https://doi.org/10.31674/book.2023srdsi015

Studying the Economic Sustainability of Stock Markets Post Arab Spring Crunch: The Case of Select GCC Countries

Dipankar Bhaumik[1], Raktim Ghosh[2]*, Rupa Mondal[3],
[1]Department of Commerce, Birpara College, West Bengal, India
[2]Department of Commerce, Maharaja Srischandra College, Kolkata, West Bengal, India
[3]Department of Commerce, University of Calcutta, Kolkata, West Bengal, India

*Corresponding Author's E-mail: raktimghosh19@gmail.com

ABSTRACT

The goal of the current study is to inspect the economic viability of a few of the stock markets in Gulf Cooperation Council (GCC) nations after the Arab Spring crisis, taking into account volatility, volatility variability, long-term consequences, and regime-switching behaviour. Five stock market indices were considered, namely Bahrain All Share (BAX) (Bahrain), Muscat Securities Market (MSM 30) (Oman), Dubai Financial Market (DFM) (United Arab Emirates), Qatar stock market (QEAS) (Qatar), and Saudi Arabia stock market (TASI) (Saudi Arabia), from the week 3, December 2010, and continued up to the week 4, July 2022, with 606 sample observations. The Jarque-Bera test indicates the non-normality of the dataset. The breakpoint unit root test indicates the stationarity of the variables along with the breakpoint dates. The FIGARCH test studies the long-memory effects of the Arab Spring, where the ARCH term and the GARCH term are statistically noteworthy for all the select stock market indices, indicating the existence of volatility and variance in volatility. The $\alpha + \beta$ term has a value greater than 1, except TASI, which indicates the incidence of long-memory effects within DFM, BAX, MSM 30, and QEAS resulting from the Arab Spring. Therefore, it can be indicated that, although the Arab Spring concluded more than a few years ago, its historic impact in the form of a long-memory effect is still persisting within the economy and definitely distressing the policy-making of the concerned stakeholders. The Markov regime-switching model indicates the stock market indices shift from regime 1 to 2.

Keywords: *Economic Sustainability; Arab Spring; Breakpoint Unit Root; FIGARCH; MRS*

Introduction

The evolution of a nation's economy depends heavily on the stock market. They cater to augmenting economic expansion and aiding in the repair of monetary charges based on the supply and demand of investors. It also subsidizes hovering capital to appeal to cross-border investors and allows growth in business. They are considered the key indicators of political, economic, and security conditions prevailing across diverse nations (El-Chaarani & El-Abiad, 2019). The stock market is crucial in acting as the foundation of the economy. The Arab countries were suffering from the sub-prime meltdown, and before they could recover from it, another shock arrived from the Arab Spring crisis. The different Arab nations witnessed a political crisis in 2010 in the form of a number of anti-government protests, disturbances, and armed uprisings that expanded across the Middle East. However, the escalation in these protests was found in 2011 during the spring, from which the term ‘Arab Spring’ was actually coined. Though there were differences in the objectives in different nations, the prime objective was to increase democracy and freedom within the nations.

The Gulf Cooperation Council (GCC), which is made up of oil-exporting nations including Kuwait, Bahrain, Oman, the UAE, Qatar, and Saudi Arabia, is a financial and radical alliance. The GCC nations are experiencing a poor return rate, a dearth of fluidity, and a surplus of unpredictability following the crisis of the Arab Spring. This can also be described as the aftermath of the crisis.

The crisis' repercussions may be seen in many stock markets in the Middle East and North Africa (Zaiane, 2018). According to certain research (Abdelbaki, 2013; Acemoglu, Hassan & Tahoun, 2018), the encounters in Syria, Lebanon, Yemen, Iraq, Libya, Tunisia, and Egypt that are geopolitical in nature have slackened the recovery of a few stock markets and the economic segment in the Middle Eastern economies (El-Chaarani & Ragab, 2018; El-Chaarani & El-Abiad, 2019). Nevertheless, Acemoglu, Hassan and Tahoun, (2018) acknowledged a link between the volume of demonstrations and the undervaluation of Egyptian stock markets.

Henceforth, the economic sustainability of the stock markets of the GCC nations post-Arab Spring crunch needs to be evaluated bearing in mind the performance of their capital markets in terms of volatility along with the long-memory effects of the anticipation of their directing power on the economic and political pronouncements in the Middle East province.

Literature Review

Existing studies on GCC republics demonstrating the post-Arab Spring scenario are hard to find. So, the authors also considered studies belonging to the Middle East and North African republics, where the impression of the Arab Spring was also evident.

The effect of the Arab Spring is examined by Korotayev and Khokhlova (2022) on the equilibrium volume of the MENA nations, where the stability volume of the domain was maintained during 2011-2012 and increased significantly between 2013-2016. Khondker, H. H. (2019) also analyses long-term prospects for democracy and growth in the MENA region while concentrating on the short-term relevance of the revolts sweeping through numerous MENA nations. They come to the conclusion that extreme results shouldn't be dismissed too quickly as failures since they can ultimately turn out to be patchy successes. According to Aras and Falk (2016), there are several paths for a final resolution in the MENA nations, which are in conflict with both regional and trans-regional efforts for a positive command. Moreover, Salam and E.A.A., (2015) argues that some of the region's most volatile issues have changed as a consequence of the Arab Spring.

After critically examining the past studies, it is noted that studies discussing the post-scenario of the Arab Spring are difficult to find. Moreover, the application of different econometric tools is also rare.

Objectives of the Study

The loopholes in the prevailing studies direct the authors to finalize the following objectives in this present study with the motive to study the economic sustainability of the stock markets of the GCC nations post-Arab Spring crisis:

- To study the existence of volatility in select stock market indices from Gulf Cooperation Council (GCC) nations post-Arab Spring crisis
- To examine the variability in the volatility of the select stock market indices from Gulf Cooperation Council (GCC) nations post-Arab Spring crisis
- To observe the long-memory effects of the Arab Spring on the select stock market indices from Gulf Cooperation Council (GCC) nations post-Arab Spring crisis
- To analyze the regime-switching manners of the select stock market indices from the period of the Arab Spring to the post-Arab Spring period.

Methodology

The closing results of a few chosen stock market indexes from Gulf Cooperation Council (GCC) nations are used as the basis for this study using weekly data. Initially, all six stock market indices from Gulf Cooperation Council (GCC) nations were selected as the samples for the study. But, after going through the data screening process, the sample size was finalized at five, including Bahrain All Share (BAX) (Bahrain), Muscat Securities Market (MSM 30) (Oman), Dubai Financial Market (DFM) (UAE), Qatar Stock Market (QEAS) (Qatar), and Saudi Arabia Stock Market (TASI) (Saudi Arabia). However, the Kuwait stock market index (BKM 50) was excluded due to the unavailability of data throughout the study phase. Apart from the stock market indices, a dummy variable is constructed to quantify Arab Spring. In order to get a flawless representation, the study period is considered from the 3rd week of December 2010 and continued up to the 4th week of July 2022, where the 3rd week of December 2010 to the 4th week of December 2013 is considered the Arab Spring period represented as ‘1’ in the dummy and the 1st week of January 2014 to 4th week of July 2022 is considered the post-Arab Spring period represented as ‘0’ in the dummy (El-Chaarani & El-Abiad 2019). During this time span, the first phase denotes a high state of unpredictability and the second phase denotes a low state of instability. The information for the various stock market indices is gathered from the investing.com database. All the data are transformed into equivalent natural logarithmic returns to eliminate the limitations associated with time-series data. 606 sample observations were finalized for the study.

The goals of the study are addressed by the authors applying the FIGARCH model propounded by Baillie, Bollerslev and Mikkelsen, (1996), although there are conventional

GARCH models. Moreover, the Markov regime-switching (MRS) model is also realistic for studing the regime-switching behavior of the variables. One aspect of the research has found that Markov regime-switching delivers greater dominance over the single-regime modelling unpredictability (Klaassen, 2002; Haas, Mittnik & Paolella, 2004; Marcucci, 2005). Also, they specify the existence of switching regimes in harmony with stylized economic actualities (Gray, 1996; Marcucci, 2005; Haas, Mittnik & Paolella, 2004). Moreover, descriptive statistics are used to analyse the dataset's features, and the breakpoint unit root test is applied to recognize the fundamental breakdowns along with the stationarity of the variables.

Breakpoint Unit Root Test

The Breakpoint Unit Root Test is a statistical measure for detecting structural breaks in time-series data and deciding if a unit root exists in each segment of the data.

A unit root refers to a statistical property of a time series where the series has a root or solution that is equal to one. This implies that the series is not stationary and has a stochastic trend. Unit root tests are commonly used in economics and finance to test for the presence of long-run dependencies in time series data.

It is based on the assumption that structural breaks may occur in the data and that the stationarity properties of the data may change before and after a break. The test is designed to detect the incidence of structural breaks and determine if a unit root exists in each segment of the data.

The test involves dividing the time series into two or more segments and then performing a unit root test on each segment separately. If the null hypothesis of a unit root is overruled in one or more segments, then it suggests that the series is stationary in those segments and that a structural break may have occurred.

Using Perron's (1989, 1997) predicted innovation outlier breakpoints, a thorough augmented Dickey-Fuller test was conducted. The models below employ an approach that depends on the correlation function and the innovation (i.e., noise) process and contains a variable for a steady change in the intercept of the trend function (Perron, 1997).

$$\Delta y_t = \mu + \theta DU_t + \beta_t + \phi D(T_b)_t + \alpha y_{t-1} + \sum_{i=1}^{k} z_i \Delta y_{t-i} + \varepsilon_t \ldots\ldots\ldots\ldots(1)$$

$$\Delta y_t = \mu + \theta DU_t + \beta_t + \omega DT_t + \phi D(T_b)_t + \alpha y_{t-1} + \sum_{i=1}^{k} z_i \Delta y_{t-i} + \varepsilon_t \ldots\ldots(2)$$

As per Perron (1989 & 1997), the breakpoint T_b can opt such that $t_{\hat{\alpha}}(T_{b,}k)$ is curtailed. The curtailed t-statistic is specified as:

$$t^*_{\hat{\alpha}} = \min_{T_{b \in (k+1,T)}} t_{\hat{\alpha}}(T_b, k). \ldots\ldots\ (3)$$

FIGARCH

Model

This model is a type of time-series model used to capture long-term dependencies and persistent volatility clustering in financial data.

The model permits the conditional variance of the data to vary over time and to be influenced by past shocks. It is a generalization of the ARCH and GARCH models, which assume that the conditional variance is a function of only the squared past shocks. The FIGARCH model relaxes this assumption by allowing for a more flexible specification of the relationship between the conditional variance and past shocks.

The FIGARCH model is characterized by a fractional differencing parameter d, which captures the long-term dependence in the series, and a parameter α, which governs the persistence of the conditional variance. The model also includes an autoregressive component, typically an AR (1) process, to capture the impact of past shocks on the conditional variance.

The FIGARCH model is commonly used in finance and economics to model volatility in asset returns, exchange rates, and other financial time series. It is particularly useful for capturing the long-memory properties of economic data, which can have important implications for risk management and asset pricing.

According to Baillie, Bollerslev, and Mikkelsen (1996), any shock can have a significant influence on how volatile a financial series is. Researchers have paid close attention to it since it emphasizes how volatile long-memory determination and grouping are. Studies of the volatility of high-frequency fiscal time series frequently take into account long-memory persistence (Baillie , Bollerslev & Mikkelsen 1996; Dacorogna *et al.,* 1993; Ding *et al.,* 1993; Granger & Ding, 1996). Therefore, there is still plenty of room to use the FIGARCH model to explore such endless shock.

The following is a representation of the GARCH (p, q) procedure's ARMA category illustration:

$$\varepsilon_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \varepsilon_{t-j}^2 - \sum_{j=1}^{p} \beta_j v_{t-j} + v_t \text{ ....(4)}$$

Where, $v_t = \varepsilon_t^2 - h_t = (z_t^2 - 1) h_t$ and the z_t 's are 0 correlated with $E(z_t) = 0$ and var (z_t) = 1. From (4), it can be witnessed that the GARCH (p, q) process can also be expressed as an ARMA (m, p) procedure in ε_t^2,

$$[1 - \alpha (L) - \beta (L)]\, \varepsilon_t^2 = \alpha_0 + [1 - \beta (L)] v_t \text{..............(5)}$$

Where, m = max{p, q} and $v_t = \varepsilon_t^2 - h_t$. The v_t method can be concluded as the "innovations" for the conditional variance, as it is a zero-mean martingale. So, an integrated GARCH (p, q) process can be inscribed as:

$$[1 - \alpha (L) - \beta (L)] (1 - L) \varepsilon_t^2 = \alpha_0 + [1 - \beta (L)]v_t \text{........}(6)$$

By changing the initial difference operator, the fractionally integrated GARCH or FIGARCH group of models may be obtained by putting (1 − L) in (6) with the fractional differencing operator $(1 - L)^d$, where d is a fraction 0 < d < 1. As a result, the FIGARCH group of models may be purchased by taking into account:

$$[1 - \alpha (L) - \beta (L)] (1 - L)^d \varepsilon_t^2 = \alpha_0 + [1 - \beta (L)]v_t \text{........}(7)$$

The supremacy of elaborating on and illustrating the historical dependencies of the financial market volatility over other forms of GARCH models is served by this (Davidson, 2004).

Markov Regime-Switching (MRS) Model

A Markov regime-switching model is a statistical model used to capture variations in the underlying structure of a time series over time. It assumes that the time series is governed by a set of latent states or regimes, each with its own set of parameters, and that the evolution amid states trails a Markov process.

In a MRS model, the parameters of the model, such as the mean and variance, are allowed to vary depending on the current state of the system. The transition between states is ruled by some set of likelihoods, which can be assessed from the data.

Markov regime-switching models are frequently used to model financial and economic time series that exhibit sudden shifts in behavior, such as stock market returns or interest rates. By allowing for changes in the underlying regime, these models can capture the dynamics of the data more accurately than customary linear models.

One popular example of a MRS model is the Hidden Markov Model (HMM), which is widely used in speech recognition, bioinformatics, and other fields. Another example is the Markov switching autoregression (MSAR), which is used to model time series data that exhibit both short-term and long-term persistence.

Hamilton and Susme (1994) developed the switching-regime ARCH, which was later generalised by Gray, based on the idea of financial structural shifts (1996). This type of model is also capable of identifying fundamental modifications in financial markets.

The first-order Markov chain with transition likelihood is which postulates the probability of moving from state *i* at time *t-1* to into state *j* at *t*.

$$P_r(S_t = j \mid S_{t-1} = i) = p_{ij} \text{ .... } (8)$$

The transition matrix is as follows allowing for two regimes:

$$P = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix} = \begin{bmatrix} p & (1-q) \\ (1-p) & q \end{bmatrix} \text{............. ....}(9)$$

The unrestricted likelihood of presence in state 1 (S_t)=1 is specified by:

$$\pi_1 = (1-p)/(2-p-q) \ldots\ldots\ldots\ldots\ldots\ldots\ldots(10)$$

The MRS model in its common procedure can be inscribed as (Marcucci, 2005):

$$r_t \mid \zeta_{t-1} \sim \begin{Bmatrix} \int(\theta_t^{(1)}) & w.p.\ p_{1,t} \\ \int(\theta_t^{(2)}) & w.p.(1-p_{1,t}) \end{Bmatrix} \ldots\ldots\ldots\ldots\ldots\ldots\ldots(11)$$

Where $\int.$ signifies one of the likely conditional disseminations which are anticipated that is normal (N), $\theta_t^{(1)}$ represents the vector of the restrictions in the *i*th regime featuring the dissemination, $p_{1,t} = P_r[S_t = 1 \mid \zeta_{t-1}]$is the ex-ante likelihood, ζ_{t-1}represents the data set at time t-1 that is the σ algebra prompted by the variables at the specified time phase that can be additionally separated into three measures as follows:

$$\theta_t^{(i)} = (u_t^{(i)}, h_t^{(i)}, v_t^{(i)}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(12)$$

Where, $u_t^{(i)} \equiv E(r_t \mid \zeta_{t-1})$ is the conditional mean, $h_t^{(i)} \equiv \text{Var}(r_t \mid \zeta_{t-1})$ is the conditional variance and $v_t^{(i)}$ is the shape limitation of the conditional dissemination (Marcucci, 2005).

Henceforth, it can be specified that MRS comprises four essentials: the conditional mean, the conditional adjustment, the regime process, and the conditional dissemination (Marcucci, 2005). With or without drift, the conditional mean equation is expressed as follows:

$$r_t = u_t^{(i)} + \varepsilon_t = \delta^{(i)} + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.....(13)$$

Where i=1,2, $\varepsilon_t = n_t\sqrt{h_t}$ and n_t is a zero mean, unit variance procedure. The chief purpose is unpredictability projecting (Marcucci, 2005).

The provisional adjustment of r_t, specified the entire regime path

$$\tilde{S}_t = (S_t, S_{t-1}, \ldots.), \text{ is } h_t^{(i)} = [\varepsilon_t \mid \tilde{S}_t\ ,\ \zeta_{t-1}] \ldots\ldots\ldots....(14)$$

For this conditional variance, the resulting GARCH (1,1) equation can be supposed as:

$$h_t^{(i)} = \alpha_0^{(i)} + \alpha_1^{(i)}\varepsilon_{t-1}^2 + \beta_1^{(i)}h_{t-1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots.........(15)$$

Where h_{t-1} is a state-independent average of historical provisional modification.

Some research works prove that the Markov regime-switching model can arrest mechanical breakdowns in monetary return sequence and worthily decrease valuation partiality caused by great persistence (Gray, 1996; Klaassen, 2002; Haas, Mittnik & Paolella, 2004; Teterin, Brooks & Enders, 2016).

Results and Discussion

Table 1: Descriptive Statistics

	DFM	BAX	TASI	MSM 30	QEAS	Arab Spring
Mean	0.001	0.004	0.001	-0.006	0.001	0.260
Median	0.001	0.004	0.002	-0.096	0.002	0
Maximum	0.126	0.047	0.137	0.123	0.124	1
Minimum	-0.191	-0.118	-0.162	-0.124	-0.118	0
Std. Dev.	0.03	0.013	0.025	0.017	0.023	0.439
Skewness	-0.758	-1.458	-0.819	-0.500	-0.280	1.090
Kurtosis	7.921	14.943	9.285	13.676	7.343	2.188
Jarque-Bera	669.77	3816.534	1065.281	2903.281	484.444	136.643
p-value	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
Sum	0.709	0.297	0.620	-0.387	0.850	158
Sum Sq. Dev.	0.564	0.107	0.403	0.182	0.337	116.805
Observations	606	606	606	606	606	606

*denotes significance at 1% level

Source: Author's own computation using E-Views 12

Table 1 indicates descriptive statistics of the Dubai financial market (DFM), Bahrain All Share (BAX), Saudi Arabia stock market (TASI), Muscat securities market (MSM 30), and Qatar stock market (QEAS) along with the dummy variable, Arab Spring. The variables are non-normal at a 1 percent level, as confirmed by the Jarque-Bera test with 606 sample observations. DFM surges to 0.126 and makes a downturn to -0.191 with a mean of 0.001. BAX surges to 0.047 and declines to -0.118, with a mean of 0.004. Similarly, TASI and MSM 30 surged to 0.137 and 0.123, respectively, and took a downturn to -0.162 and -0.124, respectively. However, their mean values are 0.001 and -0.006, respectively. QEAS surged to 0.124 and made a downturn to -0.118 with a mean of 0.001. The dummy variable Arab Spring surged to the uppermost value of 1 and decreased to the bottommost value of 0 with a mean of 0.260.

Skewness refers to an asymmetry or distortion that deviates from a dataset's normal distribution or symmetrical bell curve. MSM 30 and QEAS indicate the data is properly symmetrical. DFM, TASI, and the Arab Spring are moderately skewed. BAX has highly skewed data (Joseph *et al.,* 2017).

Kurtosis indicates the normality of a dataset on the basis of its distribution by studying the tail of the bell-shaped normal curve.

Table 2: Breakpoint Unit Root Test

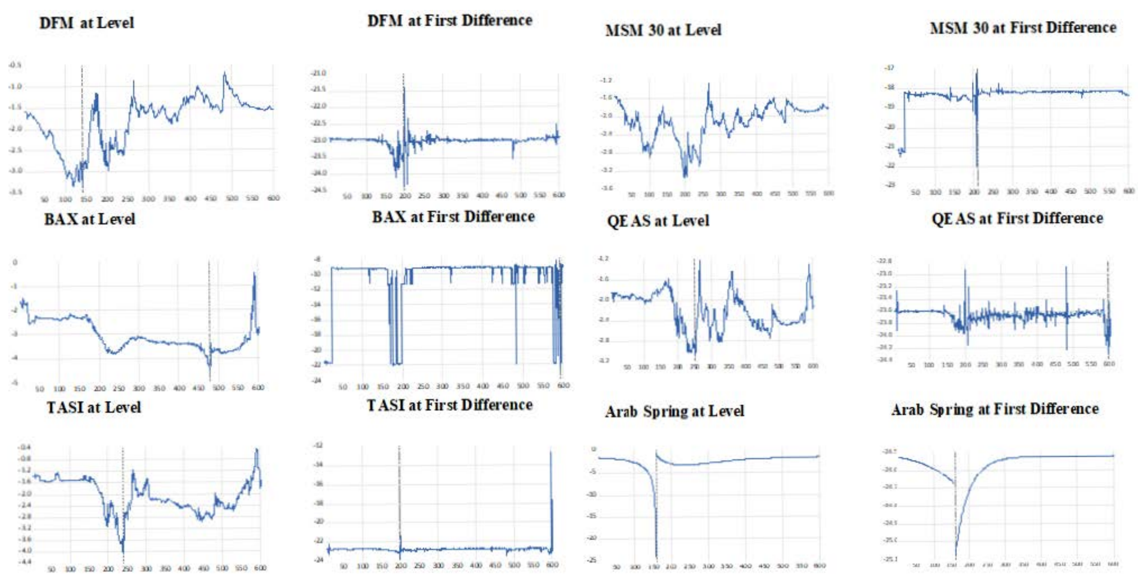
Trend & Intercept (Innovation Outlier Model)					
	Level		First Difference		
Variables	**t-statistics**	***p*-value**	**t-statistics**	***p*-value**	**Break Date**
DFM	-3.3993	0.8583	-24.38	0.01*	Aug 25, 2014
BAX	-4.4899	0.2412	-22.5071	0.01*	Feb 09, 2020
TASI	-4.0417	0.4935	-23.78	0.01*	Jul 12, 2015
MSM 30	-3.3658	0.8714	-22.0037	0.01*	Sep 28, 2014
QEAS	-3.0876	0.9491	-24.3013	0.01*	Oct 04, 2015
Arab Spring	-24.2576	0.00*	-25.0791	0.01*	Dec 15, 2013

*denotes significance at 1% level

Source: Author's own computation using E-Views 12

Table 2 provides the result of the breakpoint unit root test, where it is witnessed that the select stock market indices, namely DFM, BAX, TASI, MSM 30, and QEAS, are non-stationary at the level and stationary at the first difference, indicating the non-presence of a unit root at the first difference. However, the dummy variable Arab Spring is stationary at both level and first difference. The confidence interval for all the variables is 99 percent. The breakpoint dates of the stock market indices as well as Arab Spring are also noted in the above table, where it is seen that December 15, 2013, is the day when a change in the nature of the data in Arab Spring is noted. But for the stock market indices, the dates are different, indicating a change in the nature of the data on that particular date. Moreover, it needs to be mentioned that the stock market suffers from the shock of the Arab Spring until the break date.

The breakpoint graphs of the stock market indices as well as Arab Spring are represented below in Figure 1.



Source: Author's own computation using E-Views 12

Figure 1: Breakpoint Unit Root Test Graph

Table 3: Fractionally Integrated Generalized Autoregressive Conditional Heteroscedastic (FIGARCH) Model

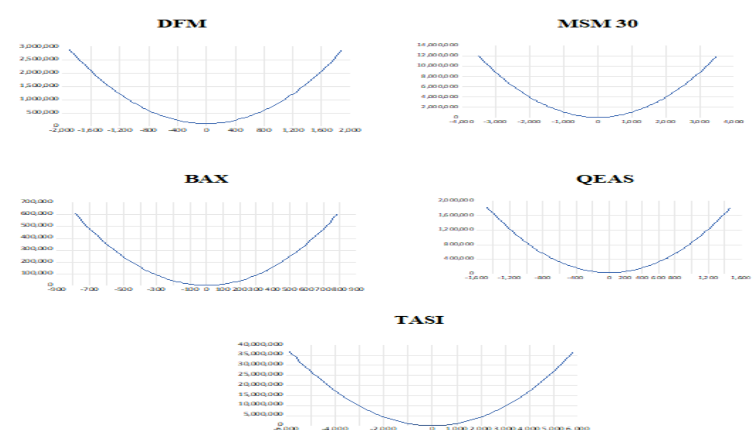
Dependent Variables	Constant (ω)	*p*-value	ARCH Effect (α)	*p*-value	GARCH Effect (β)	*p*-value	α + β
DFM	712.76	0.30	0.709	0.07***	0.3253	0.07***	1.0343
BAX	55.84	0.00*	0.4305	0.00*	0.9259	0.00*	1.3564
TASI	12578.9	0.2852	0.2173	0.07***	0.1418	0.08***	0.3591
MSM 30	201.82	0.881	0.8254	0.00*	0.6705	0.01*	1.4959
QEAS	-223.44	0.4506	0.6579	0.00*	0.4778	0.04**	1.1357

*denotes noteworthy at 1% level, ** denotes noteworthy at 5% level, *** denotes noteworthy at 10% level
Source: Author's own computation using E-Views 12

The above table provides the result of the FIGARCH test. This test allows us to capture the fractionally integrated volatility, i.e., the long-memory effect within the dependent variables, considering a slothful hyperbolic rate of decline for the effect of lagged squared originations.

It is observed that the constant values are significant for BAX only. However, α is statistically noteworthy for all the variables. DFM and TASI are noteworthy at the 10 percent level in the ARCH effect, and other stock market indices are noteworthy at the 1 percent level. This indicates the existence of volatility resulting from the shock of the Arab Spring crunch. Hence, the risk factor in these stock markets can be estimated. In the GARCH effect, DFM and TASI are noteworthy at a 10 percent level, QEAS is noteworthy at a 5 percent level, and others are noteworthy at a 1 percent level. This indicates the variability in the unpredictability, i.e., the unpredictability can upsurge if the crunch increases further or the volatility can shrink following a composed and unchanging condition within the market in the context of the shock arising out of the Arab Spring. The summation of α and β factors is greater than 1 for all the variables excluding TASI, indicating the incidence of long-memory influence within DFM, BAX, MSM 30, and QEAS resulting from the Arab Spring. Hence, it can be stated that though the Arab Spring ended several years ago, its momentous influence in the form of a long-memory influence is still persisting within the market and is certain to affect the decision-making of the interested stakeholders.

The select stock market indices are highly influenced due to the shock of Arab Spring which are depicted below in Figure 2.



Source: Author's own computation using E-Views 12

Figure 2: Impact Curve

Table 4: Markov Regime-Switching (MRS) Model

Indices	**Regime**	***c***	***p*-value**	**σ**	**LL**
DFM	1	0.0147	0.02**	0.0305	1339.06
	2	-0.0010	0.6915		
BAX	1	0.0002	0.091***	0.0133	1824.98
	2	-0.0009	0.078***		
TASI	1	-0.0012	0.0613***	0.0258	1435.33
	2	-0.0013	0.00*		
MSM 30	1	0.0019	0.0683***	0.0173	1693.34
	2	-0.0157	0.08***		
QEAS	1	0.0029	0.00*	0.0236	1486.92
	2	-0.0003	0.00*		

*denotes noteworthy at 1% level, ** denotes noteworthy at 5% level, *** denotes noteworthy at 10% level

Source: Author's own computation using E-Views 12

This model permits the variation of a dependent variable due to an independent variable, resulting in a swing from one regime to another. The viability of this model is noted in the context of an exogenous shockwave. To capture the statistical significance of regime switching, the likelihood ratio test propounded by Hansen (1992) is realistic, where the transition probabilities are considered nuisance restrictions. The above table provides the results where it is comprehended that Regime 1 is the Arab Spring state (high volatility) and Regime 2 is the post-Arab Spring state (low volatility). The constant (c) values are greater in regime 1 than in regime 2, indicating that regime 1 is comparatively more unstable in nature with greater volatility. The p-values of all the stock market indices in regime 1 are significant, indicating that they shift from regime 1 to regime, i.e., from a high volatility condition to a low volatility condition. The p-values of all the stock market indices in regime 2 are also significant, except for DFM. The switching of the stock indices from one regime to another is supported by the estimated coefficients (σ). The maximum log-likelihood is represented by LL.

Table 5: Transition Probabilities

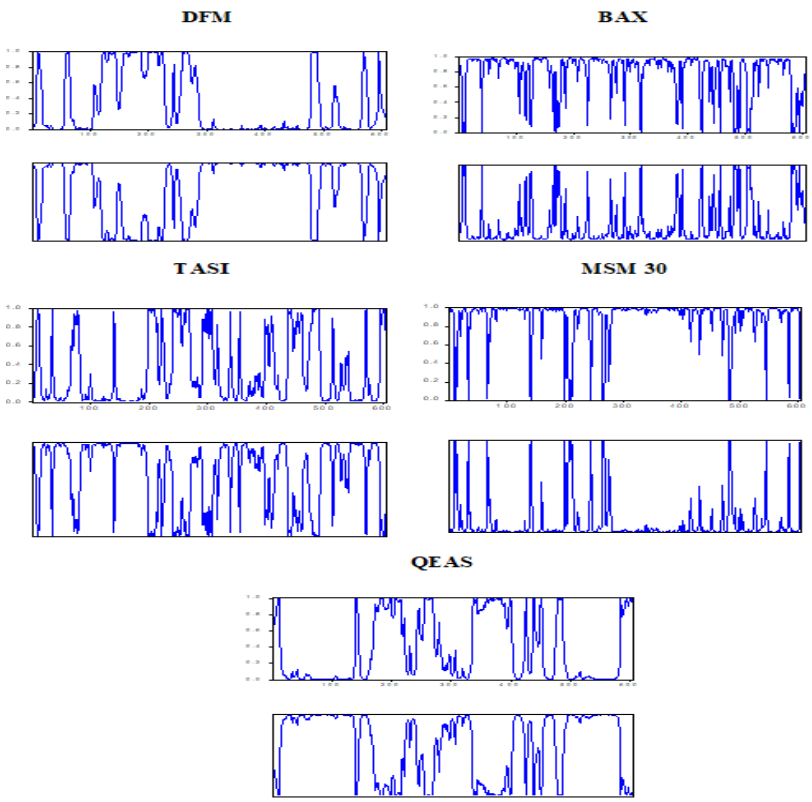
Indices	P_{11}	P_{21}
DFM	0.968658	0.031342
BAX	0.922701	0.077299
TASI	0.855945	0.144055
MSM 30	0.957352	0.042648
QEAS	0.947264	0.052736

Source: Author's own computation using E-Views 12

The above table delivers the values of the transition probability. P_{11} and P_{21} are the two matrices of the transition probabilities. The P_{11} values indicate the likelihood of the stock indices to stay in regime 1 when it is already in regime 1. The P_{21} values indicate the possibility of the stock indices coming back to regime 1 when it has already moved to regime

2. For all the stock indices, P_{11} provides a greater probability value than P_{21}. This is so because the influence of Arab Spring is greater in regime 1 than 2. When the stock indices move to a comparatively composed state i.e., regime 2, the effect is to negate out gradually.

The graphical representation of the smoothed regime probabilities is represented below:



Source: Author's own computation using E-Views 12

Figure 3: Smoothed Regime Probabilities

Conclusion

Despite knowing that it is challenging to compute with confidence the costs associated with the Arab Spring crisis, the econometric tools provide interesting results that enable the authors to conclude that during the study period, there remains volatility within the select stock markets of Gulf Cooperation Council (GCC) countries, along with variation in volatility resulting from the Arab Spring. However, the long-memory effect is very evident, and the stock markets move from a high-volatility condition to a low-volatility condition. Only the Saudi Arabian stock market (TASI) confirmed resilience in terms of the long-memory effect. It is due to the vast expenditures made by the government in terms of societal well-being. Hence, it can be stated that the stock markets are more reactive to bad news amidst political unpredictability from the Arab Spring, except for TASI. Finally, it can be stated that the select stock market indices from GCC countries have sustained the post-Arab Spring crunch, but the effect of the crisis can still be witnessed, though the magnitude of the effect has declined remarkably.

Acknowledgement

The authors express their profound gratitude to the anonymous reviewers and the respected editors for their productive recommendations and precious observations that have assisted in adding value to the study and in the completion of the current article. The authors would further like to mention that they have not received any financial support for conducting this study. Moreover, the authors declare that there are no conflicts of interest that are directly or indirectly related to this research work.

References

Abdelbaki, H. H. (2013). The impact of Arab spring on stock market performance. *British Journal of Economics, Management & Trade*, *3*(3), 169-185.

Acemoglu, D., Hassan, T. A., & Tahoun, A. (2018). The power of the street: Evidence from Egypt's Arab Spring. *The Review of Financial Studies*, *31*(1), 1-42. https://doi.org/10.1093/rfs/hhx086

Aras, B., & Falk, R. (2016). Five years after the Arab Spring: a critical evaluation. *Third World Quarterly*, *37*(12), 2252-2258. https://doi.org/10.1080/01436597.2016.1224087

Baillie, R. T., Bollerslev, T., & Mikkelsen, H. O. (1996). Fractionally integrated generalized autoregressive conditional heteroscedasticity. *Journal of Econometrics, 74*(1), 3-30. https://doi.org/10.1016/S0304-4076(95)01749-6

Dacorogna, M. M., Müller, U. A., Nagler, R. J., Olsen, R. B., & Pictet, O. V. (1993). A geographical model for the daily and weekly seasonal volatility in the foreign exchange market. *Journal of International Money and Finance*, *12*(4), 413-438. https://doi.org/10.1016/0261-5606(93)90004-U

Davidson, J. (2004). Moment and memory properties of linear conditional heteroscedasticity models, and a new model. *Journal of Business & Economic Statistics*, *22*(1), 16-29. https://doi.org/10.1198/073500103288619359

Ding, Z., Granger, C. W., & Engle, R. F. (1993). A long memory property of stock market returns and a new model. *Journal of empirical finance*, *1*(1), 83-106. https://doi.org/10.1016/0927-5398(93)90006-D

El-Chaarani, H., & El-Abiad, Z. (2019), Analysis of capital structure and performance of banking sector in Middle East countries. *International Journal of Economics and Financial Issues, 9*(2), 1-11. https://doi.org/10.32479/ijefi.7454

El-Chaarani, H., & Ragab, N.S. (2018), Financial resistance of Islamic banks in Middle East region: A comparative study with conventional banks during the Arab crises. International *Journal of Economics and Financial Issues,* 8(3), 1-12.

Granger, C. W., & Ding, Z. (1996). Varieties of long memory models. *Journal of econometrics*, *73*(1), 61-77. https://doi.org/10.1016/0304-4076(95)01733-X

Gray, S. F. (1996). Modeling the conditional distribution of interest rates as a regime-switching process. *Journal of Financial Economics*, *42*(1), 27-62. https://doi.org/10.1016/0304-405X(96)00875-6

Haas, M., Mittnik, S., & Paolella, M. S. (2004). A new approach to Markov-switching GARCH models. *Journal of financial Econometrics*, *2*(4), pp. 493-530. https://doi.org/10.1093/jjfinec/nbh020

Joseph Jr, F. Hair Jr., Barry J. Babin & Nina Krey (2017) Covariance-Based Structural Equation Modeling in the Journal of Advertising: Review and Recommendations. *Journal of Advertising*, *46*(1), 163-177. https://doi.org/10.1080/00913367.2017.1281777

Hamilton, J.D. & R. Susmel. (1994). Autoregressive conditional heteroscedasticity and changes in regime, *Journal of Econometrics,* 64, pp. 307-333, https://doi.org/10.1016/0304-4076(94)90067-1

Hansen, B. E. (1992). The likelihood ratio test under nonstandard conditions: testing the Markov switching model of GNP. *Journal of applied Econometrics*, *7*(S1), S61-S82. https://doi.org/10.1002/jae.3950070506

Khondker, H. H. (2019). The impact of the Arab Spring on democracy and development in the MENA region. *Sociology Compass*, *13*(9), e12726. https://doi.org/10.1111/soc4.12726

Klaassen, F. (2002). *Improving GARCH volatility forecasts with regime-switching GARCH* (pp. 223-254). Physica-Verlag HD. https://doi.org/10.1007/978-3-642-51182-0_10

Korotayev, A. V., & Khokhlova, A. A. (2022). Effect of the Arab Spring on stabilization capacity of the MENA monarchies. *Journal of Asian and African Studies*, *57*(2), 289-307. https://doi.org/10.1177/00219096211017309

Marcucci, J. (2005). Forecasting stock market volatility with regime-switching GARCH models. *Studies in Nonlinear Dynamics & Econometrics*, *9*(4). https://doi.org/10.2202/1558-3708.1145

Perron, P. (1989). The great crash, the oil price shock, and the unit root hypothesis. *Econometrica: Journal of the Econometric Society*, 1361-1401. https://doi.org/10.2307/1913712

Perron, P. (1997). Further evidence on breaking trend functions in macroeconomic variables. *Journal of econometrics*, *80*(2), 355-385. https://doi.org/10.1016/S0304-4076(97)00049-3

Salam, E. A. A. (2015). The Arab spring: Its origins, evolution and consequences. four years on. *Intellectual Discourse*, *23*(1), 119-139.

Teterin, P., Brooks, R., & Enders, W. (2016). Smooth volatility shifts and spillovers in US crude oil and corn futures markets. *Journal of Empirical Finance*, *38*, 22-36. https://doi.org/10.1016/j.jempfin.2016.05.005

Zaiane, S. (2018). The impact of political instability driven by the Tunisian revolution on stock market volatility: Evidence from sectorial indices. *Journal of Applied Business Research (JABR),* 34(2), 339-354. https://doi.org/10.19030/jabr.v34i2.10135