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Modelling Volatility in the Presence of Abrupt Jumps: Empirical Evidence from Islamic Stock Markets

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ABSTRACT

This study examines the abrupt jumps in the Dow Jones Islamic Market (DJIM) sectoral indices using a modified return-volatility model that allows for multiple structural breaks. The breakpoint tests for both return and volatility suggest that only several Islamic sectoral markets are insulated from the external shocks. The finding implies that the Islamic equities are merely a partial safe haven in the extreme market fluctuations. Among the sectoral indices, the oil and gas market exhibits the highest degree of volatility persistence, implying its past price can be useful to predict the future prices compared to other indices. It is also found the volatility persistence experiences a decline when abrupt jumps are incorporated into the model. These empirical results suggest the inclusion of abrupt jumps into the estimation is important to provide reliable explanatory power on the volatility dynamics of Islamic stock markets. This study may benefit the financial market participants and policymakers in making better-informed investing decision specifically for Sharia-compliant equities.

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INTRODUCTION

From the econometric perspective, abrupt jumps have caused the occurrences of level shifts (Aloui et al., 2015b; Hillebrand and Medeiros, 2016) in the financial and economic time series data. Abrupt jumps may result from economic shocks (Asian financial crisis, global financial crisis, European sovereign debt crisis etc.), political turmoil (pre and post wars effect, global election, Brexit etc.), natural disasters (earthquakes, tsunami etc.), institutional changes (monetary policy, fiscal policy etc.) and inter alia. In the context of statistical analysis, the unexpected events related to significant parameters instability in the data generating process is known as a structural break[1] (Hansen, 2001). Failure to account for this may lead to fallaciously interpreting the series as non-stationary in the preliminary unit-root diagnostic test (Zivot and Andrew, 1992; Chin, 2008), yielding spurious larger long memory property (Choi and Zivot, 2007) and overstating the volatility persistence effect (Lamoureux and Lastrapes, 1990). On the other hand, Hsieh (1991) found that disregarding the conditional heteroscedasticity in analysis might cause the rejections of linearity in stock returns. This suggests the importance of conditional heteroscedastic models for financial returns. The motivation of this study is to account for abrupt jumps in the econometric model which also allows for heteroscedasticity, an essential property in financial time series since Engle (1982). In this study, we intend to investigate the presence of abrupt jumps in both the return and volatility series in the selected Islamic stock markets.

For the past three decades, Islamic finance industries have been rapidly attaining global acceptance and are expanding at 12% to 15% annually. The total global Islamic financial assets stood at US$2.293 trillion in December 2016 (GIFR, 2017) and will continue to grow with over US$6.7 trillion by 2020 (IFSB, 2017). The Islamic capital markets are screened for business and financial activities in adherence to *Sharia* principles that are free from usury (*riba*), gambling (*maisir*) and ambiguity (*gharar*). Moreover, it promotes risk-profit sharing and asset-backing principles. These requirements may have caused the indices to be distinctive in term of behaviours and decoupling (Ahmad et al. 2018) from the conventional capital markets. It is believed that the Islamic markets are more resilient than the conventional markets especially during crisis periods (Jawadi et al., 2015). However, Nasr et al. (2016) and Rizvi et al. (2014) claim Islamic markets are susceptible to shocks due to geopolitical events and global economic crises. Hence, it is appealing to investigate how the Islamic stock volatility dynamic reacts towards unexpected events and affect stock prices.

This study contributes to the following. First, using the generalised autoregressive conditional heteroscedastic (GARCH) model with structural breaks (modified GARCH henceforth), we extend the literature on the impact of the abrupt jumps by incorporating structural breaks in the conditional mean and variance on Islamic stock markets. This study also attempts to ascertain whether Islamic markets are susceptible to major shocks and support or against the decoupling hypothesis from the conventional stock markets. Second, we compare the degree of volatility persistence among the Islamic equities using the modified GARCH model to predict future prices based on the persistent and significant stock volatility. Lastly, we use the standard and modified GARCH to provide information on how the structural shifts affect the Islamic indices in term of volatility persistence. Even though GARCH model is regarded as a simple model that may be unable to capture all the stylized facts of financial returns, it is more than adequate to deliberate the role of structural breaks (Andreou and Ghysels, 2009) in modelling the time series data.

LITERATURE REVIEW

There are two main categories of approaches in examining structural shifts in financial time series. First, it is to investigate the structural shifts within the unit root test (Mishra and Smyth, 2014; Perron, 1989). Second, it is to incorporate the structural shifts within the volatility modelling (Lamoureux and Lastraps, 1990; Wu and Hu, 2016). This study is of interest to address the second approach.

For the conventional markets, there is abundant past literature that extend the GARCH-type models (Deibold, 1986; Ewing and Malik, 2010), non-linear GARCH-type models (Hillebrand and Medeiros, 2016), stochastic-volatility jump-diffusion models (Craine et al., 2000), Markov regime-switching models (Ma et al.,

[1] Note that the terms of abrupt jump (commonly used in the mathematics and engineering contexts) and structural break/ shift (commonly used in the economics and finance contexts) are used interchangeably throughout the study.

2017) with additional explanatory variables of structural breaks. Deibold (1986) is among the earliest to argue on upward bias persistence found in returns volatility that could be a spurious feature due to the omission of structural breaks in the estimation using the GARCH model. This is because the traditional GARCH model does not perform well in the presence of abrupt jumps especially involving long horizon forecasts (Hwang and Pereira, 2009). The abrupt jumps can cause sudden breaks in the unconditional mean and variance of time series data. In other words, the jumps may cause the parameters in the GARCH model to change permanently (Hansen, 2001) at a particular time and it is irreversible (Brooks, 2002).

It is often to observe that large samples can intensify the volatility persistence due to sudden jumps are likely to occur in the series (Valentinyi-Endrész, 2004). However, Mikosch and Starica (2004) claim that shocks are less persistent when shifts in variance are accounted for. Using the adjusted iterated cumulative sum of squares (ICSS) algorithm, Ewing and Malik (2010) detect structural breaks in oil price when these breaks are modelled endogenously into a GARCH model. Their findings indicate the underlying volatility dynamics change considerably and the oil shocks have a substantial initial impact but die out much more rapidly. Similarly, after controlling for the shifts in the modified cross-correlation function testing approach, the conditional variance in the natural gas spot prices and MSCI Qatar stock prices show lower sensitivity to both past shocks and volatility (Ahmed, 2017).

Moreover, Rapach and Strauss (2008) show that the estimates in the GARCH model with structural breaks using adjusted ICSS algorithm has significantly improved the forecasts of the U.S. exchange rate returns. Additionally, Fang et al. (2008) discover that after modelling the second moment with structural shifts, the leptokurtosis in the distribution of output growth turns to normality. The above empirical evidence infers that a properly specified framework should account for structural breaks if such shifts are present in the time series in order to improve the estimation and forecasting performance.

Disregarding the presence of structural breaks may produce spurious inferences that cause model instability (Andreou and Ghysels, 2009) and may have damaging impacts on financial risk management and prediction (Arouri et al., 2012) as well as optimal asset allocations (Pettenuzzo and Timmermann, 2011). As such, the issue on how to detect the number and location of multiple endogenous breakpoints is an important step before proceeding to econometric modelling. The structural break identification tests have been progressively studied by Chow (1960), Quandt (1960), Bai and Perron (1998; 2003), Inclan and Tiao (1994), Andreou and Ghysels (2002), Sansó et al. (2004) and among others. In early studies, the break dates are determined exogenously but this procedure could cause misleading conclusions as different markets might show varying speed and response to shocks (Rusgianto and Ahmad, 2013). Thus, detecting the break dates endogenously is more appropriate to capture the market behaviour that is due to the unexpected events.

Despite the extensive past literature on modelling volatility in the presence of structural breaks in various markets, the examination on the Islamic equity markets is still of scarce especially on the sectoral level. Charles et al. (2015) show that the Islamic markets do exhibit jumps in volatility that is originated from similar extreme events that affect its conventional counterparts. Using the Autoregressive Moving Average-Fractionally integrated GARCH model (ARMA-FIGARCH) combined with different copula functions under several estimation methods, Shahzad et al. (2018) investigate the portfolio implications between Islamic bond index (*Sukuk*) with various Islamic stock markets from 2005 to 2015. All models with the regime-switching copulas framework are found to have superior estimation in each of the bond-stock pairwise in the presence of structural breaks. Besides, Nasr et al. (2016) suggest that Markov-switching multifractal (MSM) model that allows for regime changes enhances the volatility forecasting performance and market risk prediction of the DJIM returns. Aloui et al. (2015a) found that the extreme events have increased the magnitude of the dynamic correlations between *Sharia* stocks and *Sukuk* of Gulf Cooperation Council (GCC) when the breakpoints under the Bai and Perron test are incorporated into the multivariate Fractionally Integrated Asymmetric Power ARCH model with dynamic conditional correlations (MFIAPARCH-DCC). Rusgianto and Ahmad (2013) use the Exponential GARCH (EGARCH) model to incorporate breakpoints and suggest the significant effect of structural shifts on the volatility behaviour of the *Sukuk* prices. Using a multivariate GARCH model with structural breaks, Tarek and Derbali (2016) further explore the time-varying linkages between the Al Rayan Islamic index and commodities indices from 2011 to 2014. Part of their findings reveals that the volatility persistence is reduced after incorporating the structural breaks. From the above empirical evidence, it is suggested that volatility modelling can be made more reliable by controlling for structural changes.

DATA AND METHODOLOGY

The dataset used in this study are the daily closing price indices from ten sectors under the DJIM, comprising of basic materials (DJIBSC), consumer services (DJICYC), oil and gas (DJIENE), financials (DJIFIN), healthcare (DJIHCR), industrial (DJIIDU), consumer goods (DJINCY), technology (DJITEC), telecommunications (DJITLS) and utilities (DJIUTI) indices. The data was obtained from the DataStream and there are 5737 observations for each stock series. The full sample was divided into in-sample data ranges from 1st January 1996 to 31st December 2016 with 5477 observations for estimation purpose while the out-of-sample spans from 1st January 2016 to 31st December 2017 with 260 observations for forecast evaluation purpose. Besides, the sample period covers several major financial crises to ensure that the data is highly volatile with possible abrupt jumps in the indices.

The DJIM is the subset of its conventional counterpart, Dow Jones Global Index (DJGI). The DJIM is chosen in this study as it is an Islamic equity benchmark index in the world due to its large potential for growth and profitability (Nasr et al., 2016). As of July 2018, the DJIM[2] consists of 2938 component stocks with the market capitalisation approximately to US$29.6 trillion from 44 countries. Its composition allocation by sector is technology (27.8%), healthcare (18.3%), industrial (15.6%), consumer goods (12.9%), consumer services (8.1%), oil and gas (6.3%), basic materials (6.3%), financials (3.2%), telecommunications (0.9%) and utilities (0.6%). It is not surprising that price movements of the sectoral indices are correlated with DJIM, but their performance can be varied. According to Ross et al. (2013), risk modelling estimations at a more disaggregated data such as sectoral level and the firm level (Nur-Syazwani and Bulkley, 2015) may capture risk-return dynamic better. Given the rise in sectoral index investing for international diversification, it is noteworthy to explore the return behaviour at sectoral level especially on Islamic market which is still received less attention.

Return specification

The daily continuous compounded rate of return, r_t at time *t,* is calculated as follows:

$$r_t = 100(\ln P_t - \ln P_{t-1}) \text{ for } t = 1, 2, ..., T \tag{1}$$

where P_t and P_{t-1} are the corresponding closing price index days t and $t-1$, respectively for each of the stocks indices. The equation for the returns of stock indices can be expressed as:

$$r_t = \mu_t + \varepsilon_t \tag{2}$$

where μ_t denotes the conditional mean and ε_t is the disturbance term, defined as

$$\varepsilon_t = \sigma_t z_t \tag{3}$$

where σ_t is the conditional variance and z_t is normally distributed with mean zero and variance one, $z_t \sim N(0, 1)$.

Identification of structural breaks approaches

Bai and Perron (1998 and 2003) provide a rigorous procedure which allows for the detection of multiple unknown breakpoints for mean regime shift. The model proposed a multiple linear regression with m breaks ($m+1$ regimes) as follows:

$$r_t = x_t'\phi + z_t'\delta_j + \varsigma_t \qquad ; \quad t = T_{j-1}+1, ..., T_j \tag{4}$$

[2] For more details, refer to http://asia.spindices.com/indices/equity/dow-jones-islamic-market-world-index

where r_t is the return series at time t; x_t and z_t are vectors of regressors in the dimension of $p \times 1$ and $q \times 1$ respectively; ϕ and δ_j are the coefficients of the corresponding vectors of regressors; ς_t the error term at time t with $\varsigma_t \sim N(0, \sigma_t^2)$ and $j = 1, ..., m+1$. The breakpoints $(T_1, ..., T_m)$ are explicitly treated as unknown. The estimation is based on the ordinary least square (OLS) method and is a partial structural change model since the parameter vector ϕ is not subject to shifts. Therefore, it is estimated using the entire sample. However, in this study, the pure structural change model is used by setting $p = 0$ where all the coefficients are subject to change with $z_t = [1 \quad r_{t-1}]'$. Bai and Perron (1998 and 2003) developed three types of test statistics to detect multiple structural breaks. The three tests are the $SupF_T(m)$ with a null hypothesis of no structural break ($m = 0$) versus the alternative of m breaks, double maximum tests ($UD_{\max}$ and $WD_{\max}$) with a null hypothesis of no structural break against the alternative of an unknown number of breaks and $SupF_T(m+1|m)$ with a null hypothesis of m versus $m+1$ breaks. Bai and Perron suggested that the double maximum tests should be performed if at least one break is present. If the $UD_{\max}$ and $WD_{\max}$ support the presence of a structural break in the series, then the $SupF_T(m+1|m)$ is executed to identify the number of breakpoints. Overall, Bai and Perron (2003) recommended the test of $SupF_T(m+1|m)$ that is based on sequential approximation which has more robust power in locating the structural breaks.

The regime shift detection has also extended into the variance series. Inclan and Tiao (1994) develop the ICSS algorithm which is based on the cumulative sums of squares statistic (IT statistic henceforth) to detect for multiple discrete changes in the unconditional variance. The ICSS algorithm has received much attention due to its adequate statistical power and easy implementation (Kang and Yoon, 2010). However, the IT statistic assumes that the residuals are independent, homoscedastic and of the Gaussian distribution. Andreou and Ghysels (2002), Sansó et al. (2004) and Rapach and Strauss (2008) document that these assumptions had caused the number of breaks using the statistic to be spurious. Hence, a non-parametric adjustment is made to the IT statistic (adjusted IT statistic henceforth) so that it fits into the dependent process such as GARCH (Sansó et al., 2004) model. Sansó et al. (2004) proposed the Kappa-1 (κ1) and Kappa-2 (κ2) tests which are nested on the ICSS test that consider the fourth order moment properties of disturbances and conditional heteroscedasticity into explicit account. The κ1 statistic corrects for normal distribution of residuals assumption, while the κ2 statistic controls for normal distribution and conditional heteroscedasticity of the residuals. Among the several tests for structural breaks in the unconditional variance, this study employs the breaks obtain from a κ2 test of adjusted IT ICSS[3] by the Sansó et al. (2004) for the volatility modelling. The κ2 statistic can be defined as follows:

$$\kappa_2 = \sup_k \left| T^{-0.5} G_k \right| \tag{5}$$

where $G_k = \hat{\omega}^{-0.5} \left| C_k - \frac{k}{T} C_T \right|, C_k = \sum_{t=1}^{k} \varepsilon_t^2$, $k = 1,2,...T$, $\varepsilon_t \sim i.i.d.(0, \sigma^2)$ and $\hat{\omega}$ is a non-parametric estimator of long run fourth moment of the series and is given by $\hat{\omega} = \frac{1}{T}\sum_{t=1}^{T}\left(\varepsilon_t^2 - \hat{\sigma}^2\right)^2 + \frac{2}{T}\sum_{l=1}^{m}\omega(l,m)\sum_{t=l+1}^{T}\left(\varepsilon_t^2 - \hat{\sigma}^2\right)\left(\varepsilon_{t-l}^2 - \hat{\sigma}^2\right)$ where $\hat{\sigma}^2$ is the variance of the ε_t and $\omega(l,m)$ is the Bartlett kernel function defined as $\omega(l,m) = \frac{m+1-l}{m+1}$.

Standard nonlinear return and volatility GARCH model

An autoregressive, AR(1)[4] specification is included in order to remove the autocorrelation in the return series as detected in the Ljung-Box Q-statistic presented in Table 1. The conditional mean equation can be written as follows:

[3] Refer Sansó *et al.* (2004) for more details on deriving of IT ICSS and adjusted IT ICSS algorithm.
[4] All indices are found decaying geometrically in the ACF plots and are highly significant at lag 1 in the PACF plots at 95% significance level (except DJIBSC and DJITLS which are significant at lag 2 but with very weak effect). This preliminary analysis shows that the series are in favor of the AR (1) process. The ACF and PACF plots are not shown here due to brevity and it is available upon request.

$$\mu_t = \theta_0 + \lambda r_{t-1} \tag{6}$$

This study employs the conditional variance of GARCH(1, 1) which is defined as:

$$\sigma_t^2 = \omega_0 + +\alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{7}$$

where ω_0 the drift factor, α the ARCH effect and β the GARCH effect with the restriction of $\omega_0 > 0$, $\alpha \geq 0$ and $\beta \geq 0$ to ensure positive variance. The α and β are less than one to ensure the stationarity of the conditional variance. The sum of α and β is usually close to one and indicate that the shocks are highly persistent. The choice of GARCH(1, 1)[5] model used in this study is based on the Schwartz information criterion (SIC) after examining the GARCH(*p*, *q*) model of order (0, 0) to (3, 3). In practice, by far the most common *p* and *q* time lags used in the empirical studies is the GARCH(1, 1). It is simple and yet produces good fit and accurate forecasts (Andersen and Bollerslev, 1998; Hansen, 2005; Ross, 2013).

Modified nonlinear return and volatility GARCH model

Besides, this study also applied the Bai and Perron procedure[6] and adjusted IT ICSS to the return series and the squared residual series of returns in order to identify the presence of multiple break dates in the unconditional mean and variance equations respectively. Both approaches test the null hypothesis of no structural breaks against an unknown number of structural breaks. In this study, a break date in the conditional mean is defined as the break at the intercept (level) and the AR term while a break date in the conditional variance is at the intercept (level) only. Hence, the conditional mean equation of the AR(1)-GARCH(1,1) model incorporated with structural breaks is presented in the form below

$$\mu_t = \theta_0 + \sum_{i=1}^{n}\theta_i D_i + \sum_{i=1}^{n}\phi_i D_i r_{t-1} + \lambda r_{t-1} \tag{8}$$

while the conditional variance equation as:

$$\sigma_t^2 = \omega_0 + \sum_{j=1}^{n}\omega_j D_j + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{9}$$

where D_i and D_j are the break dummy variables which take the value of one from each structural break date onwards and zero otherwise. Besides, the first derivative method of Marquardt is selected in this study as the optimisation algorithm. The Marquardt algorithm is a modification of Berndt, Hall, Hall, and Hausman (BHHH) algorithm that improves the convergence rate.

RESULTS AND DISCUSSION

Preliminary Analysis

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[5] The information criterion statistics are not shown here due to brevity and it is available upon request.

[6] As explained by Choi et al. (2010), the error terms may be serial correlations and time-varying volatility. It is known that all the indices exhibit serial correlation and heteroskedastic which will violate the OLS assumptions. In order to allow for serial correlation in the errors, a quadratic spectral kernel was specified based on heteroscedasticity- and autocorrelation-consistent (HAC) (Newer and West, 1987; Greene, 2012) covariance estimation with the use of pre-whitened residuals, whereby the kernel bandwidth is determined using the Andrews AR(1) method. The distributions of standard errors are allowed to differ across breaks which in turn satisfy the heterogeneity of errors. The maximum number of structural break is set to 5 and a restricted (Andrews, 1993) data interval at [0.15, 0.85] are implemented in this study.

The sample timespan covers several episodes of significant uncertainties that seem plausible to probe for the structural stability of volatility dynamics. The crisis include the 1997–1998 Asian financial crisis, 2000–2002

Dot-com bubble, 2008–2009 global financial crisis, the 2009–2012 Eurozone sovereign debt crisis and the gradual recovery of global markets in 2010. Figure 1 depicts the stock price trajectory of the daily DJIM sectoral indices during the sampling period. Two sharp drops are seen in all the Islamic sectoral indices during the last quarter of 2002 and 2008, which corresponds to the outburst of Dot-com bubble and the collapse of Lehman Brothers bank respectively. Another downtrend is witnessed in DJIFIN in the year of 1997 which coincide with the Asian financial crisis. Overall, the majority of the Islamic sectoral indices are on an upward trend except for DJIBSC, DJIFIN, DJITEC, DJITLS, and DJIUTI.

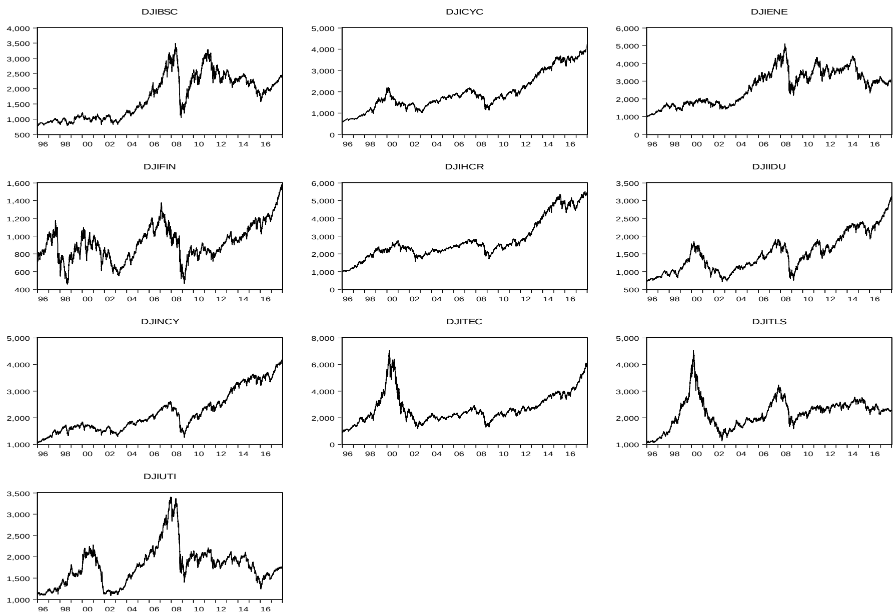

Figure 1 Daily stock price indices from 1996 to 2017

Table 1 reports the summary of the descriptive statistics of all the daily return series. All the indices show a small positive mean (profit) with the values close to zero. DJITEC is the most volatile index while the least is DJINCY. In the study by Ng et al. (2017), the findings also show that the consumer product market of the FTSE Bursa Malaysia Emas *Shariah* index (FBMS) had the lowest volatility which suggests consumer goods sector is often recession resistant.

Table 1 Summary of descriptive statistics

Indices	Mean	Std. Dev.	Skewness	Kurtosis	JB	Q	Q^2	ARCH Test	ADF	PP	BDS
DJIBSC	0.02	1.27	-0.51	12.06	19853	58.7	7026	245.49	-51.2	-60.1	0.016
					(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
DJICYC	0.03	1.06	-0.16	8.24	6576	30.9	2678	87.27	-53.4	-68.4	0.016
					(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
DJIENE	0.02	1.39	-0.48	12.05	19800	64.5	6840	220.49	-55.8	-70.0	0.012
					(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
DJIFIN	0.01	1.54	0.20	18.84	60032	51.2	4538	140.33	-77.0	-77.0	0.042
					(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
DJIHCR	0.03	0.94	-0.24	9.08	8877	54.7	2542	100.18	-54.5	-67.8	0.011
					(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
DJIIDU	0.03	1.06	-0.38	9.12	9101	33.7	4782	169.45	-51.3	-61.7	0.020
					(0.00)	(0.00)	(0.00)	(0.00)	(0.000	(0.00)	(0.00)
DJINCY	0.03	0.81	-0.28	10.16	12314	41.0	4099	147.98	-53.6	-66.7	0.011
					(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
DJITEC	0.03	1.56	0.06	7.94	5834	20.6	3279	99.43	-70.2	-70.0	0.029
					(0.00)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
DJITLS	0.01	1.10	-0.08	8.31	6732	45.9	3778	130.38	-45.0	-65.9	0.015
					(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
DJIUTI	0.01	1.04	0.05	20.56	73677	137.4	4820	194.26	-34.3	-69.7	0.019
					(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes:
1) Values in parenthesis are p-values.

2) Q and Q^2 statistics denote the Ljung–Box serial correlation test for standardized residual and standardized squared residual, Null hypothesis – No serial correlation; LM ARCH test: Null hypothesis - No ARCH effect; ADF and PP tests: Null hypothesis – The series has a unit root; BDS test: Null hypothesis – The series is of linearly dependent structure. Q, Q^2 and ARCH test are set at lag 12.

The results of skewness, kurtosis and Jarque-Bera (JB) tests show that the distributions are violated from the normality property. The Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) unit root tests reject the null hypothesis of a unit root in all series implying that the return series are stationary. Ljung-Box Q and Q^2 statistic tests also showed significant signs in standardised residual and squared standardised residual respectively for all series up to lag 12 at 1% significance level. The significant sign in the standardised residual series shows the evidence of strong serial dependence; this can be removed by fitting an Autoregressive model, AR(p) and the significant sign of the squared residual series reveals the presence of time-varying volatility effects. In the Brock-Dechert-Scheinkman test (BDS test hereafter) on the residuals of the linear autoregressive, AR(1), the test statistics[7] are found statistically significant for all series which provide evidence that the series is of a nonlinearly dependent structure. The result of the ARCH test exhibits the existence of strong ARCH effect in all indices. The ARCH model by Engle (1982) and later GARCH model by Bollerslev (1986) are the standard approaches for scrutinising time series with time-varying volatility properties. Therefore, it can be concluded that these results are in favour of the GARCH model.

EMPIRICAL ANALYSIS

Identification of structural breaks

The result of structural breaks test of Bai and Perron is summarised in Panel A of Table 2. The $SupF_T(m)$ exhibits significance up to m=5 and both the double maximum ($UD_{\max}$ and $WD_{\max}$) statistic are found significant in DJICYC, DJIENE, DJIFIN and DJITLS at 5% significance level which implies that at least one break is present in the mean series. Next, the sequential $SupF_T(m+1|m)$ test was employed to identify the exact number of breaks. For the $SupF_T(1|0)$ statistic, it is found significant in DJICYC, DJIENE and DJITLS that suggests the existence of one break (two regimes). For DJIFIN, it is found both the $SupF_T(1|0)$ and $SupF_T(2|1)$ statistic are significant which indicate two breaks (three regimes) while the rest of the indices do not experience any structural break in the unconditional mean.

On the other hand, based on the κ2 results of adjusted IT ICSS[8] algorithm in Panel B of Table 2, multiple breakpoints are detected throughout the year 1996 to 2014 in all the unconditional variance series except for DJINCY and DJIUTI with no break. It is learned that the Asian financial crisis which started in mid-1997 affect DJICYC, DJIENE, DJIHCR, DJIIDU, and DJITLS. While another break is observed during the last quarter of the year 2001 in DJIENE and DJIFIN that coincides with the terrorist attack in the U.S. The attack is seen to have an instantaneous effect in DJIENE while contagiously in DJIFIN. On the other hand, the subprime mortgage crisis emerged in the U.S. in the mid of the year 2007 which marked the beginning of the global financial crisis. Bordo (2008) pointed out that the default on mortgages affected the worldwide economy and equities market within a few months from its start in the U.S. The crisis spiked at its peak during the Lehman Brother bankruptcy on 15th September 2008 which significantly caused the stock markets to crash. The DJIBSC, DJICYC, DJIFIN, DJIIDU, DJITEC, and DJITLS series are unescapable of this crisis and several shifts are seen throughout the period from July 2007 to December 2008. During the recovery of

[7] Hsieh & LeBaron (1988) recommended choosing epsilon (distance measure) between 0.5 and 1.5 times the standard deviations of the data to optimize the size and power performance while the embedding dimension, m, is between two and five (Brock and Sayers, 1988). Therefore, in this study, m=5, epsilon=0.7 and significance level=5% are selected.

[8] This study has adopted the IT ICSS and adjusted IT ICSS (κ1 and κ2) tests. Based on the results, the total structural breaks are greatly reduced in the κ2 test as compared to IT and κ1 tests. Similarly, Ngene and Gordon (2015) noted that the IT test yielded the highest number of breaks as well. They also provide evidence of the break dummies showed stronger joint significance under κ1 and κ2 methods particularly κ2 test. Due to κ2 test has greater power in detecting multiple structural breaks, this study employs the breaks from κ2 test into modelling the return volatility. The results from IT ICSS and κ1 tests are not shown here due to brevity and it is available upon request. We would like to thank to Sansó for providing us the coding of IT ICSS, κ1 and κ2 that run in GAUSS statistical software.

the global economy, structural changes had been re-exhibited in these series in the second half of the year 2009. This is illustrated by the graphical analysis that the price series are transforming from downward to an upward trend in the year 2009. The European sovereign debt crisis began to spread in the late of the year 2009. It became systemic effect in the late of the year 2010 and the crisis persisted into the year 2012. Break

dates are discovered in the mid of the year 2010 in DJIFIN and late of the year 2011 in DJICYC, DJIIDU and DJITEC. According to Valentinyi-Endrész (2004), shifts are prone to occur more in the unconditional variance than in the case of unconditional mean which is consistent with the findings of this study that most of the series encounter breaks in the unconditional variance. Past literature has also shown that there are variations timing of the impact of a crisis from one market to another (Karunanayake et al. 2010) as a market may anticipate a particular crisis instantly or may take a longer time to react to other turmoil. Note that this study does not attempt to identify the grounds of the breakpoints but instead focus on how these observed breakpoints influence the volatility of the returns.

Table 2 Break dates identification in the unconditional mean and variance

	DJIBSC	DJICYC	DJIENE	DJIFIN	DJIHCR	DJIIDU	DJINCY	DJITEC	DJITLS	DJIUTI
Panel A: Structural breaks in the unconditional mean										
sup $F_t(1)$	1.829	19.275*	17.2*	22.26*	6.706	8.941	3.052	10.277	22.613*	5.309
sup $F_t(2)$	1.981	12.151*	9.788*	14.88*	9.44	7.033	2.02	5.895	14.255*	11.405*
sup $F_t(3)$	2.726	9.901*	9.475*	11.546*	7.004	5.353	2.626	5.551	10.444*	4.374
sup $F_t(4)$	2.464	8.226*	8.519*	9.469*	6.364	3.971	2.897	4.576	8.118*	5.498
sup $F_t(5)$	1.862	7.099*	6.724*	7.848*	6.4*	3.386	2.101	3.517	7.091*	4.902
UD_{max}	2.726	19.275*	17.2*	22.26*	9.44	8.941	3.052	10.277	22.613*	11.405*
WD_{max}	3.93	19.275*	17.2*	22.26*	12.548	8.941	4.622	10.277	22.613*	13.417
sup $F_t(1\|0)$	1.829	19.275*	17.2*	22.26*	6.706	8.941	3.052	10.277	22.613*	5.309
sup $F_t(2\|1)$		5.441	6.151	16.223*					8.874	
sup $F_t(3\|2)$				1.877						
Break Dates	-	16/11/01	30/7/02	29/8/07 27/10/10	-	-	-	-	24/7/02	-
Total breaks	0	1	1	2	0	0	0	0	1	0
Panel B: Structural breaks in unconditional variance										
Break Dates	3/12/96 23/7/07 8/9/08 8/12/08 24/6/09 27/9/12 16/4/14 24/9/14	10/10/97 11/7/03 25/7/07 5/9/08 5/12/08 1/6/09 1/8/11 20/12/11 9/12/14	30/6/97 10/9/01	5/12/01 27/5/03 6/2/07 31/7/07 12/9/08 16/12/08 4/5/09 15/7/09 22/7/10	21/1/97 23/6/03 17/12/04	22/10/97 31/12/99 19/5/03 23/7/07 3/9/08 8/12/08 1/6/09 1/8/11 30/11/11	-	29/7/98 15/10/98 28/3/00 2/6/00 12/10/00 23/4/01 2/4/03 3/10/03 27/10/04 25/7/07 12/9/08 8/12/08 1/6/09 8/7/11 3/1/12 3/4/12	7/3/97 30/7/98 22/2/99 23/8/99 20/4/01 5/4/02 18/7/02 27/11/02 29/5/03 23/7/07 12/9/08 8/12/08 3/6/09	-
Total breaks	8	9	2	9	3	9	0	16	13	0

Note: * indicate the significance level 5%

Conditional mean and variance of the modified return and volatility GARCH

The empirical results of the estimated conditional mean and variance coefficients generated from the univariate AR(1)-GARCH(1, 1) specification are reported in Table 3. The estimates of GARCH without structural breaks (standard GARCH henceforth) are shown in the first column, while the estimates of GARCH with structural breaks are in the second column. For this sub-section, the discussion focuses on the modified GARCH model to illustrate a better perception of the DJIM Islamic sectoral markets.

The estimated coefficients of the conditional mean equations are reported in Panel A of Table 3. The constant, θ_0 of all indices, are statistically significant at 1% significance level with positive values implying an upward drift in long-run. On the other hand, the current mean returns of all indices indicate a dependency on its first lagged return as observed in θ_1. This implies that the past return of the indices is affecting its current mean return. As for the coefficient of the dummy break variables in the mean equation, the first break date on 29th Aug 2007 observed in DJIFIN is negative and found statistically significant at the AR term at 1%

significance level while the second break on 27th Oct 2010 is insignificant at both level and AR term. For the coefficient of the one mean break found in DJICYC, DJIENE, and DJITLS that coincide with the Dot-com bubble is found negative and statistically significant at the AR term only. This infers that Dot-com crisis has an inverse impact on the mean return of DJICYC, DJIENE, and DJITLS.—

Table 3 Mean and volatility estimates using standard GARCH (1st column – no structural break) and modified GARCH (2nd column – with structural break) of daily return indices

	DJIBSC		**DJICYC**		**DJIENE**		**DJIFIN**	
	no SB	**with SB**	**no SB**	**with SB**	**no SB**	**with SB**	**no SB**	**with SB**
Panel A: Conditional mean equation								
Constant, θ_0	0.0392***	0.0376***	0.0587***	0.0743***	0.0570***	0.0490**	0.0470***	0.0553***
	(0.0120)	(0.0119)	(0.0106)	(0.0221)	(0.0139)	(0.0235)	(0.0119)	(0.0181)
Lag return, λ	0.2000***	0.2018***	0.0922***	0.1916***	0.1099***	0.1951***	0.0718***	0.1134***
	(0.0134)	(0.0137)	(0.0141)	(0.0256)	(0.0139)	(0.0237)	(0.0137)	(0.0182)
Dummy 1, ϕ_1				-0.1373***		-0.1239***		-0.1353***
				(0.0309)		(0.0292)		(0.0425)
Dummy 2, ϕ_2								0.0638
								(0.0464)
Dummy 1, θ_1				-0.0182		0.0137		0.0398
				(0.0251)		(0.0290)		(0.0486)
Dummy 2, θ_2								-0.0587
								(0.0481)
Panel B: Conditional variance equation								
Constant, ω_0	0.0088***	0.0138***	0.0099***	0.0315***	0.0143***	0.0103***	0.0097***	0.1200***
	(0.0024)	(0.0041)	(0.0022)	(0.007)	(0.0035)	(0.0037)	(0.0023)	(0.0231)
ARCH, α	0.0676***	0.0696***	0.0735***	0.0793***	0.0676***	0.0668***	0.0840***	0.0857***
	(0.0067)	(0.0089)	(0.0073)	(0.0105)	(0.0067)	(0.0069)	(0.0077)	(0.0096)
GARCH, β	0.9279***	0.8817***	0.9188***	0.8458***	0.9254***	0.9215***	0.9138***	0.8688***
	(0.0068)	(0.0151)	(0.0078)	(0.0198)	(0.0070)	(0.0078)	(0.0071)	(0.0137)
Dummy 1, ω_1		0.0339***		0.100***		0.0233***		-0.0404*
		(0.0079)		(0.0211)		(0.0082)		(0.0207)
Dummy 2, ω_2		0.1106***		-0.0889***		-0.0151**		-0.0460***
		(0.0363)		(0.0194)		(0.0068)		(0.0178)
Dummy 3, ω_3		1.8153***		0.0950***				0.1146**
		(0.7264)		(0.0295)				(0.0496)
Dummy 4, ω_4		-1.6836**		0.8305**				0.1182
		(0.7237)		(0.3745)				(0.0783)
Dummy 5, ω_5		-0.1886**		-0.7620**				3.6129**
		(0.1007)		(0.3744)				(1.567)
Dummy 6, ω_6		-0.0687*		-0.1573**				-3.3089**
		(0.0183)		(0.0676)				(1.5842)
Dummy 7, ω_7		- 0.0178***		0.1477**				-0.3209
		(0.0082)		(0.0638)				(0.3143)
Dummy 8, ω_8		0.0269***		-0.1654**				-0.1974
		(0.0092)		(0.0646)				(0.1424)
Dummy 9, ω_9				0.0140**				-0.0263*
				(0.0069)				(0.0143)
Degree of freedom	8.249***	9.3460	7.5320***	8.5088***	9.2782***	9.3772***	6.8873***	7.3519***
	(0.8221)	(1.0073)	(0.7683)	(0.9899)	(1.1156)	(1.1487)	(0.6689)	(0.7296)
Panel C: Estimated Volatility Persistence and Half-life								
$\alpha+\beta$	0.9955	0.9513	0.9923	0.9251	0.9930	0.9883	0.9978	0.9545
Half-life (days)	153.7	13.9	89.7	8.9	98.7	58.9	314.7	14.9
Panel D: Diagnostic Test								
Q	17.733	16.917	12.994	16.837	15.274	16.482	15.224	15.385
Q^2	7.2639	5.8174	25.07**	11.252	12.131	11.368	11.875	11.375
ARCH Test	0.5975	0.4891	2.1080**	0.9372	1.0167	0.9541	0.9403	0.9295
BDS Test	0.0001	-5.63×10^{-5}	0.0003	-0.0002	-0.0001	-0.0002	5.48×10^{-5}	-0.0003
Panel E: Model Selection								
Log Likelihood	-7948.498	-7915.649	-7222.378	-7171.835	-8636.748	-8622.463	-8370.942	-8327.446
AIC	2.9058	2.8967	2.6405	2.6261	3.1572	3.1534	3.0601	3.0489
Panel F: Out-of-sample forecast evaluation								
HMSE	1.8757	1.2919	1.6857	1.4644	1.5996	1.6328	2.2526	2.0929
HMAE	0.8806	0.831	0.869	0.8514	0.9349	0.9378	0.9918	0.9768
QLIKE	-0.4033	-0.3673	-0.5165	-0.4831	0.3393	0.3381	-0.2665	-0.2513

Note: ***, ** and * indicate the significance level at 1%, 5% and 10%. Values in parenthesis are standard errors. Q, Q^2 and ARCH test are set at lag 12. SB stands for structural break.

Table 3 (Continue)

	DJIHCR		**DJIIDU**		**DJINCY**
	no SB	**no SB**	**with SB**	**no SB**	
Panel A: Conditional mean equation					
Constant, θ_0	0.0482*** (0.0097)	0.0495*** (0.0097)	0.0541*** (0.0100)	0.0565*** (0.0099)	0.0430*** (0.0084)
Lag return, λ	0.0848*** (0.0139)	0.0828*** (0.0140)	0.1967** *(0.0140)	0.2014*** (0.0143)	0.1198*** (0.0141)
Panel B: Conditional variance equation					
Constant, ω_0	0.0145*** (0.0029)	0.0234*** (0.0067)	0.0098*** (0.0021)	0.0218*** (0.0046)	0.0105*** (0.0021)
ARCH, α	0.0835*** (0.0084)	0.0824*** (0.0094)	0.0878*** (0.0082)	0.0914*** (0.0115)	0.0835*** (0.0082)
GARCH, β	0.9017*** (0.0093)	0.8779*** (0.0137)	0.9051*** (0.0083)	0.8282*** (0.0211)	0.9001*** (0.0095)
Dummy 1, ω_1		0.0390*** (0.0106)		0.0478*** (0.0120)	
Dummy 2, ω_2		-0.0373*** (0.01)		0.0689*** (0.0208)	
Dummy 3, ω_3		-0.0024 (0.0053)		-0.1001*** (0.0225)	
Dummy 4, ω_4				0.0806*** (0.0256)	
Dummy 5, ω_5				1.2854** (0.5119)	
Dummy 6, ω_6				-0.9933* (0.5108)	
Dummy 7, ω_7				-0.3273** (0.1331)	
Dummy 8, ω_8				0.4164*** (0.1612)	
Dummy 9, ω_9				-0.4595*** (0.1633)	
Degree of freedom	6.6003*** (0.6214)	6.7742*** (0.6577)	8.013*** (0.7684)	9.1453*** (0.9968)	7.9154*** (0.8095)
Panel C: Estimated Volatility Persistence and Half-life					
$\alpha+\beta$	0.9852	0.9603	0.9929	0.9196	0.9836
Half-life (days)	46.5	17.1	97.3	8.3	41.9
Panel D: Diagnostic Test					
Q	15.552	14.673	15.912	17.731	15.065
Q^2	13.896	17.894	17.43	17.044	20.995**
ARCH Test	1.1992	1.5274	1.464964	1.423347	1.7455*
BDS Test	0.0001	-0.0001	0.0004	$-8.55\text{x}10^{-6}$	$5.54\text{x}10^{-5}$
Panel E: Model Selection					
Log Likelihood	-6699.999	-6680.493	-6985.554	-6935.972	-5780.904
AIC	2.4497	2.4437	2.554	2.5392	2.1139
Panel F: Out-of-sample forecast evaluation					
HMSE	1.2797	1.2525	1.4536	1.1474	1.3735
HMAE	0.8949	0.8921	0.8778	0.8393	0.8667
QLIKE	-0.4958	-0.4947	-0.6566	-0.6153	-0.8395

Table 3 (Continue)

	DJITEC		DJITLS		DJIUTI
	no SB	**with SB**	**no SB**	**with SB**	**no SB**
Panel A: Conditional mean equation					
Constant, θ_0	0.0707*** (0.0137)	0.0705*** (0.0137)	0.0342*** (0.0108)	0.0539** (0.0225)	0.0424*** (0.0097)
Lag return, λ	0.0910*** (0.0141)	0.0945*** (0.0144)	0.1335*** (0.0139)	0.2069*** (0.0248)	0.0653*** (0.0138)
Dummy 1, ϕ_1				-0.1071*** (0.0302)	
Dummy 1, θ_1				-0.0255 (0.0257)	
Panel B: Conditional variance equation					
Constant, ω_0	0.0091*** (0.0026)	0.1993*** (0.0423)	0.0064*** (0.0018)	0.0195*** (0.0052)	0.0111*** (0.0022)
ARCH, α	0.0749*** (0.0070)	0.0676*** (0.0103)	0.0618*** (0.0062)	0.0585*** (0.0082)	0.0837*** (0.0079)
GARCH, β	0.9235*** (0.0067)	0.8312*** (0.0252)	0.9335*** (0.0064)	0.8893*** (0.0153)	0.9064*** (0.0083)
Dummy 1, ω_1		0.7191** (0.3020)		0.0294*** (0.0096)	
Dummy 2, ω_2		-0.5335* (0.2967)		0.0836** (0.0379)	
Dummy 3, ω_3		1.4181* (0.7444)		-0.0850** (0.0404)	
Dummy 4, ω_4		-1.3396* (0.7590)		0.1088*** (0.0345)	
Dummy 5, ω_5		1.2670*** (0.4483)		-0.0700** (0.0325)	
Dummy 6, ω_6		-1.1093*** (0.4068)		0.1718* (0.0929)	
Dummy 7, ω_7		-0.4014*** (0.1138)		0.0911 (0.1687)	
Dummy 8, ω_8		-0.0617 (0.0568)		-0.2499* (0.1425)	
Dummy 9, ω_9		-0.0967*** (0.0312)		-0.0678** (0.0328)	
Dummy 10, ω_{10}		0.1192*** (0.0351)		0.0490*** (0.0166)	
Dummy 11, ω_{11}		1.6559** (0.6502)		0.6310** (0.2546)	
Dummy 12, ω_{12}		-1.4336** (0.6400)		-0.6022** (0.2537)	
Dummy 13, ω_{13}		-0.3152*** (0.1196)		-0.0821** (0.0395)	
Dummy 14, ω_{14}		0.2244*** (0.0810)			
Dummy 15, ω_{15}		-0.2634*** (0.0863)			
Dummy 16, ω_{16}		0.0176 (0.0172)			
Degree of freedom	8.014*** (0.8924)	9.4304*** (1.2318)	9.1292*** (0.9592)	10.0231*** (1.0865)	6.8912*** (0.6478)
Panel C: Estimated Volatility Persistence and Half-life					
$\alpha+\beta$	0.9984	0.8988	0.9953	0.9478	0.9901
Half-life (days)	432.9	6.5	147.1	12.9	69.7
Panel D: Diagnostic Test					
Q	9.6393	11.569	22.702**	22.595**	9.2805
Q^2	15.641	6.6886	19.016*	20.036*	13.767
ARCH Test	1.28444	0.5318	1.6448*	1.6889*	1.121912
BDS Test	0.0002	-0.0002	-7.12×10^{-5}	-0.0003	0.0002
Panel E: Model Selection					
Log Likelihood	-9003.402	-8939.975	-7366.442	-7321.976	-6765.475
AIC	3.2911	3.2738	2.6931	2.6824	2.4736
Panel F: Out-of-sample forecast evaluation					
HMSE	5.8217	4.1105	2.1843	1.5607	1.1123
HMAE	1.1222	1.0518	0.8598	0.8207	0.8138
QLIKE	0.1662	0.1542	-0.7573	-0.6623	-0.7461

The estimated coefficients in the conditional variance equations are reported in Panel B of Table 3. The ARCH effects, α , are found statistically significant in all indices at 1% significance level. This indicates their own lagged shocks influence the current conditional volatility of the indices. Among the indices, the DJIIDU (0.0914) shows the most in the magnitude of its past shocks impact on its current variance while the

least is DJITLS (0.0585). Thus, the higher the value of α implies that the recent news market has a more significant impact on its price changes due to the sensitivity of volatility to the recent market shocks. The GARCH effects, β , are found significant in all indices at 1% significance level. The findings discovered that GARCH effect is far much stronger than the ARCH effect in all indices. This indicates the past volatility has a greater impact than the past shock on the current conditional variance. In other words, the market price changes today are picking up more to the impact of price changes rather than to the 'older news'. Furthermore, it is observed that most of the estimated dummy break coefficients, ω_j in the variance equations, are statistically significant at 5% significance level. This signifies that the structural shifts do impact the current conditional variance of the series.

The diagnostic model of Q and Q^2 statistics fail to reject the null hypothesis with no serial correlation at the 5% significance level in the conditional mean and variance equations respectively except for DJITLS. Furthermore, all the series show no ARCH effects at the 5% significance level, except for DJITLS. The BDS test on the standardised residuals fails to reject the null hypothesis in all the series at the 5% significance level indicates the model successfully removes the non-linearity in the stock returns. Therefore, it can be concluded that the absence of serial correlation, no ARCH effect and linearity in the data imply that the AR(1)-GARCH(1, 1) model incorporated with structural breaks is correctly specified.

The degree of volatility persistence

This section deliberates on the volatility persistence obtained from the modified GARCH model. It addresses how persistent is the volatility when the sudden jumps are taken into consideration in the modelling. The estimated volatility persistence is reported in Panel C of Table 3. It is observed that the $\alpha+\beta$ is close to one in all markets. This exhibits the evidence that volatility is persistent and shocks tend to have a permanent impact on the conditional volatility.

We can further illustrate the degree of volatility persistence by measuring the period, in days, required for a shock to reduce persistence to one half-life with respect to its initial value. The half-life is computed as follows:

$$\text{Half life} = \frac{\log(0.5)}{\log(\alpha+\beta)} \tag{10}$$

The half-life measure reveals a similar trend as volatility persistence. When the return series is more (less) persistent, the half-life measure tends to be long (short). The change of half-life index reveals the impact of the external shock caused by the sudden event from the market. It is found that DJIENE has the highest half-life measure with 58.9 days, followed by DJIHCR (17.1 days), DJIFIN (14.9 days), DJIBSC (13.9 days), DJITLS (12.9 days), DJICYC (8.9 days), DJIIDU (8.3 days) and DJITEC (6.5 days). DJIENE is considered to have high half-life measures. This means a shock is expected to lose half of its original impact in DJIENE within 58.9 days, indicating a slow adjustment process and high volatility persistence. In general, a stock with long half-life will have weak mean reversion, inferring the stock return to take an extended period to move towards its initial volatility. Thus, the past price of DJIENE can be used to predict future price changes.

On the other hand, DJITEC has the lowest half-life measure that takes 6.5 days to return to half of its initial volatility, exhibiting a strong mean reversion. Interestingly, this is in contrast with the result claimed by Ngene and Gordon (2015) that the technology sector of MSCI does have the highest persistence among its sectoral markets. This may due to the different behaviour of return between conventional and Islamic stock markets. By and large, the empirical findings show that the external shocks caused by infrequent events hold varying volatility persistency levels across the sectoral markets. The degree of volatility persistence is of crucial property to consider when attempting to predict the variance. The higher the degree of persistence suggests the more significant impact of a shock on the future value of the variance (Aragó and Fernandez-lzquierdo, 2003). Besides, Poterba and Summers (1986) claim that shocks that permanently impact the variance will influence their asset prices to a greater degree than those that are temporary. This indicates that high persistence in volatility has a significant impact on the price of an asset and reflects the market is inefficient (Ngene and Gordon, 2015).

Comparison between standard and modified return volatility GARCH

The study further examines whether there is any implication of abrupt jumps in volatility persistence. After accounting for structural breaks, the $\alpha+\beta$ becomes smaller in all indices, inferring the impact of external shocks is comparatively short-lived than the standard GARCH model. This finding is in line with the past empirical evidence that ignoring structural shifts in volatility modelling results in overestimating the actual volatility persistence (Ewing and Malik, 2010; Tarek and Derbali, 2016). It is found that the most substantial declining degree of volatility persistence after considering structural change is DJITEC (a decline by 0.100) while the least is DJIENE (a drop by 0.005). This reveals DJITEC is the most sensitive to the impact of the external shocks while DJIENE is the least sensitive. Another noteworthy discovery is that after incorporating the breaks, the ARCH effect is seen to has increased in DJIBSC, DJICYC, DJIFIN, and DJIIDU although the overall volatility persistence has reduced. Thus, the increase of ARCH effect suggests that the new information is being reflected in prices more rapidly which is in line with the findings of Rusgianto and Ahmad (2013) in *Sukuk* market. Conversely, the GARCH effect for the series has been significantly dropped when including breaks in the model. This signifies the 'older news' will have less influence on today's price changes. In other words, the persistence of volatility tends to transform from long to shorter memory (Rusgianto and Ahmad, 2013) and consistent with the findings of Poterba and Summers (1986) and Ewing and Malik (2010) who both argue that volatility in financial markets responds reasonably stronger to unanticipated events; however, it decays rather fast.

Model selection and forecasting evaluations

For the model selection reported in Panel E of Table 3, the modified GARCH model has larger log-likelihood and a smaller value of Akaike information criterion (AIC) compared to the standard GARCH model across all indices. This demonstrates that the modified GARCH is more superior than the standard GARCH. For the out-of-sample volatility forecast evaluation, three statistical loss functions of heteroscedasticity mean square error (HMSE), heteroscedasticity mean absolute error (HMAE) and quasi likelihood (QLIKE) are reported in Panel F of Table 3. A rolling forecast approach was used to generate out-of-sample forecasts in order to include the newest market information while in the meantime to exclude out-of-date data. The size of the rolling window is fixed with 5477 observations while the last 260 observations from the total sample are selected as the out-of-sample forecasting horizon. Overall, the 1-day ahead out-of-sample forecasts performance indicate the modified GARCH outperforms the standard GARCH. This suggests that the GARCH with structural changes has efficiently captured the dynamics of the time-varying volatility behaviour and capable of improving the volatility forecast accuracy in the DJIM sectoral indices.

CONCLUSION

In this study, we examine the presence and impact of abrupt jumps that may cause structural shifts in the DJIM Islamic sectoral indices. The indices comprise of basic materials, consumer services, oil and gas, financials, healthcare, industrial, consumer goods, technology, telecommunications and utilities for a dataset from the year 1996 to 2017. The Bai and Perron (1998 and 2003) test captures jumps in the unconditional mean of the consumer services, oil and gas, financials and telecommunications sectoral markets. While the adjusted IT ICSS algorithm (Sansó et al., 2004) identified some multiple breaks in the unconditional variance of each sector except consumer goods and utilities. Thus, the consumer goods and utilities sectors are considered as an excellent defensive market during economic downturns. Also, it is discovered that the healthcare and oil and gas markets are not impacted by all the global shocks particularly the 2007 global financial crisis. The investors may be interested to seek and re-position their portfolios to these defensive stocks to protect price stability of their portfolio. The findings exhibit that not all the Islamic sectoral indices of DJIM are susceptible to major financial crises that had shaken the stock markets globally. In other words, the DJIM sectoral equity markets are not truly decoupled from the conventional stock markets; however, this evidence is not conclusive to all the Islamic stock markets.

The detected breakpoints are also incorporated into the AR(1)-GARCH(1, 1) model to estimate the impact of unanticipated news on the series. The findings found that the ARCH and GARCH effects are

statistically significant at 1% level in all the sectoral stock markets. The empirical results exhibit that the series respond differently to the impact of shocks in term of volatility persistence and half-life measures. It is found that the oil and gas sector shows the highest volatility persistence while the least is the technology sector. The indices display high volatility persistence when breaks are disregarded while volatility persistence drops when breaks are included in the model. A shock that is persistent (short-lived) will impact the variance and affect its price to move to a higher (lower) degree. This suggests that a stock price increases (decreases) will be followed by a few prices increase (decrease) for a particular time in the near future. On the other hand, when shifts are accounted for, it is found that the most significant decline in persistence is the technology sector while the lowest is in the oil and gas sector. This sheds light that among the Islamic sectoral markets, the most susceptible to the impact of shocks is the technology sector while the least is the oil and gas sector. This may be due to the common evidence that the volatility in oil prices typically triggered to broader financial markets rather than the reverse direction.

Overall, this study provides an improvement over some past research that ignores the structural breaks in the model specification which may considerably change the underlying volatility dynamics of the Islamic equity markets. The findings of this study are useful and important to investors and portfolio managers in asset pricing and portfolio selection.

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