Regime switching behavior of volatilities of Islamic equities: evidence from Markov- Switching GARCH models for some selected broad based indices

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Abstract

In this era of shaky global economic and financial conditions for about a decade now since the global financial crisis 2008, how the volatilities of Islamic equities worldwide are behaving, especially in terms of their regime changing behavior, if any, is the main issue of concern in this paper. To this end, a relatively novel technique, namely, Markov regime switching GARCH (MSGARCH) is applied to some selected broad based Islamic equity indices from both advanced and emerging world and of their combinations. The results tend to indicate that in general there is no persistence in any particular regime to prevail, rather a high regime switching behavior between volatile and less volatile regimes are present in Islamic equities around the world. This perhaps reflects the prolonged uncertainties prevailing in the world economies and therefore implies higher risk for the investors in predicting their investment outcome.

Keywords:

Markov regime switching, MSGARCH, GARCH

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1. Introduction:

In this era of turbulent financial and economic environment, especially after the great financial crisis of 2008, financial market is stumbling every now and then. Investors around the world are highly concerned of the dynamic behavior that the financial markets showing around the world. Islamic equities in this regard are of no exception. The risk and return behavior of Islamic equities are also not also very stable over time. During this vulnerable time, how Islamic equities are behaving, especially in terms of their return volatilities, how are they changing regime, if any, and what implications does this bear on the investors are of paramount importance to investigate. This paper will try to enhance our understanding on these issues.

To this end, we would first employ GARCH (Generalized Auto-Regressive Conditional Heteroscedasticity) models in different regional Islamic equity indices around the world to capture the time varying nature of return and volatilities of Islamic equities. Then moving from this whole sample implications, we would focus on subsample approaches, namely Markov Switching GARCH (MS-GARCH) to investigate the regime changing behavior of the stocks. We would like to see how leading regional Islamic equities around the world are changing their role between high volatility regime and low volatility regime. This is the first attempt of this kind of investigation in Islamic Equities, and would enlighten investors' and different stakeholders' understanding on the dynamic behavior of Islamic equities regarding regime changes and its risk implications.

1.1 The Nature of Return Data and Its Volatilities and the Relevance of GARCH Models:

Here we would start with the index and return data of Islamic equities, namely Dow Jones Islamic Equities World Index. The different nature of index and return serious is apparent from Figure 1. It shows that while the index serious is a reflection of random walk, the return series on the other hand could be a stationary process with finite variance. We can observe the fluctuation of the return series is different over time. The greatest fluctuation is around the great crash of stock market in 2008. Other fluctuations include the Asian financial crisis in 1997, dotcom crisis in 2000-2002, European debt crisis in 2011 and many other volatile periods in this turbulent era of world financial market. What is evident very clearly from the return series is that volatility is clustering around certain time periods meaning that a large changes tend to be followed by large changes of either sign and small changes tend to be followed by small changes (Mandelbrot, 1997). So though the means of the each of the volatility regimes are close to zero, the assumption seems very realistic is that volatility is dependent on past period's volatility.

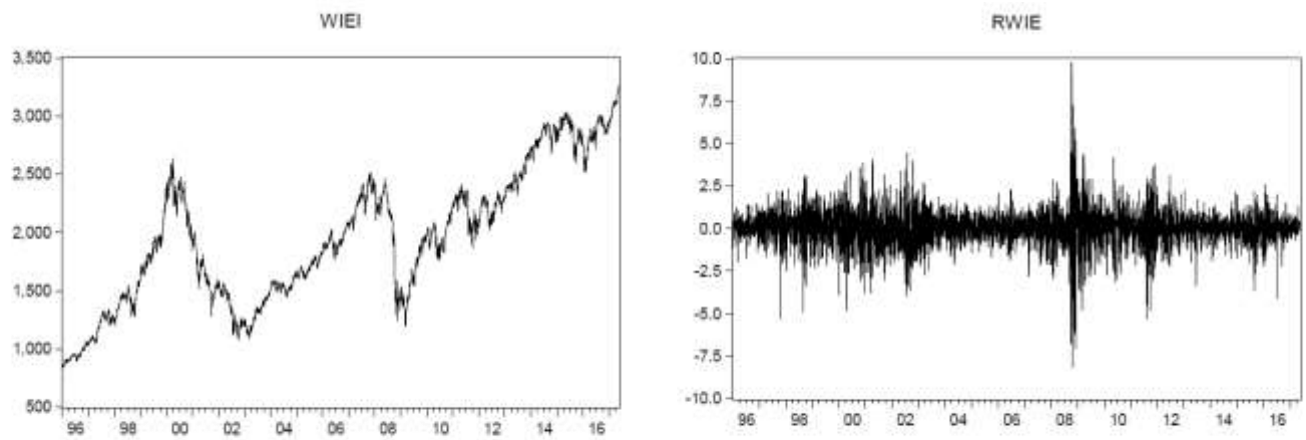

Figure 1: The Dow Jones Islamic Market World (DJIMW) Index (left) and daily returns of the index (right) in the period from 01-01-1996 to 16-5-2017.

Another way to look at the fluctuation of returns or volatility is the square of the return series as in Figure 2. The same conclusion we can draw from here is that volatility is a heteroskedastic process. Its marginal distribution has a time-varying and non-constant conditional variance, against constant variance in a homoscedastic marginal distribution. The most recognized models for modeling such heteroskedastic processes are the ARCH and GARCH model by Engle (1982) and Bollerslev (1986) respectively.

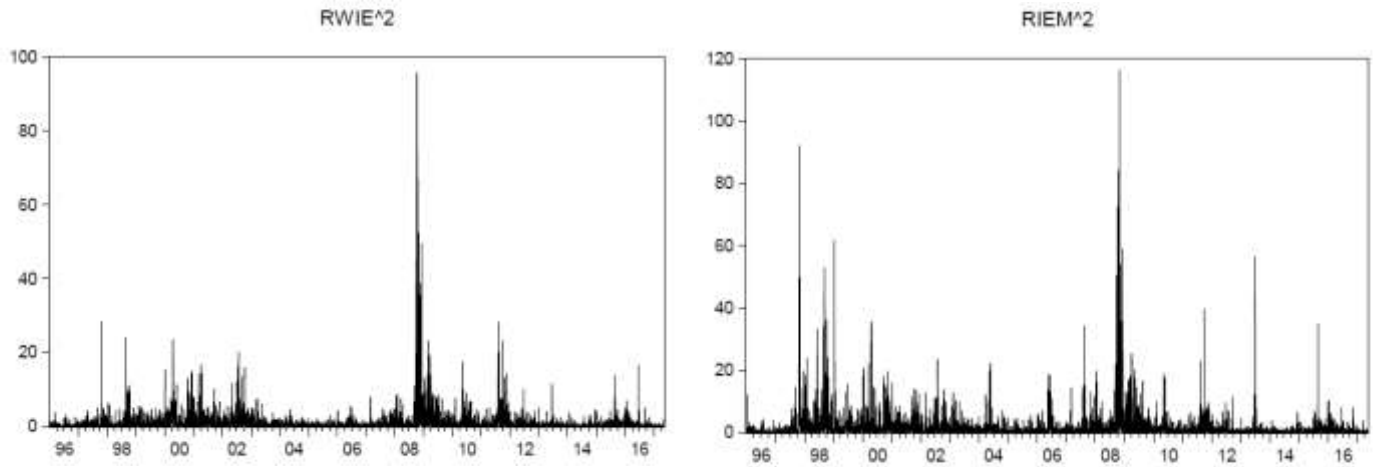

Figure 2: Squared daily returns of the Dow Jones Islamic Index for world and emerging market.

The phrase volatility clustering is used for a time series having serial dependence in the variance structure. So a process that displays volatility clustering should have significant autocorrelation in the squared returns. Such clustering is thus evidenced from the ACF curves of the return and squared return series of the world Islamic equity index in Figure 3. In the return series (left panel of the figure) there is no obvious sign of autocorrelation thus it is comparable with a white noise process. But the same figure for squared return series shows significant autocorrelations for even more than 30 lags. Which means volatility depends much on its past and hence calls for any model that want to replicate the data to capture the serial dependence in the return series. And here comes the rationality of using ARCH and GARCH model that attempt to capture non-constant volatility.

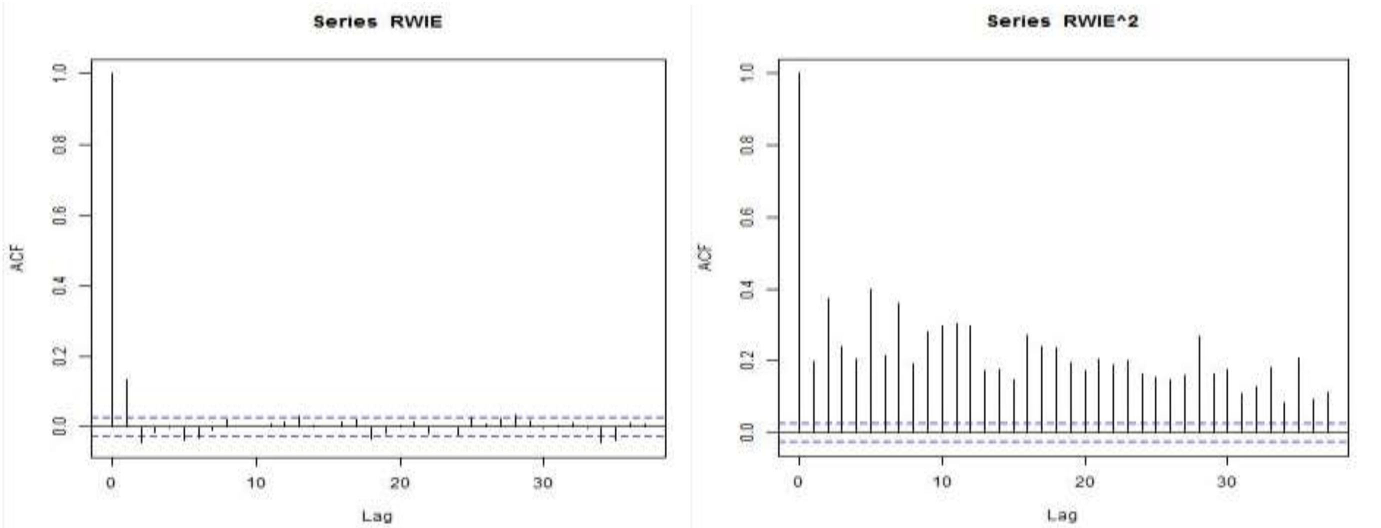

Figure 3: ACF of DJIMW index returns (left) and its squared returns (right) in the period form 01-01-1996 to 16-05-2017, together with a 95% confidence band

One of the limitations of classic ARMA model is that it assumes constant variance over time. But as mentioned earlier, many time series violates the assumption which calls for the ARCH which can accommodate time varying variance structure. Now as the required number of lags tends to increase due to the persistence nature of shock, the model lacks some flexibility as it has to estimate a number of parameters. This inability has given birth to the generalized ARCH or GARCH model, first introduced by Bollerslev (1986). This later model is capable of capturing the same autoregressive effects as the ARCH model, but with a lot less parameters to be estimated. This extra flexibility compared to ARCH comes from the fact that GARCH is based upon an ARCH (∞). As in GARCH, volatility is assumed dependent on the past conditional volatility, it allows to reduce the number of lags of square of past innovations to be included in the model and hence far less parameters to be estimated.

1.2 The Rationale of Using MSGARCH Model:

Now the GARCH model has its own limitation such as that, as the volatility of a series drops to low levels after a sudden shock, the estimated conditional variance has a hard time following the pace of shifts in the volatility level due to inherent persistence in the model. Thus it tends to overestimate the volatility in this case and vice versa. But such sudden shifts are common in financial data. So it calls for an extension of this model that can enable the model to react faster to these sudden changes and here comes the concept of Markov regime switching in GARCH model.

Lamoureux & Lastrapes (1990) showed that persistence is variance in GARCH model may be overstated due to existence of or failure to take account of structural shift in the model. One possible way to deal with this issue is to model the variance with two different models depending on whether the current period experiences high or low volatility. This is possible by merging the GARCH with a Markov Switching model, first introduced by Hamilton (1989). The basic idea behind the Markov Switching GARCH (MSGARCH) is to reduce the long GARCH persistence by switching from one variance structure to another. This MSGARCH model has been introduced both by Cai (1994), Hamilton & Susmel (1994) and later expanded by Gray (1996) and Klaassen (2002).

MSGARCH has at least two major advance over single regime GARCH model. In one hand, it improves the accuracy of GARCH forecasting with or without any structural break involved in the time series, while it also tells us the persistence of each regime, regime shifting probabilities and duration of a regime. It is in this second perspective, we would mainly concentrate in this study that whether any such regime exists in volatility of selected Islamic equities and what implication does it bear for the investors and other stakeholders.

As mentioned earlier that the financial world and the regional economies has encountered a number of crises in this study period. These crises with high volatility thus cause regime changes between at least between two regimes – low volatility high return regime and high volatility low return regimes. In our study we have assumed also these two regimes involved.

In the section 2 we would identify the data involved and the methodological details of GARCH and MSGARCH models used in this study. Section 3 will provide empirical results and discussions. And finally section 4 would conclude and highlight on some policy implications.

2. Data and Methodology:

We have chosen the Islamic equities based on development status of the economies and on different regional aspects. Specifically, these are from world, US, European, emerging, Asia-Pacific and GCC market. All of them are from Dow Jones Islamic equity indices as they are providing largest time period data and the study covers from January 1996 till May 2017. These are all broad based indices, thus would give us an overall trend in the markets round the globe. All data are sourced from Datastream. The daily log returns are calculated from each of the Indices. The following table shows the details of the variables used in this study. Programming package for MSGARCH is very new in R. We have used R programming package MSGARCH developed by (Ardia et al. 2016) for the computational purpose of the study.

Table 1: Variables used in the study

Variables	Description	Time Period
RWEI	Dow Jones Islamic Market World Index	1996-2017
RIUS	Dow Jones Islamic Market US Index	1996-2017
RIEU	Dow Jones Islamic Market Europe Index	1996-2017
RIEM	Dow Jones Islamic Emerging Market Index	1996-2017
RIAP	Dow Jones Islamic Asia-Pacific Index	1996-2017
RIGC	Dow Jones Islamic GCC Index	2004-2017

1. GARCH models

The rate of return r_t is defined as following:

$$r_t = 100[\ln(\frac{p_t}{p_{t-1}})]$$

where p_t is stock market index, t denotes the daily closing observations.

The GARCH(1,1) models for the series of returns r_t are used that they can be written as following:

$$r_t = \mu + \varepsilon_t = \mu + \xi_t \sqrt{h_t}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$$

where $\alpha_0 > 0,\ \alpha_1 \geq 0\ and\ \beta_1 \geq 0$ to ensure a positive conditional variance, and the innovation is conveniently expressed as the product of an i.i.d. process with zero mean and unit variance (ξ_t) times the square root of the conditional variance (h_t) (Marcucci, 2005).

2. Markov switching GARCH model:

The main feature of regime-switching models is the possibility for some or all the parameters of the model to switch across different regimes according to a Markov process, which is governed by a state variable, denoted s_t. The state variable is assumed to evolve according to a first-order Markov chain, with transition probability (Klaassen, 2002; Abounoori, Elmi, & Nademi, 2016)

$$\Pr(s_t = j \,|\, s_{t-1} = i) = p_{ij}.$$

That indicates the probability of switching from state *i* at time *t* −1 into state *j* at *t*. Usually these probabilities are grouped together into the transition matrix:

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} = \begin{bmatrix} p & 1-q \\ 1-p & q \end{bmatrix}$$

where for simplicity the existence of only two regimes has been considered. The ergodic probability (that is the unconditional probability) of being in state s_t= 1 is given by $\pi_1 = \frac{1-q}{2-p-q}$ (Klaassen, 2002; Abounoori, Elmi, & Nademi, 2016).

The MS-GARCH model in its most general form can be written as

$$r_t | \Omega_{t-1} \sim \begin{cases} f(\theta_t^{(1)}) & \omega.P.p_{1,t} \\ f(\theta_t^{(2)}) & \omega.P.(1-p_{1,t}) \end{cases}$$

where *f (·)* represents one of the possible conditional distributions that can be assumed, that is Normal (N) or student's t, $\theta_t^{(i)}$ denotes the vector of parameters in the *i*th regime that characterize the distribution, $p_{1,t} = \Pr(s_t = 1 | \Omega_{t-1})$ is the ex ante probability and Ω_{t-1} denotes the information set at time *t* − *1*, that is the *σ*-algebra induced by all the variables that are observed at *t* − *1*. More specifically, the vector of time-varying parameters can be decomposed into three components (Klaassen, 2002; Abounoori, Elmi, & Nademi, 2016).

$$\theta_t^{(i)} = (\mu_t^{(i)}, h_t^{(i)}, v_t^{(i)})$$

where $\mu_t^{(i)} = \mathrm{E}(r_t | \Omega_{t-1,} s_t = i)$ is the conditional mean (or location parameter), $h_t^{(i)} = Var(r_t|\Omega_{t-1})$ is the conditional variance (or scale parameter), and $v_t^{(i)}$ t is the shape parameter of the conditional distribution. Hence, the family of density functions of r_t is a location-scale family with time-varying shape parameters in the most general setting (Klaassen, 2002; Abounoori, Elmi, & Nademi, 2016).

Therefore, the MS-GARCH consists of four elements: the conditional mean, the conditional variance, the regime process and the conditional distribution. The conditional variance of r_t, given the whole regime path (not observed by the econometrician) $\tilde{s}t = (s_t, s_{t-1}, \ldots)$, is $h_t^{(i)} = V[\varepsilon_t | \check{s}, \Omega_{t-1}]$ For this conditional variance the following GARCH (1,1)-like expression is assumed

$$h_t^{(i)} = \alpha_0^{(i)} + \alpha_1^{(i)} \epsilon_{t-1}^2 + \beta_t^{(i)} h_{t-1}$$

In which, h_{t-1} is a state-independent average of past conditional variances. Actually, in a regime switching context a GARCH model with a state-dependent past conditional variance would be infeasible. The conditional variance would in fact depend not only on the observable information $\Omega t-1$ and on the current regime s_t which determines all the parameters, but also on all past states $\tilde{s}t-1$. This would require the integration over a number of (unobserved) regime paths that would grow exponentially with the sample size rendering the model essentially intractable and impossible to estimate. Therefore, a simplification is needed to avoid the conditional variance be a function of all past states. To integrate out the past regimes by also taking into account the current one, Klaassen (2002) adopts the following expression for the conditional variance

$$h_t^{(i)} = \alpha_0^{(i)} + \alpha_1^{(i)} \epsilon_{t-1}^2 + \beta_t^{(i)} E_{t-1}\{h_t^{(i)} | s_t\}$$

where the expectation is computed as

$$E_{t-1}\{h_{t-1}^{(i)}|s_t\}$$
$$= \tilde{p}_{ii,t-1}\left[\left(\mu_{t-1}^{(i)}\right)^2 + h_{t-1}^{(i)}\right] + \tilde{p}_{ji,t-1}\left[\left(\mu_{t-1}^{(j)}\right)^2 + h_{t-1}^{(j)}\right]$$
$$- \left[\tilde{p}_{ii,t-1}\mu_{t-1}^{(i)} + \tilde{p}_{ji,t-1}\mu_{t-1}^{(i)}\right]^2$$

And the probabilities are calculated as

$$\tilde{p}_{ji} = Pr(s_t = j|s_{t+1} = i, \zeta_{t-1}) = \frac{p_{ji}Pr(s_t = j|\zeta_{t-1})}{Pr(s_{t+1} = i|\zeta_{t-1})} = \frac{p_{ji}p_{j,t}}{p_{i,t+1}}$$

3. Empirical Results and Discussions:

3.1 Descriptive statistics of r_t:

Table 2 shows the descriptive statistics of the six different Islamic index daily returns examined in the study. The mean daily return is highest for the US Islamic equities (about 0.03%) though its standard deviation is comparatively high as well. The Skewness is small and negative, showing that the lower tail of empirical distribution of the return is longer than the upper tail. It means negative returns are more likely to be far below the mean than their counterparts.

Table 2: Descriptive Statistics of different Islamic equity index returns

	World IE	**US IE**	**European IE**	**Emerging IE**	**Asia-Pacific IE**	**GCC IE**
Mean	0.02394	0.02863	0.020909	0.014939	0.016226	0.017239
Std.Dev.	1.00832	1.22491	1.302994	1.288322	1.211177	1.393682
Skewness	-0.36573	-0.13997	-0.079262	-0.35261	-0.251109	-1.439338

Kurtosis	10.1034	9.8786	9.726474	9.087172	8.278331	21.10771
Jarque-Bera	11847.5	11011.1	10517.86	8724.349	6531.588	42778.4
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Observations	5576	5576	5576	5576	5576	3054

The more noteworthy information here is the Kurtosis. It is well above the normal value of 3 indicating that fat-tailed distribution, such as student-t, is necessary to correctly describe conditional distribution of r_t. That's why we have also considered t-distribution in our study along with normal distribution in both of our GARCH and MSGARCH models. This type of t-distribution modelling is also very commonly used throughout the literature of modeling financial time series (Klaassen, 2002). Many studies, including Haas & Pigorsch (2009), has shown that t-distribution is a better match on financial data relative to the normal distribution. Jarque-Bera tests are also showing that no return series is normally distributed. For all these reasons, we will focus more on t-distribution models of both GARCH and MSGARCH, though normal distribution results are also presented.

3.2 Single Regime GARCH:

Table 3 shows the single regime GARCH estimates for six broad based Islamic equity indices for the study period for both normal and t-distribution assumptions. Both the AIC and BIC criteria is favoring slightly in favor of t-distribution results for all the indices. Therefore we will continue sticking to GARCH-t findings, though we can see that the normal distribution implications are not much different for this single regime GARCH estimates.

Table 3: Estimated GARCH (1,1) parameters for normal and t-distribution models for selected Islamic equity indices

	World IE		US IE		European IE		Emerging IE		Asia-Pacific IE		GCC IE	
	GARCH-*N*	**GARCH-*t***	**GARCH- *N***	**GARCH-*t***	**GARCH- *N***	**GARCH-*t***	**GARCH- *N***	**GARCH-*t***	**GARCH- *N***	**GARCH-*t***	**GARCH- *N***	**GARCH-*t***
Mean equation												
μ	0.056759	0.069025	0.058323	0.07233	0.055891	0.063256	0.060399	0.069556	0.039631	0.049359	0.106863	0.081012
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.0014	0.0002	0.000	0.000
Variance equation												
α0	0.010484	0.007705	0.017549	0.011485	0.013037	0.011798	0.016087	0.011973	0.011556	0.008975	0.020361	14.02905
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.9102
α1	0.08932	0.08753	0.088158	0.090264	0.080364	0.083089	0.101535	0.089061	0.080354	0.070456	0.101677	41.99974
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.9101
β	0.900932	0.907626	0.899591	0.905451	0.91293	0.911997	0.891304	0.906589	0.913884	0.925306	0.896797	0.883335
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ν		7.489003		7.006304		9.32379		7.861517		8.198066		2.000961
p-value		0.000		0.000		0.000		0.000		0.000		0.000
AIC	2.487459	2.45749	2.878315	2.844247	3.014526	2.995192	2.992392	2.967574	2.94367	2.917235	2.983703	2.5566
SBC	2.492212	2.463432	2.883068	2.850189	3.019279	3.001133	2.997146	2.973516	2.948424	2.923176	2.991593	2.566462

The table 3 also shows that all the conditional mean and variance estimates are highly significant. All the mean daily returns from different Islamic indices are positive and significant with the highest daily mean return of .08% is in GCC market and lowest of .05% in Asia-Pacific market. More importantly, in the variance equation, it reveals that all the single regime models are weak stationary as $\alpha_1+\beta < 1$, which means shock to volatilities of all the indices are much persistent and only gradually decay to their mean values which is close to zero.

3.3 Markov Regime Switching GARCH:

As mentioned earlier, our main focus is to investigate not this single regime model, but to see what is the regime changing behaviors of volatilities for all of these Islamic indices across the world. Table 4 is showing us this findings from the Markov regime switching GARCH models for each of the indices. Here again we have presented the normal and t distribution results where both the AIC and SBC criteria are slightly in favor of MSGARCH-t model, as the lower their values, they indicate better fit of the model. Only in case of US Islamic equities both of them have favored normal distribution model. Though the degrees of freedom, ν from both the regime is suggesting the usefulness of t-distribution assumption, as its value is less than 30 for both the regime. Hence, we would focus on the t-distribution results mainly, though we can always compare the two results.

Table 4 also shows that there is a clear difference, as expected, in conditional volatilities (σ) of the two regimes, as the first regime is much less volatile than the second one. One thing to note that all indices for all the regimes are stable as $\alpha_1+\beta < 1$. We can also observe that the GARCH effect (β) is higher for all the indices compared to ARCH effect ($\alpha 1$), though the extent differ between regimes and among indices. This difference would affect volatility clustering for indices in higher α_1 regime and lower β regime.

More importantly, the persistence ($\alpha_1+\beta$) of shocks to volatility across indices and regimes are quite high except few exceptions. It means in both of the regimes, the shock will only gradually decay. Exception here are the World and US Islamic equities in less volatile regime one where the

Table 4: Markov Switching GARCH(1,1) estimates for normal and t-distribution assumption in both regimes for selected Islamic equity indices

	World IE		**US IE**		**European IE**		**Emerging IE**		**Asia-Pacific IE**		**GCC IE**	
	N	**t**	**N**	**t**	**N**	**t**	**N**	**t**	**N**	**t**	**N**	**t**
α0	0.00225	**0.00282**	0.00034	**0.00010**	0.00447	**0.00043**	0.00010	**0.00011**	0.00010	**0.00010**	0.02378	**0.00014**
α0	0.02315	**0.00934**	0.02464	**0.00010**	0.22419	**0.02183**	0.03726	**0.07363**	0.04141	**0.03057**	0.12408	**0.04249**
α1_1	0.03523	**0.01081**	0.01582	**0.00010**	0.06887	**0.01684**	0.00507	**0.03202**	0.01210	**0.02879**	0.01425	**0.99980**
α1_2	0.10553	**0.08256**	0.09766	**0.05672**	0.14952	**0.13761**	0.13178	**0.21087**	0.12046	**0.12661**	0.12063	**0.09207**
β1	0.87548	**0.77050**	0.75542	**0.00012**	0.91802	**0.98142**	0.98542	**0.96131**	0.97485	**0.96842**	0.36048	**0.00010**
β2	0.88941	**0.91085**	0.89641	**0.94318**	0.84738	**0.85213**	0.86405	**0.78324**	0.87461	**0.86607**	0.87470	**0.90071**
ν1	.	**10.20305**	.	**2.10000**	.	**10.38519**	.	**8.43773**	.	**6.32595**	.	**2.10000**
ν2	.	**10.71157**	.	**9.95871**	.	**13.39629**	.	**16.27110**	.	**19.06159**	.	**3.53312**
p	0.11333	**0.01014**	0.05250	**0.03425**	0.89692	**0.49269**	0.00000	**0.68593**	0.00000	**0.13194**	0.48123	**0.11510**
q	0.65846	**0.94125**	0.84165	**0.95610**	0.16943	**0.71688**	0.64983	**0.56442**	0.44672	**0.00000**	0.50824	**0.61398**
σ1	0.15888	**0.11348**	0.03876	**0.01000**	0.58393	**0.49440**	0.10256	**0.12657**	0.08859	**0.18961**	0.19502	**1.16961**
σ2	2.13745	**1.19112**	2.03899	**1.00000**	8.51275	**1.45859**	2.99031	**3.53406**	2.89861	**2.04329**	5.15820	**2.42628**
AIC	13927.7	**13798.86**	16280.92	**16946.66**	16775.23	**16721.77**	16670.02	**16560.57**	16440.04	**16325.56**	9046.211	**8759.943**
SBC	13980.71	**13865.12**	16333.93	**17012.92**	16828.24	**16788.03**	16723.03	**16626.83**	16493.04	**16391.82**	9094.405	**8820.185**

Note: Here α1 is the ARCH effect, β is the GARCH effect, ν1 and ν2 are the degrees of freedom for regime 1 and 2 respectively, and σ1 and σ2 are the conditional variances for the regime 1 and 2 respectively.

persistence is bit lower for World Islamic indices, while it is quite in strict stationary for US Islamic equities in this regime.

The fat tailed nature of the return distribution of financial market is quite evidenced as we can see the persistence probability of each regime has generally improved in the cases of t-models compared to N-models.

The most important finding, however, we can extract here is from the transition probabilities. The probability for staying in less volatile regime is very low for all indices except moderate probabilities for European and Emerging Islamic equities. And the probabilities to stay in the volatile region is quite high, i.e. much persistent for World and US Islamic equities. All other indices except that of Asia-Pacific, this probability is only moderate. This probability is quite nil for Asia-Pacific indices.

All these probabilities imply that volatile regime for World and Islamic equities are much persistent, otherwise the regime switching tendencies are much higher for all the indices and in all regimes. It means, most of the Islamic equities frequently move from volatile regime to less volatile regime and vice versa. As a result, investors and fund managers will find hard times in forecasting their investment performance. The forecasts would be frequently either upward or downward biased. This might be a reflection of the uncertainties that are highly prevalent in almost all parts of the world economy for about a decade now since the global financial crisis.

Now if we look into the details of the probabilities, we can see that while volatile regime is relatively more persistent for Islamic equities in US, Europe, and surprisingly GCC markets, less volatile regime is relatively more persistent in emerging and Asia-Pacific markets. Well, this might be because of the more turbulent and troublesome economic condition of the west or advance countries compared not so worse condition of emerging and eastern economies.

4. Conclusions and Policy Implications:

The main goal of this paper was to investigate the regime switching behavior of some selected broad based Islamic equity indices around the globe. A relatively novel MSGARCH models was mainly employed for the purpose. Our findings suggests that in this turbulent era of global economic and financial environment, there is no persistence of Islamic equities in any regime either volatile or less volatile. That is the regime switching tendency between the two regimes are very high. This might be a reflection mainly of the long standing uncertainties that is prevailing in the global economy since the global financial crisis of 2008. All it means is that Islamic equity investors should expect to face varying degrees of risk in their investment from low to high quite frequently until any persistence in regime appears in the market. It also means that they should be ready to face more forecast error in their investment outcome as there would be possibility to either overestimate or underestimate the risks involved in their investments due to high regime switching behavior of Islamic equities.

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