

Optimal Portfolio Formation Using Markowitz Model and Value at Risk Measurement with Extreme Value Theory Approach on JII Stocks

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ABSTRACT

Sharia-compliant stocks, particularly those listed in the Jakarta Islamic Index (JII), represent a significant component of Indonesia's Islamic capital market. To minimize investment risk, investors often construct diversified portfolios. This study aims to form an optimal portfolio using the Markowitz mean-variance model and assess its risk using Value at Risk (VaR), integrated with Extreme Value Theory (EVT) to capture extreme losses often missed by traditional methods. Among the selected stocks, MDKA showed the highest average return (0.112%), while UNVR had the lowest (-0.096%). ICBP exhibited the lowest volatility (1.732%), and BRPT the highest (3.350%). The optimal portfolio allocation consists of MDKA (63%), CPIN (7%), BRPT (17%), and ADRO (13%), indicating effective risk diversification. The portfolio's standard deviation (2.010%) is significantly lower than that of the most volatile individual asset, highlighting the benefit of diversification. EVT analysis identified the Generalized Extreme Value (GEV) distribution as the best fit for modeling tail risks. The estimated portfolio VaR at 90%, 95%, and 99% confidence levels were -3.64%, -3.91%, and -4.28%, respectively. These results underscore the importance of integrating modern portfolio optimization techniques with robust risk assessment tools like EVT for enhancing decision-making in sharia-compliant investment.

Keywords: Extreme Value Theory, JII, Markowitz, Value at Risk

1. INTRODUCTION

The capital market is one of the sectors that is highly considered in various countries as part of the government's efforts to encourage economic growth through the development of the investment sector. The capital market functions as a channel between investors and businesses or government institutions to invest in long-term financial instruments such as bonds, stocks, warrants, rights, mutual funds, and derivatives such as options, futures, and others (Martalena & Malinda, 2011). In Indonesia itself, there are two capital markets, namely the general or conventional capital market and the sharia capital market. The sharia capital market is a capital market that operates in accordance with the principles of Islamic law. Every activity of trading securities in this capital market is carried out in accordance with the provisions stipulated by Islamic law (Manan, 2015). In recent years, the sharia capital market in Indonesia has shown significant growth, both in terms of the number of investors and the value of market capitalization, making the sharia capital market one of the increasingly popular investment alternatives. Jakarta Islamic Index (JII), as a leading sharia stock index. However, like investments in general, investments in the Islamic capital market are also not free from risks, especially market risks due to stock price fluctuations. To mitigate investment risk, diversification through portfolio management is crucial. One of the most widely used methods for portfolio optimization is the Markowitz model, also known as the Mean-Variance model, which allows investors to achieve the maximum expected return for a given level of risk (Shkolnik et al., 2025). It is important for investors to measure risk before making an

investment. This is important to note because the results of risk measurements can be used as a reference value by investors when making portfolio investments. The way to measure the risk of an investment is with Value at Risk (VaR) which is the most popular market risk measurement (Maronrong et al., 2022), the VaR approach to measuring the risk of loss in investment has become an important strategy in dealing with market volatility and increasingly complex trading dynamics. This method analyzes risk in a certain time interval, which reflects the maximum potential loss in that period. Most financial stock data has a fat distribution tail (heavy-tail) or decreases slowly compared to the normal distribution (Ratliff-Crain et al., 2024). The impact is that the chance of extreme values occurring will be greater than modeling with a normal distribution. This increases the possibility of uncontrolled values that can harm investors. Extreme values that often appear in stock data can be overcome with the Extreme Value Theory (EVT) Approach. There are two approaches, namely Block Maxima (BM) and Peaks Over Threshold (POT) which are two techniques used to find extreme value movements (Singh et al., 2013). This study was conducted to determine the estimate of the size of the portfolio risk with the Markowitz model on JII (Jakarta Islamic Index) index stocks with the Extreme Value Theory approach because in JII index stocks the changes fluctuate due to economic, political, and global conditions.

2. LITERATURE REVIEW

2.1 Stock Return

Stock returns represent the gain or loss made by investors from investing in stocks over a certain period. These returns are a crucial indicator for both individual and institutional investors, as they reflect the performance and profitability of their investment decisions. According to (Bringham & Houston, 2007), stock returns can be defined as the results of an investment, which may take the form of capital gains (or losses) and dividend income. In addition to capital gains, total stock return may also include dividends received by investors during the holding period. As such, return is often categorized into two types: capital gain/loss and dividend yield. The sum of both is referred to as total return (Jones, 2010). The formula generally used to calculate stock returns is as follows.

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

2.2 Markowitz

The Markowitz model shows that the variance of portfolio returns on shares does not only depend on the level of risk of individual assets in the portfolio but more on the relationship of that risk to the shares, so that an optimal portfolio can be obtained according to the expectations of each investor (Mafula, 2015). The formation of optimization equations and constraints on the Markowitz model portfolio is explained in the following equation.

$$f(x) = \min \sum_{i=1}^n \sum_{j=1}^n w_i \cdot w_j \cdot S_{ij}$$

Constraint:

$$E(R_p) = \sum_{i=1}^n E(R_i)w_i; \sum_{i=1}^n w_i = 1; w_i \geq 0; i \neq j$$

2.3 Extreme Value Theory

EVT focuses on the behavior of the tail of the distribution to determine the possibility of extreme values in the data (heavy tail) that cannot be done with conventional approaches. Heavy tail is a term used to describe the part of a probability distribution that has a value that exceeds normal or is far from the average (Richards et al., 2024). There are two methods that can be used to find extreme value movements, namely the Block Maxima (BM) method and the Peaks Over Threshold (POT) method (Winston, 2023).

2.3.1 Block Maxima

Block Maxima is a method for finding extreme values based on the maximum value of observation data grouped according to certain period blocks. The maximum value in each period block formed is then included in the sample because this value is an extreme value in a certain period. This method will follow the Generalized Extreme Value (GEV) distribution, which has the following Cumulative Distribution Function (CDF) (Richards et al., 2024).

$$F(x; \mu; \sigma; \xi) = \begin{cases} -\left[1 + \xi \left(\frac{x-\mu}{\sigma}\right)\right]^{-\frac{1}{\xi}}, & \frac{-\infty \leq x < \mu - \frac{\sigma}{\xi}, \xi < 0}{\frac{\sigma}{\mu - \frac{\sigma}{\xi}} \leq x < \infty, \xi > 0} \\ 1 - \left[1 + \xi \left(\frac{x-\mu}{\sigma}\right)\right] > 0, & -\infty \leq x < \infty, \xi = 0 \end{cases}$$

2.3.2 Peaks Over Threshold

The Peaks Over Threshold (POT) method in Extreme Value Theory (EVT) is used to check the extreme value of data by setting a certain threshold and ignoring the time the event occurs. All observation data located above the threshold value (u) are identified as extreme values. The Cumulative Density function (CDF) equation of the Generalized Pareto Distribution is as follows (Diebold et al., 2021).

$$G(x; \xi; \sigma) = \begin{cases} 1 - \left(1 + \xi \frac{x-\mu}{\sigma}\right)^{-\frac{1}{\xi}}, & \text{jika } \xi \neq 0 \\ 1 - e\left(-\frac{x-\mu}{\sigma}\right), & \text{jika } \xi = 0 \end{cases}$$

2.4 Value at Risk

Value-at-Risk (VaR) is a statistical measure used to measure the potential loss of an asset or portfolio over a certain period with a certain level of confidence and one of the most widely used types of risk measurement because the VaR concept is simple (D'innocenzo et al., 2025). The calculation of VaR on the generalized extreme value distribution is explained by the following equation (Khokhlov, 2016).

$$\widehat{VaR}_{q(GEV)} = \hat{\mu} + \frac{\partial}{\xi} (-\ln \ln (1 - q))^{-\hat{\xi}}$$

The calculation of VaR on the generalized Pareto distribution is explained by the following equation (Chinhamu et al., 2015).

$$\widehat{VaR}_{q(GPD)} = u + \frac{\partial}{\xi} \left(\left(\frac{n}{n_u} (1 - q) \right)^{-\hat{\xi}} - 1 \right)$$

3. METHODS

This This research uses secondary data in the form of daily stock closing prices for the period from January 1, 2018 to July 31, 2024, totaling 1,592 data points obtained from the finance.yahoo.com and investing.com websites. The research variables used in this study are daily stock returns calculated from the closing prices of 10 stocks with the largest current market capitalization among all outstanding shares of companies listed in the Jakarta Islamic

Index (JII). The stock returns are calculated on a daily basis to capture the short-term fluctuations in stock prices and to reflect the dynamics of daily market movements more accurately. Problem limitation is needed to focus on the problems being studied. The scope limitation applied in this study is that 20 sharia stocks listed in the JII index are not included in this study because they are not included in the top 10 sharia stocks with the largest total market capitalization based on the number of outstanding shares.

4. RESULT AND DISCUSSION

4.1 Data Characteristics

Table 1. Data Characteristics Stock Return

Issuer	Mean	Standard Deviation	Minimum	Maximum
UNTR	-0.020%	2.392%	-8.670%	17.860%
UNVR	-0.096%	2.074%	-10.700%	19.380%
TLKM	-0.027%	1.881%	-8.700%	13.740%
MDKA	0.112%	2.943%	-13.410%	23.660%
Issuer	Mean	Standard Deviation	Minimum	Maximum
KLBF	-0.004%	2.131%	-7.690%	17.730%
ICBP	0.013%	1.732%	-8,960%	14.460%
CPIN	0.035%	2.689%	-10.490%	16.630%
BRPT	0.055%	3.530%	-18.180%	24.760%
ASII	-0.035%	2.040%	-11.450%	12.710%
ADRO	0.044%	2.825%	-13.990%	16.480%

Table 1 shows that the highest average stock return value is MDKA stock at 0.112%, while the lowest average stock return is UNVR stock at -0.096%. The stock with the highest maximum return value is BRPT stock with a return of 24.760%, the stock with the highest and lowest maximum return values is BRPT stock with a return of 24.760% and -18.180%. The stock with the smallest deviation size is ICBP stock with a standard deviation value of 1.732%, so it can be interpreted that ICBP stock has the smallest risk level of price changes compared to the other 9 stocks, while the one with the largest deviation size is BRPT stock with a standard deviation value of 3.350%, so it can be interpreted that BRPT stock has the highest risk level of price changes compared to the other 9 stocks.

4.2 JII Stock Selection

Table 2. Stock Selection

Number	Issuer	Mean
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1	UNTR	-0.020%
2	UNVR	-0.096%
3	TLKM	-0.027%
4	MDKA	0.112%
5	KLBF	-0.004%
6	ICBP	0.013%
7	CPIN	0.035%
8	BRPT	0.055%
9	ASII	-0.035%
10	ADRO	0.044%

Table 2 shows that issuers that have positive expected stock return values are MDKA, ICBP, CPIN, BRPT, ADRO, so that these five stocks can be selected to compile a portfolio to obtain maximum profit when investors want to invest. The other five stock issuers, namely UNTR, UNVR, TLKM, KLBF, ASII have negative expected stock return values, so that if selected for portfolio formation, they will experience losses if these stocks are compiled. However, the five stocks that have positive expected returns tend to have small values because the data used is daily data.

4.3 Markowitz Model

Table 3. Markowitz Portfolio Weights

St.Dev(p)	ER(p)	MDKA	ICBP	CPIN	BRPT	ADRO
1.57%	0.02%	0%	83%	8%	0%	9%
1.47%	0.02%	3%	70%	13%	0%	14%
1.41%	0.03%	8%	64%	12%	2%	14%
1.36%	0.03%	12%	59%	12%	3%	14%
1.33%	0.04%	17%	53%	12%	4%	14%
1.32%	0.04%	21%	47%	12%	5%	14%
1.33%	0.05%	26%	41%	12%	7%	14%
1.36%	0.05%	30%	36%	12%	8%	14%
1.41%	0.06%	35%	30%	11%	9%	14%
1.48%	0.06%	39%	24%	11%	11%	15%
1.56%	0.07%	44%	19%	11%	12%	15%
1.66%	0.07%	49%	13%	11%	13%	15%
1.77%	0.08%	53%	7%	11%	14%	15%

1.88%	0.08%	58%	1%	11%	16%	15%
2.01%	0.09%	63%	0%	7%	17%	13%
2.16%	0.09%	69%	0%	3%	17%	10%
2.31%	0.10%	76%	0%	0%	18%	7%
2.49%	0.10%	82%	0%	0%	17%	0%

Table 3 explains the combination of portfolio weights of the five selected stocks. The lowest risk level produced is 1.574% with an expected return of 0.015% with stock weighting of ICBP 83%, CPIN 8%, ADRO 9%. While the highest risk level of the resulting portfolio is 2.492% with an expected return of 0.100% with stock weighting of MDKA 82% and CPIN 17%. After calculating the stock weighting, we can see the efficient frontier curve used to compile the optimal investment portfolio.

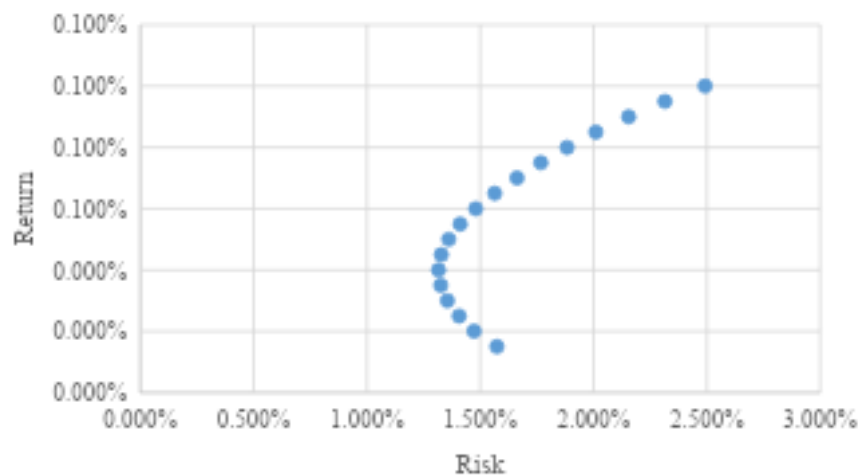


Figure 1. Efficient Frontier Portfolio

Figure 1 shows that the plot between the risk value and the return formed, thus forming an efficient frontier curve, the curve has the use to obtain the best return according to the risk level. The starting point of the inflection on the curve is the inflection point of the efficient portfolio, so that investors can choose according to their preferences for the level of return or risk in the efficient portfolio that has been formed, to choose the best portfolio can be done by measuring portfolio performance. Similar results were also found by Sriwahyuni et al. (2021), who used JII stocks and confirmed that combining positive-return stocks yielded portfolios along a convex efficient frontier with higher Sharpe ratios.

4.4 Portfolio Performance Evaluation

Table 4. Portfolio Evaluation

Portfolio Number	St.Dev(p)	ER(p)	Risk Free	Sharpe
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Portfolio 1	1.57%	0.02 %		0,001 1
Portfolio 2	1.47%	0.02 %		0,004 6
Portfolio 3	1.41%	0.03 %		0,008 3
Portfolio 4	1.36%	0.03 %		0,012 3
Portfolio 5	1.33%	0.04 %		0,016 4
Portfolio 6	1.32%	0.04 %	0,01%	0,020 3
Portfolio 7	1.33%	0.05 %		0,023 9
Portfolio 8	1.36%	0.05 %		0,027
Portfolio 9	1.41%	0.06 %		0,029 6
Portfolio 10	1.48%	0.06 %		0,031 6
Portfolio 11	1.56%	0.07 %		0,033 1

Portfolio Number	St.Dev(p)	ER(p)	Risk Free	Sharpe
Portfolio 12	1.66%	0.07%		0.034 1
Portfolio 13	1.77%	0.08%		0.034 9
Portfolio 14	1.88%	0.08%		0.035 4
Portfolio 15	2.01%	0.09 %	0.0001	0.035 7
Portfolio 16	2.16%	0.09%		0.035 6
Portfolio 17	2.31%	0.1%		0.035 3
Portfolio 18	2.49%	0.1%		0.034 8

Table 4 explains that from various efficient portfolios that have been formed, the portfolio that has the best performance is portfolio 15 with a Sharpe ratio value of 0.035 and an expected return value of 2.010% and a risk of 0.085%. Composed of each single asset with a proportion of MDKA shares of 63%, CPIN shares of 7%, BRPT shares of 17%, and ADRO shares of 13%.

This result is in line with the study by Lim et al. (2023) who concluded that optimal Islamic portfolios with moderate risk levels tend to outperform conventional benchmarks in terms of Sharpe ratios, particularly when combining sectors with diverse volatilities.

4.5 Identification of Extreme Values

Extreme value identification is used to determine the existence of extreme values in the extreme value theory approach to selected portfolio return data.

4.5.1 Extreme Data Visualization

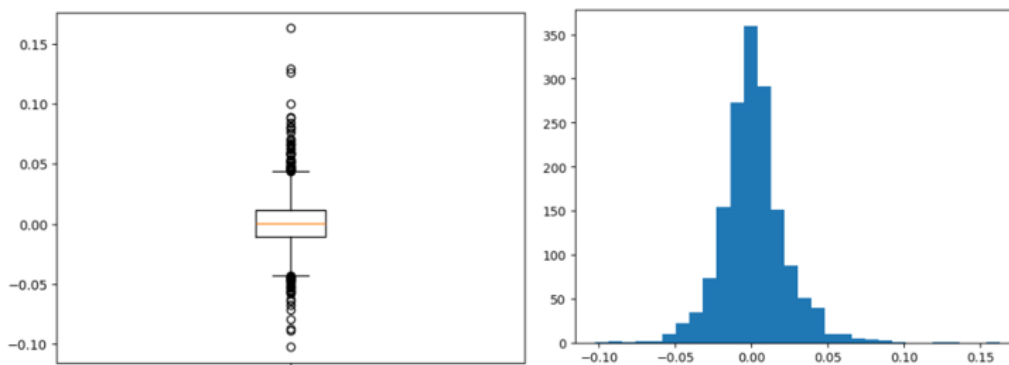


Figure 2. Histogram and Boxplot Identify Extreme Values

Figure 2 visually shows that the distribution of return data tends not to follow a normal distribution, because there is a slow-decreasing distribution tail. so that the histogram shape is not symmetrical, and is identified as having a heavy tail distribution pattern. This is supported by the portfolio return data having a kurtosis value greater than 3, which is 4.934 so that the curve on the histogram is leptokurtic which means it has a sharp peak and a thick tail. The skewness on the histogram is 0.707 which means the distribution is skewed to the right. Based on the boxplot image, it can be seen that the portfolio stock return value has many extreme values. From the extreme values contained in the portfolio return, it will be overcome using the Extreme Value Theory method. In addition, further proof is carried out using a distribution suitability test with its theoretical distribution, the normal distribution.

4.5.2 Normal Distribution Testing

Hypothesis:

$H_0 : F_n(x) = F_0(x)$ (Data is Normally Distributed)

$H_1 : F_n(x) \neq F_0(x)$ (Data is Not Normally Distributed)

Significance level: $\alpha = 0.05$

Rejection Area: Reject H_0 if $D_{\text{value}} > D(\alpha; n)$ or P-Value $< \alpha$

Table 5. Normal Distribution Goodness-of-Fit Test

D_{value}	D_{table}	P - $Value$	Decisio n
e	l		

0.07	0.03	0.000	Reject
6	1		H_0

Table 5 shows that the results of the test of the suitability of the distribution of portfolio return data whether it is normally distributed or not, can be seen that the calculated D_{value} is greater than D_{table} and the P-Value value is smaller than alpha, which means the decision is to reject H_0 with the conclusion that the portfolio return data does not follow its theoretical distribution, namely the GPD distribution.

4.6 Extreme Value Modeling

In this study, the modeling of portfolio returns was preceded by a goodness-of-fit analysis to identify the most appropriate distribution for capturing the extreme behavior of financial returns. Both the Generalized Extreme Value (GEV) and Generalized Pareto Distribution (GPD) models were considered due to their suitability in modeling extreme events in financial data.

4.6.1 Extreme Value Goodness-of-Fit Test

Hypothesis:

$H_0 : F_n(x) = F_0(x)$ (Data is GEV Distributed)

$H_1 : F_n(x) \neq F_0(x)$ (Data is Not GEV Distributed)

Significance level: $\alpha = 0.05$

Rejection Area: Reject H_0 if $D_{\text{value}} > D(\alpha; n)$ or P-Value $< \alpha$

Table 6. GEV Goodness-of-Fit Test

D_{value}	D_{tabel}	<i>P-Value</i>	Decision
0.064	0.075	0.1305	Failed to Reject
9	6		H_0

Hypothesis:

$H_0 : F_n(x) = F_0(x)$ (Data is GPD Distributed)

$H_1 : F_n(x) \neq F_0(x)$ (Data is Not GPD Distributed)

Significance level: $\alpha = 0.05$

Rejection Area: Reject H_0 if $D_{\text{value}} > D(\alpha; n)$ or P-Value $< \alpha$

Table 7. GPD Goodness-of-Fit Test

D_{valu} e	D_{tabe} l	<i>P-Value</i>	Decisio n
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0.30	0.09	0.000	Reject
8	6		H_0

The goodness-of-fit test results presented in Table 6 shows the portfolio return data are consistent with the Generalized Extreme Value (GEV) distribution, as evidenced by a D-statistic lower than the critical value and a P-Value greater than the significance level (α), leading to the failure to reject the null hypothesis. Conversely, Table 7 shows that the portfolio return data do not fit the Generalized Pareto Distribution (GPD), as the D-statistic exceeds the critical value and the P-Value is below α , resulting in the rejection of the null hypothesis. Based on these results, the GEV distribution was selected as the most appropriate model for describing the extreme behavior of portfolio returns. Following the selection of the GEV distribution, parameter estimation was performed to accurately characterize the distribution's shape, scale, and location parameters. These estimated parameters were subsequently utilized to calculate the Value at Risk (VaR), providing a quantitative measure of potential portfolio losses under extreme market conditions.

4.6.2 Parameter Estimation

Table 8. GEV Parameter Estimation

Location (μ)	Scale (σ)	Shape (ξ)
-0.0249	0.0169	0.519

Table 8 shows the results of the portfolio return distribution parameter estimation, with location (μ) -0.0249 as the distribution center, scale (σ) 0.0169 reflecting extreme data variability, and shape (ξ) 0.519 indicating a Frechet-type distribution with heavy tails, indicating a high probability of extreme events. Studies by Tlemsani et al. (2023) have similarly validated GEV as a robust choice for modeling extreme financial returns, especially when dealing with market shocks or tail losses.

4.7 Value at Risk Estimation

Table 9. VaR Estimation

VaR (10%)	VaR (5%)	VaR (1%)
-3.64%	-3.91%	-4.28%

The Value at Risk (VaR) estimation in this study was conducted using the Generalized Extreme Value (GEV) distribution approach, as it was identified as the most appropriate distribution model based on the goodness-of-fit test results. Table 9 shows the level of portfolio investment risk obtained by an investor if the invested funds are worth Rp1,000,000,000. Based on the VaR estimate generated from portfolio investment at a 90% confidence level, it provides a risk level of -3.64%, which means that with 90% confidence, investors are likely to experience a maximum loss of Rp30,640,000. At a 95% confidence level, it provides a result of -3.91%, indicating that with 95% confidence, investors are likely to experience a maximum loss of Rp39,100,000. Likewise, at a 99% confidence level, it provides a risk level of -4.28%,

suggesting that with 99% confidence, investors are likely to experience a maximum loss of Rp42,800,000.

5. CONCLUSION

The study concludes that the optimal sharia-compliant investment portfolio, identified as Portfolio 15, offers the most favorable performance based on the Markowitz mean-variance framework. This portfolio achieves a Sharpe ratio of 0.035, with an expected return of 2.010% and the lowest observed risk at 0.085%. The asset allocation consists of MDKA (63%), CPIN (7%), BRPT (17%), and ADRO (13%), reflecting a well-diversified composition that balances risk and return efficiently.

Goodness-of-fit tests revealed that the Generalized Extreme Value (GEV) distribution best describes the tail behavior of portfolio returns. Using GEV parameters, the Value at Risk (VaR) was calculated, yielding potential loss estimates of -3.64% at a 90% confidence level, -3.91% at 95%, and -4.28% at 99%. These results underscore the importance of integrating modern portfolio optimization with advanced risk modeling techniques, such as EVT, to enhance decision-making and risk management for sharia-compliant investments in volatile markets.

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