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THE VAR EVALUATION OF SHARIAH STOCK MARKET IN MALAYSIA DURING COVID-19 PANDEMIC BY USING CONDITIONAL EVT METHOD

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ABSTRACT

In the current financial market, the Islamic stock market faced with a significant challenge to sustain and maintain its stability in intensified market volatility and unexpected extreme events. It can reduce the intensity and occurrence of financial crises by eliminating the primary vulnerabilities of the conventional system. This paper aims to identify the most effective method in risk evaluation by presenting the risk evaluation performance between conventional and Islamic stock market that focusing on extreme events in stock market returns. The data analysis is divided into two periods: normal and crisis COVID-19 periods. The empirical analysis, conducted within the sample employs the conditional extreme value theory (EVT) method that combine the filtered series of GARCH and EGARCH models. This filtered series will be used to generate the threshold by using the peak-over-threshold (POT) method. This threshold then will be used to estimate the generalized Pareto distribution (GPD) distribution to forecast the one-day ahead value-at-risk (VaR). The findings indicate that, in Shariah stock markets, the conditional EVT model demonstrates superior performance in forecasting stock market risk compared to the standard GARCH and EGARCH models.

Keywords: Conditional EVT; Heavy-tailed; POT method; Value-at-risk.

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1. INTRODUCTION

An unforeseen and uncommon event typically carries a low likelihood of severe consequences, which can adversely affect the global community. Although the probability of such an event to occur is minimal, it is crucial to identify and address the issue promptly to prevent further deterioration. Previous extreme market crash has resulted in devastating financial downturn characterized by significant price movements in financial markets, currency devaluation, and

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global stock market crash. In 1997, the sudden Asian financial crisis triggered and heightened volatility in the capital markets of Asian countries, including Malaysia. The Asian financial crisis not only affected Asian nations but also several other countries. Foreign investors demonstrated hesitancy to invest in Asian markets, resulting in the downfall of banks and financial institutions as well as substantial losses for creditors and investors (Joe & Oh, 2017). In 2020, the emergence of the COVID-19 virus resulted in substantial upheaval in the world's financial markets. It caused turbulence and unprecedented levels of risk and uncertainty in the stock market, prompting investors to sell their assets quickly and incur significant losses in a short span of time.

Recently, the Islamic financial market has been highly prominent in Malaysia. Report by (S&P Global Ratings, 2022) presented that currently, the global Islamic finance industry is beginning to ascend despite the economic downturn, where the worldwide Islamic finance sector is projected to increase by 10% in 2023-2024. According to (Khan, 2023), as of September 2022, Saudi Arabia was the largest Islamic financial market driven 92% of the growth in Islamic banking assets last year. Since COVID-19 hit financial markets in year 2020, the total issuance of Saudi Arabia declined by 22% to $80 billion in 2022 due to a substantial increase in government revenue from the energy sector. This resulted in fiscal surpluses for most of the Gulf Cooperation Council (GCC) nations and contributed to a reduction in fiscal deficits in a few Islamic countries, including Malaysia. In the same report, Malaysia is anticipated to be one of the largest sovereign issuers in 2022 with 25% market share. (Nagraj, 2023) stated that the Islamic banking sector in Malaysia is expected to achieve an estimated growth rate of 8% in the next few years. Furthermore, (FitchRatings, 2023) proclaimed that the growth of Islamic financing will stabilize in 2023 after a strong growth of 13% in 2022 as increasing financial rates reduce consumer demand. However, it is expected that the growth of the sector will continue to outpace the performance of conventional banks following Malaysia's transition towards Sharia-compliant services and sustainable Islamic financial ecosystem. Additionally, Malaysia is one of the largest Islamic banking markets in the world, with the sector accounting for about 41% of local banking loans in 2022. An increase in loan rates should affect loaners' debt servicing capacity, potentially weakening the quality of Islamic banks' assets. As a result, the economic downturn and absence of post-COVID-19 aid have also contributed to the increase in delinquency. Nevertheless, the asset-quality descent is expected to be manageable as banks have taken numerous measures to overcome the issue, such as adequate provisions for impairment with the economy expected to expand by 3.5% in 2023. As Malaysia's Islamic financial ecosystem constantly adapts to the rapidly changing economic and social requirements, researchers are drawn to participate in enhancing and advancing Malaysian financial market. The unpredictable global financial crisis due to the COVID-19 pandemic has resulted in heightened stock market volatility on a global scale. Researchers have demonstrated increasing interest in conducting risk analysis of Islamic stock markets worldwide to protect investors from substantial losses in their investments as mentioned by (Alam, Akbar, Shahriar & Elahi, 2017). This study aims to enhance the existing Islamic finance literature review in Malaysia by employing the conditional EVT approach to evaluate and predict stock market risk. Value-at-risk (VaR) forecasts was utilized to evaluate the volatility performance of both Islamic and conventional stock markets in encountering uncertain extreme market conditions, reflecting the growing influence of Islamic finance in the region.

Numerous techniques have been employed in assessing and predicting stock market risk, and one of the widely adopted approaches is the utilization of VaR. A renowned model for precise VaR estimation and prediction is the GARCH model, as introduced by (Bollerslev, 1986). However, starting in the early 2000s, researchers have examined the effectiveness of classical GARCH model in comparison to extreme value theory (EVT) method. New research findings supported the notion that EVT model yields superior risk forecasts compared to classical GARCH model. They also found that the EVT outperformed the GARCH model as it provided more appropriate distributions to fit extreme events in the tail distribution that is aligned well with the purpose of VaR to measure the downside risk in the return distribution. However, there are limitations in standalone EVT model in which its distribution is normally not independently and identically distributed (*iid*), and its quantile estimation does not accurately reflect the current volatility environment. To address these issues, (Mcneil & Frey, 2000) introduced a hybrid approach known as the conditional EVT method, which combines the standard GARCH model filtered with the EVT technique. This empirical analysis of this study applied this hybrid conditional EVT model based on GARCH and EGARCH models incorporating volatility clustering and asymmetric effects to forecast VaR. A comparison of conditional EVT forecasting ability between conventional and Islamic stock markets during the pre-pandemic and pandemic periods of COVID-19 was also considered.

This study offers an empirical study of conditional EVT and contributes to the literature in three ways. Firstly, the stylized facts for conventional and Islamic stock markets in Malaysia were identified to analyze the extreme returns and volatility patterns presented in both the pre-pandemic and pandemic periods. Secondly, the conditional EVT models based on the POT method were applied to the GARCH-typed models incorporating existing stylized facts to see if it is appropriate to be used during sudden extreme events in the Malaysian financial market. Thirdly, the potential loss equation for holding the one-day ahead VaR for long position investors in the conventional and Islamic stock market in Malaysia was presented using the quantile forecast results in empirical analysis to calculate the actual losses incurred if the amount of money has been invested. This paper is organized as follows: literature review is organized and summarized in Section 2; Section 3 provides the data and methodology used in this study as well as the econometric model specifications; Section 4 provides the results and discussion and explains how the conventional and Islamic stock markets volatility pattern during the COVID-19 crisis, and how is the conditional EVT performance in measuring the risk of the conventional and Islamic stock market in Malaysia; and Section 5 concludes this study.

2. LITERATURE REVIEW

Considering the aims of this study, the literature review is segmented into three distinct sections. The first section provides a summary of previous research on the influence of COVID-19 on stock market volatility in other countries and Malaysia. In the second section, previous studies pertaining to the volatility of Islamic stock markets in response to the pandemic are presented. Finally, this review presents prior research on various approaches employed for forecasting stock market risk, including studies demonstrating the superior performance of conditional EVT compared to other methods.

2.1. Stock Market Volatility and COVID-19 Pandemic

As previously mentioned, extreme events are characterized by highly severe and rare occurrences that have significant impacts on a global scale. In financial and stock markets, extreme events manifest as sudden and substantial fluctuations in stock prices, leading to rapid stock market crashes. A notable recent extreme event is the emergence of the COVID-19 virus, which was officially declared on March 11 by the World Health Organization (WHO) after an outbreak of the transmissible virus in Wuhan, China, on January 9. According to (Zhang, Hu & Ji, 2020), COVID-19 arrival has affected the financial market and created extreme volatility in stock markets around the globe. Study conducted by (Chaudhary, Bakhshi & Gupta, 2020) found the negative mean returns of daily returns throughout the COVID-19 period (January 2020 to June 2020) and observed that the volatility persists at elevated levels thereafter.. In another study, (Albulescu, 2021) employed the robust least squares (RLS) approach and found that financial volatility in the US stock market increased in response to the increase in COVID-19 cases and the mortality rate has a considerable and favorable effect on the volatility. (Lucio & Caiado, 2022) applied the TARCH clustering approach, and found that the US stock market's volatility was significantly affected by COVID-19.

In Malaysia, the first COVID-19 case was found on January 25, 2020. From the beginning of March 2020, cases increased rapidly, forcing the Malaysian government to impose movement control order (MCO) throughout the country. The MCO implementation successfully curbed the COVID-19 cases as shown by the downward trend in new cases from mid-April 2020. Nonetheless, the escalating cases have had a significant impact on Malaysia, particularly on the financial stock market, leading to significant disruptions in economic activities as mentioned by (Yong, Ziaei & Szulczyk, 2021). Findings from (Kelvin, Jais & Chan, 2020) showed that COVID-19 has a negative impact on the KLCI Index and its sectoral indexes via OLS regression analysis. In another study, (Mehmood, Rashid, Ullah, Shafique & Shafique, 2021) examined how the COVID-19 pandemic has influenced the Malaysian stock market during various phases of MCO.

In the stock market volatility analysis, numerous researches have been conducted to see how the COVID-19 pandemic has affected the Malaysian stock market using various methods. Study conducted by (Yong et al., 2021) using the standard GARCH (1,1), GARCH-M (1,1), and EGARCH (1,1) models demonstrated strong performance in relation to the returns of the Malaysian and Singaporean stock markets during COVID-19 pandemic. Another finding from (Othman et al., 2022) indicated that Malaysia stock market returns experience high volatility during the COVID-19 pandemic as analyzed via EGARCH model and News Impact Curve (NIC). (Khairudin & Shariff, 2023) found that COVID-19 had a significant influence on stock market volatility in Malaysia using the GARCH model.

2.2. Islamic Stock Market Volatility and COVID-19 Pandemic

Despite the pessimism that has plagued the global economy, the Islamic finance sector continues to experience robust growth. Ongoing research efforts have delved into evaluating the relative performance of the Islamic stock markets rather than the conventional stock markets. Previous research findings have indicated that Islamic stock indices exhibit higher efficiency and volatility compared to their conventional counterparts as reported by (Rejeb & Arfaoui, 2019). As Islamic stock markets exhibit higher volatility, researchers have also explored the implications of the COVID-19 pandemic on Shariah-compliant stock indices. For example, (Nomran & Haron, 2021) revealed that the COVID-19 outbreak has had a substantial on both the conventional and Islamic stock markets in several countries, including Malaysia. However, the Islamic stock markets demonstrated a minor devastating effect compared to the conventional stock markets. In addition, (Irfan, Kassim & Dhimmar, 2021) claimed that TARCH model is the best volatility model, and the

BSE Shariah and Jakarta Shariah-compliant stock indices were heavily affected by the COVID-19 outbreak. Furthermore, (Saleem, Barczi & Sági, 2021) found that there was a significant increase in the volatility and persistency of the Middle East Shariah-compliant stock indices during the COVID-19 crisis based on the GARCH model.

2.3. Conditional EVT Method

Previous research, as abovementioned, used standard GARCH-type model to analyze stock market returns. Nonetheless, extreme returns are evident during the COVID-19 period, and the use of EVT method to analyze stock market volatility can produce more accurate outcomes. Numerous studies have employed the conditional EVT model to examine how extreme events affect stock market volatility. Most findings have consistently supported the effectiveness of the conditional EVT model for volatility forecasting. For instance, (Tabasi, Yousefi, Tamosaitiene & Ghasemi, 2019) investigated Tehran Stock Exchange and discovered that the GARCH-EVT model was superior in risk forecasting during economic downturn periods. Similarly, (Omari, Mundia & Ngina, 2020) reported that the GARCH-EVT model significantly improved VaR forecasting during the COVID-19 period in 12 main global stock markets. Another recent finding from (Roy, 2022) imparted that the GARCH-EVT models outperformed other conditional EVT models in forecasting intraday VaR in eight countries heavily impacted by the COVID-19 pandemic. However, in Malaysia, no prior research has been conducted on the analysis of stock market volatility during the COVID-19 period using the conditional EVT method, focusing on the tail behavior of stock market returns. This study aims to fill the gap of previous studies in forecasting the risk impacted by the COVID-19 pandemic using the conditional EVT method. Superior performance of this method has been reported in other countries but not yet explored in the Malaysian stock markets.

3. METHODOLOGY

The analysis of this study was divided into preliminary and empirical analysis. In the empirical analysis, the conditional EVT method introduced by (Mcneil & Frey, 2000) was employed. The conditional EVT model combined the GARCH and EGARCH filters with the EVT approach. As the EVT required *iid* series, the first stage of the analysis involved filtering the initial return series from the GARCH and EGARCH models. This filtering process ensured that the standardized residuals, ε_t, of the GARCH and EGARCH models were devoid of serial correlation and conditional heteroscedasticity, conforming to the *iid* assumption. In the second stage, filtered standardized residuals series were utilized to model stock market volatility, employing the peak over threshold (POT) method in the EVT framework. With the daily closing price, P_t , the returns of the daily stock prices data are calculated based on the difference between the logarithmic levels of prices on two successive days as

$$\{r_t\}_{t-1}^{T} = \log\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

The conditional expected returns, r_t, based on the ARMA (1,0) model is given by

$$\begin{aligned} r_t &= \mu_t + \varepsilon_t, \\ \varepsilon_t &= \sigma_t Z_t \end{aligned} \tag{2}$$

where, $\mu_t = a_0 + \sum_{i=1}^{p} a_i r_{t-i} + \sum_{j=1}^{q} b_j \varepsilon_{t-j}$, r_{t-1} is the passed return. The conditional standard deviation, σ_t, is modelled by standard GARCH and EGARCH models. Diagnostic test of maximum log like-hood ratio and minimum value of AIC and SIC are used to select the type of error distribution to choose in finding the best residual series, ε_t, which follows student's skewed (*skst*) distribution. The selected *skst* innovation will have a significant influence on the evaluation of VaR as it can capture the stylized facts of asymmetric and heavy tails that exist in financial asset returns (Paul & Sharma, 2018).

3.1. GARCH and EGARCH models

The GARCH (1,1) model introduced by (Bollerslev, 1986) is given by

$$\sigma_t^2 = \omega_0 + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{3}$$

In this model, the equation σ_t^2 represents the conditional variance, and the value is affected by both the historical values of the shocks captures by the lagged squared error term, ε_{t-1}^2, and the past values, σ_{t-1}^2. The GARCH (1,1) specification is quite popular as it can fit most financial time series data. It defines how the volatility changes with the lagged shocks, ε_{t-1}^2, and the momentum in the system via σ_{t-1}^2. Furthermore, the GARCH (1,1) model has the ability to detect lagged values in shocks using only a small number of parameters, which are $\omega_0, \alpha\ and\ \beta$ that yield the similar impact as the ARCH(q) model with the requirement of estimating (q+*1*) parameters when q is substantial. This makes the parsimonious GARCH (1,1) model better than the over-parameterized model (ARCH model). There are several stylized facts captured by the GARCH model, namely volatility clustering and heavy tails effects in the return distribution series. The asymmetric EGARCH (1,1) model introduced by (Nelson, 1991) is given by

$$log\ \sigma_t^2 = \omega_0 + [1-\beta(L)]^{-1}[1+\alpha(L)]g(z_{t-1}) \tag{4}$$

where, $g(z_{t-1}) = \gamma_1 z_t + \gamma_2[|z_t| - E|z_t|]$ and $E|z_t| = (4\xi^2/\xi + \xi^{-1})\Gamma\left(\frac{\nu+1}{2}\right)\sqrt{\nu-2}/\Gamma\left(\frac{\nu}{2}\right)\sqrt{\pi}(\nu-1)$; $g(z_{t-1})$ is the function of sign and magnitude effect which represents the asymmetric influence of volatility in relation to favorable and unfavorable news appearing in the stock market. The values of γ_1 and γ_1 represent the leverage effect and magnitude effect, respectively. Given that $\gamma_1 < 0$, bad or good news, the sign of volatility increases or decreases, respectively. If $\gamma_1 < 0$, the volatility is greater or smaller, given that the size of z_t is greater or smaller than the mean.

3.2. Extreme value theory (EVT)

In statistical modeling, EVT provides valuable insights into the dynamics of sudden extreme market movements, such as the impact caused by the global spread of COVID-19. In this study, the POT method was employed. In this method, observations of extreme values surpassing a predefined threshold (u) are considered, irrespective of the clustering patterns in the time series. Given the log return series of stock index, $X = \{x_1, x_2, \ldots, x_t\}$, the exceedance, *x*, is counted if it surpasses a selected threshold, u, generated from the POT method. According to (Balkema & Haan, 1974) and (Pickands, 1975), the cumulative probability function, $F_u(y)$, can be written as

$$F_u(y) = \Pr(X - u \leq y | X > u) \tag{5}$$

The conditional probability in Equation (2) can be simplified into

$$\begin{aligned} F_u(y) &= \frac{\Pr(X-u\leq y, X>u)}{\Pr(X>u)} \\ &= F(y+u) - F(u)/1 - F(u) \\ &= F(x) - F(u)/1 - F(u) \end{aligned} \tag{6}$$

The exceedance, x, series is calculated based on equation, $y = x - u$; where, $x = y + u$. At a sufficiently high threshold u, the function $F_u(y)$ will converge to the GPD distribution as defined by

$$G_{\xi\psi}(y) = \begin{cases} 1 - \left(1 + \frac{\xi y}{\psi}\right)^{-\frac{1}{\xi}}, if\ \xi \neq 0 \\ 1 - e^{-\frac{y}{\psi}}, \qquad if\ \xi = 0 \end{cases} \tag{7}$$

In Equation (7), the GPD parameters are represented by ψ and ξ as scale and shape parameters, respectively, which are estimated using the maximum likelihood (ML) method generated from the R-programming software. According to (Embrechts, Kluppelberg & Mikosch, 1997), given that $F_u(y) \approx G_{\xi\psi}(y)$, Equations (6) and (7) are then combined into

$$F(x) = \big(1 - F(u)\big)G_{\xi\psi}(y) + F(u) \tag{8}$$

When the cumulative function $F(u) = (n-k)/n$ is substituted into Equation (8), the function $F(x)$ can be simplified as

$$F(x) = (1 - (k/n))[1 + \xi(x-u)/\psi]^{-1/\xi} \tag{9}$$

where, n is total sample size and k represents the number of exceedances. At a given probability, q, the VaR can be estimated as

$$VaR_q = F^{-1}(1-q) \tag{10}$$

where, F^{-1} (.) is the inverse function of $F(.)$. By inverting Equation (9), VaR can be written as

$$VaR_q = x_q = u + \psi/\xi\big[((1-q)/(k/n)^{-\xi} - 1\big] \tag{11}$$

The 1-day-ahead conditional mean, $\hat{\mu}_{t+1}$, is given by

$$\hat{\mu}_{t+1} = \widehat{a_0} + \sum_{i=1}^{p} \widehat{a_\iota} r_{t-i+1} + \sum_{j=1}^{q} \widehat{b_\jmath} \varepsilon_{t-j+1} \tag{12}$$

Based on Equation (12), the next day conditional variance, $\hat{\sigma}^2{}_{t+1}$, is forecasted using Equations (3) and (4). The VaR quantiles are calculated by substituting the threshold, u and GPD parameters, ψ and ξ, into Equation (11). Finally, the forecasted VaR is calculated based on the VaR quantiles, VaR_q, as follows

$$VaR_q^{t+1} = \mu_{t+1} + \sigma_{t+1} VaR_q \tag{13}$$

3.3. Backtesting VaR

The result of the forecasted VaR was subjected to backtesting procedures of conditional coverage (UC) and unconditional coverage (CC) proposed by (Kupiec, 1995) and (Christoffersen, 1998), respectively, to check the accuracy of each model. Firstly, the violation ratio is calculated based on the forecasted VaR and actual returns, r_t. The frequency of violation considers the occurrence of actual returns exceeding the forecasted VaR. In other words, violation occurs when the anticipated loss surpasses the projected VaR on a particular day represented by an indicator function

$$I_{t+1} = \begin{cases} 1 & if \quad r_{t+1} \leq -VaR_{t+1}^{p} \\ 0 & if \quad r_{t+1} > -VaR_{t+1}^{p} \end{cases} \tag{14}$$

The violation ratio is calculated empirically by dividing the observed proportion of total VaR violations by the actual proportion of VaR violations as shown by the following expression

$$VR = N/pH \tag{15}$$

where, $N = \sum_{t=T+1}^{T+H} I_t(r_t < VaR_{t|t-1}^{(1-p)})$ and pH are the theoretical and actual violations proportions, respectively. Based on the guideline from (Danielsson, 2011), if VR ∈ [0.8,1.2], the forecast is good. If VR<0.5 or VR>1.5, the model is imprecise, and if VR<0.3 or VR>2, the model is not good.

The UC test examines whether the obtained proportion of violations, $\hat{p}$, is significantly different from the expected proportion, p. The total number of VaR violations calculated from Equation (14) is summed to $T_1 = \sum_{t=1}^{T} I_t$; where, T represents the total number of observations chosen, and it follows a binomial distribution. The VaR forecasted based on the proportion, p, is deemed accurate if the unconditional coverage, $\hat{p} = \frac{T_1}{T}$, is equal to $p\%$, and the null hypothesis, H_0, is given by $H_0 \colon \hat{p} = p$. The likelihood ratio statistics used to perform Kupiec POF test is

$$LR_{UC} = 2(\log(\hat{p}^{T_1}(1-\hat{p})^{\,T-T_1}) - \log(p^{T_1}(1-p)^{T-T_1})) \tag{16}$$

Subsequently, the CC test verification was conducted by examining the collective test of unconditional coverage and serial independence. The test statistics value was obtained by aggregating individual results of unconditional coverage and serial independence, $LR_{CC} = LR_{UC} + LR_{IND}$. The LR_{IND} examines whether the exceptions are statistically independent of each other. If the model does not consider the independence feature in exceptions, it may lead to exception clustering. The forecasted VaR (p) measured is considered reliable if it can demonstrate both unconditional coverage and independence characteristics. The CC test assumes that the hit sequence is dependent over time and can also be defined as first-order Markov sequence expressed as

$$\Pi = \begin{pmatrix} 1-\pi_{01} & \pi_{01} \\ 1-\pi_{11} & \pi_{11} \end{pmatrix} \tag{17}$$

Given that $\pi_{ij} = \Pr(I_t = j | I_{t+1} = i)$ is the transition probability which implies that if conditionally today is a non-violation ($I_t = 0$), then the probability of tomorrow VaR is being violated, ($I_{t+1} = 1$) is π_{01}. If conditionally today is a VaR violation, then the probability of tomorrow VaR is also being violated is π_{11}. The independent hit sequence is characterized by the absence of a relationship between today's violation and probability of tomorrow's violation. The null hypothesis of LR_{IND} is given by $H_0: \pi_{01} = \pi_{11} = \pi$. In the LR_{CC} test, the ratio of exceptions was computed to determine if it is statistically equal to the expected proportion, p, along with the exceptions of LR_{IND} in terms of the independence's indicator. The decision of LR_{CC} test is based on the null hypothesis given by $H_0: \pi_{01} = \pi_{11} = p$ and test statistics as follows:

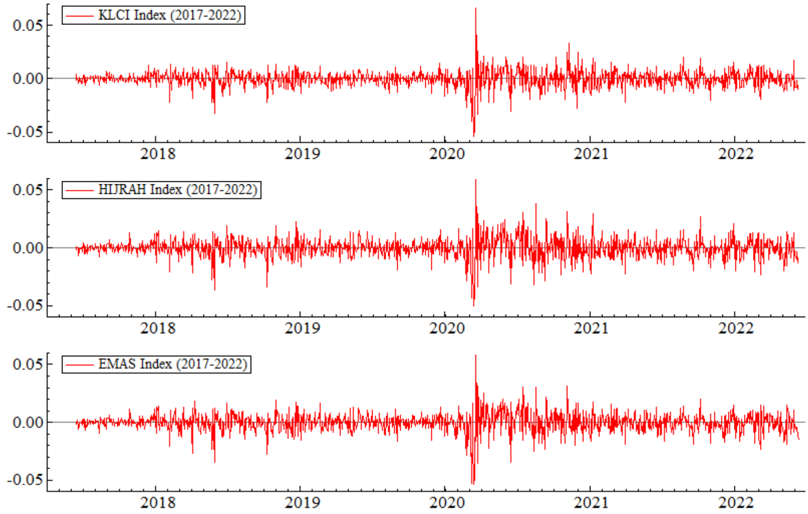
$$LR_{CC} = 2 * (\log\left(\hat{\pi}_{01}^{T_{01}}(1-\hat{\pi}_{01})\right)^{T_{00}} \hat{\pi}_{11}^{T_{11}}(1-\hat{\pi}_{11})^{T_{10}}) - \log(p^{T_{01}+T_{11}}(1-p)^{T_{00}+T_{10}})) \tag{18}$$

4. RESULTS AND DISCUSSION

4.1. Sample of data

The dataset used in this study encompassed the daily closing price of the conventional stock market (KLCI Index) and two Shariah-compliant stocks in Malaysia (HIJRAH Index and EMAS Index) downloaded from the Bloomberg database. The data analysis was segregated into two distinct subsample periods. The first subsample dated from January 1, 2017, to February 28, 2020, representing the normal period, whereas the second subsample period covered January 1, 2017, to June 13, 2022, representing the crisis period. The results are divided into graphical analysis, preliminary analysis, empirical analysis, and backtesting procedure to test the accuracy of the forecasted VaR. Graphical analysis (Figure 1) illustrated the stock returns for all three markets during the crisis period. It clearly exhibited the occurrence of volatility clustering, where periods of heightened volatility were succeeded by relatively tranquil periods. Notably, extreme positive and negative returns were observed around February 2020 to March 2020, corresponding with the onset of the COVID-19 crisis in Malaysia and MCO implementation nationwide.

Figure 1: KLCI, HIJRAH And EMAS Stock Returns from Jan 2017 to June 2022



4.2. Preliminary Analysis

Table 1 presents the statistical summary of the three indexes. Amid the crisis period, the mean returns for both conventional and Islamic indexes showed a more negative trend. Volatility estimates, derived from the standard deviation of daily returns, were higher during the crisis period, indicating increased risk. Regarding skewness, all indexes exhibited negative skewness in both periods. Additionally, positive excess kurtosis values greater than three indicated the presence of heavy-tailed distributions. In the comparison between stable and crisis periods, the kurtosis values for both conventional and Islamic indexes demonstrated an elevation during crisis states, implying heavier tails in the data series. This observation is further supported by the Q-Q plots displayed in Figure 2. These plots demonstrated an asymmetric distribution, with extreme negative returns deviating significantly from what would be expected in Gaussian distribution. Notably, during the crisis period, the Q-Q plots exhibited pronounced concavity, providing strong evidence of heavy tails in all data series. The Jarque-Bera statistics significantly rejected the null hypothesis at 5% and 1% levels, which confirmed the non-normality result for all stock indexes.

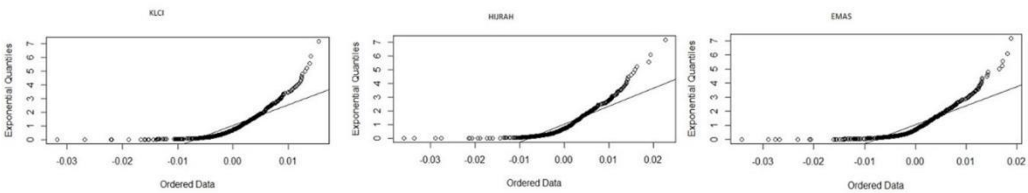
Table 1: Descriptive Statistics of KLCI, HIJRAH and EMAS Indexes

Statistical Summary	KLCI		HIJRAH		EMAS	
	Normal	Crisis	Normal	Crisis	Normal	Crisis
Mean	-0.0003	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
Standard Deviation	0.0056	0.0077	0.0066	0.0087	0.0064	0.0083
Skewness	-0.805	-0.226	-0.607	-0.111	-0.635	-0.457

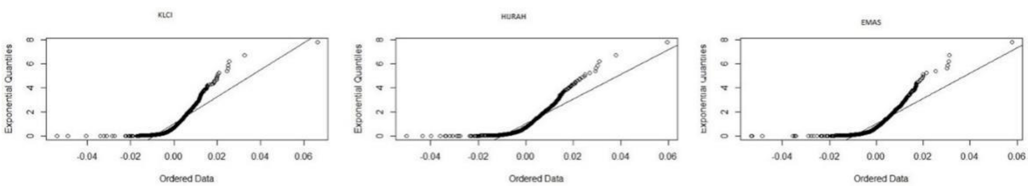
Kurtosis	6.16	12.10	6.26	7.74	5.83	9.53
JB-stats	347.74	4220.45	334.62	1146.57	266.85	2211.63
p-value	[0.00] **	[0.00] **	[0.00] **	[0.00] **	[0.00] **	[0.00] **

Note: ** reveals statistical values at 5% and 1% significance levels, respectively.

Figure 2: Q-Q Plots of KLCI, HIJRAH and EMAS Indexes During (a) Normal and (b) Crisis Periods



(a)



(b)

Tables 2 and 3 present the results of ADF, LM-ARCH and Q^2 tests on the original and filtered standardized residuals for all stock indexes during pre-crisis and crisis periods. According to (Dickey & Fuller, 1979), critical values of -3.96 and -3.41 determine the acceptance or rejection of the null hypothesis for sample sizes greater than 500. In this study, all stock indexes exhibited negative ADF values for both periods, indicating statistical significance against the null hypothesis of unit root. This implied that all data series were stationary. The result of ARCH-LM and Q^2 tests were statistically significant, leading to the rejection of the null hypothesis of no serial correlation. This finding indicated the presence of autocorrelation in the daily returns of the original dataset; therefore, it could not be implemented directly as EVT assumed *iid* distributions. To solve this issue, the original returns series were filtered using the GARCH (1,1) and EGARCH (1,1) models, and the results of heteroscedasticity and serial correlation of the new filtered series are presented in Table 3. The results showed that the new filtered residuals series were not significant, signifying that serial dependence correlation and conditional heteroscedasticity were absent. The filtered residuals resembled *iid* distribution and can be used in the subsequent stage of EVT analysis.

Table 2: Stationary, Heteroscedasticity and Serial Correlation Tests of Original Daily Returns

Index	Original daily returns		
	ADF	ARCH-LM	Q^2
KLCI (normal)	-13.66	10.027[0.0000] **	35.3311[0.0000] **
KLCI (crisis)	-18.1	57.004[0.0000] **	189.348 [0.0000] **
HIJRAH (normal)	-13.96	6.1399[0.0004] **	21.3321[0.0001] **
HIJRAH (crisis)	-19.22	23.225[0.0000] **	79.7164[0.0000] **
EMAS (normal)	-13.37	6.5296 [0.0002] **	22.266 [0.0001] **
EMAS (crisis)	-18.52	44.242[0.0000] **	147.055[0.0000] **

Notes: The Q^2 (stats) is the Box-Pierce Q statistic at lag-3; * and ** reveals the statistical values at 5% and 1% significance levels, respectively.

Table 3: Heteroscedasticity and Serial Correlation Tests of Filtered Residuals Series

Index	Filtered GARCH		Filtered EGARCH	
	ARCH-LM	Q^2	ARCH-LM	Q^2
KLCI (normal)	0.6792 [0.5650]	1.9909 [0.1583]	0.3093 [0.8187]	0.9267 [0.3357]
KLCI (crisis)	0.9567 [0.4124]	2.8283 [0.0926]	0.6774 [0.5659]	2.0272 [0.1545]
HIJRAH (normal)	0.3085 [0.8193]	0.9336 [0.3339]	0.3485 [0.7903]	1.0292 [0.3104]
HIJRAH (crisis)	0.0989 [0.9606]	0.2977 [0.5854]	0.5884 [0.6226]	1.6691 [0.1964]
EMAS (normal)	0.2011 [0.8957]	0.6278 [0.4282]	0.1328 [0.9406]	0.3886 [0.5331]
EMAS (crisis)	0.1838 [0.9074]	0.5702 [0.4502]	0.2947 [0.8293]	0.8455 [0.3579]

Notes: The Q^2 (stats) is the Box-Pierce Q statistics at lag-3

4.3. Empirical Analysis

The forecasting models were constructed using in-sample daily returns data of KLCI, HIJRAH, and EMAS indexes. The pre-crisis period spanned from June 2017 to March 2019, while the crisis period covered June 2017 to September 2020. Standard GARCH and EGARCH models were employed, incorporating different error distributions, such as normal, *skst*, and GED distributions. To determine the most suitable innovation for each stock return, various diagnostic tests were conducted, including the maximum log-likelihood ratio with the lowest AIC and SIC values. The results consistently indicated that the *skst* distribution provided the best fit, aligning with the observed negative asymmetry and elevated kurtosis in the analysis. Table 4 presents the estimation results of GARCH and EGARCH models. Notably, the α and β coefficients were statistically significant, and the summation of $\alpha+\beta$ values was close to unity, indicating persistence in all return series. Additionally, the leverage coefficient (γ) was negative and significant only for the EMAS Index during the crisis period, evidence of non-symmetrical behavior in this stock index.

Table 4: Estimation Results of GARCH (1,1) and EGARCH (1,1) Models.

Index	Model	ω	α	β	γ

KLCI (normal)	GARCH (1,1)	3.51E-07	0.0808**	0.9147**	
	EGARCH (1,1)	-0.2798**	0.15309**	0.9841**	-0.0397
KLCI (crisis)	GARCH (1,1)	4.25 E-07	0.0799**	0.9167**	
	EGARCH (1,1)	-0.2589**	0.1673**	0.9866**	-0.033
HIJRAH (normal)	GARCH (1,1)	2.34E-07	0.0599**	0.9415**	
	EGARCH (1,1)	-0.2414*	0.1490**	0.9868**	-0.0222
HIJRAH (crisis)	GARCH (1,1)	2.51E-07	0.0698**	0.9355**	
	EGARCH (1,1)	-0.2147**	0.1675**	0.9904**	-0.0258
EMAS (normal)	GARCH (1,1)	1.79E-07	0.0678**	0.9358**	
	EGARCH (1,1)	-0.2499**	0.1583**	0.9867**	-0.0393
EMAS (crisis)	GARCH (1,1)	2.67E-07	0.0870**	0.9200**	
	EGARCH (1,1)	-0.2480**	0.1847**	0.9885**	-0.0458**

Note: * and ** reveal the statistical values at 5% and 1% significance levels, respectively.

In the second stage of data analysis, the POT method was applied in the EVT framework. This method involved estimating the tail of the data series using the GPD distribution. The threshold value, denoted as u, was determined using the mean excess function (MEF) given by

$$MEF(u) = \frac{\sum_{i=1}^{n}(X_i - u)}{\sum_{i=1}^{n} I_{(X_i > u)}} \tag{19}$$

Each threshold u was selected when the MEF plot developed a linear pattern. The possible values for all threshold u selected were calculated using R-programming code. For each level of threshold u selected, the GPD parameters were estimated using the maximum likelihood method. The threshold u, number of exceedances (k), and GPD parameters, ξ and ψ, are listed in Table 5. The unconditional VaR_q was calculated using Equation (11) at 95% and 99% confidence levels. The total in-sample, n, observations of 435 represented the pre-crisis period (June 1, 2017 to March 31, 2019), while 804 was the total in-sample estimation during the crisis period (June 1, 2017 to September 30, 2020).

Table 5: GPD Parameter Estimates and VaR Quartiles.

Period	Index	Risk Model	u	k	k/n (%)	ξ	ψ	VaR	
								0.95	0.99
Normal	KLCI	G-EVT	1.189	10	2.3	-0.152	0.13	1.082	1.290
n =435		EG-EVT	1.204	10	2.3	-0.181	0.132	1.095	1.306
	HIJRAH	G-EVT	1.342	11	2.5	0.4	0.169	1.241	1.531
		EG-EVT	1.337	10	2.3	0.002	0.295	1.108	1.582

	EMAS	G-EVT	1.233	14	3.2	-0.725	0.486	0.981	1.616
		EG-EVT	1.239	14	3.2	-0.698	0.467	0.998	1.612
Crisis	KLCI	G-EVT	1.554	10	1.2	0.506	0.479	1.076	1.664
n=804		EG-EVT	1.555	11	1.4	0.704	0.336	1.269	1.673
	HIJRAH	G-EVT	2.122	11	1.4	0.545	0.412	1.739	2.262
		EG-EVT	2.119	10	1.2	0.347	0.583	1.476	2.251
	EMAS	G-EVT	1.818	10	1.2	0.274	0.693	1.016	1.973
		EG-EVT	1.821	11	1.4	0.467	0.504	1.331	1.991

Note: GPD parameters were estimated using maximum likelihood method for periods of June 1, 2017 to March 31, 2019 (normal), and June 1, 2017 to September 30, 2020 (crisis).

The forecasting and back testing of VaR performance were conducted during two distinct out-of-sample periods: April 1, 2019 to February 29, 2020, representing the normal period, and October 1, 2020 to June 15, 2022, representing the crisis period. During these periods, the forecasted one-step-ahead conditional VaR, VaR_q^{t+1}, was calculated using Equation (13). To assess the accuracy of the volatility models in forecasting VaR, the actual returns, r_t, were compared with the forecasted VaR, VaR_q^{t+1}, based on significance levels of 5% and 1%. Table 5 provides the violation ratios, UC and CC test statistics, and corresponding p-values. The violation ratios for the conventional stock market were greater than 2, suggesting that the GARCH-EVT and EGARCH-EVT models were not suitable for both normal and crisis periods. In contrast, for the Islamic index, the GARCH-EVT model showed promising results with violation ratios below 2 and above 0.3 during the pre-crisis period. Based on Table 5, the conditional EVT models were recognized as superior and suitable approaches for risk projection during the crisis period. The decision of the UC test was based on the null hypothesis, H_0, that the realized proportion of exceedances aligned with the predicted proportion of exceedances. Table 6 presents the UC and CC test statistics as well as the associated p-values for each VaR forecasting model at the 1% and 5% significance levels for pre-crisis and crisis periods. The results for conventional stock market indicated that the H_0 was rejected for both GARCH-EVT and EGARCH-EVT models during both normal and crisis periods.

In contrast, for the Islamic stock market, the null hypothesis was accepted for both GARCH-EVT and EGARCH-EVT models during the crisis period. However, during the normal period, only GARCH-EVT model demonstrated accurate results. Meanwhile, the CC test outcomes demonstrated that the null hypothesis was rejected for both GARCH-EVT and EGARCH-EVT models in the case of conventional stock market. Conversely, for the Islamic stock market, both the GARCH-EVT and EGARCH-EVT models failed to reject the null hypothesis. In summary, the VaR estimates derived from the conditional EVT approach performed poorly and were ineffective in predicting stock market risk during crisis period in conventional stock market. However, for the Islamic stock market, the conditional EVT models proved to be the most effective for risk forecasting during the crisis period. The predicted VaR_q^{t+1} for a long position in the KLCI, EMAS, and DJIA Indexes, based on RM1 million as capital, can be calculated using Equation (13).

$$VaR_q^{t+1} = Capital \times \left(\mu_{t+1} + \sigma_{t+1} VaR_q\right) \tag{20}$$

where, $capital$ refers to total money invested.

Table 6: Backtesting Results of GARCH-EVT and EGARCH-EVT Models

Index	Conventional (KLCI Index)				Shariah (HIJRAH Index)				Shariah (EMAS Index)			
VaR Model	GARCH-EVT		EGARCH-EVT		GARCH-EVT		EGARCH-EVT		GARCH-EVT		EGARCH-EVT	
Sig. level	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%
Pre-pandemic												
VR	1.984	6.349	4.206	15.476	**1.19**	2.778	4.048	11.905	**1.43**	2.778	4.524	10.317
LR(UC)	10.113	32.928	78.716	146.321	0.455	5.424	72.327	96.801	2.163	5.424	92.063	76.682
p-value	**0.001**	**0.000**	**0.000**	**0.000**	0.500	0.020	**0.000**	**0.000**	0.141	0.020	**0.000**	**0.000**
LR(CC)	11.32	32.928	78.846	146.321	1.65	5.424	72.445	96.801	10.727	5.424	92.293	76.682
p-value	**0.003**	**0.000**	**0.000**	**0.000**	0.438	0.066	**0.000**	**0.000**	**0.005**	0.066	**0.000**	**0.000**
Pandemic												
VR	2.302	3.968	3.175	10.714	**0.16**	**0.397**	**1.111**	**1.19**	2.143	**0.794**	**0.794**	**1.19**
LR(UC)	16.699	12.833	40.878	81.59	14.3	1.201	0.158	0.087	13.24	0.117	0.606	0.087
p-value	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.273	0.691	0.768	**0.000**	0.733	0.436	0.768
LR(CC)	17.471	12.833	46.141	81.59	14.3	1.202	0.158	0.087	62.251	0.117	4.854	0.087
p-value	**0.000**	**0.002**	**0.000**	**0.000**	**0.001**	0.548	0.924	0.957	**0.000**	0.943	0.088	0.957

Note: The bold figures represented a good model based on the violation ratio (VR) and null hypothesis of UC and CC tests which were rejected at critical values of 3.8415 and 6.6349 at 5% and 1% significance levels, respectively

5. CONCLUSION

Stock market responses to extreme events, such as the COVID-19 pandemic, can vary over time based on global economic conditions. Although the pandemic may have ended and no new variants have emerged to trigger major waves of cases, it remains crucial to manage any future uncertainty by developing a risk prediction model capable of accurately forecasting the risk of rare extreme events. In today's challenging and competitive financial landscape, the Islamic market is recognized as a progressively growing sector in the global financial industry. Therefore, prospective investors in Malaysia are advised to consider increasing their investment in Shariah-compliant instruments as a safeguard against potential losses during unforeseen financial crisis. From an Islamic perspective, the current conventional stock market entails several conditions that are incompatible with Shariah law, restricting Muslim investors from participating in conventional stock markets. This draws interest among investors in Islamic countries, including Malaysia, to invest in Islamic stock markets rather than the conventional stock markets.

The results of this study contribute to the addition of new knowledge regarding Islamic finance studies, particularly in stock market risk analysis. These results provide stylized facts for both conventional and Islamic stock markets in Malaysia during pre- and post-COVID-19 periods. This study suggested that Islamic indexes in Malaysia have lower risk and higher returns compared to conventional indexes during pre- and post-crisis periods. Stock market returns exhibited heavy tailed during COVID-19 period which resulted in extreme negative returns that consequently generated a spike in volatility. Based on the stylized fact results, the conditional EVT model was applied to the common GARCH and EGARCH models to better capture the properties of clustering, asymmetry and heavy tailed which existed in the data series during the COVID-19 period.

The empirical analysis of this study incorporated the GARCH and EGARCH models into the EVT model by utilizing the POT method in measuring the stock market risk of Islamic and conventional indexes in Malaysia during the COVID-19 period. This study adds new literature related to Malaysian stock market risk analysis, where previous researches have used the standard GARCH and EGARCH models. Based on the results obtained, the conditional EVT model outperformed the standard GARCH and EGARCH models in measuring Islamic stock market risk in Malaysia. However, both models did not exhibit better performance in the conventional stock market. The reason may be because extremely positive and negative returns were more likely to be seen in Shariah-compliant stock indexes compared to conventional stock indexes during COVID-19 period. These results also provide useful equations for long-position investors to estimate the actual possible losses that may occur when a specific amount of money is invested based on the quantile forecast outcomes of the empirical analysis.

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