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Global Uncertainty and Tail Risk in Indonesia's Islamic and Conventional Equity Markets

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Abstract

Is the Indonesian Islamic stock market more resilient to extreme risks compared to conventional markets when global uncertainty increases? Using daily data from the Jakarta Islamic Index (JKII) and the Jakarta Stock Exchange Composite Index (JKSE), we integrate the GARCH–EVT approach, quantile regression, and Expected Shortfall (ES) regression to simultaneously investigate the distribution structure and transmission of global uncertainty shocks. We decompose extreme risk into two main components – the structural thickness of the tail distribution and the realized conditional loss due to volatility dynamics – and show that these two dimensions can lead to different conclusions. Our results indicate that the conventional market has a thicker tail distribution, indicating a higher probability of extreme events. However, after accounting for conditional volatility, the Islamic market exhibits slightly larger average extreme losses. On the other hand, no significant difference is found in sensitivity to global uncertainty between the two markets. Our findings suggest that the difference between Islamic and conventional markets lies in the structure of extreme risk formation, not in the shock transmission mechanism. Our study contributes by demonstrating that tail risk should be understood as the result of the interaction between the distribution of extremes and volatility dynamics in the context of global uncertainty.

Keywords: Global Uncertainty, Tail Risk, Islamic Equity Markets, GARCH–EVT, Expected Shortfall, Quantile Regression

1. INTRODUCTION

Is the Indonesian Islamic stock market more resilient to extreme risks triggered by global uncertainty compared to conventional stock markets? More specifically, to what extent does global uncertainty affect both volatility and the risk of extreme losses (tail risk) across Islamic and conventional markets, and are there systematic differences in the transmission mechanisms of these risks? We hypothesize that increased global uncertainty significantly exacerbates extreme risks in the stock market, particularly in the lower tail of the return distribution. We further hypothesize that this effect differs across markets, with Islamic stock markets exhibiting greater relative resilience to global uncertainty shocks than conventional markets, both in terms of the structure of the tail distribution and their response to external shocks.

The motivation for these hypotheses stems from two interrelated strands of empirical evidence. A growing body of literature shows that global uncertainty significantly affects financial markets (Ashena et al., 2024; Chen et al., 2023; Irani et al., 2025; Jiang et al., 2024; Sarma & Rajib, 2025). For example, using an extension of the heterogeneous autoregressive model, Asgharian et al. (2023) examine the impact of global uncertainty on stock market volatility and find that global uncertainty is associated with higher investor risk aversion. Su et al. (2025) show that economic policy uncertainty increases volatility spillover in global stock markets. Li et al. (2020) document that global economic policy uncertainty is positively correlated with increased volatility in the Chinese stock market. In contrast, the Islamic finance literature suggests that the unique characteristics of Islamic markets, such as constraints on leverage consistent with Sharia principles (Ashraf et al., 2017; Ulussever et al., 2025), the prohibition on excessive speculation (Kanwal, 2022), and Sharia-compliant asset selection, may generate distinct risk characteristics compared to conventional markets (AlAbbad et al., 2019; Alhammadi et al., 2020; Raouf & Ahmed, 2022). However, empirical evidence on whether this distinction also applies to the extreme risk dimension is still limited and inconclusive.

Theoretically, the relationship between global uncertainty and extreme risk can be explained through time-varying risk premia, reflected in changes in effective risk aversion within asset pricing frameworks. This change subsequently results in a reduced demand for risky assets, which in turn can amplify volatility and increase the likelihood of extreme events. Under such conditions, risk becomes asymmetrically distributed and increasingly concentrated in the tail of the distribution (tail risk). Therefore, a normal distribution-based approach becomes inadequate, and a modeling framework that explicitly captures both volatility dynamics and tail behavior is required (Bali & Weinbaum, 2007; Longin, 2000).

To address this challenge, we adopt a two-stage GARCH–EVT-based approach as developed by McNeil and Frey (2000), in which conditional volatility is modeled using various GARCH specifications, and the tail distribution is estimated using Extreme Value Theory (EVT). This approach allows for a separation of volatility dynamics and the structure of the extreme distribution, resulting in a more accurate risk measurement. We further complement the analysis with quantile regression to test the impact of global uncertainty on different parts of the return distribution, as well as Expected Shortfall (ES) regressions to identify how global uncertainty directly affects extreme risk.

Using daily data from the Jakarta Islamic Index (JKII) and the Jakarta Stock Exchange Composite Index (JKSE) representing Islamic and conventional markets, our empirical results

reveal several key findings. First, both markets exhibit strong fat-tailed characteristics, with the conventional market having a structurally thicker tail. Second, global uncertainty significantly increases extreme risk, with the impact becoming stronger in the lower tail of the distribution. Third, although the conventional market has a more extreme tail structure, the Islamic market exhibits a slightly higher average conditional risk after accounting for volatility dynamics. Fourth, we find no significant difference in sensitivity to global uncertainty between the two markets, suggesting that global shocks are systemic.

Our study makes three main contributions. First, it addresses an important gap in the literature by explicitly combining volatility analysis (GARCH), extreme distribution analysis (EVT), and distribution heterogeneity analysis (quantile regression) within a unified framework to compare Islamic and conventional markets in Indonesia. Second, this study introduces a decomposition of extreme risk into two main components—the tail distribution structure and the dynamics of conditional volatility, demonstrating that these components may lead to different assessments of risk. Third, this study provides new empirical evidence that the differences between Islamic and conventional markets lie not only in the level of risk but also in the mechanisms by which extreme risk is generated, particularly under conditions of heightened global uncertainty.

1.1. Literature Review

The literature comparing Islamic and conventional stocks is growing rapidly. Most studies focus on differences between the two systems, particularly in terms of performance (Masih et al., 2018), the existence of decoupling (Al-Yahyaee et al., 2020; Hkiri et al., 2017), and contagion (Ahmed, 2018; Ben Rejeb, 2017). Using a systematic literature review approach, Delle Foglie and Panetta (2020) conclude that the literature has not yet reached a clear consensus regarding the role of Islamic stocks as a safe haven or as a diversification instrument. Some studies indicate that Islamic equities perform better than their conventional counterparts (Abu-Alkheil et al., 2017; Hassan et al., 2023; Jabeen & Kausar, 2022).

Recent literature confirms that dependence between Islamic and non-Islamic stocks is quantile-specific (Khalfaoui & Guesmi, 2025; Rahman et al., 2021). For example, Rahman et al. (2021) analyze the quantile dependency between Islamic and non-Islamic stock returns using a cross-quantilogram approach. Their findings indicate that under normal conditions, Islamic and non-Islamic stock markets are generally independent. However, in the lower quantiles, this dependency tends to be positive and persistent. Subsequent literature has extend the issue from quantile dependency to risk- and uncertainty-based dependency and spillovers (Chau et al., 2014; Jawadi et al., 2019; Shahzad & Naifar, 2022). Shahzad and Naifar (2022) show that

conventional stock markets exhibit stronger dependence than Islamic stock markets during the pandemic. This suggests that Islamic markets are relatively more fragmented or less connected, potentially providing better diversification benefits under certain circumstances. However, these benefits are not universal, as some Islamic stock sectors exhibit high internal interconnectedness, thus reducing diversification potential.

Over the past five years, the literature has shifted toward tail risk and extreme connectedness. Billah et al. (2024), for example, analyze tail risk spillovers between Islamic equity markets, sukuk, and green energy markets, showing that the extreme risk relationship is cross-market and strongly influenced by global factors. At the same time, Rabbani et al. (2023) demonstrate that Islamic equity markets play a key role in transmitting volatility within the broader financial system, particularly during periods of major turmoil such as COVID-19 and the Russia–Ukraine war. Recent literature has also increasingly emphasized the importance of global uncertainty indicators as determinants of market behavior. Wang et al. (2023) show that US uncertainty enhances the predictability of international stock market volatility, suggesting that global information is not only relevant for developed markets but also transmitted to non-US markets. In the context of Islamic markets, Kazak et al. (2025) demonstrate that indicators such as GEPU, GPR, WUI, and especially the VIX are important in explaining Islamic stock market behavior.

Despite significant advances in the literature, many recent studies on Islamic and conventional markets still focus on cross-market connectivity, spillovers, or dependence, rather than absolute tail risk measures such as VaR and, in particular, Expected Shortfall. From a risk management perspective, investors and regulators need to understand not only whether markets are connected but also the magnitude of potential losses when tail events materialize. Our research addresses this gap by measuring absolute extreme risk using the GARCH–EVT approach, enabling the estimation of VaR and Expected Shortfall (ES) across Islamic and conventional markets within a single, consistent framework. Furthermore, we combine tail structure and conditional risk analyses. This allows us to assess whether differences between the JKII and JKSE stem from the thickness of the distribution tails, volatility dynamics, or the interaction of the two. We also complement this research with quantile regression and Expected Shortfall regression, thus addressing not only whether tail risk differs across markets, but also how global uncertainty affects downside returns and conditional tail risk across Islamic and conventional markets.

2. METHOD

Using daily data, we use three main variables to examine the effect of global uncertainty on extreme risk (VaR and ES) in Islamic and conventional stock markets, represented by the Jakarta Islamic Index (JKII) and the Jakarta Stock Exchange Composite Index (JKSE), respectively. Our first variable is the VIX index, which represents global investor aversion to risk. The remaining variables are the daily returns of each index, calculated as log returns as follows:

$$r_{i,t} = \ln(P_{i,t}) - \ln(P_{i,t-1}) \quad (1)$$

where $P_{i,t}$ is the price of index i at time t, and $i \in \{JKII, JKSE\}$. As an additional variable, we also construct a high-uncertainty regime dummy that takes on a value of 1 when the VIX is above the 90th percentile of its distribution and 0 otherwise. We use this variable to distinguish tail-dependent behavior during periods of high and low global stress. All data for the main variables are obtained from Yahoo Finance with the help of the quantmod package from R (Ryan & Ulrich, 2022).

One common characteristic of asset returns is the presence of serial correlation (linear dependence) and volatility clustering (nonlinear dependence). To account for these features, we follow the two-stage approach of McNeil and Frey (2000) in modeling volatility and its tail distribution. In the first stage, we use the standard GARCH model from Bollerslev (1986) with the GARCH (1,1) specification as recommended by Hansen and Lunde (2005).

$$r_t - \mu = \varepsilon_t \quad (2)$$

$$\varepsilon_t = \sigma_t z_t, \qquad z_t \sim i.i.d.(0,1) \quad (3)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (4)$$

where r_t is the logarithm of the return. μ is the conditional mean return, ε_t is the error term, also called the mean corrected return, σ_t^2 is the conditional variance, and the values α_1 and β_1 indicate the ARCH and GARCH parameters. For the conditional variance equation to be positive, the parameters $\alpha_0 > 0$, $\alpha_1 > 0$ and $\beta_1 > 0$. Furthermore, ε_t is covariance stationary if and only if $\alpha_1 + \beta_1 < 1$.

To capture possible asymmetries in returns, we also propose several alternative models such as eGARCH (1,1) by Nelson (1991), gjrGARCH (1,1) by Glosten et al. (1993), and tGARCH (1,1) by Zakoian (1994). Some alternatives to our standard GARCH model for return i can be written as follows:

$$\ln(\sigma_t^2) = \alpha_0 + \delta_1 z_{t-1} + \gamma_1(|z_{t-1}| - E[|z_{t-1}|]) + \beta_1 \ln(\sigma_{t-1}^2) \quad (5)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 \Pi_{t-1}^- \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (6)$$

$$\sigma_t = \alpha_0 + \alpha_1 |\varepsilon_{t-1}| + \gamma_1 \Pi_{t-1}^- |\varepsilon_{t-1}| + \beta_1 \sigma_{t-1} \quad (7)$$

The EGARCH model in equation (5) uses a logarithmic transformation and therefore does not require a non-negativity restriction on the variance. The parameter δ_1 captures the direction of the leverage effect, where $\delta_1 < 0$. The parameter γ_1 captures the size of the leverage effect, such that $\gamma_1 > 0$. Equation 6 shows the GJR-GARCH model. To ensure positive conditional volatility, $\alpha_0 > 0$, $\alpha_1 > 0$, $\alpha_1 + \gamma_1 > 0$, and $\beta_1 > 0$ are required. The third alternative is the TGARCH model in equation (7), which models volatility in terms of standard deviation and directly accommodates the threshold effect. After the model is estimated, the standardized residuals are defined as:

$$\hat{z}_{i,t} = \frac{\hat{r}_{i,t} - \hat{\mu}_{i,t}}{\hat{\sigma}_{i,t}} \tag{8}$$

where $\hat{\mu}_{i,t}$ and $\hat{\sigma}_{i,t}$ are the estimated means and variances of JKII and JKSE, respectively. Because our analysis focuses on downside risk, we transform $\hat{z}_{i,t}$ into loss as follows:

$$x_{i,t} = -\hat{z}_{i,t} \tag{9}$$

where large positive values of $x_{i,t}$ reflect the most extreme losses.

In the second step, we first define exceedances as values of $x_{i,t}$ that exceed the threshold u. We assume that all values of $x_{i,t}$ above the threshold follow the generalized Pareto distribution as follows:

$$P\left(x_{i,t} - u_i \leq y | x_{i,t} > u_i\right) = 1 - \left(1 + \frac{\xi_i y}{\beta_i}\right)^{-1/\xi_i} \tag{10}$$

where ξ_i is the tail index and β_i is the scale parameter. Next, given the GPD parameters, the tail quantile at level α is calculated as follows:

$$q_{i,\alpha} = u_i + \frac{\beta_i}{\xi_i}\left[\left(\frac{n_i}{N_{u_i}}(1-\alpha)\right)^{-\xi_i} - 1\right] \tag{11}$$

where n_i is the total number of observations and N_{u_i} is the number of exceedances above the threshold. For the same level α, the Expected Shortfall is given by:

$$ES_{i,\alpha} = \frac{q_{i,\alpha} + \beta_i - \xi_i u_i}{1 - \xi_i} \tag{12}$$

Finally, to obtain the conditional VaR and conditional ES at the original return scale, equations (11) and (12) can be rewritten as:

$$VaR_{i,t}^{\alpha} = \hat{\mu}_{i,t} - \hat{\sigma}_{i,t} q_{i,\alpha} \tag{13}$$

$$ES_{i,t}^{\alpha} = \hat{\mu}_{i,t} - \hat{\sigma}_{i,t} ES_{i,\alpha} \tag{14}$$

After obtaining the VaR and ES values, we then use two empirical strategies to test whether global uncertainty affects extreme risk in JKII and JKSE. First, we use quantile regression to

test whether the VIX deepens downside returns at the bottom of the distribution, as shown in equation (15):

$$Q_\tau(r_{i,t}|U_{t-1}) = \alpha_i(\tau) + \beta_i(\tau)U_{t-1} \quad (15)$$

where Q_τ is the τ th quantile of returns, with $\tau = 0.05$ representing a large loss (lower tail) and $\tau = 0.01$ representing an extreme loss. U_{t-1} is the lagged value of the VIX. We use the lagged value to reduce simultaneity bias. $\alpha_i(\tau)$ is the baseline quintile return when $U_{t-1} = 0$. Our main parameter is β_i (τ), which indicates the sensitivity of the tail returns of JKII and JKSE to uncertainty. If $\beta_i(\tau)$ is more negative at lower quantiles, then global uncertainty has a stronger effect on the downside tail of JKII and JKSE. To directly compare the responses of JKII and JKSE, we also estimate a pooled model with interactions as shown in equation (16):

$$Q_\tau(r_{i,t}) = \alpha(\tau) + \delta(\tau)D_i + \beta(\tau)U_{t-1} + \gamma(\tau)(D_i \times U_{t-1}) \quad (16)$$

where D_i is a dummy that takes the value 1 for JKII and 0 for JKSE. The interaction coefficient $\gamma(\tau)$ indicates whether the sensitivity of tail returns to global uncertainty differs between JKII and JKSE.

In addition to the quintile regression on returns, we also regress the conditional ES on the VIX to test whether global uncertainty directly increases tail risk:

$$ES_{i,t}^{loss} = a_i + b_i U_{t-1} + e_{i,t} \quad (17)$$

where $ES_{i,t}^{loss}$ is the Expected Shortfall expressed in positive loss units. We also estimate a pooled model to compare JKII and JKSE:

$$ES_{i,t}^{loss} = a + \delta D_i + \beta U_{t-1} + \gamma(D_i \times U_{t-1}) + e_{i,t} \quad (18)$$

where β is the effect of the VIX on JKSE, while γ indicates whether this effect differs for JKII. If $\gamma < 0$, then JKII is relatively more resilient to increases in global uncertainty.

3. RESULTS AND DISCUSSION

3.1. Stylized Facts of Indonesia Equity Market Returns

In this section, we provide evidence that the return distributions in the Indonesian stock market, both Islamic and conventional, do not meet the assumption of normality, particularly in the tails of the distributions relevant for extreme risk analysis. Figure 1 shows that the distribution patterns of the JKII and JKSE are relatively centered around zero, with a bell-shaped distribution. In both markets, tail probabilities appear higher compared to a normal distribution.

This finding is further supported by the QQ plot. The points in the left tails of the JKII and JKSE deviate significantly below the reference line, while the points in their right tails are above the line. This pattern suggests that both extreme losses and extreme gains occur more

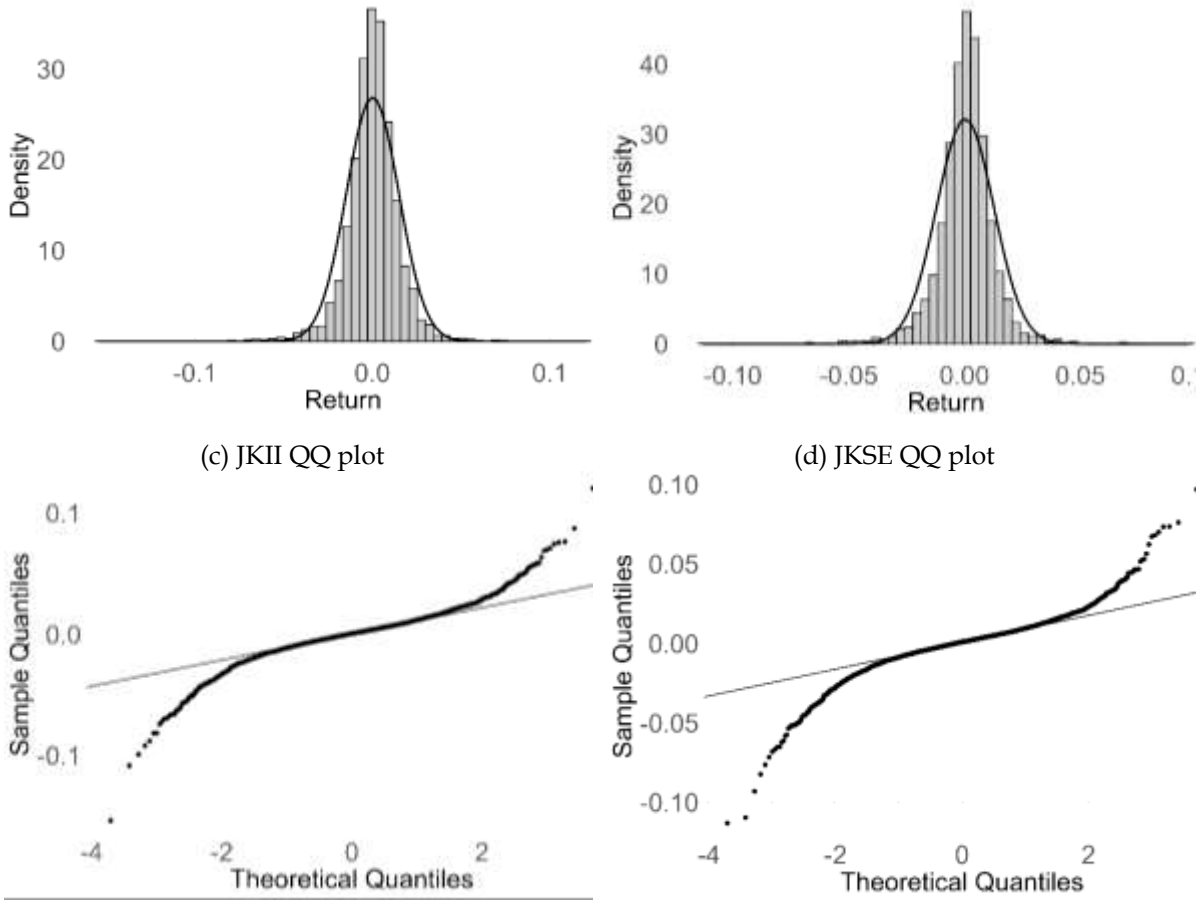
frequently than predicted by a normal distribution. However, the deviations in the QQ plot are more pronounced in the JKSE, particularly in the right tail, where some extreme observations significantly exceed the reference line. Meanwhile, the JKII also exhibits a clear deviation from normality, albeit with slightly more moderate intensity. In the left tail, both the JKII and the JKSE exhibit deep negative outliers, confirming that downside risk is a fundamental characteristic of both markets.

The skewness, kurtosis, and Jarque–Bera test results in Table 1 corroborate the findings obtained from the previous histogram and QQ plot analyses. The return distributions in both markets exhibit quite strong left-skewness, with skewness values of -0.5177 for JKII and -0.6181 for JKSE. This negative skewness indicates that extreme losses are more likely than extreme gains, and this tendency is sharper for JKSE. Furthermore, the very high kurtosis levels—10.8493 for JKII and even higher, 11.8528, for JKSE—confirm the presence of extreme fat tails in both return distributions. The excess kurtosis values of 7.8493 and 8.8528, respectively, indicate a significant deviation from the normal distribution. This finding is reinforced by the results of the Jarque–Bera test, which yielded an extremely large test statistics—12,348.7202 for Islamic stocks and 15,740.3079 for conventional stocks—with a p-value effectively equal to zero.

Table 1 also reveals several other interesting patterns related to the differences and similarities in statistical characteristics between the JKII and JKSE. Both indices have relatively small mean returns, with the JKSE recording a slightly higher value (0.0004) than the JKII (0.0002). Furthermore, the standard deviation of JKII returns is 0.0148, slightly higher than the JKSE (0.0124), indicating that the volatility of Islamic indices is not fully consistent with the conventional narrative regarding the relative stability of the Islamic market.

From a temporal dynamics perspective, returns exhibit relatively weak autocorrelation, especially at the first lag (0.0358 for the JKII and 0.0718 for the JKSE) and even approaching zero at the fifth lag. This is consistent with the weak form of the efficient market hypothesis. However, a different pattern emerges when we examine the autocorrelation of absolute and squared returns. The ACF values at the first lag for absolute returns reached 0.2451 (JKII) and 0.2733 (JKSE), while for squared returns they were 0.1766 and 0.2280, respectively. This persistence continues until the fifth lag. The combination of low autocorrelation in raw returns and high autocorrelation in volatility measures indicates the presence of volatility clustering in JKII and JKSE. Interestingly, the level of volatility persistence appears slightly stronger in JKSE, indicating greater sensitivity to systemic shocks.

(a) JKII returns (b) JKSE returns



(c) JKII QQ plot (d) JKSE QQ plot

Figure 1. Distributional Characteristics and Tail Behavior of JKII and JKSE Returns
Source: Author's Estimation
Notes: The figure compares the empirical distribution of returns using histograms and Q–Q plots for JKII and JKSE. Deviations from the normal distribution, particularly in the tails, indicate the presence of fat-tailed behavior and justify the use of extreme value methods.

Table 1
Stylized Facts of JKII and JKSE Return

Indicator	JKII	JKSE
mean	0.0002	0.0004
sd	0.0148	0.0124
skewness	-0.5177	-0.6181
kurtosis	10.8493	11.8528
excess_kurtosis	7.8493	8.8528
acf_ret_1	0.0358	0.0718
acf_abs_1	0.2451	0.2733
acf_sq_1	0.1766	0.2280
acf_ret_5	-0.0006	-0.0142
acf_abs_5	0.1975	0.2174
acf_sq_5	0.1559	0.1632
jb_stat	12348.7202	15740.3079
jb_pvalue	0.0000	0.0000
n_obs	4728	4728

Source: Author's Estimation

3.2. Tail Risk Estimation of Indonesian Equity Market using GARCH–EVT

To ensure that the volatility dynamics of JKII and JKSE are modeled appropriately, we estimate four alternative GARCH specifications—sGARCH, EGARCH, GJR-GARCH, and TGARCH—using maximum likelihood estimation and the Student-t distribution of innovation. The estimation results based on the four alternative models show a consistent pattern in describing volatility dynamics, the presence of asymmetry, and the appropriateness of the model specifications for JKII and JKSE.

In the variance equation, all models show strong evidence of volatility clustering, with the parameters α_1 and β_1 statistically significant at the 1% confidence level in all specifications. In the sGARCH model, the volatility persistence rate, measured by $\alpha_1 + \beta_1$, reaches 0.98 for JKII and JKSE, respectively, indicating that the stationarity condition is satisfied. In the EGARCH model, persistence is even higher than in the other three models, with β_1 of 0.9715 (JKII) and 0.9717 (JKSE), indicating that volatility shocks tend to persist over long periods. As expected, volatility persistence in JKSE is higher than in JKII, indicating that volatility shocks in the conventional market persist for a longer duration than in the Islamic market.

Both markets also exhibit strong and consistent volatility asymmetry. The γ_1 parameter in all models is positive and significant at the 1% level. We also find that the asymmetry parameter is consistently higher in the conventional market across both the EGARCH and GJR-GARCH model specifications. In the EGARCH specification, the asymmetry parameter is 0.1990 for JKII and 0.2210 for JKSE. Meanwhile, in the GJR-GARCH specification, the asymmetry parameter is 0.0931 (JKII) compared to 0.1046 (JKSE). This pattern suggests that the Islamic market is relatively more resilient to volatility amplification due to bad news, which is potentially related to the structural characteristics of the Islamic-based asset composition, such as leverage restrictions and exposure to high-risk sectors (Jawadi et al., 2019).

The shape parameter of the Student-t distribution provides important information regarding the tail thickness of the JKII and JKSE return distributions. This parameter value ranges from 6.63 to 6.79 for JKII and between 5.82 and 6.04 for JKSE, and all are statistically significant. These values indicate strong fat tails in both markets, so the return distributions cannot be adequately described by the normal distribution. However, the conventional market consistently has lower shape values than the Islamic market, indicating that the JKSE return distribution has thicker tails. This finding is significant because it provides strong justification for the use of the EVT approach in the next stage and indicates structural differences in extreme risk between the two markets.

Diagnostic test results indicate that all estimated GARCH models have adequate specifications. The Ljung–Box statistic for the standardized residuals (lb_resid_stat) is insignificant in all models, with p-values well above 0.05. This indicates that there is no remaining autocorrelation in the residuals after volatility filtering. Similarly, the Ljung–Box test for the squared residuals (lb_sq_stat) is also insignificant in all specifications, with p-values generally very high (above 0.80). This indicates that there is no remaining ARCH effect, and thus the model has successfully captured the dynamics of conditional heteroscedasticity.

Table 2
GARCH Model Estimation Results and Diagnostic Tests for JKII and JKSE Returns

parameter	JKII				JKSE			
	sGARCH	EGARCH	GJRGARCH	TGARCH	sGARCH	EGARCH	GJRGARCH	TGARCH
mu	0.0005**	0.0003	0.0003*	0.0003	0.0008**	0.0006**	0.0006**	0.0006**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
omega	0.0000**	-0.2497**	0.0000**	0.0004**	0.0000**	-0.2614**	0.0000**	0.0003**
	(0.0000)	(0.0163)	(0.0000)	(0.0001)	(0.0000)	(0.0240)	(0.0000)	(0.0001)
alpha1	0.1055**	-0.0688**	0.0508**	0.1118**	0.1248**	-0.0759**	0.0650**	0.1256**
	(0.0109)	(0.0103)	(0.0073)	(0.0122)	(0.0161)	(0.0106)	(0.0128)	(0.0125)
beta1	0.8707**	0.9715**	0.8727**	0.8826**	0.8565**	0.9717**	0.8560**	0.8743**
	(0.0131)	(0.0019)	(0.0068)	(0.0143)	(0.0178)	(0.0026)	(0.0161)	(0.0138)
gamma1		0.1990**	0.0931**	0.3722**		0.2210**	0.1046**	0.3664**
		(0.0172)	(0.0132)	(0.0588)		(0.0197)	(0.0200)	(0.0536)
shape	6.6329**	6.7862**	6.7792**	6.7900**	5.8297**	6.0203**	5.9878**	6.0429**
	(0.6142)	(0.6398)	(0.5258)	(0.6311)	(0.4746)	(0.5026)	(0.4929)	(0.5004)
lb_resid_stat	23.7655	22.7220	24.1526	22.4394	24.1505	23.1900	23.4798	25.0680
	[0.2528]	[0.3026]	[0.2358]	[0.3172]	[0.2359]	[0.2796]	[0.2659]	[0.1998]
lb_sq_stat	11.4011	9.6435	8.9887	14.1525	10.2042	9.2596	8.5400	13.8045
	[0.8132]	[0.7999]	[0.8508]	[0.6933]	[0.6987]	[0.7113]	[0.5565]	[0.8326]
AIC	-5.9369	-5.9439	-5.9438	-5.9428	-6.3688	-6.3778	-6.3770	-6.3760
BIC	-5.9301	-5.9357	-5.9356	-5.9346	-6.3620	-6.3696	-6.3688	-6.3678
SIC	-5.9369	-5.9439	-5.9438	-5.9428	-6.3688	-6.3778	-6.3770	-6.3760
HQIC	-5.9345	-5.9410	-5.9409	-5.9399	-6.3664	-6.3749	-6.3742	-6.3731
observations	4728	4728	4728	4728	4728	4728	4728	4728

Source: Author's Estimation

Notes: The table reports maximum-likelihood estimates for alternative GARCH specifications under a Student-t distribution. Standard errors are reported in parentheses, and p-values are reported in square brackets. ** and * indicate statistical significance at the 1% and 5% levels, respectively. The *shape* parameter denotes the degrees of freedom of the Student-t distribution and reflects the degree of tail heaviness. The Ljung–Box test on standardized residuals (*lb_resid_stat*) evaluates the presence of remaining serial correlation, while the Ljung–Box test on squared standardized residuals (*lb_sq_stat*) evaluates remaining conditional heteroskedasticity. Failure to reject the null hypothesis indicates adequate model specification. AIC, BIC, SIC, and HQIC are reported as model selection criteria.

Based on the information criteria, the EGARCH model consistently provides the best fit in both markets. For JKII, EGARCH produced the lowest AIC of −5.9439 and BIC of −5.9357. The same pattern was also found for JKSE, with an AIC of −6.3778 and a BIC of −6.3696.

Therefore, we used the standardized residuals from the EGARCH model to estimate extreme risk using the Extreme Value Theory (EVT) approach. Table 3 presents the main parameters of the Generalized Pareto Distribution (GPD) estimation, including the threshold, shape parameter (ξ), scale (β), and extreme risk measures such as Value-at-Risk (VaR) and Expected Shortfall (ES) at the 99% confidence level. We found that ξ was positive for both markets, at 0.0840 for JKII and 0.1264 for JKSE. A positive ξ value indicates that the distribution follows a heavy-tailed (Pareto-type distribution), meaning the probability of extreme events decreases slowly.

Furthermore, the higher ξ value in the conventional market indicates that the tails of the JKSE distribution are thicker than those of JKII. This finding is consistent with previous results from the shape parameters of the Student-t distribution in Table 2, which also indicate that JKSE returns have stronger fat tails than those of JKII. The threshold values used in the EVT estimation are relatively similar between the two markets, at approximately 1.64 for JKII and 1.68 for JKSE, indicating that the choice of cutoff for extreme observations is empirically consistent. The β parameter also shows comparable values, at 0.6558 (JKII) and 0.6617 (JKSE). However, our findings indicate that the tails of the JKSE distribution are more extreme than those of JKII, as reflected in the ξ and β parameters.

The difference in extreme risk between JKII and JKSE becomes more pronounced when viewed from the VaR and ES measures. At the 99% confidence level, the VaR (EVT) value for JKII is 2.7755, while for JKSE it is higher, at 2.8655. This indicates that the maximum potential loss at extreme quantiles is greater in conventional markets. This difference becomes more significant in Expected Shortfall, which measures the average loss when VaR is exceeded. The ES value for JKII is 3.5953, while for JKSE it is 3.7942. Because ES is a more tail-sensitive risk measure, this difference indicates that extreme losses in conventional markets are not only more frequent but also deeper on average.

When the tail risk measures are rescaled to returns through the conditional volatility component of the EGARCH model, we obtain the average conditional VaR and conditional ES. For JKII, the average conditional VaR is 0.0370 and the conditional ES is 0.0480, while for JKSE they are 0.0312 and 0.0414, respectively. At first glance, these values appear higher for JKII. However, this does not contradict previous results, as conditional risk is the result of the interaction between two components: conditional volatility and the tail distribution. In this context, although conventional markets have thicker tails, higher conditional volatility in a given period in the JKII can result in relatively greater conditional risk over time. This suggests

that tail risk is determined not only by the extremes of the distribution but also by the underlying volatility dynamics.

Table 3
EVT Estimates and Conditional Tail Risk Measures for JKII and JKSE Returns

	JKII	JKSE
alpha	0.9900	0.9900
threshold	1.6434	1.6823
xi	0.0840	0.1264
beta	0.6558	0.6617
q_evt	2.7755	2.8655
ES_evt	3.5953	3.7942
mean_conditional_VaR	0.0370	0.0312
mean_conditional_ES	0.0480	0.0414

Source: Author's Estimation
Note: The reported mean conditional VaR and ES represent the time-averaged conditional tail risk expressed as positive loss values. Higher values indicate greater exposure to downside risk

3.3. Global Uncertainty and Tail Risk of Indonesian Equity Market

Table 4 presents the results of quantile regression estimations at the lower quantiles ($\tau = 0.05$ and $\tau = 0.01$) to evaluate the impact of global uncertainty on extreme returns for JKII and JKSE. We find that the coefficient of U_{t-1} is negative across all specifications and increases in absolute terms at more extreme quantiles. For JKII, the coefficient increases from -0.0008 ($\tau = 0.05$) to -0.0017 ($\tau = 0.01$), while for JKSE, it increases from -0.0007 to -0.0015. The same pattern is also seen in the pooled model. These findings indicate that increased global uncertainty has a stronger impact on the lower end of the return distribution compared to normal conditions. In other words, shocks from global uncertainty not only lower average returns but also disproportionately increase the risk of extreme losses. This is consistent with the literature showing that global uncertainty tends to exacerbate downside risk through flight-to-safety mechanisms and increased risk aversion in financial markets (Chau et al., 2014; Wang et al., 2023).

When analyzed separately, the impact of global uncertainty on tail returns is relatively similar between JKII and JKSE, although slightly larger in the Islamic market in some specifications. However, this difference is not statistically significant. Pooled regression results provide more explicit insights through the islamic_dummy variable and its interaction with U_{t-1}. The coefficient of islamic_dummy is negative at both quantiles (-0.0026 at $\tau = 0.05$ and -0.0025 at $\tau = 0.05$), indicating that, on average, extreme returns in JKII tend to be lower than those in JKSE. However, the associated standard errors indicate that this difference is not statistically significant. More importantly, the coefficient of the interaction term

islamic_dummy × U_{t-1} is also negative but very small (−0.0001 and −0.0002), indicating that the sensitivity of the Islamic market to global uncertainty does not differ significantly from that of the conventional market.

Table 4

Quantile Regression Results of the Impact of Global Uncertainty for JKII and JKSE Returns

	JKII		JKSE		Pooled	
	$\tau = 0.05$	$\tau = 0.01$	$\tau = 0.05$	$\tau = 0.01$	$\tau = 0.05$	$\tau = 0.01$
intercept	-0.0065**	-0.0081**	-0.0040**	-0.0055**	-0.0040**	-0.0055**
	(0.0022)	(0.0058)	(0.0015)	(0.0045)	(0.0015)	(0.0049)
U_lag	-0.0008**	-0.0017**	-0.0007**	-0.0015**	-0.0007**	-0.0015**
	(0.0001)	(0.0003)	(0.0001)	(0.0003)	(0.0001)	(0.0003)
islamic_dummy					-0.0025	-0.0025
					(0.0027)	(0.0070)
islamic_dummy:U_lag					-0.0001	-0.0002
					(0.0002)	(0.0004)
Observations	4728	4728	4728	4728	4728	4728

Source: Author's Estimation

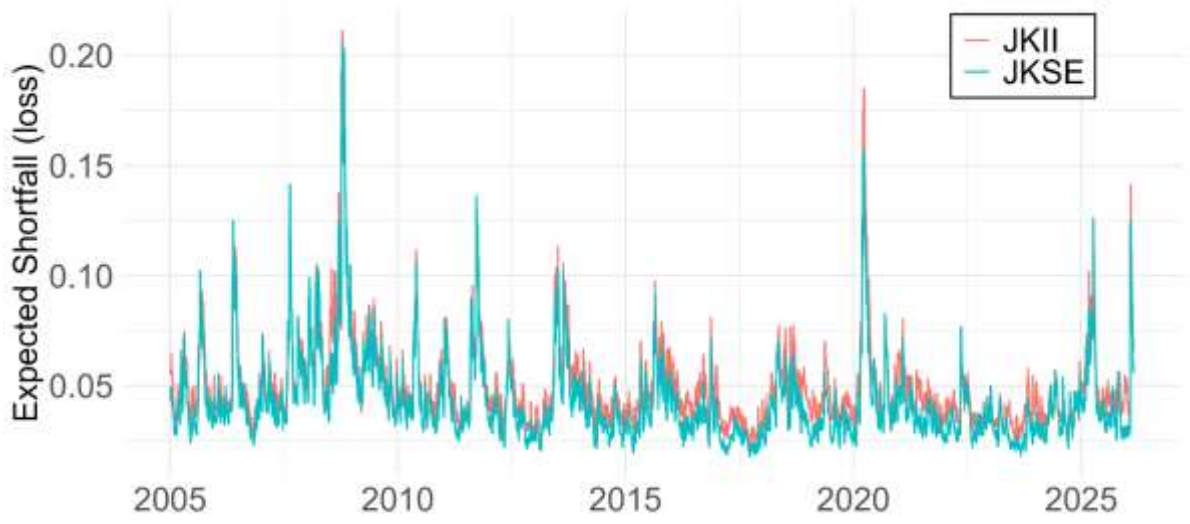
Notes: The table reports quantile regression estimates at the 5th and 1st percentiles (τ = 0.05 and τ = 0.01) for Islamic (JKII) and conventional (JKSE) equity returns, as well as pooled regressions. The dependent variable is the daily log return. U_{t-1} denotes lagged global uncertainty, proxied by the VIX index. In the pooled specification, *islamic_dummy* is a binary variable equal to 1 for Islamic equities and 0 for conventional equities. The interaction term captures differential sensitivity of Islamic returns to global uncertainty. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

To complement the distribution- and quantile-based analyses, we also evaluate the impact of global uncertainty on conditional tail risk using the ES measure. Unlike VaR, which only captures quantile boundaries, ES measures the average loss when extreme events occur, providing a more comprehensive measure of risk. Based on the rolling EVT analysis, we find that tail risk is dynamic and highly sensitive to global conditions. Figure 2 (panel a) shows that Expected Shortfall (ES) increases sharply during periods of high uncertainty, which is also evident in the spike in the VIX in Figure 2 (panel b). This finding is reinforced by Figure 3, which shows a clear positive relationship between VIX and ES. Interestingly, sensitivity to uncertainty differs slightly between JKII and JKSE.

To statistically verify the correlation between VIX and ES, we further estimate equations (17) and (18). Our estimation results in Table 5 show that the coefficient U_{t-1} is positive and highly significant across all specifications, at 0.0013 for JKII and 0.0014 for JKSE. This indicates that increased global uncertainty consistently increases the risk of extreme losses in both markets. More importantly, the individual regression results show that the

intercept value for JKII (0.0223) is higher than for JKSE (0.0146). This indicates that, on average, the expected level of extreme losses is greater in the Islamic market than in the conventional market. However, the identical U_{t-1} coefficients in both markets indicate that sensitivity to global uncertainty is relatively uniform. This means that global shocks affect both markets with similar magnitudes, increasing tail risk.

(a) Conditional Expected Shortfall (99%)



(b) Global Uncertainty (VIX)

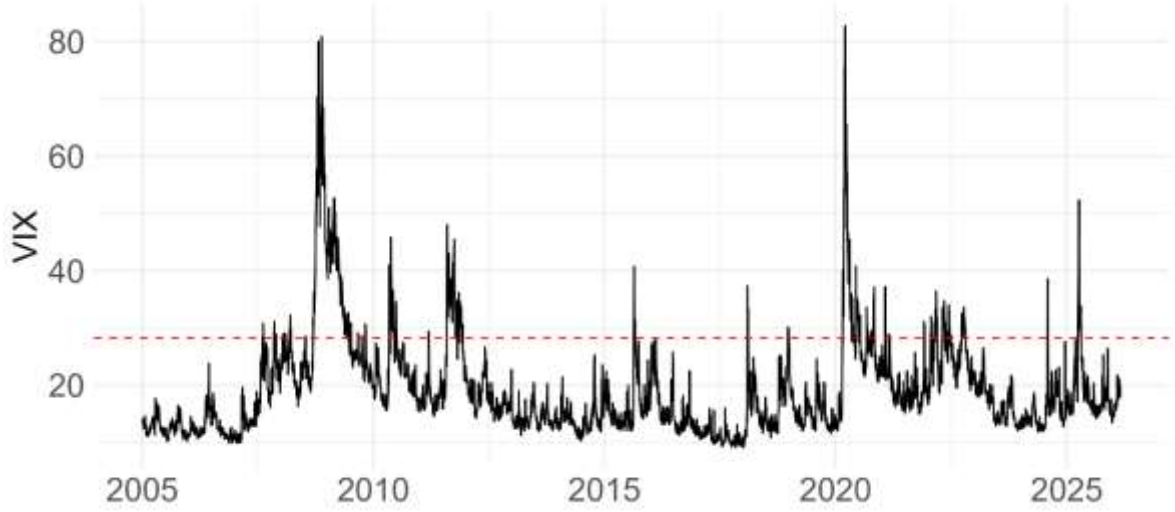


Figure 2. Conditional Expected Shortfall of JKII and JKSE and Global Uncertainty
Source: Author's Estimation

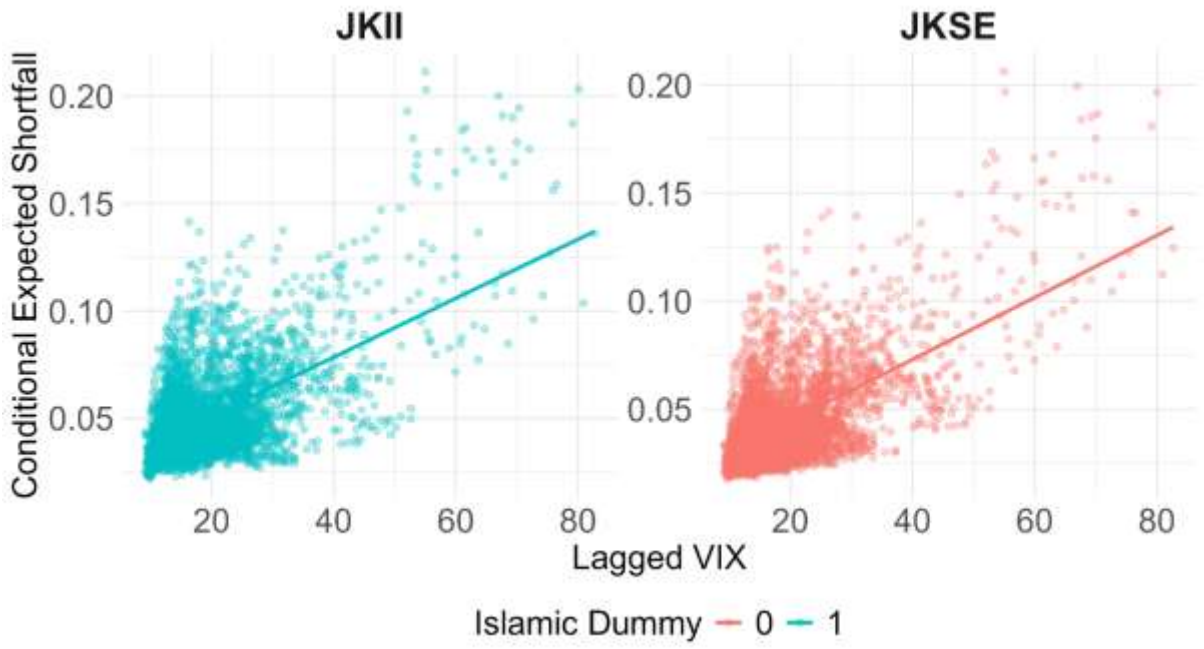


Figure 3. The Relationship Between Lagged VIX and Conditional Expected Shortfall of JKII and JKSE
Source: Author's Estimation

The pooled regression results provide a more comprehensive picture. The islamic_dummy coefficient of 0.0077, which is statistically significant, indicates that, on average, JKII has a higher conditional expected shortfall compared to the conventional market. In other words, after controlling for the influence of global uncertainty, the Islamic market still exhibits a greater level of extreme losses. The interaction coefficient of islamic_dummy × U_{t-1} is negative (-0.0001) and very small, indicating that the Islamic market's response to changes in global uncertainty is slightly lower than that of the conventional market. However, the magnitude of this effect is relatively small, so the difference is economically limited. Thus, our findings indicate that although the Islamic market has higher tail risk, its response to global shocks is slightly more moderate. This provides more nuanced insight than the previous analysis. If the EVT results for the conventional market show thicker tails (higher ξ), then the ES regression results show that in practice, the combination of conditional volatility and tail distribution results in higher average losses in the Islamic market.

Table 5

Regression Results for JKII and JKSE Conditional Expected Shortfall on Global Uncertainty

	JKII	JKSE	Pooled
intercept	0.0223**	0.0146**	0.0146**
	(0.0022)	(0.0020)	(0.0015)
U_lag	0.0013**	0.0014**	0.0014**
	(0.0001)	(0.0001)	(0.0001)
islamic_dummy			0.0077**
			(0.0005)
islamic_dummy:U_lag			-0.0001**
			(0.0000)
Observations	4728	4728	4728

Source: Author's Estimation

Notes: Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

3.4. Discussion

The main findings of this study confirm that differences between Islamic and conventional stock markets in Indonesia over the 2005–2025 period cannot be adequately explained by aggregate risk measures alone, such as volatility or mean returns. The stylized facts and GARCH–EVT estimation results indicate that both markets exhibit non-normal return distributions characterized by fat tails and negative skewness, although the intensity of these features differs across markets. Specifically, the Jakarta Stock Exchange (JKSE) exhibits greater tail thickness, as reflected by higher shape parameter. This finding is consistent with literature showing that conventional markets tend to have higher exposure to extreme risks (e.g., in studies of tail-risk connectedness), and supports the argument that extreme risk is an important dimension that cannot be captured by volatility-based analysis alone (Billah et al., 2024). However, these results also complement previous literature, which often focuses on comparisons of average performance or diversification, by showing that the main difference lies in the structure of the risk distribution (Abu-Alkheil et al., 2017).

Furthermore, our findings provide important nuances to the ongoing debate in the literature regarding whether Islamic markets are more stable than conventional markets. On the one hand, the finding that Islamic markets have thinner tail (compared to conventional markets) aligns with several studies showing that Islamic markets are relatively more fragmented or less connected within the global risk network, potentially providing diversification benefits (Azad et al., 2018). However, on the other hand, when extreme risk is measured in terms of conditional risk (using conditional VaR and Expected Shortfall), the results suggest that Islamic markets can actually experience higher average losses under certain conditions (Shahzad et al., 2017).

The results of quantile regression and Expected Shortfall regression analyses indicate that global uncertainty has a strong and consistent impact on extreme risk in both markets. The larger uncertainty coefficients at more extreme quantiles indicate that global shocks not only affect returns more broadly but also disproportionately exacerbate downside risk. These findings align with previous literature showing that inter-market dependencies are quantile-specific and amplified during crises, and are consistent with evidence that risk spillovers increase during periods of high uncertainty (Ben Rejeb, 2017). However, this study also shows that sensitivity to global uncertainty is relatively similar between Islamic and conventional markets, suggesting that the primary difference lies not in the response to shocks, but rather in the underlying risk structure (Jawadi et al., 2019). By integrating tail distribution analysis, conditional volatility, and uncertainty transmission into a single framework, this study provides a novel contribution to the literature by demonstrating that extreme risk results from the interaction between distributional factors and time-variant volatility dynamics.

4. CONCLUSION AND IMPLICATIONS

Our study aims to evaluate whether the Indonesian Islamic stock market is more resilient to extreme risks than conventional markets under conditions of global uncertainty. By integrating the GARCH–EVT approach, quantile regression, and Expected Shortfall regression, we show that the answer to this question is not straightforward and depends on how extreme risk is defined.

Our results indicate that conventional markets exhibit thicker tail distributions, suggesting a higher probability of extreme events. However, after accounting for volatility dynamics, Islamic markets actually exhibit slightly larger average extreme losses. Furthermore, no significant difference is found in sensitivity to global uncertainty between the two markets, suggesting that global shocks are systemic and affect both relatively uniformly.

Our findings confirm that tail risk should be understood as a multidimensional phenomenon reflecting the interaction between extreme distributions and conditional volatility. Thus, claims that Islamic markets are more stable or safer need to be reexamined within a more comprehensive framework. From a policy and investment perspective, our results suggest that diversification between Islamic and conventional markets does not necessarily eliminate extreme risk, but may provide benefits in understanding different sources of risk. Future research could be extended to incorporate cross-country factors,

sectoral differences, and alternative measures of global uncertainty to deepen **the** understanding of the dynamics of extreme risk in financial markets.

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