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Two Mixed Models to Predict the Volatilities of Stock Prices in Egypt

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Abstract

A new mixed model depending on mixing the dynamic conditional correlation model (DCC-GARCH) with a bootstrap mean bias corrected estimator method (BMBCE) is suggested and studied to obtain an efficient model to predict the volatilities of stock prices in Egypt. Moreover, this model is studied the conditional correlation and interactions between variables. It also made a comparison between that model and a Grey GARCH model (1,1) over the period of 26/4/2016 to 22/1/2019. The study found the results of the applied study on EGX30 and EGX70 indices of Egypt stock market showed that the DCC-GARCH-BMBCE model has much better performances in volatility forecasting than the GM-GARCH model. This is proved by analyzing the errors for these models by estimating the difference between the actual values and the estimated values in order to measure the accuracy of the models, involving root mean square error (RMSE) and mean absolute error (MAE).

Keywords: DCC-GARCH, bootstrap mean bias corrected estimator method, Grey model, stock market in Egypt, root mean square error, mean absolute error.

1. Introduction

Stock markets are considered to be the most important tools for supporting the economy, especially in countries that suffer from a lack of financial resources, so they always seek to activate their stock market. There are more techniques to address the problem of estimating volatilities of financial assets, such as ARCH generalized model is identified as autoregressive conditioned heteroscedasticity (ARCH), along with alternate associated models to a type of the prevalent models. Existent multivariate methods considering the GARCH models, as Engle's dynamic conditioned correlation GARCH (DCC-GARCH) permits the evaluation of fluctuation and covariances in connection with several financial resources. Nevertheless, the DCC-GARCH model's factors are regularly obtained according to the maximum likelihood estimation (MLE) that is highly influenced by outliers (Aric 2010). For a DCC-GARCH model, the outliers influence a consequent evaluation of fluctuation by the setup of the model. It is also potential that these outliners influence a fluctuation of evaluation of alternate financial resources inside the range of the equivalent set of resources on account of the correlated nature of the financial resource evaluation. Besides, Grey forecasting (GM(1,1)) model projected by Deng is principally aimed at a system with undetermined information (Liu and Xie 2014; Li-Yan and Zhan 2015). It indicates benefits like a high short-term forecasting accuracy, fewer samples, and uncomplicated calculations (Samvedi and Jain 2013). Chih et al. (2008) employed the forecasting property of Grey model (1,1) model to amend the error terms of GARCH model and suggested GM-GARCH model (Chih et al. 2009).

Both of dynamic conditional correlation model (the DCC-GARCH model) and the bootstrap mean bias corrected estimator model were discussed separately in many type of research. Robert and Kevin (2001) developed the empirical and theoretical properties of a new class of multivariate GARCH model to estimate large time-varying covariance matrices, DCC-GARCH. They reached that the new estimator has a very strong performance especially considering the ease of implementation of the estimator. Paramita (2008) made a comparison between the two methods regression quantile-Kalman Filter method and regression quantile method of moments. Risk evaluation test results illustrated the desirable statistical properties of the quantile estimates obtained from these methods. Aric (2010) presented the consistency of the robust method of the DCC-GARCH method estimation and examined the distribution of the structure of exchange rate data. In addition, Christian and Jean (2014) investigated the estimation of a wide class of multivariate volatility model by establishing a strong consistency and asymptotic normality of the equation by equation estimator including DCC models. Phong et al. 2017 suggested a new method to estimate the minimum variance hedge ratio (MVHR) based on the wild bootstrap. They found that the wild bootstrap percentiles-based hedging outperforms its alternatives overall, on the other hand, hedging effectiveness, downside risk, and the return variability. Chia and Michael (2018) presented that the univariate GARCH is not a special case of M-GARCH especially the full BEKK model which in practice is almost estimated exclusively, has no underlying stochastic process, regularity conditions, or asymptotic properties. Shaoya et al. (2017) used two models, GARCH-MIDAS-X and DCC-MIDAS-X, to examine the effect of Chain's business cycle on volatilities and correlations related to the Baltic dry index and chain's stock market. They concluded that the significant determinants of macroeconomic variables of the long-term component of the index.

This paper is meant to have a deeper understanding of the DCC-GARCH model, and bootstrap mean bias corrected estimator. Moreover, it checked the application of a new method "the mixed models" suggested in the study DCC-BMBCE and compared the results of this model to Grey GARCH model. Since the general index of the Egyptian stock exchange reflects changes in various prices of shares traded on a given day in the figure number one can reach a judgment on the direction of prices in the capital market, providing accurate forecasts of the values of that index and volatility during the future period benefit many who invest in the Egyptian stock market and applied it on Egyptian stock indicators (EGX30 and EGX70).

The main purpose of this study is to suggest the mixed model (DCC-GARCH with BMBCE) eliminate the outlier values in the data also improves the estimation and prediction of time series with extreme volatilities.

In the next section, we will introduce DCC-GARCH model with bootstrap mean corrected bias corrected estimator and the variances of A hybrid the GM(1,1)-GARCH model. Section 3 will discuss the variables which we used and the sample selection. Section 4 will discuss the methodology of this study in detail. Finally, we will show the conclusion of the study.

2. Methodology

Time series are important models that deal with volatilities in the stock market; they are divided into univariate time series and multivariate time series. It is known that multivariate GARCH models have the ability to predict the movements of returns in financial assets. There are many models that belong to them.

2.1. DCC-GARCH-BMBCE model

The multivariate GARCH model takes the form of the following equation:

$$\pi_t = E_t(\theta) + C_t^{1/2} Z_t, \tag{1}$$

where Z_t is errors with mean equal (zero) and variance equal (1), $C_t^{1/2}$ is conditional variance matrix, $E_t(\cdot)$ is the expected value of the conditional return π_t.

To construct the suggested model, we will begin to explain ARMA(p,q) and GARCH(r,s) models. Assume that is generated by the following:

$$Y_t = C_0 + \sum_{i=1}^{p} C_i Y_{t-i} + \sum_{j=1}^{q} \varepsilon_{t-j} + \varepsilon_t, \tag{2}$$

where $\varepsilon_t = \sqrt{h_t}\eta_t$ and $h_t = b_0 + \sum_{j=1}^{s} b_j \varepsilon_{t-j}^2 + \sum_{i=1}^{r} \beta_j h_{t-i}$; $b_0, b_j, b_i \geq 0$ and η_t is a random variable and it asymmetric distribution. The parameters spaces is a combination between λ_c, λ_b (i.e; $\lambda = \lambda_c \times \lambda_b$), $\lambda_c \subset R^{p+q+1}$ and $\lambda_c \subset R^{s+r+1}$ with $R = (-\infty, \infty)$ and $R = [-\infty, \infty)$, ε_t, h_t dependents on $\{Y_t\}$ or $\{\varepsilon_t\}$.

Let $\phi_0 = (C_0', b_0')$, $C_0 = (C_{00}C_{01}...C_{0p}, \alpha_{00}\alpha_{01}...\alpha_{0q})$ and $b_0 = (b_{00}b_{01}...b_{0s}, \beta_{01}\beta_{02}...\beta_{0r})$ be the true parameter vector,

$$\psi_c(z) = 1 - \sum_{i=1}^{p} \alpha_i Z^i, \quad \delta_c(z) = 1 + \sum_{j=1}^{q} \alpha_j Z^j, \tag{3}$$

$$\psi_b(z) = 1 - \sum_{j=1}^{s} b_j Z^j, \quad \delta_b(z) = 1 - \sum_{i=1}^{r} \alpha_i Z^i. \tag{4}$$

To estimate the parameters, we used quasi maximum likelihood because of the errors not distributed as a normal distribution like the time series with extreme volatility. The quasi maximum likelihood is as following:

$$L_T(\phi) = \frac{1}{T}\sum_{t=1}^{T}\left[-\frac{1}{2}\log h_t(\phi) - \frac{\varepsilon_t^2}{2h}(\phi)\right]. \tag{5}$$

So

$$\hat{\phi} = \arg\max L_t(\phi). \tag{6}$$

As we have N time series variance of the model A(p,q), GARCH(r,s), then each time series will be estimated. Now, we can get a non-linear combination of univarite GARCH, then as (Bollerslv 1990) shown the DCC-GARCH model is represented as:

$$H_t = D_t R_t D_t, \tag{7}$$

where H_t is positive value (i.e. less than or equal (1)).

$D_t = \text{Diag}\left(\sqrt{h_{i,j}}\right)$ of time varying standard deviations from univariate GARCH model with $\left(\sqrt{h_{i,j}}\right)$,

$$D_t = \begin{bmatrix} \sqrt{h_{11}} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{22}} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sqrt{h_{kk}} \end{bmatrix}, \tag{8}$$

$$h_{i,j} = C_{i,0} + \sum_{p=1}^{P_t} c_{i,p} r_{t-p}^2 + \sum_{q=1}^{Q_t} b_{i,q} h_{i,t-q}, \tag{9}$$

and R_t is the time varying correlation matrix.

Now, we obtained DCC-GARCH model that depends on the division of the matrix of conditional correlations into two main parts. θ_t is a covariance matrix which represented as following: $\theta_t = \phi_1\theta + \phi_2\varepsilon_{t-1}\varepsilon'_{t-1} + \phi_3\theta_{t-1}$ and θ_t^{*-1} is a diagonal matrix constructed with the diagonal elements of θ_t,

$$\theta^* = \begin{bmatrix} \sqrt{\theta_{11}} & 0 & \cdots & 0 \\ 0 & \sqrt{\theta_{22}} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sqrt{\theta_{kk}} \end{bmatrix}. \tag{10}$$

And the residual is written as following: $\varepsilon_t = H_t^{1/2} Z_t$, then $Z_t = H_t^{-1/2}\varepsilon_t$. From these equations, we can get the prediction by using the next equation:

$$\theta_{t+r} = (1-\alpha-\beta)\bar{\theta} + \alpha\left(\varepsilon_{t+r-1}\varepsilon'_{t+r-1}\right) + \beta\theta_{t+r-1}, \tag{11}$$

where

$$R_{t+r+1} = \theta_{t+r}^{*-1}\theta_{t+r}\theta_{t+r}^{*-1} \text{ and } E_t\left(R_{t+r-1}\right) = E_t\left(\varepsilon_{t+r-1}\varepsilon'_{t+r-1}\right). \tag{12}$$

To construct the value of θ_{t+1}, firstly we will find

$$E_t\left(\theta_{t+r}\right) = \sum_{i=0}^{r-2}(1-\alpha-\beta)\bar{\theta}(\alpha+\beta)^i + (\alpha+\beta)^{r-1}\theta_{t+r}, \tag{13}$$

where $i \in (1,...,r)$. From this equation,

$$R_{t+r+1} = \theta_{t+r}^{*-1}\theta_{t+r}\theta_{t+r}^{*-1}, \tag{14}$$

we can conclude that $(\theta = R)$, $(\bar{\theta} = \bar{R})$, Then the purposed structure of DCC-GARCH model is

$$E_t\left(R_{t+r}\right) = \sum_{i=0}^{r-2}(1-\alpha-\beta)\bar{R}(\alpha+\beta)^i + (\alpha+\beta)^{r-1}R_{t+r}, \tag{15}$$

and the estimate will be using quasi-likelihood, but it assumed that the time series is stationary and this is not consistent with the stock market. Also, it will affect estimators because of the existence of the outliers.

There are many methods to bias corrected parameter estimators, for instance; bootstrap mean bias corrected estimator, Andrews-Chen estimator, Roy-fuller estimator, and bootstrap median bias estimator. In this study, we suggested mixing bootstrap mean bias corrected with DCC-GARCH; DCC-GARCH-BMBCE to eliminate the outliers and estimate the corrected estimator.

The DCC-GARCH-BMBCE are summarized as follow:

Step 1. Estimate the parameters by using quasi maximum likelihood which is explained in (5)-(6).

Step 2. Estimate the heteroscedasticity of GARCH models for each time series by applying (2) and estimated it's parameters.

Step 3 Calculating the time varying correlation matrix.

Step 4 From (7) we calculate the residuals which written as following: $\varepsilon_t = H_t^{1/2} Z_t$, then $Z_t = H_t^{-1/2}\varepsilon_t$.

Step 5. After the previous four steps, the prediction equation is as following: Now, the estimation process will be using bootstrap mean bias corrected estimator method

Step 6. Compute the parameters of autoregressive model.

Step 7. Fitting AR equation.

Step 8. Calculate errors $\varepsilon_t = y_i - \hat{y}_i$.

Step 9. Draw a n sized bootstrap random sample with replacement $(\varepsilon_1^{(b)}, \varepsilon_2^{(b)}, \ldots, \varepsilon_n^{(b)})$ from the values calculating from previous step (Dervis and Suat 2007).

Step 10. Calculate bootstrap of Y values by adding the resampled errors, then we will obtain bootstrap estimators by using ordinary least square (OLS) as the following equation:

$$\hat{y}_t = \hat{\alpha} + \hat{\beta}_t + \hat{\alpha}_1 \hat{y}_{t-1} + \cdots + \hat{\alpha}_p \hat{y}_{t-p} + \hat{\varepsilon}_t. \tag{16}$$

Step 11. Repeat Steps 8, 9 and 10 for $r = 1, 2, \ldots, b$ and proceed as in resampling with replacement.

Step 12. Compute the bootstrap bias by using OLS as following:

$$Bias\left(\hat{\omega}\right) = \overline{\omega^*} - \hat{\omega}, \tag{17}$$

where $\overline{\omega^*}$ is the mean estimator's parameter of the sample.

2.2. GARCH and Grey model (1, 1)

According to the models acquired from GARCH-type, the current conditional variance σ_t^2 is fundamentally dependent on the preceding error terms $\varepsilon_t (\tau < t)$ yet this is variable with the realistic situation. In the actual financial market, given the circumstances of the exception of the prior price, the error terms are also affected by the undetermined parameters, such as the economic, political, ecological plus other intricate factors. Such factors produce a continuous change of errors (Geng and Zhang 2015). So, we discussed how to forecasting the variances of the hybrid the GM(1,1)-GARCH Model.

It can be said that the random error contains a mixture of known and unknown information that is based on a set of information in the past at time t (Chih et al. 2008). The GM(1,1)-GARCH model provides a way to modify errors in the GM model, The successive amendments are as follows:

1. The original sequence of errors $\varepsilon^{(0)}$, where $\forall \varepsilon_{(i)}^{(0)} \in \varepsilon^{(0)}$, $\varepsilon_{(i)}^{(0)} \in \mathbb{R}$, $i = 2, 3, \ldots, n$ are as follows

$$\varepsilon^{(0)} = \left\{ \varepsilon_{(1)}^{(0)}, \varepsilon_{(2)}^{(0)}, \ldots, \varepsilon_{(n)}^{(0)} \right\}. \tag{18}$$

Move sequential errors by adding minimum value in original sequence. Then the new sequence is

$$X^{(0)} = \left\{ x_{(1)}^{(0)}, x_{(2)}^{(0)}, \ldots, x_{(n)}^{(0)} \right\},$$

where $x_{(t)}^{(0)} = \varepsilon_{(t)}^{(0)} + \min\left(\varepsilon_{(1)}^{(0)}, \varepsilon_{(2)}^{(0)}, \ldots, \varepsilon_{(n)}^{(0)}\right)$ and $x_{(t)}^{(0)} \in \mathbb{R}$ for $t = 2, 3, \ldots, n.$

2. Obtaining first-order cumulative sum sequence by using AGO $X^{(1)} = \left\{ x_{(1)}^{(1)}, x_{(2)}^{(1)}, \ldots, x_{(n)}^{(1)} \right\}$ so we can express generating series for the cumulative summation as follows

$$x_{(t)}^{(1)} = \left\{ \sum_{t=1}^{n} x_{(t)}^{(0)}, t = 1, 2, \ldots, n \right\}. \tag{19}$$

3. From the 3 steps, we can write the Grey model (1,1) as

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \text{ or } x_{(t+1)}^{(1)} = \left(x_{(1)}^{(0)} - \frac{b}{a} \right) e^{-at} + \frac{b}{a}. \tag{20}$$

By using the differential equations:

$$\frac{dx^{(1)}}{dt} = \lim_{\Delta t \to 0} \frac{x_{(t+1)}^{(1)} - x_{(t)}^{(1)}}{\Delta t} \text{ and let } \Delta t = 1, \frac{x_{(t+1)}^{(1)} - x_{(t)}^{(1)}}{1} = x_{(t)}^{(0)},$$

then the original differential equation will be written

$$x_{(t)}^{(0)} + az_{(t)}^{(1)} = b, \tag{21}$$

where $z_{(t)}^{(1)} = ax_{(t)}^{(1)} + (1-a) x_{(t-1)}^{(1)}$. Taking into consideration $t \geq 2$ and a, b will obtained by

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = (B'B)^{-1} B'y,$$

where $y = \left[x_{(2)}^{(0)}, x_{(3)}^{(0)}, \ldots, x_{(n)}^{(0)} \right]$ and $B = \begin{bmatrix} -z_{(2)}^{(1)} & \cdots & 1 \\ \vdots & \ddots & \vdots \\ -z_{(t)}^{(1)} & \cdots & 1 \end{bmatrix}$.

4. Finally, placing back a and b derived from Grey's differential equation into the general equation with $\hat{x}^{(1)} = \hat{x}_{(1)}^{(0)} - \hat{x}_{(1)}^{(1)}$. Since the forecast model is not formed using an authentic sequence, but rather modes from a distinct cumulative addition, as a mean to reclaim the forecasted sequence reversed addition is to be demanded (Yi-Hsien and Chin 2008)

$$\hat{x}^{(0)} = \hat{x}_{(i+1)}^{(1)} - \hat{x}_{(i)}^{(1)},$$

$$\hat{x}_{(t+1)}^{(0)} = \left(1 - e^{a}\right) \left(x_{(1)}^{(0)} - \frac{b}{a} \right) e^{-at}. \tag{22}$$

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

$$\hat{\varepsilon}_{(t+1)}^{(0)} = \left(1 - e^{a}\right) \left(x_{(1)}^{(0)} - \frac{b}{a} \right) e^{-at} - \min\left(\varepsilon_{(1)}^{(0)}, \varepsilon_{(2)}^{(0)}, \ldots, \varepsilon_{(t)}^{(0)} \right). \tag{23}$$

After the predicted time inaccuracy $t+1$ is obtained by GM(1,1) model, this value is then put in the GARCH model to evaluate conditioned variance at time $t+1$. Thus, the production of the one-step-ahead variance predictions is rendered by the above-mentioned processes, and by repeating this procedure the multiple conditioned variance predictions for estimation interval can be acquired. (Yi-Hsien 2009).

3. Sample Selection and Data Collection

The current study depended on Egyptian stock market indicators (EGX30 and EGX70) from the Egyptian stock exchange, after exclusion cross holding. The bonds are not included. This data is divided into two parts; firstly, data for the estimation process during the period (26/4/2016) to 22/1/2019. Secondly, data for the forecasting process during the period 23/1/2019 to 20/2/2019.

4. Applied Study

4.1. Appling DCC-GARCH-BMBCE model

4.1.1 Estimate the dynamic conditional correlation model

1) Descriptive study of series to indexes

This study depended on EGX30 index; this indicator is not focused on a particular industry but provides a good representation of the various industries and sectors within the Egyptian economy. Also, it depends on EGX70 index which measures the performance of seventy of the most active companies after the companies listed in the EGX30 index. It aims to measure the change in closing prices of companies without weighing the market capital.

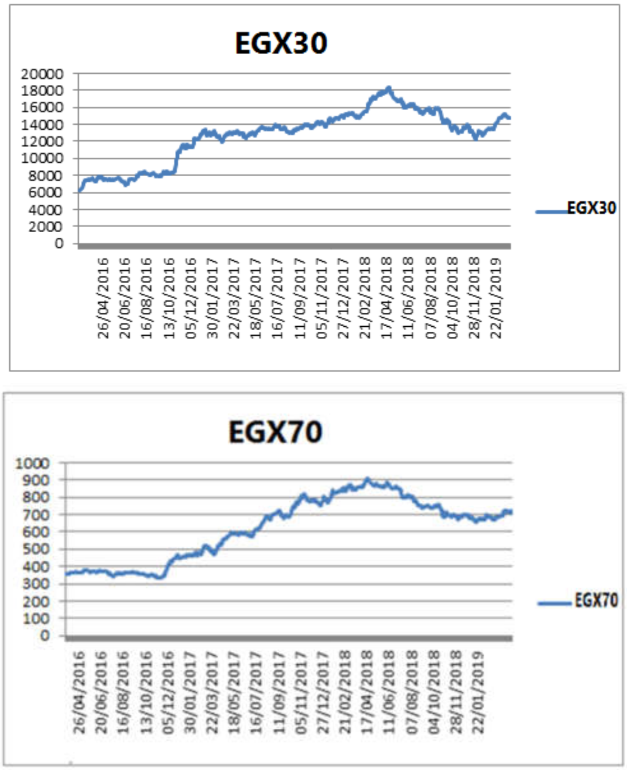

Figure 1 Graph representation of the EGX30 and EGX70 indexes

The figure clearly states that the period 4/2016–10/2016 witnessed low stock prices in both indices. On the other hand, the period 12/2016–4/2018 illustrates that there were fluctuations between a rise and fall, but in general, these fluctuations had a general trend is the rise in stock prices. Finally, from 5/2018–1/2019 there was another decline in stock prices in both series which shows that the indicators are of no consistency in the values of any fluctuations. Also, to decline the fluctuations we compute the daily return from the indexes generated from the following function

$$r_{i,t} = 100 \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right).$$

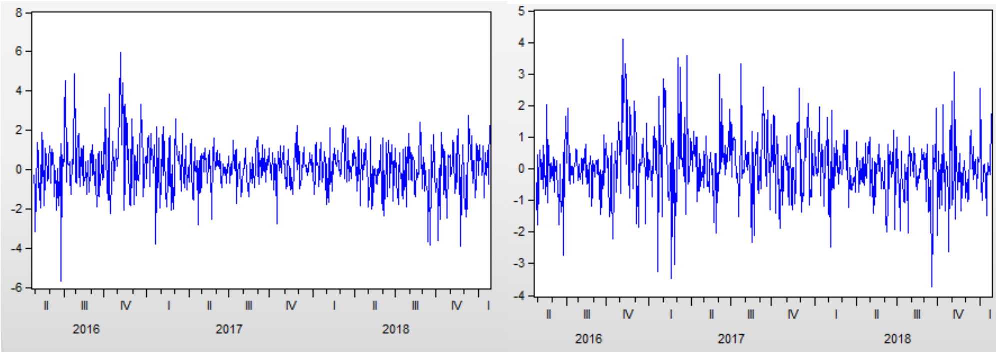

Figure 2 The log return of EGX30 and EGX70

From Figure 2, the series appear to fluctuate around a sample average of zero. After that, we must study the stability of the time series that will be illustrated in the next section.

2) Stability of time series

There are many different ways to check the stability of series, such as autocorrelations, partial autocorrelations and Dickey-Fuller test which consider the most popular one. This study depends on Dickey-Fuller test. The approach used is quite straightforward. Also, there are three variations of Dickey-Fuller test designed to take account of the role of the constant term and the trend. So, we will use Dickey-Fuller test (Carter et al. 2011).

Table 1 Dickey-fuller test for both indexes (EGX30 and EGX70) during period 2016-2019

EGX30 index			
		t-statistic	p-value
Augmented Dickey-Fuller test		−20.14254	0.0000*
Test critical values	1% level	−3.439925	
	5% level	−2.865656	
	10% level	−2.569019	
EGX70 index			
		t-statistic	p-value
Augmented Dickey-Fuller test		−20.30589	0.0000*
Test critical values	1% level	−3.439925	
	5% level	−2.865656	
	10% level	−2.569019	

From previous table we noticed that the value of Dickey-Fuller is smaller than the critical values for both of indexes. Then, it means that the two indexes are stable.

3) Studying the univariate GARCH model for both indexes

Before we start to estimate the model, we must make a test to emphasize that GARCH model will be suitable for forecasting; we will use the Ljung-Box Q statistic (LBQ). The following table shows the results of test (Carter et al. 2011).

Table 2 Ljung-Box Q statistic results

	EGX30 index		EGX70 index	
	Q-statistic	p-value	Q-statistic	p-value
Q (5)	41.822	0.0000000**	57.566	0.0000000**
Q (10)	45.392	0.0000000**	62.195	0.0000000**
Q (20)	52.523	0.0000000**	71.282	0.0000000**
Q (35)	62.851	0.0000000**	85.082	0.0000000**

From this table, we noticed that the lag values are 5, 10, 20, 35 and the calculated Q-statistic for both indexes are more than critical values at a significant level 5%, which means the GARCH model is suitable for data used. The second step is to estimate the univariate GARCH model of the stock market. Using the Marquardt maximum likelihood estimation method, we got the following estimation function, and the result in detail is shown in Table 3.

Table 3 Estimating parameters of GARCH(1,1) model results

EGX30 index				
	Coefficient	Std. Error	z-statistic	p-value
C	0.016931	0.007945	2.131163	0.0331
Resid(-1)^2	0.042593	0.009285	4.587306	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.135644	0.040732	3.08847	0.0000
GARCH(-1)	0.945080	0.011852	79.74026	0.0000
No.observations: 66 Mean: 0.083939 Std.Dev: 1.197822 Skewness: 0.182229 Kurtosis 5.874074				
EGX70 index				
	Coefficient	Std. Error	z-statistic	p-value
C	0.095897	0.025547	3.753736	0.0002
Resid(-1)^2	0.157269	0.031586	4.979008	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.044018	0.015406	2.126221	0.0000
GARCH(-1)	0.752192	0.045314	16.59968	0.0000
No.observations: 669 Mean: 0.089050 Std.Dev: 0.0987474 Skewness: 0.219043 Kurtosis 4.822652				

As we can see from Table 3, EGX30 has a larger standard deviation compared to that of the EGX 70. In addition, EGX30 has s smaller mean than EGX70. Also, skewness and kurtosis, we can notice that EGX70 is more right-skewed and with less leptokurtic. So, we can say that EGX70 is better than EGX30. The parameters of asymmetric innovation for both indexes are significantly different from zero based on normal standard errors.

4) Estimate the dynamic conditional correlation model

To estimate the dynamic conditional correlation model, remember the DCC function shown as:

$$\theta_{t+r} = (1-\alpha-\beta)\overline{\theta} + \alpha\left(\varepsilon_{t+r-1}\varepsilon'_{t+r-1}\right) + \beta\theta_{t+r-1}.$$

Table 4 DCC estimation of EGX30 and EGX70

	Coefficient	Std. Error	z-Statistic	p-value
α	0.212650	0.015471	5.675	0.0000
β	0.670677	0.226205	3.847	0.0001

Shown in Table 4 the result of DCC model estimation for EGX30 and EGX70. The coefficients are significant and we can notice that the persistence of conditional correlation is significant and the stability condition is met. Also, we noticed that the sum of $\alpha+\beta$ for both indexes are less than one which indicated the stability of the two indexes. Finally, by using Ox metrics program, we found the correlation between both indexes is 0.750487 and the conditional variance is 0.01916731 and 0.10856342 for EGX30 and EGX70, respectively. By applying (8), we calculate the matrix and the result is

$$H_t = \begin{bmatrix} 0.01916731 & 0.08147544 \\ 0.01438482 & 0.10856342 \end{bmatrix}.$$

The main aim of this matrix is to help us for estimating and forecasting processes. After we finished this part, now we go to the second part which is estimating the parameters by using the Bootstrap mean bias corrected estimator method.

4.1.2 Bootstrap mean bias corrected estimator method

In this part, we estimated the coefficient of the rank autoregressive of two indexes the performance of the bootstrap mean bias corrected estimators to two indexes by determining the rank of autoregressive model and extract the coefficients by an ordinary least square method. For that aim we will use Akaike information criterion (AIC), Bayesian information criterion (BIC) and Hannan Quinn criterion (HQC). The following table will show the results for both indexes.

From the last table, we saw that regarding EGX30, the rank of AR was equal in the three criteria which equal (4). Secondly, for EGX70, the rank of AR for BIC equal (1) and for HQC equal (1). Then if we compare between three criteria, HQC is the same in both indexes which equal (1) then the AR model is AR(1) then, this is the best one comparing to the others. The following table will illustrate the results of coefficients of EGX30 and EGX70 by using bootstrap method for iteration 1000.

As we can see from Table 6, by using the bootstrap method the trend in EGX30 is positive that means the prices will increase, this indicates that stock prices are in a profit trend. On the other hand, the trend in EGX70 is positive that means the prices will decrease, this indicates that stock prices are in a loss trend.

Table 5 Results of criterions after calculating returns

EGX30 index			EGX70 index		
Critical values			Critical values		
AIC	BIC	HQC	AIC	BIC	HQC
−8.850211	**−8.877967**	**−8.902724**	−9.237996	**−9.264302**	**−9.282813**
−8.904664	−8.877724	−8.894228	−9.291243	−9.217791	−9.280807
−8.905143	−8.871468	−8.892098	−9.290781	−9.257105	−9.277736
−8.918377	−8.830006	−8.842384	−9.298466	−9.258056	−9.230169
−8.916126	−8.868980	−8.897863	**−9.299265**	−9.252119	−9.281002
−8.915158	−8.861278	−8.894287	−9.297028	−9.243147	−9.276157
−8.913249	−8.852633	−8.889768	−9.295648	−9.235032	−9.272168
−8.916607	−8.849256	−8.890518	−9.292742	−9.225391	−9.266653
−8.914579	−8.840493	−8.885881	−9.291071	−9.216985	−9.262373
−8.915196	−8.834375	−8.883889	−9.290479	−9.209658	−9.259172
−8.913269	−8.825713	−8.879353	−9.288117	−9.200561	−9.254201
−8.916246	−8.821955	−8.879721	−9.292316	−9.198024	−9.255790
−8.913849	−8.812822	−8.874715	−9.289344	−9.188317	−9.250210
−8.913120	−8.805359	−8.871377	−9.286419	−9.178657	−9.244676
−8.910511	−8.796014	−8.866159	−9.286471	−9.171975	−9.242119
−8.916114	−8.794882	−8.869153	−9.284566	−9.163334	−9.237605
−8.913446	−8.785479	−8.863876	−9.290789	−9.162823	−9.241220
−8.914655	−8.779953	−8.862476	−9.294304	−9.159602	−9.242126
−8.914361	−8.772923	−8.859573	−9.295628	−9.154191	−9.240840
−8.911686	−8.763514	-8.854289	−9.292845	−9.144673	−9.235448
p^* 4	1	1	p^* 5	1	1

Table 6 Results of coefficients of EGX30 and EGX70 by using bootstrap method

EGX30 index		EGX70 index	
	Coefficients		Coefficients
AR1	2.45603×10^{-2}	AR1	5.222178×10^{-3}
Constant	3.897655×10^{-3}	constant	2.190158×10^{-2}
Trend	4.826273×10^{-6}	Trend	-1.223959×10^{-7}

4.1.3 Mixing dynamic conditional correlation model with bootstrap mean bias corrected estimator model

As mentioned above, this paper suggested a new mixed model depends on mixing dynamic conditional correlation model (DCC-GARCH model) with the bootstrap mean bias corrected estimator model (BMBCE) to obtain an efficient model to predict the volatilities of stock prices. The following table will illustrate the trend of series in different sizes of samples. We used the R package to generate the model.

Table 7 Results of coefficients of EGX30 by using mixed model

	Iteration=1000	Iteration=5000	Iteration= 10000
	Coefficients	Coefficients	Coefficients
AR1	2.433034×10^{-2}	2.438382×10^{-2}	2.408012×10^{-2}
Constant	2.096019×10^{-3}	2.097122×10^{-3}	2.098227×10^{-3}
Trend	4.749976×10^{-6}	4.752551×10^{-6}	4.755136×10^{-6}

Table 8 Results of coefficients of EGX70 by using mixed model

	Iteration=1000	Iteration=5000	Iteration= 10000
	Coefficients	Coefficients	Coefficients
AR1	5.866075×10^{-3}	4.905698×10^{-3}	5.442108×10^{-3}
Constant	1.744538×10^{-3}	1.747990×10^{-3}	1.746886×10^{-3}
Trend	3.570905×10^{-6}	3.578185×10^{-6}	3.575856×10^{-6}

As we can see from Tables 7 and 8, we can easily notice that the trend of series is positive and approximately equally in three different sizes (1000, 5000, 10000) iteration that mean the prices of stocks will increase.

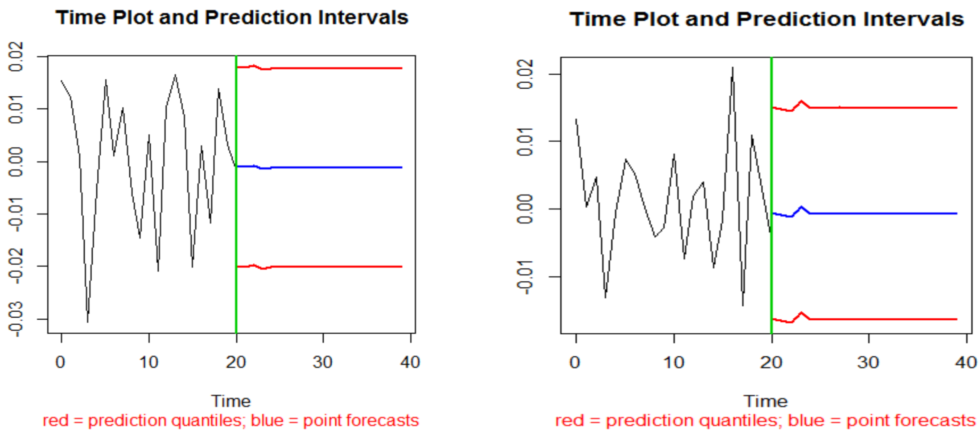

Figure 3 Time plot and prediction intervals of the EGX30 and EGX70 indexes

In Figure 3, the time point of forecasts and the prediction interval for EGX30 and EGX70. Where, the red lines indicate to prediction quantiles and the blue line is point forecast.

4.2. Applying GARCH and Grey model (1,1)

4.2.1 Descriptive statistics and estimation result

We examined the variance forecasting ability of GM(1,1)-GARCH model among two indexes EGX30 and EGX70. As we have shown above in table (3) the descriptive statistics. Now, we will show the estimation results of GM(1,1)-GARCH(1,1).

Table 9 Estimation results GARCH(1,1) of GM(1,1)-GARCH(1,1) model

GARCH(1,1)		
Parameter	EGX30	EGX70
ω	0.000002	0.000009
α	0.050992	0.150992
β	0.933342	0.765751
Log-Likelihood	2041.118	2170.467
Q^2	4.671	26.640
GM(1,1)-GARCH(1,1)		
Ω	0.000004	0.000015
A	0.0524354	0.154862
B	0.942132	0.785961
Log-Likelihood	2034.204	2087.532
Q^2	5.818	29.870

Table 9 illustrated the estimation results of GARCH(1,1) and GM(1,1)-GARCH(1,1) model for two indices. For both models are all statistically significant at α = 1%, which indicates that volatilities during the period do not stable.

In both models, the sums of parameters α and β are less than one and, thus, enclose that the conditions for stationary covariance constant. In addition, the parameters β of both models reveal that there are substantial memory effects in volatility.

4.3. Criteria to evaluate the forecasting performance

In order to compare the models we presented in this paper, we will analyze the errors for these models by estimating the difference between the actual values and the estimated values in order to measure the accuracy of the models, Involving root mean square error (RMSE) and mean absolute error (MAE). The following table shows the results for two mixed models.

Table 10 RMSE, MAE of two types of volatility models for EGX30 and EGX70

Indices	Model	RMSE	MAE
	DCC-GARCH-BMBCE		
EGX30	For iteration 1000	0.165772607	0.099916304
	For iteration 5000	0.165776816	0.09991757
	For iteration 10000	0.165776062	0.099917472
	GM-GARCH	0.455606031	0.82873164
	DCC-GARCH-BMBCE		
EGX70	For iteration 1000	0.103829659	0.064719543
	For iteration 5000	0.103828219	0.064714644
	For iteration 10000	0.103829297	0.064715221
	GM-GARCH	0.327606839	0.699010164

The above table showed that RMSE and MAE values by using DCC-GARCH-BMBCE model is less than by using GM-GARCH they means the first model is more efficient comparing to the other model to predict stock prices.

5. Conclusions

This study suggests a new mixed model depending on mixing dynamic conditional correlation model (DCC-GARCH) with bootstrap mean bias corrected estimator method (BMBCE) to predict the volatilities of stock prices in Egypt over the period from 26/4/2016 to 22/1/2019. Particularly, the study uses the daily stock prices of indicators (EGX30 and EGX70) to obtain an efficient model to predict the volatilities of stock prices in Egypt. To check the stability of the series we use Dickey-fuller test, we noticed that the value of Dickey-Fuller is smaller than the critical values for both indexes. However, after estimating parameters of GARCH(1,1) model results we found that EGX70 is better than EGX30. The parameters of asymmetric innovation for both indexes are significantly different from zero based on normal standard errors. Further, the result of DCC model estimation for EGX30 and EGX70. The coefficients are significant and we can notice that the persistence of conditional correlation is significant and the stability condition is met. Also, by using the bootstrap method the trend in EGX30 is positive that mean the prices will increase. On the other hand, the trend in EGX70 is positive that means the prices will decrease. After applying mixing dynamic conditional correlation model with bootstrap mean bias corrected estimator model, we noticed that the trend of the series is positive and approximately equally in three different sizes (1000, 5000, 10000) iteration that mean the prices of stocks will increase. Further, the study uses a Grey GARCH model (1,1) in the same period and same indicators. The results illustrate the estimation results of GARCH(1,1) and GM(1,1)-GARCH(1,1) model for two indices. For both models are all statistically significant at α = 1%, which indicate that volatilities during the period do not stable. In addition, the parameters β of both models reveal that there are substantial memory effects in volatility. Finally, to compare the models we presented in this paper, we will analyze the errors for these models by estimating the difference between the actual values and the estimated values in order to measure the accuracy of the models, Involving root mean square error (RMSE) and mean absolute error (MAE). The following table shows the results for two mixed model. The results of the applied study on EGX30 and EGX70 indices of Egypt stock market shows that the DCC-GARCH-BMBCE model has superior performances in volatility forecasting than the GM-GARCH model.

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