Scopus®

Contents lists available at Scopus

ECONOMICS - Innovative and Economics Research Journal

Journal homepage: www.economicsrs.com

VALUE AT RISK ESTIMATION USING MARKOV-SWITCHING GARCH-EVT(POT) MODEL: A GEOPOLITICAL RISK PERSPECTIVE FROM THE IRAN-ISRAEL CONFLICT

Darmanto Darmanto[1*], Isnani Darti[2], Suci Astutik[1], Nurjannah Nurjannah[1]

Received 13.10.2025. | Sent to review 03.11.2025. | Accepted 28.02.2026.

Original article

[1] Universitas Brawijaya, Faculty of Mathematics and Natural Sciences, Department of Statistics, Indonesia

[2] Universitas Brawijaya, Faculty of Mathematics and Natural Sciences, Department of Mathematics, Indonesia

[*]**Corresponding Author:**
Darmanto Darmanto

Email:
darman_stat@ub.ac.id

JEL Classification:
C58, F51, G15, G32

Doi: 10.2478/eoik-2026-0015

UDK: 339.738:336.748.3

ABSTRACT

This study investigates the impact of geopolitical conflict, specifically the Iran–Israel tension, on the volatility and extreme risk of stock markets in six indirectly involved countries: China, Russia, Turkey, the United States, the United Kingdom, and Germany. Using daily log returns from June 2023 to July 2025, the analysis begins with modelling the conditional mean using ARMA, followed by volatility modelling via the MS-GARCH(1,1) framework to capture regime changes between calm and turbulent market conditions. The presence of heavy tails and volatility clustering justifies the application of the Extreme Value Theory (EVT) using the Peaks Over Threshold (POT) method to estimate tail-related risks. The results reveal that stock markets in Iran-aligned countries (China, Russia, Turkey) generally remained in the calm regime, while Israel-aligned countries (USA, UK, Germany) exhibited more frequent transitions to high-volatility regimes. EVT parameters confirm the existence of substantial tail risks, especially in high quantiles. Value-at-Risk (VaR) estimation using the MS-GARCH–EVT(POT) model shows strong performance in capturing extreme losses. Backtesting using Kupiec's tests validates the model's accuracy in both frequency and timing of violations, with only minor exceptions. Overall, the combined MS-GARCH–EVT(POT) model proves to be an effective and statistically robust approach for quantifying extreme market risks during geopolitical uncertainty. These findings offer valuable insights for risk managers and policymakers in navigating financial markets under external shock scenarios.

Keywords: *Extreme Value Theory (EVT), Geopolitical Risk, Iran-Israel Conflict, Markov-Switching GARCH, Regime-Switching, Stock Market Volatility, Value at Risk (VaR)*

1. INTRODUCTION

Geopolitical tensions in the Middle East, particularly the conflict between Iran and Israel and their respective allies, have become a critical factor influencing global economic and financial stability. This conflict not only threatens regional security but also impacts international financial markets, as it involves major world powers such as the United States, China, Russia, Turkey, the United Kingdom, and Germany (Pandey, 2024; Zhang et al., 2023). As the conflict escalates, it raises the risk of widespread uncertainty and volatility in global capital markets (Dugbartey, 2025; Factset.Insight, 2025; Fava et al., 2024; Niu et al., 2023; Segnon et al., 2024;

Borisov Stoyanov, 2025). In response to rising geopolitical risks, investors often adjust their strategies by engaging in hedging, reallocating their portfolios, and shifting their investments from high-risk assets like equities to safer options such as government bonds, foreign currencies, or gold (Segnon et al., 2024; Zhang et al., 2023; Paidi, Sirojuzilam, Lubis, & Purwoko, 2025). These shifts can lead to sudden and unpredictable changes in asset prices due to large-scale capital movements (Sohag et al., 2022).

Furthermore, this shift in investment patterns may trigger more extreme stock price fluctuations than usual across various countries, including those not directly involved in the conflict, thereby increasing overall market volatility (Baker et al., 2019; Li et al., 2022). In other words, stock closing price movements are no longer stationary or linear, but instead exhibit regime-switching behaviour, characterized by random yet systematic transitions between calm periods (low volatility) and crisis periods (high volatility) (Valenti et al., 2018).

The phenomenon of stock price movements that are dynamic, extreme, highly volatile, and time-varying indicates that financial markets cannot be accurately modelled using linear approaches. Therefore, a more adaptive and precise risk measurement method is required (Bui Quang et al., 2018; Darmanto, Darti, Astutik, Nurjannah, et al., 2025). In finance, Value at Risk (VaR) is one of the most widely used methods to measure potential extreme losses in financial markets by estimating the maximum possible loss of a portfolio at a certain confidence level and time horizon (Bali & Cakici, 2004; Duffie & Pan, 1997; Linsmeier & Pearson, 2000). When conflict escalates, investor risk expectations also increase, which is reflected in surging stock price volatility. Under such extreme conditions, researchers and practitioners have found that financial market data tend to follow non-normal distributions, characterized by asymmetry, leptokurtosis, and fat tails (H. Chen et al., 2019; Gui & Zhu, 2020). This suggests the potential for very large losses within a short period of time (Qammar, 2019).

Similar conditions can also arise during extreme events such as natural disasters, global pandemics, or major macroeconomic policy changes (Gechev, 2025). As a result, methods for estimating and forecasting VaR continue to evolve using statistical and mathematical approaches. One such advancement is the Markov-Switching GARCH (MS-GARCH) model, which is designed to estimate VaR by capturing financial market dynamics across two or more market regimes (Alemohammad et al., 2020; Ardia, 2008; Ardia et al., 2017; Darmanto, Darti, Astutik, & Nurjannah, 2025; Faruq et al., 2025; Haas et al., 2004; Sajjad et al., 2008). This model allows for the probabilistic identification of regime shifts and is capable of detecting volatility spikes that occur suddenly due to external shocks such as wars or natural disasters (Maciel, 2020).

However, although the MS-GARCH model can capture short-term volatility dynamics and regime transitions, it is less accurate in estimating the probability of extreme events that rarely occur but have significant economic impacts. Therefore, an additional approach is needed, such as Extreme Value Theory (EVT), which is designed to analyse the extreme tail of a data distribution, events that cannot be explained by standard distribution models. EVT, particularly through the Peaks Over Threshold (POT) method and the Generalized Pareto Distribution (GPD), enables the analysis of the frequency and severity of extreme events such as stock market crashes, which are highly relevant during armed conflicts like the Iran–Israel situation (Balmaceda et al., 2022; X. Chen et al., 2023; Echaust & Just, 2020). By combining MS-GARCH with EVT, referred to as the MS-GARCH-EVT(POT) approach, VaR analysis can be conducted more accurately and become more relevant to highly volatile and uncertain market conditions.

The MS-GARCH-EVT(POT) approach is particularly important when markets face major events originating outside the economic system, such as geopolitical tensions or natural disasters. The Iran–Israel conflict, supported by various strategic allies such as the United States, China, Russia, Turkey, the United Kingdom, and Germany, creates a highly complex network of risk exposure (Pandey, 2024; Umar, Bossman, et al., 2022; Zhang et al., 2023). Countries that maintain trade, political, or military relationships with Iran and Israel are likely to be affected, directly or indirectly, by the escalation of this conflict (Bossman & Gubareva, 2023; Umar, Polat, et al., 2022). Given that global financial markets are now highly integrated, any systemic shock can generate spillover effects across multiple countries, especially developing nations whose financial systems are more vulnerable to shifts in international capital flows (Hossain et al., 2024). Therefore, investors in countries such as Indonesia, Malaysia, and India cannot overlook the risks arising from geopolitical conflicts in the Middle East. As market volatility rises, portfolio risk also increases, making investment decisions more complex. For this reason, it is essential for market participants and regulators to understand how geopolitical conflicts such as the Iran–Israel crisis can significantly affect financial markets and stock investment risks. Thus, calculating VaR using the MS-GARCH-EVT(POT) approach is not only academically relevant, but also practically valuable for market participants and policymakers, particularly in countries directly or indirectly exposed to the Iran–Israel conflict and its allied powers.

Building on this context, it becomes clear that a more comprehensive risk measurement framework is needed, one that not only models volatility clustering and regime switching but also accurately captures the behaviour of extreme losses during turbulent periods. While previous studies have largely examined volatility modelling (using GARCH or MS-GARCH) and tail risk modelling (using EVT) separately, few have integrated these approaches to address the unique challenges posed by systemic shocks such as the Iran–Israel conflict. This study seeks to fill that gap by assessing whether the MS-GARCH-EVT(POT) framework provides more accurate and theoretically consistent VaR estimates compared to conventional models, particularly during periods of heightened geopolitical uncertainty. More specifically, it aims to determine (i) whether combining EVT with MS-GARCH mitigates under- and over-coverage of VaR, (ii) whether emerging and transition markets demonstrate longer high-volatility regime persistence and heavier tails relative to developed markets, and (iii) whether the integrated model delivers more reliable risk signals for portfolio managers and regulators navigating global contagion effects.

2. DATA AND METHODS

The data used in this study consist of the natural logarithm (ln) closing prices of stock indices from several major countries that are allies of either Iran or Israel. Russia, China, and Turkey are considered allies of Iran (i.e. Bloc A), while the United States of America (USA), United Kingdom (UK), and Germany are considered allies of Israel (i.e. Bloc B). The transformation into natural logarithm (ln) is applied to stabilize the variance, make returns additive over time for easier aggregate analysis and interpretation of relative price changes, and to reduce distortions from dividend payments, as stock prices typically drop by the dividend amount on the ex-dividend date (Brooks, 2019; Campbell et al., 2012; Tsay, 2010). The data were collected from Investing.com for the period from June 1, 2023, to July 11, 2025, and were extracted using the R Studio. Detailed information on the data is presented in Table 1.

Table 1. Detail Information of Stock Data for Several Countries

Group	Country	Index	Num. of Obs.
Iran-Aligned Bloc (Bloc A)	China	Shanghai Composite	512
	Russia	MOEX Russia Index	539
	Turkey	BIST 100	528
Iran-Aligned Bloc (Bloc B)	Germany	DAX	538
	UK	FTSE 100	536
	USA	Nasdaq Composite	529

Source: Author's calculation

Let P_t and P_{t-1} denote the closing prices of a stock index at time t and t-1, respectively, then the return (r_t) is calculated and transformed into natural logarithmic form as follows,

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

In analysing return behaviour, the first step is to construct a mean model to capture time dependence. The mean model used in this study is the Autoregressive Moving Average (ARMA)(p,q) model, as it effectively captures short-term dynamics in return data. The model is expressed as follows (Grillenzoni, 1993; Khan & Alghulaiakh, 2020; Y. Wang & Guo, 2020),

$$r_t = \sum_{i=1}^{p} \phi_i r_{t-i} + \varepsilon_t - \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \text{ or } \phi(B) r_t = \theta(B)\varepsilon_t \tag{2}$$

In this context, B is the backshift (or lag) operator, define such that $B^i r_t = r_{t-i}$. The term ε_t represents a white noise process, meaning that the value of ε_t are uncorrelated overtime, have a mean of zero and a constant variance σ^2 (i.e., $\varepsilon_t \sim WN(0,\sigma^2)$). The ARMA ($p, q$)model is considered stationary when the condition $\phi(B)r_t = 0$ is satisfied.

2. 1. THE GARCH AND MARKOV-SWITCHING GARCH (MS-GARCH) MODEL

Volatility in financial time series data is not analysed directly from the return values, but rather through the residuals generated by a mean model such as ARMA (p, q). This is because volatility reflects the uncertainty or variation in the error term relative to its expected value, not the direct observation itself (Bollerslev, 1986; Engle, 1982). In other words, volatility indicates the degree to which actual values deviate from model-based expectations. Therefore, the common approach to modelling volatility focuses on the conditional variance of the residuals, which can change over time (i.e., is heteroskedastic). To address this, (Engle, 1982) introduced the ARCH model, which was later extended by (Bollerslev, 1986) into the more flexible and efficient GARCH (Generalized ARCH) model for capturing the dynamic nature of market volatility. In general, the GARCH(P,Q) model states that the current residual variance is influenced by squared past errors (the ARCH component) and past variances (the GARCH component).

Let ε_t represent the error term at time t and ψ_{t-1} be the information set up to time t - 1 . The general form of the GARCH (P,Q) model is,

$$\varepsilon_t|\psi_{t-1} \sim N(0,\sigma_t^2) \tag{3}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{Q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{P} \beta_j \sigma_{t-j}^2 \tag{4}$$

Here, σ_t^2 is the conditional variance of the error term, ω is a constant, α_i (for i = 1, 2, ..., Q) are the ARCH parameters representing the influence of past squared errors, and β_j (for j = 1, 2, ..., P) are the GARCH parameters representing the effect of past variances.

The GARCH(1,1) model is the most widely used specification in empirical studies for modelling financial volatility. Analytically, it provides a balance between structural simplicity and estimation efficiency, incorporating only one lag of past squared residuals and one lag of past conditional variance, yet it is sufficiently flexible to capture key features such as volatility clustering and high persistence commonly observed in financial time series (Bollerslev, 1986; Engle & Bollerslev, 1986; Medeiros & Veiga, 2009). The form of the GARCH(1,1) is derived from Eq.(4) as follows

$$\sigma^2_t = \omega + \alpha_1\varepsilon^2_{t-1} + \beta_1\sigma^2_{t-1} \tag{5}$$

The parameters are constrained such that $\omega > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$. Empirically, numerous studies have found that GARCH(1,1) yields stable and consistent results across a wide range of markets and data frequencies, including equities, bonds, and currencies. Even when compared with higher-order GARCH models, the GARCH(1,1) specification often delivers comparable or superior forecasting performance by avoiding the risk of overfitting (Bollerslev, 1986; Gokcan, 2000; Molnár, 2016; Y. Wang et al., 2021; Thangaraju & Palani, 2025). In line with this practice, the present study also employs the GARCH(1,1) model to analyse volatility dynamics in the stock indices of countries allied with Iran and Israel.

While standard GARCH is effective in capturing volatility clustering and leverage effects, it assumes that financial markets operate under a single, stable regime over time. However, empirical evidence shows that financial markets often experience regime shifts, triggered by events such as economic crises, political instability, monetary policy changes, or geopolitical shocks. These structural changes cause abrupt transitions between low and high volatility periods, which cannot be adequately modelled by conventional GARCH approaches.

To address this limitation, the MS-GARCH model was introduced (Haas et al., 2004; Hamilton & Susmel, 1994). This framework integrates GARCH dynamics with a hidden Markov process, allowing the model parameters to change according to an unobservable regime variable S_t. This latent variable represents the market state at time t and typically takes discrete values $S_t \in \{1, 2, \ldots, K\}$, where K is the total number of regimes. Each regime may reflect a distinct volatility condition, such as tranquil versus turbulent market states.

The MS-GARCH (P,Q) model specifies that the conditional variance at time t, denoted σ_t^2, depends not only on past squared shocks up to lag Q and past variances up to lag P, but also on the current regime S_t. The general form of the model is given by

$$\sigma_t^2 = \omega^{(s_t)} + \sum_{i=1}^{Q} \alpha_i^{(s_t)} \varepsilon_{t-i}^2 + \sum_{j=1}^{P} \beta_j^{(s_t)} \sigma_{t-j}^2 \tag{6}$$

Here, each parameter ω, α_i, β_j is regime-specific, meaning they take different values depending on the prevailing market state S_t, which is typically modelled as a first-order Markov process. Given that this study adopts a GARCH(1,1) framework for modelling conditional volatility, the MS-GARCH(1,1) specification is applied. The model is thus simplified as follows:

$$\sigma_t^2 = \omega^{(s_t)} + \alpha_1^{(s_t)} \varepsilon_{t-1}^2 + \beta_1^{(s_t)} \sigma_{t-1}^2 \tag{7}$$

This form allows volatility dynamics to shift across two regimes, typically interpreted as low-volatility and high-volatility states, capturing asymmetric market behaviours during different periods of financial stress and stability.

For instance, in a high-volatility regime, the parameters may reflect a stronger response to past shocks than in a low-volatility regime. Transitions between regimes follow a first-order Markov chain, governed by a transition probability matrix:

$$\mathrm{P}_{(2\times 2)} = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix} \tag{8}$$

where $p_{ij} = Pr\,(S_t = j|S_{t-1} = i)$ denotes the probability of moving from regime i at time t - 1 to regime j at time t. The sum of each row must equal 1, ensuring that all possible transitions are accounted for. This regime-switching mechanism allows the MS-GARCH model to better capture nonlinear shifts in volatility dynamics, offering a more flexible representation of financial markets that are sensitive to extreme events and structural changes.

Parameter estimation in MS-GARCH models is commonly conducted using the Quasi-Maximum Likelihood (QML) method (Ardia et al., 2019; Augustyniak, 2014; Xie, 2005). Although this model typically assume conditional normality, QML remains consistent and asymptotically normal even when the true distribution deviates from normality (Francq & Zakoïan, 2010; Lee & Hansen, 1994; Lumsdaine, 1996; Okafor & Onyeka-Ubaka, 2023). Estimation is carried out by maximizing the log-likelihood function constructed through the Hamilton filter, enabling efficient inference of volatility parameters and regime-switching dynamics (Ardia et al., 2019; Hamilton & Susmel, 1994).

2. 2. THE EXTREME VALUE THEORY (EVT)

Extreme Value Theory (EVT) is a statistical approach that focuses on modelling the behaviour of extreme observations, such as very large losses or gains in financial markets. The foundation of EVT was established by (Fisher & Tippett, 1928), and later formalized by (Gnedenko, 1943), who demonstrated that the distribution of extreme values from independent and identically distributed (i.i.d.) variables converges to one of three forms: Gumbel, Fréchet, or Weibull. In finance, EVT is widely used to estimate the probability and impact of rare and extreme market events that cannot be adequately captured by the normal distribution. Traditional risk models often underestimate the likelihood of large losses, particularly during periods of financial stress. (Longin, 2000) and (Embrechts et al., 1997) highlighted the importance of EVT in modelling financial tail risk, offering a more reliable framework for extreme market behavior.

There are two major approaches in EVT: the Bloc Maxima (BM) method and the Peak Over Threshold (POT) method. The Bloc Maxima method uses the maximum value from fixed time intervals (e.g., monthly or yearly maxima), modelled using the GEV distribution. In contrast, the POT method uses all data points that exceed a high threshold, modelled with the Generalized Pareto Distribution (GPD). The POT approach is considered more efficient because it utilizes more extreme observations (Bücher & Zhou, 2021; Q. J. Wang, 1991; Zheng et al., 2014).

Let X is a random variable with observations $x_1, x_2, \ldots, x_t$. In the Peak Over Threshold (POT) method, a fixed threshold is selected over the observed period. The exceedances over this threshold are defined as the excess values $Y = X - u$, where $X > u$. The cumulative distribution function (CDF) of these excess values, denoted by $F_Y(y)$, is referred to as the conditional excess distribution function. As the threshold $u \to \infty$, the conditional distribution of Y converges to the Generalized Pareto Distribution (GPD), which is given by (Balkema & Haan, 1974; Gilli & Këllezi, 2006; Pickands III, 1975; Singh et al., 2013):

$$F_Y(y) \approx G_{\xi,\beta}(y) = \begin{cases} 1 - \left(1 + \frac{\xi}{\beta} y\right)^{-\frac{1}{\xi}}, & if\ \xi \neq 0 \\ 1 - e^{-\frac{y}{\beta}}, & if\ \xi = 0 \end{cases} \tag{8}$$

where ξ is the shape parameter, β is the scale parameter, and $y > 0$. Parameter estimation for the GPD is typically carried out using the Maximum Likelihood Estimation (MLE) method, which is known for its efficiency and consistency in large samples. MLE estimates the shape (ξ) and scale (β) parameters by maximizing the likelihood function based on the excesses over a predefined threshold. Under standard regularity conditions, the MLE estimators are asymptotically unbiased, consistent, and asymptotically normal (Castillo & Serra, 2015; Davison & Smith, 1990).

2. 3. THE VALUE AT RISK AND BACKTESTING

Value at Risk (VaR) is a widely used risk measure in financial risk management that quantifies the maximum expected loss of a portfolio over a specified time horizon at a given confidence level. VaR answers the question: "*What is the worst expected loss over a given period under normal market conditions at a certain confidence level?*" Mathematically, for a confidence level α, the VaR at time t over horizon h is defined as the quantile of the return distribution:

$$\begin{aligned} VaR_{\alpha,t} &= \inf\{x \in \mathbb{R}: P(R_t > x) \leq 1 - \alpha\} \\ &= \inf\{x \in \mathbb{R}: P(R_t \leq x) \geq \alpha\} \end{aligned} \tag{9}$$

where R_t denotes the portfolio return. VaR does not indicate how much the loss could exceed this threshold, but it provides a benchmark for capital allocation and regulatory compliance (Acharya et al., 2017; Bernard et al., 2017; Choudhry, 2013; Jorion, 2007).

Backtesting VaR is essential to evaluate the accuracy of the VaR model by comparing the predicted number of violations (actual losses exceeding VaR) with the observed ones. Two popular approaches are the Kupiec Proportion of Failures (POF) test and the Time Until First Failure (TUFF) test (Kupiec, 1995). The Kupiec test checks whether the observed violation rate matches the expected rate under the null hypothesis of correct coverage. If N denotes the total number of observations and x is the number of VaR violations, then using the Likelihood Ratio (LR) statistic, the POF test can be expressed as

$$\begin{aligned} LR_{POF} &= -2\ln\left[(1-\alpha)^{N-x}\alpha^{x}\right] + 2\ln\left[\left(1-\frac{x}{N}\right)^{N-x}\left(\frac{x}{N}\right)^{x}\right] \\ &= 2\ln\left[\frac{\left(1-\frac{x}{N}\right)^{N-x}\left(\frac{x}{N}\right)^{x}}{(1-\alpha)^{N-x}\alpha^{x}}\right] \sim \chi^2_{(1)} \end{aligned} \tag{10}$$

Meanwhile, the TUFF test defines V as the number of observations until the first VaR violation occurs, and its LR statistic is given as follows,

$$\begin{aligned} LR_{TUFF} &= -2\ln\left[\alpha(1-\alpha)^{V-1}\right] + 2\ln\left[\left(\frac{1}{V}\right)\left(1-\left(\frac{1}{V}\right)\right)^{v-1}\right] \\ &= 2\ln\left[\frac{\left(\frac{1}{V}\right)\left(1-\left(\frac{1}{V}\right)\right)^{v-1}}{\alpha(1-\alpha)^{V-1}}\right] \sim \chi^2_{(1)} \end{aligned} \tag{11}$$

3. 3.EMPIRICAL RESULTS AND DISCUSSION

3. 1. DESCRIPTIVE ANALYSIS OF CLOSING PRICES AND LOG RETURNS OF STOCK INDICES

The Figure 1 shows the closing prices of stock indices from six countries, divided into two geopolitical blocs: Iran's allies (China, Russia, Turkey) and Israel's allies (the United States, the United Kingdom, Germany), covering the period before and during the Iran–Israel conflict.

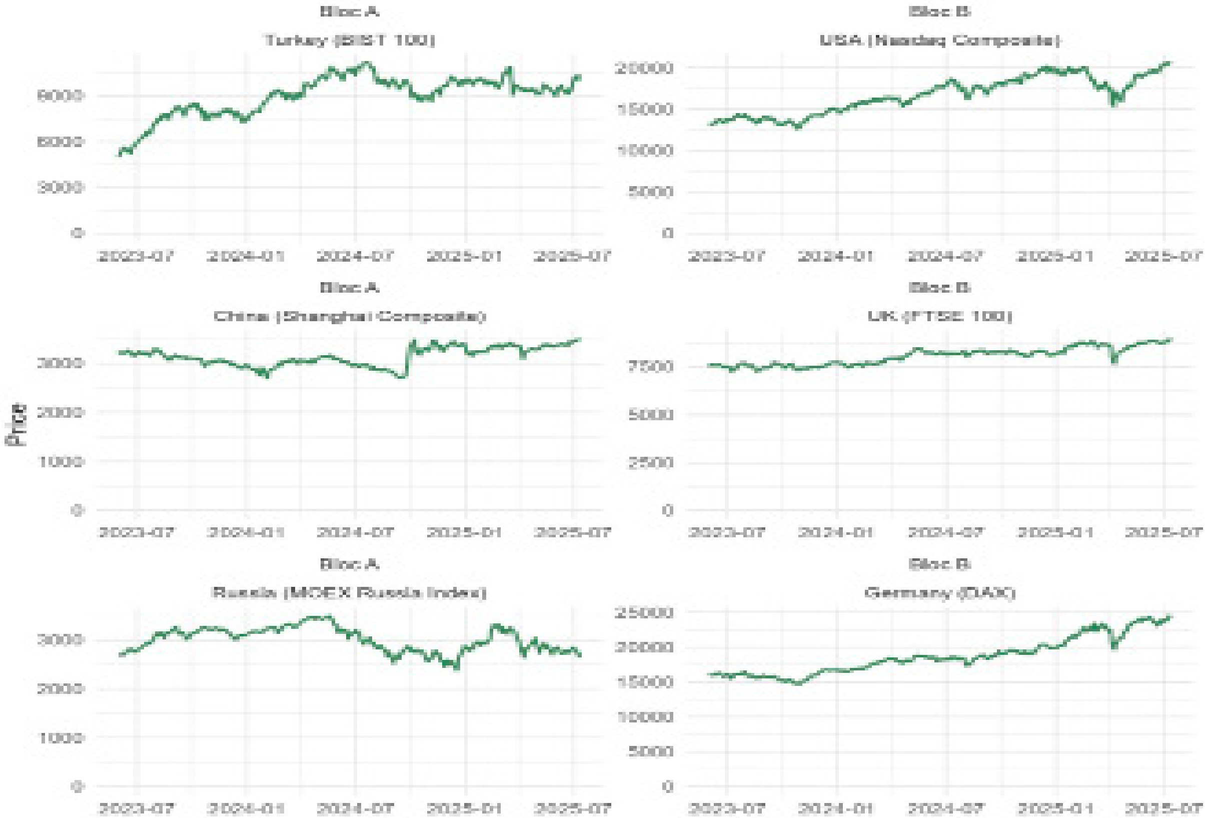
Before the war, stock indices of the Israel-aligned bloc, especially the U.S. and the U.K. showed relatively stable trends with moderate fluctuations. However, volatility increased significantly once the conflict began. In contrast, the indices of the Iran-aligned bloc, particularly Russia and Turkey, exhibited more frequent and sharper price swings. These patterns suggest the presence of volatility clustering, where periods of high volatility are followed by more high volatility, and calm periods are followed by more stability. This is a common market response under geopolitical uncertainty. The difference in price behaviour between the two blocs indicates that Iran's allies were more exposed to market shocks, while the Israel-aligned bloc appeared more resilient early on but were still affected as tensions rose. Overall, the conflict had a clear impact on global equity markets, marked by increased volatility and the emergence of clustered price movements, especially in countries directly or indirectly involved.

Figure 2 illustrates the log returns of stock indices from two geopolitical blocs, during the period before and during the Iran–Israel conflict. Using log returns in market analysis offers advantages over raw price analysis, as it produces a symmetric and continuous scale of change, allows for the observation of relative percentage changes over time, and facilitates the detection of shocks and volatility that may be obscured in standard price charts. Compared to Figure 1, which displays closing prices, Figure 2 provides a more sensitive view of short-term market dynamics. In Figure 1, price fluctuations appear smoother and are dominated by long-term trends, making daily variability harder to identify visually. In contrast, the log return plot in Figure 2 shows clear spikes, both positive and negative, that are especially noticeable before and during the conflict. These patterns indicate the presence of volatility shocks, or sharp market reactions to escalating geopolitical tensions.

Visually, countries in the Iran-aligned bloc, particularly Russia and Turkey, exhibit more frequent and irregular log return fluctuations, suggesting higher risk exposure and greater market vulnerability to external shocks. Meanwhile, countries in the Israel-aligned bloc, such as the United States and Germany, tend to show more stable log return patterns, although volatility also increased during the conflict. China and the United Kingdom display relatively moderate return movements. The most striking difference between Figures 1 and 2 lies in the presence of volatility clustering. In Figure 1, such patterns are difficult to detect due to the slow accumulation of prices and the dominance of long-term trends. However, in Figure 2, clustering becomes clearly visible, especially in Russia and Turkey, where extreme log returns occur in close succession, reflecting persistent market instability. In contrast, Israel-aligned countries also experience volatility clustering, but with shorter durations and a quicker return to stability, suggesting stronger market adjustment capacities.

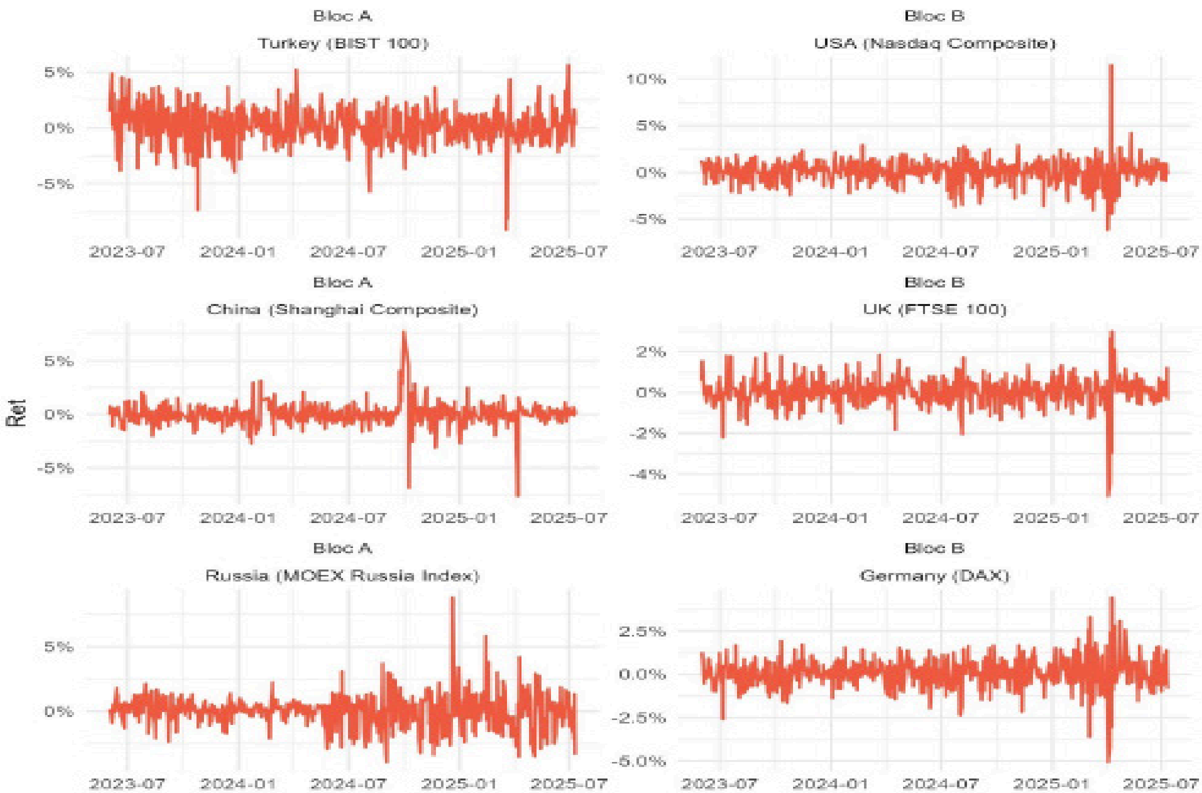
Overall, Figure 2 not only reveals hidden risk dynamics and fluctuations not captured in Figure 1 but also highlights the differing market responses between the two geopolitical blocs. This log-return-based visualization provides an important foundation for applying econometric models, specifically MS-GARCH combined with EVT to more accurately capture extreme risks and the dynamics of market volatility.

Figure 1. The Movement of Closing Prices of Stock Indices in Two Geopolitical Blocs



Source: Author's Graphs

Figure 2. The Movement of Stock Index Log Returns of Two Geopolitical Blocs During the Iran–Israel Conflict



Source: Author's Graphs

3. 2. THE ARMA (*p,q*) MEAN MODEL AND RESIDUAL DIAGNOSTICS

The ARMA(*p,q*) model was used to estimate the mean component of the log return for each stock index before modelling volatility. The results (see Table 2) show that the mean structure differs across countries: China and Turkey follow an ARMA(2,2); the United Kingdom fits an ARMA(3,1) model; Germany fits an ARMA(2,0); the United States (USA) shows ARMA(0,0); while Russia follows ARMA(0,1). The ARMA(0,0) model in the USA indicates that its return series behaves like white noise, with no linear dependence over time, unlike indices such as Russia and Turkey, which display significant autocorrelation in either the AR or MA terms.

Table 2. ARMA Model and Residual Diagnostics for Stock Index Log Returns

Group		Iran-Aligned Bloc			Israel-Aligned Bloc		
Country		China	Russia	Turkey	Germany	UK	USA
Index		Shanghai Composite	MOEX Russia Index	BIST 100	DAX	FTSE 100	Nasdaq Composite
ARMA(p,q)		ARMA(2,2)	ARMA(0,1)	ARMA(2,2)	ARMA(2,0)	ARMA(3,1)	ARMA(0,0)
Skewness		-0,392	0,674	-0,552	-0,391	-0,985	0,488
Kurtosis		17,507	8,329	6,052	6,535	11,113	14,562
Error Normality Test	Lilliefors	0.10 (0)	0.08 (0)	0.04 (0.05)	0.06 (0)	0.06 (0)	0.09 (0)
	AD	10.83 (0)	6.84 (0)	1.41 (0)	2.75 (0)	4.8 (0)	6.6 (0)
Ljung-Box Non-Auto-correlation Test	Lag 1	0.057 (0.811)	0.001 (0.969)	0.297 (0.586)	0.012 (0.914)	0.021 (0.883)	1.916 (0.166)
	Lag 2	0.682 (0.711)	0.08 (0.961)	1.304 (0.521)	0.012 (0.994)	0.059 (0.971)	4.694 (0.096)
	Lag 3	0.688 (0.876)	0.962 (0.81)	1.7 (0.637)	1.761 (0.623)	0.111 (0.99)	10.136 (0.017)
	Lag 4	1.457 (0.834)	1.197 (0.879)	1.7 (0.791)	1.812 (0.77)	0.223 (0.994)	11.045 (0.026)
	Lag 5	3.643 (0.602)	1.218 (0.943)	6.315 (0.277)	2.559 (0.768)	0.315 (0.997)	11.198 (0.048)
ARCH LM-Test	Lag 1	27.593 (0)	3.165 (0.075)	0.647 (0.421)	160.109 (0)	193.692 (0)	18.526 (0)
	Lag 2	103.776 (0)	5.194 (0.075)	47.681 (0)	231.594 (0)	274.269 (0)	18.687 (0)
	Lag 3	108.515 (0)	7.378 (0.061)	47.811 (0)	291.277 (0)	306.283 (0)	42.359 (0)
	Lag 4	123.4 (0)	11.758 (0.019)	49.874 (0)	347.818 (0)	315.115 (0)	78.004 (0)
	Lag 5	124.14 (0)	12.479 (0.029)	49.975 (0)	363.457 (0)	315.205 (0)	83.754 (0)

Source: Author's Calculation

After estimating the mean model, residual diagnostic tests were conducted to evaluate three aspects: normality, autocorrelation, and heteroskedasticity. The normality tests, based on skewness, kurtosis, and formal tests (Lilliefors and Anderson–Darling), indicate that the residuals are not normally distributed. For example, China shows skewness of –0.39 and a very high kurtosis of 17.50, while the USA has skewness of –0.61 and similarly high kurtosis. These heavy tails suggest a high probability of extreme return values (outliers). All normality tests are statistically significant ($p < 0.01$), rejecting the assumption of normal distribution in all series. This justifies the use of non-Gaussian approaches such as the EVT to better capture tail risks.

The Ljung–Box test confirms that the ARMA model has effectively removed autocorrelation from the residuals. This is shown by high p-values at multiple lags, for instance, China (lag-1: 0.811; lag-5: 0.925), Russia (lag-1: 0.969; lag-5: 0.974), and the USA (lag-1: 0.708; lag-5: 0.925), indicating that no significant autocorrelation remains in the residuals. However, the ARCH-LM test reveals strong evidence of heteroskedasticity in most indices. For example, China shows an ARCH-LM statistic of 124.14 (p = 0.000) at lag 5, Germany 363.63 (p = 0.000), and the UK 265.43 (p = 0.000). Even Russia, though with a smaller value, shows significance at lag 5 (p = 0.029). These results imply that volatility is not constant over time and that conditional heteroskedasticity exists.

Overall, the residual diagnostics suggest that while the ARMA models effectively remove autocorrelation from the mean process, the residuals remain non-normal and show significant heteroskedasticity. These statistical findings are also visually supported by Figure 2, where volatility clustering and extreme movements are clearly visible, especially in indices such as Russia, China, and Turkey. The visual patterns reinforce the diagnostic results, including heavy-tailed distributions and strong ARCH effects. Therefore, more advanced volatility models such as the MS-GARCH are appropriate to capture regime-switching behaviour and market responses to new information. Combining these with EVT can provide a more accurate analysis of extreme risks and volatility clustering in stock return data under geopolitical uncertainty.

Parameter Estimation of ARMA-GARCH(1,1) Models

The mean model is used to capture the average dynamics of log returns for each stock index. The estimation results presented in Table 3 show that the ARMA structure varies across countries. For instance, the Chinese stock index follows an ARMA(2,2) model, indicated by two significant AR parameters ($\widehat{\phi}_1 = -0.457$; $\widehat{\phi}_2 = -0.938$) and two MA parameters ($\widehat{\theta}_1 = 0.490$; $\widehat{\theta}_2 = 0.978$), all statistically significant at the 1% level. This suggests a strong linear dependence on past returns, indicating that China's market tends to have a deeper historical memory in forming current return patterns. A similar structure is found in the UK and Turkey indices, reflecting the complexity of their mean models and the markets' sensitivity to past shocks.

On the other hand, markets like Russia are adequately represented by a single MA component ($\widehat{\theta}_1 = 0.139$), implying a simpler dynamic while still exhibiting sensitivity to past innovations. Meanwhile, the U.S. stock index shows no significant AR or MA parameters. This confirms the previous ARMA(0,0) result, suggesting that U.S. market returns follow a random walk without a prominent linear pattern, possibly reflecting higher market efficiency in processing information.

To model volatility dynamics, a GARCH specification is applied, focusing on two main parameters: α (shock effect) and β (volatility persistence). Each index shows unique characteristics. The Chinese index, for example, has $\widehat{\alpha} = 0.168$ and $\widehat{\beta} = 0.483$, both significant. The sum $\widehat{\alpha} + \widehat{\beta} = 0.651$ indicates a moderate degree of volatility persistence, with sizeable shock effects that do not last too long. In contrast, Russia's index shows $\widehat{\alpha} = 0.105$ and $\widehat{\beta} = 0.894$, resulting in $\widehat{\alpha} + \widehat{\beta} = 0.999$, close to one. This reflects highly persistent volatility, meaning that market shocks during the geopolitical conflict have long-term effects on market fluctuations.

Table 3. Parameter Estimates of ARMA–GARCH(1,1) Models for Each Stock Index

Parameter Estimates	Iran-Aligned Bloc			Israel-Aligned Bloc		
	China	Russia	Turkey	Germany	UK	USA
Mean Model – ARMA(p,q)						
$\hat{\mu}$	-0.000 [SE: 0.000]	0.000 [SE: 0.000]	0.001* [SE: 0.001]	0.001** [SE: 0.000]	0.000*** [SE: 0.000]	0.001* [SE: 0.000]
$\hat{\phi}_1$	-0.457*** [SE: 0.028]		1.902*** [SE: 0.007]	0.028 [SE: 0.048]	1.029*** [SE: 0.019]	
$\hat{\phi}_2$	-0.938*** [SE: 0.017]		-0.969*** [SE: 0.006]	0.049 [SE: 0.046]	0.029** [SE: 0.011]	
$\hat{\phi}_3$					-0.110*** [SE: 0.028]	
$\hat{\theta}_1$	0.490*** [SE: 0.019]	0.139** [SE: 0.046]	-1.926*** [SE: 0.001]		-1.000*** [SE: 0.000]	
$\hat{\theta}_2$	0.978*** [SE: 0.011]		0.988*** [SE: 0.001]			
Error Model – GARCH(1,1)						
$\hat{\omega}$	0.000*** [SE: 0.000]	0.000 [SE: 0.000]	0.000 [SE: 0.000]	0.000*** [SE: 0.000]	0.000*** [SE: 0.000]	0.000*** [SE: 0.000]
$\hat{\alpha}_1$	0.168** [SE: 0.054]	0.105** [SE: 0.040]	0.125** [SE: 0.046]	0.170*** [SE: 0.025]	0.259*** [SE: 0.062]	0.103*** [SE: 0.013]
$\hat{\beta}_1$	0.483*** [SE: 0.131]	0.894*** [SE: 0.039]	0.636** [SE: 0.239]	0.712*** [SE: 0.030]	0.167 [SE: 0.131]	0.851*** [SE: 0.018]
Goodness of Fit Model						
Number of Obs.	512	539	528	538	536	529
AIC	-6.47	-6.15	-5.34	-6.73	-7.27	-6.00
RMSE	0.01	0.013	0.017	0.009	0.007	0.013
MAE	0.007	0.009	0.013	0.007	0.005	0.009

Source: Author's Calculation

The U.S. market also exhibits high volatility persistence, with $\hat{\alpha} + \hat{\beta} = 0.954$, even though its mean model is random. This suggests that past volatility and new shocks continue to influence the market, highlighting global contagion effects during the conflict. Meanwhile, the UK index has $\hat{\alpha} = 0.259$ and $\hat{\beta} = 0.167$, yielding $\hat{\alpha} + \hat{\beta} = 0.426$, a much lower value than other markets. This implies that the UK market tends to react quickly to new information with high intensity, but the effects fade rapidly and do not persist.

The variance constant $\hat{\omega}$ is very small across all indices, which is consistent with the GARCH assumption that most of the variation in returns is driven by shocks and persistence rather than a constant variance. This supports the notion of time-varying volatility during the conflict period.

From a statistical perspective, the GARCH models exhibit a good fit, as shown by low Akaike Information Criterion (AIC) values in several indices, such as the UK (–7.27), Germany (–6.73), and China (–6.47). Lower AIC values indicate better model performance while penalizing for complexity. These findings confirm the relevance of the GARCH framework for analysing stock market volatility during geopolitical crises and provide a solid foundation for further approaches like MS-GARCH and its integration with EVT to assess extreme market risks.

3. 3. ANALYSIS OF MS-GARCH(1,1)

Generally, the results in Table 4 indicate that the bloc aligned with Iran exhibits relatively stable dynamics with a strong tendency to remain in the calm regime. China's stock market shows significance only in the $\widehat{\beta}_1 = 0.945$ parameter in Regime 1, suggesting highly persistent volatility under stable conditions. The absence of significant parameters in Regime 2, along with transition probabilities $\widehat{P}_{(1|1)} = 0.987$ and $\widehat{P}_{(2|1)} = 0.013$, indicates that transitions into the turbulent regime are extremely rare. This reinforces the notion that the Chinese government's interventions are effective in containing uncertainty from external shocks, including geopolitical conflict.

Table 4. MS-GARCH(1,1) Parameter Estimates and Regime Transition Probabilities

Parameter Estimates	Iran-Aligned Bloc			Israel-Aligned Bloc		
	China	Russia	Turkey	Germany	UK	USA
Regime 1						
$\widehat{\omega}_{01}$	0.000+ [SE: 0.000]	0.000* [SE: 0.000]	0.000* [SE: 0.000]	0.000* [SE: 0.000]	0.000 [SE: 0.000]	0.000** [SE: 0.000]
$\widehat{\alpha}_{11}$	0.011 [SE: 0.015]	0.096* [SE: 0.054]	0.110 [SE: 0.108]	0.064 [SE: 0.058]	0.000 [SE: 0.002]	0.020 [SE: 0.017]
$\widehat{\beta}_1$	0.945*** [SE: 0.030]	0.879*** [SE: 0.015]	0.642*** [SE: 0.144]	0.795*** [SE: 0.069]	0.544 [SE: 11.261]	0.901*** [SE: 0.031]
Regime 2						
$\widehat{\omega}_{02}$	0.000 [SE: 0.000]	0.000 [SE: 0.004]	0.001 [SE: 0.016]	0.000 [SE: 0.000]	0.000+ [SE: 0.000]	0.000 [SE: 0.000]
$\widehat{\alpha}_{12}$	0.150 [SE: 0.384]	0.001 [SE: 0.015]	0.000 [SE: 0.007]	0.419 [SE: 0.366]	0.952* [SE: 0.493]	0.145 [SE: 1.353]
$\widehat{\beta}_2$	0.588 [SE: 0.544]	0.240 [SE: 6.337]	0.606 [SE: 8.494]	0.275 [SE: 0.306]	0.004 [SE: 0.079]	0.854*** [SE: 0.010]
Transition Matrix						
$\widehat{P}_{(1\|1)}$	0.988*** [SE: 0.132]	0.968*** [SE: 0.139]	0.986*** [SE: 0.224]	0.996*** [SE: 0.056]	0.985*** [SE: 0.192]	0.993*** [SE: 0.050]
$\widehat{P}_{(2\|1)}$	0.187*** [SE: 0.012]	0.346*** [SE: 0.040]	0.460*** [SE: 0.018]	0.044*** [SE: 0.005]	0.244*** [SE: 0.013]	0.060*** [SE: 0.006]
Goodness of Fit Model						
Num.Obs.	512	539	528	538	536	529
AIC	-3415.90	-3334.19	-2837.90	-3620.62	-3895.70	-3182.72

Source: Author's Calculation

Russia exhibits more active dynamics. In Regime 1, both $\widehat{\alpha}_1 = 0.096$ and $\widehat{\beta}_1 = 0.879$ are statistically significant, implying that the market responds to new shocks and maintains elevated volatility over time. However, similar to China, no significant parameters are found in Regime 2. Transition probabilities of $\widehat{P}_{(1|1)} = 0.959$ and $\widehat{P}_{(2|1)} = 0.041$ indicate that while regime switching is possible, the market tends to remain stable. This stability may reflect domestic policy responses and control mechanisms, particularly in the context of sanctions and Russia's involvement in global conflicts.

Turkey also displays dominance in the calm regime, with only $\widehat{\beta}_1 = 0.642$ being significant. This indicates some degree of volatility memory, but overall, the market appears relatively unresponsive to major geopolitical shocks. Transition probabilities of $\widehat{P}_{(1|1)} = 0.955$ and $\widehat{P}_{(2|1)} = 0.045$ further support the tendency to remain in the calm regime. The lack of other significant parameters may suggest that domestic economic factors exert a greater influence on Turkey's market than international conflict.

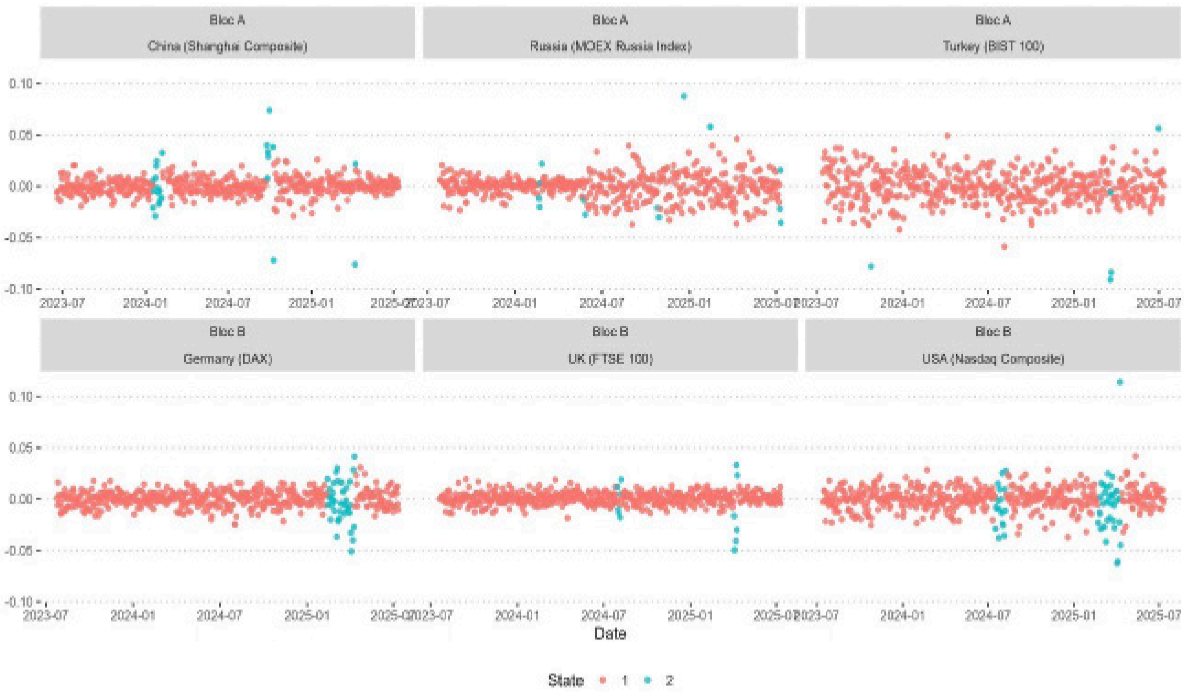
In contrast, markets within the Israel-aligned bloc show more varied regime dynamics and appear more sensitive to external pressures. Germany only has a significant $\widehat{\beta}_1 = 0.795$ in Regime 1. Transition probabilities $\widehat{P}_{(1|1)} = 0.961$ and $\widehat{P}_{(2|1)} = 0.039$ suggest that while the market predominantly operates in the calm regime, a transition into turbulence may occur under intensified external pressure. The UK stands out by showing a significant $\widehat{\alpha}_2 = 0.952$ in Regime 2, implying a strong market reaction to new information during periods of turbulence. This is supported by relatively active transition probabilities ($\widehat{P}_{(1|1)} = 0.956$, $\widehat{P}_{(2|1)} = 0.044$) indicating that the UK market is more flexible and responsive to shifts in global conditions.

The United States, as a global financial hub, displays a more balanced two-regime dynamic. Significant β parameters in both regimes ($\widehat{\beta}_1 = 0.901$ and $\widehat{\beta}_2 = 0.854$) suggest that volatility, both low and high, is persistent. Transition probabilities ($\widehat{P}_{(1|1)} = 0.958$, $\widehat{P}_{(2|1)} = 0.042$) indicate a general market stability, though regime shifts are still possible in the face of major shocks. These findings highlight that, while the US market is efficient, it remains highly responsive to international geopolitical developments, including armed conflict in the Middle East.

Overall, the high $\widehat{P}_{(1|1)}$ values observed across all countries (> 0.95) indicate that stock markets tend to remain in the calm regime, and transitions into high-volatility states are not random but require substantial triggers. The resistance to regime switching reflects the effectiveness of macroeconomic policy, the credibility of financial authorities, and market expectations concerning the impact of geopolitical conflict. In this regard, the MS-GARCH model successfully captures structural dynamics that conventional GARCH models fail to identify.

The visualization of regime states based on the MS- GARCH model, as presented in Figure 3, illustrates the dynamic shifts in stock market volatility conditions across countries during the observation period. Each panel depicts the regime classification at each point in time, distinguishing between two primary market states: the calm regime (low volatility) and the turbulent regime (high volatility). This regime distribution provides a more tangible representation of market sensitivity to geopolitical pressures, particularly in the context of the Iran–Israel conflict.

Figure 3. Regime State Plot Based on MS-GARCH(1,1) Estimation



Source: Author's Graphs

In the bloc of countries aligned with Iran, namely China, Russia, and Turkey, the markets appear relatively stable, predominantly operating under the calm regime. For instance, China remains almost entirely in the calm regime throughout the sample period, reflecting effective market control policies and limited direct exposure to external tensions. Russia shows slightly more dynamic behaviour, with a few episodes of transition into the turbulent regime, although it generally remains stable. This suggests that shocks affecting the Russian market may be more closely linked to sanctions or foreign policy developments rather than the Iran–Israel conflict itself. Turkey also demonstrates a strong dominance of the calm regime with very limited transitions, indicating that market sentiment is likely more influenced by domestic factors than by geopolitical tensions.

In contrast, countries in the bloc aligned with Israel are Germany, the United Kingdom, and the United States, exhibit more volatile and fluctuating patterns. The German stock market experiences several shifts into the turbulent regime, pointing to its sensitivity to external shocks such as energy price fluctuations or regional conflicts. The UK market shows a higher frequency of regime transitions, reflecting its openness and high responsiveness to global news. The United States displays a more balanced pattern between the two regimes, with numerous periods in the turbulent regime, underscoring the central role of the U.S. market in responding to global uncertainty, including armed conflicts in the Middle East.

Overall, the regime patterns illustrated in Figure 3 align with the previously estimated parameters and transition probabilities. Countries in the Israel-aligned bloc appear more prone to shifting into high-volatility regimes, while those aligned with Iran demonstrate greater resilience to external shocks. This highlights fundamental differences in market structures, domestic policy effectiveness, and each country's sensitivity to international geopolitical dynamics.

From a model fit perspective (see Table 4), the presence of the Akaike Information Criterion (AIC) in the estimation results provides an additional statistical foundation for assessing the adequacy of the MS-GARCH model. Although AIC values cannot be directly compared across countries due to differences in data structure and market variability, relatively low AIC values suggest that the model effectively captures the dynamics of volatility. For instance, the model for the United States stock market yields the lowest AIC value at -5.68, indicating that it provides the best fit among the countries analysed. This finding aligns with the significance of parameters in both regimes and the relatively active transition probabilities, confirming the statistical relevance of the two-regime structure in the U.S. market.

In contrast, markets such as Turkey and China, although demonstrating stability within a single regime, show higher AIC values (-4.62 and -4.48, respectively), implying that the model may be less effective in capturing the variations in volatility structures. This could indicate that volatility dynamics in these countries are more complex or insufficiently reflected in the daily frequency data used, thus opening avenues for future model development, whether through the inclusion of exogenous variables or the use of higher-resolution data.

Therefore, the inclusion of AIC values strengthens the justification for employing MS-GARCH as a primary analytical tool. Not only does it allow for the separation of distinct market regimes, but it also provides efficient and reliable estimates that can be further utilized in extreme risk assessments, including VaR analysis and approaches based on EVT.

3. 4. EXTREME RISK ANALYSIS USING THE POT APPROACH OF EVT

The estimation results of the EVT parameters using the POT approach, as presented in Table 5, provide deeper insights into the extreme distribution characteristics of stock market returns across countries. The two key parameters analysed are the scale parameter (β) and the shape parameter (ξ), each estimated at three extreme quantile levels: 1%, 2.5%, and 5%. The scale parameter reflects the dispersion of the tail distribution; larger values indicate a greater potential for extreme deviations in returns. Meanwhile, the shape parameter describes the nature of tail risk: positive values imply a heavy-tailed distribution (indicating potential for unbounded extreme losses), values close to zero suggest a Gumbel-type light-tailed distribution, and negative values imply a bounded tail (with limited extreme loss potential).

In the bloc aligned with Iran, China's market exhibits relatively low scale values across all quantiles, such as 0.568 at the 1% quantile, indicating market stability and the effectiveness of domestic interventions in mitigating volatility. Interestingly, the shape parameter for China remains consistently positive across all quantiles (e.g., $\hat{\xi}$ = 1.021 at the 1% level), implying that while the market is stable, extreme tail risk still exists and warrants attention. The Russian market displays moderate scale values (e.g., 0.615 at 1%) and a negative shape parameter at the lowest quantile ($\hat{\xi}$ = -0.301), suggesting that although the market can be volatile, extreme losses are likely to be capped, possibly due to strong government control over financial dynamics. Turkey stands out with a highly irregular pattern, showing a very large-scale value at the 1% quantile (3.223) and a much smaller value at 2.5% (0.355), reflecting the potential for rare but sharp spikes in volatility. The consistently negative shape parameters further imply that the tail of the distribution is bounded, limiting the scope of extreme losses.

Table 5. Estimated Scale $\hat{\beta}$ and $\hat{\xi}$ Shape Parameters of Tail Return Distribution Across Extreme Quantiles

Bloc		Iran-Aligned Bloc			Israel-Aligned Bloc		
Country		China	Russia	Turkey	Germany	UK	USA
Scale $\hat{\beta}$	q = 1%	0.568	0.615	3.223	1.807	2.68	0.851
	q = 2.5%	0.551	0.635	0.355	1.362	0.405	0.643
	q = 5%	0.503	0.497	0.481	0.627	0.497	0.731
Shape $\hat{\xi}$	q = 1%	1.021	-1.046	-1.036	-0.571	-0.426	0
	q = 2.5%	0.644	-0.631	0.836	-0.193	0.866	0.154
	q = 5%	0.459	-0.251	0.413	0.277	0.466	0.035

Source: Author's Calculation

In contrast, countries aligned with Israel exhibit heavier-tailed and more volatile return distributions. Germany and the UK display relatively large-scale values at the lower quantiles (e.g., 1.807 for Germany and 1.191 for the UK at 1%), indicating exposure to substantial return deviations. Germany's shape parameter remains mildly positive (e.g., 0.277 at 5%), suggesting that tail risk, though present, is moderately controlled. The UK shows a similar pattern but with greater variability in shape values. The United States presents a more consistent profile of extreme risk: high scale values (e.g., 1.203 at 1%) and strongly positive shape parameters across all quantiles (e.g., $\hat{\xi}$ = 0.698 at 1%), indicating that even a highly efficient market like the U.S. remains susceptible to extreme events under global geopolitical uncertainty.

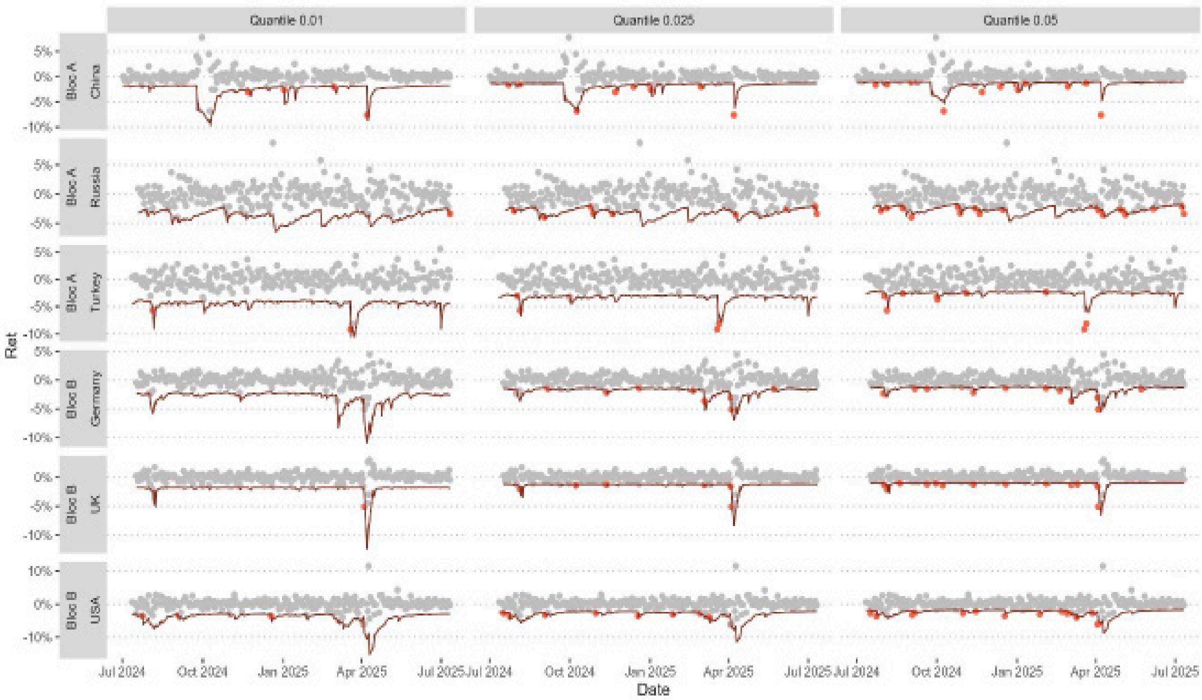
Overall, the EVT parameter estimates reinforce earlier findings that countries in the Israel-aligned bloc are more exposed to extreme risk and rapid market condition shifts, while those in the Iran-aligned bloc tend to exhibit more stable markets with better-contained risk structures. Nevertheless, the presence of positive shape parameters in countries like China suggests that tail risk should not be overlooked and must be accounted for in long-term risk mitigation and financial planning strategies.

Figure 4 visually illustrates the tail behaviour of stock market return distributions for each country using the Peaks Over Threshold (POT) approach of the Extreme Value Theory (EVT). The figure displays fitted Generalized Pareto Distributions (GPD) across different quantiles, capturing the characteristics of extreme market movements. These plots reinforce the quantitative estimates previously presented in Table 5, particularly the scale (β) and shape (ξ) parameters of the GPD for each country.

In countries aligned with Iran, such as China, Russia, and Turkey, the plots confirm the relatively thinner tails of return distributions. This observation is consistent with the lower scale ($\widehat{\beta}$) values reported in Table 5, indicating smaller magnitudes of extreme losses. Moreover, the shape parameters ($\widehat{\xi}$) for these countries are generally negative or close to zero, implying a bounded or short-tailed distribution. This means that while market shocks exist, they are not expected to escalate into highly extreme or unbounded risk, reinforcing the earlier finding that these markets are relatively resilient and less reactive to geopolitical escalations like the Iran–Israel conflict.

In contrast, the countries aligned with Israel exhibit heavier tails in the distribution plots, especially for the lower quantiles. These patterns support the higher σ values and notably positive $\widehat{\xi}$ values shown in Table 5, which suggest a higher probability of extreme losses and a tendency toward fat-tailed distributions. For instance, the U.S. market demonstrates a distinctly heavy left tail, aligning with the estimated shape parameter $\xi > 0$, indicating a high potential for rare but severe market downturns. This tail behavior reflects heightened market sensitivity to geopolitical uncertainty and confirms the structural risk exposed in previous GARCH and MS-GARCH estimations.

Figure 4. Tail Distribution Visualization of Extreme Stock Market Returns Using EVT (POT) Approach



Source: Author’s Graphs

Thus, the visual representation in Figure 4 complements the numerical evidence in Table 5, highlighting that countries within the pro-Israel bloc face more pronounced extreme risk exposure. In contrast, the markets within the Iran-aligned bloc are characterized by more moderate tail risks, likely due to stronger regulatory insulation or lesser integration with global financial networks. Together, both pieces of evidence support the validity of the EVT-POT approach in capturing asymmetric extreme risk behaviour across geopolitically distinct market environments.

3. 5. MODEL VALIDATION OF VAR THROUGH POF AND TUFF BACKTESTING TESTS

The accuracy of the VaR model was evaluated using two main statistical approaches: Kupiec's POF Test and the TUFF Test. These methods assess whether the model's estimation of extreme risk aligns with the actual occurrences of violations during the observation period.

Based on Table 6, generally, the results of Kupiec's POF test indicate that most VaR models across different countries and quantile levels passed the statistical validation. This is evidenced by *p-values* greater than the 5% significance level, suggesting that the number of observed violations is not significantly different from the expected number. For example, in the United States and United Kingdom at the 1% quantile level, no significant violations occurred, indicating that the EVT-based approach provides realistic and well-calibrated thresholds for extreme risk.

Meanwhile, the TUFF test offers additional insights into the timing accuracy of the first violation. If a model anticipates the first violation either too early or too late, it will be reflected in the TUFF test statistics and *p-values*. In most cases, the TUFF test also produced favourable results, with no significant deviations, indicating that the models are not only accurate in terms of violation frequency but also reliable in predicting the timing of extreme risk events. For instance, in Turkey and USA, high *p-values* from the TUFF test suggest that the first violations occurred within the expected probabilistic timeframe, reinforcing the model's temporal validity.

Interestingly, the Kupiec POF test results show that none of the countries had a p-value below 0.05, suggesting that the VaR model based on the MS-GARCH–EVT(POT) framework generally passes the statistical validity test even in certain quantile, 1%, China failed to pass the TUFF test. This reinforces the model's suitability and effectiveness in capturing extreme risk dynamics in the stock markets of the respective countries.

Table 6. Backtesting Results of VaR Using Kupiec's POF and TUFF Tests

Group		Iran-Aligned Bloc			Israel-Aligned Bloc		
Country		China	Russia	Turkey	Germany	UK	USA
POF							
Num. of Violation(s)	$q = 1\%$	4	1	2	1	1	4
	$q = 2.5\%$	9	9	5	9	6	9
	$q = 5\%$	14	19	9	13	13	15
Statistic (p-value)	$q = 1\%$	0.769 (0.62)	1.176 (0.722)	0.108 (0.258)	1.176 (0.722)	1.176 (0.722)	0.769 (0.62)
	$q = 2.5\%$	1.095 (0.705)	1.095 (0.705)	0.275 (0.4)	1.095 (0.705)	0.01 (0.081)	1.095 (0.705)
	$q = 5\%$	0.183 (0.331)	3.091 (0.921)	1.138 (0.714)	0.021 (0.115)	0.021 (0.115)	0.496 (0.519)
TUFF							
First Violation	$q = 1\%$	97	12	250	16	184	9
	$q = 2.5\%$	16	12	7	15	14	4
	$q = 5\%$	16	12	7	15	13	4
Statistic (p-value)	$q = 1\%$	0.001 (0.024)	2.547 (0.89)	1.176 (0.722)	2.031 (0.846)	0.464 (0.504)	3.092 (0.921)
	$q = 2.5\%$	0.656 (0.582)	1.051 (0.695)	1.94 (0.836)	0.739 (0.61)	0.831 (0.638)	3.031 (0.918)
	$q = 5\%$	0.049 (0.175)	0.236 (0.373)	0.865 (0.648)	0.08 (0.222)	0.172 (0.321)	1.801 (0.82)

Source: Author's Calculation

In conclusion, the backtesting results provide strong justification for the use of the MS-GARCH–EVT(POT)-based VaR model as a risk analysis tool. Its success in both frequency and timing validation tests demonstrates that the model is not only statistically sound but also practically applicable in real-world risk management, particularly under high uncertainty conditions such as the ongoing geopolitical tensions between Iran and Israel.

4. CONCLUSION

An analysis of the stock index log return data from six countries indirectly involved in the Iran–Israel conflict reveals that all return series exhibit non-normal distributions, characterized by significant skewness and heavy tails. An ARMA model was employed to capture the mean dynamics, and diagnostic tests on the residuals indicated no evidence of autocorrelation, but the presence of heteroskedasticity in the squared residuals. This finding underscores the need for an advanced modelling approach to better capture the volatility dynamics. The MS-GARCH model successfully identified two distinct volatility regimes (calm and turbulent), with regime distributions aligning with the geopolitical exposure of each country: the Iran-aligned bloc demonstrated relative stability, while the Israel-aligned bloc exhibited higher volatility and more frequent regime shifts.

The EVT(POT) approach was applied to capture extreme risk in the return distributions. Parameter estimates indicated substantial tail risk, particularly in markets with heavy-tailed and large-scale distributions at extreme quantiles. The validity of the combined MS-GARCH–EVT(POT) framework in estimating VaR was assessed through backtesting using Kupiec's tests. All countries passed the POF test across various quantile levels, confirming the model's accuracy in forecasting the frequency of extreme risk events. However, some violations of the TUFF test, such as China at the 1% quantile, suggest room for improvement in the model's timing accuracy for predicting initial violations. Thus, the MS-GARCH-EVT(POT) proved to be statistically robust and effective in measuring and managing extreme market risks amid global geopolitical tensions.

Acknowledgment

The author would like to express sincere appreciation to Diego for his technical assistance and support in coding implementation, which significantly contributed to the success of this research.

REFERENCES

Acharya, V. V., Pedersen, L. H., Philippon, T., & Richardson, M. (2017). Measuring Systemic Risk. T*he Review of Financial Studies*, 30(1), 2–47. https://doi.org/10.1093/rfs/hhw088

Alemohammad, N., Rezakhah, S., & Alizadeh, S. H. (2020). Markov switching asymmetric GARCH model: Stability and forecasting. *Statistical Papers,* 61(3), 1309–1333. https://doi.org/10.1007/s00362-018-0992-2

Ardia, D. (Ed.). (2008). Bayesian Estimation of the Markov-Switching GJR(1, 1) Model with Student-t Innovations. In Financial Risk Management with Bayesian Estimation of GARCH Models: Theory and Applications, 109–153. *Springer*. https://doi.org/10.1007/978-3-540-78657-3_7

Ardia, D., Bluteau, K., Boudt, K., & Catania, L. (2017). Forecasting Risk with Markov-Switching GARCH Models: A Large-Scale Performance Study. *Capital Markets: Asset Pricing & Valuation eJournal.* https://doi.org/10.2139/ssrn.2918413

Ardia, D., Bluteau, K., Boudt, K., Catania, L., & Trottier, D.-A. (2019). Markov-Switching GARCH Models in R: The MSGARCH Package. *Journal of Statistical Software*, 91, 1–38. https://doi.org/10.18637/jss.v091.i04

Augustyniak, M. (2014). Maximum likelihood estimation of the Markov-switching GARCH model. *Computational Statistics & Data Analysis,* 76, 61–75. https://doi.org/10.1016/j.csda.2013.01.026

Baker, S., Bloom, N., Davis, S., & Kost, K. (2019). *Policy News and Stock Market Volatility*. https://doi.org/10.3386/w25720

Bali, T. G., & Cakici, N. (2004). Value at Risk and Expected Stock Returns. *Financial Analysts Journal*, 60(2), 57–73. https://doi.org/10.2469/faj.v60.n2.2610

Balkema, A., & Haan, L. (1974). Residual Life Time at Great Age. T*he Annals of Probability*, 2. https://doi.org/10.1214/aop/1176996548

Balmaceda, J. F., Miranda, M. A., Parba, M. H. J., & Zapanta, P. A. (2022). Forecasting Value-at-Risk During Crises in Select ASEAN Stock Market Indices Through GARCH-EVT Models. *Financial Management Bachelor's Theses.* https://animorepository.dlsu.edu.ph/etdb_finman/27

Bernard, C., Rüschendorf, L., & Vanduffel, S. (2017). Value-at-Risk Bounds With Variance Constraints. *Journal of Risk and Insurance*, 84(3), 923–959. https://doi.org/10.1111/jori.12108

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, 31(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Borisov Stoyanov, S. (2025). Geopolitical Risk and the Effects on Companies' Financial Performance. *Collection of papers new economy*, 3(1), 155-169. https://doi.org/10.61432/CPNE0301155s

Bossman, A., & Gubareva, M. (2023). Asymmetric impacts of geopolitical risk on stock markets: A comparative analysis of the E7 and G7 equities during the Russian-Ukrainian conflict. *Heliyon*, 9(2), e13626. https://doi.org/10.1016/j.heliyon.2023.e13626

Brooks, C. (2019). Introductory Econometrics for Finance. *Cambridge University Press*. https://doi.org/10.1017/9781108524872

Bücher, A., & Zhou, C. (2021). A Horse Race between the Bloc Maxima Method and the Peak–over–Threshold Approach. *Statistical Science*, 36(3), 360–378. https://doi.org/10.1214/20-STS795

Bui Quang, P., Klein, T., Nguyen, N. H., & Walther, T. (2018). Value-at-Risk for South-East Asian Stock Markets: Stochastic Volatility vs. GARCH. *Journal of Risk and Financial Management*, 11(2), Article 2. https://doi.org/10.3390/jrfm11020018

Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (2012). The Econometrics of Financial Markets. *Princeton University Press*. https://doi.org/10.2307/j.ctt7skm5

Castillo, J. del, & Serra, I. (2015). Likelihood inference for generalized Pareto distribution. *Computational Statistics & Data Analysis*, 83, 116–128. https://doi.org/10.1016/j.csda.2014.10.014

Chen, H., Zhang, J., Tao, Y., & Tan, F. (2019). Asymmetric GARCH type models for asymmetric volatility characteristics analysis and wind power forecasting. *Protection and Control of Modern Power Systems*, 4(1), 29. https://doi.org/10.1186/s41601-019-0146-0

Chen, X., Shan, Z., Tang, D., Zhou, B., & Boamah, V. (2023). Interest rate risk of Chinese commercial banks based on the GARCH-EVT model. *Humanities and Social Sciences Communications*, 10, 1–11. https://doi.org/10.1057/s41599-023-02321-6

Choudhry, M. (2013). An Introduction to Value-at-Risk (5th ed.). John Wiley & Sons. https://www.wiley.com/en-us/An+Introduction+to+Value-at-Risk%2C+5th+Edition-p-9781118316726

Darmanto, D., Darti, I., Astutik, S., & Nurjannah, N. (2025). Identifying Instability in the G7 Stock Market Using Two-Regime MS-GARCH Family Model as Risk. *Proceedings of the 2nd International Conference on Sciences, Mathematics, and Education 2023* (ICOSMED 2023), 927, 24. https://doi.org/10.2991/978-2-38476-410-5_4

Darmanto, D., Darti, I., Astutik, S., Nurjannah, N., Lee, M. H., Damayanti, R. H. P. Y., & Irsandy, D. (2025). Strengthening Syariah Financial Markets With Garch-Based Stock Price Forecasting And Var-Risk Assessment. *Barekeng: Jurnal Ilmu Matematika Dan Terapan*, 19(2), Article 2. https://doi.org/10.30598/barekengvol19iss2pp1217-1236

Davison, A. C., & Smith, R. L. (1990). Models for Exceedances over High Thresholds. *Journal of the Royal Statistical Society*. Series B (Methodological), 52(3), 393–442. https://doi.org/10.1111/j.2517-6161.1990.tb01796.x

Duffie, D., & Pan, J. (1997). An Overview of Value at Risk. *The Journal of Derivatives*, 4(3), 7–49. https://web.mit.edu/people/junpan/ddjp.pdf

Dugbartey, A. N. (2025). Systemic financial risks in an era of geopolitical tensions, climate change, and technological disruptions: Predictive analytics, stress testing and crisis response strategies. *International Journal of Science and Research Archive*, 14(2), 1428–1448. https://doi.org/10.30574/ijsra.2025.14.2.0563

Echaust, K., & Just, M. (2020). Value at Risk Estimation Using the GARCH-EVT Approach with Optimal Tail Selection. *Mathematics,* 8(1), Article 1. https://doi.org/10.3390/math8010114

Embrechts, P., Klüppelberg, C., & Mikosch, T. (1997). Modelling Extremal Events. *Springer*. https://doi.org/10.1007/978-3-642-33483-2

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica,* 50(4), 987–1007. https://doi.org/10.2307/1912773

Engle, R. F., & Bollerslev, T. (1986). Modelling the persistence of conditional variances. *Econometric Reviews*, 5(1), 1–50. https://doi.org/10.1080/07474938608800095

Factset.Insight. (2025). Geopolitical Risk Scenarios Revisited: Stress Testing Investment Strategies Amid the Israel-Iran Conflict. https://insight.factset.com/geopolitical-risk-scenarios-revisited-stress-testing-investment-strategies-amid-the-israel-iran-conflict

Faruq, U. A., Salim, D. F., & Kristanti, F. T. (2025). Risk measurement model on top 10 cryptocurrency market capitalization. *Edelweiss Applied Science and Technology,* 9(4), Article 4. https://doi.org/10.55214/25768484.v9i4.6554

Fava, S. D., Gupta, R., Pierdzioch, C., & Rognone, L. (2024). Forecasting international financial stress: The role of climate risks. *Journal of International Financial Markets, Institutions and Money,* 92, 101975. https://doi.org/10.1016/j.intfin.2024.101975

Fisher, R. A., & Tippett, L. H. C. (1928). Limiting Forms Of The Frequency Distribution Of The Largest Or Smallest Member Of A Sample. *Mathematical Proceedings of the Cambridge Philosophical Society*, 24(2), 180–190. https://doi.org/10.1017/S0305004100015681

Francq, C., & Zakoïan. (2010). Estimating GARCH Models by Quasi-Maximum Likelihood. *In GARCH Models*, 141–184. John Wiley & Sons, Ltd. https://doi.org/10.1002/9780470670057.ch7

Gechev, V. (2025). Economic Policy Instruments for Innovative Growth in the European Union - The Case of AI. *ECONOMICS - Innovative and Economics Research Journal*, 13(3), 397–407. https://doi.org/10.2478/eoik-2025-0071

Gilli, M., & Këllezi, E. (2006). An Application of Extreme Value Theory for Measuring Financial Risk. *Computational Economics,* 27, 207–228. https://doi.org/10.1007/s10614-006-9025-7

Gnedenko, B. (1943). Sur La Distribution Limite Du Terme Maximum D'Une Serie Aleatoire. *Annals of Mathematics*, 44(3), 423–453. https://doi.org/10.2307/1968974

Gokcan, S. (2000). Forecasting volatility of emerging stock markets: Linear versus non-linear GARCH models. *Journal of Forecasting,* 19(6), 499–504. https://doi.org/10.1002/1099-131X(200011)19:6<499::AID-FOR745>3.0.CO;2-P

Grillenzoni, C. (1993). ARIMA Processes with ARIMA Parameters. *Journal of Business & Economic Statistics*, 11(2), 235–250. https://doi.org/10.2307/1391375

Gui, P., & Zhu, Y. (2020). Value at Risk and the Cross-Section of Expected Returns: Evidence from China (SSRN Scholarly Paper No. 3579848). *Social Science Research Network*. https://doi.org/10.2139/ssrn.3579848

Haas, M., Mittnik, S., & Paolella, M. S. (2004). A New Approach to Markov-Switching GARCH Models. *Journal of Financial Econometrics,* 2(4), 493–530. https://doi.org/10.1093/jjfinec/nbh020

Hamilton, J. D., & Susmel, R. (1994). Autoregressive conditional heteroskedasticity and changes in regime. *Journal of Econometrics,* 64(1), 307–333. https://doi.org/10.1016/0304-4076(94)90067-1

Hossain, A. T., Masum, A.-A., & Saadi, S. (2024). The impact of geopolitical risks on foreign exchange markets: Evidence from the Russia–Ukraine war. *Finance Research Letters,* 59, 104750. https://doi.org/10.1016/j.frl.2023.104750

Jorion, P. (2007). Value at Risk: The New Benchmark for Managing Financial Risk. *McGraw-Hill*. https://doi.org/10.1007/s11408-007-0057-3

Khan, S., & Alghulaiakh, H. (2020). ARIMA Model for Accurate Time Series Stocks Forecasting. I*nternational Journal of Advanced Computer Science and Applications* (IJACSA), 11(7), Article 7. https://doi.org/10.14569/IJACSA.2020.0110765

Kupiec, P. H. (1995). Techniques for Verifying the Accuracy of Risk Measurement Models. *The Journal of Derivatives*, 3(2), 73–84. https://doi.org/10.3905/jod.1995.407942

Lee, S.-W., & Hansen, B. E. (1994). Asymptotic Theory for the Garch(1,1) Quasi-Maximum Likelihood Estimator. *Econometric Theory*, 10(1), 29–52. https://doi.org/10.1017/S0266466600008215

Li, S., Wang, Y., Zhang, Z., & Zhu, Y. (2022). Research on the Factors Affecting Stock Price Volatility. 2884–2889. https://doi.org/10.2991/aebmr.k.220307.469

Linsmeier, T. J., & Pearson, N. D. (2000). Value at Risk. *Financial Analysts Journal*, 56(2), 47–67. https://doi.org/10.2469/faj.v56.n2.2343

Longin, F. M. (2000). From value at risk to stress testing: The extreme value approach. *Journal of Banking & Finance*, 24(7), 1097–1130. https://doi.org/10.1016/S0378-4266(99)00077-1

Lumsdaine, R. L. (1996). Consistency and Asymptotic Normality of the Quasi-Maximum Likelihood Estimator in IGARCH(1,1) and Covariance Stationary GARCH(1,1) *Models. Econometrica*, 64(3), 575–596. https://doi.org/10.2307/2171862

Maciel, L. (2020). Cryptocurrencies value-at-risk and expected shortfall: Do regime-switching volatility models improve forecasting? *International Journal of Finance & Economics*, 26(3), 4840–4855. https://doi.org/10.1002/ijfe.2043

Medeiros, M. C., & Veiga, A. (2009). Modeling Multiple Regimes In Financial Volatility With A Flexible Coefficient Garch(1,1) Model. *Econometric Theory,* 25(1), 117–161. https://doi.org/10.1017/S026646660809004X

Molnár, P. (2016). High-low range in GARCH models of stock return volatility. *Applied Economics*, 48(51), 4977–4991. https://doi.org/10.1080/00036846.2016.1170929

Niu, Z., Wang, C., & Zhang, H. (2023). Forecasting stock market volatility with various geopolitical risks categories: New evidence from machine learning models. *International Review of Financial Analysis,* 89, 102738. https://doi.org/10.1016/j.irfa.2023.102738

Okafor, R. U., & Onyeka-Ubaka, J. N. (2023). Analyzing Dynamic Regimes of GARCH Model on Stock Price Volatility. *International Journal of Statistical Distributions and Applications*, 9(1), Article 1. https://doi.org/10.11648/j.ijsd.20230901.13

Pandey, D. K. (2024). Effects of Israel-Iran conflict: Insights on global stock indices and currencies. *Journal of Economic Studies,* 52(4), 762–783. https://doi.org/10.1108/JES-04-2024-0286

Pickands III, J. (1975). Statistical Inference Using Extreme Order Statistics. *The Annals of Statistics,* 3(1), 119–131. https://doi.org/10.1214/aos/1176343003

Qammar, R. (2019). Is Stock Price Volatility A Risk ?: An Evaluation Review. *International Journal of Management, Accounting and Economics*. 6(1). https://dor.isc.ac/dor/20.1001.1.23832126.2019.6.1.5.0

Paidi, Sirojuzilam, Lubis, S., & Purwoko, A. (2025). Efficiency Analysis of Regional Government Expenditure on Development: Evidence from Indonesia. *ECONOMICS - Innovative and Economics Research Journal*, 13(3), 105–124. https://doi.org/10.2478/eoik-2025-0058

Sajjad, R., Coakley, J., & Nankervis, J. C. (2008). Markov-Switching GARCH Modelling of Value-at-Risk. *Studies in Nonlinear Dynamics & Econometrics*, 12(3). https://doi.org/10.2202/1558-3708.1522

Segnon, M., Gupta, R., & Wilfling, B. (2024). Forecasting stock market volatility with regime-switching GARCH-MIDAS: The role of geopolitical risks. *International Journal of Forecasting,* 40(1), 29–43. https://doi.org/10.1016/j.ijforecast.2022.11.007

Singh, A. K., Allen, D. E., & Robert, P. J. (2013). Extreme market risk and extreme value theory. *Mathematics and Computers in Simulation,* 94, 310–328. https://doi.org/10.1016/j.matcom.2012.05.010

Sohag, K., Vasilyeva, R., Urazbaeva, A., & Voytenkov, V. (2022). Stock Market Synchronization: The Role of Geopolitical Risk. *Journal of Risk and Financial Management,* 15(5), Article 5. https://doi.org/10.3390/jrfm15050204

Thangaraju, K., & Palani, P. (2025). The Influence of AI-Driven Sustainable Human Resource Management on Employee Creative Performance: Analysing Idiosyncratic Deals in the Indian Information Technology Sector. *ECONOMICS - Innovative and Economics Research Journal,* 13(3), 579–595. https://doi.org/10.2478/eoik-2025-0081

Tsay, R. S. (2010). Analysis of Financial Time Series. *John Wiley & Sons*. https://www.wiley.com/en-us/Analysis+of+Financial+Time+Series%2C+3rd+Edition-p-9780470414354

Umar, Z., Bossman, A., Choi, S.-Y., & Teplova, T. (2022). Does geopolitical risk matter for global asset returns? Evidence from quantile-on-quantile regression. *Finance Research Letters*, 48, 102991. https://doi.org/10.1016/j.frl.2022.102991

Umar, Z., Polat, O., Choi, S.-Y., & Teplova, T. (2022). The impact of the Russia-Ukraine conflict on the connectedness of financial markets. *Finance Research Letters*, 48, 102976. https://doi.org/10.1016/j.frl.2022.102976

Valenti, D., Fazio, G., & Spagnolo, B. (2018). Stabilizing effect of volatility in financial markets. *Physical Review E*, 97(6), 062307. https://doi.org/10.1103/PhysRevE.97.062307

Wang, Q. J. (1991). The POT model described by the generalized Pareto distribution with Poisson arrival rate. *Journal of Hydrology,* 129(1), 263–280. https://doi.org/10.1016/0022-1694(91)90054-L

Wang, Y., & Guo, Y. (2020). Forecasting method of stock market volatility in time series data based on mixed model of ARIMA and XGBoost. *China Communications*, 17(3), 205–221. https://doi.org/10.23919/JCC.2020.03.017

Wang, Y., Xiang, Y., Lei, X., & Zhou, Y. (2021). Volatility Analysis Based On GARCH-Type Models: Evidence From The Chinese Stock Market. *Economic Research-Ekonomska Istraživanja*, 35(0), 1–25. https://doi.org/10.1080/1331677X.2021.1967771

Xie, Y. (2005). Consistency of quasi-maximum likelihood estimators for the regime-switching GARCH model. *Research Report* (Centre of Biostochastics), 2005(3). https://doi.org/10.1080/02331880701442619

Zhang, Y., He, J., He, M., & Li, S. (2023). Geopolitical risk and stock market volatility: A global perspective. *Finance Research Letters*, 53, 103620. https://doi.org/10.1016/j.frl.2022.103620

Zheng, L., Ismail, K., & Meng, X. (2014). Freeway safety estimation using extreme value theory approaches: A comparative study. *Accident Analysis & Prevention,* 62, 32–41. https://doi.org/10.1016/j.aap.2013.09.006