Abstract

Different techniques of forecasting can be employed in financial markets. This paper introduces one of these techniques which is known as Box-Jenkins model, in which it can be employed for analyzing a financial time series data. The major target of this study is to predict the banking sector volatility in Amman Stock Exchange as an emerging market. This can be achieved by finding the tentative ARIMA model that has the ability to forecast the volatility behavior of the banking sector. The data are obtained from the website of “Amman Stock Exchange” (ASE) on a weekly basis using the historical indices in the period from 1/1/2010-1/4/2015. We tested the stationarity by using the unit root test which indicates that there is stationary at the level, then used a minimum mean square error, t-statistics value and p-statistics value for selecting most appropriate ARIMA model at 95% confidence interval. On the other hand, the capability of ARIMA model in modelling and forecasting ASE evaluated by using “Akaike’s Information Criterion” (AIC). The resulted model for banking sector volatility is ARIMA (2, 0, 2). Finally, the best ARIMA model was formed and tabulated in the entire paper.

Keywords: Financial Time Series, Volatility, Forecasting, ARIMA Model.

1. INTRODUCTION

The country’s economy mainly relies on capital market in which the investors exploit the money they had to acquire the yield. Stock exchange as a part of the capital market plays an important function in the national economy. The investors purchase the security of diverse companies on the priority basis. A number of buyers, as well as investors, generally do not have a greater understanding regarding the forecast of future prices and market analysis of different securities. Therefore, they spend most of the time and money to purchase securities of different companies without any plans about the future prices expectations. Several investors are not well-aware of suitable investment in the market. Therefore there is a possibility to afford a better model for the stock market which can assist the investors to forecast the prices in advance; it would help the investors as well as keep stability of the national economy [1].

Widespread work has been completed on the financial time series as a process of modeling, together as a theory and empirical either on developed or emerging markets like Europe, Asia, Middle East, and the United States. There exists a huge amount of literature on volatility modeling [2]. Forecasting volatility in financial markets is very important information in hedging, asset pricing, asset allocation and portfolio management [3, 4]. Likewise, an increased financial market volatility entails appropriate risk management and well-organized power for managing their fund and set the competition in the capital market [5].

Different techniques have been employed in modelling and forecasting volatility in stocks markets like “Autoregressive Integrated Moving Average” (ARIMA), “Generalized Autoregressive Conditional Heteroskedasticity” (GARCH) and “Vector Autoregressive” (VAR) models. Researchers differentiate between those models according to the behavior of time series data they interested in. They sometimes compared among them to pick the best model that can be fitted the data. For example, Miswan et al. [6] concluded ARIMA model has shown improved performance as compared to the GARCH model in forecasting and modelling the instability of Malaysian properties and market shares.

Furthermore, Alfaki and Mash introduced a short review about Box-Jenkins model that acknowledged as ARIMA model [7]. They specified a proper tentative model for the monthly sales of “Naphtha product (in Azzawiya Oil Refining Company” – Libya), the best-fitted model according to “Acaike Information Criterion” (AIC), Mean Squared Error (MSE) criteria, and “Box-Ljung test” was the ARIMA (1, 1, 1) for the monthly sales of Naphtha product. Alshiaib studied the predictability of Amman stock exchange (ASE) general daily index Performance [8]. He found the forecasting model was not consistent with actual performance during the same period of the prediction over the 150 coming days. While Al-zoubi and Bashir [9] studied the “time-varying risk-return relationship”, ASE asymmetric effect, and time-varying volatility in the capital market. The researchers assessed stock volatility
persistence and stock return behavior of the investors. In this research, the univariate statistics indicated that there is a deviation from normality and negative skewness in the index of ASE.

Additionally, a research conducted by Ritab et al. assessed the attitude of “daily stock return volatility” in the ASE price limit [10]. The main features of their study were the utilization of the ARIMA model and “unit root test” to distinguish the standing of the time series. Moreover, ARIMA model employed in different types of time series data. For instance, Contreras et al. employed ARIMA model for the forecasting of electronic prices in the coming days [10]. Another example of ARIMA model employment is the prediction of pelagic fish production as presented by Tsitsika et al. [12]. The banking sector in ASE containing the real-estate and sector insurance has been funded with 18.82% of “Gross Domestic Product” (GDP) in market price. On the other hand, the Jordanian banking sector’s economic significance can be highlighted by the GDP’s captivating influence.

In the present paper, we focus more on short historical time series. The main problem of this paper is to model and quantify the volatility of banking sector indices on ASE using ARIMA model. Then, we applied the model on emerging stock market (ASE) by using a high-frequency data for empirical analysis. Finally, we can effectively forecast volatility and identify a convenient technique to achieve the appropriate goals. The paper is organized into five major sections. The first section presents the research background and introduction to the research problem, second describes the volatility and ARIMA model, third covers the results, fourth is for discussion of the resulted ARIMA model, and the fifth section concludes the entire research by presenting the main findings and research implications.

2. MATERIALS AND METHODS

Volatility

The volatility is defined as “the rate at which the price of a security increases or decreases for a given set of returns”. It can be calculated using historical stock price data or inferred from options data, and the latter exercise allows us to determine the market’s expectation of future volatility. Volatility designates the estimating conduct of the security and advantages to estimate the oscillations which can occur in short time period. In the case of oscillation in the security prices in the shorter time period, this will be considered to possess increase volatility. On the other hand, if the process if vices versa, the condition will say to be decreased volatility [13 – 15]. Almost all the financial uses of volatility models bring about forecasting what deals with future returns [16].

In general, a volatility model is employed to predict the absolute magnitude of returns. According to Stephen and John, a forecast plays an important role in managing the risk in the capital market, derivation in the hedging and pricing, many financial actions, portfolio selection, market timing, and market making [17]. The behavior of stocks volatility in the financial markets is affected by many factors. Ross (1989) found that the volatility of price was directly linked to the rate of information flow in the market. As indicated above, Schwert [14] also showed that macroeconomic was one of the underlying forces that affected the stock’s market volatility.

There are 2 dominant characteristics exhibited by financial time series, including time-varying volatility and non-stationary volatility. The time-varying volatility as indicated by its title varies with the time, while the non-stationary characteristic indicates that the financial time series have no ability towards a liner trend. It can be calculated as:

\[ r_t = |log(x_t) - log(x_{t-1})| \]  

“where; \( r_t \) is the returns, \( x_t \) is the observation at time \( t \), \( x_{t-1} \) is the observation time \( t-1 \), the log is the logarithm and \( |.| \) is the absolute value” [19].

Box-Jenkins Model

Various refined dynamic time-arrangement models have created genuinely common autoregressive as well as “moving average models” [20]. The “ARIMA model approach” possess 3 points of interest as compared to numerous other conventional single-arrangement techniques. The foremost is that the ideas related with ARIMA models are acquired from utilizing the traditional likelihood hypothesis and scientific insights. Numerous other generally prominent univariate strategies are determined instinctively. Furthermore, “ARIMA models” should be considered as a combination of models; not only a solitary model.

Box and Jenkins have built up an approach that aids the investigator in picking at least one suitable models out of this bigger group of models. Thirdly, it can be demonstrated that a fitting ARIMA show produces ideal univariate estimates. That is, no other standard single-arrangement model can give gauges with a littler mean-squared estimate mistake [21]. Box and Jenkins proposed a down to earth three-organize method for finding a decent model. The three-organize are analytic checking, estimation, and identification.

In the primary stage, two graphical gadgets used to quantify the connection between the perceptions inside a solitary information arrangement. These gadgets are called an expected “Autocorrelation Function” (ACF) and an expected “Partial Autocorrelation Function” (PACF) [22]. In any case, they are useful in giving us an indication for the examples in the accessible information.

At 2nd stage, beginning assessments of the model’s constraints should be completed keeping in mind the end goal to begin the cycle procedure for the calculation of the last gauges [23]. At long last, the demonstrative checking stage, in which residuals from the fitted models are utilized to distinguish indications of insufficiency. The
changed “Box-Pierce measurement”, t-measurement, and the connection network for the parameters, and in addition, the greatness of MSE will be utilized [24].

Box and Jenkins proposed some analytic checks to decide whether an expected model is measurably sufficient or not [25]. Besides, the outcomes at this stage may likewise demonstrate how a model could be progressed. In the event that the model blown-up in this stage, this leads the researchers back to the organization of identification of the model. We repeated the cycle of distinguishing proof, estimation, and indicative checking until the point that we locate the best-fitted model to utilize it to gauge.

The iterative idea of the “three-series Univariate Box-Jenkins” (UBJ) demonstrating system is critical [18]. The Box-Jenkins system is a training for achieving the model past estimations of the time arrangement variable and past estimations of the mistake terms. The Box-Jenkins approach comprises of extricating the anticipated from the watched information through a progression of emphases [26]. The most well-known ARIMA display included three parameters: p, d, and q where p is the quantity of autoregressive parameters, d is the quantity of various parameters, and q is the quantity of moving normal parameters. A general ARIMA is shown in the equation:

\[ z_t = \theta_1 z_{t-1} + \theta_2 z_{t-2} + \cdots + \theta_p z_{t-p} + \varepsilon_t \]

“Where; t : is the periodic time, \( z_t \) : is the numerical value of an observation, \( \theta_i \) : for \( i = 1,2,\ldots,p \) are the autoregressive parameters, \( \theta_j \) : are the moving average parameters, for \( j = 1,2,\ldots,q \) \( a_r \) : is the shock element at time \( t \)”.

The linear multiple regressions performed to estimate the parameters \( \theta_i \) and \( \theta_j \) for a fixed \( p \) and \( q \), as follows:

\[ \hat{z}_t = \mu + \phi_1 z_{t-1} + \phi_2 z_{t-2} + \cdots + \phi_p z_{t-p} - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q} \]  

(3)

Furthermore, it has also been indicated that there is no constant trend indicated by the stationary time series as it revolves about the constant mean. On the other hand, the variance in a main subset of the series may also occur if the data series are stationary. Besides, the observations fluctuate around the constant mean. The autocorrelation between \( z_t \) and \( z_{t+k} \) measures the correlation between the pairs \((z_t,z_{t+k}), (z_2,z_{2+k}) \cdots \cdots (z_n,z_{n+k})\). The sample autocorrelation coefficients \( r_k \) is an estimate of \( \rho_k \), where

\[ r_k = \frac{\sum (z_t - \bar{z})(z_{t+k} - \bar{z})}{\sum (z_t - \bar{z})^2} \]  

(4)

Where,

"\( z_t \) : is the data from the stationary time series”

\( z_{t+k} \) : “The data from k time period ahead of \( t \)”

\( \bar{z} \) : is the mean of the stationary time series.

An “estimated partial autocorrelation function PACF” can be utilized as the guide in combination with the expected ACF in the selection of 1 or more models of ARIMA. However, its suitability with the available data will be checked. The idea of partial auto-correlation may be utilized to evaluate the correlation between \( \hat{z}_t \) and \( \hat{z}_{t+k} \).

The below equation presents the estimation of partial auto-correlation:

\[ \hat{\phi}_{kk} = \frac{r_k - \sum_{j=1}^{k-1} \hat{\phi}_{k-j} r_{k-j}}{1 - \sum_{j=1}^{k-1} \hat{\phi}_{k-j} r_{k-j}}, k=2,3,\ldots (5) \]

Where:

\[ \hat{\phi}_{kj} = \hat{\phi}_{k-j} - \hat{\phi}_{kk} \hat{\phi}_{k-1,k-j} \]

“\( k = 3,4,\ldots ; j = 1,2,\ldots,k-1 \)”

However, most non-stationary series that arise in practice could be converted into stationary series through relatively simple operations [21].

3. RESULTS AND DISCUSSION

There are many tests used to prepare the ARIMA model for the banking sector in ASE. The volatilities for banking sector were calculated by using Equation (1). While unit root test is utilized to test the stationarity for the arrangement. At long last, the auto-correlation and partial auto-correlation was accomplished by checking the relationship among the file slacks, they used to pick the advantageous speculative models for managing the banking sectors.

Descriptive Statistics

The first phase of the analysis is based on the descriptive statistics of the banking sector. Table 1 shows the descriptive statistics for the banking sector. The original values of the banking sector are shown in Figure 1, and Table 1 shows the plot of the volatilities.

Unit root test

The “unit root test” determines if variable of the time series is stationary or not by using the auto-regressive model. A standout amongst the most renowned tests is the "Augmented Dickey-Fuller test" (ADF). This test utilizes the presence of a unit root as the invalid speculation. It has all the reserves of being important to check the stationary in levels or at contrasts, on the grounds that there is a basic issue related with non-stationary factors that are the counterfeit connection. The more negative ADF is, the more grounded dismissal of the theory that there is unit root at some level of certainty [27]. The non-stationary time arrangement could create a frail outcome. To dodge the misleading relationship issue, it is fundamental to test
for unit foundation of the managing an account segment for ASE.

The ADF regression condition because of Dickey and Fuller (1979) and Said and Dickey (1984) is given by

$$\Delta y_t = \mu_0 + \mu_t + \phi y_{t-1} + \sum_{j=1}^{p} \alpha_j \Delta y_{t-j} + \epsilon_t$$  \hspace{1cm} (6)

Where,

“t = p+1, p+2,…T.”

“$\mu_0$ is the intercept”

“$\mu_t$ represents the trend in case it is present”

“$\phi$ is the coefficient of the lagged dependent variable”

“$y_{t-1}$ and p lags of $\Delta y_{t-j}$ with coefficients $a_j$ are added to account for serial correlation in the residuals.”

“The null hypothesis $H_0: \phi = 0$ is that the series has unit root while the alternative hypothesis $H_1: \phi \neq 0$ is that the series is stationary.”

The ADF test statistics are given by:

$$ADF = \frac{\hat{\phi}}{SE(\hat{\phi})}$$  \hspace{1cm} (7)

Where,

$SE (\hat{\phi})$ is the standard error for $\hat{\phi}$ and the hat denotes estimate.

In this study, the ADF test is proposed to examine the stationarity of the stock market index for banking sector [28]. Table 2 shows the ADF test for stock market indices for banking sector at levels 1%, 5% and 10%. The results strongly confirm is stationary in level at the standard 5% significance level, so that there is no need to use any transformation on it.

### Table 2. Unit Root Test (stationary test using ADF) of variable (Banks) at level 1%, 5%, and 10%

<table>
<thead>
<tr>
<th>Level</th>
<th>1% Statistic</th>
<th>5% Statistic</th>
<th>10% Statistic</th>
<th>ADF Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Critical</td>
<td>-3.4280</td>
<td>-5.737522</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Value</td>
<td>3.9958</td>
<td>3.1371</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3. Results of ARIMA

<table>
<thead>
<tr>
<th>(ARIMA)</th>
<th>AIC</th>
<th>MSE</th>
<th>(ARIMA)</th>
<th>AIC</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1,0,0)</td>
<td>3.468</td>
<td>0.000</td>
<td>(2,1,0)</td>
<td>3.4680</td>
<td>0.0001</td>
</tr>
<tr>
<td>9</td>
<td>1019</td>
<td>1</td>
<td>1</td>
<td>007</td>
<td></td>
</tr>
<tr>
<td>(1,0,1)</td>
<td>3.468</td>
<td>0.000</td>
<td>(1,2,2)</td>
<td>3.4672</td>
<td>0.0002</td>
</tr>
<tr>
<td>6</td>
<td>1002</td>
<td>0</td>
<td>2</td>
<td>696</td>
<td></td>
</tr>
<tr>
<td>(1,0,2)</td>
<td>3.468</td>
<td>0.000</td>
<td>(1,2,2)</td>
<td>3.4575</td>
<td>0.0001</td>
</tr>
<tr>
<td>4</td>
<td>1027</td>
<td>1</td>
<td>1</td>
<td>336</td>
<td></td>
</tr>
<tr>
<td>(1,1,0)</td>
<td>3.472</td>
<td>0.000</td>
<td>(2,0,2)</td>
<td>3.4695</td>
<td>0.0001</td>
</tr>
<tr>
<td>0</td>
<td>1333</td>
<td>0</td>
<td>0</td>
<td>020</td>
<td></td>
</tr>
</tbody>
</table>

**Table 3. Results of ARIMA**

**Autocorrelation and Partial Autocorrelation**

The plot of the autocorrelation function (ACF) is significant while assessing the stationary as well as non-stationary models. Auto-correlation can be considered as a significant device in “time series modelling” (as the direction in picking terms to incorporate into an ARIMA display).

Additionally, the plot of the “partial autocorrelation function” (PACF) is also a significant instrument in “time series modelling”. While, Figure 3 demonstrates the ACF for banking sector files, while the instability information demonstrates a vast positive noteworthy spike at slack 1. It implies that the auto-correlation of the progressive sets of perceptions is inside. Furthermore, Figure 4 demonstrates the PACF for the keeping banking sector; instability information demonstrates a vast positive noteworthy spike at slack 1. All other partial auto-correlations (for lags 2 to 15) are within the 95% confidence limits.
We should set 

\[ p = 0 \] 

which implies that we should **reject** \( H_0: \theta = 0 \) in favor of \( H_0: \theta \neq 0 \), by setting \( \alpha = 0.05 \). Then we conclude that \( \theta \) is important in the model by using a test that allows only a 0.05 probability of concluding that \( \theta \) is important when it is not. That is usually regarded as strong evidence that \( \theta \) is important.

### 4. RESULTS

#### ARIMA Model Analysis

"ARIMA models" is the broadest class of models for a brief anticipation of time series. This model displays an arithmetical articulation picked in light of the accessible acknowledgment. The most imperative general qualities of hypothetical AR and MA in light of the development of ACF's and PACF's are characterized as taking after Stationary Autoregressive (AR) forms have hypothetical ACF's that rot or ‘sodden out’ toward zero. In any case, they have hypothetical PACF's that sliced off pointedly to zero after a couple of spikes. The slack length of the last PACF spike measures up to the AR arrange \( (p) \) of the procedure. Moving-normal (MA) forms have hypothetical ACF's that sliced off to zero after a specific number of spikes. The slack length of the last ACF spike squares with the MA request of the procedure. The hypothetical PACF's rot or 'cease to exist' toward to zero. Mean square mistake is essentially the normal of the squared blunders for all estimates. It can be characterized as a measure of exactness of the fitted model. We can utilize Akaike Information Criteria (AIC) to pick the best ARIMA display to arrange which is given by [29].

\[ \text{AIC} = (-2L/T) + 2k/T \] 

Where, 

\[ L \] is “the log likelihood, \( k \) is the number of parameters.” 

\[ T \] is “the number of observations.” 

The MSE cannot prove to be revealing by itself, though it can be used to compare the fits of different ARIMA models to choose which one does better. It can be defined as:

\[ MSE = \frac{1}{n} \left( \sum_{t=1}^{n} (e_t)^2 \right) + \frac{1}{n} \left( \sum_{t=1}^{n} (y_t - \hat{y}_t^2) \right) \] 

(9)

Let, \( \theta \) denotes “any particular parameter in a Box-Jenkins model”;

\( \theta' \) denotes “the point estimate of \( \theta' \);

\( S_{\theta'} \) denotes “the standard error of the point estimate \( \theta' \).”

Then the \( t \)-value associated with \( \theta' \) is calculated by the following equation:

\[ t = \frac{\theta'}{S_{\theta'}} \] 

(10)

If the absolute value of \( t \) is large, then \( \theta' \) is large [30]. This implies that \( \theta \) is not equal to zero, and thus that we should reject \( H_0: \theta = 0 \), which implies that we should include the parameter \( \theta \) in the Box-Jenkins model.

Additionally, the \( p \)-value is defined to be tested regarding to the value of \( \theta \) which is the level of significance. In this study, the value of \( \alpha \) is assumed to be 0.05, since most financial studies used this value. If we reject \( H_0: \theta = 0 \) in favor of \( H_0: \theta \neq 0 \), by setting \( \alpha = 0.05 \), then we conclude that \( \theta \) is important in the model by using a test that allows only a 0.05 probability of concluding that \( \theta \) is important when it is not. That is usually regarded as strong evidence that \( \theta \) is important.

Table 3 shows all the varieties of ARIMA models choices between the model \( (0,0,0) \) to \( (2,2,2) \) for the banking sector volatility with their AIC and MSE values. The best model for the banking sector is ARIMA \( (2, 0, 2) \), since this model gives the minimum mean square error with the lowest value of AIC, the general formula for ARIMA \( (2, 0, 2) \) is defined as follows:

\[ Z_t = \mu + \varphi_1 Z_{t-1} + \varphi_2 Z_{t-2} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} \] 

(11)

The best-fitted model according to the above is given by:

\[ Z_t = 0.011441 + 0.0095 Z_{t-1} + 0.6930 Z_{t-2} + 0.0023745 + 0.1469 a_{t-1} - 0.6866 a_{t-2} \] 

(12)

Moreover, Table 4 shows the final estimate of the parameters for the banking sector volatility data; the \( t \)-value, \( p \)-value for both coefficients AR \( (2) \), MA \( (2) \) and for the constant term are significant.
Based on Table 3, the ARIMA model (2, 0, 2) can be derived to check the adequacy of a Box-Jenkins model that is to analyze the residuals $(Y_t - \hat{Y}_t)$. Figures 5 and 6 showed the residuals of ACF and PACF respectively. The residuals ACF and PACF for banking sector volatility are indicated as significant. Thus, the residuals are random and the model is a good fit to the data. Besides, the spikes are surrounded by the confidence limits.

<table>
<thead>
<tr>
<th>Type</th>
<th>Coef</th>
<th>SE Coef</th>
<th>T</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR 1</td>
<td>0.0995</td>
<td>0.1354</td>
<td>0.73</td>
<td>0.463</td>
</tr>
<tr>
<td>AR 2</td>
<td>0.6930</td>
<td>0.0942</td>
<td>7.35</td>
<td>0.000</td>
</tr>
<tr>
<td>MA 1</td>
<td>-0.1469</td>
<td>0.1398</td>
<td>1.05</td>
<td>0.294</td>
</tr>
<tr>
<td>MA 2</td>
<td>0.6866</td>
<td>0.1042</td>
<td>6.59</td>
<td>0.000</td>
</tr>
<tr>
<td>Mean</td>
<td>0.011441</td>
<td>0.001358</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 5. Autocorrelation Function of Residuals

Figure 6. Partial Autocorrelation Function of Residuals

The four-in-one residual plot is showed in Figure 7. The normal probability plot indicated that the residuals are normally distributed. Moreover, the fit regression line showed that the residuals are closed to the straight line. Furthermore, the histogram indicated that approximately the whole data is centered on the mean of data. The residuals versus fitted values indicated that the variance is approximately constant. And as it is shown in the last graph, that residuals versus order observations which is weekly for banking sector volatility, it is clear that the whole residuals are centered on and near to the x-axis.
### Table 5. Forecasted values using ARIMA (2,0,2) Model

<table>
<thead>
<tr>
<th>Period</th>
<th>Forecast</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>273</td>
<td>0.0077137</td>
<td>-0.0119227</td>
<td>0.0273501</td>
</tr>
<tr>
<td>274</td>
<td>0.0081052</td>
<td>-0.0121183</td>
<td>0.0283288</td>
</tr>
<tr>
<td>275</td>
<td>0.0085263</td>
<td>-0.0117064</td>
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<td>276</td>
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<td>277</td>
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<tr>
<td>278</td>
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<td>-0.0112654</td>
<td>0.0300887</td>
</tr>
<tr>
<td>279</td>
<td>0.0096602</td>
<td>-0.0110311</td>
<td>0.0303516</td>
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<tr>
<td>280</td>
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<td>281</td>
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<td>282</td>
<td>0.0102054</td>
<td>-0.0106137</td>
<td>0.0310246</td>
</tr>
<tr>
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<td>0.0103539</td>
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<td>0.0311823</td>
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<td>284</td>
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</tr>
<tr>
<td>285</td>
<td>0.0105918</td>
<td>-0.0102653</td>
<td>0.0314489</td>
</tr>
</tbody>
</table>
At forecasting stage, the fitted model has been selected; it can be used to produce the forecasts for future time periods for the banking sector volatility. The final model for the volatility of banking sector is demonstrated in Equation 12, while, Table 5 showed the predicted 13 weeks ahead of the volatility of banking sector. Whereas, Figure 8 showed the plot of the actual and predicted values for the volatility of banking sector, the 95% percent prediction interval for the forecasts also are computed. Since, the values of the lower interval are negative signs, we can ignore these boundaries.

4. CONCLUSION

ARIMA model introduces a good way for forecasting any oscillated variables. Its power reclines in the truth that the technique is very useful for any time series with any outline of change and it does not need the forecaster to pick any parameters in advance. Results show that the ARIMA (2,0,2) is found to be the best appropriate model for predicting the volatility of the banking sector time series data in ASE.

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