Asian Social Science; Vol. 10, No. 10; 2014
ISSN 1911-2017 E-ISSN 1911-2025
Published by Canadian Center of Science and Education

Stock Market Volatility in Saudi Arabia: An Application of Univariate GARCH Model

Lakshmi Kalyanaraman[1]

[1] King Saud University, Riyadh, Saudi Arabia

Correspondence: Lakshmi Kalyanaraman, King Saud University, Riyadh, Saudi Arabia. E-mail: kaylakshmi@gmail.com

Received: February 7, 2014 Accepted: March 14, 2014 Online Published: April 29, 2014

doi:10.5539/ass.v10n10p142 URL: http://dx.doi.org/10.5539/ass.v10n10p142

Abstract

Study of stock market volatility has been the focus of financial economics. Modelling stock market volatility has great contributions to make in the areas of portfolio management, asset allocation, risk management, etc. We estimate the conditional volatility of Saudi stock market by applying AR (1)-GARCH (1, 1) model to the daily stock returns data spanning from August 1, 2004 to October 31, 2013. We show that a linear symmetric GARCH (1, 1) model is adequate to estimate the volatility of the stock market of the country. We find that Saudi stock market returns are characterised by volatility clustering and follow a non-normal distribution. Saudi stock market returns show a time varying volatility, show persistence and are predictable. Past volatility impacts the current period volatility and past returns play a role in determining the current period return. Saudi stock market is nervous in its reactions to market fluctuations. This finding of the study offer important input into the decisions relating to asset allocation and risk management strategies of investors and treasury managers in Saudi stock market.

Keywords: stock volatility, GARCH model, Saudi stock market, volatility clustering, stock return, univariate analysis, volatility models, conditional volatility, non-normal distribution, risk management

1. Introduction

A stock's volatility gives the range of its outcomes. Markowitz (1952) defined risk as volatility. Volatility study has been at the core of financial economics research. Volatility arises due to the arrival of news in the market and the consequent trading activity by the traders. Dispersion of beliefs among the traders will cause a rise in the level of volatility. When volatility is high compared to the equilibrium values of the stocks, it impacts the return on the stock investment. Describing volatility and the ability to forecast it can provide valuable inputs for decisions relating to asset allocation, portfolio management and risk management.

There is a large number of research studies that examine stock market volatility carried out in the context of both developed and developing countries. However, such a study does not exist for Saudi Arabia. The review of literature on the stock market volatility studies shows that varied range of econometric models are employed by the studies and no single model has emerged superior till date. This requires the study of every single market to help the investors and the regulators as no general lessons can be drawn based on the studies carried out elsewhere. We try to fit an adequate model for Saudi stock returns.

The study of Saudi stock market volatility is of paramount importance to treasury managers and investors in the market. Hence, we carry out the study of stock market volatility in Saudi Arabia. The results of the study have important implications for asset allocation, portfolio construction, risk management and other allied areas related to investment management. Investors looking forward to reduce the uncertainty of their portfolios many reduce it by pulling down their exposure to stocks that are expected to face increased volatility of returns in the future or by adopting appropriate diversification strategy to hedge the risk of increased estimated future volatility.

The reminder of this study is organized as follows: section 2 discusses a brief review of previous works; section 3 presents some stylized facts about Saudi stock market prices and returns; Section 4 narrates the data and methodology used by the study; section 5 presents the results and section 6 gives the concluding remarks.

2. Literature Review

Stock market volatility is widely studied both in developed markets like U.S. (Baillie & Degennaro, 1990), Japan

(Tse, 1991), Australia (Brailsford & Faff, 1996) and emerging markets like India (Karmakar, 2005), Jordon (Al-Raimony & El-Nader, 2012), Sudan (Ahmed & Suliman, 2011), Bangladesh (Alam et al., 2013), China (Fabozzi, 2004), Nigeria (Emenike, 2010), Egypt (Ezzat, 2012), etc. However, studies in the context of Saudi Arabia are almost non-existent.

Many earlier works (see for example Akgiray, 1989; Pagan & Schwert, 1990: Brailsford & Faff, 1996; Brooks, 1998) applied GARCH to US stock data and argue that GARCH models perform better than the competing models. Corhay and Rad (1994) find that GARCH (1, 1) model fits well to the stock market data from France, Germany, Netherlands and UK with the exception of Italy. Hsieh (1989) show that GARCH (1, 1) capture the stochastic dependencies of time series data well. This result is supported by the findings of Taylor (1994), Brook and Burke (2003), Frimpong and Oteng-Abayie (2006) and Olowe (2009). Tse (1991) and Tse and Tung (1992) show that the model that best fits the Japanese and Singaporean markets is the exponential moving average models. Frances and Van Dijk (1996) show that asymmetric GARCH models like GJR model do not perform better than standard GARCH while stock market indices' volatility is forecasted. Alexander and Lazar (2006) argue that GARCH models are at the core of dynamic volatility models. This is due to the ease of their estimation and the availability of diagnostic tests. (Drakos et al., 2010) However, GARCH model does not completely capture the skewness and leptokurtosis of the data. In case of non-normal distribution data, the need for introducing non-normal conditional densities arises. Bollerslev (1986) offers the student t-GARCH model. According to Alexander and Lazar (2006), if the data happens to be non-normal, normal GARCH model could not capture the entire leptokurtosis in the data, hence GARCH model that takes into account this characteristic is more appropriate.

Some of the previous works find that asymmetric models do a better job in forecasting as a strong inverse association exist between volatility and shock. (See for example Lee, 1991; Cao & Tsay, 1992; Heynen & Kat, 1994) Poon and Granger (2003) review 93 papers, of which seventeen works evaluate alternative versions of GARCH. That GARCH dominates ARCH is clearly brought out. Models that include volatility asymmetry such as EGARCH and GJR-GARCH outperform GARCH. Bekaert and Harvey (1997) and Aggarwal et al. (1999) conclude that asymmetric GARCH models capture asymmetry in stock return volatility adequately from their study on emerging market volatility. Su (2010) applies GARCH and EGARCH models to assess the financial volatility of daily data of Chinese stock market. He shows that EGARCH model explain the volatility in the daily stock market data from January 2000 to April 2010 better than GARCH model.

The results of various studies carried out so far are not consistent. This can be attributed to the fact that the models, sampling period, frequency of data and forecast horizon used vary. (Vilhelmsson, 2006) We apply GARCH (1, 1) model which is considered as the most appropriate model for estimating conditional volatility by many studies.

3. Stylized Facts about Saudi Stock Market Prices and Returns

Before, we decide on the methodology employed by the study, we analyse the Saudi stock prices and returns to bring out a few stylized facts about them.

Earlier works show that financial time series data is characterized by volatility clustering (Poon, 2005), leverage effects (Christie, 1982), deviate from the mean value (Dowd, 2005), have fat tails and a greater peak at the mean than normal distribution. (Brooks, 2008) Cont (2001) argues that the stylized facts about the financial time series data render the common statistical approaches to its analysis invalid. In order to freeze an appropriate methodology, we study if these characteristics are present in Saudi stock market prices and returns. Before we present this analysis, we present data on some indicators of the market.

Table 1. Saudi stock market indicators

End of year	Listed companies		Market capitalization of issued shares (Billion RLs)		Market capitalization to GDP (%)
	No.	Annual % change	Value	Annual % change	
2004	73	4	1149	94.7	123
2005	77	5	2439	100.12	208
2006	86	12	1226	-49.7	92.5
2007	111	29	1946	58.8	136
2008	127	14	924.5	-52.5	52.2
2009	135	6	1195.5	29.3	82.8
2010	146	8	1325.4	10.9	79.6

End of year	Listed companies		Market capitalization of issued shares (Billion RLs)		Market capitalization to GDP (%)
	No.	Annual % change	Value	Annual % change	
2011	150	3	1270.8	-4.1	58.75
2012	158	5.3	1400.3	10.2	52.5

Source: Saudi Arabian Monetary Agency Annual Report, various issues

Existence of Saudi stock exchange can be traced back to 1970s, when it came into being informally. Saudi stock exchange is known as Tadawul. As at the end of 2012, Saudi stock exchange has shares listed from companies that span 15 sectors. Table 1 presents data on some of the indicators of Saudi stock market during the study period, 2004 to 2012. The number of listed companies during the period increased from a mere 73 in 2004 to 158 in 2012 which is an increase of around 207%. As of 2012, the market capitalization of the shares issued by the listed companies stand at around 1,400 billion Saudi riyals which is around 52.5% of the country's gross domestic product.

TASI, Saudi stock market composite index, was around 6,100 points on August 1, 2004. It registered a steady increase during the year and closed at around 8,200 at the year end. This increasing trend persisted and the index breached the 20,000 level on February 2006 and touched its zenith at 20,634 on February 25, 2006. However, from February end, TASI started sliding and fell below 10,000 on 31st October 2006. Before the onset of the impact of global financial crisis on the Saudi stock market, TASI was at 8,700 points at the close of August 2008. During September 2008, the index further fell and reached around 7,400 on 28th September 2008. Though the index showed trend reversal, it could never reach its historic highs again. Index was at 8,400 on the 31st October 2013. During our period of study, Saudi stock index suffered two major downturns, one in 2006 and another in 2008.

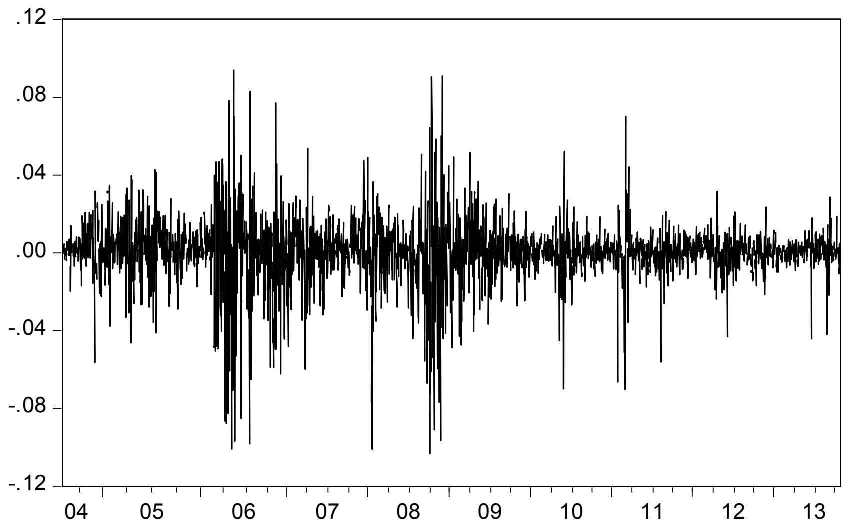

Figure 1. TASI

Table 2. Descriptive statistics of Saudi stock market

Mean	0.000112
Median	0.001102
Maximum	0.093907
Minimum	-0.103285
Standard Deviation	0.017134
Skewness	-0.920527
Kurtosis	10.73372
Jarque-Bera	6298.916
Prob. of Jarque-Bera	0.0000
No. of observations	2392

Table 2 presents the descriptive statistics for the Saudi stock market return series. Jarque-Bera (1987) test checks if the Saudi stock market return is normally distributed. The test statistic rejects the null hypothesis of normality at 1% level. The mean is less than the median and the data series is skewed towards the left. The mean return is positive which indicates that the investors have earned a positive rate of return on their investments in TASI during the study period. The value of kurtosis is greater than 10 which mean that the Saudi stock market return series has a heavier tail than a standard normal distribution. In conclusion, we decide that Saudi stock market returns are non-normally distributed.

That Saudi stock returns are not normally distributed can be ascertained by looked at the figure 2 also that presents the histogram along with the normal distribution plot. The high peak and the fat tails of the Saudi stock market return distribution brings out the fact that it is leptokurtic. That stock market returns follow leptokurtic distribution is well established in finance literature.

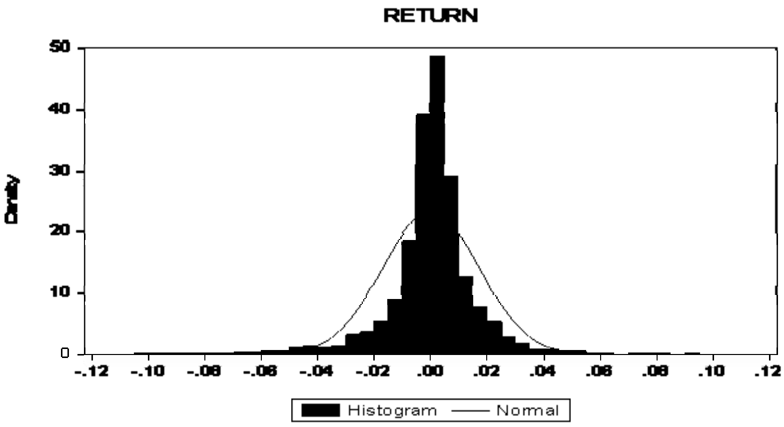

Figure 2. Histogram and normal distribution of Saudi stock returns

Figure 3 shows that Saudi stock returns show volatility clustering. Large price fluctuations are followed by large price fluctuations and small price variations are followed by small price variations, of both signs. Volatility clustering is explained by the theory by heterogeneous expectations. (Kirchler & Huber, 2007). Returns fall as traders learn from their past strategies. As a result, the market tends to remain in a state of partial equilibrium till new information arrives. Statistically speaking, volatility clustering stands for strong autocorrelation in squared returns.

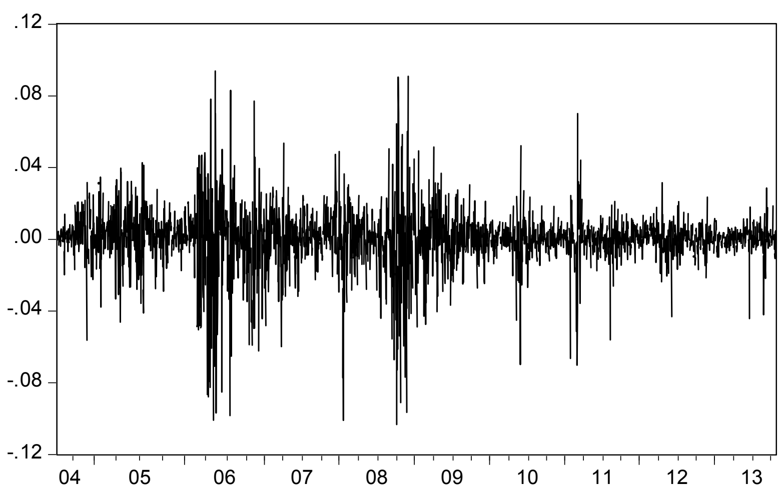

Figure 3. Saudi stock market return

That our data has autocorrelation is supported by the results of Ljung-Box (1978) Q-statistics given below. These results reject the null hypothesis of no autocorrelation up to 36 months.

Table 3. Ljung-box Q-statistics for Saudi stock market returns

Lag	Raw stock market return		Absolute stock market return		Squared stock market return	
	Q-Test	P-Value	Q-Test	P-Value	Q-Test	P-Value
1	15.053	0.000	232.03	0.000	117.63	0.000
4	22.235	0.000	1044.30	0.000	694.45	0.000
8	41.931	0.000	1955.80	0.000	1252.3	0.000
12	52.998	0.000	2663.2	0.000	1618.4	0.000
16	68.706	0.000	3298.3	0.000	1964.3	0.000
20	84.480	0.000	3839.4	0.000	2316.8	0.000
24	94.323	0.000	4352.9	0.000	2598.6	0.000
28	105.590	0.000	4864.8	0.000	2940.1	0.000
32	111.510	0.000	5246.2	0.000	3120.8	0.000
36	120.920	0.000	5620.3	0.000	3289.1	0.000

Table 4 gives the results of ARCH-LM test which shows the existence of ARCH effect in the residuals of mean equation of TASI return.

Table 4. ARCH-LM test for residuals of share prices on Saudi stock market

F-statistics	66.26214	Probability	0.0000
Obs*R-Squared	520.2904	Probability	0.0000

ADF test results shows that returns are stationary in level. Hence, we can now apply the ARCH family models.

Table 5. ADF unit root test results

Level	t-statistic	Test critical values		
		1% level	5% level	10% level
Intercept	-45.1483	-3.432890	-2.862548	-2.567352
Intercept and Trend	-45.13878	-3.961883	-3.411688	-3.127721

The findings about the Saudi stock market returns are in line with the suggestions of some of the earlier works. For example, Mandelbrot (1963) and Fama (1965) suggest, among others, that stock returns tend to follow non-normal distribution. Rydberg (2000) show that stock market returns are characterized by leptokurtosis, skewness and volatility clustering. GARCH model is most apt for data series with volatility clustering and tail behavior time series data. According to Bollerslev (1986) and Engle (1993), standard GARCH (1, 1) specification is adequate for modeling many high frequency time series data. Engle (2001) argues that higher order models are applicable only when the data span a long period of time or of a higher frequency of hourly data. Hence, the study adopts GARCH (1, 1) model.

4. Data and Methodology

To ascertain this stylized fact about Saudi stock market volatility, daily stock returns on the Saudi stock market composite index, Tadawul All-Share Index, TASI, for the period from August 1, 2004 through October 31, 2013 is used. Daily stock returns (r_t) at time t is defined as the logarithm of TASI indices.

$$r_t = \log\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where,

r_t is the logarithmic daily return at time t. P_{t-1} and P_t are the daily values of TASI at two consecutive days, t-1 and t.

A dummy is inserted for the days of market downturn during 2006 and 2008.

Since volatility of asset returns are serially correlated, to capture the serial correlation characteristic of volatility, Engle (1982) presented a new approach for the analysis of time-series data that demonstrates time-varying variance called autoregressive conditional heteroskedasticity (ARCH). ARCH model writes conditional variance as a distributed lag of past squared innovations:

$$\sigma_t^2 = \omega + \alpha(L)\eta_t^2 \tag{2}$$

α(L) is a polynomial in the lag operator. In order to have the conditional variance positive, ω and the coefficients in α(L) must be non-negative.

However, Fan and Yao (2003) argue that ARCH (p) model is apt for financial time series only with a large number of lags. This warranted the extensions of the ARCH model. Generalized autoregressive conditional heteroskedasticity (GARCH) model is the extension of the ARCH (ρ) model offered by Bollerslev (1986). This approach models the conditional variance as an ARMA process where it is determined by the innovations and its own lags. GARCH captures the serial dependence of the volatility. On account of its conditional property, GARCH draws on immediate past observations to model future observations.

The simplest GARCH (1, 1) model can be specified as follows:

Mean equation:

$$r_t = \mu = \varepsilon_t \tag{3}$$

Variance equation:

$$\sigma_t^2 = \omega + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \tag{4}$$

Where,

$\omega > 0$; $\alpha_1 \geq 0$; $\beta_1 \geq 0$; r_t = return at time t; μ = average return; $\varepsilon_t = \sigma_t z_t$; z_t= standardized residual returns; σ_t^2 = conditional variance

GARCH (1, 1) requires the constraints, $\alpha_1 \geq 0$ and $\beta_1 \geq 0$ to ensure σ_t^2 is strictly positive. The coefficient α_1 measures the degree to which volatility shock that occurs now feeds through into next period's volatility. If β_1 coefficient is high, it can be inferred that the shocks to conditional variance dies after a long time. Volatility is said to be persistent in such a case. If α_1 is high, it can be inferred that the responses of volatility to market movements is intense. If α1 is high and β1 is low, volatilities are sharp. The sum of α_1 and β_1 measures the rate at which this effect dies out over time. If the sum of α_1 and β_1 is close to one, a shock at time t will persist for a long time in the future. If the sum of α_1 and β_1 is high, it indicates a long memory. If the sum of these two variables is equal to one, it implies that any shock will lead to a permanent change in all future values. GARCH captures the serial dependence of the volatility. On account of its conditional property, GARCH draws future observations based on the immediate past observations. Variance of the current error term is modeled as a function of the previous period's error terms' variances. GARCH, thus, depends on the time-varying variance.

5. Results

In order to determine the dynamics of the conditional mean, we look at the Schwarz information criterion (SIC) to decide on the ARMA specification appropriate for modelling Saudi stock market returns. Enders (2010) argues that SIC always select a model better than Akaike information criterion (AIC) as the penalty for the inclusion of more repressors is higher with SIC than with AIC. We estimate many combinations of ARMA (p, q) models up to 5 lags.

Table 6. Sic for the mean equation for Saudi stock market returns

AR MA Lag (p, q)	0	1	2	3	4	5
0	-5.30462	-5.30112	-5.30411	-5.30103	-5.29779	-5.29547
1	-5.30721*	-5.30368	-5.30054	-5.29735	-5.29430	-5.29188
2	-5.30006	-5.30019	-5.29694	-5.29809	-5.30314	-5.30033
3	-5.29757	-5.29656	-5.29350	-5.30069	-5.29760	-5.29670
4	-5.29391	-5.29393	-5.29076	-5.29784	-5.29623	-5.29635
5	-5.29214	-5.29060	-5.28745	-5.29027	-5.28708	-5.28811

* indicates optimal lag

We find that ARMA (1, 0) is the most appropriate model for our data. This is also confirmed by the results shown in table 7.

Table 7. Serial correlation LM test and Heteroskedasticity tests for the estimated residuals of the ARMA (1, 0) model

Lags	Breusch-Godfrey Test F-Test (P-Values)	ARCH-LM Test Chi-Square Test (P-Values)
1	0.365729 (0.5454)	125.3905 (0.0000)
2	0.502321 (0.6052)	301.9412 (0.0000)
3	0.435509 (0.7276)	386.5735 (0.0000)
4	0.867294 (0.4827)	387.0723 (0.0000)
5	0.868438 (0.5014)	434.9429 (0.0000)

The results of AR (1)-GARCH (1, 1) model is presented below.

Mean equation estimated is

$$r_t = \mu + DUM = \varepsilon_t \tag{5}$$

where DUM is the dummy variable.

Table 8. Estimates of AR (1)-GARCH (1, 1) model

Mean Equation				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
Constant	0.001057	0.000233	4.543926	0.0000
DUM	-0.008712	0.002052	-4.245026	0.0000
AR(1)	0.094476	0.024057	3.927265	0.0001
Variance Equation				
Constant	3.70E-06	2.70E-07	13.71714	0.0000
α_1	0.143683	0.011125	12.91492	0.0000
β_1	0.852637	0.008923	95.55788	0.0000
Log likelihood		7066.481	Akaike info criterion	-5.905882
			Schwarz criterion	-5.891379

Coefficients of the constant and the ARCH term are higher than zero and the GARCH term is positive that confirm that the conditional variance is non-negative. The coefficients of both the lagged squared residual, α_1, and lagged conditional variance terms in the conditional variance equation, β_1, are highly statistically significant. This can be inferred as the news regarding the volatility of the previous periods can explain the current volatility. The sum of both α_1 and β_1 indicate the short run dynamics of the resultant volatility time series. β_1 at 0.85 shows that shocks to conditional variance take a long time to fade out. Volatility is persistent. α_1 show the intensity of the volatility to market fluctuations. α_1 of 0.14 shows that the Saudi stock market is quite nervous in its reactions to market variations. Since α_1 and β_1 is close to one, a shock that occurs at a particular time will prolong for many periods in future. Since the sum of α_1 and β_1 is less than one, it also indicates that the unconditional variance of ε_t is stationary. α_1 is less than β_1. It can be inferred that the volatility of the stock market is affected by past volatility more than by related news from the previous period. The dummy variable included is significant and bears an expected negative sign. Significance of AR (1) term means that the past period returns have a crucial role to play in deciding the current period returns.

We applied a set of tests to check the adequacy of the fitted model. ARCH-LM test checks if the standardized residuals exhibit ARCH behaviour. If the variance equation is specified correctly, there should be no ARCH effect left in the standardized residuals. Ljung-Box Q-test is to check the presence of autocorrelation of order m in the residuals. This test is applied to check for the adequacy of the fitted model. (Tsay, 2005). Q^2 test checks for the presence of autocorrelation of order m in squared residuals. This test checks for the presence of ARCH effect that remains in the variance equation.

Table 9. Residual diagnostic fits

Ljung-Box Q-Statistics			ARCH-LM test		
Order	Q-test	Q^2-test	Order	F-Statistic	Obs.*R-sqd.
2	2.5967 (0.107)	0.6964 (0.706)	1	0.024378 (0.8759)	0.024398 (0.8759)
12	21.864 (0.075)	5.1142 (0.954)	2	0.346846 (0.7070)	0.694362 (0.7067)
24	32.599 (0.088)	36.913 (0.405)	4	0.531908 (0.7123)	2.130197 (0.7118)
36	42.654 (0.175)	39.817 (0.304)	5	0.425527 (0.8312)	2.131092 (0.8307)

Notes: 1. Probabilities are in parenthesis

Diagnostic test results show the absence of ARCH effect and autocorrelation in the standardized residuals. This can be inferred to mean that the variance equation specified is adequate.

To check if the Saudi stock market return data requires a non-linear specification during the sample period, we apply the test developed by Brock, Dechert and Scheinkman (1986) to the residuals of the AR (1)-GARCH (1, 1) model to detect remaining dependence and the presence of omitted nonlinear structure. If null hypothesis is not rejected, then the original linear model is adequate. If null hypothesis is rejected, then the fitted linear model is not adequate and this can be inferred as indicating the presence of nonlinearity.

Table 10. BDS test results

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.000875	0.001787	0.489660	0.6244
3	0.003887	0.002841	1.368260	0.1712
4	0.006378	0.003384	1.884515	0.5950
5	0.006278	0.003529	1.778986	0.0752

The results of the BDS test shown in the table above indicates that AR (1)-GARCH(1, 1) model is adequate and we are not required to specify a non-linear model. Our results are in alignment with the results of many of the earlier works. Anderson and Bollerslev (1998) argue that the GARCH models give the most accurate forecasts.

6. Conclusion

Modelling and forecasting volatility of stock market returns is an important area of research in financial economics. Understanding stock market volatility offers important input for portfolio management, risk management, treasury management, asset allocation decisions and many related areas related to investments. We find that Saudi stock market is characterized by volatility clustering. Market dynamics results in volatility clustering. Volatility clustering is due to leptokurtosis in the returns distribution. It refers to the fact that large price changes are followed by large changes and small price changes are followed by small changes in either direction. Gallant et al. (1991) argues that this is due to the quality of information arriving in the market in clusters. According to Engle et al. (1990) this is mainly due to two reasons; first, when the information reaches the market in clusters; second, when the market participants have varied beliefs about the market and they take time to absorb the information shocks and resolve the differences in their expectations. Saudi stock market returns are found to be non-normal and follow leptokurtic distribution. Application of AR (1)-GARCH (1, 1) shows that past returns play an important role in determining the current period return. Saudi stock market volatility is found to be persistent. Past volatility affects the current period volatility. Investors in Saudi stock market can greatly benefit from the findings of this study.

References

Aggarwal, R. C., Inclan, & Leal, R. (1999). Volatility in Emerging Stock Markets. *Journal of Financial and Quantitative Analysis, 34*, 33-55. http://dx.doi.org/10.2307/2676245

Ahmed, A. E. M., & Suliman, S. Z. (2011). Modelling Stock Market Volatility Using GARCH Models: Evidence from Sudan. *International Journal of Business and Social Science, 2*, 114-128.

Akgiray, V. (1989). Conditional Heteroskedasticity in Time Series of Stock Returns: Evidence and Forecast. *Journal of Business, 62*, 52-80. http://dx.doi.org/10.1086/296451

Alam, M. Z., Siddikee, M. N., & Masukujjaman, M. (2013). *Forecasting Volatility of Stock Indices with ARCH Model, 4*, 126-143.

Alexander, C., & Lazar, E. (2006). Normal Mixture GARCH (1, 1): Application to Exchange Rate Modelling. *Journal of Applied Econometrics and Economic Review, 39*, 885-905.

Al-Raimony, & El-Nader, H. M. (2012). The Sources of Stock Market Volatility in Jordon. *International Journal of Economics and Finance, 4*, 108-121.

Anderson, T. G., & Bollersleve, T. (1998). Answering the Sceptics: Yes, Standard Volatility Models Do Provide Accurate Forecasts. *International Economic Review, 39*, 347-370.

Baillie, R., & Degennaro, R. (1990). Stock Returns and Volatility. *Journal of Financial and Quantitative Analysis, 25*, 203-214. http://dx.doi.org/10.2307/2330824

Bekaert, G., & Harvey, C. R. (1997). Emerging Market Volatility. *Journal of Financial Economics, 43*, 29-77. http://dx.doi.org/10.1016/S0304-405X(96)00889-6

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics, 31*, 307-327. http://dx.doi.org/10.1016/0304-4076(86)90063-1

Brailsford, T. J., & Faff, R. W. (1986). An Evaluation of Volatility Forecasting Techniques. *Journal of Banking and Finance, 20*, 419-438. http://dx.doi.org/10.1016/0378-4266(95)00015-1

Brock, W. A., Dechert, W. D., Scheinkman, J. A., & Baron, L. (1996). A Test for Independence Based on Correlation Dimension. *Econometric Review ,15*, 197-235. http://dx.doi.org/10.1080/07474939608800353

Brooks, C. (1998). Predicting Stock Index Volatility: Can Market Volume Help? *Journal of Forecasting, 17*, 59-80. http://dx.doi.org/10.1002/(SICI)1099-131X(199801)17:1<59::AID-FOR676>3.0.CO;2-H

Brooks, C. (2008). *Introductory Econometrics for Finance* (2nd ed.). Cambridge University Press. http://dx.doi.org/10.1017/CBO9780511841644

Brooks, C., & Burke, S. P. (2003). Information Criteria for GARCH Model Selection: An Application to High Frequency Data. *European Journal of Finance, 9*, 557-580. http://dx.doi.org/10.1080/1351847021000029188

Cao, C. Q., & Tsay, R. S. (1992). Non-linear Time-series Analysis of Stock Volatilities. *Journal of Applied Econometrics December Supplement, 1*, s165-s185.

Christie, A. A. (1982). The Stochastic Behaviour of Common Stock Variances: Value, Leverage, and Interest Rate Effect. *Journal of Financial Economics, 10*, 407-432. http://dx.doi.org/10.1016/0304-405X(82)90018-6

Cont, R. (2001). Empirical Properties of Asset Returns: Stylized Facts and Statistical Issues. *Quantitative Finance, 1*, 223-236. http://dx.doi.org/10.1080/713665670

Corhay, A., & Rad, T. (1994). Statistical Properties of Daily Returns: Evidence from European Stock Markets. *Journal of Business Finance and Accounting, 21*, 271-282. http://dx.doi.org/10.1111/j.1468-5957.1994.tb00318.x

Dowd, K. (2005). *Measuring Market Risk* (2nd ed.). John Wiley & sons Ltd, England. http://dx.doi.org/10.1002/9781118673485

Drakos, A. A., Kouretas, G. P., & Zarangas, L. P. (2010). Forecasting Financial Volatility of the Athens Stock Exchange Daily Returns: An Application of the Asymmetric Normal Mixture GARCH Model. *International Journal of Finance and Economics*, 1-4.

Emenike, K. O. (2010). Modelling Stock Returns Volatility in Nigeria Using GARCH Models. *Munich Personal RePEC Archive*. Retrieved from http://mpra.ub.uni-muenchen.de/23432/

Enders, W. (2010). *Applied Econometric Time Series* (3rd ed.). John Wiley & Sons Inc., New York.

Engle, R. F. (1982). Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of the United Kingdom Inflation. *Econometrical, 50*, 157-168. http://dx.doi.org/10.2307/1912773

Engle, R. F. (1993). Statistical Models for Financial Volatility. *Financial Analysts Journal, 49*, 72-78. http://dx.doi.org/10.2469/faj.v49.n1.72

Engle, R. F. (2001). GARCH 101: The Use of ARCH/GARCH Models in Applied Econometrics. *Journal of Economic Perspectives, 15*, 157-168. http://dx.doi.org/10.1257/jep.15.4.157

Engle, R. F., Ito, T., & Lin, W. (1990). Meteor Showers or Heat Waves? Heteroskedastic Intra-daily Volatility in the Foreign Exchange. *Econometrical, 58*, 525-542. http://dx.doi.org/10.2307/2938189

Ezzat, H. (2012). The Application of GARCH and EGARCH in Modelling the Volatility of Daily Stock Returns during Massive Shocks: The Empirical Case of Egypt. *Munich Personal RePEC Archive*. Retrieved from http://mpra.ub.uni-muenchen.de/50530/

Fabozzi, F. J., Tunarv, R., & Wu, T. (2004). Modelling Volatility for the Chinese Equity Markets. *Annals of Economics and Finance, 5*, 79-92.

Fama, E. (1965). The Behaviour of Stock Market Prices. *Journal of Business, 38*, 34-105. http://dx.doi.org/10.1086/294743

Fan, J., & Yao, Q. (2003). *Nonlinear Time Series: Nonparametric and Parametric Methods*. New York: Springer-Verlag. http://dx.doi.org/10.1007/b97702

Franses, P. H., & Van Dijk, D. (1996). Forecasting Stock Market Volatility Using Non-linear GARCH Models. *Journal of Forecasting, 15*, 229-235. http://dx.doi.org/10.1002/(SICI)1099-131X(199604)15:3<229::AID-FOR620>3.0.CO;2-3

Frimpong, J. M., & Oteng-Abayie, E. F. (2006). Modelling and Forecasting Volatility of Returns on the Ghana Stock Exchange Using GARCH Models. *Munich personal RePEc Archive, 593*, 1-21.

Gallant, A. R., Hsieh, D. A., & Tauchen, G. E. (1991). On Fitting a Recalcitrant Series: The Pound/Dollar Exchange Rate, 1974-1983. In W. A. Barnett (Ed.), *Parametric and Semiparametric Statistics: Proceedings of the Fifth International symposium in Economic Theory and Econometrics.* UK: Cambridge University Press.

Heynen, R. C., & Kat, H. M. (1994). Volatility Prediction: A Comparison of Stochastic Volatility: GARCH (1, 1) and EGARCH (1, 1) Models. *Journal of Derivatives, 2*, 50-65. http://dx.doi.org/10.3905/jod.1994.407912

Hsieh, D. (1989). Modelling Heteroskedasticity in Daily Foreign Exchange Rates. *Journal of Business and Economic Statistics, 7*, 307-317.

Jarque, C. M., & Bera, A. K. (1987). An Efficient Large-sample Test for Normality of Observations and Regression Residuals. *Australian National University Working Papers in Econometrics, 40*. Canberra.

Karmakar, M. (2005). Modelling Conditional Volatility of the Indian Stock Markets. *Vikalpa, 30*, 21-37.

Kirchler, M., & Huber, J. (2007). Fat Tails and Volatility clustering in Experimental Asset Markets. *Journal of Economic Dynamics and Control, 31*, 1844-1874. http://dx.doi.org/10.1016/j.jedc.2007.01.009

Lee, K. Y. (1991). Are the GARCH Best in Out-Of-Sample Performance? *Economics Letters, 37*, 305-308. http://dx.doi.org/10.1016/0165-1765(91)90227-C

Ljung, G. M., & Box, G. P. E. (1978). On a Measure of Lack for Fit in Time Series Models. *Biometrika, 66*, 66-72.

Mandelbrot, B. (1963). The Variation of Certain Speculative Prices. *Journal of Business, 36*, 394-419. http://dx.doi.org/10.1086/294632

Markowitz, H. (1952). Portfolio Selection. *Journal of Finance, 7*, 77-91. http://dx.doi.org/10.1111/j.1540-6261.1952.tb01525.x

Olowe, R. A. (2009). Modelling Naira/Dollar Exchange Rate Volatility: Evidence from GARCH and Asymmetric Models. *International Review of Business Research Papers, 5*, 377-398.

Pagan, A., & Schwert, G. W. (1990). Alternative Models for Conditional Stock Volatilities. *Journal of Econometrics, 45*, 267-290. http://dx.doi.org/10.1016/0304-4076(90)90101-X

Poon, S. (2005). *A Practical Guide to Forecasting Financial Market Volatility*. Wiley Finance, England.

Poon, S., & Granger, C. W. J. (2003). Forecasting Financial Market Volatility: A Review. *Journal of Economic Literature, 41*, 478-539. http://dx.doi.org/10.1257/jel.41.2.478

Rydberg, T. H. (2000). Realistic Statistical Modelling of Financial Data. *International Statistical Review, 68*, 233-258. http://dx.doi.org/10.1111/j.1751-5823.2000.tb00329.x

Su, C. (2010). *Application of EGARCH Model to Estimate Financial Volatility of Daily Returns: The Empirical*

Case of China. Retrieved from https://gupea.ub.gu.se/bitstream/2077/22593/1/gupea_2077_22593_1.pdf

Taylor, S. (1994). Modelling Stochastic Volatility: A Review and Comparative Study. *Mathematical Finance, 4*, 183-204. http://dx.doi.org/10.1111/j.1467-9965.1994.tb00057.x

Tsay, R. S. (2005). *Analysis of Financial Time Series.* John Wiley & Sons. http://dx.doi.org/10.1002/0471746193

Tse, Y. K. (1991). Stock Return Volatility in the Tokyo Stock Market. *Japan and World Economy, 3*, 285-298. http://dx.doi.org/10.1016/0922-1425(91)90011-Z

Tse, Y. K., & Tung, S. H. (1992). Forecasting Volatility in the Singapore Stock Market. *Asia Pacific Journal of Management, 9*, 1-13. http://dx.doi.org/10.1007/BF01732034

Vilhelmsson, A. (2006). GARCH Forecasting Performance under Different Distribution Assumptions. *Journal of Forecasting, 25*, 561-578. http://dx.doi.org/10.1002/for.1009