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Regime shifts in asymmetric GARCH models assuming heavy-tailed distribution: evidence from GCC stock markets

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Abstract

In this study, we have investigated GCC stock market volatilities exploiting a number of asymmetric models (EGARCH, ICSS-EGARCH, GJR-GARCH, and ICSS-GJR-GARCH).This paper uses the weekly data over the period 2003-2010. The ICSS-EGARCH and ICSS-GJR-GARCH models take into account the discrete regime shifts in stochastic errors. The finding supports the widely accepted view that accounting for the regime shifts detected by the iterated cumulative sums of squares (ICSS) algorithm in the variance equations overcomes the overestimation of volatility persistence. In addition, we have discovered that the sudden changes are generally associated with global, regional, and domestic economic as well as political events. Importantly, the asymmetric model estimations use normal as well as heavy-tailed conditional densities.

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Keywords: asymmetric models, ICSS, EGARCH, GJR-GARCH, heavy-tailed process, GCC stock market

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1 Introduction

While the general trend of assessing the impact of regime shifts on conditional volatility is towards the models based on normal distribution, however, the regime changes based on heavy tailed distributions appear to be less common in this context. Moreover, the studies on regime changes in stock market volatility in the GCC countries utilizing asymmetric GARCH family models have received little research attention.

As defined by Daly [6], the volatility is a changeableness of a variable under consideration. In other words, the more variable fluctuates over a period of time, the more volatile the variable is said to be. The problem with volatility is that, unlike returns, it cannot be observed directly and therefore needs to be estimated. Hence, the proxies need to be constructed in order to measure and subsequently model the volatility (see, for example [25]). In addition here one should note that the degree of persistence is important factor in predicting the future volatility. To this end, one should be cautious in overestimation of persistence in underlying GARCH family models. The existing literature suggests that the ignorance of structural changes in volatility modeling might overestimate the volatility persistence [10, 12, 14, 15, 16, 17, 19, 20, 26].

Inclan and Tiao developed the iterated cumulative sums of squares (ICSS) algorithm [11], which identifies time points and location observation which sudden change in unconditional variances occurs. Since our paper deals with the modeling of volatility accounting for the regime changes detected by using ICSS algorithm, below, several ICSS-related papers are reviewed in order to highlight the contribution of this paper. The application of this algorithm has earned a good empirical record in various financial markets. For example, Aggarwal et al. initially examine large sudden shifts in the volatility in some emerging markets in Asia and Latin America, [1]. They have detected the breaking points of the sudden shifts using the ICSS algorithm, and then directly incorporated regime dummies into the GARCH model. Their finding suggests that accounting for sudden changes significantly reduces the persistence in the GARCH model. Several recent empirical investigations have extended the approach of applying for stock price returns, [1]. In a similar vein, Malik et al. finds that controlling regime shifts considerably reduces volatility persistence in the Canadian stock market [21]. It is worth mentioning that following a Monte Carlo study by Sanso et al. [24], Malik et al. [21] use the different critical values for the break detection. Cheong investigates the impact of structural breaks on the parameters of fractionally integrated GARCH (FIGARCH) volatility model in the Malaysian stock market, [5]. More recently, Wang and Moore assess the influence of sudden shifts on volatility persistence in the several east European transition economies, [26]. Unlike many earlier studies, these authors analyze regime changes in stock markets and their association with the exchange rate arrangements. Using the data of Japanese and Korean stock markets, Kang at el. investigate the impact of regime shifts on volatility utilizing the standard GARCH as well as FIGARCH models, [12]. The authors conclude that when sudden changes are incorporated in the variance of GARCH and FIGARCH, the evidence of persistence or long memory has been vanished in both markets under consideration. Hence, according to the authors, including the information on sudden changes in the second moment improves the accuracy of estimating the volatility dynamics and forecasting performance of future volatility. The study by Malik shows that taking into account endogenously determined structural breaks within the asymmetric GARCH models decreases volatility persistence and good news significantly reduces volatility [20]. Based on Monte Carlo simulations for validation of his empirical results, Malik suggests that good news does not seem to have an impact on volatility if structural breaks are ignored [20]. Although GCC stock markets have been examined in number of studies, however, the modeling approach accounting for structural changes for volatility is employed in a limited number of studies for these emerging markets. A paper by Hammoudeh and Li has examined volatility persistence for GCC stock markets using the daily sample period from February 15, 1994 to December 25, 2001, [10]. The authors' finding suggests that GCC stock markets are more sensitive to major global events than to those of local. In addition, like many earlier studies in this context, their GARCH (1, 1) estimations support the reduction of volatility persistence. All in all, it is important to mention that the results of above reviewed empirical studies support the widely-held view that the inclusion of dummy variables for regime shifts in the variance of GARCH family models leads to a considerable reduction in the persistence of volatility in stock returns.

Our study differs from a number of earlier investigations in several ways. First, given the existence of various conditional densities for estimations of GARCH models, in this paper, we estimate various asymmetric GARCH models assuming normal and heavy-tailed distributions. Second, the asymmetries are broadly examined by utilizing news impact curves and relying on the magnitude and statistical significance of asymmetric parameters. Third, the analysis is based on recent statistical observations which include important economic and political events.

The purpose of this paper is to document the importance of sudden change in variance detected by ICSS in asymmetric models (EGARCH and GJR-GARCH) under different distribution assumptions. Unlike many earlier studies, the regime shifts in unconditional variance are detected in the residual series and incorporated in the variance equations. In addition, we attempt to improve the parameter estimations incorporating the dummies for sudden changes in the variance equations of asymmetric models. Finally, we examine the asymmetric and leverage effects of bad and good news on volatility by estimated asymmetric parameters in the variance equation as well as scrutinizing news impact curve proposed by Engle and Ng [8]. To our best knowledge, this paper first considers asymmetric model estimations under various distribution hypotheses (normal, Student-t, and GED) including the binary variables in variance equations.

2 Data and Descriptive Statistics

The weekly data are obtained from Datastream 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 series4. The indices are Bahrain all share (Bahrain), Kuwait SE Kuwait Companies (Kuwait), Oman Muscat Securities (Oman), Qatar Exchange index (Qatar), Saudi Tadawul all share –TASI- (Saudi Arabia) and ADX General (United Arab Emirate). Moreover, as noted by Aggarwal et al. [1], weekly data should be used in the estimations due to the nonsynchronous trading and noisy events issues. 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*.

3 Methodology

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

3.1 The GARCH family models

Conventionally, autoregressive integrated moving-average (ARIMA) models, developed by Box and Jenkins [4], assume the conditional variance of the errors is constant over time (homoscedaticity). 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

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[4]Before using the weekly data in the analysis, we have also attempted to detect the break points utilizing the data in daily frequency. However, the algorithm has found too many break points which may eventually bias our estimation results. Hence, the results for daily frequency are not reported here due to the space consideration. The results for daily data are available upon request from the first author.

leverage effects which cannot be captured by conventional ARIMA models. To overcome the weaknesses of ARIMA models, Engel [7] and Bollerslev [3] proposed the (Generalized) Autoregressive Conditional Heteroscedasticity (G)ARCH models to account for the several properties of volatility phenomenon. Although standard GARCH model successfully captures volatility clustering, however, it is unable to take into account asymmetry and leverage effects phenomena which appear to be common in financial time series. The leverage effect is first noted by Black [2]. The author argues that currentstock returns are negatively correlated with future volatility. In addition, one may note that standard GARCH model requires all parameters in variance equation to be positive to ensure the strict positivity of conditional variances.

3.2 Asymmetric GARCH models

The EGARCH model was first introduced by Nelson to overcome the several weaknesses of standard GARCH model, [22]. As mentioned above, the problems with the standard GARCH model are that it cannot take into consideration asymmetry, leverage effects, and coefficients restrictions. Unlike standard GARCH model, the EGARCH model can capture size effects as well as sign effects of shocks. The variance equation of EGARCH model is given as follows,

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{q} a_i \frac{|\varepsilon_{t-i}| + \lambda_i \varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{p} \beta_j \ln(\sigma_{t-j}^2) \qquad (2)$$

Note that when ε_{t-i} is positive or there is ‘good news’, the total effect of ε_{t-i} is $(1+\lambda_i)|\varepsilon_{t-i}|$. In contrast, when ε_{t-i} is negative or there is ‘bad news’, the total impact of ε_{t-i} is $(1-\lambda_i)|\varepsilon_{t-i}|$. Besides, this model captures the leverage effect which exhibits the negative association between lagged stock returns and contemporaneous volatility. The presence of leverage effects can be tested by the hypothesis that $\lambda < 0$. If $\lambda \neq 0$, then the impact is asymmetric.

3.3 Asymmetric GJR-GARCH model

The GJR-GARCH model was first proposed by Glosten et al. [9]. As an alternative method to EGARCH model, the GJR-GARCH model has earned a good empirical record in the literature. The variance of GJR-GARCH can be written as,

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \lambda S_{t-i}^{-} \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad (3)$$

where S_{t-i}^{-} is a dummy variable

$$S_{t-i}^{-} = \begin{cases} 1, & \text{if} \quad \varepsilon_t < 0 \\ 0, & \text{if} \quad \text{otherwise} \end{cases}$$

The formula declares the impact of ε_t^2 on the conditional variance σ_t^2. It is clearly seen from Eq. 3 that, in this model, the bad news ($\varepsilon_t < 0$) and good news ($\varepsilon_t > 0$) might have different effects on conditional variance. If the leverage effect exists, we expect λ to be positive. The leverage effect is observed as the impulse ($a+\lambda$) of negative shocks is larger than the impulse (a) of positive shocks. In this model, good news and bad news have different effects on the conditional variance--good news has an impact of a, while bad news has an impact of ($a+\lambda$). If $\lambda > 0$, we say that the leverage effect exists. If $\lambda \neq 0$, then, the asymmetry does not exist.

3.4 News impact curve

The news impact curve is useful tool for the analysis of asymmetry. This concept shows the relationship between the contemporaneous volatility and last returns. As noted by Pagan and Schwert [23] and Engle and Ng [8], the news impact curve illustrates how new information affects the volatility. Engle and Ng provide a functional form for the news impact curve [8]. For the standard GARCH(1,1) model, the news impact curve can be drawn using the following formula $h_t = A + a\varepsilon_{t-1}^2$ ($A = \omega + \beta\sigma^2$). Here, the coefficients ω and β are the parameters of variance of equation of standard GARCH process. The graph typically takes a shape of quadratic function and it is symmetric and centered at $\varepsilon_{t-1} = 0$. Moreover, it has the same slope coefficient at both sides. In the other words, this curve shows positive and negative return shocks of the same magnitude produce the similar magnitude of conditional volatility.

Now we turn to the discussion of NIC for EGARCH and TGARCH asymmetric models. For the EGARCH model, conditional variance reaches its minimum at $\varepsilon_{t-1} = 0$, and it is exponentially increasing in both direction but with different parameters. In other words, the curve is not symmetric around zero ($\varepsilon_{t-1} = 0$). Literature commonly suggests that the negative shocks (bad news) appear to have more effects on volatility than positive shocks (good news) do. Generally speaking, today's news affects tomorrow's volatility to surge. In particular, as proposed by Engle and Ng [8], the news impact curve for the EGARCH model can be illustrated with the following set of equations

$$h_t = A \cdot \exp\left[\frac{\lambda + a}{\sigma}\varepsilon_{t-1}\right], \quad \text{for} \quad \varepsilon_{t-1} > 0,$$

and

$$h_t = A \cdot \exp\left[\frac{\lambda - a}{\sigma}\varepsilon_{t-1}\right], \quad \text{for} \quad \varepsilon_{t-1} < 0,$$

where

$$A \equiv \sigma^{2\beta} \cdot \exp\left[\omega - a\sqrt{2/\pi}\right].$$

Like EGARCH model, the news impact curve drawn for the GJR-GARCH model depicts the asymmetry in the stock market volatility by displaying a steeper slope on its negative side than on its positive side.

As suggested by Engle and Ng [8], the equations for news impact curve of GJR-GARCH can be written as follows

$$h_t = A + a\varepsilon_{t-1}^2, \quad \text{for} \quad \varepsilon_{t-1} > 0,$$

and

$$h_t = A + (a + \lambda)\varepsilon_{t-1}^2, \quad \text{for} \quad \varepsilon_{t-1} < 0$$

where

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

3.5 Distribution hypotheses

Probability distribution of asset returns often exhibits fatter tails than the standard normal distribution. The existence of heavy-tailedness is probably due to a volatility clustering in stock markets. In addition, another source for heavy-tailedness seems to be the sudden changes in stock returns. An excess kurtosis also might be originated from fat tailedness. Moreover, in practice, the returns are typically negatively skewed (see Table 1). The probability density functions that can capture this phenomenon (e.g. heavy-tailedness) are Student-t and GED distributions.

3.5.1. Normal distribution

The normal density function of the standard normal distribution is given as

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

The following log-likelihood function is maximized assuming normal distribution

$$\mathrm{L}_{\text{normal}} = \frac{1}{2}\sum_{t=1}^{T}(\ln(2\pi) + \ln(\sigma_t^2) + Z_t^2)$$

where T is the number of the observations.

3.5.2 Student-t distribution

The following log-likelihood function is maximized assuming Student-t distribution of Engle [7] and Bollerslev [3],

$$\mathrm{L}_{\text{Student-t}} = \ln\left(\Gamma(\frac{\nu+1}{2})\right) - \ln\left(\Gamma(\frac{\nu}{2})\right) - 0.5\ln(\nu-2) - 0.5\sum_{t=1}^{T}[\ln(\sigma_t^2) + (1+\nu)\ln(1+\frac{Z_t^2}{\nu-2})]$$

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

3.5.3 Generalized error distribution

The generalized error distribution (GED) was proposed by Nelson [22]. The log-likelihood function assuming GED takes following form

$$\mathrm{L}_{\text{GED}} = \sum_{t=1}^{T}[\ln(\nu/\lambda) - 0.5\left|\frac{Z_t}{\lambda}\right|^{\nu} - (1+\frac{1}{\nu})\ln(2) - \ln\left(\Gamma(1/\nu)\right) - 0.5\ln(\sigma_t^2)]$$

where

$$-\infty < Z_t < \infty,\ \ 0 < \nu \le \infty, \text{ and } \ \lambda = \sqrt{\frac{2^{(-2/\nu)}\,\Gamma(1/\nu)}{\Gamma(3/\nu)}}.$$

3.6 ICSS methodology

The CUSUM-type tests are basically designed to test a single structural break. However, the ICSS algorithm advocated by Inclan and Tiao can be applied even there are multiple breaks in the series. First the entire sample is tested for the presence of a single break in the series using the statistics tabulated in [11]. If a signification break is present, the sample is split into two sub-samples. Next, each sub-sample is examined for presence of structural breaks. If such breaks is found in any sub-sample it is further split into two segments. This procedure is continued until no more structure breaks are detected in any of the sub-sample.

In the study by Aggarwal et al. [1], the volatility of stock prices in emerging markets is analyzed. The finding suggests that the volatility in these markets is subject to frequent regime shifts.

A number of papers employ ICSS algorithm to detect sudden shifts in unconditional variance and incorporated these shifts into variance equations (see, for example, Malik [19] for exchange market; Law [17] and Hammoudeh and Li [10] for stock markets, among others). Employing ICSS algorithm, Malik finds a number of structural breaks in the data and analyzes five exchange rates over the sample period from January 1990 to September 2000, [19].The ICCS algorithm identifies breaks in the returns or estimated stochastic errors and assumes that the variance between two breaks points is constant. The ICSS methodology can detect a number of break points in the series, hence, it also allows for complete classification on regime shifts in the underlying data. It assumes that the data display a constant variance over an initial period until a sudden shift occurs resulting from various economic or political events. The procedure detecting the sudden changes is discussed further.

Let us assume that I_x is a volatility change interval that due to structural breaks, where $x = 0,1,2,\ldots,N$. Where N is a number of structural changes the series. The location of detected points by ICSS is S_{C_i}, $i = 0,1,\ldots,N$.

One may write the intervals corresponding change points as

$$S_{C_0} \le I_0 < S_{C_1} \le I_1 < S_{C_2} \cdots S_{C_N} \le I_N \le T .$$

We use CUSUM to detect one breakpoint in variance of our data as follows

$$C_k = \sum_{\tau=1}^{k} \varepsilon_\tau^2$$

let $D_k = \dfrac{C_k}{C_T} - \dfrac{k}{T}$, where $k = 1,2,\ldots,T$ and D_k in the border is zero ($D_0 = D_T = 0$). To standardize the D_k series, we compute following series $\sqrt{\dfrac{T}{2}}\,|D_k|$. The $\{\varepsilon_t\}$ process is independently identically distributed with $(0, \sigma_x^2)$, where $t = 1,2,\ldots,T$ and T is the number of observations. The series $\{\varepsilon_t\}$ is the innovations generated from the chosen AR(1)-EGARCH(1,1) model under Student-t distribution for all markets.

The null hypotheses that the unconditional variance of the series is constant that is $\sigma_t^2 = \sigma^2$, against the alternative hypotheses, that is

$$\sigma_t^2 = \begin{cases} \sigma_1^2, & \text{for } t = 1,2,\ldots,k^* \\ \sigma_2^2, & \text{for } t = k+1, k+2,\ldots,T \end{cases}$$

where k^* is a change point when $\sqrt{\dfrac{T}{2}}\,|D_k|$ reaches its maximum. Hence, is max of $\sqrt{\dfrac{T}{2}}\,|D_k|$ bigger than the critical value tabulated in [11], we reject the null hypotheses. In addition, the authors conclude that using D_k statistic to detect the break points suffers from "masking effect”. This may cause difficulties in detecting change points especially when series contain multiple variance changes. This issue might arise when major break point followed by moderate-sized break points. The authors suggest overcoming this problem, using the D_k function to systematical detection of break points at different parts of the series. By applying the D_k with a long span of sample to detect the first possible break point, then apply D_k function again to detect break points in two sub-sample which divided by the first possible break point. We continue this process until no longer break point in the series.

3.7 Incorporating structural breaks

We combine the asymmetric GARCH models with dummy variables detected by ICSS algorithm.

Mean equation: $R_t = \mu + \phi R_{t-1} + \varepsilon_t$,

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

Variance equation : (EGARCH and GRJ-GARCH models respectively)

$$\ln(\sigma_t^2) = \omega + d_1 D_1 + \cdots + d_n D_n + a \frac{|\varepsilon_{t-1}| + \lambda \varepsilon_{t-1}}{\sigma_{t-1}} + \beta \ln(\sigma_{t-1}^2)$$

$$\sigma_t^2 = \omega + d_1 D_1 + \cdots + d_n D_n + a\varepsilon_{t-1}^2 + \lambda S_{t-1}^- \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

where $D_1, D_2, \ldots, D_n$ are dummy variable such that

$$D_t = \begin{cases} 1, & \text{if there is sudden change} \\ 0, & \text{if elsewhere} \end{cases}$$

4 Result and Discussion

4.1 Descriptive statistics

The result in Table 1 reports the descriptive statistics for the stock price returns of GCC countries. The mean values for all stock returns are positive. This appears to indicate that positive changes in stock price indices in GCC countries are more dominant than negative changes. The stock prices tend to increase in emerging markets unlike stock prices in advanced countries. 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%. This important point has also been highlighted in Hammoudeh and Li that the volatility is usually relatively high in emerging stock markets [10]. 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). However, in the period of from February 15, 1994 to December 25, 2001, as discovered by Hammoudeh and Li in [10], only Saudi Arabia and Kuwait stock returns are negatively skewed which are consistent with those of many emerging markets (see, for example, [1]). Here, it is important to note that our results document that all GCC markets appear to behave like advanced economies in terms of negative skewness. In sum, kurtosis and skewness coefficients indicate the significant departure from normality. The Jarque-Bera test statistics also rejects the hypothesis that stock market returns are normally distributed for all countries under investigation. The Q statistics computed up to lag 12 for the returns and squared returns exhibit serial correlation except the returns of Saudi Arabia and Qatar. In Table 1, we report the standard Engle’s ARCH Lagrange multiplier (LM) test for heteroscedasticity, [7]. According to the LM statistic, the returns in the six countries show strong evidence of ARCH effects. Since the meaningful GARCH estimations need all stock returns used are stationary, we initially test for a unit root by using augmented Dickey-Fuller (ADF) test for stock returns of all GCC countries under investigation. As presented in Table 1, the computed test statistics reject the null hypothesis of existence unit root at 1 percent significance level. Hence, the stock returns follow a stationary process despite whether a trend and/or intercept is incorporated in the model.

4.2 Estimation and diagnostics

We begin the analysis by discussing the standardized residual diagnostics for each country under study. As reported in Table 2, the results of the Ljung-Box Q [18] statistics for the standardized residuals and squared standardized residuals suggest that the stochastic errors do not seem to be serially correlated in Bahrain, Oman, Saudi Arabia and UAE. However, estimated models slightly suffer from serial correlation in standardized residuals in Kuwait, Qatar. It is important to emphasize that the innovations in all models do not appear to exhibit any serial correlation according to computed Q test statistics for squared standardized residuals. In addition, the ARCH LM test results reveal that there are no further signs of heteroskedasticity in all countries’ estimated models except the EGARCH model assuming all distributions for Kuwait. The parameters of ARCH and

GARCH effects are found to be highly significant for all asymmetric models under all distribution hypotheses. On other hand, we turn to the models which the regime shifts are taken into account. The innovations seem to have serial correlation in several estimated models of Kuwait and UAE while the rest of countries under study exhibit no serial correlation in the disturbances. Similarly, the Ljung-Box test statistics for squared standardized residuals do not appear to show any serial correlation in the stochastic disturbances in all cases except for UAE's EGARCH under Student-t and GED distributions.

However, the comparison between models with each density with and without dummy variable shows that, according to AIC and Log likelihood measures used for volatility model selection, in all markets except Saudi Arabia and Bahrain, the models with dummy variables have been found to be favored.

One of the compelling findings in this study is that heavy-tailed distributions (Student-t, GED) perform well when the dummy variables are incorporated in the variance equation for Qatar, Kuwait, and UAE. Moreover, Student-t distribution has been found to be favored for both models (EGARCH and GJR-GARCH) without dummy variables for Saudi Arabia and Bahrain. The GED conditional density performs well in Qatar and UAE models with dummy variables. The Student-t distribution is preferred for Kuwait models incorporating dummy variables for regime changes. However, the only country that favors normal conditional density is Oman. In sum, our results reveal that fat-tailed distributions provide better fit in both cases (with and without dummies in the variance equation). In the literature, commonly documented finding is that volatility persistence reduces considerably in case the regime changes are accounted for in the second moment equations when the estimations are based on conditional normal density. This finding seems to be more robust when heavy-tailed conditional density is considered. In our case, the results suggest that persistence is reduced more when heavy-tailed densities are assumed in comparison with the normal distribution.

4.3 Volatility Persistence

The Table 3 shows that the volatility persistence significantly decreased in all estimated models when sudden changes are taken into account using dummy variables. Especially, the considerable reduction in persistence can be observed in estimated EGARCH models of four countries (SA,BH,QA and UAE). Apart from that, the lowest persistence can be seen in the estimated GJR-GARCH models for OM and KU markets. It is interesting to note that heavy-tailed distributions play an important role in the reduction of persistence in the models that incorporate binary variables in the variance equation. As Table 3 reports, when we assume heavy-tailed distributions, the persistence has reduced considerably in four countries' models out of total six cases in comparison with models under normal distribution. In sum, distribution hypothesis also seems to play important role in the estimation of persistence. Furthermore, as Table 2 presents, it is interesting to note that all countries satisfy the inequality constraint, that is, $a+\beta<1$, except Saudi's GJR-GARCH model assuming all distribution as well as the UAE's GJR-GARCH model assuming Student's-t conditional density.

4.4 Asymmetric and leverage effects

The asymmetric and leverage effects can be examined by the nonlinear asymmetric variance specifications, EGARCH and GJR-GARCH, under different distribution assumptions. In models with and without dummy variable, the coefficient λ has not been found statistically significant in models for Qatar and Oman. However, the sign is positive in GJR-GARCH model and negative in EGARCH model under all distributions for these countries. Interestingly, the parameter λ carries significant value in GJR-GARCH model without dummy variable for Kuwait. However, this parameter is not statistically different from zero in EGARCH model. Here, it is important to emphasize that once we account for regime shifts in the variance equations all the asymmetric parameters are found to be statistically significant at conventional levels for Kuwait. This finding supports our contention that the dynamic and asymmetric behavior of stock market volatility in Kuwait is affected by the regime shifts. In addition, in these markets, negative news seems to have more impact on volatility than the good news. As descriptive statistics suggests, the returns of all markets under study are negatively skewed. This indicates that negative shocks are more common than the positive shocks in these markets.

As Table 4 presents, the models for Kuwait, Oman and Qatar markets indicate that bad news has an impact on volatility more than good news in all estimated models under different distribution assumptions. For instance, in the GJR-GARCH models under Student-t without dummy variables, the effects of bad news on conditional volatility are about 2.73, 1.11 and 1.43 times more than good news in Kuwait, Oman and Qatar respectively. Similarly, in the GJR-GARCH models under Student-t with the dummies for regime shifts, the effects of bad news are approximately 6.44, 3.07 and 4.49 times greater than good news. It is also important to note that the magnitudes of bad news effects, in the GJR-GARCH models under Student-t with the dummies for regime shifts, are found to be greater than those of GJR-GARCH models under Student-t without the dummies. Among the countries under study, Kuwait has been found to be more affected by bad news than good news.

4.5 News impact curves

The news impact curves are drawn for all countries' models assuming normal distribution. Panels A, B, and C in figure2, show that the news impact curves for standard GARCH and GJR-GARCH estimates under normal distribution for all countries under study fulfill following conditions:

$$\omega > 0, \quad 0 \le \beta < 1 \;, \quad 0 \le a < 1, \quad a + \beta < 1, \text{and} \quad (\lambda > 0 \,\text{GJR-GARCH})$$

where ω, a, and β are the parameters of variance equations. However, the EGARCH models satisfy all the conditions given in [8] except $\omega > 0$. In all these markets, the news impact curves exhibit symmetry in standard GARCH models and asymmetry in EGARCH and GJR-GARCH models. This asymmetry indicates that bad news have more impact on volatility than good news. However, as the panels D and F show, the positive returns side is bigger than negative returns side which implies that good news seems to have more impact in volatility than bad news. This is probably due to the fact that $\lambda > 0$ in EGARCH and $\lambda < 0$ GJR-GARCH. In addition, we need to emphasize that all other conditions are satisfied. To sum up, we may conclude that the rotational behavior of news impact curves are controlled solely by the coefficient of asymmetry. On the contrary, the standard GARCH model does not take into account the asymmetric behavior of shocks; hence, the shape of news impact curve is always symmetric in negative and positive sides. As shown in panel E, the news impact curve for Bahrain exhibits slightly clockwise rotational behavior which implies that bad news have an impact on volatility more than good news although the some important conditions ($\lambda < 0$ in EGARCH and $\lambda > 0$ GJR-GARCH) are not satisfied.

4.6 Sudden shifts in variance and ICSS algorithm

The ICSS algorithm has been utilized to detect the sudden shifts in residuals. The graphs displayed in Figure 1 and figures in Table 5 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 Table1, 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. In [1], the number of the sudden changes in the returns of emerging stock markets is four during their period under study. Also, Hammoudeh and Li mention that the number of sudden changes for GCC markets ranges from three to eight during the weekly period from 1994 to 2001, [10]. Analyzing the data for Japan and Korea, Kang et al. have detected six and eight sudden changes in Nikkei 225 index (January, 1986 to December, 2008) and KOSPI 200 (January, 1990 to December, 2008) respectively during the period, [12]. According to the results of ICSS algorithm, in this study, from Figure 1, one may see that GCC markets exhibit change points that range from two to eleven corresponding to three and twelve distinct volatility regimes respectively. 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 5 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 5 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. This shows that the highest effect on this event on Oman. This is probably due the fact that Oman is highly integrated with several industrial countries like US and UK. The recent global crisis started from US and affected much especially highly integrated emerging markets like Oman. In the beginning of global financial default, another factor that increases the volatility is that the price of crude oil was severely hit dropping from \$126.16 in July 2008 to \$ 32.94 in November 2008 due to the sudden decrease in global demand for oil. It is worth mentioning that all GCC economies except Bahrain are heavily dependent on crude oil exports.

In addition, the other common and regional event that has led a considerable increase in the GCC stock market volatility with the exception of Bahrain occurred in 2006. In this default, Saudi stock market was severely hit compared to other GCC countries. For example, as Table 5 reports, the average volatility sharply increased by 14.15 times with respect to previous relatively tranquil volatility period. On the other hand, Bahrain seems to be not affected by this regional crisis. The main reasons for this are: first, this country is not oil exporting country; second, it is highly integrated with world stock markets. This finding corroborates the study by Hammoudeh and Li in [10], which has found that Bahrain has lowest number of regime changes among GCC and it is more integrated with the world stock market for their sample period. Compared to the previous tranquil period, in this period, the average of conditional variances increased by 2.40, 2.61, 7.20 times in Kuwait, Qatar, and UAE respectively. As expected, the ICSS algorithm does not detect any regime shifts in 2006 for Oman and Bahrain.Apart from that, 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) is characterized with 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 affected by Gulf war in 2003.

5 Conclusion

Overall, in this paper, we have investigated the volatility of the GCC stock price indices employing the asymmetric EGARCH and GJR-GARCH models incorporating dummies that account for regime shifts detected by utilizing ICSS methodology. Moreover, for comparative analysis, these asymmetric models are also estimated without dummy variables in the variance equations. It is important to highlight that, in the estimations, due to the fat-tailedness facts in stochastic errors, the heavy-tailed conditional densities are also assumed together with conventional normal distribution.

Our study differs from a number of earlier investigations in several ways. First, the analysis is based on recent statistical observations which include important economic and political events. Second, given the existence of various conditional densities for estimations of GARCH models, in this paper, we estimate various asymmetric GARCH models assuming normal and heavy-tailed distributions. Third, the asymmetries are broadly examined by utilizing news impact curves and relying on the magnitude and statistical significance of asymmetric parameters.

When the heavy-tailed distributions are assumed, the persistence has found to be reduced considerably in four countries' models out of total six cases in comparison with models under normal distribution. Hence, in sum, distribution assumption also seems to play an important role in the estimation of persistence together with accounting for the regime shifts. Besides, for the analysis of asymmetry, this study relies on asymmetric parameters as well as news impact curves. The results suggest that both ways of analysis do not appear to contradict each other.

One of the important findings is that heavy-tailed distributions (Student-t, GED) perform relatively well when the dummy variables are incorporated in the variance equation for Qatar, Kuwait, and UAE. Moreover, Student-t distribution has been found to be favored for both models (EGARCH and GJR-GARCH) without dummy variables for Saudi Arabia and Bahrain. The GED conditional density performs well in the models for Qatar and UAE with dummy variables. The Student-t distribution is preferred for Kuwait models incorporating dummy variables for regime changes. However, the only country that favors normal conditional density is Oman. In sum, our results reveal that fat-tailed distributions provide better fit in both cases (with and without dummies in the variance equation).

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Table 1: Summary statistics of stock market 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	-9.5779 [0.000]	-15.4933 [0.000]	-15.8467 [0.000]	-13.8761 [0.000]	-4.967 [0.000]	-7.483 [0.000]
Trend and intercept	-13.8402 [0.000]	-15.6772 [0.000]	-15.9274 [0.000]	-14.0176 [0.000]	-5.099 [0.000]	-7.996 [0.000]
No trend no intercept	-9.5658 [0.000]	-15.4704 [0.000]	-15.7759 [0.000]	-13.8603 [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 2: The asymmetric models estimation results for Saudi Arabia

	EGARCH			GJR-GARCH		
	Normal	Student-t	GED	Normal	Student-t	GED
A. Without dummy variable						
μ	0.4650 [0.028]	0.7794 [0.000]	0.7023 [0.000]	0.5517 [0.007]	0.8040 [0.000]	0.7325 [0.000]
Φ	0.3189 [0.000]	0.3275 [0.000]	0.2922 [0.000]	0.2819 [0.000]	0.3198 [0.000]	0.2778 [0.000]
ω	-0.1975 [0.000]	-0.1550 [0.102]	-0.1892 [0.050]	0.4310 [0.031]	0.6382 [0.075]	0.4913 [0.130]
α	0.4824 [0.000]	0.4961 [0.000]	0.4906 [0.000]	0.3408 [0.000]	0.3631 [0.016]	0.3602 [0.005]
β	0.9317 [0.000]	0.9144 [0.000]	0.9251 [0.000]	0.7406 [0.000]	0.7219 [0.000]	0.7284 [0.000]
γ	0.0444 [0.245]	0.0396 [0.573]	0.0530 [0.403]	-0.1100 [0.102]	-0.1274 [0.390]	-0.1395 [0.258]
Diagnostics for the models without dummy variables						
Q(12)	8.1515 [0.700]	7.3111 [0.770]	8.7789 [0.642]	9.4378 [0.582]	6.2365 [0.857]	8.2400 [0.692]
$Q^2(12)$	5.7701 [0.888]	5.9643 [0.876]	5.9234 [0.878]	5.6501 [0.896]	5.9214 [0.879]	6.2192 [0.858]
LM[12]	5.4054 [0.943]	5.7518 [0.928]	5.6161 [0.932]	5.3435 [0.945]	5.8625 [0.922]	6.1345 [0.909]
AIC	5.11167	5.00296	5.01418	5.13776	5.00377	5.01897
HQ	5.17022	5.07128	5.08250	5.19632	5.06232	5.07752
Log L	-1047.00	-1023.61	-1025.92	-1052.38	-1024.78	-1027.91
B. With dummy variable						
μ	0.6338 [0.000]	0.6941 [0.000]	0.7501 [0.000]	0.6404 [0.000]	0.7153 [0.000]	0.7692 [0.000]
ω	0.1642 [0.234]	0.2451 [0.249]	0.1645 [0.412]	0.8515 [0.014]	0.9948 [0.064]	0.7826 [0.099]
α	0.3348 [0.000]	0.3541 [0.004]	0.3609 [0.006]	0.3308 [0.006]	0.3460 [0.026]	0.3572 [0.032]
β	0.7507 [0.000]	0.7443 [0.000]	0.7443 [0.000]	0.6414 [0.000]	0.6177 [0.000]	0.6411 [0.000]
γ	0.0940 [0.133]	0.0792 [0.315]	0.0863 [0.309]	-0.2619 [0.028]	-0.2477 [0.092]	-0.2652 [0.097]
Diagnostics for the models with dummy variables						
$Q^2(12)$	5.8225 [0.925]	6.3261 [0.899]	6.0853 [0.912]	6.9787 [0.859]	6.3409 [0.898]	6.6266 [0.881]
LM[12]	5.6561 [0.932]	6.1677 [0.907]	5.9862 [0.916]	6.6127 [0.882]	6.1402 [0.908]	6.4123 [0.893]
AIC	5.09814	5.05242	5.05069	5.09617	5.05102	5.04781
BIC	5.19556	5.15959	5.15785	5.19359	5.15818	5.15497
Log L	-1042.77	-1032.33	-1031.97	-1042.36	-1032.04	-1031.37

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 $Q^2(12)$ 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 heterscedasticity.

Table 3: GARCH estimation results for Bahrain

	EGARCH Normal	EGARCH Student-t	EGARCH GED	GJR-GARCH Normal	GJR-GARCH Student-t	GJR-GARCH GED
A.Without dummy variable						
μ	0.1748 [0.120]	0.1720 [0.060]	0.1840[0.043]	0.1988 [0.061]	0.1743 [0.051]	0.1975 [0.0259]
Φ	0.4661 [0.000]	0.4244 [0.000]	0.4208[0.000]	0.4330 [0.000]	0.4035 [0.000]	0.4008 [0.000]
ω	-0.2920 [0.000]	-0.2953 [0.000]	-0.2838 [0.000]	0.1899 [0.001]	0.2299 [0.033]	0.1932 [0.029]
α	0.4837 [0.00 0]	0.4964 [0.000]	0.4651 [0.000]	0.2136 [0.000]	0.2267 [0.018]	0.1986 [0.018]
β	0.7747 [0.0000]	0.7789 [0.000]	0.7915 [0.000]	0.6870 [0.000]	0.6406 [0.000]	0.6838 [0.000]
γ	0.0285 [0.568]	0.0095[0.895]	0.0086 [0.899]	-0.0182 [0.789]	0.0196 [0.869]	0.0098 [0.919]
Diagnostics for the models without dummy variables						
Q(12)	14.572 [0.203]	16.556 [0.122]	16.512 [0.123]	13.460 [0.264]	15.335 [0.168]	15.101 [0.178]
$Q^2(12)$	11.653 [0.390]	11.653 [0.390]	11.584 [0.396]	10.973 [0.446]	11.335 [0.416]	11.269 [0.421]
LM[12]	10.655 [0.558]	10.656 [0.558]	10.584 [0.564]	10.018 [0.614]	10.048 [0.611]	10.229 [0.595]
AIC	3.20649	3.17667	3.18048	3.21267	3.18120	3.18407
BIC	3.26505	3.24499	3.24880	3.27123	3.24961	3.25239
Log L	-654.538	-647.395	-648.181	-655.811	-648.344	-648.920
B. With dummy variable						
μ	0.1830 [0.006]	0.1712 [0.003]	0.1770 [0.002]	0.2096 [0.001]	0.1818 [0.001].	0.1897 [0.001]
ω	-0.2774 [0.000]	-0.3230 [0.002]	-0.3049 [0.004]	0.4126 [0.000]	0.4340 [0.009]	0.4058 [0.010]
α	0.5605 [0.000]	0.5804 [0.000]	0.5678 [0.000]	0.3077 [0.002]	0.3515 [0.014]	0.3319 [0.018]
β	0.6030 [0.000]	0.6185 [0.000]	0.6176 [0.000]	0.4768 [0.000]	0.4044 [0.008]	0.4520 [0.001]
γ	0.0153 [0.812]	0.0057 [0.944]	0.0168 [0.839]	-0.0147 [0.894]	0.0093 [0.954]	-0.0159 [0.918]
Diagnostics for the models with dummy variables						
$Q^2(12)$	16.486 [0.17]	16.431 [0.172]	16.375 [0.175]	16.313 [0.177]	18.153 [0.111]	17.034 [0.148]
LM[12]	15.911 [0.195]	15.699 [0.205]	15.699 [0.205]	14.864 [0.248]	16.789 [0.157]	15.568 [0.211]
AIC	3.32561	3.30100	3.30561	3.33881	3.30901	3.31450
BIC	3.39381	3.37891	3.38362	3.40702	3.38700	3.39242
Log L	-679.757	-673.665	-674.621	-682.467	-675.325	-676.446

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 $Q^2(12)$ 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 heterscedasticity

Table 4: GARCH estimation results for Qatar

	EARCH Normal	Student-t	GED	GJR-GARCH Normal	Student-t	GED
A. Without dummy variable						
μ	0.4766 [0.033]	0.4075 [0.035]	0.4553 [0.010]	0.5211 [0.033]	0.3801 [0.061]	0.4334 [0.019]
Φ	0.3593 [0.000]	-0.1149 [0.086]	0.3084 [0.000]	0.3653 [0.000]	0.3230 [0.000]	0.3080 [0.000]
ω	-0.0931[0.027]	-0.1149 [0.086]	-0.1057 [0.099]	0.8010 [0.004]	0.6875 [0.034]	0.6936 [0.046]
α	0.4368 [0.000]	0.4012 [0.000]	0.4052 [0.000]	0.2306 [0.000]	0.1733 [0.010]	0.1922 [0.009]
β	0.8969 [0.000]	0.9231 [0.000]	0.9142 [0.000]	0.7098 [0.000]	0.7523 [0.000]	0.7419 [0.000]
γ	-0.0108 [0.798]	-0.0505 [0.377]	-0.030 [0.611]	0.0105 [0.892]	0.0752 [0.450]	0.0421 [0.677]
Diagnostics for the models without dummy variables						
Q(12)	20.681 [0.037]	19.643 [0.050]	20.223 [0.042]	19.013 [0.061]	18.695 [0.067]	19.467 [0.053]
$Q^2(12)$	16.764 [0.115]	17.902 [0.084]	17.367 [0.097]	18.613 [0.068]	21.404 [0.029]	20.120 [0.044]
LM[12]	18.768 [0.094]	20.035 [0.066]	19.179 [0.084]	18.665 [0.096]	21.277 [0.046]	19.977 [0.067]
AIC	5.12458	5.09665	5.08374	5.11491	5.09463	5.07993
BIC	5.18314	5.16497	5.15206	5.17347	5.16295	5.14824
Log L	-1049.67	-1042.91	-1040.25	-1047.67	-1042.5	-1039.47
B. With dummy variable						
μ	0.4238 [0.071]	0.5072 [0.004]	0.4357 [0.020]	0.4712 [0.037]	0.4028 [0.039]	0.4511 [0.013]
Φ	0.3422 [0.000]	0.2922 [0.000]	0.3039 [0.000]	0.3422 [0.000]	0.3159 [0.000]	0.2961 [0.000]
ω	0.4151 [0.110]	0.8471 [0.138]	0.4397 [0.170]	2.1637 [0.031]	2.3880 [0.039]	2.2838 [0.075]
α	0.2730 [0.004]	0.0604 [0.625]	0.2275 [0.080]	0.1084 [0.072]	0.0334 [0.636]	0.0599 [0.434]
β	0.6599 [0.000]	0.5423 [0.069]	0.6689 [0.000]	0.5422 [0.001]	0.5612 [0.001]	0.5555 [0.008]
γ	-0.0143 [0.794]	-0.0550 [0.458]	-0.0358 [0.623]	0.0336 [0.667]	0.1167 [0.296]	0.0725 [0.493]
Diagnostics for the models with dummy variables						
Q(12)	16.373 [0.128]	15.310 [0.169]	15.406 [0.165]	15.402 [0.165]	14.106 [0.227]	14.586 [0.202]
$Q^2(12)$	17.434[0.096]	20.210 [0.042]	18.074 [0.080]	17.871 [0.085]	18.595 [0.069]	18.302 [0.075]
LM[12]	17.501 [0.131]	19.497 [0.077]	17.621 [0.127]	17.133 [0.144]	17.392 [0.135]	17.129 [0.144]
AIC	5.07448	5.07449	5.05151	5.07929	5.06416	5.05443
BIC	5.17208	5.18184	5.15887	5.17689	5.17152	5.16179
Log L	-1035.34	-1034.35	-1029.61	-1036.34	-1032.22	-1030.21

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 $Q^2(12)$ 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 heterscedasticity

Table 5: GARCH estimation results for United Arab Emirate

	EGARCH			GJR-GARCH		
	Normal	Student-t	GED	Normal	Student-t	GED
A. Without dummy variable						
μ	0.2200 [0.159]	0.2180 [0.078]	0.2141 [0.054]	0.1907 [0.276]	0.2561 [0.049]	0.2238 [0.052]
Φ	0.3612 [0.000]	0.3235 [0.000]	0.3184 [0.000]	0.3544 [0.000]	0.3084 [0.000]	0.3091 [0.000]
ω	-0.1495 [0.000]	-0.1633 [0.016]	-0.1586 [0.019]	0.2188 [0.010]	0.2308 [0.085]	0.2070 [0.113]
α	0.3536 [0.000]	0.4305 [0.000]	0.3835 [0.000]	0.1849 [0.000]	0.1908 [0.015]	0.1749 [0.007]
β	0.9411 [0.000]	0.9308 [0.000]	0.9358 [0.000]	0.8188 [0.000]	0.8166 [0.000]	0.8202 [0.000]
γ	0.0390 [0.145]	0.0264 [0.615]	0.0287 [0.565]	-0.0350 [0.388]	0.0073 [0.927]	-0.0076 [0.918]
Diagnostics for the models without dummy variables						
Q(12)	16.544 [0.122]	18.840 [0.064]	19.280 [0.056]	15.422 [0.164]	18.605 [0.069]	18.752 [0.066]
$Q^2(12)$	6.1349 [0.864]	7.1530 [0.787]	6.9158 [0.806]	4.1561 [0.965]	4.9350 [0.934]	4.6920 [0.945]
LM[12]	5.7829 [0.926]	6.5891 [0.883]	6.4753 [0.890]	4.0212 [0.983]	4.8861 [0.961]	4.6363 [0.969]
AIC	4.62429	4.55667	4.53675	4.64480	4.56437	4.54602
BIC	4.68285	4.62499	4.60507	4.70336	4.63269	4.61434
Log L	-946.605	-931.675	-927.572	-950.829	-933.261	-929.481
B. With dummy variable						
μ	0.3438 [0.025]	0.3077 [0.011]	0.2754 [0.014]	0.3732 [0.014]	0.3385 [0.005]	0.2754 [0.015]
Φ	0.3028 [0.000]	0.2941 [0.000]	0.2999 [0.000]	0.3177 [0.000]	0.3020 [0.000]	0.3034 [0.000]
ω	1.3150 [0.000]	-0.0349 [0.785]	1.0697 [0.000]	0.7036 [0.000]	0.5642 [0.006]	0.5947 [0.004]
α	0.2198 [0.015]	0.3695 [0.003]	0.2714 [0.024]	0.3354 [0.000]	0.4446 [0.013]	0.3781 [0.014]
β	-0.4640 [0.000]	0.6334 [0.000]	-0.5340 [0.000]	0.5086 [0.000]	0.4508 [0.000]	0.4748 [0.000]
γ	0.1634 [0.018]	0.2167 [0.010]	0.1948 [0.043]	-0.3373 [0.000]	-0.4127 [0.021]	-0.3660 [0.020]
Diagnostics for the models with dummy variables						
Q(12)	18.000 [0.082]	22.860 [0.018]	18.261 [0.076]	16.526 [0.123]	19.242 [0.057]	18.823 [0.064]
Q2(12)	18.958 [0.062]	21.63 0 [0.027]	23.203 [0.017]	8.5731 [0.661]	10.817 [0.459]	9.8010 [0.548]
LM[12]	17.515 [0.131]	20.315 [0.061]	20.873 [0.052]	7.95711[0.788]	10.338 [0.586]	9.1223 [0.692]
AIC	4.59151	4.50568	4.51083	4.55721	4.50224	4.49164
BIC	4.69886	4.62279	4.62795	4.66457	4.61930	4.60876
Log L	-934.852	-916.17	-917.233	-927.787	-915.462	-913.279

Table 6: GARCH estimation results for Kuwait

	EGARCH Normal	EGARCH Student-t	EGARCH GED	GJR-GARCH Normal	GJR-GARCH Student-t	GJR-GARCH GED
A. Without dummy variable						
μ	0.3409 [0.011]	0.5174 [0.000]	0.5480 [0.000]	0.3946 [0.007]	0.5108 [0.000]	0.5633 [0.000]
Φ	0.3901 [0.000]	0.3781 [0.000]	0.3510 [0.000]	0.3817 [0.000]	0.3798 [0.000]	0.3547 [0.000]
ω	-0.1064 [0.092]	-0.2190 [0.016]	-0.2075 [0.007]	0.9776 [0.000]	0.7416 [0.002]	0.6963 [0.001]
α	0.6073 [0.000]	0.6860 [0.000]	0.6136 [0.000]	0.2814[0.000]	0.3170 [0.022]	0.3041 [0.006]
β	0.72879 [0.000]	0.7790 [0.000]	0.7981 [0.000]	0.4017 [0.000]	0.4052 [0.000]	0.3604 [0.165]
γ	-0.0889 [0.123]	-0.1426 [0.110]	-0.1108 [0.185]	0.2939 [0.067]	0.5475 [0.072]	0.4416 [0.000]
Diagnostics for the models without dummy variables						
Q(12)	23.906 [0.013]	20.249 [0.042]	21.972 [0.025]	22.632 [0.020]	18.813 [0.065]	20.158 [0.043]
$Q^2(12)$	16.689 [0.117]	18.734 [0.066]	20.393 [0.040]	13.258 [0.277]	13.819 [0.243]	14.426 [0.210]
LM[12]	21.730 [0.040]	28.994 [0.003]	30.729 [0.002]	15.300 [0.225]	17.899 [0.118]	18.495 [0.101]
AIC	4.138606	4.03777	4.050898	4.151621	4.047716	4.060843
BIC	4.197165	4.106088	4.119216	4.210179	4.116034	4.129161
Log L	-846.553	-824.781	-827.485	-849.234	-826.829	-829.534
B. With dummy variable						
Φ	0.4306 [0.000]	0.4306 [0.000]	0.4332 [0.000]	0.4330 [0.000]	0.4407 [0.000]	0.4342 [0.000]
ω	0.6731 [0.012]	0.6453 [0.013]	0.6639 [0.009]	3.5767 [0.000]	3.7378 [0.000]	3.7020 [0.000]
α	0.3190 [0.012]	0.3420 [0.014]	0.3278 [0.016]	0.0753 [0.294]	0.0586 [0.388]	0.0776 [0.340]
β	0.4651 [0.000]	0.4667 [0.000]	0.4658 [0.000]	0.1485 [0.341]	0.1195 [0.301]	0.1238 [0.351]
γ	-0.1708 [0.035]	-0.1805 [0.042]	-0.1754 [0.043]	0.2906 [0.066]	0.3195 [0.065]	0.2915 [0.087]
Diagnostics for the models with dummy variables						
Q(12)	25.732 [0.007]	25.339 [0.008]	25.505 [0.008]	28.392 [0.003]	27.164 [0.004]	28.350 [0.003]
Q2(12)	10.143 [0.518]	9.5445 [0.572]	10.008 [0.530]	7.655 [0.744]	7.3109 [0.773]	8.3426 [0.682]
LM[12]	7.3883 [0.830]	6.7326 [0.874]	7.2289 [0.842]	5.5187 [0.938]	5.5964 [0.935]	6.0837 [0.911]
AIC	3.956837	3.956908	3.95976	3.971822	3.971283	3.958073
BIC	4.112993	4.122824	4.125676	4.127978	4.137199	4.123989
Log L	-799.109	-798.123	-798.711	-802.195	-801.084	-798.363

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 $Q^2(12)$ 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 heterscedasticity

Table 7: GARCH estimation results for Oman

	EGARCH Normal	EGARCH Student-t	EGARCH GED	GJR-GARCH Normal	GJR-GARCH Student-t	GJR-GARCH GED
	A. Without dummy variable					
μ	0.4789 [0.000]	0.4295 [0.000]	0.3950 [0.000]	0.4438 [0.000]	0.3990 [0.000]	0.3819 [0.000]
Φ	0.3497 [0.000]	0.3419 [0.000]	0.3470 [0.000]	0.3459 [0.000]	0.3415 [0.000]	0.3433 [0.000]
ω	-0.235 [0.000]	-0.2350 [0.000]	-0.2380 [0.000]	0.1676 [0.030]	0.1930 [0.062]	0.1781 [0.090]
α	0.3879 [0.000]	0.4057 [0.000]	0.4050 [0.000]	0.2220 [0.001]	0.2216 [0.005]	0.2243 [0.010]
β	0.9487[0.000]	0.9397 [0.000]	0.9423 [0.000]	0.7468[0.000]	0.7349 [0.000]	0.7413 [0.000]
γ	-0.0075 [0.843]	-0.0189 [0.705]	-0.0156 [0.777]	0.0080 [0.909]	0.0235 [0.797]	0.0135 [0.890]
Diagnostics for the models without dummy variables						
Q(12)	17.752 [0.088]	18.454 [0.072]	18.287 [0.075]	16.143 [0.136]	16.666 [0.118]	16.510 [0.123]
Q2(12)	8.6823 [0.651]	8.8960 [0.631]	8.5619 [0.662]	9.5520 [0.571]	9.6570 [0.56]1	9.4160 [0.584]
LM[12]	8.9620 [0.706]	9.1730 [0.688]	8.8100 [0.719]	9.3646 [0.671]	9.4929 [0.660]	9.2665 [0.680]
AIC	4.01342	4.00905	3.99465	4.01253	4.00774	3.99321
BIC	4.07198	4.07737	4.06297	4.07109	4.07606	4.06153
Log L	-820.766	-818.866	-815.899	-820.582	-818.595	-815.603
	B. With dummy variable					
Φ	0.4002 [0.000]	0.3942 [0.000]	0.3947 [0.000]	0.4067 [0.000]	0.3989 [0.000]	0.4001 [0.000]
ω	0.3305 [0.194]	0.3658 [0.190]	0.3459 [0.232]	1.5322 [0.000]	1.8627 [0.003]	1.6173 [0.050]
α	0.1415 [0.168]	0.1399 [0.214]	0.1438 [0.218]	0.0629 [0.349]	0.0399 [0.530]	0.0343 [0.609]
β	0.4942 [0.007]	0.4961 [0.009]	0.4929 [0.016]	0.2373 [0.037]	0.1936 [0.092]	0.2435 [0.380]
γ	-0.0603 [0.364]	-0.0512 [0.499]	-0.0499 [0.516]	0.0906 [0.418]	0.0828 [0.493]	0.0794 [0.503]
Diagnostics for the models with dummy variables						
Q(12)	16.966 [0.109]	16.234 [0.133]	16.386 [0.127]	17.713 [0.088]	15.937 [0.143]	16.010 [0.141]
Q2(12)	10.048 [0.526]	10.375 [0.497]	10.255 [0.508]	7.5102 [0.756]	9.1058 [0.612]	9.3992 [0.585]
LM[12]	10.532 [0.569]	10.863 [0.540]	10.760 [0.549]	8.3307 [0.758]	9.6430 [0.647]	9.8595 [0.628]
AIC	3.94792	3.94758	3.94598	3.950933	3.94444	3.94160
BIC	4.09405	4.10345	4.10185	4.097063	4.10031	4.09747
Log L	-800.247	-799.176	-798.845	-800.868	-798.527	-797.941

Table 8: Persistence for all GCC markets

	EGARCH			GJR-GARCH		
	Normal	Student-t	GED	Normal	Student-t	GED
SA						
Without	0.9317	0.9144	0.9251	1.0260	1.0213	1.0188
With	0.7507	0.7124	0.7443	0.8414	0.8399	0.8657
Ratio	0.8057	0.7791	0.8046	0.8201	0.8224	0.8497
BA						
Without	0.7747	0.7789	0.7915	0.8915	0.8772	0.8874
With	0.6030	0.6185	0.6176	0.7771	0.7606	0.7760
Ratio	0.7784	0.7941	0.7803	0.8717	0.8671	0.8745
QA						
Without	0.8969	0.9231	0.9142	0.9458	0.9633	0.9553
With	0.6599	0.5423	0.6689	0.6675	0.6529	0.6518
Ratio	0.7358	0.5875	0.7317	0.7058	0.6778	0.6823
UA						
Without	0.9411	0.9308	0.9358	0.9862	1.0111	0.9913
With	-0.4640	0.6334	-0.5340	0.6754	0.6891	0.6695
Ratio	0.4930	0.6805	0.5706	0.6849	0.6815	0.6754
OM						
Without	0.9487	0.9398	0.9424	0.9729	0.9684	0.9725
With	0.4942	0.4961	0.4930	0.3457	0.2750	0.3176
Ratio	0.5210	0.5279	0.5231	0.3553	0.2839	0.3266
KU						
Without	0.7288	0.7790	0.7981	0.8301	0.9961	0.9259
With	0.4651	0.4667	0.4658	0.3693	0.3380	0.3473
Ratio	0.6382	0.5991	0.5837	0.4449	0.3393	0.3751

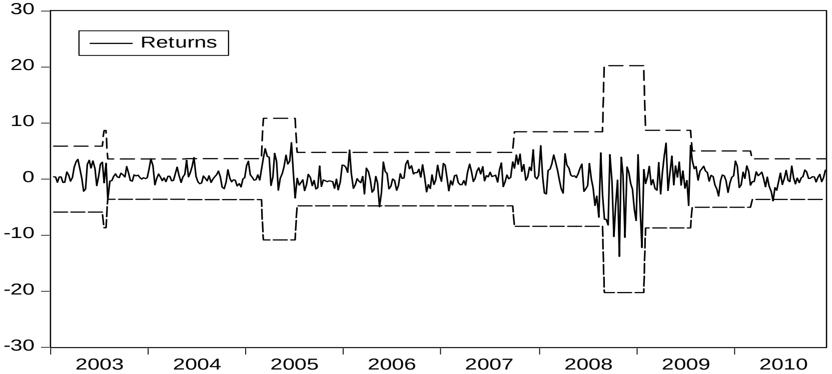
The persistence is calculated as $(a + \gamma/2 + \beta)$ for GJR-GARCH and (β) for EGARCH estimation [20]. "Without" denotes that GARCH models without any regime dummies in the variance equation. "With" means that GARCH estimations with regime dummies in the variance equation. Ratio is calculated as persistence in the model with dummies divided by the persistence of GARCH models without dummies

Table 9: The magnitude of news impact on volatility

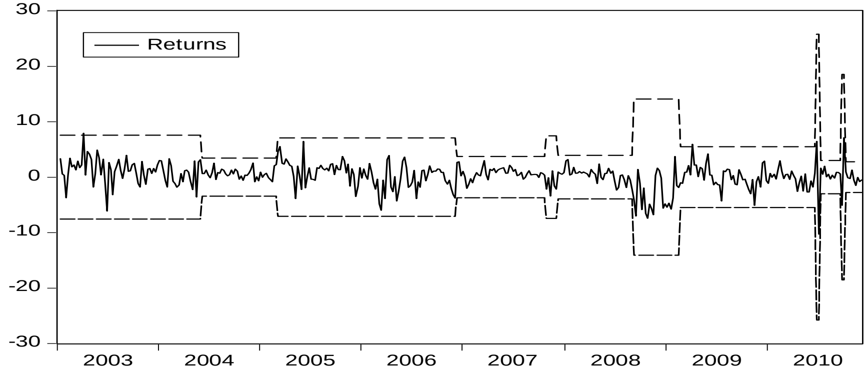
	News impact	EGARCH Normal	EGARCH Student-t	EGARCH GED	GJR-GARCH Normal	GJR-GARCH Student-t	GJR-GARCH GED
Saudi Arabia							
Without dummy	Bad news	0.43796	0.456512	0.437604	0.229966	0.235751	0.220622
	Good news	0.526828	0.535884	0.54376	0.340827	0.363174	0.360207
With dummy	Bad news	0.240327	0.27493	0.274494	0.068974	0.098363	0.091975
	Good news	0.429403	0.43333	0.44741	0.330894	0.346059	0.357249
Bahrain							
Without dummy	Bad news	0.51236	0.505965	0.47377	0.195411	0.24648	0.208557
	Good news	0.455162	0.486941	0.45657	0.213649	0.22679	0.19866
With dummy	Bad news	0.54516	0.57471	0.550924	0.292953	0.360851	0.316059
	Good news	0.575938	0.586168	0.58472	0.307732	0.351545	0.331976
Qatar							
Without dummy	Bad news	0.447704	0.451848	0.435305	0.241203	0.248672	0.23442
	Good news	0.42597	0.35074	0.375163	0.230649	0.173382	0.192251
With dummy	Bad news	0.287367	0.115472	0.263415	0.142175	0.150147	0.132562
	Good news	0.258661	0.005462	0.191673	0.108491	0.033444	0.059969
UAE							
Without dummy	Bad news	0.314577	0.404121	0.354868	0.149725	0.198152	0.167344
	Good news	0.392701	0.456971	0.41232	0.184923	0.190837	0.174941
With dummy	Bad news	0.056393	0.152728	0.076545	-0.0019	0.031859	0.011279
	Good news	0.383237	0.586302	0.466273	0.335452	0.444619	0.378177
Oman							
Without dummy	Bad news	0.395751	0.424738	0.420712	0.230105	0.245256	0.237981
	Good news	0.380055	0.386764	0.389384	0.222088	0.221669	0.224389
With dummy	Bad news	0.201908	0.191231	0.193785	0.153679	0.122728	0.113838
	Good news	0.081266	0.088719	0.093937	0.062981	0.039923	0.034345
Kuwait							
Without dummy	Bad news	0.696255	0.828664	0.724469	0.575348	0.86462	0.66451
	Good news	0.518449	0.543452	0.502801	0.281429	0.317053	0.304102
With dummy	Bad news	0.489914	0.52258	0.503218	0.366002	0.378224	0.369212
	Good news	0.148264	0.161482	0.152394	0.075392	0.058683	0.077647

The Good news in EGARCH model calculated as $a+\gamma$ and bad news calculated as $a-\gamma$. The Good news in GJR-GARCH model calculated as calculated as a and bad news calculated as calculated as $a+\gamma$, [20].

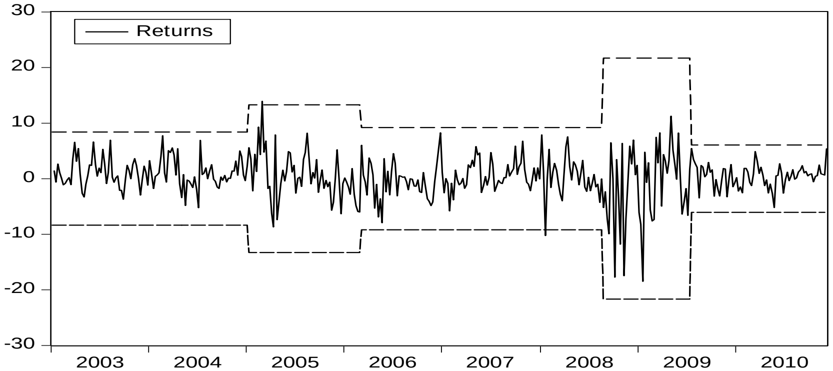
Panel A: Oman



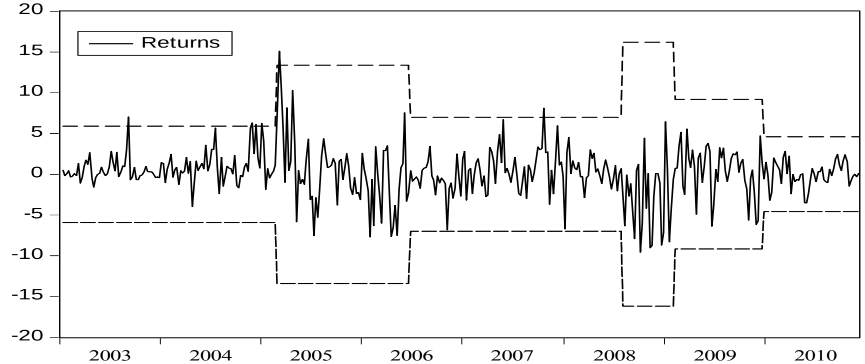
Panel B: Kuwait



Panel C: Qatar



Panel D : United Arab Emirates



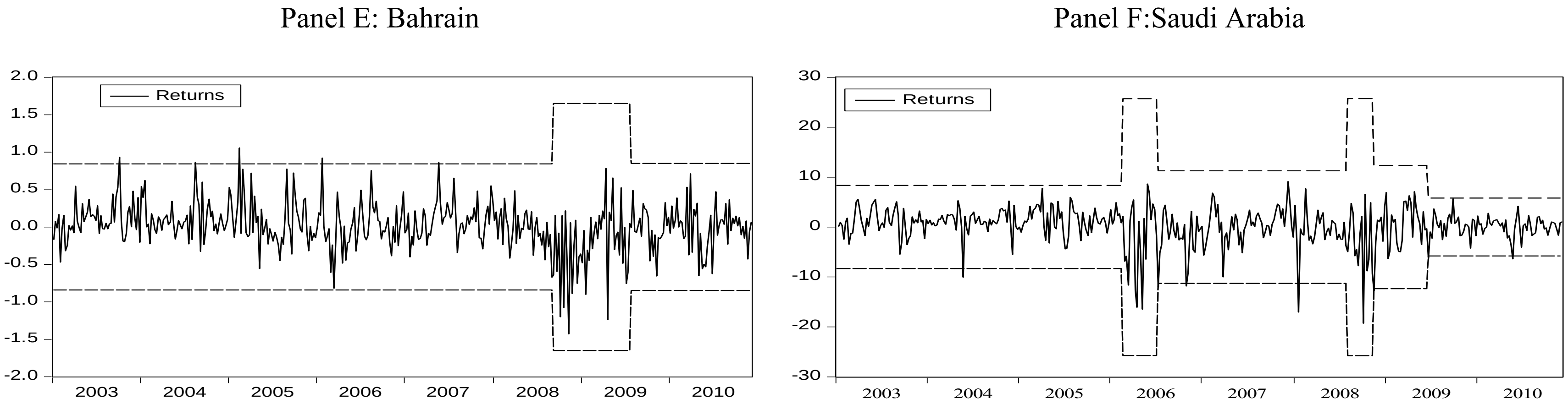


Figure 1: Weekly GCC stock price returns

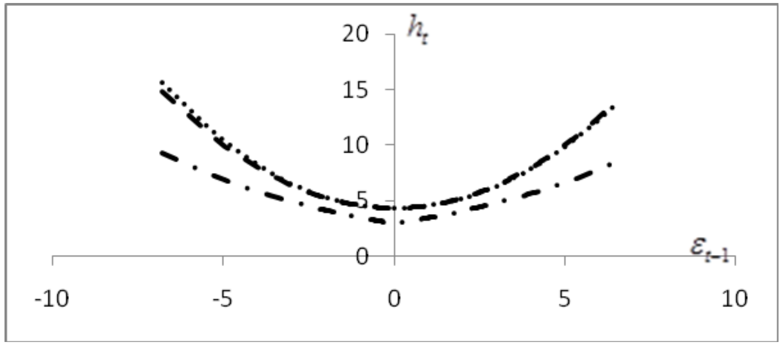
Note: Bands are at ± 3 standard deviations and change points are detected by ICSS algorithm.

Table 10: Sudden changes in volatility and corresponding dummy variables detected by ICSS algorithm

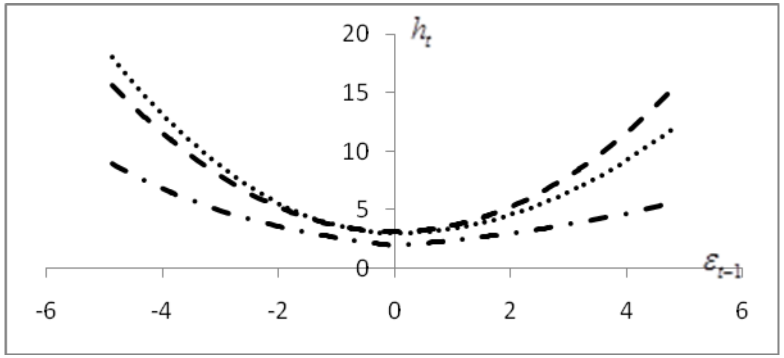
Country	Number of dummy variable	Dummy variable parameter estimation		The number of regime	Time period of regime		Mean conditional variance	Ratio of change with respect of previous regime
					From	To		
		Parameters	p-value		1/6/2003	2/20/2006	6.56052	
Saudi Arabia	1	0.80466	0.0286	6	2/27/2006	7/10/2006	92.89431	14.15959
	2	-0.55401	0.0426		7/17/2006	8/4/2008	13.70501	0.147533
	3	0.545879	0.0588		8/11/2008	11/17/2008	77.8150	5.677851
	4	-0.48754	0.1166		11/24/2008	6/22/2009	23.87864	0.306864
	5	-0.38641	0.1855		6/29/2009	12/6/2010	4.088077	0.171202
					1/6/2003	2/21/2005	2.732877	
United Arab Emirates	1	5.811243	0.0152	6	2/28/2005	6/19/2006	19.66033	7.194003
	2	-4.46709	0.0464		6/26/2006	7/28/2008	6.174635	0.314066
	3	11.47616	0.1034		8/4/2008	2/2/2009	37.11357	6.01065
	4	-8.99373	0.2006		2/9/2009	12/21/2009	12.44856	0.335418
	5	-3.67189	0.0747		12/28/2009	12/6/2010	2.522628	0.202644
					1/6/2003	8/25/2008	1.563123	
Bahrain	1	0.572777	0.0282	3	9/1/2008	7/20/2009	6.305583	4.033964
	2	-0.62309	0.0396		7/27/2009	12/6/2010	1.444496	0.229082
					1/6/2003	1/10/2005	6.205036	
Qatar	1	3.31471	0.1909	5	1/17/2005	3/6/2006	16.21638	2.613423
	2	-2.69558	0.2389		3/13/2006	8/25/2008	8.574404	0.528749
	3	15.06571	0.1567		8/25/2008	7/20/2009	52.97092	6.177796
	4	-16.6765	0.1431		7/27/2009	12/6/2010	3.843818	0.072565
					1/6/2003	5/31/2004	12.22903	
Kuwait	1	-0.99559	0.0035	12	6/7/2004	2/28/2005	3.2392564	0.2648825
	2	0.909675	0.005		3/7/2005	12/4/2006	7.7497141	2.3924361
	3	-0.99974	0.0008		12/11/2006	10/22/2007	0.8777766	0.1132657
	4	1.464639	0.0461		10/29/2007	12/3/2007	7.6904808	8.7613194
	5	-1.20235	0.0956		12/10/2007	8/25/2008	3.0786684	0.400322
	6	1.419020	0.0045		9/1/2008	2/16/2009	11.849956	3.8490523
	7	-0.90109	0.026		2/23/2009	6/21/2010	5.0783762	0.4285566
	8	3.1176	0.3568		6/21/2010	6/28/2010	11.65112	2.2942609
	9	-4.11386	0.2546		7/12/2010	9/20/2010	1.328460	0.1140199
	10	3.964536	0.0461		9/20/2010	10/4/2010	77.406216	58.267631
	11	-3.65904	0.0692		10/11/2010	12/6/2010	3.1076537	0.0401473
				11	1/13/2003	7/14/2003	2.2057349	
Oman	1	17.22269	0.000		7/28/2003	8/4/2003	3.5705601	1.6187621
	2	-18.3088	0.000		8/4/2003	5/17/2004	2.101859	0.5886637

3	0.54136	0.0205	5/24/2004	2/28/2005	1.7756616	0.8448053
4	4.283075	0.135	3/7/2005	7/4/2005	5.5178229	3.1074744
5	-3.61958	0.1991	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

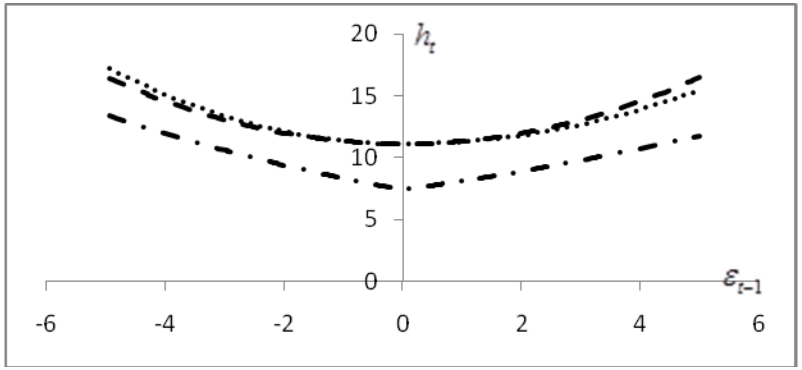
Panel A: Oman



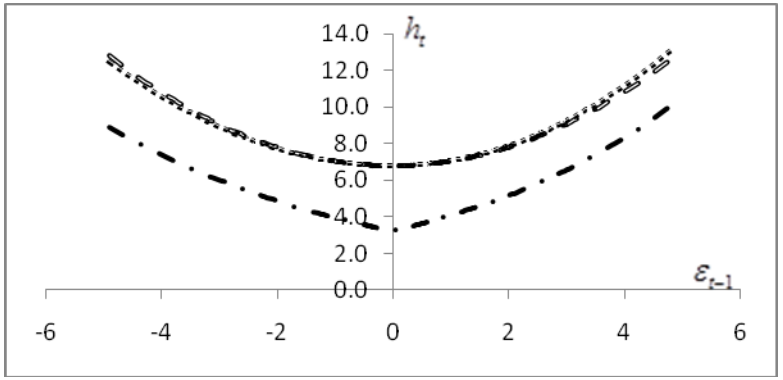
Panel B: Kuwait



Panel C: Qatar



Panel D : United Arab Emirates



Panel E: Bahrain Panel F: Saudi Arabia

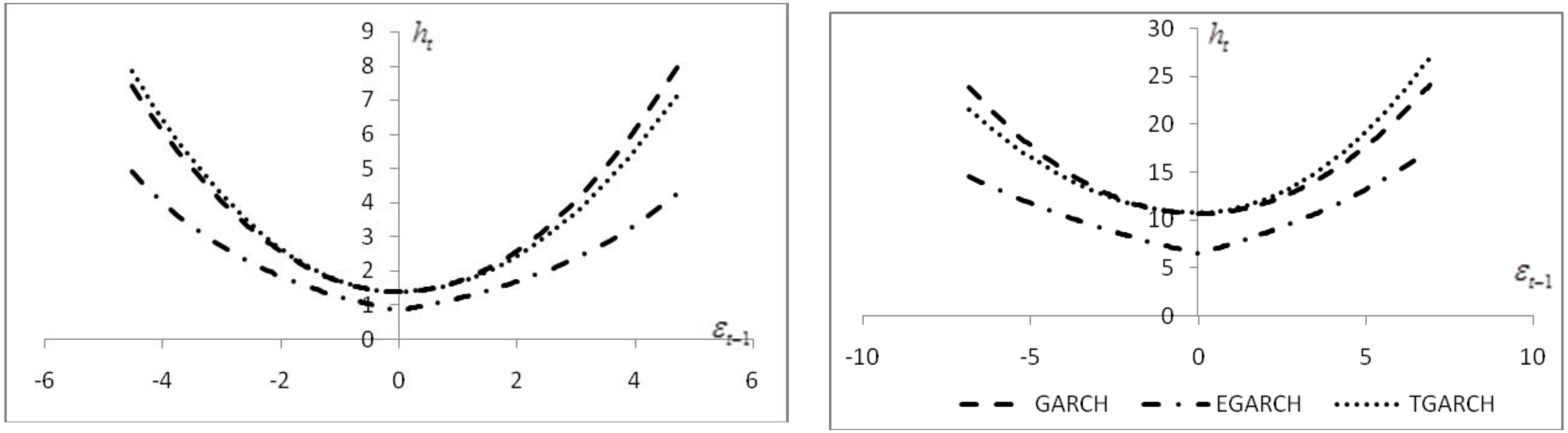


Figure 2: News impact curve all GCC markets of symmetric and asymmetric models