

Estimating Return Volatility of Stock Market Indices: The Case of Boursa Kuwait

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ABSTRACT: This study empirically investigates the conditional variance (volatility) in the daily returns of Boursa Kuwait's market index, along with seven sectoral indices, for the period of 13 May 2012 to 1 March 2018. The returns results exhibited leptokurtosis, were skewed left, and were not normally distributed; additionally, there was evidence of ARCH effects. The symmetric GARCH model results demonstrated evidence of volatility clustering and persistence; the GARCH-M model results showed a negative relationship between the indices' returns and risk. The conditional variance (volatility) is affected by positive shocks, leading to positive asymmetric values of EGARCH and negative asymmetric values of TGARCH. From this, it can be inferred that good news has a greater impact on the volatility of index returns than bad news. The research results are crucial for investors, risk forecasters, and policy makers.

Keywords: Boursa Kuwait, Indices, Symmetric and asymmetric GARCH models, Volatility

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1. INTRODUCTION

Capital markets effectively impact economic growth by channelling available funds to promising long-term future investments. The stock market, where securities are bought and sold publicly according to known regulations, is an important component of a capital market, and a main factor in its development is the market capitalisation of listed companies, along with market volatility and trading volume [1].

Assessing market volatility can help explain the behaviour of a stock market. The concept of volatility is generally defined in the areas of finance and investment; Poon [2] describes it as the range of possible events for an uncertain variable, and Tsay [3] describes it as the measure of dispersion of returns for a given security or market index. Standard deviations or variances of returns are used in assessing volatility, that is, when current returns move notably from past returns. A high rise in securities volatility usually leads to higher levels of concern for regulators, portfolio managers, brokers, and investors. In some scenarios, high volatility in the stock market reduces profits, causing large losses and seriously impacting the confidence level of stock market participants.

A number of studies on emerging markets have investigated volatility. Bekaert and Harvey [4] described emerging markets as distinct due to their low correlation with developed markets; that is, their returns are low and predictable, and their volatilities are high. Further, Barry et al. [5] found high volatility in emerging markets, and when the portfolios of

developed markets included assets from developing markets, they offered diversification.

Since the establishment of public stockholding companies in 1950, stock trading has been an important element of the Kuwait economy. Stock trading in Kuwait's market underwent several different stages prior to the opening of a modern stock exchange in 1983 called the Kuwait Stock Exchange, making it the oldest regulated market in the Arabian Gulf States. A privatisation process of the Government of Kuwait took place when the Capital Markets Authority passed Law No. 37/2013 to privatise the Kuwait Stock Exchange. This was followed by the establishment of the Boursa Kuwait Company on 21 April 2014, and it was granted the official licence to own the Kuwait Stock Exchange on 25 April 2016¹.

Boursa Kuwait (previously the Kuwait Stock Exchange) is divided into 13 sectors: banks, oil and gas, basic materials, industry, consumer goods, health care, consumer services, telecommunications, insurance, real estate, financial services, technology, and utilities. There were 125 listed companies on Boursa Kuwait in 2004, increasing to 214 companies by 2012. Six years later, the number decreased to 163 listed companies. The volume of trade decreased from 7,215.9 million KD in 2012 to 4,127.8 million KD in 2018. The OPEC Reference Basket prices (crude oil prices) fluctuated from approximately \$105 on March 2012 to approximately \$29 a barrel on 2016 and then rising to approximately \$61 a barrel on March 2018², and this had an effect on the state of Kuwait as it is largely dependent on oil exporting. When oil prices go down, Kuwait's government spending is reduced, which has a negative effect on the economy. Consequently, most stock market activities as well as its overall performance will be affected. Table 1 shows the characteristics of Boursa Kuwait

¹ www.boursakuwait.com.kw

² OPEC: Monthly Oil Market Reports (www.opec.org/opec_web/en/publications/338.htm)

from 2012 to 2018, including the number of companies, volume of trade, and total market capitalization³.

Year	No. of Companies	Volume of Trade (Millions KD)	Total Market Capitalisation (Millions KD)
2012	214	7,215.9	29,376.4
2013	215	11,389.4	31154.7
2014	212	6,175.73	30,246.8
2015	179	3,943.7	24,241.7
2016	196	2,880.475	26,243.8
2017	177	5,728.730	27,900.00
2018	163	4,127.8	28,700.00

Table 1: Characteristics of Boursa Kuwait (Boursa Kuwait Annual Books 2012, 2013, 2014, 2015, 2016, and 2017 and Annual Report of Kuwait Central Bank 2017/2018).

The stock market is divided into different sectors. The present study assesses the Boursa Kuwait market index sectors by applying the time series techniques of GARCH models (GARCH, GARCH-M, EGARCH, and TGARCH). As there is no conclusive evidence regarding the performance of these models in emerging stock markets, the market index and seven sectoral indices of the emerging Boursa Kuwait are investigated with the aim of measuring the conditional volatility and comparing their performance using market data from 13 May 2012 to 31 March 2018. As such, the results of the study will add to the growing body of literature on Boursa Kuwait. The remainder of this paper is organised as follows: A literature review is presented in section 2. The data and methodology used are described in section 3. Section 4 provides the empirical findings, and section 5 concludes.

2. LITERATURE REVIEW

The empirical examination of the statistical properties of stock returns by Mandelbrot [6] and Fama [7] demonstrated volatility clustering in financial time series. Black [8] first noted a leverage effect on volatility and that stock market returns are negatively affected by volatility fluctuations (bad news). Despite this, estimators continue assuming constant volatility (unconditional volatility) even though earlier studies have shown different results.

During the 1980s, scholars began to investigate conditional volatilities, including Engle [9], who examined UK inflation data by identifying this problem. He introduced the autoregressive conditional heteroscedastic model (ARCH) and used it to allow the conditional variance to change over time as a function of past errors, leaving the unconditional variance constant. Volatility studies then began to garner attention from academics, regulators, and financial analysts.

The limitation of the ARCH model led Bollerslev [10] to extend it to the generalised autoregressive conditional heteroscedastic model (GARCH), which made the conditional variance dependant on its last lagged values and the disturbance term squared lagged values. The ARCH and GARCH models were recognised for being easy to estimate, which was advantageous, and for their available diagnostic tests.

Engle, Lilien, and Robins [11] developed the GARCH-in-Mean model (GARCH-M), which is one of the GARCH model variations that allows the conditional variance of the asset returns to be in the conditional mean equation to assess the risk return relationship.

The ARCH, GARCH, and GARCH-M models capture volatility clustering and leptokurtosis (fat tails), but they fail to model leverage effects because of their symmetric distribution. That led to the development and extension of other models, such as EGARCH, GJR-GARCH, TGARCH, PGARCH, QARCH, FIGARCH, and FIAPARCH. These models are used to capture the empirical features of asset returns, such as volatility clustering and persistence, leptokurtosis, and leverage effects. Nelson [12] developed the exponential generalised model (EGARCH), allowing the conditional volatility to be expressed logarithmically, where non-negative constraints are not imposed on the model parameters, which allows the asymmetric effects on the financial data to be distinguished. Here, the asymmetric effect displays the relationship between current returns and future volatility. When this relation is negative and significant, the market has a leverage effect. Subsequently, Glosten et al. [13] developed the GJR-GARCH model, and Zakoian [14] developed the Threshold GARCH (TGARCH) model (the authors worked separately from one another). The two models identified the relationship between asymmetric volatility and returns. Ding, Granger, and Engle [15] developed the Power GARCH (PGARCH) by using the standard deviation, instead of variance in the GARCH model, to measure the effect of negative and positive news on asset returns. These models are used to forecast the conditional volatility of financial time series by studying past uncertain changes in the returns series, and they have been applied widely in financial markets.

Sentana [16] presented the Quadratic ARCH Models, and Baillie, Bollerslev, and Mikkelsen [17] introduced the fractional integrated GARCH (FIGARCH). Later, a model was developed by Tse [18] by extending the APARCH model to a fractionally integrated process (FIAPARCH) and incorporating the fractional process into the conditional variance. Understanding the effects of good news and bad news (positive and negative shocks) on the conditional variance was an important reason these models were adopted by scholars.

The GARCH family of models are used to forecast the changing of volatility during different time periods. With great success, GARCH models have been applied in research of the financial market [19]. In their review of 93 research studies on

³ The average exchange rate for the U.S. dollar against Kuwait Dinars (Fills) was 0.305 in the year 2017/2018, ending 31 March 2018.

forecasting volatility, Poon and Granger [20] found that ARCH/GARCH models forecasted volatility successfully. Their successful use in many empirical studies of stock returns volatility demonstrates different specifications of GARCH models and covering different types of data and regions of the world.

2.1 Empirical Tests of GARCH Models on Emerging Markets

De Santis and Imrohoroglu [21] found that in emerging markets, conditional volatility is higher, and price changes are larger compared to matured markets. Emenike [22] investigated monthly data from January 1999 to December 2008 for the returns series of the Nigerian market. The results of the GARCH model showed volatility clustering and leptokurtic distribution, and the result for the GJR-GARCH model showed leverage effects. In addition, Emenike and Friday [23] examined the daily closing prices from January 1996 to December 2011 of the Nigerian Stock Exchange, and, using the GARCH model, they found that volatility of the Nigerian market was clustered as well as persistence in the returns. They found a significant positive asymmetric value for the EGARCH model and significant negative asymmetric value for the GJR-GARCH model, indicating an asymmetric volatility effect. The positive and negative signs of the two models mean that positive news increases volatility more than negative news.

Suliman [24] used the daily returns from 1 January 2007 to 26 November 2011 for the general market index in Saudi Arabia. The GARCH models result showed evidence of persistence of time-varying volatility as a positive risk premium and asymmetry in stock returns.

In Singh and Makkar's [25] study on the daily data of the Indian banking sector, they applied GARCH models to capture the impact of the crisis on bank volatility. Their results showed a high persistence of volatility and a significant negative association between stock returns and their volatility during both sub-periods of crisis. They concluded that the crisis had a significant impact on the stock volatility of the Indian banking sector.

Mhmoud and Dawalbait [26] used GARCH models to estimate the volatility of the Saudi stock market by using the daily price of the Tadawul Index for eight years, beginning in 2005. Their results showed conditional variance and confirmed leverage effects on Saudi market returns.

Tamilselvan and Vali [27] used daily data from January 2001 to November 2015 for four active indices from the Muscat Securities Market. The GARCH model findings showed a high level of volatility persistence, and the relation between risk and return was positive. The TGARCH model showed a presence of asymmetry between return shocks and volatility, and the positive coefficients result of the EGARCH model also reflected an asymmetric effect across all four indices.

Al-Najjar [28] investigated the volatility characteristics of the Aman Stock Exchange Index by using the daily stock returns from 1 January 2005 to 31 December 2014. The symmetric models, ARCH and GARCH, provided evidence of clustering and persistence of volatility, whereas the asymmetric EGARCH model output revealed no leverage effect in the stock returns.

Nguyen and Nguyen [29] applied GARCH models to their study of daily data from 1 March 2001 to 1 March 2019 for the VN-Index in the Vietnam market. Their GARCH (1,1) results showed clustering volatility, and there was a positive relation between profit and market risk by GARCH-M (1,1). The value of the TGARCH (1,1) showed an asymmetric effect, meaning that bad news has more effect on the market. The value of the EGARCH (1,1) was negative but was not statically significant.

To the best of our knowledge, no studies have been conducted on the volatility of the sectoral indices of Boursa Kuwait. Therefore, studying the volatility pattern of market and sectoral indices will identify their stylised facts, and testing the volatility techniques using data from Boursa Kuwait will fill this research gap in volatility studies.

3. DATA AND METHODOLOGY

The main weighted market index and seven weighted sectoral indices were chosen based on the secondary data for continuous daily trading, without any missing figures, available from the official website (www.boursakuwait.com.kw) of Boursa Kuwait gathered from 13 May 2012 to 1 March 2018. The weighted sectoral indices included are banking, financial services, oil and gas, real estate, consumer goods, industry, and telecommunication. Excel 2010 software and Eviews 10 econometric package were used for analysing the data. The following steps were applied:

3.1 Calculating the Rate of Return

Calculating the rate of return: The rate of return of the transformed daily closing index prices of the series, measured on local currency, is calculated as the logarithm of successive price relatives to avoid non-stationarity in raw index prices:

$$R_t = \ln(P_t / P_{t-1}) * 100, \quad (1)$$

Where R_t is the return on index of a series on time t , \ln is the natural logarithm, P_t is the closing price index of the current day, and P_{t-1} is the last closing price index.

3.2 Descriptive Statistics

The descriptive statistics presented are mean, standard deviation, skewness, kurtosis, and the Jarque-Bera statistics for normality to draw inferences about the behaviour and distribution pattern of the indices' returns.

3.3 Testing the Presence of Unit Roots

Time series are stationary when their statistical proprieties (mean, variance, and autocorrelation) are stable. Before modelling volatility, pre-testing is required to ensure that a

stationary relationship exists among the variables. The Augmented Dickey-Fuller (ADF) test [30] is used to examine if there is a unit root and stationarity in the daily market index return series and sectoral indices return series.

3.4 Testing for Heteroscedasticity (ARCH effects)

Before estimating GARCH models, this study used the Lagrange Multiplier (LM) diagnostics test to examine whether there is evidence of heteroscedasticity (ARCH effect) in the residual of the return series of the indices, as in Engle [9].

3.5 Symmetric Volatility Measurement

The GARCH model [10] is a general extension of the ARCH model used to analyse the impact of past shocks on future volatility and the extent of volatility persistence. The model allows the conditional variance to be dependent on its previous lags with the conditional variance equation in the simplest form GARCH (1,1). The mean equation is

$$r_t = \mu + \varepsilon_t \quad (2)$$

Where, r_t is the return of asset at time t , the average return is μ , and ε_t is the residual return ($\varepsilon_t = \sigma_t z_t$), in which z_t is the standardised residual returns.

The variance equation is:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (3)$$

Where, $\omega \geq 0$, $\alpha \geq 0$ and $\beta_1 \geq 0$ are required constraints to ensure that σ_t^2 is strictly positive. The forecast variance of period σ_t^2 is based on past information, and it is a function of three terms: the constant term ω is long-term average volatility; ε_{t-1}^2 is the last period volatility news, which is measured by the lag of the residual square from the mean equation α , the ARCH term; and σ_{t-1}^2 is forecast variance period of the previous period β , the GARCH term. In this model, volatility has a symmetrical effect from good and bad news.

The GARCH-M model was developed by Engle, Lilien, and Robins (1987) to determine the impact of conditional volatility on the return, and applying the GARCH-M (1,1) model is as follows:

$$\text{Mean equation: } r_t = \mu + \lambda \sigma_t^2 + \varepsilon_t \quad (4)$$

$$\text{Variance equation: } \sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (5)$$

As this model is an extension of the GARCH model that allows the conditional mean of a series to depend on the conditional variance or standard deviation, in the mean equation, λ is the risk premium. A positive and significant λ indicates that the return has a positive relation with its volatility. A rise in the mean return is due to an increase on the

conditional variance. The risk premium is a function of the conditional variance of ε_t , meaning a rise in the conditional variance of the return will be met by investor expectation of higher compensation to hold this asset.

3.6 Asymmetric Volatility Measurement

The conditional variance of GARCH and GARCH-M are unable to respond to asymmetric rise and fall in residual prices; as a result, a leverage effect will be present. That is, when negative news has a greater effect on asset price than positive news, the volatility is increased because of the decrease in general prices.

Nelson (1991) proposed the EGARCH model to measure the effects of bad news and good news on volatility. It is specified as follows:

$$\log(\sigma_t^2) = \omega + \beta \log(\sigma_{t-1}^2) + \alpha \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (6)$$

The logarithm of conditional variance at time t is on the left side, and the coefficients to be estimated are ω , α , β , and γ , while ε_t is the innovation at time t . The GARCH effect is measured by the parameter β (shock persistence) and α (ARCH effect). The asymmetry coefficient γ is used to assess leverage presence when the parameter is negative ($\gamma < 0$) and significant, when negative shocks increase the volatility or uncertainty, and when $\gamma = 0$, the model is symmetric.

Glosten, Jaganathan, and Runkle (1993) and Zakoian (1994) independently developed the Threshold ARCH (TGARCH). This model considers the asymmetry between good and bad news shocks on volatility. The conditional variance specification for TGARCH (1,1) is given by

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} \quad (7)$$

Where, a dummy variable is $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ (bad news), and $I_{t-1} = 0$ otherwise. The asymmetry (leverage) parameter is represented by γ . When $\gamma > 0$, the sign of γ should be positive, meaning the effect on σ_t^2 by negative shocks is larger than positive shocks. When the effect is negative, the volatility measure will rise by $\gamma \varepsilon_{t-1}^2$. Thus, the volatility is affected by good and bad news differently, where α is influenced by good news, and $\alpha + \gamma$ is influenced by bad news.

3.7 Information Criteria

The appropriate performing model for symmetric and asymmetric GARCH models is taken based on the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC). When the model has the minimum value of AIC and SIC, it is regarded as the appropriate performing model.

4. EMPIRICAL FINDINGS

This study conducts an analysis of secondary data sets, which are the daily returns of the overall weighted market index and seven weighted sectoral indices from 13 May 2012 to 1 March 2018.

4.1 Descriptive Statistics

A number of descriptive statistics are computed in Table 2: the mean, standard deviation, skewness, kurtosis, and Jarque-Bera

(J-B) test of normality. The mean values of indices' returns were positive and negative, with high values of standard deviations, indicating fluctuations in the daily indices' returns. The values of the following three indices' returns are positive: Bank Index, Industry Index, and Real Estate Index. The values of the following five indices' returns are negative: Market Index, Consumer Goods Index, Financial Services Index, Oil and Gas Index, and Telecommunications Index. The returns of these indices are subject to high volatility.

Indices	Mean	Standard Deviation	Skewness	Kurtosis	Jarque-Bera Probability
Market	-0.000766	0.6097	-0.441176	9.744610	0.00000
Banks	0.000822	0.7545	-0.256019	8.646772	0.00000
Consumer Goods	-0.004013	1.515486	-1.037806	18.27186	0.00000
Financial Services	-0.014511	0.804886	-0.445392	6.664536	0.00000
Industrial Services	0.027766	0.749412	-0.382199	6.263418	0.00000
Oil & Gas	-0.03621	1.12354	0.018767	4.862447	0.00000
Real Estate	0.008541	0.818389	-0.361347	6.719313	0.00000
Telecommunications	-0.026979	1.252455	0.053928	4.286891	0.00000

Table 2: Descriptive Statistics of Daily Returns.

Positive and negative skewness is an indication of asymmetry in the series. Six indices have negative skewness values, indicating that the distribution of the returns has a long-left tail, and the Telecommunications Index has a positive skewness value. The kurtosis values for the returns of all eight indices are greater than 3, indicating that these returns are leptokurtic or fat tailed. All series of sectoral indices' returns and market index returns based on Jarque-Bera (J-B) test values reject the normality hypothesis at the 1% level, indicating they are not normally distributed, which aligns with the skewness and leptokurtosis results.

4.2 Testing the Presence of Unit Roots

The ADF test is used to check the null hypothesis of the stationarity for each series of returns, and there is no unit root present. The results are presented in the third column of Table 3, showing that the indices' returns are stationary at the 1% level when performing the ADF unit root test. This result is important to ensure the model's stability through the non-existence of autocorrelation (unit roots).

Indices	t-statistics	Prob.	Critical Value 1% 5%	ARCH-LM (p-VALUE)
Market	-34.46829	0.0000	-3.434705 -2.863351	101.2874 [0.0000]
Banks	-38.11430	0.0000	-3.434705 -2.863351	104.1360 [0.0000]
Consumer Goods	-37.34076	0.0000	-3.434705 -2.863351	14.22280 [0.0000]
Financial Services	-18.53785	0.0000	-3.434711 -2.863351	6.531290 [0.0000]
Industrial Services	-34.66493	0.0000	-3.434705 -2.863351	32.76829 [0.0000]
Oil & Gas	-38.89509	0.0000	-3.434705 -2.863351	48.56755 [0.0000]
Real Estate	-37.79615	0.0000	-3.434705 -2.863351	128.1537 [0.0000]
Telecommunication	-40.17415	0.0000	-3.434705 -2.863351	60.81809 [0.0000]

Table 3: Result of Unit Root Test and ARCH-LM Test for Residuals.

4.3 Heteroskedasticity Test

ARCH-LM tests the residuals by regressing the squared residuals on a constant and 1 lag; the results are presented in the last column of Table 3. The findings suggest that significant ARCH effects are present for the market index and all sectoral indices according to the p-value of the chi-squared at the 1% significance level. The null hypothesis states that no arch effect is rejected for any index; therefore, these results are justified to estimate GARCH models.

4.4 Symmetric Models

The results show that the returns of the market index and indices are stationary and exhibit ARCH effects that allow for the running of the GARCH models in Eviews. To capture stock return volatility clustering and leptokurtosis on the returns of the sectoral indices and market index of Boursa Kuwait, the GARCH (1,1) is applied along with GARCH-M (1,1).

The GARCH model coefficients - the constant ω , ARCH

effect α , and GARCH effect β -for all indices are presented in Table 4, showing all are significant at the 1% level. In the equation for conditional variance, the value of α means that recent news is related to the current market volatility. Further, we notice the GARCH effect coefficient of β is larger than the coefficient of α , indicating current news and past news have an effect on market volatility, resulting in long-term volatility, and the volatility is not affected by new surprises. A significant positive value ($\alpha + \beta$), more than 0.90, for six indices indicates a high volatility level of persistence of any shock return. In addition, the Bank Index and Telecommunication Index have high sum values of ($\alpha + \beta$), 0.892 and 0.794, respectively. These values indicate that the market and sector indices are volatile and symmetric. Here, if a shock is observed in the present, future returns will experience its effects for a long time, a fact that must be considered by investors and participants in the market. The results of GARCH (1,1) meet the requirements that specify that the estimated parameters should not be negative.

Indices	Mean Equation	Variance Equation				
Index	Constant	Constant ω	ARCH Effect α	GARCH Effect β	(Persistence) $\alpha + \beta$	Residual Diagnostics: ARCH-LM Test (p-VALUE)
Market	0.000156 (0.2269)	0.029203 (0.0000)	0.175160 (0.0000)	0.749034 (0.0000)	0.924194	0.545989 0.4600
Banks	0.00011282 (0.4932)	0.061774 (0.0000)	0.172753 (0.0000)	0.719386 (0.0000)	0.892139	0.358626 0.5493
Consumer Goods	0.013504 (0.7219)	0.087851 (0.0000)	0.057696 (0.0000)	0.902430 (0.0000)	0.960126	0.079677 0.7777
Financial Services	-0.0001768 (0.9220)	0.046879 (0.0000)	0.172843 (0.0000)	0.765733 (0.0000)	0.938576	1.584303 0.2081
Industry	0.033796 (0.0543)	0.047256 (0.0000)	0.128787 (0.0000)	0.789120 (0.0000)	0.917907	0.724892 0.3945
Oil & Gas	-0.034946 (0.2383)	0.047974 (0.0013)	0.050289 (0.0000)	0.917606 (0.0000)	0.967895	3.511850 0.0609
Real Estate	0.000198 (0.2454)	0.062621 (0.0000)	0.194485 (0.0000)	0.715393 (0.0000)	0.909878	2.164587 0.1412
Telecommunications	0.033097 (0.2864)	0.318454 (0.0008)	0.134993 (0.0000)	0.659697 (0.0008)	0.79469	0.206358 0.6496

Table 4: GARCH Model (1,1).

The GARCH-M model is estimated by allowing the mean equation of the return series to depend on the function of the conditional variance σ^2 . The findings of the GARCH-M model for the three coefficients from Table 5, ω (constant), ARCH term α , and GARCH term β , show that the returns of all indices are significant. The current volatility of this model

is explained by the volatility news of the past day because of the impact of the lagged GARCH term (conditional variance) and lagged ARCH term (squared disturbance) on conditional variance.

Table 5 shows that the risk premium (λ) of the variance values (σ^2) in the mean equation for the eight indices is negative,

ranging from -0.2755 to -0.0475, where six indices' values are significant at the 1% and 10% levels. The Oil & Gas and Telecommunications indices have values that are not significant, indicating no link between risk and return. Most of the sectoral indices and the market index of Boursa Kuwait have a negative risk premium, meaning that volatility increases will lead to a decrease in the returns, which is opposite to the theory of a positive risk premium. A negative

relationship means that there will be a negative reward for volatility risk. When there is a higher volatility in Boursa Kuwait, the participants and investors will abandon measuring standard deviation of the indices from their past mean, and they will consider other measures. An expectation of market volatility will lead market investors who want to avoid the risk to sell their stocks, leading to a decrease in stocks prices. This means that risky stocks are not indemnified by higher returns.

Indices Index	Mean Equation		Variance Equation				Residual Diagnostics: ARCH-LM Test (p-VALUE)
	Constant	λ	Constant ω	ARCH Effect α	GARCH Effect β	(Persistence) $\alpha+\beta$	
Market	0.090874 (0.0002)	-0.275503 (0.0003)	0.025586 (0.0000)	0.158819 (0.0000)	0.773335 (0.0000)	0.932154	1.382401 0.2397
Banks	0.066456 (0.0682)	-0.12661 (0.0757)	0.054903 (0.0000)	0.158796 (0.0000)	0.744814 (0.0000)	0.90361	0.776264 0.3783
Consumer Goods	0.131612 (0.0797)	-0.06986 (0.0549)	0.087238 (0.0000)	0.056972 (0.0000)	0.903272 (0.0000)	0.960692	0.092279 0.7613
Financial Services	0.058474 (0.1265)	-0.114525 (0.0980)	0.047393 (0.0000)	0.171141 (0.0000)	0.765893 (0.0000)	0.937034	1.798637 0.1799
Industry	0.165318 (0.0007)	-0.275237 (0.0038)	0.045017 (0.0000)	0.118560 (0.0000)	0.801572 (0.0000)	0.920132	0.897336 0.3435
Oil & Gas	0.026611 (0.7713)	-0.045238 (0.4754)	0.052153 (0.0008)	0.052677 (0.0000)	0.912462 (0.0000)	0.965139	3.247667 0.0715
Real Estate	0.105951 (0.0015)	-0.178665 (0.0030)	0.060148 (0.0000)	0.185604 (0.0000)	0.726035 (0.0000)	0.911639	4.055220 0.0440
Telecommunications	-0.021458 (0.8296)	-0.08384 (0.9001)	0.315385 (0.0008)	0.134245 (0.0000)	0.662408 (0.0000)	0.796653	0.222990 0.6368

Table 5: GARCH-M.

The results of the ARCH-LM test of the GARCH model and the GARCH-M model in the last column in Tables 4 and 5 are accepting of the null hypothesis that there are no ARCH effects on the indices' returns for the study period at the 1% significance level.

4.5 Asymmetry Models

Since the GARCH and GARCH-M models do not explain the effects of the negative and positive returns on volatility, we used the EGARCH and TGARCH asymmetric models to show the occurrence of the asymmetry and leverage effect in the indices' returns and market index returns.

Table 6 shows seven values of indices with a high β , greater than 0.90, and the value for the Telecommunication Index is 0.84. This high persistence of volatility indicates a slow moving of the variance over time; that is, the effect of shocks has a slow decline. The Consumer Goods Index value has a low β value of 0.010, and when there is a low value of β , which is not significant, the shocks die rapidly. Additionally, the EGARCH (1,1) sum of $(\alpha + \beta)$ for seven indices were greater than 1, meaning that the conditional variance is explosive and that the model is unstable, whereas the EGARCH (1,1) sum of $(\alpha + \beta)$ for Consumer Goods sum is low (0.02).

Indices	Mean Equation	Variance Equation					
Index	Constant	Constant ω	ARCH Effect α	GARCH Effect β	Leverage γ	Persistence $\alpha+\beta$	Residual Diagnostics: ARCH-LM Test

							(p-VALUE)
Market	0.023110 (0.0784)	-0.255196 (0.0000)	0.272076 (0.0000)	0.958435 (0.0000)	0.072451 (0.0000)	1.230511	2.950658 0.0858
Banks	0.018487 (0.2642)	-0.250582 (0.0000)	0.269844 (0.0000)	0.934291 (0.0000)	0.047106 (0.0127)	1.204135	2.511863 0.1130
Consumer Goods	-0.004013 (0.9252)	0.830774 (0.1038)	0.010000 (0.3085)	0.010000 (0.9868)	0.010000 (0.2411)	0.02000	6.608573 0.0101*
Financial Services	0.007015 (0.7041)	-0.264235 (0.0000)	0.301726 (0.0000)	0.937711 (0.0000)	0.063263 (0.0001)	1.239437	1.063767 0.3024
Industry	0.034737 (0.05677)	-0.233950 (0.0000)	0.244849 (0.0000)	0.930162 (0.0000)	0.054822 (0.0003)	1.175011	2.849445 0.0914
Oil & Gas	-0.017143 (0.5282)	-0.087035 (0.0000)	0.143715 (0.0000)	0.945843 (0.0000)	0.023893 (0.1172)	1.086734	3.249636 0.0714
Real Estate	0.032177 (0.0590)	-0.291181 (0.0000)	0.321013 (0.0000)	0.918569 (0.0000)	0.080947 (0.0000)	1.239582	5.961801 0.0146*
Telecommunications	-0.025557 (0.4088)	-0.123359 (0.0000)	0.240238 (0.0000)	0.844299 (0.0000)	0.045651 (0.0000)	1.084537	0.651766 0.4195

Table 6: EGARCH (1,1).

When the sign of gamma (γ), as an indicator of asymmetric volatility in the EGARCH model, is negative and significant, then we expect there will be a leverage effect. Table 6 shows that all γ values are positive, which is a similar result to Al-Najjar [28] for the Amman Stock Exchange. Five values of γ are significant at the 1% level, whereas the Banks, Consumer Goods, and Oil and Gas Index values of γ are not statically significant, suggesting that the model for these sectors is symmetric. The asymmetry coefficients of γ that are positive for five indices show that the variance increases more after positive residuals than after negative ones. Therefore, good news affects market volatility more than negative news. The volatility in the stock market will increase differently by good and bad news for a long time. Thus, investors in Boursa

Kuwait will react to positive and bad information differently, affecting the direction of their investment decisions.

The values of high persistence ($\alpha + \beta$) are significant in Table 7 for six sector indices in the TGARCH model, and they are less than the unity value of one. That is an indication that the shocks effect is slowly declining and showing evidence of long memory. The market index value is 1.002418, and the Financial Services Index value is 1.01428, meaning that these indices' series are not mean reverting. The presence of high persistence of volatility in TGARCH (1,1) in six sector indices reveals the existence of consistency among these different sectors.

Indices	Mean Equation	Variance Equation					
Index	Constant	Constant ω	ARCH Effect α	GARCH Effect β	Leverage γ	Persistence $\alpha + \beta$	Residual Diagnostics: ARCH-LM Test (p-VALUE)
Market	0.02429 (0.0753)	0.02409 (0.0000)	0.217454 (0.0000)	0.78496 (0.0000)	-0.123925 (0.0000)	1.002418	1.288084 0.2564
Banks	0.01745 (0.3166)	0.05862 (0.0000)	0.194617 (0.0000)	0.73312 (0.0000)	-0.059989 (0.0786)	0.927738	0.501721 0.4787
Consumer Goods	0.02450 (0.5272)	0.09383 (0.0000)	0.079004 (0.0000)	0.89552 (0.0000)	-0.031319 (0.0003)	0.974532	0.023874 0.8772
Financial Services	0.00567 (0.7628)	0.04262 (0.0000)	0.232457 (0.0000)	0.78182 (0.0000)	-0.132927 (0.0000)	1.01428	1.312025 0.2520
Industry	0.04126 (0.0239)	0.04392 (0.0000)	0.175102 (0.0000)	0.79991 (0.0000)	-0.098698 (0.0001)	0.97502	1.931190 0.1646
Oil & Gas	0.03114	0.02198	0.047924	0.95110	-0.02729	0.99903	5.837598

	(0.3119)	(0.0067)	(0.0000)	(0.0000)	(0.0330)		0.0157
Real Estate	0.03504 (0.0538)	0.06181 (0.0000)	0.265255 (0.0000)	0.72230 (0.0000)	-0.147652 (0.0000)	0.98756	2.366096 0.1240
Telecommunications	0.00026 (0.4075)	0.29520 (0.0006)	0.153114 (0.0000)	0.67913 (0.0000)	-0.045899 (0.2387)	0.832251	0.156101 0.6928

Table 7: TGARCH Model (1,1).

TGARCH parameter γ is an asymmetric effect or leverage; good news ($\varepsilon_{t-1} > 0$) and bad news ($\varepsilon_{t-1} < 0$) have a differential effect on the conditional variance. Good news has an impact of α , while bad news has an impact of $\alpha + \gamma$. Table 7 shows that the results of γ are negative, and six values of γ are significant at the 1% level. The value of the Oil and Gas Index is significant at the 5% level, while the Telecommunications Index value is not significant. The significant asymmetric negative effect (γ) for the TGARCH model on Table 7 for seven of the indices' values suggests that the volatility increases more with positive news (positive shocks) than negative news (negative shocks) of the same magnitude. This indicates that the high prices caused by an increase in the volume of trading, is leading to higher volatility for positive returns in Boursa Kuwait. The findings of the TGARCH and EGARCH models' values are consistently unaffected by negative shocks to the market.

The results of the ARCH-LM test of the EGARCH and TGARCH models in the last columns of Tables 6 and 7 are accepting of the null hypothesis that there are no ARCH effects on the indices' returns for the study period at the 1% significance level.

4.6 Performance Measures

Table 8 shows that there are minor differences between the values of the accuracy measures for the estimated GARCH models. The AIC and SIC for the GARCH-M have their lowest values for the Market, Banks, and Industrial sectors. The AIC and SIC values with the lowest values for the TGARCH model are in the sectors of Consumer Goods, Oil and Gas, and Real Estate, whereas the lowest values of AIC and SIC for the EGARCH model are in the Telecommunications sector.

Indices	GARCH	GARCH -M	EGARCH	TGARCH	Appropriate Model
Market					
AIC	1.642143	1.633343	1.635200	1.636765	GARCH-M has the lowest AIC and lowest SC
SC	1.656838	1.651712	1.653569	1.655134	
Banks					
AIC	2.110933	2.109935	2.112006	2.111262	GARCH-M has the lowest AIC and lowest SC
SC	2.125628	2.218304	2.130375	2.129631	
Consumer Goods					
AIC	3.478105	3.477259	3.669897	3.477091	TGARCH has the lowest AIC and lowest SC
SC	3.492800	3.495628	3.688266	3.495460	
Financial Services					
AIC	2.283905	2.281662	2.271246	2.277338	EGARCH has the lowest AIC and lowest SC
SC	2.298601	2.300031	2.289615	2.295706	
Industry					
AIC	2.163678	2.157341	2.160270	2.158059	GARCH-M has the lowest AIC and lowest SC
SC	2.178373	2.175710	2.178639	2.176428	
Oil & Gas					
AIC	3.203767	3.204836	3.209653	3.203114	TGARCH has the lowest AIC and lowest SC
SC	3.218462	3.223205	3.228022	3.221483	
Real Estate					
AIC	2.257623	2.251594	2.252794	2.250859	TGARCH has the

SC	2.272318	2.269963	2.271163	2.269228	lowest AIC and lowest SC
Telecommunications					
AIC	3.232797	3.234180	3.232687	3.233451	EGARCH has the lowest AIC and lowest SC
SC	3.247492	3.252549	3.251056	3.251820	

Table 8: Performance Measures.

5. CONCLUSION

Volatility estimation is important for finance research, and a new empirical research direction for Boursa Kuwait has been conducted by examining the conditional volatility. This was done by applying GARCH models to the returns of the market index and seven sectoral indices using daily data from 13 May 2012 to 1 March 2018. The results of the volatility estimation by the GARCH, GARCH-M, EGARCH, and TGARCH models are worthy of consideration by investors, researchers, and financial regulators.

The results indicate that the returns of the indices exhibited characteristics of stationarity, non-normality, leptokurtosis; further, they were skewed to the left and showed evidence of ARCH effects. The symmetric volatility hypothesis measured by the GARCH model shows that bad and good news had an equivalent effect on the upcoming volatility. Therefore, understanding volatility clustering helps investors forecast volatility when analysing recent and historical news. The results of the GARCH-M model are comparable to the GARCH model result, except in assessing risk premium, which reflects the negative relation between returns and volatility. An increase in risk will not be rewarded by an increase in stock returns. Hence, market investors should consider other risk measures.

The inferences from the estimated results of the positive significant asymmetric values of the EGARCH and negative significant asymmetric values of the TGARCH model suggest that the volatility of most indices increases with good news (positive shocks) more than with negative news (negative shocks).

The analysis results based on the lowest values of the AIC and SIC present the market and bank indices, and their returns have a low value of GARCH-M (1,1), suggesting this model captures their symmetric volatility in Boursa Kuwait during the study period at a 1% level of significance. Also, three of the indices' returns-Consumer Goods, Banks, and Real Estate-have a low value of the TGARCH (1,1) model, suggesting that this model has symmetric and asymmetric coefficients that are significant enough to capture the volatility clustering and asymmetric effects of these indices. These selected models were confirmed to have captured all ARCH effects using the ARCH-LM statistic.

Choosing other conditional variance models such as APARCH, FIGARCH, and FIAPARCH to conduct a future analysis of these sectoral indices and the market index of

Boursa Kuwait would make another important contribution to the literature. It would be especially useful to apply a different period and compare it with other stock markets in the Gulf region, which would provide a better understanding of the fluctuations in these markets.

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