

Comparative Multidimensional Risk Analysis of Stock and Cryptocurrency Returns Using Factor Analysis and Logistic Regression

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ABSTRACT



Type: Research Paper

Article:

Received: April 01, 2026

Revised: May 19, 2026

Accepted: August 20, 2026

Issued: October 30, 2026

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This study presents a comparative multidimensional risk analysis of IDX30 stocks and CMC100 cryptocurrencies to examine whether both asset classes exhibit fundamentally different empirical risk-return structures beyond conventional single-indicator measures such as volatility or average return. Daily log returns of 30 IDX30 stocks and 30 CMC100 cryptocurrencies from July 2023 to February 2026 were analyzed using eleven statistical indicators representing distribution moments and extreme tail behavior. Factor analysis was employed to reduce these indicators into latent risk dimensions, followed by binary logistic regression to classify the two asset classes. Portfolio optimization was conducted using the Mean Absolute Deviation approach, while extreme downside risk was evaluated using Historical Value at Risk. The analysis extracted two dominant latent factors, namely the Tail Factor and the Moment Factor, explaining 85.70% of the total variance. Logistic regression identified the Tail Factor as the main distinguishing variable, with confusion matrix evaluation correctly classifying 56 of 60 assets and achieving an accuracy rate of 93.33%. Portfolio optimization results show that a diversified portfolio combining stocks and cryptocurrencies achieved the highest Sharpe ratio, indicating superior risk-return efficiency compared with single-asset portfolios. However, the portfolio remained exposed to significant tail risk under extreme market conditions.

Keywords: *Comparative risk analysis, Stocks, Cryptocurrency assets, Factor analysis, Logistic regression, Portfolio optimization.*

1. INTRODUCTION

Investment instruments in financial markets continue to expand and diversify, with stocks and cryptocurrencies emerging as two of the most widely traded asset classes [1]. Stocks represent ownership claims in publicly listed companies, and their price movements are generally influenced by firm performance as well as broader macroeconomic conditions [2]. In contrast, cryptocurrencies are digital assets built on blockchain technology and do not have a physical underlying asset. Their price dynamics are often driven by market sentiment, technological adoption, and shifts in supply and demand within the digital ecosystem [3]. In this study, the stock market is represented by the IDX30 Index, which reflects large capitalization and highly liquid stocks listed in Indonesia. Meanwhile, the cryptocurrency market is represented by 30 digital assets with relatively high capitalization and liquidity that are included in the CoinMarketCap 100 Index.

The number of investors has also increased substantially in both markets. Data from BAPPEBTI shows that the number of cryptocurrency investors in Indonesia exceeded 21 million by 2024. At the same time, the Indonesia Stock Exchange reported that the number of Single Investor Identification accounts reached 17 million by mid 2025, rising significantly from 3.8 million in 2020. This growth demonstrates increasing public participation in capital markets and digital asset-based investments, making a more comprehensive understanding of the risk and return characteristics of both asset classes increasingly relevant.

Although stocks and cryptocurrencies are both traded as investment instruments, there is no clear consensus on whether they can be viewed as asset classes with comparable risk characteristics. Differences in economic structure and pricing mechanisms between the two could potentially result in different return distribution behaviors [4]. Research shows that cryptocurrencies exhibit risk-return patterns that are not fully explained by traditional asset classes such as stocks, currencies, or commodities [5]. These findings indicate that cryptocurrencies may have a fundamentally different risk structure compared to conventional assets.

One way to examine these differences is by comparing the statistical characteristics of

daily return distributions. A number of studies report that cryptocurrency returns generally show higher volatility, higher kurtosis, and stronger heavy tail behavior than traditional financial assets [6]. In addition, studies focusing on downside risk indicate that estimating Value at Risk for cryptocurrencies often requires more advanced volatility models because of substantial tail risk [7], [8]. These results imply that the traditional two moment framework, which considers only the mean and variance, is not sufficient to fully describe the risk characteristics of cryptocurrency markets.

Another approach in the literature compares the performance of cryptocurrencies with other investment instruments through the evaluation of risk-adjusted returns. A study finds that the volatility of cryptocurrencies is significantly higher than that of Islamic stocks [9], while other studies show that Bitcoin, stocks, and gold exhibit significant differences in performance based on the Sharpe, Treynor, and Jensen ratios [10]. Although these studies provide an overview of differences in risk levels and relative performance, the analyses are generally conducted in a partial manner by focusing on a single indicator or a specific evaluation framework.

In contrast to previous studies, this study proposes a comparative multidimensional risk analysis framework integrating factor analysis, logistic classification, portfolio optimization, and downside risk evaluation. This approach allows the integration of multiple distribution moments within a single analytical framework, enabling the model to capture the complexity of return behavior that is often non-normal and characterized by extreme risk.

Furthermore, logistic regression is used to test whether the resulting risk structure can systematically classify IDX30 stocks and cryptocurrencies from the CMC100 Index into statistically distinct groups. Beyond the classification stage, this study also performs portfolio optimization using the Mean Absolute Deviation approach. This method is considered more robust to non-normal distributions and extreme risk compared with the traditional variance based approach [11], [12]. After obtaining the optimal portfolio, the study estimates Value at Risk at a given confidence level to measure the potential maximum loss that may occur under unfavorable market conditions. This step provides an additional

evaluation of extreme risk exposure from the resulting asset combination [13], [14].

Most previous studies evaluate stocks and cryptocurrencies using isolated indicators such as volatility, Sharpe ratio, or Value at Risk separately, leaving limited understanding of their multidimensional risk structure within an integrated analytical framework. To address this limitation, this study develops a comparative multidimensional framework that integrates latent risk extraction, asset classification, and portfolio evaluation.

This study seeks to answer the following research questions: (1) How can the statistical characteristics of stock and cryptocurrency assets be identified using factor analysis? (2) How effectively can logistic regression classify the two asset classes based on their multidimensional risk characteristics? (3) How can an optimal portfolio consisting of stocks and cryptocurrencies be constructed using the Mean Absolute Deviation (MAD) approach?, and (4)

What is the level of risk associated with the resulting optimal portfolio when measured using Historical Simulation Value at Risk?

Based on these research questions, two hypotheses are proposed. The first hypothesis is that IDX30 stocks and CMC100 cryptocurrencies exhibit statistically significant differences in their empirical risk characteristics. The second hypothesis is that these differences in statistical characteristics have meaningful implications for optimal portfolio construction and the measurement of extreme downside risk.

Therefore, this study aims to evaluate whether IDX30 stocks and cryptocurrencies from the CMC100 Index exhibit statistically different empirical risk structures using a multidimensional approach based on factor analysis and logistic classification, and to assess the implications for optimal portfolio construction and the associated level of extreme downside risk.

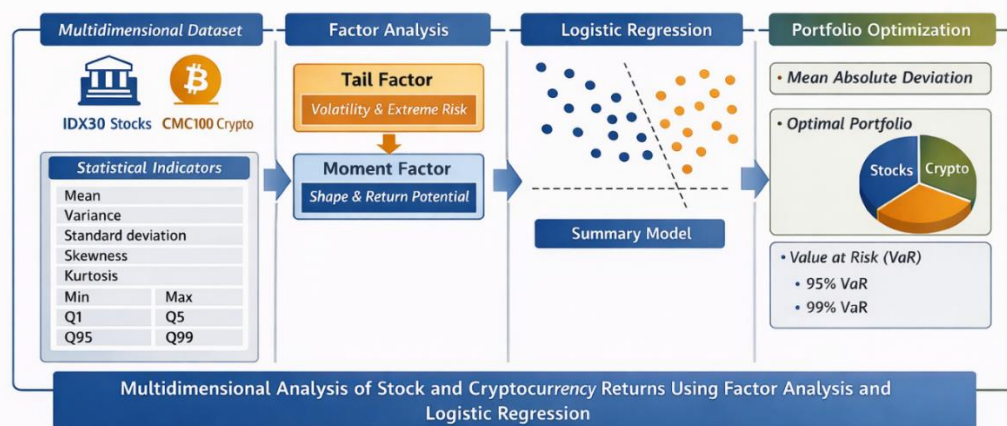


Figure 1. Research Flowchart

Figure 1 shows a flowchart of this research, with four layers used in the stages. Layer 1 describes the formation of a multidimensional dataset used to assess the statistical behavior of the asset's daily log return time series, including indicators such as mean, variance, standard deviation, skewness, kurtosis, minimum, maximum, and extreme quantiles calculated for 30 IDX30 stocks and 30 selected cryptocurrency assets from the CMC100 Index. Layer 2 applies dimensionality reduction and orthogonalization techniques using Exploratory Factor Analysis to extract orthogonal latent factors, maximize explained variance, and represent the multidimensional risk structure contained in the return distribution. Layer 3 uses a classification

2. METHODS

technique, namely binary logistic regression, to test whether the resulting latent factors can systematically differentiate stocks and cryptocurrency assets based on their empirical risk characteristics. Layer 4 evaluates the practical implications of the identified risk structure through portfolio optimization using the Mean Absolute Deviation approach, followed by estimating Value at Risk at a certain confidence level to measure the potential for extreme losses from the optimal portfolio formed.

2.1. Multidimensional Dataset

The initial dataset of this study consists of the daily closing prices of 30 IDX30 stocks and 30 selected cryptocurrency assets from the CMC100 Index, covering the period from 2023/07/17 to 2026/02/11, obtained from the website finance.yahoo.com. The selection of 30 stocks and 30 cryptocurrencies was intended to create a balanced binary classification dataset and to ensure comparability between the two asset classes. The IDX30 Index was chosen because it contains highly liquid and large-capitalization stocks that represent the most actively traded equities in the Indonesia Stock Exchange. Similarly, cryptocurrencies were selected from the CoinMarketCap 100 Index based on their relatively high market capitalization and liquidity. Restricting the sample to 30 assets in each group also maintains a sufficient ratio between the number of observations and the eleven statistical indicators used in the analysis, thereby improving the stability and interpretability of factor analysis and logistic regression estimates.

The observation period from July 17, 2023 to February 11, 2026 was selected to provide a recent and sufficiently long sample that captures a variety of market conditions, including bullish and bearish episodes, while ensuring data availability and consistency across all selected assets. This period spans more than two and a half years and includes major developments in both the Indonesian stock market and the cryptocurrency market, allowing the estimated return distributions to reflect both normal fluctuations and extreme movements.

Since stock data follow exchange trading days and are unavailable on weekends and national holidays, whereas cryptocurrencies are traded continuously, a preprocessing step was conducted by removing cryptocurrency closing prices on non-stock trading days. This procedure ensures a homogeneous sampling frequency and consistent observation dates across all assets. However, this adjustment may lead to information loss because cryptocurrency price movements occurring during weekends are excluded. As a result, extreme returns and tail behavior may be slightly underestimated. This limitation should be considered when interpreting the comparative results, as the analysis focuses on return behavior observed

under a synchronized trading calendar rather than the full 24/7 cryptocurrency market.

Subsequently, log returns were calculated because they are able to stabilize variance and represent proportional price changes over time [15]. To systematically classify stocks and cryptocurrency assets, a set of statistical indicators derived from the distribution of daily log returns was constructed. Suppose there are n assets indexed by time $t \in \{1, \dots, T\}$, then the daily log return of asset i is defined as:

$$R_{i,t} = \log(P_{i,t}) - \log(P_{i,t-1}) \quad (1)$$

where $P_{i,t}$ denotes the closing price on day t . Based on these returns, an indicator matrix $X \in \mathbb{R}^{n \times p}$ is constructed, where p represents the number of statistical indicators used.

First, we employ basic distributional characteristics, which include mean, variance, standard deviation, skewness, kurtosis, as well as minimum and maximum values. Mean and variance describe the central tendency and dispersion, while skewness and kurtosis capture asymmetry and tail thickness of the distribution [16], [17]. The literature shows that cryptocurrency returns tend to be asymmetric and leptokurtic compared with traditional assets, making distribution moments relevant for distinguishing risk structures [18], [19].

Second, extreme quantiles $Q_{0.01}, Q_{0.05}, Q_{0.95}, Q_{0.99}$ are used to explicitly capture tail behavior in the distribution. Left tail quantiles represent downside risk and can be associated with the concept of Value at Risk, while right tail quantiles reflect the potential for extreme upward movements [20], [21]. Quantile based approaches have been shown to be more informative in identifying risk under extreme market conditions compared with mean based approaches [20], [21]. Thus, a total of 11 indicators are employed, most of which focus on measuring risk within the return distribution. This study specifically focuses on distinguishing assets based on the characteristics of their underlying log return distributions. Therefore, the selected indicators primarily represent risk dimensions, both in the overall distribution structure and in the tail regions associated with extreme movements.

2.2. Dimensionality Reduction

Common methods used to reduce dimensionality and extract meaningful

information from high-dimensional datasets are Principal Component Analysis (PCA) and Factor Analysis (FA). Factor Analysis is designed to identify latent structures that encompass a set of overlapping variables so that a large number of indicators can be reduced to a few representative factors without losing meaningful information [24]. Furthermore, comparative studies have shown that FA is not only effective as a dimensionality reduction technique, but under certain conditions, it can perform better than PCA in maintaining the discriminatory ability of data after reduction [25]. The use of FA is also widely recommended when the research objective is complex data infrastructure while maintaining the interpretability of latent factors [26]. Therefore, this study uses factor analysis to reduce return distribution indicators before the asset classification stage is carried out.

2.3. Asset Classification

To separate assets based on their characteristics, this study uses Binary Logistic Regression as a classification method. Logistic regression has been widely used in financial research to examine the influence of variables on the probability of an event and to interpret the direction and magnitude of the influence through coefficients and odds ratios [27]. In the context of the crypto markets, this model is also used as a classification approach based on historical return characteristics [28]. Thus, this method is not only capable of binary classification but also provides an inferential basis for explaining the factors that statistically differentiate asset groups.

The logistic regression model was estimated using maximum likelihood estimation. Model performance was evaluated using a confusion matrix and several classification metrics, including accuracy, precision, recall, and F1-score, to assess the model's ability to distinguish between stock and cryptocurrency assets based on the extracted latent risk factors.

This study primarily adopts an exploratory and comparative framework based on descriptive statistics, factor analysis, and logistic classification. Formal statistical tests for comparing distributions, such as independent sample t-tests, Mann-Whitney U tests, and Kolmogorov-Smirnov tests, were not conducted for each indicator. Therefore, the

observed differences between stocks and cryptocurrencies should be interpreted as empirical patterns rather than definitive evidence of statistically significant differences for every individual metric.

2.4. Portfolio optimization

Portfolio optimization in this study is based on the Mean Absolute Deviation (MAD) model introduced by Konno and Yamazaki as an alternative to the Mean Variance model proposed by Markowitz [29]. MAD model measures risk as the average absolute deviation of returns from their expected value, so it does not require a covariance matrix and does not rely on the assumption of normally distributed returns [18], [30]. The expected return of asset i is calculated as

$$E(R_i) = \frac{1}{T} \sum_{t=1}^T R_{it} \quad (2)$$

The risk of each asset is measured using

$$MAD_i = \frac{1}{T} \sum_{t=1}^T |R_{it} - E(R_i)| \quad (3)$$

The optimization model is formulated as a linear programming problem with the objective of minimizing $\sum_{i=1}^n MAD_i w_i$, subject to the constraints $\sum_{i=1}^n E(R_i) w_i \geq R_{min}$, $\sum_{i=1}^n w_i = 1$, and $0 \leq w_i \leq u_i$. Because the formulation is linear, the problem can be solved using the simplex method [11]. Empirical studies indicate that the MAD model is computationally more efficient than variance based models and tends to be more robust when the return distribution is not normal. This characteristic makes it suitable for stock and cryptocurrency returns, which often exhibit high skewness and kurtosis [12].

After the optimal weights are obtained, portfolio performance is evaluated using the Sharpe Ratio to determine the best portfolio. The expected portfolio return is calculated as $E(R_p) = \sum_{i=1}^n w_i E(R_i)$, while portfolio risk is measured by the standard deviation of portfolio returns. The Sharpe Ratio is defined as

$$S = \frac{E(R_p) - R_f}{\sigma_p} \quad (4)$$

where R_f denotes the risk free rate and σ_p represents portfolio risk. The optimal portfolio is the one with the highest Sharpe Ratio because it provides the largest excess return per unit of total risk [31]. In addition, extreme risk is measured using Historical Value at Risk based on the historical simulation approach [32], [33]. The portfolio return series is sorted from the largest loss to the largest gain,

after which the α -percentile is determined using $P_\alpha = \alpha \times n$. For an initial investment V_0 , confidence level $1 - \alpha$, and holding period T days, Value at Risk is calculated as

$$\text{VaR} = -V_0 \times P_\alpha \times \sqrt{T} \quad (5)$$

The value P_α represents the return percentile at significance level α , which is typically negative. Therefore, VaR provides an estimate of the maximum potential loss that may occur at a given confidence level without relying on parametric distribution assumptions [34], [35].

In addition, this study does not compare the predictive and classification performance of the proposed framework with alternative methods such as Principal Component Analysis, Support Vector Machines, Random Forests, Conditional Value at Risk, or GARCH-based models. Consequently, the findings should be interpreted as evidence of the internal effectiveness of the proposed approach rather

than as proof of superiority over other analytical techniques.

3. RESULTS AND DISCUSSION

3.1. Comparative Statistical Characteristics of Returns

Daily closing price data for stock and cryptocurrency assets was obtained. The initial data processing step was to calculate the log return for each asset. Next, the resulting log returns were analyzed using 11 statistical indicators that comprehensively reflect the characteristics of return distributions: mean, variance, standard deviation, lower and upper extreme quantiles, skewness, kurtosis, and minimum and maximum values. To obtain a representation of the characteristics of each asset, these indicator values were then averaged across the stock and cryptocurrency asset groups.

Table 1. Statistic Descriptive

Asset	Mean	Variance	Standard Deviation	Skewness	Kurtosis	Min	Max
Stock	0.000164	0.000661	0.024628	0.046996	7.915922	-0.131052	0.119846
Crypto	0.000575	0.003496	0.056840	0.950996	21.627130	-0.308785	0.412854

Table 2. Quantile Extreme

Asset	Q1	Q5	Q95	Q99
Stock	-0.061572	-0.035778	0.040582	0.070005
Crypto	-0.145255	-0.075074	0.085262	0.158689

Based on tables 1 and 2, cryptocurrency assets exhibit higher average returns than stocks, but are accompanied by substantially greater levels of risk, reflected in higher variance and standard deviation. The relatively high positive skewness values for

cryptocurrency assets indicate a rightward asymmetric return distribution, while very high kurtosis values indicate strong tail risk. Conversely, stocks exhibit a more symmetric return distribution with lower kurtosis, reflecting greater relative stability. These differences suggest that the return distributions of both asset classes exhibit non-normal characteristics and contain information about extreme risks that cannot be captured by a single risk indicator [36].

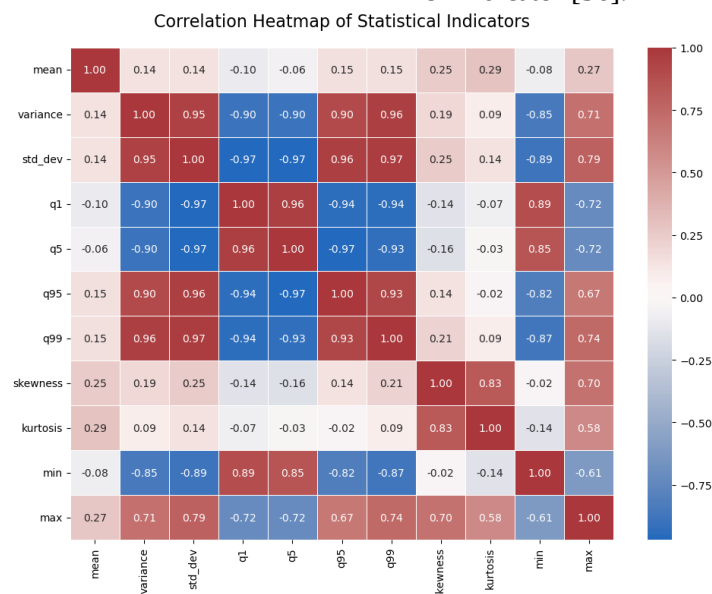


Figure 2. Heatmap of Statistical Indicator Correlations

Based on Figure 2, the results of the correlation test between statistical indicators indicate a very strong correlation between several key indicators. Variance and standard deviation have a positive correlation approaching one, indicating that they convey nearly identical risk information. The upper extreme quantiles q95 and q99 also show a high correlation with variance and standard deviation, while the lower extreme quantiles q1 and q5 have a strong negative correlation with these risk indicators. Furthermore, skewness and kurtosis have a relatively high correlation with each other, indicating a link between asymmetry and tail thickness of the return distribution. The high correlation between these indicators indicates information redundancy, so the simultaneous use of all indicators has the potential to cause multicollinearity. Therefore, dimensionality reduction is a crucial step in extracting latent factors that more efficiently represent the risk structure and return distribution without losing key information, while simultaneously improving the stability and interpretability of further analysis in optimal portfolio formation.

3.2. Multidimensional Risk Structure Extraction

Factor analysis was used to identify the latent structure among eleven log return statistical indicators, with the aim of reducing dimensionality without losing key information. The initial stage was carried out by estimating the correlation matrix between all indicators, then extracting factors based on eigenvalues, and rotating factors to obtain a more interpretable loading structure. The sample fit test showed a KMO value of 0.7645, which is above the minimum limit of 0.5, so the data was deemed adequate for factor analysis [37]. In addition, the results of the Bartlett test produced a Chi-Square value of 1311.9870 which was significant, indicating that the correlation matrix was not in the form of an identity matrix and there was sufficient correlation between the variables to be extracted into latent factors. Thus, factor analysis is suitable for detecting the structure of risk dimensions and return distribution. Based on the Kaiser criterion, factors retained are those with an eigenvalue greater than one. Figure 3 shows that two factors meet this criterion, so two main factors were selected. To obtain a clearer factor structure and minimize cross-loading between variables, Varimax orthogonal rotation was used.

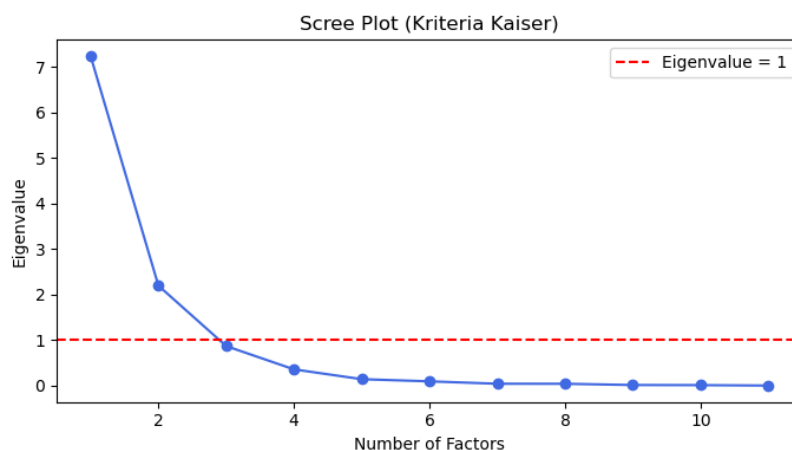


Figure 3. Scree plot eigen Value

Based on the loading pattern in Figure 4, the following interpretations can be made: 1) Factor 1 can be interpreted as the Tail Risk Factor. This factor has very high loadings on variance, standard deviation, lower extreme quantiles (q1, q5), upper extreme quantiles (q95, q99), and the minimum value. This pattern indicates that the first factor captures the dimensions of volatility and extreme risk, both

on the loss and gain side. High factor values reflect greater volatility intensity and the probability of extreme events; and 2) Factor 2 can be interpreted as the Moment Factor. This factor has dominant loadings on skewness, kurtosis, mean return, and maximum value. This structure indicates that the second factor represents the characteristics of the distribution shape and potential returns [38]. The factor

labels are interpretive and exploratory in nature, based on the dominant loading structure rather than confirmatory factor analysis. High factor

values indicate a more asymmetric, heavy-tailed distribution and a greater opportunity for high returns.

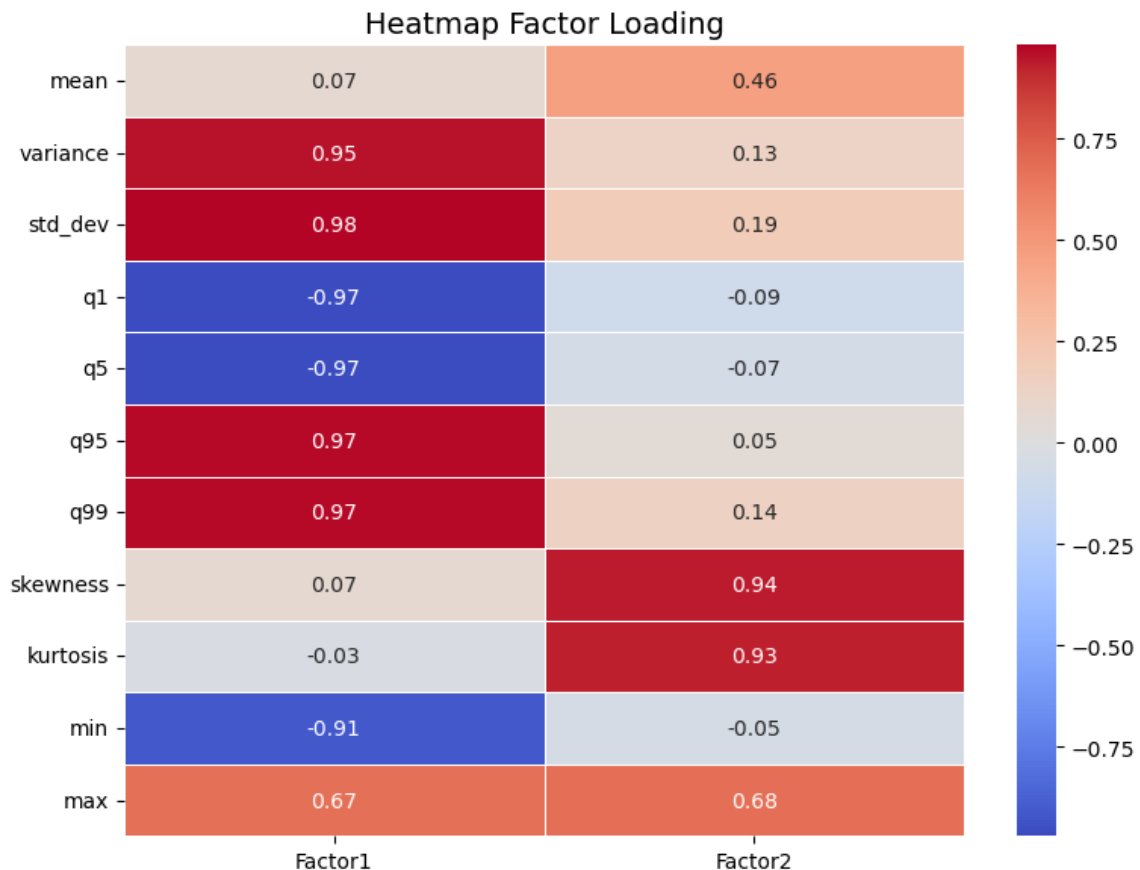


Figure 4. Heatmap Loading Factor

Table 3. Cumulative Variance

Factor	Eigenvalue	Variance Explained (%)	Cumulative (%)
Factor1	6.91	62.86	62.86
Factor2	2.51	22.84	85.70

Based on Table 3, Factor 1 explains 62.86 percent of the total variation, while Factor 2 explains an additional 22.84 percent of the variation, so that cumulatively, the two factors are able to represent 85.70 percent of the overall variation in the statistical indicators. This value indicates that the reduction of eleven indicators to two latent factors still retains most of the information contained in the data. Therefore, the use of these two factors is sufficient to represent the risk structure and characteristics of the return distribution.

3.3. Comparative Asset Classification

Asset classification is performed using a Binary Logistic Regression model with the dependent variable Y_i , where $Y_i = 1$ represents cryptocurrency assets and $Y_i = 0$ represents

stocks. The independent variables consist of two orthogonal factors obtained from factor analysis, namely F_1 (Tail Factor) and F_2 (Moment Factor).

Table 4. Summary Model Logistic regression

Variable	Coefficient (Std. Error)	z-stat	p-value
Const	1.301 (1.001)	1.300	0.194
Factor1	5.312*** (1.614)	3.290	0.001
Factor2	3.249 (2.186)	1.486	0.137
Observations	60		
Pseudo R ²	0.782		

Table 4 shows that the factor that is statistically significant in separating an asset is Factor1 (Tail Factor). The coefficient is 5.312 with z-value of 3.290 and p-value of 0.001, indicating significance at the 1 percent level. The positive sign of the coefficient indicates that the higher the dimension of extreme risk and volatility of an asset, the greater the probability that the asset is classified as cryptocurrency. This finding confirms that tail risk characteristics and extreme fluctuations are

the main distinguishing factors between stocks and cryptocurrency in the model [39].

In contrast, Factor 2 (Moment Factor) is not statistically significant because it has a p-value of 0.137, which is greater than the 5 percent significance level. Although the direction of the coefficient is positive, its contribution to distinguishing the two asset classes is not empirically strong. Thus, distribution moment characteristics such as mean, skewness, and kurtosis are not the main determinants in the classification process in this study.

From the perspective of model fit, the Pseudo R^2 value of 0.782 indicates a very good level of goodness of fit. This value suggests that approximately 78 percent of the variation in the probability of asset classification can be explained by the two latent factors in the model. Although this measure is not identical to the R^2 in linear regression, its high value strengthens the finding that the model has a strong ability to distinguish between stocks and cryptocurrency, particularly through the dominant role of the Tail Factor as a significant variable.

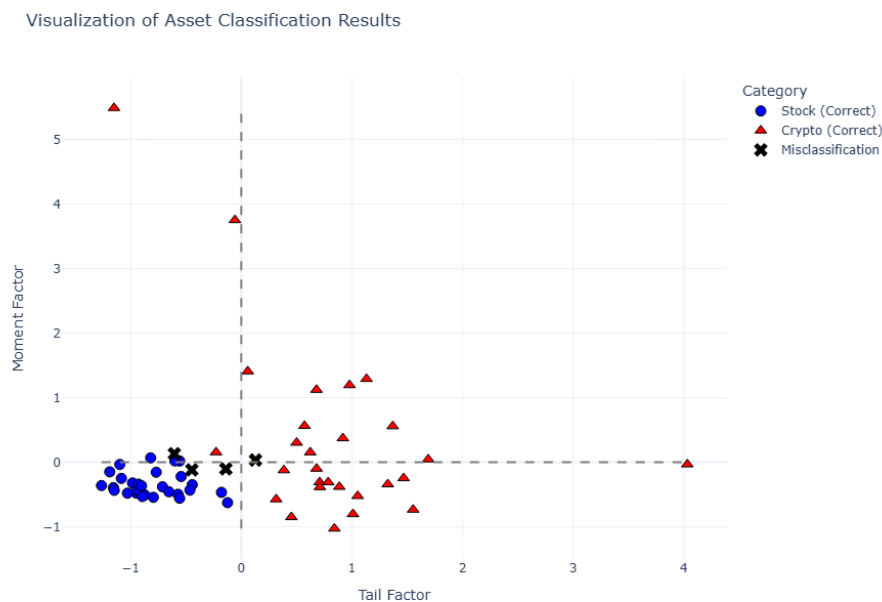


Figure 5. Asset Classification Visualization

Figure 5 shows that stocks and cryptocurrencies are relatively clearly separated in the area formed by the Tail Factor and Moment Factor. Stocks are concentrated in areas with a low Tail Factor, reflecting a more controlled level of extreme risk. Conversely, cryptocurrencies are dominant in areas with a high Tail Factor, indicating greater volatility and tail risk. This pattern reinforces the logistic regression results that the Tail Factor is a key dimension in asset separation.

If the Tail Factor and Moment Factor areas are divided into four quadrants, each quadrant reflects a distinct risk and return profile: 1) Quadrant I (High Tail, High Moment). Assets with high extreme risk but

high potential returns. An aggressive and speculative profile; 2) Quadrant II (Low Tail, High Moment). Low extreme risk but relatively high potential returns. Assets in this quadrant are attractive because they offer a balance between risk and return; 3) Quadrant III (Low Tail, Low Moment). Dominated by stocks. Relatively low risk and moderate returns, reflecting a defensive profile; 4) Quadrant IV (High Tail, Low Moment). Extremely high risk but relatively low potential return, making it less efficient in terms of risk-return.

Table 5. Confusion Matrix

True \ Predicted	Crypto	Stock
Cryptocurrency	28	2
Stock	2	28

Table 6. *Misclassified Asset Observations*

Asset	True	Predicted	Prob (Crypto)	Factor1	Factor2
MBMA.JK	Stock	Cryptocurrency	0.556	-0.139	-0.103
BRPT.JK	Stock	Cryptocurrency	0.891	0.129	0.035
LEO-USD	Cryptocurrency	Stock	0.185	-0.605	0.132
BTC-USD	Cryptocurrency	Stock	0.189	-0.447	-0.118

Based on Table 5, the model was able to correctly classify 56 of the 60 assets, with an accuracy rate of 93.33 percent. The error rate was relatively small and balanced across classes, indicating that the model was not biased toward one category. Furthermore, based on Table 6, prediction errors occurred in assets located around the dividing line between the two classes in the factor field. These assets have risk and return characteristics that are relatively similar to other classes, making it difficult for the model to clearly distinguish them. For example, some misclassified stocks had relatively higher Tail Factor values than other stocks, approaching the characteristics of cryptocurrencies. Conversely, some misclassified cryptocurrencies had lower Tail Factors than the majority of other cryptocurrencies. Because the sample consists of only 60 assets and no alternative classification models were tested, the reported accuracy should be interpreted as evidence of strong exploratory discrimination rather than definitive predictive superiority.

3.4. Portfolio Optimization

The initial portfolio is formed by grouping assets into four quadrants, formed from a combination of Tail Factor and Moment Factor. Each quadrant represents different risk characteristics and potential returns, allowing for more structured asset segmentation. For the initial optimization phase, assets selected from each quadrant are those with positive expected returns, with the goal of ensuring that the portfolio meets the basic investment principle of providing an expected return greater than zero.

After identifying assets with expected returns greater than zero in each quadrant, the next step is to calculate the Mean Absolute Deviation and expected return for each selected asset. Once these two metrics are obtained, the next step is to determine the minimum portfolio return by calculating the average expected return of all assets in the relevant quadrant. This average value is used as the minimum return limit in the portfolio optimization process, ensuring that the resulting asset combination

still meets a reasonable return target. The results of the Expected Return and MAD calculations are shown in Tables 7-10.

Table 7. *Portfolio 1*

Portfolio 1		
Asset	Expected Return	MAD
BRPT.JK	0.002	0.030
XRP-USD	0.001	0.034
DOGE-USD	0.0004	0.040
XLM-USD	0.0003	0.034
BCH-USD	0.001	0.034
HBAR-USD	0.001	0.044
CRO-USD	0.0004	0.036
TAO22974-USD	0.001	0.055
ZEC-USD	0.003	0.046
BGB-USD	0.003	0.028

Table 8. *Portfolio 2*

Portfolio 2		
Asset	Expected Return	MAD
ADRO.JK	0.0012	0.0174
AKRA.JK	0.0002	0.0164
MEDC.JK	0.0011	0.0212
BNB-USD	0.0015	0.0243
TRX-USD	0.0020	0.0184
LEO-USD	0.0012	0.0148
OKB-USD	0.0008	0.0277

Table 9. *Portfolio 3*

Portfolio 3		
Asset	Expected Return	MAD
ANTM.JK	0.0013	0.0202
ASIL.JK	0.0004	0.0132
BBNI.JK	0.0002	0.0143
BMRI.JK	0.0002	0.0142
EXCL.JK	0.0008	0.0159
INCO.JK	0.0001	0.0217
INKP.JK	0.0001	0.0191
ISAT.JK	0.0001	0.0198
ITMG.JK	0.0003	0.0096
JPFA.JK	0.0012	0.0193
PGAS.JK	0.0011	0.0134
PTBA.JK	0.0003	0.0112
TLKM.JK	0.0001	0.0150
UNTR.JK	0.0006	0.0137
BTC-USD	0.0013	0.0223

Table 10. *Portfolio 4*

Portfolio 4		
Asset	Expected Return	MAD
ETH-USD	0.00002	0.03020
SOL-USD	0.00177	0.04118
LINK-USD	0.00024	0.04173
SUI20947-USD	0.00035	0.04926
MNT27075-USD	0.00031	0.03876
XMR-USD	0.00118	0.02801
AAVE-USD	0.00058	0.04348
PEPE24478-USD	0.00113	0.05654

To obtain the investment weight of each stock using the MAD portfolio model, the simplex method can be used by compiling an equation consisting of an objective function and a constraint function.

Portfolio 1

Minimize:

$$\sigma(W_1) = 0.030w_1 + 0.034w_2 + 0.040w_3 + 0.034w_4 + 0.034w_5 + 0.044w_6 + 0.036w_7 + 0.055w_8 + 0.046w_9 + 0.028w_{10}$$

with constraints

$$0.0018w_1 + 0.001w_2 + 0.0004w_3 + 0.0003w_4 + 0.0012w_5 + 0.0009w_6 + 0.0004w_7 + 0.0013w_8 + 0.0033w_9 + 0.0026w_{10} \geq 0.0013$$

$$w_1 + w_2 + w_3 + w_4 + w_5 + w_6 + w_7 + w_8 + w_9 + w_{10} = 1$$

$$0 \leq w_i \leq 0.3, i = 1, 2, \dots, 10$$

Portfolio 2

Minimize :

$$\sigma(W_2) = 0.0174w_1 + 0.0164w_2 + 0.0212w_3 + 0.0243w_4 + 0.0184w_5 + 0.0148w_6 + 0.0277w_7$$

with constraints

$$0.0012w_1 + 0.0002w_2 + 0.0011w_3 + 0.0015w_4 + 0.0020w_5 + 0.0012w_6 + 0.0008w_7 \geq 0.0011$$

$$w_1 + w_2 + w_3 + w_4 + w_5 + w_6 + w_7 = 1$$

$$0 \leq w_i \leq 0.3, i = 1, 2, \dots, 7$$

Portfolio 3

Minimize:

$$\sigma(W_3) = 0.0202w_1 + 0.0132w_2 + 0.0143w_3 + 0.0142w_4 + 0.0159w_5 + 0.0217w_6 + 0.0191w_7 + 0.0198w_8 + 0.0096w_9 + 0.0193w_{10} + 0.0134w_{11} +$$

$$0.0112w_{12} + 0.0150w_{13} + 0.0137w_{14} + 0.0223w_{15}$$

with constraints

$$0.0013w_1 + 0.0004w_2 + 0.0002w_3 + 0.0002w_4 + 0.0008w_5 + 0.0001w_6 + 0.0001w_7 + 0.0001w_8 + 0.0003w_9 + 0.0012w_{10} + 0.0011w_{11} + 0.0003w_{12} + 0.0001w_{13} + 0.0006w_{14} + 0.0013w_{15} \geq 0.0005$$

$$w_1 + w_2 + w_3 + w_4 + w_5 + w_6 + w_7 + w_8 + w_9 + w_{10} + w_{11} + w_{12} + w_{13} + w_{14} + w_{15} = 1$$

$$0 \leq w_i \leq 0.3, i = 1, 2, \dots, 15$$

Portfolio 4

Minimize:

$$\sigma(W_4) = 0.03020w_1 + 0.04118w_2 + 0.04173w_3 + 0.04926w_4 + 0.03876w_5 + 0.02801w_6 + 0.04348w_7 + 0.05654w_8$$

with constraints

$$0.00002w_1 + 0.00177w_2 + 0.00024w_3 + 0.00035w_4 + 0.00031w_5 + 0.00118w_6 + 0.00058w_7 + 0.00113w_8 \geq 0.0007$$

$$w_1 + w_2 + w_3 + w_4 + w_5 + w_6 + w_7 + w_8 = 1$$

$$0 \leq w_i \leq 0.3, i = 1, 2, \dots, 8$$

After all objective functions and constraints are formulated in linear programming form, the optimal weights are determined using the simplex method. The computational process is completed with the help of the Python library, which uses the HiGHS solver for linear programming problems to efficiently obtain optimal solutions according to the established MAD model.

Table 11. Portfolio Optimization Results

Portfolio	Asset	Weight	Expected return	Sharpe ratio	MAD
1	BRPT.JK	0.3	0.0016	0.045	0.031
	XRP-USD	0.3			
	XLM-USD	0.1			
	BGB-USD	0.3			
2	ADRO.JK	0.3	0.0011	0.052	0.016
	AKRA.JK	0.23			
	TRX-USD	0.17			
	LEO-USD	0.3			
3	ASIL.JK	0.17	0.0005	0.023	0.011
	ITMG.JK	0.3			
	PGAS.JK	0.23			
	PTBA.JK	0.3			
4	ETH-USD	0.3	0.0007	0.014	0.033
	SOL-USD	0.15			
	MNT27075-USD	0.25			
	XMR-USD	0.3			

Table 11 shows the optimal weighting of each asset in each portfolio based on the MAD model with a minimum return constraint and a maximum weight limit of 30 percent. Portfolio 1 consists of a combination of one stock and three cryptocurrencies, namely BRPT.JK, XRP-USD, XLM-USD, and BGB-USD, with an expected return of 0.0016 and a MAD value of 0.031, and a Sharpe ratio of 0.045. Portfolio 2 is also a combination of stocks and cryptocurrencies consisting of ADRO.JK, AKRA.JK, TRX-USD, and LEO-USD, with an expected return of 0.0011, a MAD value of 0.016, and a Sharpe ratio of 0.052. Portfolio 3 contains entirely stocks, namely ASII.JK, ITMG.JK, PGAS.JK, and PTBA.JK, with an expected return of 0.0005, a MAD of 0.011, and a Sharpe ratio of 0.023. Meanwhile, Portfolio 4 consists entirely of crypto assets: ETH-USD, SOL-USD, MNT27075-USD, and XMR-USD, with an expected return of 0.0007, MAD of 0.033, and a Sharpe ratio of 0.014.

Based on the Sharpe ratio comparison, Portfolio 2 is the best portfolio, having the highest Sharpe ratio of 0.052. This indicates that Portfolio 2 provides the highest excess return per unit of risk compared to other portfolios. Its composition, combining stocks and crypto, allows for more optimal risk diversification than portfolios containing only stocks or only crypto. Therefore, in terms of risk-return trade-off, Portfolio 2 can be considered the most efficient asset combination in this study. Although the Sharpe ratio of 0.052 is relatively modest in absolute financial terms, it remains the highest among all portfolios evaluated, indicating superior relative efficiency within the sample.

Once the optimal portfolio is obtained, its Value at Risk is calculated using a Historical Simulation approach to measure the maximum potential loss at a given confidence level. Based on the optimization results, Portfolio 2 is the best portfolio, with a VaR of 0.019996 at the 95 percent confidence level and 0.034955 at the 99 percent confidence level. These values indicate that under normal market conditions, the maximum potential daily loss will not exceed approximately 1.9996 percent of the investment value at a 95 percent confidence level. In a more extreme scenario with a 99 percent confidence level, the maximum potential daily loss is estimated to not exceed approximately 3.4955 percent. These results indicate that although Portfolio 2 has the best risk-return efficiency, it

still has significant exposure to tail risk, in line with the characteristics of crypto which has high volatility and tail risk [40]. Future studies may compare these results with alternative tail-risk measures such as Conditional Value at Risk (CVaR) and GARCH-based models to further assess portfolio robustness.

CONCLUSION

The results of this study suggest that IDX30 stocks and CMC100 Index crypto assets exhibit substantial differences in their observed risk characteristics. Descriptively, crypto has a mean return of 0.000575, higher than stocks at 0.000164, but accompanied by a variance of 0.003496 and a standard deviation of 0.056840, much greater than stocks which only have a variance of 0.000661 and a standard deviation of 0.024628. The difference is increasingly clear in the distribution tail dimension, where crypto kurtosis reaches 21.627130 compared to stocks at 7.915922. The extreme lower quantile of crypto in Q1 of -0.145255 and Q5 of -0.075074 indicates a greater downside risk than stocks at -0.061572 and -0.035778 , respectively. Factor analysis results indicate that two main factors explain 85.70 percent of the total variation, with Factor 1, or Tail Factor, explaining 62.86 percent and Factor 2, or Moment Factor, explaining 22.84 percent. Factor visualization shows that stocks are concentrated in the low Tail Factor region, while crypto is more dispersed in the high Tail Factor region. Logistic regression results support this finding with a Pseudo R^2 value of 0.7818 and a significant Tail Factor coefficient at $p = 0.001$, indicating that the extreme risk dimension is the main differentiator between stocks and crypto. This study suggests that a comparative multidimensional framework provides deeper insight into cross-asset risk structures than conventional single-indicator approaches.

The practical implications of these differences in risk structure are reflected in the results of portfolio optimization based on Mean Absolute Deviation. The best portfolio was obtained by Portfolio 2 with a Sharpe ratio of 0.052, higher than Portfolio 1 (0.045), Portfolio 3 (0.023), and Portfolio 4 (0.014). Portfolio 2, consisting of a combination of two stocks and two cryptocurrencies, has an expected return of 0.0011 and a MAD of 0.016, demonstrating a

more balanced risk-return efficiency than a single portfolio. Measuring extreme risk using Historical Value at Risk indicates that at a 95 percent confidence level, the optimal portfolio's maximum potential daily loss is 0.019996, while at a 99 percent confidence level, it is 0.034955. This means that under unfavorable market conditions, daily losses are expected to not exceed approximately 1.9996 percent at a 95 percent confidence level and 3.4955 percent at a 99 percent confidence level. These findings confirm that while the combination of stocks and cryptocurrencies can improve portfolio efficiency, exposure to tail risk remains significant and requires careful management. Although the selected portfolio achieved the highest Sharpe ratio within the sample, its absolute magnitude remains modest, indicating that the economic benefits should be interpreted cautiously.

The findings should be interpreted within the limitations of a relatively small sample, a fixed observation period, and the absence of alternative classification and risk models. Future research may extend this framework by incorporating longer observation periods, out-of-sample validation, alternative classification methods such as Support Vector Machines and Random Forests, and advanced tail-risk models including Conditional Value at Risk (CVaR) and GARCH-based approaches.

DECLARATIONS

Author Contributions: All authors contributed to the research and preparation of this manuscript. The first author conducted the data collection, data curation, and formal analysis. The second author contributed to the research methodology and interpretation of the results. The third author provided supervision and contributed to reviewing and editing the manuscript. The research was conducted under the guidance and supervision of the academic advisor(s). All authors reviewed and approved the final version of the manuscript.

Funding: This research received no external funding.

Conflict of Interest: The authors declare no conflict of interest.

Generative Artificial Intelligence Use Statement: Generative AI was not used to generate research data, conduct data analysis, interpret research findings, or draw scientific conclusions. The authors take full responsibility for the originality, accuracy, integrity, citations, analysis, interpretation, and conclusions presented in this manuscript.

Ethics Approval and Informed Consent: Not applicable. This study used secondary financial market data obtained from publicly accessible sources and did not involve human participants or require informed consent.

Data Availability: The data supporting the findings of this study consist of historical daily closing prices of stocks and cryptocurrencies obtained from Yahoo Finance (<https://finance.yahoo.com>), covering the period from July 17, 2023, to February 11, 2026. The selected cryptocurrency assets were drawn from the CoinMarketCap 100 Index. No supplementary dataset was made publicly available as part of this study.

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