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Nonlinear neural network forecasting model for stock index option price: Hybrid GJR–GARCH approach

Yi-Hsien Wang

Department of Finance, Yuanpei University, Hsin Chu 300, Taiwan, ROC

Abstract

This study integrated new hybrid asymmetric volatility approach into artificial neural networks option-pricing model to improve forecasting ability of derivative securities price. Owing to combines the new hybrid asymmetric volatility method can be reduced the stochastic and nonlinearity of the error term sequence and captured the asymmetric volatility simultaneously. Hence, in the ANNS option-pricing model, the results demonstrate that Grey-GJR–GARCH volatility provides higher predictability than other volatility approaches.

Keywords: Artificial neural networks; GARCH; Grey forecasting model; Option-pricing model

1. Introduction

Neural network model is an emerging computational technology that provides a new avenue for exploring the dynamics of various economic and financial applications. Artificial neural networks are an information processing technology for modeling mathematical relationships between input variables and output variables. Based on the construction of the human brain, a set of processing elements or neurons (nodes) are interconnected and organized in layers (Malliaris & Salchenberger, 1996). Recently, related researches have used of ANNs on the economic applications is expanding rapidly (Meraviglia, 1996; Shachmurove, 2005; Zhang & Berardi, 2001). For example, some studies have empirically rated bonds (Dutta & Shekar, 1988; Heston, 1993), some studies have empirically forecasted macroeconomic variables such as inflation, interest rates and exchange rate (Binner, Bissoondeeal, Elger, Gazely, & Mullineux, 2005; Plasmans, Verkooijen, & Daniels, 1998; Qi & Wu, 2003; Saltoglu, 2003). Furthermore, studies provided evidences of ANNs that to focus evaluation and prediction of consumer loans, corporate failures and bankruptcy (Ahn, Cho, & Kim, 2000; Altman, Marco, & Varetto, 1994; Mahlhotra & Malhotra, 2003; Tam & Kiang, 1992).

Most studies have focused on the estimation and forecast of financial data (Medeiros, Teräsvirta, & Rech, 2005). This approach is effective for input and output relationship modeling even for noisy data, and has been demonstrated to effectively model nonlinear relationships. Such as, related studies have empirically estimated and forecasted stock prices (Black & McMillan, 2004; Donaldson & Kamstra, 1996; Jasic & Wood, 2004; Kanas, 2001; Kanas & Yannopoulos1, 2001; Maasoumi & Racine, 2002; Qi, 1999; Rapach & Wohar, 2005; Shively, 2003) and stock volatilities (Dunis & Huang, 2002; Hamid & Iqbal, 2004). Moreover, major studies on derivative securities pricing using neural network have attracted researchers and practitioners, and they applied the neural network model and obtained better results than using the traditional option-pricing model (Amilon, 2003; Binner et al., 2005; Heston & Nandi, 2000; Hutchinson, Lo, & Poggio, 1994; Lin & Yeh, 2005; Malliaris & Salchenberger, 1996; Qi, 1999; Yao, Li, & Tan, 2000).

Therefore, given lessons learned from the existing literature, the purpose of our paper is twofold. Our first objective is to develop a new model for conditional stock

E-mail address: holland@mail2000.com.tw

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returns volatility which can capture important asymmetric effects that existing models do not capture. To this end we develop a ***Grey-GJR–GARCH*** approach to reduce the stochastic and nonlinearity of the error term sequence and then to improve the predicted ability of option-pricing model further. Our second objective is to integrate Grey-GJR–GARCH volatility approach into ***Artificial Neural Networks*** (ANNs), that has the functional flexibility to capture the nonlinearities in financial data.

Firstly, we employ the forecasting property of GM(1, 1) model to continually modify the squared error terms sequence (Deng, 1982), and the traditional symmetric GARCH model and GM(1, 1) model are combined, Grey-GJR–GARCH, to construct the conditional volatility. Moreover, we use different estimated volatility approaches, GARCH volatility, GJR–GARCH volatility, and Grey-GJR–GARCH, to estimate volatilities which these estimated volatilities provide an input in backpropagation ANN-pricing model in order to compare the performance of option-pricing. The remainder of this paper is organized as follows. section 2 outlines the different approaches to estimate volatility and demonstrates how each is calculated. Next, Section 3 describes the neural network model as prediction model. Moreover, Section 4 presents the empirical results. Finally, section 5 presents the conclusions.

2. Methodology

2.1. Option-pricing model

Black and Scholes (1973) provided the famous model, B-S option-pricing model, to estimate the price of derivatives. In this model, the reasonable price of an option is strongly dependent on the volatility of the pricing process of the underlying financial asset and assumed that stock prices follow the standard lognormal diffusion: $\mathrm{d}S_t/S_t = \mu d_t + \sigma \mathrm{d}W_t$, where S_t denotes the current stock price, μ represents the constant drift,σ is the constant volatility, and W_t denotes a standard Brownian motion. The standard Black–Scholes option-pricing formula for calculating the equilibrium price is

$$C_t = S_t N(d_1) - Xe^{-rt}N(d_2) \tag{1}$$

where $d_1 = [\ln(S_t e^{-rt}/X) + (r + \sigma^2/2)t]/(\sigma\sqrt{T})$; $d_2 = d_1 - \sigma\sqrt{t}$; C is the call price; S denotes the current underlying asset price; X is the exercise price; t denotes the time-to-maturity (in years); σ represents the volatility of the underlying asset; r is the short-term risk-free interest rate and $N(d_i)$ is the cumulative probability function for d_i, $i = 1,2$. Eq. (2) presents the Black–Scholes function (BS) in simple form.

$$\text{Option price} = \mathrm{BS}(S, X, t, \sigma, r) \tag{2}$$

All of the variables besides volatility are easily obtainable from the market. σ is the only unknown factor in the formulas, and is frequently assumed to be unchanged when forecasting option prices. Estimating the asset volatility thus becomes the focus of attention for both academics and practitioner and becomes the main issue.

2.2. Asymmetric volatility approach

Recently, empirical studies have found different estimating approaches around the volatility problem (Bates, 1996; Kim & Kim, 2004; Watanabe, 1999). As alternative to the historical and implied approach, numerous models are devised that correspond to the stochastic volatility process characteristic. One widespread approach is ARCH or general ARCH (GARCH), devised by Engle (1982) and Bollerslev (1986), respectively. This volatility approach is calculated using observations of historical daily asset prices and considering both the conditional and unconditional variance in the estimation process.

However, ARCH or GARCH approaches are failure to capture asymmetric features of returns behavior, volatility is not only time-varying but the future volatility is asymmetrically related to past innovation, with negatively unexpected returns influencing future volatility more than positively unexpected returns, may cause incorrect evaluation of asset pricing and lead to the inappropriate strategies of asset allocation. Hence, recent related studies attempt to developed asymmetric GARCH approaches to capture the asymmetric volatility and to promote the predictability of financial derivatives (Campbell & Hentschell, 1992; Ding, Engle, & Granger, 1993; Duan, 1995; Engle & Ng, 1993; Fornari & Mele, 1997; Hentschel, 1995; Nelson, 1991; Pagan & Schwert, 1990; Sabbatini & Linton, 1998; Szakmary, Ors, Kim, & Davidson, 2003; Zakoian, 1994). Additionally, to allow asymmetric volatility effects, Glosten, Jagannathan, and Runkle (1993) add an additional term in the conditional variance that to be the GJR–GARCH approach, the specification for the variance is defined as follows:

$$\sigma_t = \tau_0 + \sum_{j=1}^{q} \beta_j h_{t-i} + \sum_{i=1}^{p} \alpha_{1i}\varepsilon_{t-i}^2 + \alpha_2 S_{t-1}^- \varepsilon_{t-1}^2 \tag{3}$$

Here, $S_{t-1}^- = 1$ if $\varepsilon_{t-1} < 0$ and $S_{t-1}^- = 0$ if $\varepsilon_{t-1} \geqslant 0$. We denote this asymmetric GARCH or GJR–GARCH. The process is well-defined if the conditions $p \geqslant 0$, $q \geqslant 0$, $\tau_0 > 0$, $\alpha_i > 0$, $i = 1, 2, 3\ldots p$, $\beta_j > 0$, $j = 1,2,3 \ldots q$.

2.3. Hybrid asymmetric volatility approach

In general, the error terms sequence, ε_t, containing a mix of known and unknown information based on the set of past information at time t. The GM(1, 1)-GARCH offers a range of techniques for dealing with "grey" information sequence and therefore potentially assists the prediction of GARCH in an uncertainty time sequence. Consequently, this paper adopts the characteristics of GM(1, 1) to modify the error terms and propose the Grey-GJR–GARCH volatility approach. The procedures of error terms sequence's modification are as follows:

1. Define the original error terms, $\varepsilon^{(0)}$, where $\forall\varepsilon^{(0)}(i) \in \varepsilon^{(0)}$, $\varepsilon^{(0)}(i) \in R$, for $i = 1,2,3,\dots t$.

$$\varepsilon^{(0)} = \{\varepsilon^{(0)}(1), \varepsilon^{(0)}(2), \dots, \varepsilon^{(0)}(t)\} \tag{4}$$

2. Shift the original error terms sequence by adding the minimum value of the original sequence to meet the non-negative condition and the new sequence $\mu^{(0)}$ is given by

$$\mu^{(0)} = \{\mu^{(0)}(1), \mu^{(0)}(2), \dots, \mu^{(0)}(t)\} \tag{5}$$

where $\mu^{(0)}(i) = \varepsilon^{(0)}(i) + \min\ (\varepsilon^{(0)}(1), \dots, \varepsilon^{(0)}(t))$ and $\mu^{(0)}(i) \in R^{+}$ for $i = 1,2,3,\dots t$.

3. Obtain the first-order cumulative sum sequence $\mu^{(1)}$ from $\mu^{(0)}$ through once of accumulated generating operation (AGO).

$$\mu^{(1)} = \{\mu^{(1)}(1), \mu^{(1)}(2), \cdots, \mu^{(1)}(t)\} \tag{6}$$

where the generating series for the cumulative summation will be

$$\mu^{(1)}(i) = \left\{\sum_{k=1}^{i} \mu^{(0)}(k), \mathrm{i} = 1, 2, \dots, t\right\} \tag{7}$$

4. If the original error terms series $\mu^{(0)}$ lacks any apparent trend, the generating series $\mu^{(1)}$ would then have an apparent trend with an absolute value increasing one-by-one. This provides a basis for establishing a calculus using differential equations. When the differential equation model is of order one and includes just one variable, the model is referred as to as GM(1, 1). The general form of GM(1, 1) has the following form:

$$\frac{\mathrm{d}\mu^{(1)}}{\mathrm{d}t} + a\mu^{(1)} = b \tag{8}$$

5. In Eq. (8), a is the development coefficient and b is the grey control parameter. From the time response function of the first derivative, the general solution to Eq. (8) is:

$$\mu^{(1)}(i+1) = (\mu^{(0)}(1) - b/a)e^{-ai} + b/a \tag{9}$$

According to the definition of differential equation:

$$\frac{\mathrm{d}\mu^{(1)}(i)}{\mathrm{d}i} = \lim_{\Delta i \to 0} \frac{\mu^{(1)}(i+1) - \mu^{(1)}(i)}{\Delta i} \tag{10}$$

If $\Delta i = 1$, then Eq. (10) can be written as:

$$\frac{\mu^{(1)}(i+1) - \mu^{(1)}(i)}{1} = \mu^{(0)}(i) \tag{11}$$

Then the original differential equation can be described by:

$$\mu^{(0)}(i) + az^{(1)}(i) = b \tag{12}$$

where $\mathrm{z}^{(1)}(i)$ is the background value, and $\mathrm{z}^{(1)}(i) = \delta\mu^{(1)}(i) + (1-\delta)\mu^{(1)}(i-1)$, $i \geqslant 2$. δ denotes a horizontal adjustment coefficient, and $0 < \delta < 1$. Parameters a and b in Eq. (12) can be obtained from $\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = (B'B)^{-1}B'Y$, where $Y = \begin{bmatrix} \mu^{(0)}(2) & \mu^{(0)}(3) & \dots & \mu^{(0)}(t) \end{bmatrix}'$ and $B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & 1 \\ -z^{(1)}(t) & 1 \end{bmatrix}$.

6. Putting a and b obtained from the grey differential equation back into the general equation with $\hat{\mu}^{(1)} = \hat{\mu}^{(0)}(1) = \hat{\mu}^{(1)}(1)$. Since the prediction model is not constructed with original sequence but modes from one accumulative addition, reverse addition is required to recover the predicted sequence. From $\hat{\mu}^{(0)}(i+1) = \hat{\mu}^{(1)}(i+1) - \hat{\mu}^{(1)}(i)$, one can obtain Eq. (13), which is the dynamic situation of future values generated by the GM(1, 1).

$$\hat{\mu}^{(0)}(i+1) = (1 - e^{a})(\mu^{(0)}(1) - b/a)e^{-ai} \tag{13}$$

Finally, forecasted original error at time $t+1$ is given by

$$\hat{\varepsilon}^{(0)}(t+1) = (1 - e^{a})(\mu^{(0)}(1) - b/a)e^{-at} - \min(\varepsilon^{(0)}(1), \cdots, \varepsilon^{(0)}(t)) \tag{14}$$

After acquiring the forecasted error of time $t+1$ by GM(1, 1) model, we put this value in Eq. (3), GJR–GARCH approach, to estimate the conditional variance at time $t+1$. Hence, the one-step-ahead variance forecasts are generated by the above-mentioned procedures and the multiple conditional variance forecasts for evaluation period can be obtained by repeating this procedure.

3. Artificial neural networks

3.1. Backpropagation neural networks

Neural networks can be classified into feedforward and feedback networks. Feedback networks contain neurons that are connected to themselves, enabling a neuron to influence other neurons. Kohonen self-organizing network and Hopfield network are the type of feedforward network. Backpropagation neural network, take inputs only from the previous layer and send outputs only to the next layer (see Fig. 1).

This study employs a backpropagation neural network, the most widely used network in business applications. A

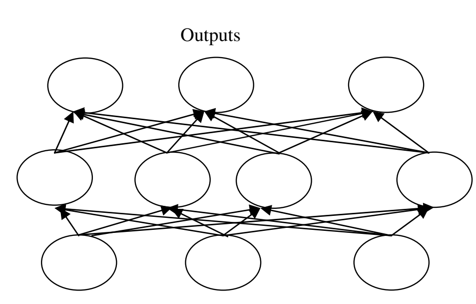

Fig. 1. Backpropagation neural network.

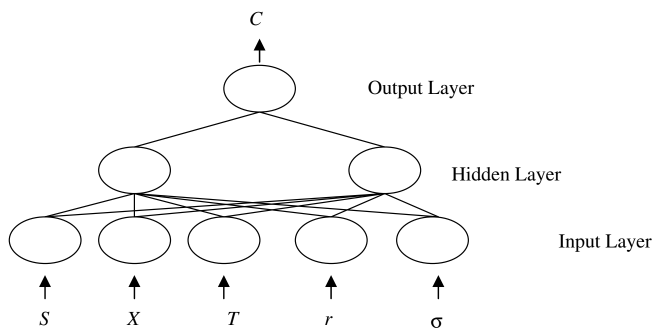

Fig. 2. One hidden layer neural network.

three-layer backpropagation neural network is shown in Fig. 2. The backpropagation process determines the weights for the connections among the nodes based on data training, yielding a minimized least-mean-square error measure of the actual, desired and the estimated values from the output of the neural network. The connections weights are assigned initial values. Furthermore, the error between the predicted and actual output values is back-propagated via the network for updating the weights. The supervised learning procedure then attempts to minimize the error between the desired and forecast outputs. Theoretically, neural networks can simulate any kind of data pattern given sufficient training. The neural network must be trained before being applied for forecasting. During the training procedure, the neural network learns from experience based on the proposed hypotheses. Besides, this study employs one hidden layer for each neural network model and the sigmoid function serves as the activation function.

3.2. Evaluation of ANNs forecasting model with different volatility

Furthermore, three loss functions are also considered to be the criteria to evaluate the forecasting performance relative to the market real price, C_n^{MP}, measure of different volatility, including mean absolute error (MAE), root mean-square error (RMSE), and mean absolute percentage error (MAPE). The loss functions are expressed as follows:

$$\mathrm{MAE} = T^{-1}\sum_{n=1}^{T} |C_n^{\mathrm{MP}} - C_n(\sigma_i)^{1/2}| \tag{15}$$

$$\mathrm{RMSE} = \left(T^{-1}\sum_{n=1}^{T} (C_n^{\mathrm{MP}} - C_n(\sigma_i)^{1/2})^2\right)^{1/2} \tag{16}$$

$$\mathrm{MAPE} = T^{-1}\sum_{n=1}^{T} |(C_n^{\mathrm{MP}} - C_n(\sigma_i)^{1/2})/C_n^{\mathrm{MP}}| \tag{17}$$

The forecasting performance is better when the value is smaller, and if the results are not consistent among three criterions, we choose the MAPE, suggested by Makridakis (1993), to be the benchmark with relative stable than other two criteria.

4. Preliminary analysis and empirical results

4.1. Basic statistics description

In December 24 2001, the Taiwan Futures Exchange (TAIFEX) introduced the Taiwan stock index options (TXO). The TXO market has since become one of the fastest growing markets in the world, with annual trading volume reached 3 million contracts in 2006. The data used in this study is transaction data of Taiwan stock index options (TXO) traded on the Taiwan Futures Exchange (TAIFEX). This study investigated a sample of 21,120 call option price data from January 3, 2005 through December 29, 2006. Only traded prices were used. The trend of Taiwan stock market and return are shown in Figs. 3 and 4, respectively.

Table 1 (Panel A) lists the basic statistics of daily Taiwan stock market during the sample period. The statistics include the sample size, mean return, standard deviation, skewness, kurtosis, the median, minimum, maximum

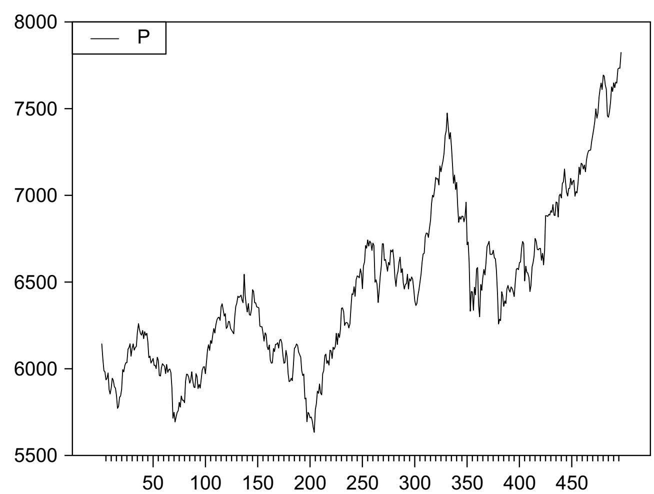

Fig. 3. The trend graph of taiex.

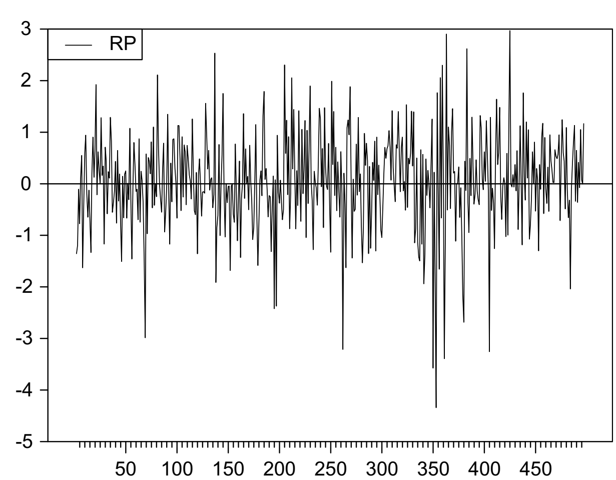

Fig. 4. The trend graph of taiex returns.

Table 1
Description for taiex returns

Panel A. Basic statistics			
Mean	0.0099	Std. Dev.	1.7328
Maximum	12.4303	Minimum	−16.1354
Skewness	−0.1209**	Kurtosis	8.7343**
$Q^2(6)$	553.1136**	$Q^2(12)$	684.2160**
ADF test	−36.5821**	P–P test	−78.9974**
Jarque–Bera	8461.5316**		

Panel B. Volatility asymmetry test				
ARCH (3)	SBT	NSBT	PSBT	JT
34.9007**	3.5571 **	−5.4827 **	−2.1349**	35.3113**

Notes: 1. **(*) denotes statistical significance at 1%(5%) level. 2. *ARCH* denotes the Lagrange Multiplier test of Engle (1982) and the criterion is 7.82 at the 5% significant level. 3. SBT, NSBT and PSBT denote the sign bias test, negative size bias test and positive size bias test respectively and the criterion is 2.353 at the 5% significant level. 4. JT denotes the joint test and the criterion is 7.82 at the 5% significant level.

returns, Jarque–Bera test statistic and Ljung–Box Q test statistics. Regarding, the TAIEX has the circulation tendency but the real situation in the Fig. 3 is still presented a rise tendency. Notably, the shape of the TAIEX show clearly random walk and non-normal distribution, and TAIEX returns reveal the volatility clustering, that is the tendency for volatility periods of similar magnitude to cluster. Moreover, based on the examination Table 1 (Panel B), the volatility of TAIEX returns exhibits conditional herters-cedastical and asymmetry. Therefore, usually asymmetric GARCH models can take into account the time-varying volatility phenomenon over a long period and provide very good in-sample estimates.

4.2. Empirical results

This study uses as inputs the primary Black–Scholes model variables that influence the option price, such as, current fundamental asset price, strike price and time-to-maturity, and then defines the option price as the output into which the learning network maps the inputs. Given proper training, the network "becomes" the option-pricing formula, and used in the same way that formulas obtained from the parametric pricing method are used for pricing. When the study began, the time-to-maturity based on the trading and expiration dates was calculated first. The option strike price is the price agreed upon in the option contact. When the contract expires, the market price should be the same as the strike price. If the market price of an underlying asset is below the strike price, the option holder will not exercise the option because to do so would not be profitable. Furthermore, if the market price exceeds the strike price, then exercising option will be profitable.

Table 2
Data partition according to moneyness

Subset	Moneyness	Number
In-the-money	$S/X > 1.02$	6713
At-the-money	$0.95 < S/X \leqslant 1.02$	7275
Out-of-the-money	$S/X \leqslant 0.95$	7132

Notes: S is the current underlying asset price; X is the strike price.

While the Black–Scholes function of Eq. (2) holds, S,X,T,σ,r can be used as the inputs, and the option price can be used as the output for establishing a neural network. To mitigate the influence of price discreteness on option valuation, the volume of every trade was below five were excluded. Different strike prices occur on a trading day. This study divides the option data into three subsets according to the moneyness (S/K), including in-the-money, at-the-money and out-of-the-money. Quotients of stock prices to strike prices of less than 0.95, between 0.95 and 1.02 and exceeding 1.02 are used for data partitioning and to balance the number in neural network of different sets. Table 2 lists all the sets used.

This study employs 70% of the data from the data set as the training set, the remaining 30% then comprises the testing set (Yao et al., 2000). Given these preparations, this study uses moneyness, the time-to-maturity, risk-free rate and volatility as inputs and the option price as outputs in the neural network. In Fig. 5, Grey-GJR–GARCH volatility exhibited the markedly better ability to capture the asymmetric effect of conditional heteroskedasticity than GARCH and GJR–GARCH volatility. Additionally, the

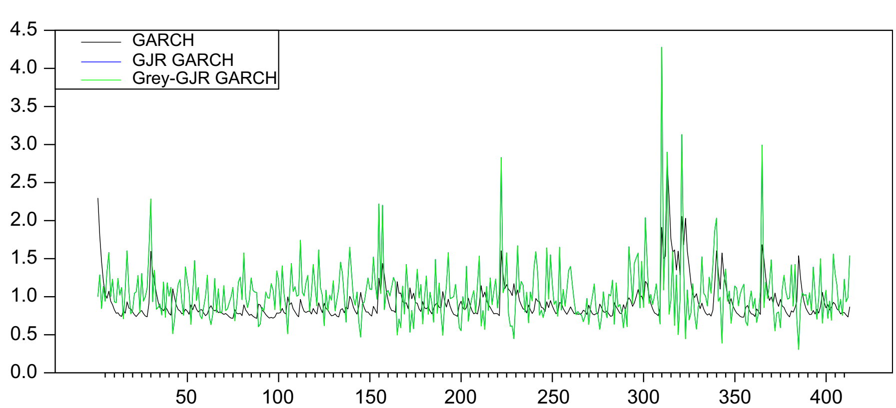

Fig. 5. The graph of taiex returns volatilities.

Table 3
Volatility approach results in RMSE, MAE and MAPE

Indices/Moneyness	RMSE			MAE			MAPE		
	GARCH	GJR	Grey-GJR	GARCH	GJR	Grey-GJR	GARCH	GJR	Grey-GJR
In	85.49	76.19	73.76*	67.54	59.28	56.13*	0.16	0.14	0.12*
At	44.02	41.06*	40.11	34.73	31.67	30.21*	3.98	3.68	3.59*
Out	25.73	25.53*	25.89	18.78	17.41*	17.26	17.25*	18.33	18.33

Notes: 1. * denotes the smallest value. 2. GJR denotes GJR–GARCH model. 3. Grey-GJR denotes Grey-GJR–GARCH model.

Grey-GJR–GARCH volatility employed grey modeling (GM(1,1)) to reduce the stochastic and nonlinearity of the error term sequence, and then to forecast the parameter estimates to further adjust the transformation of the error term sequence.

Moreover, Table 3 lists the neural network for the different volatility models results in RMSE, MAE and MAPE. First, for the in-the-money option, the Grey-GJR–GARCH volatility has smaller testing error than the other nonlinear approaches (GARCH volatility and GJR–GARCH volatility). For the at-the-money option, the Grey-GJR–GARCH volatility has smaller testing error than the other nonlinear approaches in MAE and MAPE. Finally, for the out-of-the-money options, the approach with the smaller testing error is the GARCH volatility. For the evaluation of three loss functions, our findings show that the hybrid asymmetric volatility approach which combines grey forecasting model with the GJR–GARCH model is indeed beneficial for enhancing the option price forecasts of the popular GARCH volatility and traditional GJR–GARCH volatility, although Grey-GJR–GARCH volatility fails to beat GARCH volatility and traditional GJR–GARCH volatility for some cases.

Finally, the performances of each volatility approach are using Wilcoxon sign-rank test in Table 4. The P_G represents the option pricing model evaluated using GARCH volatility approach, P_{G-GJR}represents the model evaluated using Grey-GJR–GARCH volatility approach, P_{GJR} represents the model evaluated using GJR–GARCH volatility approach. In Table 4, all Z statistics are statistically significant at the 5% significance level. These indicate that there existed significant difference in the option-pricing model evaluated using three volatility approaches.

Table 4
Wilcoxon sign -rank test

Hypothesis/ Moneyness	H_0: P_G–P_{GJR}	H_0: P_G–P_{G-GJR}	H_0: P_{GJR}–P_{G-GJR}
In-the-money	−38.08	−38.36	−38.62
At-the-money	−39.73	−39.66	−39.21
Out-of-the-money	−39.32	−38.92	−38.11

Notes: 1. ** (*) denotes statistical significance at 1%(5%) level. 2. The values in Wilcoxon sign-rank test are all significance at 5% level. 3. Wilcoxon sign-rank test is then applied to calculate the statistical significance of the error in the different volatility: $Z = \frac{R^+ - E(R^+)}{\sqrt{Var(R^+)}} \sim N(0,1)$ where $E(R^+) = n(n+1)/4$, $Var(R^+) = n(n+1)(2n+1)/24$.

5. Conclusions

This study applies the nonlinear neural network forecast models with different volatility approaches to investigate the predictability of Taiwan stock index option price. Overall, the in-the-money option is valuable to call option price and the empirical result exhibits that The empirical result has been demonstrated to the in-the-money option Grey-GJR–GARCH volatility approach has relatively good market forecasting ability for TXO. Moreover, the Grey-GJR–GARCH volatility approach achieves better forecasting performance than GARCH and traditional GJR–GARCH volatility approaches.

The predictability of market volatility is important for options practitioners to forecast closing prices and determine expected market return. Estimating stock market volatility has received considerable attention by both academics and practitioners. Owing to the error term always exist ‘‘noise’’ in an econometric model, the error term sequence was possessed of unpredictable random and nonlinear phenomena. Therefore, in this paper we adjust the error term sequence to solve the stochastic and nonlinear problems on the basis of grey prediction model (GM(1,1)). This result reveals that Grey-GJR–GARCH volatility employs the forecasting property of the GM(1,1) to continually modify the squared error terms sequence, and combines the traditional symmetric GARCH for estimating the volatility. Therefore, Grey-GJR–GARCH approach promoted the pricing predictability of ANNs forecasting model on financial derivatives in the emerging stock market.

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