

Bold font stands for the minimum value for *RMSE* and *MAE*; Bold font is the highest value, close to 1 for *CE*

Table 12 The comparison of forecasting ability of neural network for consumer ETFs

Category	ETF	All variables			High GRG variables			Low GRG variables		
		RMSE	CE	MAE	RMSE	CE	MAE	RMSE	CE	MAE
BPN										
US	XLY	**0.358**	**− 27.850**	**0.333**	**0.333**	− 44.603	**0.374**	**0.434**	− 51.014	**0.407**
	XLP	**0.360**	**− 14.538**	**0.337**	0.434	− 26.237	0.414	0.399	− 23.215	0.372
EX− US	IPD	0.291	− 27.108	0.265	0.307	− 34.334	0.281	**0.368**	− 57.444	**0.341**
	IPS	0.231	**− 6.440**	0.216	0.256	− 8.572	0.246	**0.309**	**− 16.701**	**0.290**
Emerging Market	ECON	0.368	− 15.519	**0.268**	0.276	− 5.015	0.227	0.396	− 15.233	0.346
Brazil	BRAQ	0.357	− 2.769	0.319	0.302	− 1.641	0.262	0.272	− 1.432	0.243
China	CHIQ	0.212	− 13.336	0.147	0.176	− 4.962	0.164	0.227	− 10.471	0.186
India	INCO	0.434	− 9.856	0.326	0.253	− 2.468	0.206	0.391	− 5.383	0.331
RNN										
US	XLY	0.371	− 30.745	0.347	0.396	**− 40.812**	0.376	0.447	**− 50.998**	0.422
	XLP	0.363	− 15.245	0.341	**0.419**	**− 22.617**	**0.400**	**0.345**	**− 9.833**	**0.319**
EX-US	IPD	**0.276**	**− 26.344**	**0.251**	**0.286**	**− 25.859**	**0.263**	0.377	**− 56.655**	0.345
	IPS	**0.225**	− 8.441	**0.211**	**0.239**	**− 6.261**	**0.231**	0.326	− 17.791	0.309
Emerging Market	ECON	0.405	− 20.362	0.279	**0.158**	**− 0.822**	**0.138**	0.442	− 19.488	0.361
Brazil	BRAQ	0.364	− 3.818	0.322	0.336	− 2.418	0.295	0.340	− 3.305	0.294
China	CHIQ	0.360	− 25.707	0.259	**0.152**	**− 3.710**	**0.141**	0.325	− 21.589	0.222
India	INCO	0.481	− 12.874	0.354	**0.215**	**− 1.464**	**0.185**	0.471	− 12.789	0.396
RBFNN										
US	XLY	0.469	− 62.328	0.445	0.460	− 62.766	0.439	0.471	− 58.356	0.446
	XLP	0.470	− 31.867	0.449	0.463	− 29.751	0.444	0.475	− 31.163	0.455
EX− US	IPD	0.435	− 69.655	0.408	0.444	− 71.299	0.417	0.382	− 67.465	0.350
	IPS	0.398	− 24.059	0.387	0.354	− 21.306	0.344	0.347	− 21.938	0.331
Emerging Market	ECON	0.340	− 9.347	0.321	0.327	− 8.354	0.306	**0.310**	**− 7.226**	**0.289**

Table 12 (continued)

Category	ETF	All variables			High GRG variables			Low GRG variables		
		RMSE	CE	MAE	RMSE	CE	MAE	RMSE	CE	MAE
Brazil	BRAQ	**0.243**	− 0.958	**0.200**	**0.239**	**− 0.853**	**0.194**	**0.241**	**− 0.883**	**0.199**
China	CHIQ	0.194	− 6.107	0.179	0.179	− 5.180	0.164	**0.176**	− 6.734	**0.157**
India	INCO	**0.336**	**− 4.879**	0.290	0.330	− 4.175	0.282	**0.314**	**− 4.155**	**0.272**
TDRNN										
US	XLY	0.469	− 58.185	0.446	0.455	− 57.145	0.431	0.484	− 63.685	0.461
	XLP	0.459	− 28.246	0.438	0.453	− 28.196	0.433	0.472	− 30.617	0.451
EX− US	IPD	0.414	− 56.939	0.387	0.416	− 59.130	0.391	0.440	− 70.567	0.412
	IPS	0.382	− 20.805	0.370	0.372	− 19.474	0.362	0.403	− 30.234	0.390
Emerging Market	ECON	**0.334**	**− 9.166**	0.306	0.285	− 6.012	0.265	0.367	− 11.623	0.340
Brazil	BRAQ	0.249	**− 0.939**	0.208	0.267	− 1.273	0.227	0.243	− 1.733	0.205
China	CHIQ	**0.164**	**− 5.197**	**0.141**	0.187	− 5.474	0.173	0.178	**− 4.799**	0.161
India	INCO	0.344	− 5.121	**0.287**	0.288	− 3.328	0.240	0.342	− 4.316	0.302

Use Average of RMSE the root-mean-square error, *CE* coefficient of efficiency, *MAE* mean absolute error

Bold font stands for the minimum value for *RMSE* and *MAE*; Bold font is the highest value, close to 1 for *CE*

such as ECON, CHIQ, and BRAQ, are suitable for selecting different percentage data for prediction.

We compare the forecastability for consumer ETFs as shown in Table 12. The BPN and RNN models have the lowest values for consumer ETFs, based on the average use of RMSE, CE, and MAE. The specifications of all variables in the BPN model show that XLY and XLP have the lowest test values. Wang et al. (2013) found that the RNN model has a better forecast accuracy and generalization performance on real-time data. Using the RNN model, they revealed that the specifications of XLP, IPD, IPS, ECON, CHIQ, and INCO were suitable for higher GRG variables. The results showed that the RNN model has a relatively strong predictive capacity for high GRG variables. In contrast, RBFNN is the best predictor of low GRG variables. In line with Pradhan and Kumar (2008) conclusions, ANN models are a powerful tool to predict economic growth.

Compliance with Ethical Standards:

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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