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Evaluating and assessing risk of big three stocks' pharmaceutical sector in Indonesia based on asymmetric GARCH-EVT modeling

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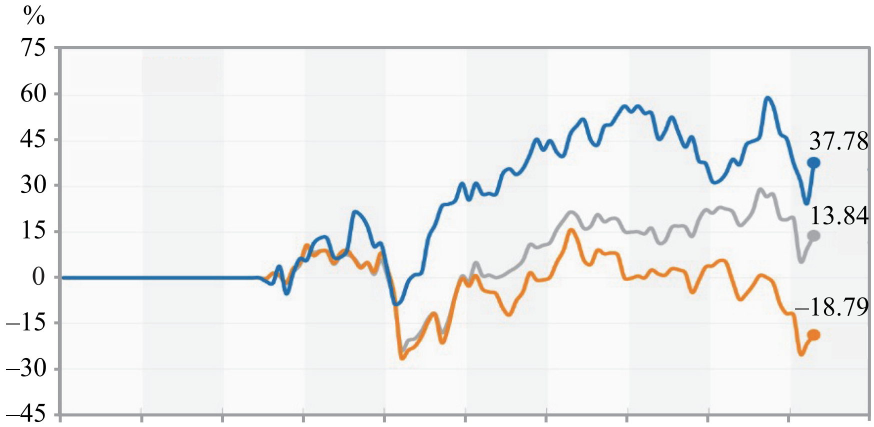
This study aims to model the volatility of the top three pharmaceutical sector stocks in Indonesia using a two-stage modeling approach. The first stage involves GARCH and its variations, followed by residual modeling using the GPD-based EVT approach. The three stocks analyzed are Mitra Keluarga Karyasehat Tbk (IDX: MIKA), Kalbe Farma Tbk (IDX: KLBF), and Medikaloka Hermina Tbk (IDX: HEAL). The dataset comprises return data spanning July 1, 2019, to April 30, 2025 (a total of 1,412 observations), sourced from Yahoo Finance. The findings reveal that the best-fitting models for capturing volatility are ARMA(0,1)–GARCH(1,1) for MIKA.JK, ARMA(1,2)–TGARCH(1,1) for KLBF.JK, and ARMA(0,0)–GJRGARCH(1,1) for HEAL.JK. Backtesting and the Kupiec test confirm that these models provide highly accurate VaR predictions at the 1%, 2.5%, and 5% quantiles.

Keywords: GARCH-EVT, pharmaceutical stocks, risk measurement, value at risk, volatility

In 2025, the pharmaceutical sector in Indonesia continues to present an intriguing trend worthy of examination, particularly regarding stock issuances within the industry. With a population of 270 million, Indonesia represents a significant market for health needs. This potential drives the growth of pharmaceutical companies involved in producing medical devices, medications, and herbal products, suggesting that the market will likely maintain a positive trajectory this year and in the coming years. The sector peaked during the global Covid-19 pandemic, with the pharmaceutical industry experiencing a 10% growth in 2021, reaching total assets of Rp 90–95 trillion just a year after the lockdown. Although this upward momentum persisted until the end of 2022, the sector began a gradual decline that continued until late 2023. According to Figure 1, fluctuations in the healthcare index persisted into early 2025, before trending upwards again by the end of the first half of 2024.

Figure 1

Fact sheet index health sector Indonesia



			2018a)	2019	2020	2021	2022	2023	2024	2025b)
IDXHEALTH	–	–	6.3	4.7	17.8	8.4	10.2	–12.1	5.8	–5.4
JCI	–	–	4.2	1.7	–5.1	10.1	4.1	6.2	–2.7	–4.4
LQ45	–	–	4.8	3.2	–7.8	–0.4	0.6	3.6	–14.8	–7.9

IDXHEALTH JCI LQ45

a) 13 July 2018. b) 20 April 2025.
Source: [1].

According to the quarterly report from the Research Division of the Indonesia Stock Exchange as of April 2025, the top three constituents in the healthcare sector, specifically within pharmaceuticals, based on the highest index weight and assets, are Mitra Keluarga Karyasehat Tbk (IDX: MIKA), Kalbe Farma Tbk (IDX: KLBF), and Medikaloka Hermina Tbk (IDX: HEAL). Together, these three companies represent 70% of the index weight and account for nearly IDR 35 trillion of the total IDR 52 trillion in assets held by all constituents in the healthcare sector [2]. This indicates their dominant position in Indonesia's pharmaceutical market, which comprises around 20 constituents in total. However, despite their significant index weights and asset values, investors in these companies are not insulated from the risk of loss. Unpredictable natural events like floods, disease outbreaks, and earthquakes can greatly influence market stability *(Alogoskoufis et al., 2021; Battiston et al., 2021)*. Additionally, shifts in macroeconomic and microeconomic regulations, both domestically and globally, can have widespread effects on financial market fluctuations *(Boikos et al., 2023; Ciapanna et al., 2024)*. Political changes, whether recovery or instability, also significantly impact the market, highlighting the importance for investors to stay informed about investment risk assessment and price forecasting in financial markets *(Al-Thaqeb–Algharabali, 2019; Boubaker et al., 2022; Boungou–Yatié, 2022)*.

The phenomenon of market risk instability from a statistical point of view means that there is heterogeneity of variance in time series data. Variety heterogeneity is caused by volatility. According to *Bhowmik and Wang (2020), Bollerslev et al. (2020), Fassas and Siriopoulos (2021),* low volatility represents financial market stability, while high volatility indicates dominance in financial transactions. This causes commodity prices to fluctuate sharply and makes it difficult to measure the risk of loss in financial transactions. J.P. Morgan in 1994 introduced Value at Risk (VaR) which measures the maximum loss of financial market risk that may occur in an asset or portfolio at a certain confidence level (%) *(Choudhry, 2013; Jorion, 2007)*. In the study of financial transactions, investment risk is identified by analyzing return data to obtain the VaR of an investment. Based on the statements of researchers, it is known that the nature of return data includes non-normally distributed, thick-tailed, and leptokurtic *(Bollerslev, 1986; Fernandez, 2003; Narayan et al., 2016; Sheikh–Qiao, 2009)*.

The volatility present in return data results in varying variance across different time horizons, which makes it challenging for the ARIMA Box-Jenkins time series model to accurately capture crucial information that may be hidden due to this volatility. To tackle this problem, *Engle (1982)* developed the autoregressive conditional heteroscedasticity (ARCH) model, which was subsequently enhanced into the Generalized ARCH (GARCH) model by *Bollerslev (1986)*. However, shifts in economic policy can affect return data, leading to asymmetric volatility – where volatility may be either positive or negative, commonly referred to as the leverage effect. To accommodate this leverage effect, the GARCH model was further refined into an asymmetric GARCH model *(Glosten et al., 1993; Nelson, 1991; Zakoian, 1994)*. Moreover, return data are often characterized by non-normal distributions and heavy tails due to sharp and extreme fluctuations, necessitating adjustments for these characteristics. In climatology, extreme data patterns are modeled using extreme value theory (EVT), which was first introduced by *Fisher and Tippett (1928).* In the financial field, however, the EVT method became widely utilized since in the early 2000s. *McNeil and Frey (2000)* specifically integrated the GARCH model with EVT to improve the accuracy of Value at Risk (VaR) measurements.

In this study, an empirical study will be conducted on the three leading constituents in the pharmaceutical sector in Indonesia: MIKA, KLBF, and HEAL. To date, there has been no specific research the investment risk in the three constituents with a mixed modeling approach that integrates between GARCH/asymmetric GARCH and EVT. The objective is to determine for the most suitable model for each constituent, and derive VaR calculations based on the selected model. Therefore, the research conducted is the first review so that the results obtained can be taken into consideration by investors in investing.

Beyond the Indonesian market, a growing body of evidence shows that combining GARCH-type volatily models with EVT improves tail-risk measurement across assets and geographies. For example, GARCH-EVT delivers more reliable VaR forecasts than plain GARCH in equity and commodity settings, especially at low quantiles where heavy-tail behavior matters most. These gains are documenters in emerging and developed markets, and during turbulent periods such as the Covid-19 shock. Situating our Indonesia-specific analysis within this broader literature clarifies both the external validity of our approach and its limits when sectoral and macro conditions differ *(Echaust–Just, 2020; Gençay–Selçuk, 2004; Kayani et al., 2024; Maharana et al., 2024)*. We further note the health-care and pharmaceutical equities exhibit policy-sensitive volalitility, tied to public-health interventions and fiscal health spending, which shapes both conditional variance and downside risk. International evidence on healthcare indices underscores that model choice and backtesting should reflect there policy linkages, lending support to our use of asymmetric GARCH-EVT for Indonesian pharma constituents *(Li et al., 2024)*.

1. Literature survey

The ARCH/GARCH model was introduced due to the limitations of the Box-Jenkins ARIMA model in adequately capturing variance information affected by volatility *(Bollerslev, 1986; Engle, 1982)*. Subsequently, the GARCH model was further refined into an asymmetric GARCH model to account for leverage effects on volatility. This includes the exponential GARCH (E-GARCH) model *(Nelson, 1991)*, the Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) model *(Glosten et al., 1993)*, and the threshold GARCH (T-GARCH) model (Zakoian, 1994).

Numerous researchers have applied these models to financial data in recent years. For instance, *Naik et al. (2020)* used the GARCH model to predict stock market crises. Additionally, *Endri et al. (2020)* employed the GARCH model to identify factors influencing the Composite Stock Price Index (CSPI). *Pham Thi et al. (2023)* analyzed economic resilience and natural resource prices in China post-Covid-19 using GARCH (1,1) and TGARCH(1,1) models. In India, *Shahani–Taneja (2022)* explored the volatility patterns of raw materials in the energy sector using GARCH(1,1), TGARCH(0,1), and EGARCH(1,1) models.

Although EVT was initially utilized for climatology modeling, it has been adapted in finance since the early 2000s to analyze extreme data. EVT can be approached in two ways: block-maxima (BM) and peak over threshold (POT*) (Balkema–Haan, 1974; Gilli–Këllezi, 2006; Gnedenko, 1943; Pickands III, 1975)*. While the GARCH model focuses on the error of mean model, integrating EVT with GARCH results in the GARCH-EVT model, which effectively incorporates information about extreme data. This combined approach enhances the accuracy of VaR calculations *(Balmaceda et al., 2022; Echaust, 2018; Echaust–Just, 2020; Huang et al., 2017; Khan et al., 2023; Tabasi et al., 2019)*. Empirical research employing the GARCH-EVT model continues to be prevalent among researchers. For example, *Ke et al. (2022)* successfully modeled Bitcoin patterns, particularly for negative tails, using the GARCH-EVT(POT) method. Additionally, *Ren et al. (2023)* applied the GARCH-EVT(POT) approach to model extreme risks in the crude oil market in China, finding that the model effectively estimates VaR.

2. Methods

2.1 Return data and identification of its characters

Let P_t and P_{t-1} denote the closing price of a stock index at time t and $t-1$ respectively, then the log of return (r_t) is calculated as in equation (1) *(Aliyev et al., 2020; Chocholatá, 2022; Sema et al., 2021)*.

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

Many researchers conducted studies and modeling of return data and then concluded empirically that return data tends to have non-normal distribution with fat tails, leptokurtic, skewed, volatile, volatility clustering and also asymmetric *(Bollerslev, 1986; Caporin–Costola, 2019; Ding et al., 2017; Fernandez, 2003; Glosten et al., 1993; Mittnik et al., 1998; Sheikh–Qiao, 2009).*

Normality distribution is identified using two methods: descriptive analysis involving skewness and kurtosis, and statistical tests such as Anderson–Darling and Lilliefors. The values for skewness and kurtosis are computed using equation (2a) and equation (2b) *(Karagiorgis–Drakos, 2022).*

$$Skew = \frac{1}{N}\sum_{t=1}^{N}\frac{(r_t-\hat{\mu})^3}{\hat{\sigma}^3} \tag{2a}$$

$$Kurt = \frac{1}{N}\sum_{t=1}^{N}\frac{(r_t-\hat{\mu})^4}{\hat{\sigma}^4} \tag{2b}$$

Return data is said to be Normal distribution if the value of $Skew = 0$ and $Kurt = 3$ (mesokurtic). As for if $Skew < -0.5$ or $Skew > 0.5$, the data indicates negative or positive skewed and if $Kurt < 3$ or $Kurt > 3$, the data indicates negative kurtosis (platykurtic) or positive kurtosis (leptokurtic) *(Wilcox, 2020)*. Meanwhile, the Anderson–Darling and the Lilliefors statistic test with the null hypothesis that the random sample r_t is normally distributed $[H_0: r_t \sim N(\mu, \sigma^2)]$ use equation (3) and equation (4) respectively *(Anderson–Darling, 1954; Lilliefors, 1967)*:

$$A^2 = -n - \frac{1}{n}\left[\sum_{t=1}^{n}(2t-1)\left\{\ln F^*\left(Z_{r_{t(i)}}\right) + \ln\left(1 - F^*\left(Z_{r_{n+1-t(i)}}\right)\right)\right\}\right] \tag{3}$$

with $F^*\left(Z_{r_{t(i)}}\right)$ and $F^*\left(Z_{r_{n+1-t(i)}}\right)$ are the cumulative distribution functions of the standard normal distribution, and

$$D = \max_{r_t}\left|F^*\left(Z_{r_{t(i)}}\right) - S_n\left(Z_{r_{t(i)}}\right)\right| \tag{4}$$

where $Z_{r_{t(i)}}$ is the standardized ordered return data, $S_n\left(Z_{r_{t(i)}}\right)$ is the cumulative distribution function of $Z_{r_{t(i)}}$, and $F^*\left(Z_{r_{t(i)}}\right)$ is the standard normal cumulative distribution function.

2.2 Time dependency modeling of return data

One of the models that can be used to capture time dependency in return data (r_t) is the Autoregressive Moving Average (ARMA)(p, q) model which is a combination of AR(p) and MA(q) models as in equation (5) *(Box et al., 2015; Grillenzoni, 1993; Hyndman–Athanasopoulos, 2018; Montgomery et al., 2015)*.

$$r_t = \sum_{i=1}^{p}\phi_i r_{t-i} + \varepsilon_t - \sum_{i=1}^{q}\theta_i\varepsilon_{t-i} \rightarrow \left(1 - \sum_{i=1}^{p}\phi_i B^i\right)r_t = \left(1 - \sum_{i=1}^{q}\theta_i B^i\right)\varepsilon_t \tag{5}$$

The backshift operator (B) acts as the lag operator, where $B^i r_t = r_{t-i}$, and ε_t represents a white noise process, meaning its rows are uncorrelated with a mean of 0 and variance σ^2, $\varepsilon_t \sim WN(0, \sigma^2)$. The ARMA)$(p, q)$ model is considered stationary if $\phi(B)r_t = 0$.

The identification of the ARIMA(p, d, q) model relies on the patterns observed in the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. To aid in identifying the ARMA(p, q) model, *Cryer and Chan (2008)* presented a summary in Table 1.

Table 1

Identification tentative model of ARMA$(\boldsymbol{p}, \boldsymbol{q})$

Model	Pattern	
	ACF	PACF
AR(p)	Tails off	Cuts off after lag p
MA(q)	Cuts off after lag q	Tails off
ARMA(p, q), $p > 0, q > 0$	Tails off	Tails off

Source: *Cryer and Chan (2008).*

The parameters of the ARIMA(p, d, q) model can be estimated using Maximum Likelihood Estimation (MLE) through a conditional likelihood function approach *(Box et al., 2015)*. Assuming that ε_t follows a normal distribution, the probability density function for ε_t can be expressed as follows:

$$p(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n) \propto \frac{1}{(\sigma_\varepsilon^2)^{\frac{n}{2}}} \exp\left[-\left(\sum_{t=1}^{n} \frac{\varepsilon_t^2}{2\sigma_\varepsilon^2}\right)\right] \tag{6}$$

with $\mathbf{w}$ data, the Log-Likelihood function with parameter values $(\boldsymbol{\phi}, \boldsymbol{\theta}, \sigma_\varepsilon^2)$ conditional on the initial selection $(\mathbf{w}^*, \boldsymbol{\varepsilon}^*)$ is defined as in equation (7).

$$L^*(\boldsymbol{\phi}, \boldsymbol{\theta}, \sigma_\varepsilon^2) = -\frac{n}{2}\ln(\sigma_\varepsilon^2) - \frac{S^*(\boldsymbol{\phi}, \boldsymbol{\theta})}{2\sigma_\varepsilon^2} \tag{7}$$

where

$$S^*(\boldsymbol{\phi}, \boldsymbol{\theta}) = \sum_{t=1}^{n} \varepsilon_t^2(\boldsymbol{\phi}, \boldsymbol{\theta} | \mathbf{w}^*, \boldsymbol{\varepsilon}^*, \mathbf{w}) \tag{8}$$

The estimated value is obtained by minimizing the conditional sum of squares function $\left(S^*(\boldsymbol{\phi}, \boldsymbol{\theta})\right)$.

2.3 The family of GARCH model

The GARCH model, introduced by *Bollerslev (1986)*, builds upon the ARCH model developed by *Engle (1982)* to effectively capture volatility. Volatility is indicated by the error variance derived from the ARMA(p, q) mean model, which may exhibit heteroscedasticity, affecting the efficiency of parameter estimators. The presence of ARCH/GARCH effects in the model can be assessed using the Lagrange Multiplier (LM) test as in equation (9)

$$LM = T \times R^2 \sim \chi_{\alpha,q}^2 \tag{9}$$

Let ε_t represent the error of the stochastic process at discrete time t, and ψ_t denote the information set related to the error variance at that time. The general form of the GARCH(P, Q) model is as follows:

$$\varepsilon_t|\psi_{t-1} \sim N(0, \sigma_t^2) \quad (10)$$
$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j\, \sigma_{t-j}^2 \quad (11)$$

To ensure σ_t^2 is always positive, $\alpha_0 > 0, \alpha_i \geq 0, i = 1,2,\ldots,q, \beta_j \geq 0, j = 1,2,\ldots p$ and $\alpha_i + \beta_j < 1$ *(Boonyakunakorn et al., 2019; Chocholatá, 2022; Echaust–Just, 2020)*. In many studies, it is stated that the GARCH(1,1) model is sufficient to capture volatility clustering *(Aliyev et al., 2020; Brooks–Burke, 2003)*.

2.3.1 EGARCH model

The EGARCH(P, Q) model, as shown in equation (12), employs a logarithmic form of σ_t^2, which eliminates the need for parameter restrictions *(Nelson, 1991)*. In this model, the GARCH parameter is denoted by β, while parameters α and γ capture the size and direction of the leverage effect.

$$ln(\sigma_t^2) = \omega + \sum_{i=1}^{Q} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}} - E\left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right)\right| + \sum_{j=1}^{P} \beta_j\, ln\left(\sigma_{t-j}^2\right) + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \quad (12)$$

It has been noted that asymmetric volatility occurs only when $\gamma \neq 0$. Specifically, if $\gamma < 0$, negative events have a greater impact on volatility than positive ones *(Do et al., 2020; Milošević et al., 2019; Wang et al., 2021)*. Conversely, if $\gamma > 0$, positive events are more strongly correlated with volatility, indicating that they exert a greater influence. The presence of asymmetric volatility is confirmed when $\gamma \neq 0$. The effect of positive prior returns on volatility is represented by $\alpha + \gamma$, while the effect of negative prior returns is captured by $\gamma - \alpha$ *(Naimy et al., 2021)*.

2.3.2 GJRGARCH model

The GJRGARCH model is also a development of the GARCH model to capture asymmetric volatility with the parameter γ in the GJRGARCH(P, Q) model and by adding d_{t-1} as a virtual indicator with a value of 0 or 1 as in equation (13) *(Du–He, 2015; Glosten et al., 1993; Naimy et al., 2021; Noori–Mohammad, 2021)*.

$$\sigma_t^2 = \omega + \sum_{i=1}^{Q} \alpha_i\, \varepsilon_{t-i}^2 + \sum_{j=1}^{P} \beta_j\, \sigma_{t-j}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} \quad (13)$$

with

$$d_{t-1} = \begin{cases} 1, & \varepsilon_{t-1} < 0 \\ 0, & \varepsilon_{t-1} \geq 0 \end{cases}$$

At time t, if a positive event occurs, it will raise volatility by α_t, while a negative event will increase volatility by $\alpha_t + \gamma_t$. When $\gamma > 0$, this indicates that negative events from the previous period have a stronger impact on current volatility compared to positive events, and the opposite is true when $\gamma < 0$ *(Naimy et al., 2021)*.

2.3.3 TGARCH model

Zakoian (1994) introduced the TGARCH model as a more advanced version of the GARCH model and an extension of the GJRGARCH model to analyze asymmetric volatility features. equation (14) is a TGARCH(P, Q) model,

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j\, \sigma_{t-j}^2 + \sum_{k=1}^{r} \gamma_k \varepsilon_{t-k}^2 d_{t-k} \tag{14}$$

In this equation, the magnitude of σ_t^2 is influenced by the square of the error from the previous period (ε_{t-i}^2) and the variance of the prior period's error $\left(\sigma_{t-j}^2\right)$. The model accounts for volatility asymmetry through the term $\gamma_k \varepsilon_{t-k}^2 d_{t-k}$, where $d_{t-k} = 1$ indicates the occurrence of a negative event, and *vice versa*. A positive value of γ suggests the presence of volatility asymmetry, while a negative value indicates a reduction in the asymmetric effect on volatility *(Ausloos et al., 2020; Caporale–Zakirova, 2017; Hongwiengjan–Thongtha, 2021; Wang et al., 2021; Zakoian, 1994)*.

2.4 Tail characteristics and extreme value theory (EVT)

The EVT method was initially introduced by *Fisher and Tippett* in 1928 and was applied in hydrological research. There are two primary approaches within the EVT framework: the Annual Maxima Series (AMS) method, also known as the Block-Maxima (BM) method, and the Peak Over Threshold (POT) method. In this research, POT will be implemented.

The POT method employs a specific threshold value u to classify data as extreme observations. If X represents a random variable with observations $x_1, x_2, \dots, x_t$, then the cumulative distribution function (CDF) $[F_u(y)]$ for observations exceeding u (the excess), where $y = x - u$, is referred to as the conditional excess distribution function is *(Gilli–Këllezi, 2006)*

$$F_u(y) = P(X - u \le y | X > u), 0 \le y \le x_F - u \tag{15}$$

or

$$F_u(y) = \frac{F(u+y) - F(u)}{1 - F(u)} = \frac{F(x) - F(u)}{1 - F(u)}. \tag{16}$$

Theorem 1. *(Balkema and Haan, 1974; Pickands III, 1975)*

For a sufficiently large sample size with a cumulative distribution function (CDF) F, the CDF of the conditional excess $F_u(y)$ for a large threshold u can be accurately approximated by:

$$F_u(y) \approx G_{\xi,\sigma}(y), \qquad u \to \infty,$$

with

$$G_{\xi,\sigma}(y) = \begin{cases} 1-\left(1+\frac{\xi}{\sigma}y\right)^{-\frac{1}{\xi}}, \ jika\ \xi \neq 0 \\ 1-e^{-\frac{y}{\sigma}}, \qquad\qquad jika\ \xi = 0 \end{cases} \tag{17}$$

for $y \in [0, (x_F - u)]$ if $\xi \geq 0$ and $y \in [0, -\frac{\sigma}{\xi}]$ if $\xi < 0$. The distribution $G_{\xi,\sigma}$ is called the Generalized Pareto Distribution (GPD).

Equation (16) can be written as follow

$$F(x) = [1 - F(u)]F_u(y) + F(u) \tag{18}$$

Assuming the tails of the distribution conform to the Generalized Pareto Distribution (GPD), we can say that $F(u)$ follows a GPD and is estimated as $\frac{n-N_u}{n}$, where n is the total number of observations and N_u is the count of observations exceeding the threshold u. Consequently, the estimator for $F(x)$ can be derived as follows,

$$\hat{F}(x) = \frac{N_u}{n}\left[1-\left(1+\frac{\hat{\xi}}{\hat{\sigma}}(x-u)\right)^{-\frac{1}{\hat{\xi}}}\right] + \frac{n-N_u}{n} = 1 - \frac{N_u}{n}\left(1+\frac{\hat{\xi}}{\hat{\sigma}}(x-u)\right)^{-\frac{1}{\hat{\xi}}}. \tag{19}$$

Estimates of the parameters $\hat{\xi}$ and σ can be obtained by MLE.

2.5 Value at risk (VaR) and backtesting

Let L represent the loss of an asset, stock, or portfolio over a period T. The VaR is a risk metric that quantifies the risk associated with that asset, stock, or portfolio during the same period T. Assuming F_L is the distribution function of L, *(Bernard et al., 2017; Brodin–Klüppelberg, 2014; Jorion, 2007)* define it at the level $\alpha \in (0,1)$ as follows:

$$VaR_\alpha^T = \inf\{x \in \mathbb{R}: P(L > x) \leq 1-\alpha\} = \inf\{x \in \mathbb{R}: F_L \geq \alpha\}. \tag{20}$$

Typically, VaR is assessed at a confidence level of $(1-\alpha)100\%$, meaning it is defined as $P(Risk < -VaR_\alpha)$, with α usually set between 1% and 5% *(Acharya et al., 2017)*.

According to *Zhang and Nadarajah (2018)*, the accuracy of VaR estimations and the effectiveness of the models used to calculate VaR can be assessed using backtesting methods. The results from VaR backtesting indicate whether the estimated VaR is smaller (underestimated) or larger (overestimated) compared to the actual VaR. Among the simplest and most commonly used backtesting methods for VaR research are the Kupiec-POF (Proportion of Failures) test and the Kupiec-TUFF (Time Until First Failure) test *(Kupiec, 1995)*. If N represents the total number of observations and x denotes the number of VaR prediction errors, the Kupiec-POF test can be expressed using the likelihood ratio (LR) statistic as shown in equation (21) *(Dowd, 2005)*.

$$LR_{POF} = -2\ln[(1-\alpha)^{N-x}\alpha^{x}] + 2\ln\left[\left(1-\frac{x}{N}\right)^{N-x}\left(\frac{x}{N}\right)^{x}\right]$$
$$= 2\ln\left[\frac{\left(1-\frac{x}{N}\right)^{N-x}\left(\frac{x}{N}\right)^{x}}{(1-\alpha)^{N-x}\alpha^{x}}\right]\sim\chi^2_{\alpha,1} \tag{21}$$

The Kupiec-TUFF test defines V as the average number of observations until the first VaR prediction error happens. The test statistic for the Kupiec-TUFF method is defined as follows:

$$R_{TUFF} = -2\ln[\alpha(1-\alpha)^{V-1}] + 2\ln\left[\left(\frac{1}{V}\right)\left(1-\left(\frac{1}{V}\right)\right)^{v-1}\right]$$
$$= 2\ln\left[\frac{\left(\frac{1}{V}\right)\left(1-\left(\frac{1}{V}\right)\right)^{v-1}}{\alpha(1-\alpha)^{V-1}}\right]\sim\chi^2_{\alpha,1} \tag{22}$$

The model is considered to provide accurate VaR estimates if $LR_{TUFF} < \chi^2_{\alpha,1}$, where α represents the significance level of the hypothesis test being applied.

3. Results

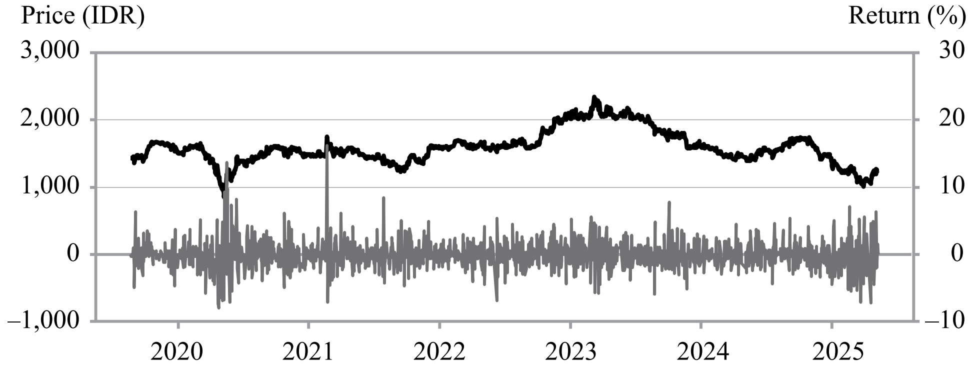
3.1 Descriptive statistics and data characteristics

This study employs the logarithm of daily stock return data from the three largest pharmaceutical companies in Indonesia: Mitra Keluarga Karyasehat Tbk (IDX: MIKA), Kalbe Farma Tbk (IDX: KLBF), and Medikaloka Hermina Tbk (IDX: HEAL), collected from Yahoo Finance for the period between July 1, 2019, and April 30, 2025 (1,412 obs.). The analyses were performed using R software with the MS-GARCH package by *Ardia et al. (2019)*. Figure 2 illustrates that the closing prices of these stocks show considerable fluctuations and a positive trend, suggesting that, the closing price data is non-stationary on mean. According to *Chocholatá (2022),* this mean non-stationarity in stock data can influence the stationarity of the mean of return data. In addition, based on the Augmented Dikkey-Fuller (ADF) test conducted on the three-return data used, it shows that all three are proven to be stationary (see Table 2).

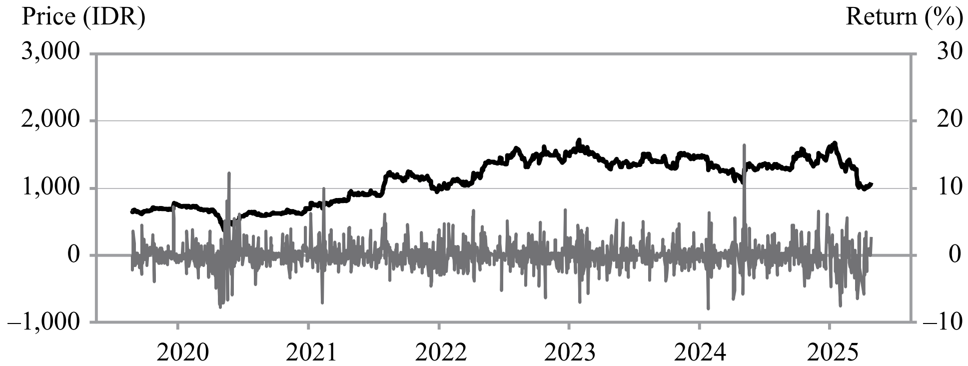
Figure 2

Closing price and return data per July 1, 2019–July 30, 2024

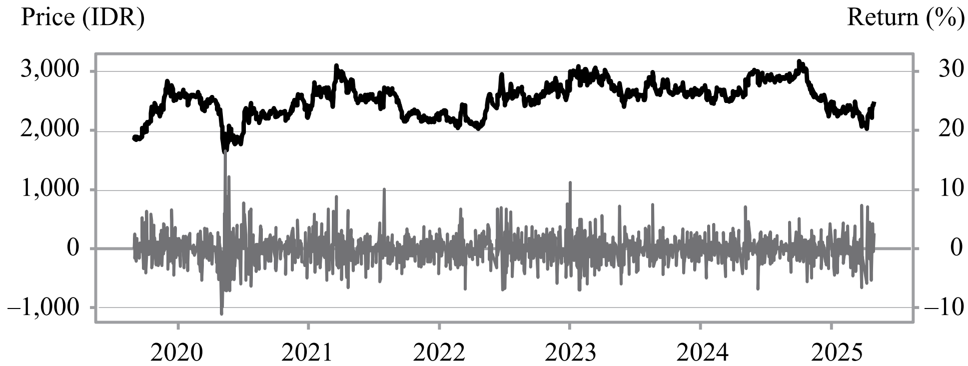
Kalbe Farma (KLBF.JK)



Medikaloka Hermina (HEAL.JK)



Mitra Keluarga Karyasehat (MIKA.JK)



As shown in Figure 2, the return data for a specific period experienced significant increases and decreases. This suggests that over the last five years, a phenomenon impacted the Indonesian economy, leading to extreme fluctuations in the return data for the pharmaceutical sector. One major event that caused dramatic shifts in stock prices and returns was the global Covid-19 pandemic, which affected Indonesia from late 2019 to mid-2022. Although stock prices initially plummeted at the onset of the pandemic, the demand for medications surged sharply until mid-2021, drawing investor interest toward pharmaceutical stocks. The ongoing instability of the Covid-19 situation continues to affect the volatility of pharmaceutical stocks, causing companies in the hospital, pharmaceutical, and laboratory sectors to experience uncertainty in their investment decisions due to the fluctuating returns.

Figure 2 also illustrates that stock prices in the first half of 2023 declined as the Covid-19 outbreak diminished and Indonesia worked to revive its economy. The country's recovery efforts included a quantitative easing policy, which contributed to a commodity boom driven by high inflation in raw materials and commodities. Consequently, stock returns experienced a gradual decrease during this period. Additionally, this situation compelled Indonesia, along with the rest of the world, to implement high-interest rate policies to curb inflation. According to the IDX factsheet for the year-to-date (YTD) period from January to May 2023, the healthcare sector saw a 6.9% decline attributed to the recovery from the Covid-19 pandemic.

Table 2

Statistics descriptive, stationarity and normality test of return data

Constituent	Mean	St. Dev.	Skewness	Kurtosis	ADF test	Normality test	
						AD	Lilliefors
HEAL.JK	0.00035	0.02015	0.607	9.23	–10.316 (<0.01)	27.936 (<0.01)	0.105 (<0.01)
KLBF.JK	–0.00010	0.02148	0.657	8.00	–10.492 (<0.01)	13.986 (<0.01)	0.088 (<0.01)
MIKA.JK	0.00021	0.02468	0.408	6.68	–12.47 (<0.01)	11.482 (<0.01)	0.061 (<0.01)

Note: the value in bracket is the p-value of the test results.

Table 2 provides insight into the distribution of the three return data sets, showing that they do not center around the mean. This is evident from the skewness values, which exceed 0.5, indicating that the distributions are skewed to the right. Such a rightward skew suggests that there are more extreme positive returns than negative ones in the data sets. Moreover, the kurtosis values for all three return data sets are significantly greater than 3, which indicates that they are leptokurtic. This means that the distributions have heavier tails and a sharper peak compared to a normal distribution, suggesting a higher likelihood of extreme values. These findings from the descriptive statistics support the conclusions drawn from the normality tests performed using the Anderson–Darling and Lilliefors methods. Both tests indicate that at a 5% significance level, the return data does not follow a normal distribution. In summary, the combination of high skewness and kurtosis values highlights the non-normal characteristics of the return data sets, suggesting a more complex underlying behavior in the data.

3.2 Mean model and residual diagnostics

The model employed to calculate the model error is the ARIMA Ljung-Box model, specifically the ARMA(p, q) variant. This choice is justified because the return data has been demonstrated to be stationary around its mean, which implies that the integrated component is of order 0 (see ADF Test in Table 2). To determine the appropriate order of the ARMA(p, q) model, we utilize the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. These plots help in identifying the order of the model, leading to the formulation of the average model for the three constituents under study. The results of this analysis are summarized in Table 3.

Table 3

The ARMA(p, q) identification

Constituent/ticker	p	q
Medikaloka Hermina (HEAL.JK)	0	0
Kalbe Farma (KLBF.J K)	0	2
Mitra Keluarga Karyasehat (MIKA.JK)	0	1

Note that the constituent model of HEAL.JK is ARMA(0,0) which means that the model only takes into account the average of the return data without regard to past values (AR order) and no disturbance is calculated from past errors (MA order) or the model can be written as,

$$r_t = \mu + \varepsilon_t$$

where ε_t represents the model error, which is assumed to follow a normal distribution with a mean of zero and constant variance. However, upon further examination using the Lagrange Multiplier (LM) test (see Table 4), the results indicate that the model errors exhibit ARCH effects. This means that the variance of the errors is not constant and is influenced by previous values of the errors. In other words, even though the

ARMA(0,0) model is employed, the data reveals that the variance of the errors is unstable and tends to fluctuate over time, indicating volatility.

Table 4

LM test of ARCH/GARCH effect

Constituent/ticker	ARCH effect test (ARCH-LM)				
	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
Medikaloka Hermina (HEAL.JK)	20.98 (<0.01)	42.58 (<0.01)	73.58 (<0.01)	82.96 (<0.01)	88.31 (<0.01)
Kalbe Farma (KLBF.JK)	20.59 (<0.01)	136.47 (<0.01)	173.27 (<0.01)	199.94 (<0.01)	220.06 (<0.01)
Mitra Keluarga Karyasehat (MIKA.JK)	26.03 (<0.01)	49.33 (<0.01)	109.66 (<0.01)	140.06 (<0.01)	171.13 (<0.01)

The same phenomenon is observed in the other two constituents, KLBF.JK and MIKA.JK, where the underlying models used to analyze the errors are ARMA(0,2) and ARMA(0,1), respectively. As shown in Table 4, all three return data sets display ARCH/GARCH effects. Consequently, a GARCH model or one of its family is considered essential for capturing the dynamics of the changing error variance effectively.

3.3 The GARCH and its family modeling

Based on table 5, it can be seen that the ARCH component (α) represented by the constituents of HEAL.JK (Medikaloka Hermina) lies between 19% to 21%, KLBF.JK (Kalbe Farma) by 7% to 13%, and MIKA.JK (Mitra Keluarga Karyasehat) between 8.5% to 10%. This suggests that the three constituents are quite sensitive to market disturbances. Based on table 5, ARCH-GARCH component ($\alpha + \beta$) can also be seen that the values for the three constituents are very high and significant in all models, especially for the MIKA.JK (Mitra Keluarga Karyasehat) constituent which around 94%. As for the very small values of ω and towards 0 for each model used in each constituent indicates that actually all models are very good at modeling the diversity of return data. Another thing that can be seen from table 5 is the size of the persistence parameter, which is close to the value of 1, indicating that the variance is not stationary. In addition, the leverage parameter estimates for the constituents HEAL.JK (Medikaloka Hermina) and MIKA.JK (Mitra Keluarga Karyasehat) is significant only shown by the EGARCH(1,1) model, while it is stated to have a significant effect on the constituent KLBF.JK (Kalbe Farma) for all models, namely TGARCH(1,1), EGARCH(1,1), and GJRGARCH(1,1). The estimated value of leverage effect (γ) ranges from 0.16 to 0.39 for all constituents indicating that positive shocks are more influential than negative shocks. Based on the AIC value, although the difference between models is very small, it can be concluded that the best model in modeling return data for HEAL.JK (Medikaloka Hermina) constituents is GJRGARCH(1,1), KLBF.JK (Kalbe Farma) is TGARCH(1,1), and while MIKA.JK (Mitra Keluarga Karyasehat) is well modeled by GARCH(1,1).

Table 5

Parameter estimators of the GARCH model and its family

Ticker/ constituent	Parameter	GARCH(1,1)	TGARCH(1,1)	EGARCH(1,1)	GJRGARCH (1,1)
HEAL.JK (Medikaloka Hermina)	μ	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
	ω	**0.000** (0.000)	**0.003** (0.001)	**–1.274** (0.227)	**0.000** (0.000)
	α	**0.203** (0.031)	**0.186** (0.025)	–0.052 (0.024)	**0.196** (0.033)
	β	**0.646** (0.046)	**0.714** (0.041)	**0.835** (0.029)	**0.652** (0.051)
	$\alpha+\beta$	**0.849**	**0.900**	–	**0.848**
	γ		0.163 (0.077)	**0.358** (0.043)	**0.161** (0.057)
	Num.Obs.	1412	1412	1412	1412
	RMSE	0.02	0.02	0.02	0.02
	MAE	0.014	0.013	0.013	0.013
	AIC	–5.127	–5.125	–5.123	–5.131
KLBF.JK (Kalbe Farma)	μ	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
	θ_1	**0.179** (0.030)	**–0.183** (0.030)	**–0.179** (0.029)	**–0.180** (0.029)
	θ_2	**–0.098** (0.031)	**–0.120** (0.028)	**–0.109** (0.029)	**–0.096** (0.028)
	ω	**0.000** (0.000)	**0.001** (0.000)	**–0.392** (0.079)	**0.000** (0.000)
	α	**0.130** (0.036)	**0.114** (0.025)	**–0.073** (0.018)	**0.072** (0.018)
	β	**0.766** (0.069)	**0.852** (0.036)	**0.949** (0.010)	**0.877** (0.025)
	$\alpha+\beta$	**0.896**	**0.966**	**0.876**	**0.949**
	γ		**0.336** (0.117)	**0.200** (0.034)	**0.393** (0.111)
	Num.Obs.	1412	1412	1412	1412
	RMSE	0.021	0.021	0.021	0.021
	MAE	0.015	0.015	0.015	0.015
	AIC	–5.027	–5.040	–5.037	–5.038
MIKA.JK (Mitra Keluarga Karyasehat)	μ	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
	θ_1	**–0.160** (0.030)	**–0.167** (0.029)	**–0.162** (0.028)	**–0.161** (0.030)
	ω	**0.000** (0.000)	**0.002** (0.000)	**–0.474** (0.169)	**0.000** (0.000)
	α	**0.088** 0.017)	**0.101** (0.017)	–0.015 (0.018)	**0.085** (0.017)
	β	**0.852** (0.031)	**0.850** (0.030)	**0.936** (0.023)	**0.857** (0.030)
	$\alpha+\beta$	**0.940**	**0.951**	–	**0.942**
	γ		0.074 (0.102)	**0.189** (0.030)	0.084 (0.074)
	Num.Obs.	1412	1412	1412	1412
	RMSE	0.024	0.024	0.024	0.024
	MAE	0.017	0.017	0.017	0.017
	AIC	–4.699	–4.690	–4.689	–4.698

Notes: The value in parentheses indicates the standard error value. Bold text indicates significance at the 5% level.

3.4 The EVT modeling based on POT

Table 6 is the threshold value based on the quantile that extracts the model error included in the extreme value with the POT approach for each constituent. It can be seen from Figures 3 to 5 that the red dots are model errors categorized as extreme points. In general, the frequency of extreme points for the three constituents is relatively the same and is found in periods that are also relatively the same. This indicates that the three constituents have relatively similar data patterns. The variance of all three is influenced by the same type of shocks.

Table 6

Threshold point

Ticker/constituent	Model	Quantile		
		5%	2.5%	1%
HEAL.JK (Medikaloka Hermina)	GJRGARCH(1,1)	–0.028	–0.039	–0.063
KLBF.JK (Kalbe Farma)	TGARCH(1,1)	–0.031	–0.042	–0.057
MIKA.JK (Mitra Keluarga Karyasehat)	GARCH(1,1)	–0.037	–0.049	–0.062

Figure 3

Residual plot for quantile 5%

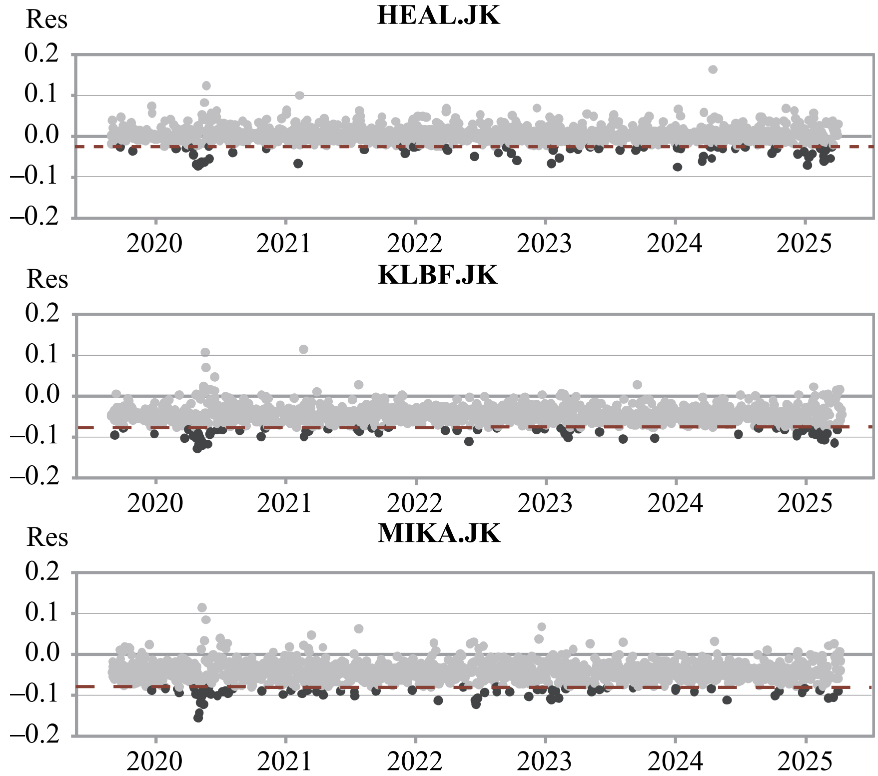


Figure 4

Residual plot for quantile 2.5%

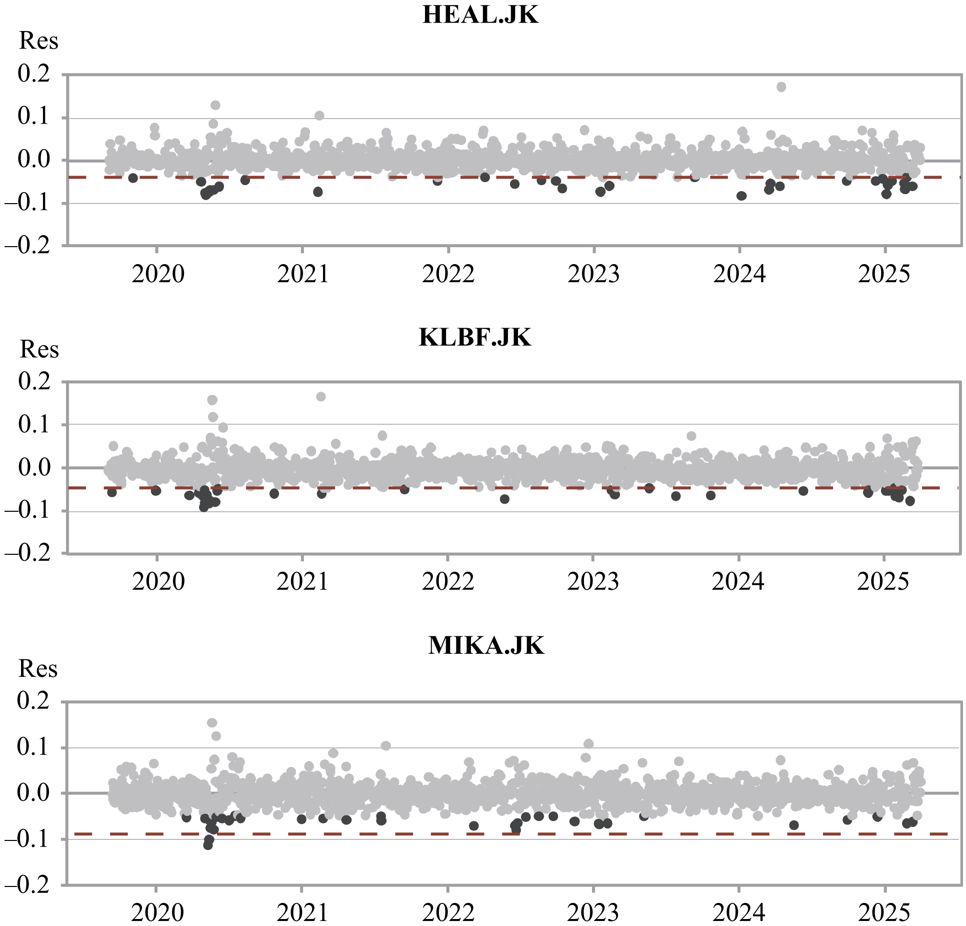


Figure 5

Residual plot for quantile 1%

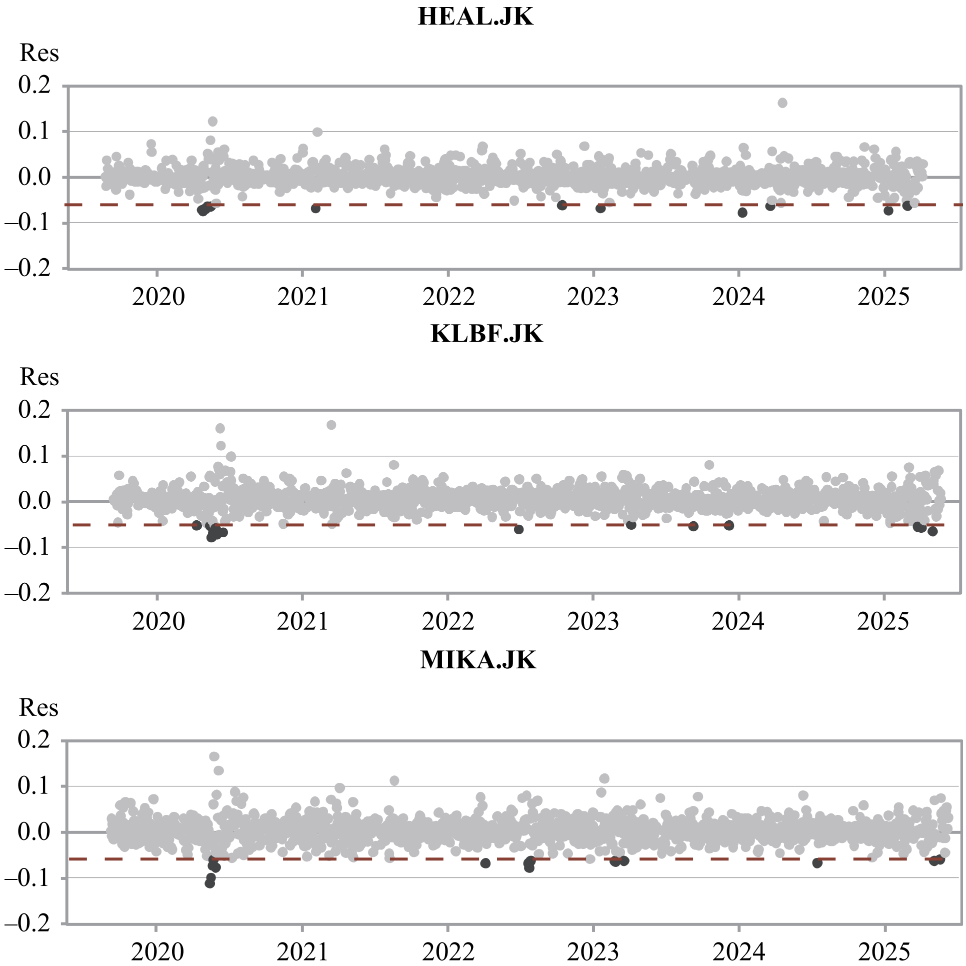


Table 7

Parameter estimation of VaR GPD

Ticker/constituent	Model	σ	ξ	Mean VaR		
				1%	2.5%	5%
HEAL.JK (Medikaloka Hermina)	GJRGARCH(1,1)	1.190	–0.354	2.863	2.137	1.467
KLBF.JK (Kalbe Farma)	TGARCH(1,1)	0.819	–0.210	2.605	2.016	1.488
MIKA.JK (Mitra Keluarga Karyasehat)	GARCH(1,1)	0.758	–0.124	2.627	2.026	1.523

Furthermore, the extreme points obtained based on POT are modeled with the GPD approach. Table 7 shows the estimation of GPD parameters with shape parameter and scale parameter. Based on the estimation results, it is known that the statistic of shape parameter $(\hat{\xi})$ for the constituents KLBF.JK (Kalbe Farma) and MIKA.JK (Mitra Keluarga Karyasehat) are negative, indicating that the error patterns of the two constituents are light-tailed and tend to be normal. The constituent HEAL.JK (Medikaloka Hermina) has a value that tends to follow an exponential distribution. In addition, based on Table 7, it can be seen that the average VaR for 1%, HEAL.JK has the highest risk of loss compared to the other two constituents. At 2.5% and 5%, MIKA.JK shows the highest risk compared to the other two constituents.

3.5 Backtesting and Kupieck test

Figures 6, 7, and 8 show the visualization of the backtesting of each model for each constituent at 1%, 2.5%, and 5% VaR, respectively. In general, it can be seen that the model can describe well the prediction of VaR values at all three quantiles. This is supported by the Kupiec test as in Table 8 which shows a p-value greater than the 5% significance level, which means that the model used to predict VaR is very suitable. The suitability of the model used, namely the GJRGARCH(1,1) model for HEAL.JK (Medikaloka Hermina), TGARCH(1,1) for KLBF.JK (Kalbe Farma), and GARCH(1,1) model for MIKA.JK (Mitra Keluarga Karyasehat) applies to all VaR levels used.

Figure 6

Plot VaR 5%

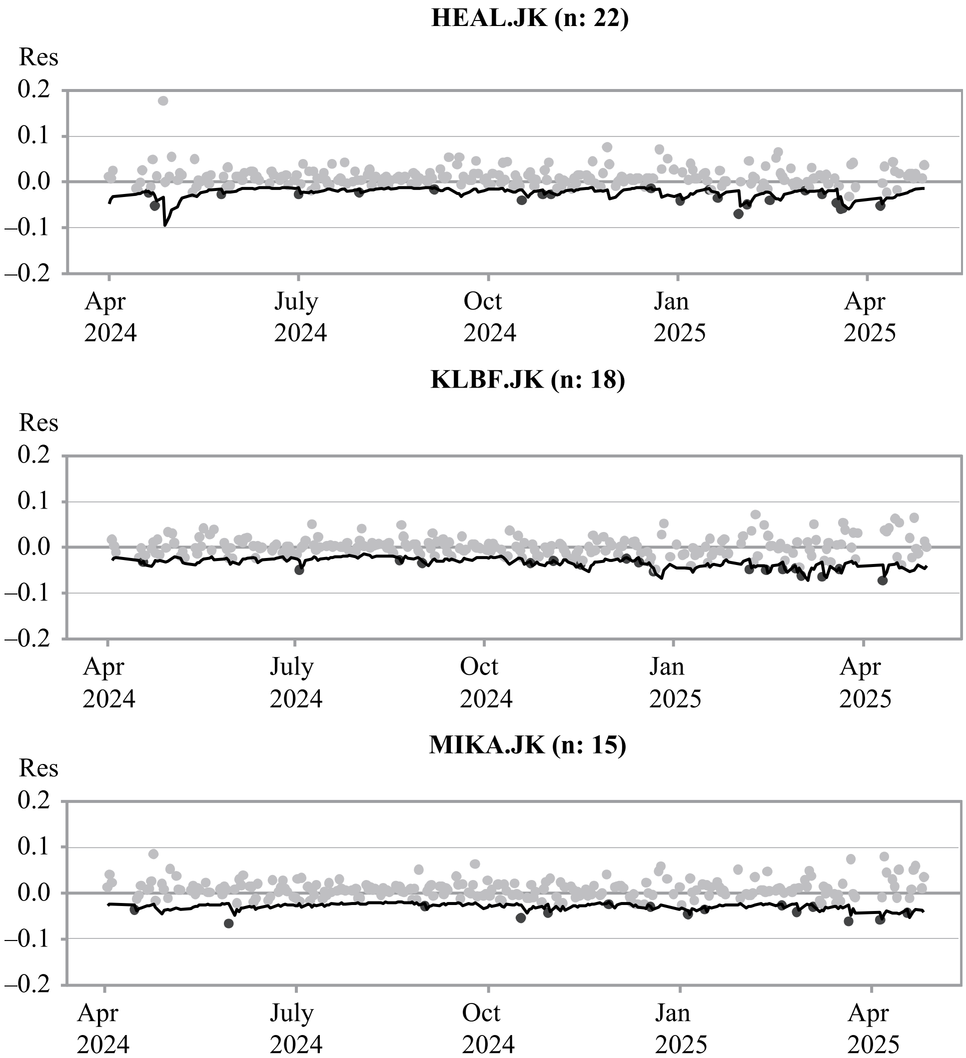


Figure 7

Plot VaR 2.5%

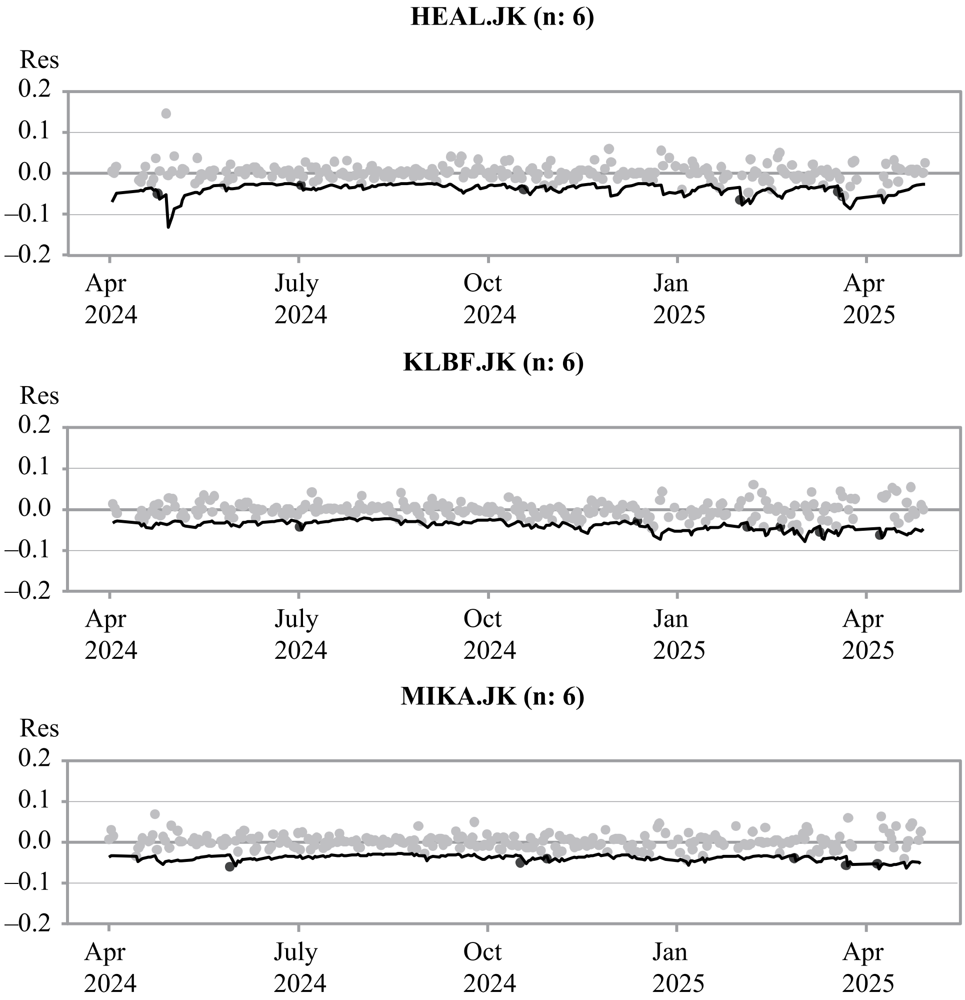


Figure 8

Plot VaR 1%

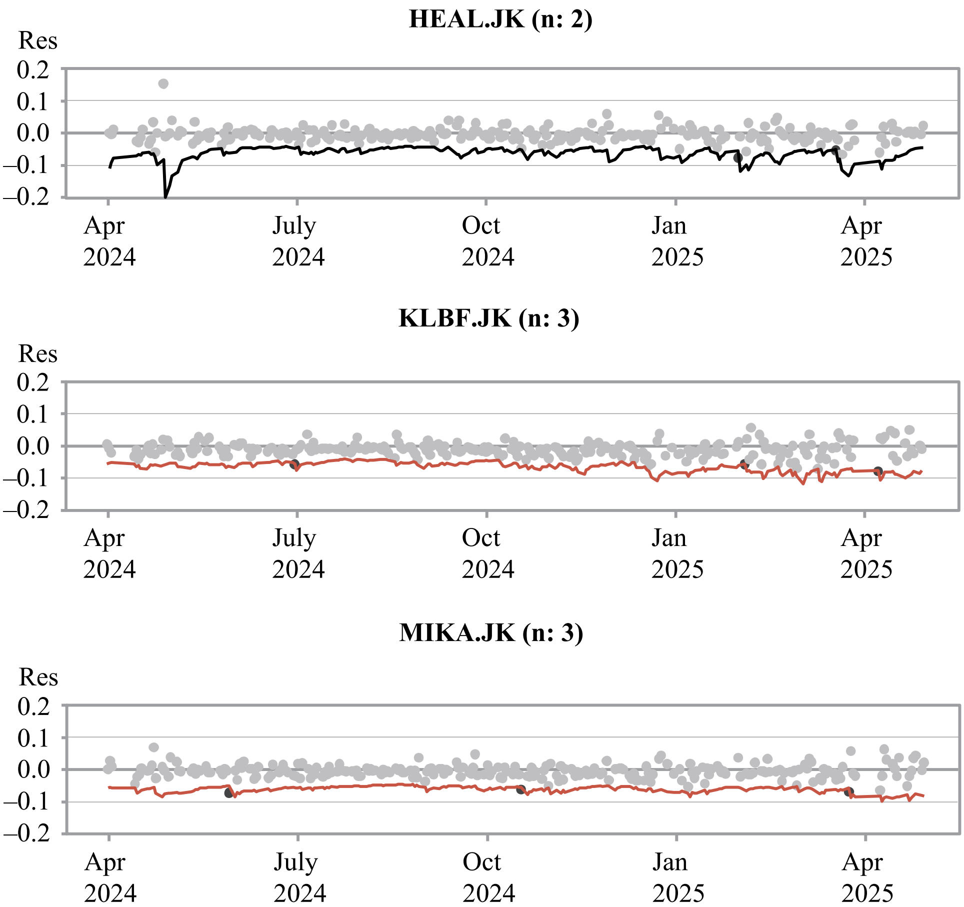


Table 8

Backtesting of VaR estimation

Ticker/constituent	Model	No. of violations	First violations	POF	TUFF
VaR 5%					
HEAL.JK (Medikaloka Hermina)	GJRGARCH(1,1)	22	8	6.259 (0.988)	0.681 (0.591)
KLBF.JK (Kalbe Farma)	TGARCH(1,1)	18	6	2.256 (0.867)	1.098 (0.705)
MIKA.JK (Mitra Keluarga Karyasehat)	GARCH(1,1)	15	4	0.496 (0.519)	1.801 (0.820)
VaR 2.5%					
HEAL.JK (Medikaloka Hermina)	GJRGARCH(1,1)	6	11	0.01 (0.081)	1.182 (0.723)
KLBF.JK (Kalbe Farma)	TGARCH(1,1)	6	52	0.01 (0.081)	0.077 (0.219)
MIKA.JK (Mitra Keluarga Karyasehat)	GARCH(1,1)	6	32	0.01 (0.081)	0.048 (0.173)
VaR 1%					
HEAL.JK (Medikaloka Hermina)	GJRGARCH(1,1)	2	195	0.108 (0.258)	0.569 (0.549)
KLBF.JK (Kalbe Farma)	TGARCH(1,1)	3	52	0.095 (0.242)	0.352 (0.447)
MIKA.JK (Mitra Keluarga Karyasehat)	GARCH(1,1)	3	32	0.095 (0.242)	0.934 (0.666)

Note: the value in parentheses indicates p-value.

4. Discussion

The closing price data of the three stocks – HEAL.JK (Medikaloka Hermina), KLBF.JK (Kalbe Farma), and MIKA.JK (Mitra Keluarga Karyasehat) – is graphically non-stationary in terms of mean, which affects the return data. This observation is supported by the results of the ADF test, which confirm that the return data is stationary at a 5% significance level. Additionally, the return data for all three stocks exhibit positive skewness and leptokurtosis. However, these characteristics are not consistent with the residuals derived from modeling the return data. For instance, the estimated shape parameters $(\hat{\xi})$ of the residuals based on GPD show values less than 0, $(\hat{\xi} < 0)$, for KLBF.JK and MIKA.JK, indicating a thin-tailed distribution, similar to a Normal distribution. Meanwhile, HEAL.JK has $\hat{\xi} \approx 0$, suggesting an exponential distribution for its residuals.

Despite the absence of heavy tails in the residuals, the use of the EVT model for estimating VaR proves highly effective, as validated by the Kupiec test for the 1%, 2.5%, and 5% quantiles. This demonstrates that integrating the EVT model with the GARCH family enhances the accuracy of VaR predictions. Although EVT is primarily designed to model extreme values, its application successfully accommodates the patterns of extreme observations, improving VaR estimation even when the tail structure of the distribution does not become significantly heavier.

Our findings, that asymmetric GARCH specifications combined with POT-GPD tails yield accurate VaR backtests, align with cross-market results. In equity and commodity applications, GARCH-EVT consistently improves tail quantile forecasts relative to Normal or Student-t GARCH alone, particularly at 1-5% VaR levels. Similar improvements have been reported for agricultural commodities and broad emerging-market equities, indicating that EVT enhaced filters capture extremal clustering that standard conditional variance models tend to miss *(Echaust–Just, 2020; Gençay–Selçuk, 2004)*. Sectorally, healthcare indices outside Indonesia display volatility that co-moves with government health measures and spending, echoing our context where pandemic and policy-related shocks are prominent drivers. This supports the interpretation that asymmetric terms (EGARCH/GJRGARCH/TGARCH) are economically meaningful in pharma and healthcare settings, not only statistically convenient *(Li et al., 2024)*.

At the same time, international studies remind us that the "best" asymmetric form can be market- and regime-dependent. For instance, post-crisis and pandemic periods often strengthen leverage-type asymmetries and alter volatility spillovers, which can favor EGARCH/GJR in some markets, while plain GARCH or TGARCH dominates elsewhere. Our model selection by ticker (GARCH for MIKA, TGARCH for KLBF, GJRGARCH for HEAL) is therefore consistent with the literature's asset-specific heterogeneity and with evidence from other emerging markets (e.g., Brazil's IBOVESPA) where different GARCH families rotate in and out of favor across horizons and regimes *(Maharana et al., 2024; Tabash et al., 2024)*.

Finally, studies on tail-risk dependence within pharmaceutical markets indicate that VaR co-movements can intensify under stress, reinforcing the need for extreme-value adjustments when drawing inferences about portfolio-level risk. While our article focuses on univariate VaR accuracy, these insights suggest a natural path to extend the framework toward multivariate EVT or copula-GARCH for joint tail assessment across pharma constituents (Zhou).

5. Conclusion

This article employs a two-stage VaR prediction approach, combining GARCH modeling and its family to capture volatility in data variance, followed by residual modeling using GPD-based EVT. The methodology is applied to the top three pharmaceutical sector stocks in Indonesia: Mitra Keluarga Karyasehat Tbk (IDX: MIKA), Kalbe Farma Tbk (IDX: KLBF), and Medikaloka Hermina Tbk (IDX: HEAL). Based on the lowest AIC values from the volatility modeling, the optimal models identified are GARCH(1,1) for MIKA.JK, TGARCH(1,1) for KLBF.JK, and GJRGARCH(1,1) for HEAL.JK.

The residuals from these volatility models are further analyzed using GPD-based EVT to account for potential heavy-tailed characteristics. However, the GPD analysis reveals that the residuals are not significantly heavy-tailed, showing a tendency toward Normal or exponential distributions. Despite this, the Kupiec test confirms that all three models perform excellently in predicting VaR at the 1%, 2.5%, and 5% quantiles.

Placing our results alongside international evidence, the two-stage asymmetric GARCH-EVT pipeline we employ is broadly validated in the literature as a robust approach for downside-risk estimation in turbulent regimes. In practical terms, this suggests that investors and risk managers operating in other emerging healthcare/pharmaceutical markets can adapt our specification and backtesting protocol with reasonable expectations of performance, while still re-checking model form against local policy cycles and crisis phases. Future work can generalize our contribution by incorporating multivariate tail dependence (e.g., copula-GARCH with EVT margins) and by benchmarking to sectoral studies abroad to further gauge portability.

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