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Intraday return volatility in Saudi Stock Market: An evidence from Tadawul All Share Index

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A B S T R A C T

The association between risk and return is a significant concept in finance that has been studied in the past to a large extent. The stock market volatility is closely associated with the risk. The current study examines the intraday volatility pattern of stock market of Saudi Arabia by reviewing the stocks of Tadawul All Share Index (TASI). We obtain return data at 5-minute frequency from the SASEIDX starting on 25 October 2017 and ending on 9 May 2018. We examine the stock market volatility by using different symmetric and asymmetric GARCH models and observe that, the symmetric GARCH models showed a significant positive association between risk and return. Similarly, the asymmetric GARCH models show that the estimates were significant and the leverage estimate was negative and significant, indicating a no-leverage effect in the return series. Moreover, the asymmetric results suggest that negative shocks do not entail to future higher volatility than positive shocks. Therefore, the symmetric and asymmetric GARCH models are comfortable to capture the volatility of Saudi stock market from Intraday data.

1. Introduction

The prediction and modelling of stock market volatility has become significant in these recent years in the field of finance, and is considered point of interest for academicians and finance professionals. The association between risk and return is a significant concept in finance that has been studied in the past to a large extent (Markowitz & Blay, 2013). The stock market volatility is closely associated with the risk. In other words, measuring risky assets is volatility. Stock market volatility brings variations in stock returns, hence has an effect on risk. There are studies that examined inter-daily volatility where it is difficult to find out the difference of daily open-to-open volatility and close-to-close volatility (Tian & Guo, 2007), and which is captured by the intraday market volatility. The study of intraday market dynamics is made easy due to widened availability of high-frequency data. The underlying volatility measurement methods are relevant and the generalized autoregressive conditional heteroscedasticity (GARCH) models are frequently in usage to examine the market volatility dynamics. The previous studies introduced many models to investigate the stock market volatility and evaluate the performance of

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stock market, such as ARCH (Engle, 1982), GARCH (Bollerslev, 1986; Andersen & Bollerslev, 1997), EGARCH (Nelson, 1991), TGARCH (Glosten et al., 1993), FIGARCH (Baillie et al., 1996). Further, there have been different studies that employed various models and their extensions to model the conditional variance, and they are found in both developed and emerging stock markets, such as Abdalla and Winker (2012), Goudarzi and Ramnarayanan (2010), Jiang (2012), Mandimika and Cinzara (2012), Matei (2009), El Aal (2011), Muller (2009), Chuang et al. (2013), Han et al. (2012), Haniff and Pok (2010), Hansen et al. (2012), Hussain et al. (2011) and Lim and Sek (2013).

Ezzat and Uludag (2015) studied information arrival and volatility in Saudi stock market. They found strong evidence of decrease in persistence of volatility due to the inclusion of trading volume and number of trades in conditional variance equation. Further, they suggested number of trades over trading volume in predicting volatility. Arouri (2013) examined the spillover effects between global oil prices and Saudi stock market in terms of risk and return, and reported that the spillovers in Saudi stock sectors are due to shocks rather than volatility. Ulussever et al. (2011) studied the day-of-the week effect of Tadawul stocks with the help of non-linear GARCH, and found mean daily returns different from each other, hence validating the day-of-the week effect. Abdalla and Idris (2013) investigated the volatility spillovers between return and exchange rate in Saudi Arabian and Egyptian stock markets. They reported volatility spillover in Egyptian markets, while no evidence of volatility was found between returns and exchange rate in Saudi stock market. Recent research on stock market extensively used intraday data to reveal the effect of flow of new information on stock market movements (Nikkinen et al., 2006; Rigobon & Sack, 2003). Further, a good number of research papers concentrated particularly, in analyzing the monetary policy news and its effect on stock returns (Rigobon & Sack, 2003; Wongswan, 2006). Su (2010) studied the application of EGARCH model to observe the existence of volatility in Chinese stock market with the help of daily data. He suggested that EGARCH model is the best fit to measure the volatility in the Chinese stock market than the normal GARCH model. Afsal and Haque (2016) found a no dynamic association between the gold and stock markets by using GARCH model.

A number of studies largely relying on US data have sought to rationalize the U-shaped pattern in intraday volatility in stock markets (Harris, 1986; Foster & Viswanathan, 1990; Spiegel & Subrahmanyan, 1995; Andersen et al., 2000; Tabak & Guerra, 2007). According to Sequential Information Arrival Hypothesis (SIAH), the market reaches final equilibrium when the new information is passed to all the traders in the market. This hypothesis has been explained by Copeland (1976) and Jennings et al. (1981). If the past information of stock prices is reflected in the current stock prices, the market is treated as weak-form efficient (Fama, 1970). This hypothesis assumes that the stock market traders receive the information on new arrivals simultaneously leading to a new equilibrium, and there is no partial equilibrium (Harris, 1987; Anderson, 1997). Further, there are few number of studies on Saudi stock market return and volatility. The stock returns of Saudi stock market are characterized by time varying volatility, and also the market is too sensitive to market fluctuations (Kalyanaraman, 2014). Badshah et al. (2016) examined the asymmetries in the intraday return and volatility. They found negative association between return and volatility over all the return horizons. Shen et al. (2016) examined the impact of trading and non-trading period information on volatility, and found reduction in volatility persistence due to simultaneous information.

The current study examines the volatility pattern of Saudi stock market. We choose the stock market of Saudi Arabia for different reasons. Firstly, the emerging markets stand for enthusiastic atmosphere for stock market volatility, because some of these markets are highly volatile due to information imbalance, investors unfamiliar with the arrival of new information, asynchronous trading, embryonic financial analysis, and probably social facets, such as inclination towards herd behavior. A contemporary research by Rahman et al. (2013) observed the Saudi Arabian investors are more exposed towards mass behavior, which may influence volatility in stock market returns. Saudi financial market normally trades in ordinary stocks, since there is no market for derivatives, and short-selling is entirely restricted. The investors of other countries except GCC are not permitted to invest precisely in Saudi stocks. The turnover of Saudi stock market consists of 92 percent and more of Domestic investors (Arab Monetary Fund, 2011). The investors of Saudi stock market are more inclined towards aggressive trading. The turnover of domestic investors is very high, i.e. 118 times compared to other mutual funds which have a turnover of 30 times (NCB Capital, 2008). Accordingly, the Saudi financial market having the characteristics of heterogeneity form a testing ground to examine the volatility of stock market returns. The interests of unfamiliar investors may cause the stock prices adjust relatively to market information, conferring the existence of volatility. Secondly, the kingdom is diligently thinking of opening the Saudi financial market to foreign investors in the near future. Therefore, it becomes significant for the foreign investors to understand the movement of Saudi stock prices. The Saudi Capital Market Law governs the securities market in the Kingdom, and the Capital Markel Authority (CMA) was established by the Royal Decree dated back to 1424H. The CMA acts as a regulator of the Saudi Arabian Capital Market which drafts the rules and regulations to implement the capital market law. According to this law, the "Saudi Stock Exchange" was established in the year 2007 which is also called as the "Tadawul" to carry out securities trading in the Kingdom. It is the sole organization authorized to act as a Securities Exchange with 170 companies listed, and tops among the GCC countries with a market capitalization of 1.9 trillion dollars. It is an exchange with high liquidity having huge number of market traders, large trade volume, and exceptional microstructure for efficient trading. Further, as a move towards implementing the economic reforms in the Kingdom, the Saudi Stock Exchange on 15th June, 2015 opened the doors lo Qualified Foreign Investors (QFI). Furthermore, a forecast by the MSCI has classified Tadawul as an emerging market index by 2017. In light of the above discussed literature, we observed that Saudi securities market returns are depicted with volatility clustering due to skewed distribution of returns. Further, the Saudi stock market movements are influenced by the economic fluctuations. An appreciable amount of literature focuses on the capital markets in advanced economies like U.S. and Europe, while Arab world markets are at scarce and specifically meagre in Saudi Arabian context. Also, there are no studies in the Saudi market context examining intraday stock volatility at 5-minute trade interval. The models employed in the previous research studies on market volatility in Saudi market were unable to capture the fluctuations, where the Kingdom of Saudi Arabia is journeying through many fluctuations, such as oil price change, economic reforms, international relations, etc. The study of intraday stock volatility with the help of different GARCH models might better ensnare the stock market movements. Therefore, it becomes significant to adopt the research in stock market volatility in the Kingdom of Saudi Arabia. The current study intends to examine the intraday volatility in Saudi stock market by considering the stocks of Tadawul All Share Index (TASI).

The remaining paper is arranged in the following manner. Section 2 explains the data and methodology followed by the empirical results in Section 3. Finally, Section 4 discusses the observed results and concludes the study.

2. Data and Methodology

The current study examines the intraday stock market volatility of Tadawul All Share Index (SASEIDX herein after). We have obtained return data at 5-minute frequency of SASEIDX from the Bloomberg Database starting on 25 October 2017 and ending on 9 May 2018. The closing prices of SASEIDX have been used to calculate returns. The stock market of Saudi Arabia is open from Sunday to Thursday. The stock trading session starts at 11.00 am in the morning and ends at 3.55 pm in the afternoon. We calculate the stock returns measured in percentage at 5-minute frequency as the first lognormal difference of index closing prices.

$$R_t = Ln(\frac{P_t}{P_{t-1}}) \times 100, \tag{1}$$

where R_t is the lognormal return at 5-minute frequency, P_t is the index price at close at time t and P_{t-1} is the corresponding period index price at close at time $t-1$. We have obtained 8348 observations at 5-minute frequency.

2.1. Intraday Stock Market Volatility

There are some univariate models to examine the volatility, such as ARCH model given by Engle (1982), GARCH model given by Bollerslev (1986), EGARCH model given by Nelson (1991). The stock market volatility has been reviewed by many researchers by using univariate and multivariate GARCH models. Muller et al. (2009) assert that the GARCH model has been more contributory and effective in obtaining the stylized facts of financial time series data, hence commonly used in financial research. According to Matie (2009) forecasting stock market volatility is appropriate through GARCH model compared with any other alternative model when seen in a unifacial context. In light of the above suggestions, we have selected three volatility models that are commonly used in forecasting market volatility, such as GARCH, EGARCH and TARCH to model the intraday stock market volatility of SASEIDX.

We examine the symmetric association between the return and volatility by using GARCH models.

The Generalized ARCH Model

All the GARCH models consists of a mean equation and variance equation. The mean equation in its simplest from is written as:

$$R_t = \mu + \varepsilon_t . \tag{2}$$

The GARCH model was initially developed by Bollerslev (1986), where the conditional variance in the equation depends on the previous own lags, and this conditional variance equation is written in its simplest form as:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{3}$$

$$\omega \rhd 0 ,\ \alpha_1 \geq 0 ,\ \beta_1 \geq 0$$

where R_t is the return on stock at time t, μ is the average stock return, and ε_t is the residual return. The conditional variance (σ_t^2) is the weighted function that depends on the previous period volatility (ε_{t-1}^2) and previous period conditional variance (σ_{t-1}^2). The process is assumed as stationary if $\alpha_1 + \beta_1 \lhd 1$. Further, the size of coefficients determines the change in volatility in the short-run. Therefore, if $\alpha_1 + \beta_1 = 1$, then any market shock to the conditional variance is said to be endured.

The GARCH-in-Mean Model

The GARCH-M model was suggested by Engle et al. (1987), where conditional variance enters the mean equation. The GARCH-M (1,1) model specification is as follows:

$$R_t = \mu + \phi \sigma_{t-1} + \varepsilon_t \tag{4}$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{5}$$

The coefficient ϕ in the above equation is interpreted as risk premium. A positive correlation can be established between mean return and conditional variance, when ϕ is positive and significant. Further, we also examine the asymmetric relation between return and volatility by using EGARCH and TGARCH models.

The Exponential GARCH Model

The exponential GARCH model was suggested by Nelson (1991) and is modelled as log(σ_t^2). This model is the best fit to test the leverage effect, where it captures the asymmetric relation between returns and volatility.

$$\ln(\sigma_t^2) = \omega + \alpha \ln(\sigma_{t-1}^2) + \lambda \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \beta \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right], \tag{6}$$

where $\ln(\sigma_t^2)$ is the log of conditional variance, λ shows the leverage effect, and can be hypothetically tested as $\lambda \lhd 0$.

The Threshold GARCH Model

The threshold GARCH or TGARCH model was proposed by Rabemananjara and Zakoian (1993). This model is the best fit to apprehend the leverage or asymmetry through differential effect on the conditional variance. This model is defined as:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \lambda_1 S_{t-1} \varepsilon^2{}_{t-1} + \beta_1 \sigma_{t-1}^2, \tag{7}$$

where λ_1 apprehends the asymmetric or the leverage effect. According to the model, the differential effect on conditional variance can be known when $\varepsilon_{t-1} \rhd 0$ which means a good information denoted as α_1, and $\varepsilon_{t-1} \lhd 0$ which means a bad information denoted as $\alpha_1 + \lambda_1$. Therefore, a positive and significant λ_1 shows the presence of leverage effect.

2.2. Descriptive Statistics

We report the descriptive statistics of SASEIDX return series in Table 1, such as Mean ($\overline{X}$), Standard Deviation (σ), Skewness (*S*), Kurtosis (*K*), and Jarque-Bera test.

2.3. Unit Root Test

We test the stationarity of residual series through Augmented Dickey-Fuller Test (ADF) and Philips-Perron Test (PP) to check whether the data is stationary or non-stationary, and report the results in Table 2.

2.4. Heteroscadasticity Test

This test is utmost important before applying the GARCH model to examine the presence of heterosce-dasticity in residual series. We use Lagrange Multiplier (LM) test to examine the heteroscedasticity.

3. Empirical Results

Table 1
Descriptive Statistics of return on SASEIDX

Mean	0.001716	Std. Dev.	0.070505
Median	0.001669	Skewness	-1.233443
Maximum	0.932991	Kurtosis	58.19974
Minimum	-1.633362	Jarque-Bera	1061969
		Observations	8348

We report the descriptive statistics of returns on SASEIDX in Table 1. The positive mean of the returns indicates growth in price over the period. The maximum (0.932991), the minimum (-1.633362), and the standard deviation (0.070505) of returns indicates that the market is volatile. The skewness (-1.233443) of returns is negative and kurtosis (58.19974) is positive suggesting leptokurtic distribution of returns. Finally, the Jarque-Bera test statistic is highly significant at the 1% level, rejecting the normality of return series. Hence, we calculate the logarithmic return series from the closing prices to make the data station-ary.

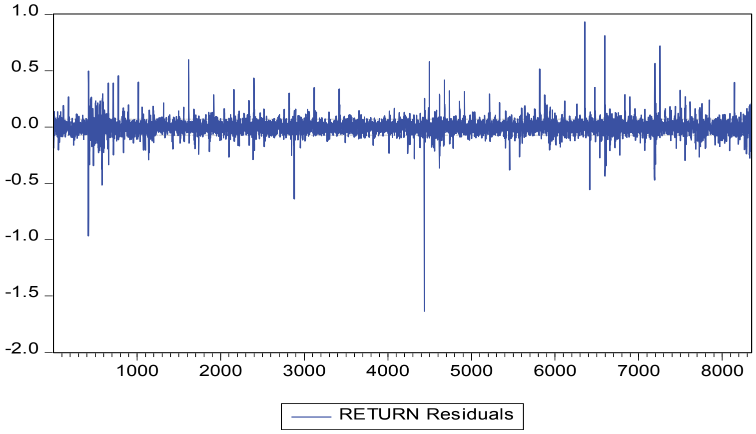

Fig. 1. Volatility Clustering of returns on 5-minute frequency of SASEIDX from 25 October 2017 to 9 May 2018

We report the volatility clustering of 5-minute frequency returns of SASEIDX from 25 October 2017 to 9 May 2018 in Fig. 1. We presume from the figure that; volatility pretends to happen in spurts, and also it is evidenced that volatility is high during the starting of the study period and also at the close. The figure also displays a fraction of high volatility during the first 20 minutes and higher furthermore during the last 5 minute.

Table 2
ADF and LM Test Result

Value	ADF	PP
t-statistic	-72.38532	-72.18709
Probability	**0.0001**	**0.0001**
Critical Value		
1%	-3.430957	-3.430957
5%	-2.861693	-2.861693
10%	-2.566893	-2.566893
ARCH-LM Test	161.93	

We report the results of stationarity using ADF and PP tests, and heteroscadasticity using ARCH-LM test in Table 2. We found that the unit root is present in the return series, since the p-values of ADF and PP tests are less than 5% level, which shows that the returns data is stationary throughout the study period. Further, we also found the presence of ARCH effects in residuals of return series, since the p-value is less than 5% level. Therefore, these results allow us to estimate the models of GARCH family.

Table 3
Result of GARCH (1,1) and GARCH-M (1,1) Models

Model Coefficients	GARCH (1,1)	GARCH-M (1,1)
Mean Equation		
C	0.001716**	-0.004362***
Risk Premium		0.112468**
Variance Equation		
C (ω)	0.001716*	0.000488*
ARCH effect (α_1)	0.150000*	0.192466*
GARCH effect (β_1)	0.600000*	0.638933*
$\alpha_1+\beta_1$	0.750000	0.831399
Log likelihood	310717.9	12488.24
AIC	-74.44009	-2.990714
SIC	-74.43588	-2.986504
ARCH-LM Test Result		
ARCH-LM Test statistic	0.200267	0.003164
Prob. Chi-square (1)	0.6545	0.9551

***Significant at the 10% level, **Significant at the 5% level, and *Significant at the 1% level.

We report the results of GARCH (1,1) and GARCH-M (1,1) models in Table 3 above. The GARCH (1,1) model result shows that the coefficients of ARCH (α_1) and GARCH (β_1) are significant at the 1% level. Further, we evidenced that the conditional return volatility appears to be stationary, as the sum of parameters ($\alpha_1 + \beta_1$) is less than one, which resembles the volatility to persist for longer periods and that it is more sensitive to past values than to the new market shocks. The model shows a positive relationship between risk and return. Moreover, we found no additional ARCH effect remaining in the residuals, since the test statistic of ARCH-LM test is more than 5%, which implies that the GARCH (1,1) model is comfortable to capture the volatility from Intraday data. The GARCH-M (1,1) model result shows that the parameter of risk premium is positive and significant indicating a risk-return trade-off. The parameters of ARCH (α_1) GARCH (β_1) are significant at the 1% level, and the sum of these parameters is less than one, implying stationarity in the conditional return volatility. This shows the persistence of volatility in the market. Further, we found no additional ARCH effect remaining in the residuals, since the test statistic of ARCH-LM test is more than 5%, which indicates that the GARCH-M (1,1) model is also comfortable for the Saudi stock market.

Table 4
Result of EGARCH and TGARCH Models

Model Coefficients	EGARCH	TGARCH
Mean Equation		
C	-0.000159	0.000770
Variance Equation		
C (ω)	-2.053652*	0.001648*
ARCH effect (α)	0.444607*	0.311846*
GARCH effect (β)	0.678114*	0.404964*
Leverage effect (λ)	0.045042*	-0.036796*
α+β	1.122721	0.71681
Log likelihood	11021.42	11071.09
AIC	-2.639295	-2.651195
SIC	-2.635084	-2.646984
ARCH-LM Test Result		
ARCH-LM Test statistic	0.009154	0.003227
Prob. Chi-square (1)	0.9238	0.9547

***Significant at the 10% level, **Significant at the 5% level, and *Significant at the 1% level.

We have examined the asymmetric effect of volatility in the return series with the help of two models, such as EGARCH and TGARCH and the results are reported in Table 4. We explain the best model by comparing the fitness of these two models similar to that explained in Table 3. The result of EGARCH model shows that the estimates of ARCH (α) GARCH (β) are significant at the 1% level, and the leverage estimate (λ) is positive and significant, indicating a no-leverage effect in the return series. This asymmetry of return and volatility cannot be captured from the GARCH (1,1) model. Moreover, we found no additional ARCH effect remaining in the residuals, since the test statistic of ARCH-LM test is more than 5%, which implies that the EGARCH model is comfortable to capture the asymmetric effects from Intraday data. The result of TGARCH model shows that the estimates of ARCH (α) GARCH (β) are significant at the 1% level, and the leverage estimate (λ) is negative and significant, indicating a no-leverage effect in the return series.. This asymmetry of return and volatility cannot be captured from the GARCH (1,1) model. Moreover, we found no additional ARCH effect remaining in the residuals, since the test statistic of ARCH-LM test is more than 5%, which implies that the EGARCH model is comfortable to capture the asymmetric effects from Intraday data.

4. Discussion

We have examined the symmetric association between return and volatility with the help of GARCH (1,1) and GARCH-M (1,1) models. The GARCH (1,1) model result shows that the estimated coefficients are significant, and that the conditional return volatility appears to be stationary, as the sum of coefficients is less than one, which resembles the persistence volatility for longer periods. Further, the estimated coefficients are positive, which shows a positive association between return and risk. Similarly, The

GARCH-M (1,1) model result shows that the estimated parameters are significant at the 1% level, and the sum of these parameters is less than one, implying stationarity in the conditional return volatility. This shows the persistence of volatility in the market. The results of current study are in line with the previous research works of Goudarzi and Ramanarayan (2011), Abdalla and Winker (2012), Banumathy and Azhagaiah (2015). Further, we have examined the asymmetric association between return and risk with the help of EGARCH and TGARCH models. To evidence a leverage effect in the return series, the leverage estimate (λ) should be negative and significant. The result shows that the association between the returns and volatility is positive, suggesting that positive shocks does entail to future higher volatility than negative shocks, hence suggesting no risk-return trade-off. The sum of the estimated ARCH and GARCH coefficients is more than one suggesting an explosive persistency of volatility shocks. Similarly, the results of TARCH model shows that the association between the returns and volatility was negative, suggesting that negative shocks does not entail to future higher volatility than positive shocks. To evidence a leverage effect in the return series, the leverage estimate (λ) should be positive and significant. The asymmetric results of the current study support the study of Ezzat and Uludag (2014), and are contrary to the previous research works of Haniff and Pok (2010), Goudarzi and Ramanarayan (2011), Abdalla and Winker (2012). We have explained the best model by comparing the fitness of different GARCH models with the help of the Log likelihood (LL), the Akaike Information Criterion (AIC), and the Schawrz Information Criterion (SIC). The model with minimal values of AIC and SIC and the highest value of log likelihood has been determined as the best model fit. The AIC, SIC values for GARCH (1,1) model is (-74.44009; -74.43588) and the value of log likelihood is 310717.9, while the AIC, SIC values for GARCH-M (1,1) model is (-2.990714; -2.986504) and the value of log likelihood is 12488.24. Therefore, the GARCH (1,1) model is found to be best symmetric model for the Saudi stock market. Similarly, the AIC, SIC values for EGARCH (1,1) model is (-2.639295; -2.635084) and the value of log likelihood is 11021.42, while the AIC, SIC values for TGARCH model is (-2.651195; -2.646984) and the value of log likelihood is 11071.09. Therefore, the TGARCH model is found to be best asymmetric model for the Saudi stock market.

5. Conclusion

The association between risk and return is a significant concept in finance that has been studied in the past to a large extent. The stock market volatility is closely associated with the risk. The current study has examined the intraday volatility pattern of stock market in Saudi Arabia by reviewing the stocks of Tadawul All Share Index (TASI). We have obtained return data at 5-minute frequency from the SASEIDX starting on 25 October 2017 and ending on 9 May 2018. We have examined the symmetric and asymmetric association between the return and volatility by using different GARCH models. The GARCH (1,1) model result shows a positive relationship between risk and return. The GARCH-M (1,1) model result shows that the parameter of risk premium was positive and significant indicating a risk-return trade-off. Similarly, the result of EGARCH model has shown that the estimates were positive and significant, while the leverage estimate was negative and significant, indicating a no-leverage effect in the return series. The result of TGARCH model has shown that the estimates were significant and the leverage estimate was negative and significant, indicating a no-leverage effect in the return series. The result has indicated that the association between the returns and volatility was negative, suggesting that negative shocks did not entail to future higher volatility than positive shocks. We have concluded this study by suggesting that, GARCH (1,1) and TGARCH models are comfortable to capture the symmetric and asymmetric volatility effects of Saudi stock market. The study of Saudi stock market volatility is a point of importance to financial professionals. The results of the current study might add value to the stock market and the investors in investment management, such as allocations of assets, construction of investment portfolio, managing risk, etc. Improvements can be made in this paper by comparing the Saudi stock market volatility with other developed markets and examining the structural break in the TADAWUL return series.

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