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Artificial neural network model of the hybrid EGARCH volatility of the Taiwan stock index option prices

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Abstract

This investigation integrates a novel hybrid asymmetric volatility approach into an Artificial Neural Networks option-pricing model to upgrade the forecasting ability of the price of derivative securities. The use of the new hybrid asymmetric volatility method can simultaneously decrease the stochastic and nonlinearity of the error term sequence, and capture the asymmetric volatility. Therefore, analytical results of the ANNS option-pricing model reveal that Grey-EGARCH volatility provides greater predictability than other volatility approaches.

Keywords: Artificial neural networks; EGARCH; Grey forecasting model

1. Introduction

The neural network model is an emerging computational technology that provides a new avenue for examining the dynamics of various economic and financial applications. The application of ANNs to model economic conditions is expanding quickly [54,36,46]. For instance, some studies empirically forecast macroeconomic variables such as inflation, interest rates and exchange rate [38,40,44,5,16], and others have adopted ANNs to model the evaluation and prediction of consumer loans, corporate failures and bankruptcy [49,2,1,32].

Most studies focus on the estimation and forecasting of financial data. This approach is effective for input and output relationship modeling even for noisy data, and has been revealed to model nonlinear relationships effectively. For instance, related investigations have empirically estimated and forecasted stock prices [12,39,27,28,34,47,7,26,42] and stock volatilities [15,19]. Furthermore, modeling derivative security pricing with neural networks has been found to achieve better results than the traditional option-pricing model [25,39,53,3,5,29].

Therefore, this study has two aims based on the existing literature. The first objective is to develop a novel model for conditional stock returns volatility to capture important asymmetric effects that are not captured by existing models.

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Accordingly, a ***Grey-EGARCH*** approach is developed to decrease the stochasticity and nonlinearity of the error term sequence, and then further elevate the predicted ability of option-pricing model. The second goal is to integrate the ***Grey-EGARCH*** volatility approach into ***Artificial Neural Networks*** (ANNs), providing the functional flexibility to capture the nonlinearities in financial data. First, the forecasting property of GM(1,1) model is employed to continually modify the squared error terms sequence [11]. The traditional symmetric GARCH model and GM(1,1) model are combined as ***Grey-EGARCH*** to build the conditional volatility. Furthermore, different estimated volatility approaches, ***EGARCH*** volatility and ***Grey-EGARCH***, are applied to estimate volatilities, which are utilized to provide input to the backpropagation ANN-pricing model in order to compare the performance of option-pricing models.

2. Methodology

2.1. Option-pricing model

In the well-known B–S option-pricing model to estimate the price of derivatives [6], the reasonable price of an option is strongly dependent on the volatility of the pricing process of the underlying financial asset. Hence, the stock prices are assumed to follow the standard lognormal diffusion: $\mathrm{d}S_t/S_t = \mu\,\mathrm{d}_t + \sigma\,\mathrm{d}W_t$, where S_t indicates the current stock price; μ denotes the constant drift; σ represents the constant volatility, and W_t denotes a standard Brownian motion. The standard Black–Scholes option-pricing formula for computing the equilibrium price is

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

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

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

All these variables apart from volatility are easily obtainable from the market. The only unknown factor in the formulae is σ, and it is frequently assumed to be unchanged when forecasting option prices. Estimating the asset volatility thus becomes the focus of attention for both academics and practitioners, and becomes the main issue [45,14,22,24,43].

2.2. Asymmetric volatility approach

Recently, numerous models based on the stochastic volatility process have been proposed as alternatives to the historical and implied approach. One widespread method is ARCH or GARCH [17,8,18]. In these approaches, the volatility is derived with observations of historical daily asset prices and addressing both the conditional and unconditional variance in the estimation process. However, ARCH or GARCH approaches fail to capture asymmetric features of returns behavior. Not only is volatility time-varying, but future volatility is asymmetrically linked to past innovation, with negatively unexpected returns affecting future volatility more than positively unexpected returns, may result in incorrect evaluation of asset pricing, and produce unsuitable asset allocation strategies. Therefore, related research seeks to develop asymmetric GARCH approaches to capture the asymmetric volatility, and to encourage the predictability of financial derivatives [41,13,23,35].

Motivated by the existing empirical literature about the market volatility, we assume here that second-order moments fit to an EGARCH process, introduced by Nelson [37]. Unlike ARCH or GARCH, the EGARCH model imposes no positive constraints on estimated parameters and explicitly accounts for asymmetry in market return volatility, thereby avoiding possible misspecification in the volatility process. Therefore, to enable asymmetric volatility effects, Nelson [37] add an extra term in the conditional variance that to be the ***Grey-EGARCH*** approach, the specification for the variance is defined as follows:

$$R_t = \omega + \sum_{i=1}^{n} a_i R_{t-i} + \varepsilon_t \tag{3}$$

$$\varepsilon_t | \Phi_{t-1} \sim t\,(0, h_t) \tag{4}$$

$$\ln h_t = \tau + \alpha\left[|u_{t-1}| - E\,|u_{t-1}| + \theta u_{t-1}\right] + \beta \ln h_{t-1}. \tag{5}$$

Where in equation (4), central t distribution allows stock returns have thicker tails, but is still symmetric [20,21,4]. Therefore, we assume that TAIEX returns come from a non-central t distribution. Furthermore, in equation (5), EGARCH model stressed an asymmetric function for past innovation shocks. u_t is the innovation standardized by dividing the random error by conditional variance, $u_t{=}\varepsilon_t/\sqrt{h_t}$. In other words, $(|u_{t-1}| - E\,|u_{t-1}|)$ signifies the impact magnitude, size effect, coming from the unexpected shock and θu_{t-1} indicates the sign effect in which the impact goes. Under such the condition, the positive coefficient, θ, denotes the nonexistence of asymmetric volatility, while θ is negative, which is also statistically significant, represents the presence of leverage effect. Moreover, $\beta \ln h_{t-1}$ denotes the linkage between current volatility and past volatility. When β is positive and statistically significant, it denotes that current volatility is a function of past volatility. Furthermore, to be as parsimonious as possible as suggested by Bollerslev et al. [9], EGARCH (1,1) model is practiced to capture the asymmetric volatility.

2.3. Hybrid asymmetric volatility approach

The error terms sequence, ε_t, contains a mix of known and unknown information based on the set of past information at time t. The GM(1,1)-GARCH provides a range of techniques for managing "grey" information sequence, and thus potentially aids the prediction of GARCH in an uncertainty time sequence.[1]

Consequently, this investigation utilizes the attributes of GM(1,1) to alter the error terms, and develops the Grey-GJR-GARCH volatility approach. The procedures of modification of error terms sequences 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 $i = 1, 2, 3, \ldots t$.

$$\varepsilon^{(0)} = \left\{\varepsilon^{(0)}(1), \varepsilon^{(0)}(2), \ldots, \varepsilon^{(0)}(t)\right\}. \tag{6}$$

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

$$\mu^{(0)} = \left\{\mu^{(0)}(1), \mu^{(0)}(2), \ldots, \mu^{(0)}(t)\right\} \tag{7}$$

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

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

$$\mu^{(1)} = \left\{\mu^{(1)}(1), \mu^{(1)}(2), \ldots, \mu^{(1)}(t)\right\} \tag{8}$$

   where the generating series for the cumulative summation will be

$$\mu^{(1)}(i) = \left\{\sum_{k=1}^{i} \mu^{(0)}(k), i = 1, 2, \ldots, t\right\}. \tag{9}$$

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:

$$\frac{\mathrm{d}\mu^{(1)}}{\mathrm{d}t} + a\mu^{(1)} = b. \tag{10}$$

5. In Eq. (10), 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. (11) is:

[1] In recent years, related researches have used GM(1,1) on the economic and financial applications is expanding rapidly. Some studies provided evidences of Grey forecasting model to evaluate and predict consumer loans, corporate failures and bankruptcy [30,48,31], some studies focus on derivative securities pricing using GM(1,1) to promote the predictability of different option-pricing models that have attracted researchers and practitioners (Chang, 2005; Lin and Yeh, 2007). Moreover, major studies have empirically forecasted empirically estimated and forecasted stock market (Chang et al. 2000), [50–52,10].

$$\mu^{(1)}(i+1) = (\mu^{(0)}(1) - b/a)\mathrm{e}^{-ai} + b/a. \tag{11}$$

According to the definition of differential equation:

$$\frac{\mathrm{d}\mu^{(1)}(i)}{\mathrm{d}i} = \lim_{\Delta i \to 0} \frac{\mu^{(1)}(i+1) - \mu^{(1)}(i)}{\Delta i}. \tag{12}$$

If $\Delta i = 1$, then Equation (12) can be written as:

$$\frac{\mu^{(1)}(i+1) - \mu^{(1)}(i)}{1} = \mu^{(0)}(i). \tag{13}$$

Then the original differential equation can be described by:

$$\mu^{(0)}(i) + az^{(1)}(i) = b \tag{14}$$

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

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).

$$\hat{\mu}^{(0)}(i+1) = (1 - \mathrm{e}^{a})(\mu^{(0)}(1) - b/a)\mathrm{e}^{-ai}. \tag{15}$$

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

$$\hat{\varepsilon}^{(0)}(t+1) = (1 - \mathrm{e}^{a})(\mu^{(0)}(1) - b/a)\mathrm{e}^{-at} - \min\left(\varepsilon^{(0)}(1), \ldots, \varepsilon^{(0)}(t)\right). \tag{16}$$

After acquiring the forecasted error of time $t+1$ by GM(1,1) model, we put this value in Equation (5), EGARCH 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. The forecast of h_t given information at time $t-1$ and the one-step-ahead conditional variance forecast for time $t+1$ is given by

$$\ln h_{t+1} = \hat{\tau} + \hat{\alpha}\left[|u_{t-1}| - E\,|u_{t-1}| + \hat{\theta}u_{t-1}\right] + \hat{\beta}\ln h_t \tag{17}$$

where the parameter estimates used are obtained by the EGARCH, and the parameters are the fitted values for the squared error and the conditional variance for observations from 1 to T. We divide the observations into an estimation period and an evaluation period:

$$t = \underbrace{-T+1, \ldots, 0}_{\text{estimation period}}, \quad \underbrace{1, \ldots, R.}_{\text{evaluation period}}$$

It is worth noting that multiple one-step-ahead conditional variance forecast are replaced by repeating the above-mentioned one-step-ahead conditional variance forecast. In other words, we employ the procedure of rolling window to re-estimate the models for the reserving R observations. Out-of-sample conditional variance forecasts were based on these estimates and these estimates ($\hat{\tau}$, $\hat{\alpha}$, $\hat{\beta}$) were updated daily. The multiple conditional variance forecasts for the reserving R observations can be generated by

$$\ln h_{t+i} = \hat{\tau}_i + \hat{\alpha}_i\left[|u_{t-1+i}| - E\,|u_{t-1+i}| + \hat{\theta}_i u_{t-1+i}\right] + \hat{\beta}_i \ln h_{t-1+i} \quad \text{for } i = 1, 2, \ldots, R. \tag{18}$$

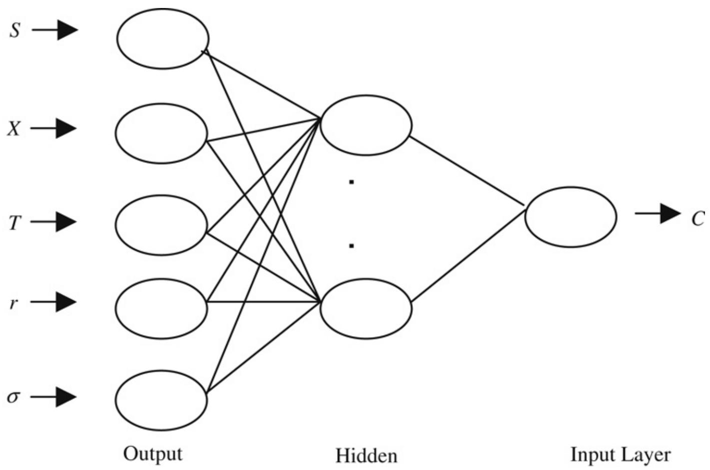

Fig. 1. One hidden layer neural network.

3. Artificial neural networks

3.1. Backpropagation neural networks

Neural networks can be categorized into feedforward and feedback networks. Feedback networks contain neurons that are linked to themselves, allowing a neuron to affect other neurons. Kohonen self-organizing network and Hopfield network are the feedforward networks. Backpropagation neural networks take inputs only from the previous layer, and send outputs only to the next layer.

This study applies a backpropagation neural network, which is the most widely utilized network in business applications. Fig. 1 depicts a three-layer backpropagation neural network. The backpropagation process calculates the weights for the connections among the nodes according to the results of data training, forming a minimized least-mean-square error measure of the actual, required and estimated values from the output of the neural network. The connections weights are assigned initial values. Moreover, the error between the predicted and actual output values is backpropagated via the network to update the weights. The supervised learning procedure then seeks to minimize the error between the desired and forecast outputs. Neural networks can theoretically simulate any data patterns given sufficient training. The neural network needs to be trained before it can be applied for forecasting. The neural network learns from experience based on the proposed hypotheses during the training procedure. This study uses one hidden layer for each neural network model, and the sigmoid function acts as the activation function.

4. Preliminary analysis and empirical results

4.1. Basic statistics description

The Taiwan Futures Exchange (TAIFEX) introduced the Taiwan stock index options (TXO) in December 24, 2001. The TXO market has since become one of the fastest growing markets in the world, with annual trading volume reaching 3 million contracts in 2006. The data utilized in this investigation were the transaction data of Taiwan stock index options (TXO) traded on the Taiwan Futures Exchange (TAIFEX). A sample comprising 21,120 call option price data from January 3, 2005 through December 29, 2006 was studied OR examined. Only traded prices were employed.

Fig. 2 reveal the trend of Taiwan stock return and Table 1 (Panel A) presents the basic statistics of the daily Taiwan stock returns in the sample period. The statistics include the sample size, mean return, standard deviation, skewness, kurtosis, the median, minimum, maximum returns, Jarque–Bera test statistic and Ljung–Box Q test statistics. Interestingly, the shape of the TAIEX clearly reveal random walk and non-normal distribution, and TAIEX returns reveal volatility clustering, which is the tendency for volatility periods of similar magnitude to cluster. Furthermore, Table 1 (Panel B), indicates that the volatility of TAIEX returns exhibits conditional heterscedasticity and asymmetry.

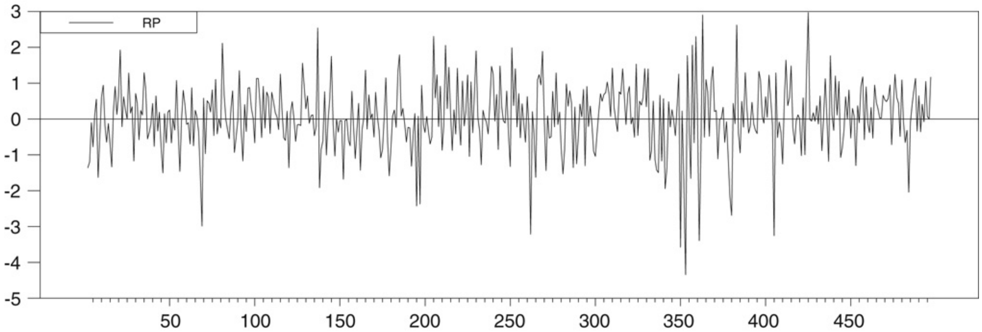

Fig. 2. The trend graph of TAIEX returns.

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**	$Q^2(9)$	684.2160**
ADF test	−36.5821**	P–P test	−78.9974**
Jarque–Bera	8461.5316**		

Panel B. Volatility asymmetry test				
ARCH(2)	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 [17] 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.

Hence, asymmetric GARCH models can normally address the time-varying volatility phenomenon over a long period, and provide very good in-sample estimates.

4.2. Empirical results

This study employed as inputs the primary Black–Scholes model variables that affect the option price. These variables are the current fundamental asset price, strike price and time-to-maturity. The option price was then defined as the output into which the learning network maps the inputs. Given appropriate training, the network "becomes" the option-pricing formula, and is utilized like formulae obtained from the parametric-pricing method are used for pricing. The time-to-maturity based on the trading and expiration dates was initially obtained when the study started. The option strike price is the price agreed upon in the option contact. The market price should be the same as the strike price when the contract expires. If the market price of an underlying asset is below the strike price, then the option holder does not exercise the option, because to do so would not be profitable. Moreover, if the market price exceeds the strike price, then exercising the option is profitable.

While the Black–Scholes function of Eq. (2) holds, S, X, T, σ, r can be applied as the inputs, and the option price can be utilized as the output for establishing a neural network. To mitigate the impact of price discreteness on option valuation, trades with volumes below 5 were excluded. Different strike prices occur on a trading day. This study divided the option data into three subsets according to the moneyness (S/K), namely 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 were adopted for data partitioning, and to balance the numbers of neural networks in different sets. Table 2 lists all of the sets used.

This study used 70% of the data from the data set as the training set. The remaining 30% was adopted as the testing set [53]. Given these preparations, this study utilized moneyness, the time-to-maturity, risk-free rate and volatility

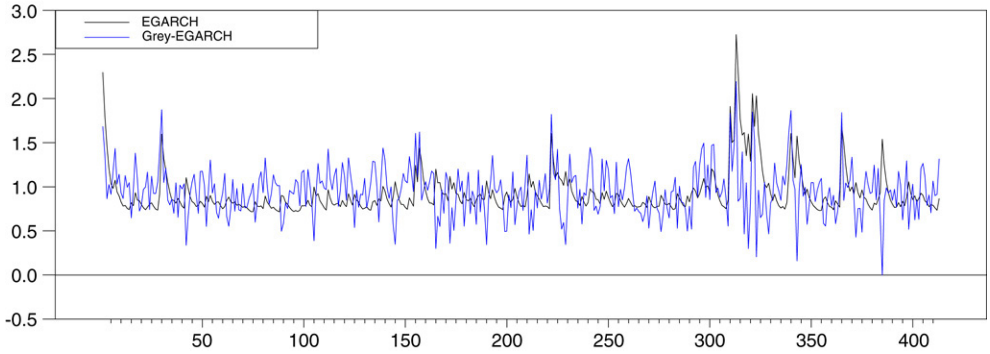

Fig. 3. The comparison of different volatility approaches.

Table 2
Data partition according to moneyness

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

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

as inputs and the option price as outputs in the neural network. According to Fig. 3, *Grey-EGARCH* volatility exhibited markedly better ability to capture the asymmetric effect of conditional heterscedasticity than EGARCH volatility. Additionally, the *Grey-EGARCH* 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 modify the transformation of the error term sequence.

Table 3 presents the neural network for the different volatility models results in RMSE, MAE and MAPE and these loss functions are also considered to be the criteria to evaluate the forecasting performance relative to the market real price. Thus, for the in-the-money and out-the-money option, the Grey-EGARCH volatility has a smaller testing error than the traditional EGARCH volatility approaches. For the at-the-money option, the Grey-EGARCH volatility has a smaller testing error than the other nonlinear approaches in RMSE. Finally, the approach with the smallest testing error for the in-the-money options is the EGARCH volatility in MAE, and the at-the-money options is the EGARCH volatility in MAE and MAPE. For the evaluation of three loss functions, the findings of this work demonstrate that the hybrid asymmetric volatility approach combining the grey forecasting model with the EGARCH model is indeed beneficial for elevating the option price forecasts of the traditional EGARCH volatility, although Grey-EGARCH volatility fails to beat traditional EGARCH volatility in some cases.

5. Conclusions

This study applies the nonlinear neural network forecast models with different volatility approaches to explore the predictability of Taiwan stock index option prices. Overall, the in-the-money option is useful for predicting option prices. Empirical results reveal that the in-the-money option Grey-EGARCH volatility approach has the best market forecasting ability for TXO. Furthermore, the Grey-EGARCH volatility approach achieves better forecasting performance than traditional EGARCH volatility approaches.

The predictability of market volatility is significant for options practitioners in predicting closing prices and determining the expected market return. Estimating stock market volatility has received considerable attention from both academics and practitioners. Since an econometric model always has the error term “noise”, the error term sequence has unpredictable random and nonlinear phenomena. Therefore, this study modifies the error term sequence to solve stochastic and nonlinear problems on the basis of the grey prediction model. The result of this analysis demonstrates that Grey-EGARCH volatility adopts 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. Hence,

Table 3
Volatility approach results in RMSE, MAE and MAPE

Moneyness	Indices					
	RMSE		MAE		MAPE	
	EGARCH	Grey-EGARCH	EGARCH	Grey-EGARCH	EGARCH	Grey-EGARCH
In	73.90	72.11*	57.02*	57.26	0.13	0.12*
At	41.35	40.26*	32.17*	32.51	3.60*	3.66
Out	26.34	26.13*	18.30	18.26*	18.25	17.96*

Notes: 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:

$$\text{MAE} = T^{-1}\sum_{n=1}^{T}\left|C_n^{MP} - C_n(\sigma_i)^{1/2}\right|$$

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

$$\text{MAPE} = T^{-1}\sum_{n=1}^{T}\left|(C_n^{MP} - C_n(\sigma_i)^{1/2})/C_n^{MP}\right|.$$

The forecasting performance is better when the value is smaller, and if the results are not consistent among three criteria, we choose the MAPE, suggested by Makridakis [33], to be the benchmark with relative stable than other two criteria. * is the smallest value.

Grey-EGARCH approach enhances the pricing predictability of ANNs forecasting model on financial derivatives in the emerging stock market.

This study applies the neural network model to forecast stock index call option prices. The neural network model possesses several notable merits over traditional parametric models enhance its practicality. adaptive and responsive to structural changes in data-generating in methods that are flexible in modeling real-world phenomena for which observations are generally available, but for which the theoretical relationships are not known or testable, and therefore is relatively simple to implement. Future study will involve elevating network architectures using approaches other than that utilized in this study.

Although asymmetric volatility is widely researched in developed markets, no similar studies have been undertaken in imperfect markets, such as that of Taiwan, especially concerning the imposition of price limits. The empirical results of this study indicate that volatile asymmetry indeed exists in the Taiwan stock index option market. Therefore, future investigations should pay more attention to forecast volatility in future market.

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