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Does heavy-tailedness matter in regime shifts and persistence in volatility estimation? Evidence from six GCC economies

Ajab A. Alfreedi¹, Zaidi Isa² and Abu Hassan³

Abstract

This study examines the regime shifts in volatility in the stock markets of Gulf Cooperation Council (GCC) countries by employing the iterated cumulative sum of squares generalized autoregressive conditional heteroscedasticity (ICSS-GARCH) model. Using the weekly data over the period 2003-2010, the GARCH models are estimated accounting for the sudden shifts detected by ICSS algorithm. The unexpected changes in stock price volatility seem to arise from the important global, regional, and domestic political as well as economic events. The findings also suggest that the ignorance of structural changes in volatility seems to lead to overestimation of persistence parameters of GARCH models. This finding corroborates many earlier studies in this context.

Mathematics Subject Classification: 62M10, 91B84

Keywords: GCC, stock market volatility, ICSS-GARCH, heavy-tailed conditional density

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1 Introduction

The studies on stock market volatility still occupy a large part of literature in financial time series analysis. The policy makers usually are concerned about the behavior of stock market fluctuations because it might affect the macroeconomic variables (e.g. inflation, exchange rates, GDP) by increasing risk and uncertainty. Financial volatility literature documents numerous volatility modeling techniques ranging from non-parametric statistical techniques to GARCH family (Engle, 1982; and Bollerslev, 1986) and stochastic volatility (SV) models (Taylor, 1986)⁴. Nonparametric techniques (e.g. within-period standard deviation, moving standard deviation, and rate of change) have been widely criticized in the literature because they do not follow any information set (see, for instance, Qian and Varangis, 1994; Arize, 1997). Hence, these conventional statistical techniques are unable to capture the stochastic properties of the stock returns. Although the SV models have earned a good empirical record in the financial volatility literature, however, the estimations of SV models are usually computationally burdensome compared to those of the GARCH family models (Kim et al., 1998; Broto and Ruiz, 2004). Due to the ability of being estimated conveniently using maximum likelihood (ML) technique, the GARCH models have entered quick expansion phase and been successful in capturing a number of stylized facts of financial time series, such as time-varying volatility, persistence and clustering, and asymmetric reactions to positive and negative shocks of equal magnitude (Morimune, 2007). Besides, as noted by Daly (2008), a wide variety of applications of GARCH has been documented in the literature since its introduction.

A study by Inclan and Tiao (1994) proposed an algorithm so-called the iterated cumulative sums of squares (ICSS), which endogenously detects sudden shifts in unconditional variances. Since our study focuses on the volatility modeling accounting for the structural breaks detected by employing ICSS methodology. We review a number of relevant studies here to highlight the specific contribution of this paper. The application of this algorithm has entered quick expansion phase and it has been used for volatility modeling of various financial markets. In a seminal paper by Aggarwal et al. (1999), initially, the large sudden shifts in the volatility are investigated using the data of several emerging markets in Asia and Latin America. The authors have combined standard GARCH model with dummy variables for structural changes detected by using the ICSS algorithm. Following this paper, the numbers of papers have surged in different areas. Here it is worth noting that an application of combined version of GARCH models and ICSS algorithm for stock market volatility especially has been gaining ground (see Malik et al., 2005; Cheong, 2008; Hammoudeh and Li, 2008; Kang et al. 2009; Wang and Moore, 2009; and Malik, 2011 among others). A similar

⁴ See, for example, Shephard, N. (2005), and Morimune (2007) for relatively recent survey of GARCH family and SV models.

methodological approach has been adopted by Hammoudeh and Li (2008) for GCC stock markets over the daily period from February 15, 1994 to December 25, 2001. A primary focus of this study is to examine a sensitivity of stock market volatility to global and domestic economic or political events. The authors find that GCC stock markets are more sensitive to major global events than to those of local. Note that our finding also supports that the global events play more important role in volatility of GCC stock markets than regional and/or local events do.

Importantly, the authors do not exclude the examination of volatility persistence in GARCH models combined with structural break dummies. The finding is supportive for widely-held perception that persistence is reduced when sudden changes are taken into account (Lastrapes, 1989; Lamoureux and Lastrapes, 1990).

In this paper, we examine the sudden volatility changes in GCC stock markets exploiting the standard GARCH model combined with dummies detected by ICSS methodology of Inclan and Tiao (1994). Hence, first, we detect the break points in the residual series. Second, we attempt to match these sudden changes to global or domestic events. Third, we estimate the standard GARCH models assuming various conditional densities. Apart from that, indeed, we also estimate these models incorporating the dummies which take into account the sudden changes in volatility detected by ICSS algorithm. Finally, we compare the volatility persistence across all estimated models.

Our paper differs from earlier papers in several ways: first, the more recent stock price data is used; second, the behavior of news impact curves for symmetric GARCH models are analyzed; third, the heavy-tailedness in stochastic errors is considered assuming heavy-tailed conditional densities in model estimations. The remainder of the paper is organized as follows. Section 2 describes descriptive statistics for stock returns. Section 3 briefly presents the methodology for the ICSS algorithm and GARCH models. Section 4 provides the empirical results. The final section, section 5, provides some concluding remarks.

2 Data and descriptive statistics

The weekly data are collected from Data stream database for all GCC countries under investigation. The market indices spanned from 2 March 2003 to 9 December 2010, yielding 414 weekly observations in total for each series. The indices are Bahrain all share, Kuwait SE Kuwait Companies, Oman Muscat Securities, Qatar Exchange index, Saudi Tadawul all share –TASI and ADX General (United Arab Emirates). In the database, the weekly return of market i at time t are measured in local currency and constructed as

$$R_{i,t} = \ln \left(\frac{P_t}{P_{t-1}} \right) \times 100,$$

where $P_{i,t}$ is a weekly closing price of a market i .

The Table 1 reports the descriptive statistics for the stock price returns of GCC countries. The mean values for all stock returns are positive. The lowest mean value (0.0756) is found for Bahrain while the highest (0.3134) is computed for Qatar. The sample standard deviation for the Bahrain stock market returns (1.38%) is lower than the standard deviation computed for the rest of GCC countries. The highest standard deviation is found for Saudi Arabia which takes the value of 3.74% whilst the standard deviation for Kuwait, Oman, Qatar, and UAE are in the range from about 2.24% to 3.73%. The skewness and kurtosis coefficients indicate that stock market returns are leptokurtic and negatively skewed with respect to the normal distribution (skewness =0, kurtosis =3). The Jarque-Bera test statistics also rejects the hypothesis that stock market returns are normally distributed for all the countries under study. The Q statistics computed up to lag 12 for the returns and squared returns for all countries exhibit serial correlation except the returns of Saudi Arabia and Qatar. In Table 1, we present the standard Engle's ARCH Lagrange multiplier (LM) test. According to the LM statistic, the returns in the six countries show strong evidence of ARCH effects. The ARCH-LM test statistics for the lag 12 are significant at the conventional significance levels for all countries under study. We test for a unit root by employing conventional augmented Dickey-Fuller (ADF) test for stock returns of all GCC economies under study. As reported in Table 1, the test statistics reject the null of unit root at 1 percent significance level. This implies that the stock returns follow a stationary process whether a trend and/or intercept is included in the model.

3 Methodology

In this section, we outline the methodology used in this study. In order to analyze the volatility phenomenon, we rely on standard GARCH models. Thus, we describe the standard GARCH model assuming normal, Student- t , and GED distributions. In addition, in the estimations, we account for the regime shifts detected by ICSS algorithm in the second moment equations. Hence, in this section, the detection of the structural breaks employing ICSS algorithm is also discussed. Moreover, news impact curves are discussed.

3.1 The standard GARCH model

Numerous economic models such as autoregressive integrated moving-average (ARIMA) models, developed by Box and Jenkins (1976), assume the conditional variance of the errors is constant over time (homoscedasticity). However, the financial market evidence usually rejects this assumption (see

Figure 1). Moreover, the financial markets exhibit several stylized facts such as heavy-tailedness, volatility clustering, and leverage effects, which cannot be captured by conventional ARIMA models. To overcome the weakness of ARIMA models, Engel (1982) and Bollerslev (1986) developed the (Generalized) Autoregressive Conditional Heteroscedasticity (G) ARCH models to address the several properties of volatility phenomenon.

The GARCH models allow the variance not only to be dependent on the past shocks but also to be dependent on the most recent variance of itself. The variance equation of GARCH model is given as,

$$\sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2 \tag{1}$$

where α_i, β_j are non-negative constants.

As mentioned in introduction, Lastrapes (1989) and Lamoreux and Lastrapes (1990) argue that standard (G) ARCH model may overestimate the parameters if sudden change in volatility are ignored. Thus, in order to estimate the model parameters accurately, the dummies that represent structural change sought to be included in the standard GARCH model outlined in Eq. (1). Then we combine these dummies for regime changes identified by using ICSS methodology with a GARCH model as in Eq. (3). A dummy variable is constructed as it takes one from each point of sudden change of variance onwards, zero otherwise. Due to the evidence of structural changes in stock price volatility of countries under study, one may expect that the persistence of volatility, measured by $\alpha+\beta$, would be significantly smaller when regime shifts in volatility are considered. The standard GARCH model combined with dummies in the variance equation takes the following form:

$$R_t = \mu + \phi R_{t-1} + \varepsilon_t \tag{2}$$

$$\varepsilon_t / I_{t-1} \sim N(0, h_t), \quad \varepsilon_t / I_{t-1} \sim t(0, v, h_t) \quad \text{and} \quad \varepsilon_t / I_{t-1} \sim \text{GED}(0, v, h_t)$$

$$\sigma_t^2 = \omega + d_1 D_1 + \dots + d_n D_n + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2 \tag{3}$$

3.2 Reaction of standard GARCH model to news

News impact curve shows the relationship between the contemporaneous volatility and last returns shocks (news). The studies by Pagan and Schwert (1990) and Engle and Ng (1993) discuss how lagged shocks affect conditional volatility. A formula provided by Engle and Ng (1993) for the news impact curve of standard GARCH (1, 1) model is as follows

$$h_t = A + \alpha \varepsilon_{t-1}^2$$

where

$$A = \omega + \beta\sigma^2$$

and the coefficients ω , α and β are taken from a variance equation of standard GARCH model. A graph takes the shape of quadratic function which is symmetric and centered at ε_{t-1} . This indicates that the conditional volatility responses symmetrically to both negative and positive shocks.

3.3 Distribution assumptions

The probability distribution of asset returns in practice often exhibits fatter tails than the standard normal distribution. A heavy-tailedness may appear due to the volatility clustering and aberrant observations. The excess kurtosis is a good signal for heavy-tailedness (see Table 1). The probability density functions that address heavy-tailedness are Student-t and GED distributions.

3.3.1 Normal distribution

The Normal density function can be written as follows

$$f_v(\varepsilon_t | I_{t-1}) = \frac{\exp(-0.5z_t^2)}{\sigma_t \sqrt{2\pi}}$$

The following log-likelihood function is maximized

$$L_{\text{normal}} = \frac{1}{2} \sum_{t=1}^T [\ln(2\pi) + \ln(\sigma_t^2) + z_t^2]$$

where T is the number of observations.

3.3.2 Student-t distribution

When the Student t conditional density is considered, log-likelihood function can be specified as follows

$$L_{\text{student}} = \ln \left[\Gamma\left(\frac{\nu+1}{2}\right) \right] - \ln \left[\Gamma\left(\frac{\nu}{2}\right) \right] - 0.5 \ln(\nu - 2) - 0.5 \sum_{t=1}^T \left[\ln \sigma_t^2 + (1 + \nu) \ln \left(1 + \frac{z_t^2}{\nu - 2} \right) \right]$$

where ν is the degrees of freedom, $0 < \nu \leq \infty$ and $\Gamma(\cdot)$ is the gamma function.

3.3.3 Generalized error distribution

The GED proposed by Nelson (1991) successfully accounts for the heavy-tailedness in the error process. The following log-likelihood function is maximized assuming GED

$$L_{GED} = \sum_{t=1}^T \ln(v/\lambda) - \ln[\Gamma(1/v)] - (1 + v^{-1}) \ln(2) - 0.5 \ln(\sigma_\tau^2) - 0.5 \left| \frac{z_t}{\lambda} \right|^v$$

where $-\infty < z_t < \infty$, $0 < v \leq \infty$ and $\lambda = \sqrt{\frac{2^{-2/v} \Gamma(1/v)}{\Gamma(3/v)}}$.

3.4 ICSS methodology

In this paper, we use the ICSS algorithm proposed by Inlan and Tiao (1994) to detect sudden shifts in unconditional variance. The ICSS algorithm focuses on detecting an unconditional variance change due to structural changes that affect the variance. This approach is proven to be an effective technique in identification sudden shifts when the series suffer from structural changes even there is 'masking effect'. As Malik et al. (2005) notes, 'masking effect' is a phenomenon that moderate-sized break points may be overlooked because of a major break point.

Let r_t be the series and with unconditional variance, σ^2 . The variances within each interval are given by τ_j^2 , $j = 0, 1, \dots, N_T$. Here, N_T is the total number of variance changes in T observations and $1 < k_1 < k_2 < \dots < k_{N_T} < T$ are the change points.

To identify the variance changes, the iterative cumulative sum of squares of the series are generated using $C_k = \sum_{t=1}^k r_t^2$ for $k=1, \dots, T$. Then D_k series is defined as

$$D_k = \frac{C_k}{C_T} - \frac{k}{T}, \quad k=1, \dots, T \text{ with } D_0 = D_T = 0.$$

If there is no change in variance D_k oscillates around zero when plotted against k . However, if there is change in variance D_k series dramatically moves up and down from zero. In this case, sudden changes in variance are detected using the critical values which are tabulated in Table 1 in the study by Inlan and Tiao (1994).

According to Inlan and Tiao (1994), the significant changes are detected using the critical values obtained from the distribution of $\sqrt{\frac{T}{2}} |D_k|$ where $\sqrt{\frac{T}{2}}$ is multiplied by D_k to standardize the distribution. To identify significant changes we do not consider D_k series rather we examine $\sqrt{\frac{T}{2}} |D_k|$ series. The null hypothesis of homogeneous variance can be rejected if the maximum of $\sqrt{\frac{T}{2}} |D_k|$ exceeds the

critical value. Let k^* denote the value at which $\max_k k \sqrt{\frac{T}{2}} |D_k|$ reached. If $\max_k k \sqrt{\frac{T}{2}} |D_k|$ falls outside the predetermined boundary, then k^* is taken as point in unconditional variance change.

Frequently, D_k series only is not enough to detect multiple variance changes because of the 'masking effect'. Masking effect' means that moderate variance changes may not be detected because of the large variance changes. To solve this problem, Inclan and Tiao (1994) developed an algorithm that is able to detect the multiple changes in the series. D_k statistic allows to find only one break point at a time. After finding one break point then the sample is segmented into parts and will be checked for other break points that exist in the series.

If there is two or more potential change points it is important that these points must be in ascending order. Let cp be the vector of all change points found in previous steps. Two extreme values are defined by $cp_0 = 0$ and $cp_{NT+1} = T$. Check each possible change point by computing

$$D_k(a[cp_{j-1} + 1 : cp_{j+1}]) j = 1, 2, \dots, N_T.$$

If $M[cp_{j-1} + 1 : cp_{j+1}] > D^*$ then the change point is kept, otherwise eliminated.

4 Result and discussion

In this part, we analyze the volatility behavior of GCC market over eight years. In this period, GCC stock markets are considerably affected by a number of global and domestic events. For instance, it is important to mention that the events such as the financial default in all GCC countries except Bahrain in 2006 and the global economic meltdown during 2008-2009.

We begin the analysis by discussing the standardized residual diagnostics for each country under study. In Table 2, the results of the Ljung-Box Q (Ljung and Box, 1978) statistics for the standardized residuals and squared standardized residuals suggest that the stochastic errors do not seem to be serially correlated in Bahrain, Oman, and Saudi Arabia. However, estimated models slightly suffer from serial correlation in Kuwait, Qatar, and UAE. In addition, ARCH LM test results reveal that there are no further signs of heteroskedasticity in all countries' estimated models except the model for Qatar. Furthermore, as Table 2 presents, it is interesting to note that all countries satisfy the inequality constraint that is, $\alpha + \beta < 1$, except Saudi GARCH model assuming normal distribution as well as the models for Kuwait and UAE assuming Student's-t conditional density. The parameters of ARCH and GARCH effects are found to be highly significant for all GARCH(1,1) models. On the other hand, we turn to the models which taken into account the regime shifts. The innovations seem to have serial correlation in the

estimated models of Bahrain, Kuwait and Saudi Arabia while the rest of countries under study exhibit no serial correlation in the disturbances. The Ljung-Box test statistics for squared standardized residuals do not appear to show any serial correlation in the stochastic disturbances.

The Table 3, shows that the persistence of volatility (i.e. $\alpha+\beta<1$) reduced significantly in all countries under study. The average of persistence in the models without dummy variable was 0.9597 while it is 0.5571 in the models that include dummy variables for regime shifts in the variance equations. Among all GCC markets, the largest decline in persistence is found in the model under GED distribution (0.2291) for Oman. It is important to emphasize that the persistence decreased at a greater degree when the heavy-tailed distributions (Student-t and GED) are assumed in the estimations compared to normal distribution in all cases except for the models for Saudi. The results show that, according the AIC and Log-likelihood values, the GARCH models combined with dummies are found to be more favored model compared to the models without dummies for all countries under study except Saudi Arabia and Bahrain. Apart from that, one of other findings is that the heavy-tailed distributions perform very well in the models accounting for the dummies in all cases except for Oman. Moreover, for Saudi Arabia and Bahrain, the most favored model appears to be the model without binary variables assuming Student-t conditional density. The GED outperforms in the estimated models combined with dummies for Qatar and UAE. Similarly, the Student-t is found to be better distribution assumption for Kuwait. However, as mentioned earlier, the model assuming a normal distribution is favored for Oman. All in all, our results suggest that non-Gaussian distributions provide better fit for almost all GCC stock markets.

A news impact curve advocated by Engle and Ng (1993) is an alternative way of displaying the effect of good and bad news on conditional volatility. The new impact curve displayed in Figure2 shows that negative and positive shocks have a similar impact on conditional volatility when standard GARCH models are considered. This is consistent with notion by Engle and Ng (1993). As can be seen, the minimum point of the curve differs from country to country. Among the rest of GCC countries, Bahrain has been found to be less affected by good and bad news. In contrast, the volatility in Qatar and Saudi stock markets seem to have much influence from good and bad news.

The ICSS algorithm has been utilized to detect the sudden shifts in residuals. The graphs displayed in Figure 1 and figures in Table 3 suggest the sudden shifts in stochastic errors. The Figure 1 plots the return series for each market with the points of structural changes and ± 3 S.E. From Table 1, one may gather that all GCC markets appear to have high mean of returns as well as high standard deviation except for Bahrain. These computed values are probably associated with regime changes in stock returns. According to the results of ICSS algorithm, from Figure 1, one may see that GCC markets exhibit change points that range from two to eleven. Here, it is important to note that these changes are associated with important economic and political events. Moreover, the detected changes can be

categorized as global, regional, and country-specific. For example, during the recent global crisis in 2008-2009, as Table 3 reports, a high level of volatility is observed in all countries' stock markets. The mean conditional variance has risen sharply in this period compared to the previous relatively tranquil period. The Table 4 presents that mean conditional variances during global financial crisis increase by about 3.85, 4.03, 5.67, 6.01, 6.17, and 7.05 times in Kuwait, Bahrain, Saudi Arabia, UAE, Qatar, and Oman respectively. As can be seen, among other GCC countries, Oman has been affected much from this default. This might be because of the fact that Oman is highly integrated with a number of developed countries. At the beginning of global economic meltdown, another factor that seems to have led to a considerable increase in the stock market volatility is that the price of crude oil dropped from about \$126.16 in July 2008 to about \$32.94 in November 2008 due to the sudden reduction in world demand for oil. All GCC economies are heavily dependent on crude oil exports except Bahrain. Moreover, the other common and regional event that has caused a considerable increase in the GCC stock market volatility except Bahrain happened in 2006. In this period, Saudi stock market was severely affected compared to the rest of GCC countries. For example, as Table 4 presents, the mean volatility sharply rises by about 14.15 times with respect to previous relatively tranquil volatility period. In contrast, Bahrain does not appear to be affected by this regional crisis. The main reasons for this can be: first, this economy is not dependent on crude oil exports; second, it is highly integrated with world stock markets. This finding is consistent with the finding by Hammodeh and Li (2008) which suggests that Bahrain has the least number of regime shifts among GCC and it is more integrated with the world stock market for their sample period. In comparison with the previous tranquil period, in this crisis period, the mean conditional variances increased sharply by approximately 2.40, 2.61, 7.20 times in Kuwait, Qatar, and UAE respectively. As one expects, the ICSS methodology does not detect any regime shifts in 2006 for Oman and Bahrain. Furthermore, in 2006, the sudden shift in stock market volatility was closely related with the death of the President of Kuwait. The end of our sample period (in 2010) has exhibited a relatively tranquil period for all GCC countries except Kuwait. Interestingly, the ICSS algorithm results suggest that the GCC stock markets do not seem to be influenced by Gulf war in 2003.

4 Conclusion

In this paper, we have examined the volatility of the GCC stock price indices employing the GARCH model combined with dummy variables that account for regime shifts in volatility. In addition, we have also estimated standard GARCH models assuming various distributions without regime dummies. The model comparisons rely on two different aspects: first, the difference between models with dummy and without dummy; second, the difference between normal and heavy-tailed distributions in the estimations. We have discovered that the

persistence of volatility have reduced significantly in all GCC stock market volatility models when the regime shifts are taken into account. This finding is consistent with many earlier studies. Moreover, the estimation results generally reveal that the heavy-tailed conditional densities are found to be favored more compared to the normal distribution. Finally, the behavior of news impact curves has been analyzed for each standard GARCH model of the countries under study. This finding is consistent with the construction of theoretical news impact curve which suggests that the bad and good news effects are symmetric in standard GARCH models. Importantly, the size effects of news appear to vary in different GCC countries.

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Table 1 : Summary statistics for stock market returns of GCC region

	Bahrain	Saudi Arabia	Qatar	United Arab Emirate	Oman	Kuwait
Mean	0.0756	0.2176	0.3134	0.1686	0.3010	0.2516
Median	0.1500	0.7348	0.3369	0.2817	0.3586	0.5079
Maximum	4.7091	9.0914	13.922	15.094	6.4885	7.8974
Minimum	-6.0682	-19.289	-18.4691	-9.5518	-13.809	-10.287
Std. Dev.	1.3880	3.7402	3.7317	2.9477	2.3651	2.2442
Skewness	-0.3733	-1.5226	-0.7948	-0.0046	-1.4597	-0.7296
Kurtosis	5.2068	7.8344	7.0728	6.0688	9.8564	5.4525
J Bera	93.393 [0.000]	561.76 [0.000]	328.93 [0.000]	162.06 [0.000]	955.63 [0.000]	140.14 [0.000]
Q(12)	105.51 [0.000]	15.156 [0.233]	14.694 [0.258]	36.172 [0.000]	76.968 [0.000]	56.936 [0.000]
Q ² (12)	70.302 [0.000]	142.82 [0.000]	143.28 [0.000]	89.259 [0.000]	163.57 [0.000]	121.42 [0.000]
LM	46.835 [0.000]	79.069 [0.000]	86.460 [0.000]	50.866 [0.000]	84.492 [0.000]	219.52 [0.000]
Number observations	414	414	414	414	414	414
Panel B: Unit root tests ADF						
Intercept	-9.577 [0.000]	-15.493 [0.000]	-15.846 [0.000]	-13.876 [0.000]	-4.967 [0.000]	-7.483 [0.000]
Trend and intercept	-13.840 [0.000]	-15.677 [0.000]	-15.927 [0.000]	-14.017 [0.000]	-5.099 [0.000]	-7.996 [0.000]
No trend no intercept	-9.5658 [0.000]	-15.470 [0.000]	-15.775 [0.000]	-13.860 [0.000]	-3.260 [0.000]	-7.404 [0.000]

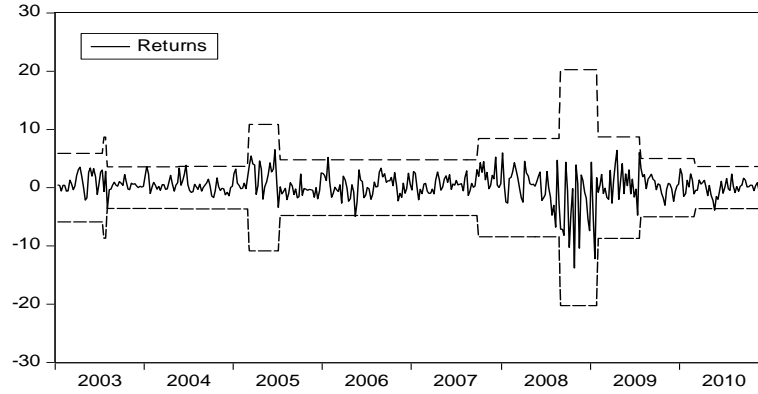
J.Bera corresponds to the test statistic for the null hypothesis of normality in sample returns distribution, The Ljung-Box statistic, $Q(12)$, check for the serial correlation of the return series up to the 12th order, $Q^2(12)$ is the Ljung-Box test for squared returns LM (12) is the Engle's Lagrange Multiplier test for conditional heteroskedasticity with 12 lags.

Table 3: Persistence of GARCH models

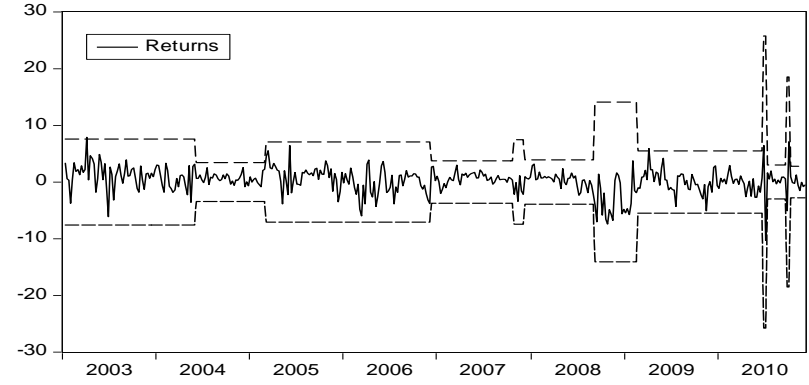
	Normal	Student-t	GED
Saudi Arabia			
<i>Without</i>	1.0063	0.9945	0.9907
<i>With</i>	0.6932	0.7100	0.7314
<i>Ratio</i>	0.6889	0.7139	0.7383
Bahrain			
<i>Without</i>	0.8893	0.8784	0.8884
<i>With</i>	0.7712	0.7610	0.7730
<i>Ratio</i>	0.8672	0.8663	0.8701
Qatar			
<i>Without</i>	0.9465	0.9662	0.9583
<i>With</i>	0.6760	0.6823	0.6718
<i>Ratio</i>	0.7142	0.7062	0.7010
UAE			
<i>Without</i>	0.9835	1.0117	0.9909
<i>With</i>	0.5980	0.5663	0.5904
<i>Ratio</i>	0.6080	0.5598	0.5958
Oman			
<i>Without</i>	0.9735	0.9693	0.9730
<i>With</i>	0.3330	0.3072	0.2291
<i>Ratio</i>	0.3421	0.3169	0.2354
Kuwait			
<i>Without</i>	0.8578	1.0422	0.9637
<i>With</i>	0.2535	0.2469	0.4012
<i>Ratio</i>	0.2955	0.2369	0.4163

Note: The persistence is calculated as $(\alpha+\gamma/2+\beta)$ for GJR-GARCH and (β) for EGARCH estimation (Maik (2011)) “Without” denotes that GARCH models without any regime dummies in the variance equation. “With” means that GARCH estimations with regime dummies in the variance equation. Ratio is calculated as persistence in the model with dummies divided by the persistence of GARCH models without dummies.

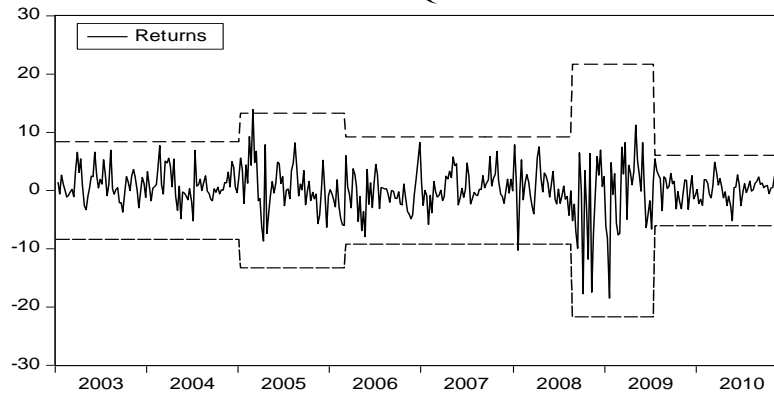
Panel A: Oman



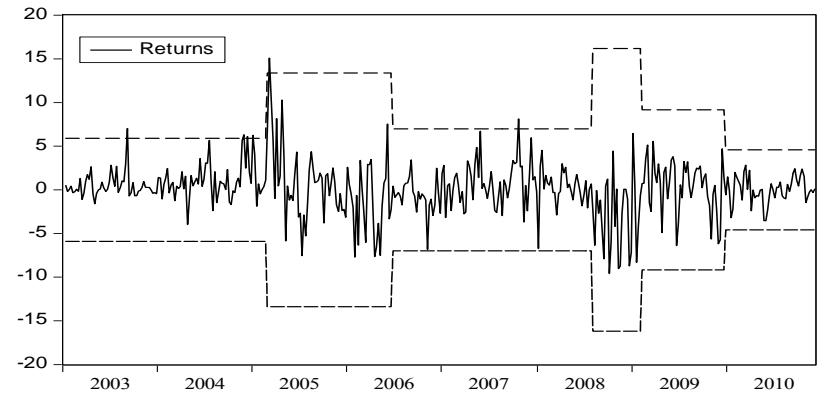
Panel B: Kuwait



Panel C: Qatar



Panel D : United Arab Emirates



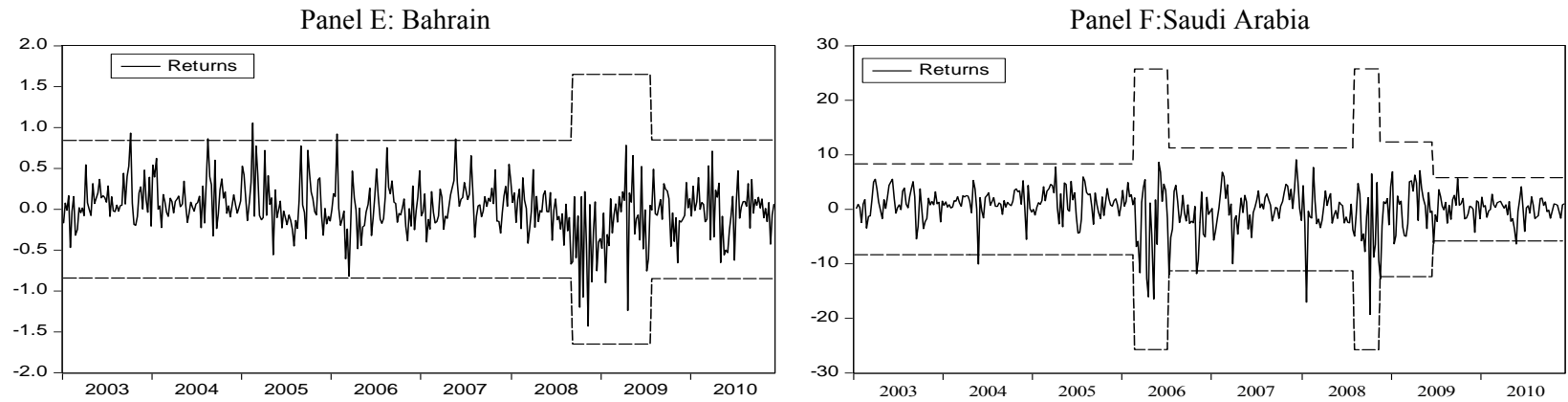


Figure 1: Weekly GCC stock price returns. Note: Bands are at ± 3 standard deviations and change points are detected by ICSS algorithm

Table 4: Sudden changes in volatility and corresponding dummy variables detected by ICSS algorithm

Country	Number of dummy variable	Dummy variable parameter estimation		The number of regime	Time period of regime		Mean conditional variance	Ratio of change with respect of previous regime
		Parameters	p-value		From	To		
Saudi Arabia	1	0.80466	0.0286	6	1/6/2003	2/20/2006	6.56052	14.15959
	2	-0.55401	0.0426		2/27/2006	7/10/2006	92.89431	
	3	0.545879	0.0588		7/17/2006	8/4/2008	13.70501	
	4	-0.48754	0.1166		8/11/2008	11/17/2008	77.8150	
	5	-0.38641	0.1855		11/24/2008	6/22/2009	23.87864	
United Arab Emirates	1	5.811243	0.0152	6	6/29/2009	12/6/2010	4.088077	0.171202
	2	-4.46709	0.0464		1/6/2003	2/21/2005	2.732877	
	3	11.47616	0.1034		2/28/2005	6/19/2006	19.66033	
	4	-8.99373	0.2006		6/26/2006	7/28/2008	6.174635	
	5	-3.67189	0.0747		8/4/2008	2/2/2009	37.11357	
Bahrain	1	0.572777	0.0282	3	2/9/2009	12/21/2009	12.44856	0.335418
	2	-0.62309	0.0396		12/28/2009	12/6/2010	2.522628	
Qatar	1	3.31471	0.1909	5	1/6/2003	8/25/2008	1.563123	2.613423
	2	-2.69558	0.2389		9/1/2008	7/20/2009	6.305583	
	3	15.06571	0.1567		7/27/2009	12/6/2010	1.444496	
	4	-16.6765	0.1431		1/6/2003	1/10/2005	6.205036	
Kuwait	1	-0.99559	0.0035	12	1/17/2005	3/6/2006	16.21638	0.072565
	2	0.909675	0.005		3/13/2006	8/25/2008	8.574404	
	3	-0.99974	0.0008		8/25/2008	7/20/2009	52.97092	
	4	1.464639	0.0461		7/27/2009	12/6/2010	3.843818	
	5	-1.20235	0.0956		1/6/2003	5/31/2004	12.22903	
	6	1.419020	0.0045		6/7/2004	2/28/2005	3.2392564	
	7	-0.90109	0.026		3/7/2005	12/4/2006	7.7497141	
	8	3.1176	0.3568		12/11/2006	10/22/2007	0.8777766	
	9	-4.11386	0.2546		10/29/2007	12/3/2007	7.6904808	
	10	3.964536	0.0461		12/10/2007	8/25/2008	3.0786684	
	11	-3.65904	0.0692		9/1/2008	2/16/2009	11.849956	
Oman	1	17.22269	0.000	11	2/23/2009	6/21/2010	5.0783762	0.4285566
	2	-18.3088	0.000		6/21/2010	6/28/2010	11.65112	
	3	0.54136	0.0205		7/12/2010	9/20/2010	1.328460	
	4	4.283075	0.135		9/20/2010	10/4/2010	77.406216	
	5	-3.61958	0.1991		10/11/2010	12/6/2010	3.1076537	
	1	17.22269	0.000		1/13/2003	7/14/2003	2.2057349	1.6187621
	2	-18.3088	0.000		7/28/2003	8/4/2003	3.5705601	
	3	0.54136	0.0205		8/4/2003	5/17/2004	2.101859	
	4	4.283075	0.135		5/24/2004	2/28/2005	1.7756616	
	5	-3.61958	0.1991		3/7/2005	7/4/2005	5.5178229	
					7/11/2005	9/24/2007	2.8789115	0.5217477

6	3.45215	0.0127	10/1/2007	8/25/2008	5.1355894	1.783865
7	17.33886	0.000	9/1/2008	1/26/2009	36.207814	7.0503716
8	-15.5597	0.000	2/2/2009	7/20/2009	13.026362	0.3597666
9	-5.58342	0.059	7/27/2009	3/1/2010	4.2585308	0.3269164
10	-0.51763	0.2318	3/8/2010	12/6/2010	1.8892902	0.4436484

Table 2: The GARCH estimation results

	Saudi Arabia			Bahrain			Kuwait		
	Normal	Student-t	GED	Normal	Student-t	GED	Normal	Student-t	GED
A. Without dummy variable									
μ	0.4979 [0.005]	0.7789 [0.000]	0.6977 [0.000]	0.1941 [0.064]	0.1772 [0.046]	0.1992 [0.024]	0.4749 [0.000]	0.5832 [0.000]	0.6010 [0.000]
\square	0.2991 [0.000]	0.3303 [0.000]	0.2834 [0.000]	0.4310 [0.000]	0.4048 [0.000]	0.4013 [0.000]	0.3708 [0.000]	0.3658 [0.000]	0.3441 [0.000]
ω	0.5574 [0.005]	0.7655 [0.046]	0.6195 [0.067]	0.1913 [0.001]	0.2302 [0.021]	0.1927 [0.021]	0.8510 [0.000]	0.6437 [0.005]	0.5959 [0.004]
α	0.2820 [0.000]	0.2831 [0.004]	0.2763 [0.002]	0.2013 [0.000]	0.2409 [0.005]	0.2054 [0.004]	0.4020 [0.000]	0.6042 [0.001]	0.4800 [0.000]
β	0.7242 [0.000]	0.7113 [0.000]	0.7144 [0.000]	0.6880 [0.000]	0.6374 [0.000]	0.6829 [0.000]	0.4557 [0.000]	0.4378 [0.000]	0.4836 [0.000]
Diagnostics for the models without dummy variables									
Q(12)	8.1826 [0.697]	6.2365 [0.857]	8.2400 [0.692]	13.417 [0.267]	15.440 [0.163]	15.177 [0.175]	23.453 [0.015]	19.220 [0.057]	21.015 [0.033]
Q ² (12)	6.0064 [0.873]	5.9214 [0.879]	6.2192 [0.858]	11.033 [0.441]	11.315 [0.417]	11.247 [0.423]	10.878 [0.454]	8.8061 [0.640]	10.412 [0.494]
LM[12]	5.8699 [0.922]	5.8625 [0.922]	6.1345 [0.909]	10.027 [0.613]	10.061 [0.610]	10.229 [0.595]	11.874 [0.455]	9.6512 [0.646]	12.015 [0.444]
AIC	5.13616	5.00377	5.01897	3.20792	3.17649	3.17924	4.156559	4.057656	4.064229
BIC	5.18496	5.06232	5.07752	3.25672	3.23505	3.23780	4.205358	4.116214	4.122787
Log L	-1053.05	-1024.78	-1027.91	-655.833	-648.358	-648.925	-851.251	-829.877	-831.231
B. With dummy variable									
μ	0.5445 [0.000]	0.7020 [0.000]	0.74491 [0.000]	0.2093 [0.001]	0.1818 [0.001]	0.1895 [0.000]	0.4129 [0.000]	0.4123 [0.000]	0.4443 [0.000]
\square	--	--	--	--	--	--	0.4129 [0.000]	0.4123 [0.000]	0.4443 [0.000]
ω	1.9220 [0.002]	1.8601 [0.051]	1.6156 [0.095]	0.4223 [0.000]	0.4329 [0.008]	0.4112 [0.008]	4.1577 [0.000]	4.2738 [0.000]	3.2812 [0.001]
α	0.1689 [0.004]	0.1817 [0.034]	0.1831 [0.050]	0.3011 [0.000]	0.3559 [0.004]	0.3246 [0.005]	0.1340 [0.112]	0.1679 [0.068]	0.2235 [0.020]
β	0.5243 [0.000]	0.5282 [0.002]	0.5483 [0.004]	0.4701 [0.000]	0.4050 [0.007]	0.4484 [0.001]	0.1193 [0.353]	0.0789 [0.408]	0.1776 [0.301]
Diagnostics for the models with dummy variables									
Q(12)	40.449 [0.000]	40.674 [0.000]	39.952 [0.000]	40.201 [0.000]	40.108 [0.000]	39.657 [0.000]	28.681 [0.003]	29.077 [0.002]	30.197 [0.001]
Q ² (12)	7.2875 [0.838]	7.0881 [0.852]	6.7207 [0.876]	16.391 [0.174]	18.191 [0.110]	17.043 [0.148]	6.6464 [0.827]	6.6377 [0.828]	6.2066 [0.859]
LM[12]	7.3383 [0.834]	7.1676 [0.846]	6.8322 [0.868]	14.964 [0.243]	16.832 [0.156]	15.584 [0.211]	5.3373 [0.945]	5.3336 [0.945]	4.1748 [0.980]
AIC	5.11308	5.05553	5.05440	3.33401	3.30424	3.30961	3.966602	3.963542	4.002952
BIC	5.20076	5.15295	5.15182	3.39246	3.37244	3.37780	4.112999	4.119698	4.159108
Log L	-1046.85	-1033.97	-1033.73	-682.474	-675.327	-676.452	-802.12	-800.49	-808.608

Notes: Figures in square brackets denote p-values; AIC, BIC, and Log L denote Akaike Information Criterion and maximum log-likelihood value, respectively; Q(12) and Q²(12) are Ljung-Box Q statistics for standardized residuals and squared standardized residuals, respectively at lag 12. LM represents an ARCH LM test statistics at lag 12 for heteroscedasticity.

Table2: The GARCH estimation results (Continued)

	Qatar			UAE			Oman		
	Normal	GARCH Student-t	GED	Normal	GARCH Student-t	GED	Normal	GARCH Student-t	GED
A. Without dummy variable									
μ	0.5280 [0.029]	0.4219 [0.037]	0.4553 [0.014]	0.1705 [0.331]	0.2577 [0.047]	0.2203 [0.055]	0.4477 [0.000]	0.4074 [0.000]	0.3856 [0.000]
\square	0.3648 [0.000]	0.3240 [0.000]	0.3070 [0.000]	0.3523 [0.000]	0.3091 [0.000]	0.3081 [0.000]	0.3457 [0.000]	0.3413 [0.000]	0.3432 [0.000]
ω	0.7960 [0.003]	0.6470 [0.035]	0.6690 [0.046]	0.2268 [0.008]	0.2309 [0.082]	0.2066 [0.109]	0.1654 [0.027]	0.1872 [0.057]	0.1748 [0.085]
α	0.2364 [0.000]	0.2133 [0.001]	0.2148 [0.001]	0.1640 [0.000]	0.1965 [0.006]	0.1693 [0.002]	0.2253 [0.000]	0.2300 [0.000]	0.2295 [0.002]
β	0.7101 [0.000]	0.7528 [0.000]	0.7434 [0.000]	0.8194 [0.000]	0.8151 [0.000]	0.8215 [0.000]	0.7481 [0.000]	0.7387 [0.000]	0.7434 [0.000]
Diagnostics for the models without dummy variables									
Q(12)	19.057 [0.060]	19.087 [0.060]	19.719 [0.049]	15.635 [0.155]	18.508 [0.071]	18.892 [0.063]	16.133 [0.136]	16.655 [0.119]	16.507 [0.123]
Q ² (12)	18.322 [0.074]	18.528 [0.070]	18.586 [0.069]	4.7464 [0.943]	4.8058 [0.940]	4.8466 [0.938]	9.4420 [0.581]	9.3097 [0.593]	9.2062 [0.603]
LM[12]	18.452 [0.102]	19.112 [0.085]	18.855 [0.092]	4.6451 [0.968]	4.7455 [0.965]	4.8043 [0.964]	9.2626 [0.680]	9.1687 [0.688]	9.0695 [0.697]
AIC	5.11001	5.09149	5.07561	4.64116	4.55953	4.54119	4.007704	4.00306	3.98842
BIC	5.15881	5.15005	5.13417	4.68996	4.61809	4.59975	4.056503	4.06162	4.04697
Log L	-1047.68	-1042.85	-1039.58	-951.081	-933.264	-929.487	-820.587	-818.631	-815.615
B. With dummy variable									
μ	0.4825 [0.032]	0.4270 [0.031]	0.4653 [0.010]	0.2813 [0.087]	0.3032 [0.011]	0.2672 [0.018]	---	---	---
\square	0.3409 [0.000]	0.3177 [0.000]	0.2949 [0.000]	0.3262 [0.000]	0.2933 [0.000]	0.3002 [0.000]	0.4109 [0.000]	0.3087 [0.000]	0.3847 [0.000]
ω	2.1034 [0.032]	2.0792 [0.058]	2.1115 [0.089]	1.1292 [0.000]	1.0297 [0.020]	0.9549 [0.010]	1.4600 [0.000]	1.6033 [0.000]	1.7264 [0.009]
α	0.1289 [0.013]	0.1009 [0.101]	0.1035 [0.120]	0.1322 [0.008]	0.2264 [0.054]	0.1769 [0.054]	0.0780 [0.139]	0.0554 [0.230]	0.0655 [0.274]
β	0.5470 [0.000]	0.5813 [0.001]	0.5683 [0.006]	0.4658 [0.000]	0.3399 [0.050]	0.4135 [0.009]	0.2549 [0.077]	0.2517 [0.026]	0.1635 [0.292]
Diagnostics for the models with dummy variables									
Q(12)	15.546 [0.159]	14.632 [0.200]	14.874 [0.188]	16.822 [0.113]	20.950 [0.034]	19.384 [0.055]	15.378 [0.166]	20.919 [0.034]	15.346 [0.167]
Q ² (12)	17.303 [0.099]	16.373 [0.128]	16.956 [0.109]	11.144 [0.431]	17.273 [0.100]	12.937 [0.297]	11.733 [0.384]	6.8796 [0.809]	8.1901 [0.696]
LM[12]	16.808 [0.156]	16.013 [0.190]	16.364 [0.175]	10.999 [0.528]	15.855 [0.197]	12.284 [0.423]	10.280 [0.591]	6.3750 [0.896]	8.0926 [0.777]
AIC	5.074754	5.06196	5.05068	4.58984	4.51716	4.50812	3.92403	3.99526	3.95058
BIC	5.162591	5.15956	5.14828	4.68744	4.62451	4.61547	4.07016	4.14139	4.09671
Log L	-1036.40	-1032.77	-1030.44	-935.508	-919.535	-917.673	-795.313	-810.022	-800.796

Notes: Figures in square brackets denote p-values; AIC, BIC, and Log L denote Akaike Information Criterion and maximum log-likelihood value, respectively; Q(12) and Q²(12) are Ljung-Box Q statistics for standardized residuals and squared standardized residuals, respectively at lag 12. LM represents an ARCH LM test statistics at lag 12 for heteroscedasticity

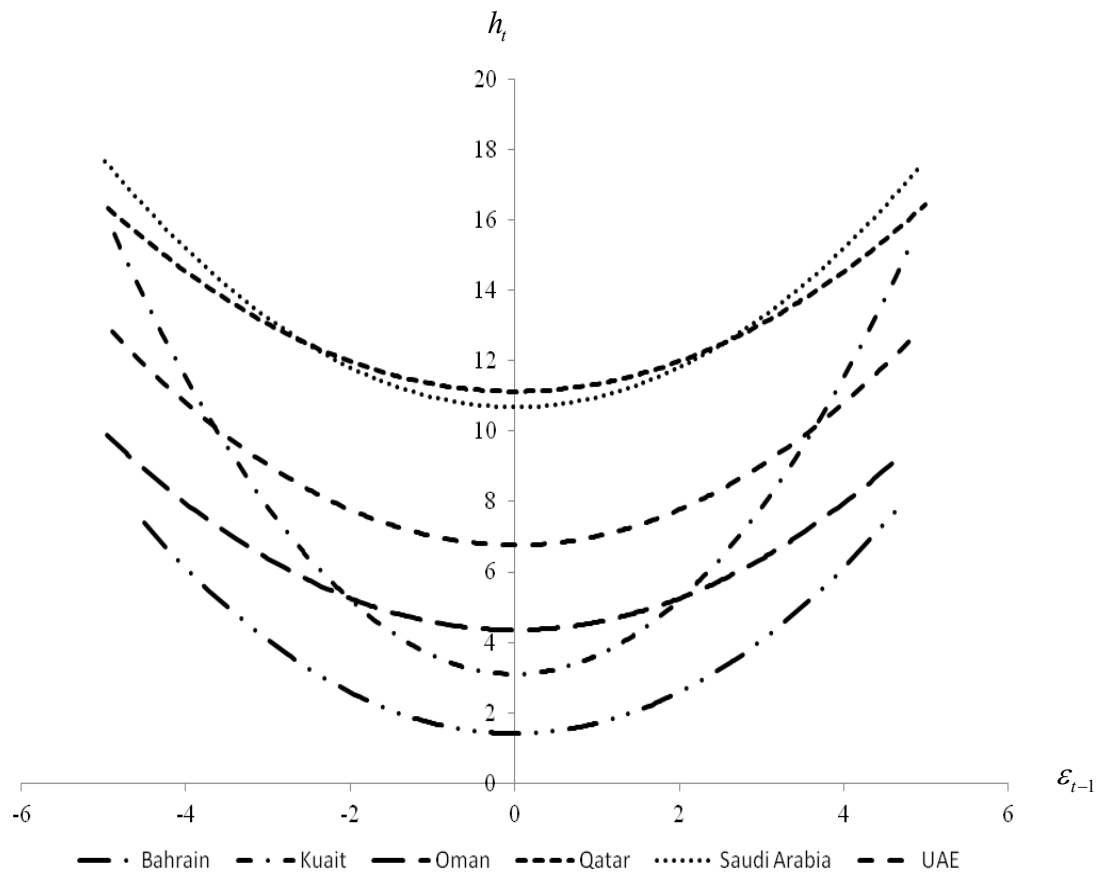


Figure 2: News impact curve for all GCC markets using standard GARCH model