A Study of The Saudi Stock Market Using Some Statistical Models

Abdelgalal O. I. Abaker

Applied College, Khamis Mushait, King Khalid University, Abha, Saudi Arabia, a.adaam@tu.edu.sa

Abdalla S. Mahmoud

Department of Mathematics, University College at Raniah, P.O. Box 11099, Taif University, Taif 21944, Saudi Arabia, a.adaam@tu.edu.sa

Badawi O. Mohammed

Department of MIS, Faculty of Business Administration, Alba University, Alba, Saudi Arabia,
Department of Statistics, Faculty of Economics and Political Science, Omdurman Islamic University,
Sudan, a.adaam@tu.edu.sa

Ali R. R. Alzahrani

Department of Mathematics, Faculty of Sciences, Umm Al-Qura University, Makkah, 24382, Saudi Arabia, a.adaam@tu.edu.sa

Adil. O. Y. Mohamed

Department of Computer Science, College of Computer, Qassim University, Buraydah 52571, Saudi Arabia, a.adaam@tu.edu.sa

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A Study of The Saudi Stock Market Using Some Statistical Models

Abdelgalal O. I. Abaker¹, Abdalla S. Mahmoud², Badawi O. Mohammed³, Ali R. R. Alzahrani⁴, Adil. O. Y. Mohamed⁵, and Azhari A. Elhag⁶

¹Applied College, Khamis Mushait, King Khalid University, Abha, Saudi Arabia
²Department of Mathematics, University College at Raniah, P.O. Box 11099, Taif University, Taif 21944, Saudi Arabia
³Department of MIS, Faculty of Business Administration, Albahah University, Albahah, Saudi Arabia
⁴Department of Statistics, Faculty of Economics and Political Science, Omdurman Islamic University, Sudan
⁵Department of Mathematics, Faculty of Sciences, Umm Al-Qura University, Makkah, 24382, Saudi Arabia
⁶Department of Computer Science, College of Computer, Qassim University, Buraydah 52571, Saudi Arabia
⁷Department of Mathematics and Statistics, College of Science, P.O. Box 11099, Taif University, Taif 21944, Saudi Arabia

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Abstract: The objective of this paper is to estimate the diversification effects/benefits of an investment in a portfolio consisting of the South African Industrial (J520) and the Financial (J580) Indices using the Generalised Pareto Distributions (GPDs) with an extreme value Gumbel copula. The GPD is used as the marginal distribution to both assets to better characterize the extreme risk of returns in both Indices tails. The extreme value Gumbel copula captures the dependence structure (co-movement) of the financial assets in the portfolio. The Akaike information criterion (AIC) and Bayesian information criterion (BIC) goodness of fit tests and the scatterplots indicate that the upper tail of the gains (the larger gains) risk and the losses tail (the larger losses) are best captured using the extreme value Gumbel copula. Monte Carlo simulation of an equally weighted portfolio of the two Indices is used to estimate the portfolio risk. The univariate marginal risks and the portfolio risks are used to calculate the diversification effects/benefits. The results show that there are benefits in diversification since the riskiness of the portfolio is less than the sum of the risk of the two financial assets. This implies that VaR, although not additive theoretically, is sub-additive in this practical situation. This property of sub-additivity represents the benefits of diversification for a portfolio. The implication is that investors investing in individual risky assets can benefit from constructing such a portfolio to reduce extreme risk. Due to high dependence and contagion between developed markets/Global markets, this is useful information for local and international investors seeking a portfolio which includes developing countries' market Indices, such as South African assets, which are less correlated with other Global markets, thereby reducing the risk of contagion.

Keywords: Machine Learning, GARCH models, Stock market, Statistical Model, ARIMA models, Volatility clustering, Leverage effect

1 Introduction

The problem of modeling and forecasting stock market volatility in literature has taken wide considerable attention around the world in both developing and developed countries. The models of univariate GARCH are used by Dana [1] in the Amman stock market to test the behavior of returns volatility. The models of ARCH/GARCH have presented a piece of strong evidence for the existence of each Leptokurtic and volatility clustering. Moreover, the results shown in Amman stock market returns that, there is no evidence for the presence of a leverage effect. Prashant Joshi [2] used three different models of GARCH to predict the daily volatility of the Bombay Stock Exchange's Sensex. According to their findings, the stock market shows volatility persistence and the existence of a leverage effect. Moreover, using a variety of macroeconomic variables, the predictive performance of linear and non-linear models are compared to the Johannesburg Stock Exchange by Michael Van et al. [3] when predicting financial returns. The authors used a variety of models such as Markov switching ARMA and Dynamic Regression, linear specifications, and univariate GARCH to capture conditional heteroscedasticity. According to their findings, the best in-sample fit is Markov switching models, while findings for the out-of-sample periods reveal the outperformance of linear models. Adolphus et al. [4] attempted to determine the most efficient GARCH models to predict the volatility of the Nairobi stock exchange. The (SBC), (AIC), and Mean Squared Error were used to evaluate the models. The results showed that IGARCH models are the best models for modeling and forecasting the volatility of the Nairobi stock exchange.

2 Methodology

*Corresponding author e-mail: adaam@tu.edu.sa
In modeling and forecasting of stock market volatility, GARCH models are the most commonly used methodologies, see Hassan and Hassan [5]. The symmetric and asymmetric models present two types of volatility models. This paper employs one of the symmetric models known by the GARCH (1,1) model and two GARCH asymmetric models known by EGARCH (1,1) and TGARCH (1,1).

2.1 ARCH model

ARCH models are developed by Engle [6]. These models are used in modeling and predicting the volatility of the financial time series. The model is written as follows:

\[ y_t = \varepsilon_t \]  
\[ \varepsilon_t \sim N(0, \sigma_t^2) \]  
\[ \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \] 

ARCH(q) is the name of this model. For q= 1 ARCH model is reduced to

\[ \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \] 

Where \( y_t \) denotes the observed time series, \( \varepsilon_t \) denotes the residual, \( \alpha_0 \) is a constant, \( \alpha_i \) denotes to the ARCH effect, q denotes the duration of ARCH lags and \( \sigma_t \) denotes the conditional variance. \( \alpha_0 \) and \( \alpha_i \) are nonnegative normally values to satisfies positive conditional variance.

2.2 GARCH model

The GARCH model is capturing the volatility of the variance and volatility clustering of financial time series developed by Bollerslev [7] as follows:

\[ \sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \] 

Where equation (5) denotes conditional variance equation with \( \alpha_0 > 0, \alpha_i > 0, \beta_i > 0 \)

The model (5) referred to as GARCH(p, q). Then, GARCH(1,1) can be specified by:

\[ \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1} \]  

The shortcomings of GARCH model are that the asymmetric effect does not capture what characterizes the most stock market return data.

2.3 Exponential generalized auto regressive conditional heteroskedastic (E-GARCH) model

EGARCH model suggested by Nelson, which allows for asymmetric effects, see [8]. The model can be written as follows:

\[ \sigma_t^2 = \omega + \alpha_i \varepsilon_{t-1}^2 - \beta_i \sigma_{t-1}^2 + \gamma d_{t-1} \] 

Where \( d_{t-1} \) is a dummy variable that takes the value 1 if \( \varepsilon_{t-1} < 0 \) (bad news) and the value 0 if \( \varepsilon_{t-1} > 0 \) (good news). \( \gamma \) represents the leverage term. \( \varepsilon_{t-1} > 0 \) indicates good news. The coefficient \( \gamma \) is the leverage term.

2.4 Time series analysis in statistics and Econometrics

The model of Autoregressive Moving Average (ARMA) is generalized by Autoregressive Integrated Moving Average (ARIMA) model, see [9,10,11] and [12]. Therefore, the time series data is used under both these two models in order to better understand the data or to forecast it by the future points in the series [13] and [14].

Let \( Z_t \) a time series data, which represents an integer index, and \( Z_t \) be a real number, then

\[ Z_t = Z_{t-1} + \alpha_t \sim WN(0, \sigma^2) \] 
\[ Z_t - Z_{t-1} = \alpha_t \sim WN(0, \sigma^2) \] 
\[(1 - B)Z_t = \alpha_t \] 
\[ Z_t = \frac{1}{(1 - B)} \alpha_t \] 
\[ \psi(B) = \frac{1}{(1 - B)} \] 

Where the weighed \( \psi_1, \psi_2, \psi_3, \ldots \)  
\[ \psi(B)(1 - B) = 1 \]
\[
(1 + \psi_1 B + \psi_2 B^2 + \psi_3 B^3 + \ldots)(1 - B) = 1
\]

\[
B : \psi_1 - 1 = 0 \Rightarrow \psi_1 = 1
\]  
(14)

\[
B^2 : \psi_2 - \psi_1 = 0 \Rightarrow \psi_2 = \psi_1 = 1
\]  
(15)

\[
B^3 : \psi_3 - \psi_2 = 0 \Rightarrow \psi_3 = \psi_2 = 1
\]  
(16)

\[
B^j : \psi_j - \psi_{j-1} = 0 \Rightarrow \psi_j = \psi_{j-1} = 1
\]  
(17)

(18)

That is, the weights for the random walk model are

\[
\psi_j = 1, \ j \geq 1
\]  
(19)

2.5 Some properties of the weighted function \(\psi(B)\)

The auto regressive moving average model of degree ARMA (P,q) can be written like that:

\[
Z_t - \mu = \psi(B) a_t; \ a_t \sim WN(0,\sigma^2)
\]  
(20)

This relationship could be written as follows [15]:

\[
Z_t - \mu = a_t + \psi_1 a_{t-1} + \psi_2 a_{t-2} + \ldots = \sum_{j=0}^{\infty} \psi_j a_{j-1}; \ \psi_0 = 1
\]  
(21)

3. Data Analysis

The daily closing prices of Saudi Stock Exchange represents the data used in this article from January 1-1-2003 to June 18-6-2020[16]. The following formula was used to measure daily returns \(r_t\):

\[
r_t = \left( \frac{P_t}{P_{t-1}} \right)
\]  
(22)

where:

- \(r_t\) is the index's daily return at time \(t\)
- \(P_t\) denotes closing price index

The results in table (1) show a negative skewness coefficient which supports previous findings and confirms the fact that many financial data have a large left tail. The normality at the 1% level of significance of the high value of Jarque-Bera is rejected. Furthermore, the LM test statistics of Engle (1982) suggest the presence of ARCH effects, the variance of the return series has indicated that the later series is time-varying.

<table>
<thead>
<tr>
<th>Skewness</th>
<th>-0.944936</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kurtosis</td>
<td>14.08645</td>
</tr>
<tr>
<td>Jarque- Bera</td>
<td>10002.53</td>
</tr>
<tr>
<td>Probability of Jarque- Bera</td>
<td>0.00000</td>
</tr>
<tr>
<td>ARCH-LM (2)</td>
<td>8.017619</td>
</tr>
<tr>
<td>Probability of ARCH- LM</td>
<td>0.0182</td>
</tr>
</tbody>
</table>

In Fig. 1, we notice that periods of higher changes are pursued by periods of higher changes whereas periods of low changes are followed by periods of low changes. This pattern of stock return suggests that TASI returns show strong signs of volatility clustering. As a result, residuals are conditionally heteroscedastic, and ARCH and GARCH models can be used to describe it.

The distribution of TASI log returns is shown in Fig. 2, which clearly reveals a deviation from normality.
The stationarity is determined under unit root test of return series; the results, which are described in table (2), show that non-stationary returns were rejected, and we conclude that TASI returns are stationary in level.

**Table 2: TASI daily return series, stationery test**

<table>
<thead>
<tr>
<th>Augmented Dickey-Fuller unit root test</th>
<th>-38.35</th>
</tr>
</thead>
<tbody>
<tr>
<td>critical values</td>
<td></td>
</tr>
<tr>
<td>1%</td>
<td>-3.43</td>
</tr>
<tr>
<td>5%</td>
<td>-2.86</td>
</tr>
<tr>
<td>10%</td>
<td>-2.57</td>
</tr>
</tbody>
</table>

This section contains estimates for Saudi Exchange returns series from various GARCH and ARMA models. Also diagnostic test of the models are achieved.

**Table 3.** The estimation values of TASI index under different GARCH models

<table>
<thead>
<tr>
<th></th>
<th>GARCH (1,1)</th>
<th>EGARCH(1,1)</th>
<th>TGARCH(1,1)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>The Equation of the Mean</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\phi_0$</td>
<td>0.000333</td>
<td>0.000262</td>
<td>0.000285</td>
</tr>
<tr>
<td></td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
</tr>
<tr>
<td><strong>The Equation of the Variance</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\phi_1$</td>
<td>6.21E-07</td>
<td>-0.57554</td>
<td>5.99E-07</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.173918</td>
<td>0.231682</td>
<td>0.054040</td>
</tr>
<tr>
<td></td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0082)</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.812225</td>
<td>0.963812</td>
<td>0.829462</td>
</tr>
<tr>
<td></td>
<td>(0.0000)</td>
<td>(0.0000)</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>-</td>
<td>-1.07144</td>
<td>0.179816</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0000)</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>7751.398</td>
<td>7785.570</td>
<td>7779.557</td>
</tr>
<tr>
<td>AIC</td>
<td>-8.163749</td>
<td>-8.161704</td>
<td>-8.192368</td>
</tr>
<tr>
<td>SIC</td>
<td>-8.152055</td>
<td>-8.184088</td>
<td>-8.17751</td>
</tr>
<tr>
<td>ARCH-LM(1)</td>
<td>0.14073</td>
<td>0.171168</td>
<td>0.181503</td>
</tr>
<tr>
<td>Test</td>
<td>(0.9321)</td>
<td>(0.9180)</td>
<td>(0.9132)</td>
</tr>
</tbody>
</table>

The p-value is putted in parentheses

The results in Table 3 reveal that the constant coefficients of ARCH and GARCH in the conditional variance equation for GARCH (1,1) model are positive and statistically significant at 1%. The sum of parameters ($\alpha + \beta$) of ARCH and GARCH is close to unity. Also, the results suggest that volatility shocks are quite persistent.

From Table 3, The EGARCH model results indicate that the parameters at 1% are statistically significant. The parameter $\gamma$ has asymmetric effect captured by significant with negative sign, meaning that good news produce less volatility than bad news.

TGARCH is an alternative asymmetric model for investigating existence of leverage effect in TASI index. The results of
TGARCH model displayed in table (3) reveal that the parameter of the asymmetric term $\gamma$ is positive and significant at the 1% level. This

The ARCH- LM test of order 1 shows that there is no ARCH effect remaining in the residuals of the variance equations for all GARCH models, as shown in table (3). This shows that the variance equations are correctly defined. The identified model in table (4) for this data is ARIMA (1, 0, 1) where it succeeded in estimated parameter significance test and it succeeded in residual analysis test.

**Table 4:** The identified model ARIMA (1, 0, 1)

<table>
<thead>
<tr>
<th>Par.</th>
<th>Value</th>
<th>Met. error</th>
<th>St. error</th>
<th>95% Lower bound</th>
<th>95% upper bound</th>
<th>Asy. St. error</th>
<th>95% Lower bound</th>
<th>95% upper bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR(1)</td>
<td>-0.368</td>
<td>0.156</td>
<td></td>
<td>-0.674</td>
<td>-0.063</td>
<td>0.128</td>
<td>-0.619</td>
<td>-0.118</td>
</tr>
<tr>
<td>MA(1)</td>
<td>0.504</td>
<td>0.158</td>
<td></td>
<td>0.196</td>
<td>0.813</td>
<td>0.119</td>
<td>0.272</td>
<td>0.737</td>
</tr>
</tbody>
</table>

The GARCH and ARMA models were evaluated by using maximum log likelihood criteria, Akaike Information Criteria (AIC) and minimum Schwartz Bayesian Criteria (SBC) values. The results in table (5) show that the GARCH (1,1) outperforms the other models depending on the min AIC and SBC values. While the biggest log likelihood criteria reveal that EGARCH (1,1) model outperforms the other models. However, because of the asymmetric response to news, this study suggests that the EGARCH (1,1) model is the best model for predicting the volatility of Saudi stock market returns.

**Table 5.** The Criteria to evaluate Models

<table>
<thead>
<tr>
<th>Criteria</th>
<th>GARCH (1,1)</th>
<th>TGARCH (1,1)</th>
<th>EGARCH (1,1)</th>
<th>ARIMA (1,0,1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log likelihood</td>
<td>7881</td>
<td>7896</td>
<td>7901</td>
<td>7375</td>
</tr>
</tbody>
</table>

4. Conclusion

For academics and market participants, modelling the volatility of stock returns has become an important field of study in the financial markets. In this article ARIMA models and GARCH models were used to estimate and predict volatility returns of TASI series, from January 1, 2013 to August 16, 2020. Findings indicate that the daily returns of TASI are characterized by clustering characteristics of volatility, leptokurtosis and by the presence of heteroscedasticity in the residuals. Besides, the study has shown that the EGARCH model is superior to the other models in estimating and predicting the volatility returns of the Saudi stock exchange.

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References


