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Modelling Islamic Stock Market Volatility in ASEAN-5: A Standard GARCH and Asymmetric GARCH Models

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Abstract

Purpose: This study aims to estimate volatility characteristics and compare different volatility models for ASEAN-5 Islamic stock markets. The distinct characteristic of the volatility of the particular capital market is not directly noticeable. Therefore, selecting the proper volatility model in evaluating the Islamic stock returns volatility behavior is crucial when analyzing risk-to-risk interaction between two financial series.

Design/methodology/approach: Time series weekly data of Morgan Stanley Composite Index for ASEAN-5 Islamic stock price were collected, covering the periods from 01 January 2010 to 25 December 2020. Several volatility models of standard Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and asymmetric GARCH models of Threshold GARCH, Exponential GARCH, and Power GARCH were used to examine the persistence and leverage effects in the volatility structure. This study compares the volatility models based on several diagnostic tests, the likelihood ratio, and whether the model violates the essential assumptions. The STATA version 16 will use to analyze the obtained data.

Findings: The findings revealed that the ASEAN-5 Islamic stock returns are sensitive to prior volatility movements, with negative shocks having a bigger impact on volatility than positive shocks. The standard GARCH (1,1) model is adequate for capturing ASEAN-5 market volatility by treating both positive and negative shocks symmetrically. Yet, considering the asymmetry effects of financial markets, the Power GARCH (1,1) model is adequate for Islamic stock markets in Malaysia, Singapore, and the Philippines. The Exponential GARCH (1,1) model is appropriate for Islamic stock markets in Indonesia.

Research limitations/implications: The present paper examines the volatility characteristics and compares different types of volatility models for ASEAN-5 Islamic stock returns. These findings should be further explored by including the recent study timeframe and making a comparison with the volatility behavior of conventional stock returns. Besides that, this study has been focusing on ASEAN-5 countries. Further, the research could explore other regions and countries.

Practical implications: The study's findings provide a better understanding of the volatility features and volatility models used. The results of recommending the appropriate GARCH-type models for each country may benefit the portfolio advisor, investors, and related parties in estimating the stock market volatility behavior.

Originality/value: In terms of context contribution, there is still a scarcity of research focusing on simulating the volatility of the Islamic stock market, as most previous studies focused on conventional stock markets. As a result, this study fills a gap by adding to the body of knowledge on evaluating volatility behavior in the ASEAN-5 Islamic stock market. This study could serve as a concise guide for future research.

Keywords: Volatility, Standard GARCH, Asymmetric GARCH, Islamic Stock Market, ASEAN-5

Introduction

The study of the nature and behavior of volatility for financial variables has sparked increased interest, notably among researchers, academicians, portfolio advisors, and investors. There are several stylized facts that may be posed for financial variables, particularly in the capital market, such as volatility clustering, symmetrical information, asymmetry effects, and leptokurtic. Volatility clustering suggests that small price changes are followed by smaller price movements and vice versa. Symmetrical information means both past positive and negative information (shocks/news) yield similar impact on the volatility. Black (1976) proposed the concept of the leverage effect that negative news or shocks have a greater impact on volatility than positive shocks. Meanwhile, the financial variable tends to be leptokurtic, which means the variables are typically not normally distributed but show fat tails. In addition, econometric modeling can be used to capture all these stylized facts. Again, estimating financial series will advantage the investment decisions, portfolio optimization, or even form sound policy to mitigate financial risk.

Among the Association of Southeast Asian Nations (ASEAN) members, ASEAN-5 (Malaysia, Singapore, Indonesia, the Philippines, and Thailand) was recognized as the best destination for investment with a fast-growing emerging economy. The financial market is crucial to economic development. Due to its features and continuing growth in the global market, the Islamic stock market has recently gained wider attention from Muslim and non-Muslim investors. As a result, the Islamic stock market may serve as an alternative to the conventional stock market. Meanwhile, the Islamic stock market posed several features, such as following the principles of Shariah (Islamic law), industrial screen, and financial screen process. The stock is only classified as shariah-compliant stock as it is prohibited from usury (riba), deception (gharar), alcohol (khamr), and gambling (maysir).

Furthermore, based on the past empirical studies, the findings were varied. Questions were raised as to which volatility model is best suited to estimate capital markets and does the volatility model sufficiently captures the volatility characteristic of the market. There are scarce studies that solely focus on the Islamic stock market and model its volatility properties. Hence, this study aims to estimate volatility characteristics for ASEAN-5 Islamic stock markets and compare several volatility models of standard GARCH and asymmetric GARCH models of TGARCH, EGARCH, and PGARCH. Again, choosing proper volatility models to evaluate market volatility behavior may provide further evidence and insight into the capital market.

Literature Review

Numerous studies have explored the volatility estimation for the capital market to examine the volatility characteristics and compare the ability of different GARCH family models. Herbert et al. (2019) examined the phenomenon of volatility clustering and leverage effect in stock returns of the Nigerian stock market using GARCH and GJR-GARCH models from January 2010 to August 2016. The GARCH (1,1) model indicated persistent volatility clustering in the Nigerian stock market, while the GJR-GARCH (1,1) model adequately captured the leverage effects. Nurdany et al. (2021) revealed that both GARCH (1,1) and TGARCH (1,1) models show the existence of volatility and leverage effects on the Indonesian Shariah Stock Index (ISSI) for January 2020 to July 2020. Samineni et al. (2021) demonstrated leverage effects in the National Stock Exchange of India using EGARCH (1,1) model for January 2011 to December 2020. Umar et al. (2021) examined the volatility structure of equity returns in Pakistan from 2006 to 2020. The GJRGARCH and EGARCH models' results indicate the occurrence of persistence and asymmetry in volatility. Yet, Sali and Nazar (2021) discovered that both EGARCH (1,1) and TGARCH (1,1) models failed to explain the impact of information assimilation on the Indian stock index.

Khan et al. (2019) analyzed and compared the ability of different GARCH family models on eleven Religion Dominant Countries' market returns from 2011 to 2017. The findings revealed that the EGARCH (1,1) and GJR-GARCH (1,1) models executed better results than the standard GARCH (1,1) model in estimating the volatility of RDCs stock markets. The coefficient of leverage terms indicated that negative shocks had a greater effect on conditional variance than positive news. Rusere and Kaseke (2021) revealed that EGARCH (1,1) model is the best-suited model for capturing the volatility of the Johannesburg Stock Exchange, as it has the highest estimated log-likelihood and the lowest AIC and SIC. Naik and Reddy (2021) attempted to model and test the predictive ability of symmetric GARCH and asymmetric TGARCH and EGARCH models in the India Volatility Index from 2009 to 2016. The results revealed that the variance equation for all models was close to one, implying that the conditional variance innovation takes longer to die down and is exceedingly persistent. Meanwhile, the asymmetric models indicated that positive shocks have larger impacts on India Volatility Index than the negative shocks. Yet, the GARCH (1,1) model was the best fit for estimating the India Volatility Index due to the lowest AIC, SIC, and no additional ARCH effects.

In short, the past empirical studies focus on different study time-frame, different estimated countries, distinct stock markets, and different data frequencies used. In addition, there is still limited research that focuses on modeling the volatility of the Islamic stock market since most of the prior studies emphasized conventional stock markets. Thus, this study aims to fill this gap by providing another body of knowledge on estimating the volatility behavior of the ASEAN-5 Islamic stock market, comparing and recommending a sound proper volatility model for each ASEAN-5 Islamic stock market.

Method

Secondary time series weekly data of Morgan Stanley Composite Index (MSCI) for ASEAN-5 Islamic stock price were collected from 01 January 2010 to 25 December 2020. All data were retrieved from the Bloomberg website. The MSCI act as the global stock price benchmark, which investor may consider before entering a particular nation's stock market. The data will be transformed into natural logarithm form using the equation (1). R_t represents the returns, $ln\, P_t$ and $ln\, P_{t-1}$ refer to the natural logarithm of current and previous prices, respectively.

$$R_t = ln\, P_t - ln\, P_{t-1} \qquad (1)$$

The Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) unit root tests will be used in this study to assess the stationarity of the financial market data series as essential for data analysis. The null hypothesis states that the data exhibit a unit root problem and vice versa for the alternative hypothesis. Using non-stationary data might leads to spurious or misleading regressions and outputs. The ARCH (Autoregressive Conditional Heteroscedasticity) test is used to detect whether or not the residual series exhibits the ARCH effect. If the ARCH effect is apparent, proceed to the GARCH-type models.

Bollerslev (1986) proposed the Generalized ARCH (GARCH) model, which expands the ARCH(p) model by incorporating lagged conditional variance terms as autoregressive terms that allows for both longer memory and more flexible lag structure. The GARCH (p,q) model can be define as equation (2). The term h_t denotes the condition variance at time t, $\sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2$ and $\sum_{j=1}^{q} \beta_j h_{t-j}$ represent the ARCH and GARCH terms, p and q refer to the lagged term of squared error and conditional variance, α_0, α_i, and β_j refer to the constant, coefficient for ARCH and GARCH term, respectively. Note that the sufficient condition for GARCH model is met as $\alpha_0 > 0$, $\alpha_i > 0$, and $\beta_j > 0$ and the sum of α_i and β_j must lower than one to ensure the stationarity purpose.

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \tag{2}$$

However, the standard GARCH model treats both “bad” and “good” news symmetrically as yield similar impact on future volatility. Noted that the bad and good news is more sensible for financial markets, and the impact could be asymmetrical. Therefore, several asymmetric GARCH models have been proposed to capture the leverage effect. These asymmetric GARCH models include the Exponential GARCH (EGARCH) by Nelson (1991), Threshold GARCH (TGARCH/GJR-GARCH) by Zakoian (1994) and Glosten et al. (1993), and Power GARCH (PGARCH) by Ding et al. (1993). Equation (3) refers to the EGARCH (p,q) model, which constructs the conditional variance equation in logarithms form. The model captures the asymmetric effect through the coefficient of gamma (γ). If $\gamma > 0$, suggests that positive shocks cause higher volatility than negative shocks. If $\gamma < 0$, leverage effects are exhibited in volatility. There are no restrictions of positive constraints on the parameters α_0, α_i, and β_j.

$$\log(h_t) = \alpha_0 + \sum_{i=1}^{p} \left(\alpha_i \left| \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} \right| + \gamma_i \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} \right) + \sum_{j=1}^{q} \beta_j \log(h_{t-j}) \tag{3}$$

The PGARCH (p,q) model can be specified as equation (4), where the d denotes as the power term parameter, while γ represents the asymmetry parameter used to capture the leverage effects of the volatility and is required to be $-1 < \gamma < 1$. The non-negative parameter restriction is imposed and the sum of α_i and β_j must be lower than one. Equation (5) refers to the TGARCH (p,q) model with the ARCH and GARCH terms of $\alpha_1 \varepsilon_{t-1}^2$ and $\beta_1 h_{t-1}$ and γ represents the leverage terms. The non-negative parameter restrictions were imposed and the sum of α_i, β_j, and $\gamma_i/2$ must less than one. $\gamma > 0$ imply the presence of asymmetric effects while $\gamma < 0$ implies that the positive shocks may have a larger impact on volatility.

$$\sigma_t^d = \alpha_0 + \sum_{i=1}^{p} \alpha_i (|\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i})^d + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^d \tag{4}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \beta_i h_{t-i} + \sum_{i=1}^{p} (\alpha_i + \gamma_i I_{t-i}) \varepsilon_{t-i}^2 \tag{5}$$

In terms of model selection, the best-suited model is found when the Akaike Information Criterion (AIC) and Schwartz Information Criterion (SIC) values are minimum, maximum for log-likelihood, and free of diagnostic tests such as the ARCH-LM test, correlogram, and squared correlogram test.

Findings

Table 1 shows the results of the unit root test and ARCH test for ASEAN-5 Islamic stock returns. Based on the outputs, the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests indicate no unit root problems presented in the financial data set. All data were stationary at level. The ARCH test results demonstrate that the Islamic stock returns exhibit ARCH effects for all ASEAN-5 economies and shall proceed to GARCH-type models, except for Thailand's Islamic stock returns.

Table 1: Outputs for Unit Root Tests and ARCH test.

			IMR	ISR	IIR	IPR	ITR
ADF	Level	Intercept	-24.00*** (0.00)	-23.36*** (0.00)	-29.48*** (0.00)	-23.99*** (0.00)	-15.35*** (0.00)
		intercept & trend	-24.04*** (0.00)	-23.42*** (0.00)	-29.48*** (0.00)	-24.03*** (0.00)	-15.35*** (0.00)
	First Difference	Intercept	-13.40*** (0.00)	-12.53*** (0.00)	-13.80*** (0.00)	-15.44*** (0.00)	-15.17*** (0.00)
		intercept & trend	-13.40*** (0.00)	-12.52*** (0.00)	-13.79*** (0.00)	-15.42*** (0.00)	-15.15*** (0.00)
PP	Level	Intercept	-24.05*** (0.00)	-23.36*** (0.00)	-29.89*** (0.00)	-24.47*** (0.00)	-24.20*** (0.00)
		intercept & trend	-24.13*** (0.00)	-23.41*** (0.00)	-29.90*** (0.00)	-24.72*** (0.00)	-24.19*** (0.00)
	First Difference	Intercept	-193.55*** (0.00)	-237.58*** (0.00)	-235.61*** (0.00)	-239.27*** (0.00)	-247.36*** (0.00)
		intercept & trend	-193.41*** (0.00)	-237.18*** (0.00)	-235.29*** (0.00)	-239.11*** (0.00)	-247.34*** (0.00)
ARCH test			4.09** (0.04)	119.11*** (0.00)	33.07*** (0.00)	174.8*** (0.00)	0.018 (0.89)

Note: ***, **, and * represent the significant level at 1%, 5%, and 10%, respectively. The value in the parentheses refer to p-value. The null hypothesis of the ARCH test state there is no ARCH effects in the model, while alternative hypothesis state there is ARCH effects in the model.

Table 2 shows the summary results of standard GARCH and asymmetric GARCH models for ASEAN-5 Islamic stock returns. Based on the standard GARCH (1,1) model outputs, the positive and significant GARCH terms for all Islamic stock returns indicate a long moment in the current variance. While the statistically significant positive ARCH term signifies the impact of historical news on the volatility of the ASEAN-5 Islamic stock returns. The higher coefficient for GARCH terms than ARCH terms implies that ASEAN-5 Islamic stock returns volatilities are more sensitive to past volatility than new surprise. All these values reveal a volatility clustering in the ASEAN-5 Islamic stock markets. Malaysia's Islamic stock returns show the highest persistency of volatility followed by the Philippines, Singapore, and Indonesia, as derived from the sum of ARCH and GARCH terms. These findings affirm that the current volatility of weekly Islamic stock returns can be explained by past volatility and tends to persist over time. Meanwhile, there are no further diagnostic issues of heteroscedasticity and autocorrelation found in the models as the ARCH-LM test,

Correlogram of standardized residuals, and Correlogram of residuals squared tests are statistically insignificant.
Due to the concern of leverage effects, three asymmetric GARCH models of TGARCH (1,1), EGARCH (1.1), and APGARCH (1,1) models were estimated. Based on the outputs, all three asymmetric models reveal that the volatility for ASEAN-5 Islamic stock returns is more sensitive to its past volatility movement than new surprise, evidenced by the statistically significant GARCH term and higher coefficients than the ARCH terms. These findings also signified the volatility clustering phenomenon in all Islamic stock markets. Based on the sum values, all Islamic stock markets show high volatility persistency except for the Indonesian Islamic stock market indicates slightly low volatility persistency. Besides that, the leverage terms are statistically significant at one percent and positive for TGARCH (1,1) and APGARCH (1,1) models while negative for EGARCH (1,1) models. These imply that the leverage or asymmetric effects are adequately captured, implying that the volatility caused by negative returns would be more pronounced than good returns in the subsequent period. These findings were in harmony with the outcome of Herbert et al. (2019), Samineni et al. (2021), and Nurdany et al. (2021), which demonstrated that downward movement of the stock returns is followed by higher volatility than the upward movement of the same magnitude. Yet, the TGARCH (1,1) model for Singapore and Indonesia stock returns violates the non-negative constraint assumption that is, all parameters of α_0, α_1, and $\beta_1$must be in positive sign. Meanwhile, the ARCH term (α_1) for Singapore and Indonesia stock returns were statistically insignificant. Besides that, except for Indonesia's Islamic stock return, the EGARCH (1,1) model for all ASEAN-5 Islamic stock returns violates the premise that the sum of α_1, β_1, and γ must be smaller than one. These imply that the model may be spurious since the stationarity condition does not hold.
In terms of model comparison, the standard GARCH (1,1) model is adequate for assessing the volatility of Islamic stock returns and passing all diagnostic tests. The PGARCH (1,1) model is found to be sufficient for Malaysia, Singapore, and the Philippines Islamic stock market to estimate their return volatility, as evident by the highest log-likelihood ratio, the lowest AIC and SIC, and no further diagnostic issues. Yet, the EGARCH (1,1) model is suited for Indonesia's Islamic stock market.

Conclusion

This study aims to estimate the volatility features of each ASEAN-5 Islamic stock market from 01 January 2010 to 25 December 2020 and compare the findings for different GARCH-type models. The unit root and ARCH test results indicated that the data were stationary at level and exhibited an ARCH effect for major ASEAN-5 Islamic stock markets except for Thailand. The findings revealed that the ASEAN-5 Islamic stock returns are sensitive to the prior volatility movements, while negative shocks tend to have a larger impact on volatility than positive shocks. The standard GARCH (1,1) model is adequately sufficient to capture the return volatility for ASEAN-5. In terms of asymmetric GARCH models, EGARCH (1,1) model is more suitable for estimating the volatility behavior of Indonesia's Islamic stock market returns. Meanwhile, APGARCH (1,1) model is suited for Malaysia, Singapore, and the Philippines Islamic stock markets. Again, the distinct characteristic of the volatility of the capital market is not directly noticeable. The findings of this study may at least provide an essential understanding related to the volatility properties and volatility models used and recommend the appropriate GARCH type models for each country's Islamic stock market. Selecting suitable volatility models is crucial when analyzing risk to risk interaction between two financial series, which generate volatility variables for financial series. Hence, this study serves as the foundation or a simple guide for future studies. The portfolio advisors, investors, and related parties may need to consider the appropriate uses of volatility models in estimating the stock market volatility behavior to avoid inaccurate evaluation.

Table 2: Summary Results for GARCH and Asymmetric GARCH Models for ASEAN-5 Islamic Stock Returns.

	IMR	ISR	IIR	IPR	ITR
Standard GARCH (1,1) Model					
α_0	1E-05** (0.033)	2.69E-05*** (0.000)	0.0002*** (0.000)	4.69E-05*** (0.001)	-
α_1	0.111*** (0.000)	0.137*** (0.000)	0.212*** (0.000)	0.151*** (0.000)	-
β_1	0.853*** (0.000)	0.804*** (0.000)	0.538*** (0.000)	0.806*** (0.000)	-
γ	-	-	-	-	-
Sum	0.964	0.941	0.75	0.957	-
Log likelihood	1604.315	1455.969	1277.011	1222.296	-
AIC	-5.602	-5.082	-4.455	-4.264	-
SIC	-5.564	-5.044	-4.417	-4.226	-
ARCH-LM test	0.397 (0.528)	0.318 (0.573)	0.055 (0.814)	0.188 (0.664)	-
Corr.	0.278 (0.598)	0.001 (0.976)	0.276 (0.599)	0.144 (0.704)	-
Corr. Sq	0.400 (0.527)	0.321 (0.571)	0.056 (0.814)	0.190 (0.663)	-
TGARCH (1,1) Model					
α_0	1.18E-05*** (0.001)	2.62E-05*** (0.000)	0.0002*** (0.000)	4.81E-05*** (0.001)	-
α_1	0.032* (0.078)	-0.021 (0.332)	-0.0003 (0.992)	0.056* (0.033)	-
β_1	0.846*** (0.000)	0.831*** (0.000)	0.551*** (0.000)	0.808*** (0.000)	-
γ	0.158*** (0.000)	0.264*** (0.000)	0.356*** (0.000)	0.189*** (0.000)	-
Sum	0.957	0.984	0.729	0.9585	-
Log likelihood	1610.821	1469.757	1288.631	1228.783	-
AIC	-5.621	-5.127	-4.93	-4.283	-
SIC	-5.575	-5.081	-4.469	-4.237	-
ARCH-LM test	0.786 (0.375)	0.074 (0.785)	0.030 (0.863)	0.133 (0.715)	-
Corr.	0.112 (0.738)	0.008 (0.930)	0.074 (0.786)	3.00E-06 (0.999)	-
Corr. Sq	0.792 (0.373)	0.074 (0.785)	0.030 (0.862)	0.1344 (0.714)	-
EGARCH (1,1) Model					
α_0	-0.617*** (0.001)	-0.864*** (0.000)	-1.762*** (0.000)	-0.421*** (0.000)	-
α_1	0.214*** (0.000)	0.207*** (0.000)	0.229*** (0.000)	0.222*** (0.000)	-
β_1	0.946***	0.911***	0.783***	0.965***	-

	IMR	ISR	IIR	IPR	ITR
	(0.000)	(0.000)	(0.000)	(0.000)	
γ	-0.115*** (0.000)	-0.187*** (0.000)	-0.203*** (0.000)	-0.132*** (0.000)	-
Sum	1.103	1.0245	0.911	1.121	-
Log likelihood	1611.308	1467.875	1284.111	1230.937	-
AIC	-5.623	-5.12	-4.477	-4.29	-
SIC	-5.577	-5.075	-4.431	-4.245	-
ARCH-LM test	0.969 (0.325)	0.0002 (0.987)	0.538 (0.463)	0.068 (0.794)	-
Corr.	0.020 (0.887)	0.011 (0.918)	0.098 (0.755)	0.063 (0.801)	-
Corr. Sq	0.977 (0.323)	0.00002 (0.988)	0.542 (0.462)	0.068 (0.794)	-
PGARCH (1,1) Model					
α_0	0.001*** (0.005)	0.002*** (0.000)	0.006*** (0.000)	0.001*** (0.002)	-
α_1	0.121*** (0.000)	0.113*** (0.000)	0.127*** (0.000)	0.129*** (0.000)	-
β_1	0.853*** (0.000)	0.833*** (0.000)	0.676*** (0.000)	0.869*** (0.000)	-
γ	0.585*** (0.000)	1.000*** (0.000)	0.95*** (0.000)	0.628*** (0.000)	-
Sum	0.975	0.946	0.803	0.998	-
Log likelihood	1611.71	1467.742	1283.778	1231.293	-
AIC	-5.624	-5.12	-4.476	-4.292	-
SIC	-5.579	-5.074	-4.43	-4.246	-
ARCH-LM test	1.017 (0.313)	0.107 (0.743)	0.930 (0.334)	0.128 (0.720)	-
Corr.	0.002 (0.962)	0.001 (0.971)	0.051 (0.821)	0.120 (0.729)	-
Corr. Sq	1.025 (0.311)	0.109 (0.742)	0.937 (0.333)	0.129 (0.719)	-

Note: α_0, α_i, β_j, and γ_i refer to the constant, ARCH term, GARCH term, and leverage term, respectively. AIC, SIC, Corr, and Corr. Sq denote as the Akaike Information Criterion, Schwartz Information Criterion, Correlogram of standardized residuals and squared tests. The symbol *, **, and *** represent the significant level at 10%, 5%, and 1%. The values under ARCH-LM test are F-statistics, while the values under Corr. and Corr. Sq. refer to Q-statistics. The values in the parentheses refer to the p-value.

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